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Performance Evaluation of Fuzzy Logic and DQN for Energy Optimization in WSNs with variable BS positions

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Abstract
Wireless Sensor Networks (WSNs) play an im-portant role in Internet of Things (IoT) appli-cations because they enable continuous envi-ronmental monitoring and data collection. Nu-merous previous studies introduced clustering and routing algorithms for efficient data trans-fer in WSN. However, they still face issues such as high latency, minimum network life-time, high energy consumption, and commu-nication delay. To address these issues, this study proposes a novel Energy-Aware Cluster Optimization Routing (EACO-R) protocol. Ini-tially, Fuzzy Enhanced Hierarchical Clustering (FEHC) is utilized to generate stable and bal-anced clusters by accounting for uncertainty in sensor node distribution. The best cluster heads are then selected by an Adaptive Levy Mutation-based Dynamic Enzyme Action Op-timizer (ALM-DEAO) employing residual en-ergy, local node density, and Euclidean dis-tance to the base station. Finally, the Multi-Head Attention-assisted Dynamic Priority Ad-justment Deep Q-Network (MHA-DPA-DQN) creates adaptive energy-aware routing paths de-pending on residual energy, connection stability, transmission distance, and network congestion. The simulation results demonstrate that the pro-posed model obtained 42.4J in energy consumption analysis, which is lower than the existing approach.

1. Introduction

The WSN consists of various collaborating components that facilitate data gathering, pro-cessing and communication [1] [2]. The sensor node is the fundamental building block, consist-ing of a sensing unit for collecting environmen-tal data, a processing unit for analyzing the in-formation, and a communication unit for wire-lessly transmitting the information to a base sta-tion or other network nodes [3]. These sen-sor nodes are typically small, low-power de-vices with sensors for motion, light, humidity, and temperature [4]. Maintaining long term net-work functionality is crucial for WSN develop-ers. Sensors may now be used in a variety of industries, including the military, medical care, transport, and protection [5]. As a result, creat-ing energy-saving methods has transformed the condition of the arts during the last two decades. To create a stochastic routing framework, these small devices collect data and send it over the entire network using a routing algorithm that primarily uses WSN capabilities [6]. The ex-isting data mining techniques have been altered, and new algorithms have been developed to han-dle the data produced by sensor networks [7]. Over the past decade, a multitude of knowl-edge discovery techniques, strategies and algo-rithms have been developed. The majority of the proposed protocols attempted to extend the net-work's lifespan by balancing the energy usage of the sensor network and the power consump-tion of the sensor battery across the multi-hop data allocation pattern of flat and structured net-works [8]. When applied to on-sensor data, a va-riety of algorithm techniques, including cluster-ing and common patterns, have proven effective. However, the current design and deployment of the sensor network present unique research ob-stacles due to its vast scale, restricted energy supply, loss of interaction context, unsafe instal-lation, and elevated failure probability [9]. One of the most critical issues with WSN is data col-lecting, which is one of, if not the most energy-intensive, procedures that limits the network's lifespan. In order to accomplish this, they intend to develop a novel strategy in this study that will increase the network lifespan in terms of power, capacity, overall energy, and resource utilization in the given network [10].

1.1. Motivation

Existing clustering and routing algorithms pri-oritize energy-efficient routing, but they still face issues such as high computational over-head, communication delay between nodes, ex-cessive latency, and a short network lifetime. Furthermore, many contemporary models lack cognitive learning algorithms capable of dynamically identifying energy-efficient paths while reducing transmission overhead. By motivating these concerns, this study presented an EACO-R methodology that incorporates FEHC for sta-ble cluster formation. ALM-DEAO for opti-mal CH selection; MHA-DPA-DQN for adap-tive routing. The proposed framework differs in that it combines fuzzy clustering, bio-inspired optimization, and attention-based DRL learning to create unified routing characteristics that bal-ance energy use, increase network lifespan, and improve speed and reliability beyond existing WSN routing protocols. The planned study's contributions include the following:

- To create clusters by using the Fuzzy En-hanced Hierarchical Clustering (FEHC) al-gorithm, which creates the cluster.
- To select the CHs by using Adaptive Levy Mutation based Dynamic Enzyme Action Optimizer (ALM-DEAO) based on local node density, residual energy, as well as Euclidean distance to the BS.
- To find the energy-aware route by using Multi-Head Attention assisted Dynamic Priority Adjustment with Deep Q-Network (MHA-DPA-DQN), which establishes both inter and inter-cluster data transmission paths to minimize communication over-head.

The paper organization for this investigation is as follows: Section 2 summarizes the research review based on methodology. Section 3 dis-cusses the suggested model technique, while Section 4 presents the outcomes and a discus-sion. Finally, Section 5 provides the study's con-clusion as well as recommendations for further research.

2. Literature Review

Vijayalakshmi et al. [11] devised an energy-efficient strategy to maximize network lifespan in WSN. This work combined the single ob-jective genetic algorithm (SOGA) with the ad-vanced exhaustive search algorithm (AESA). Four quality parameters were included in the proposed technique to maximize energy-efficient routing: local ranging, network life-time, interaction counts, and connection effi-cacy. The created model had a reduced mean edge delay, higher latency, and a higher PDR.

Priyadarshi et al. [12] presented an AI-based navigation algorithm system for improving en-ergy efficiency and latency in WSN. This sys-tem was created by combining the Genetic algo-rithm (GA) as well as particle swarm optimiza-tion (PSO) under resource limitations. The in-troduced model was assessed using MATLAB R2021b. The developed model improved the ac-curacy, flexibility, and viability of WSNs. The introduced paradigm was hampered by its high intricacy and lack of implementation on inte-grated sensor nodes.

Alshammri et al. [13] suggested a strategy for improving WSN performance by optimiz-ing the CH selection framework with the SSA. In WSN, the Squirrel Search Algorithm (SSA) was used to select the optimal CH. The up-graded SSA includes various enhancements to increase solution quality and hasten conver-gence. R2021a's MATLAB version evaluated these investigations. The suggested solution ob-tained an 88% packet delivery ratio while con-suming only 210mJ of energy. The absence of sensor nodes and the lack of learning were limi-tations in this suggested investigation. Alauthman et al. [14] developed a modified intelligent energy efficiency cluster algorithm (MIEEC-A) for WSNs. The MIEEC algorithm improved WSN energy efficiency by selecting cluster heads that had high residual energy and were near their neighbours. The developed model achieved high lifetime, improved data ag-gregation and boosted energy efficiency. Delays in communication were limited of these devel-oped study. Rahul Priyadarshi et al. [15] suggested a PSO-based method for enhancing coverage and connectivity in WSNs using effective node de-ployment. A POS-based deployment mecha-nism was designed specifically for a heteroge-neous WSN. The introduced system had an av-erage coverage of 91.4%, 50% node activity, and 3,400 rotations. High complexity and inter-ference of the environment were limited in this study.

3. Proposed Methodology

This study suggests using an EACO-R protocol to extend the practical longevity and energy ef-ficiency of sensor nodes. The proposed protocol comprises three stages: stable cluster creation, cluster head selection, and energy-aware route discovery. The sensor nodes are initially dis-persed randomly in the WSN environment, as well as random information is collected from the base station. The cluster was created using the Fuzzy enhanced hierarchical clustering (FEHC) algorithm. After clustering, the ALM-DEAO algorithm selects the CH based on node metrics such as residual energy, distance between nodes, and Euclidean distance between nodes, ensuring balanced energy utilization and long-term network functioning. Finally, the MHA-DPA-DQN is employed to find the path between CHs and BS. Figure 1 displays the overall workflow architecture of the suggested method. Figure 2 represents the system model for the proposed approach.

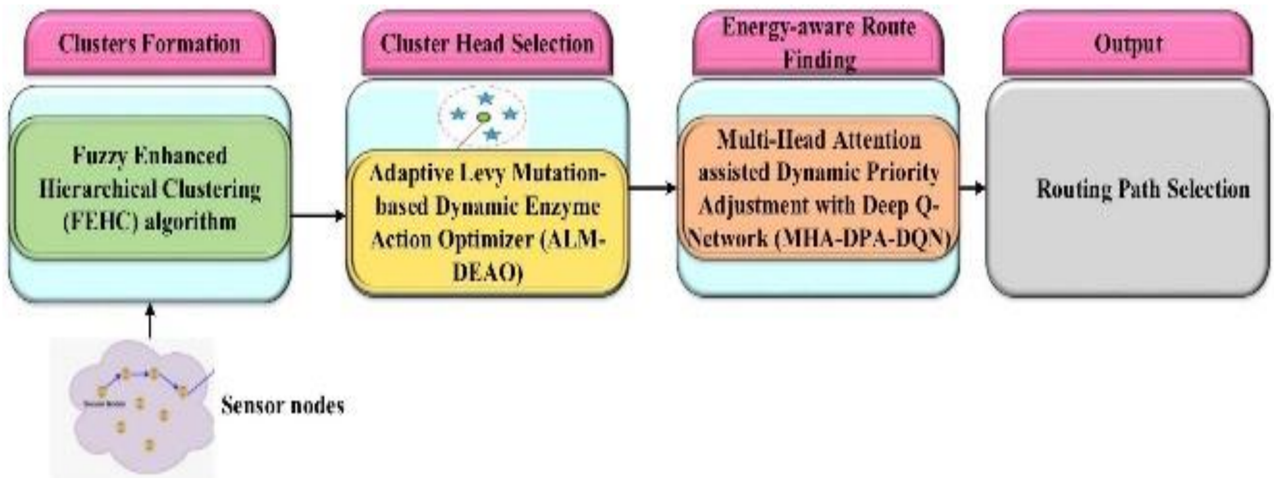


Figure 1 **Overall Workflow Architecture**

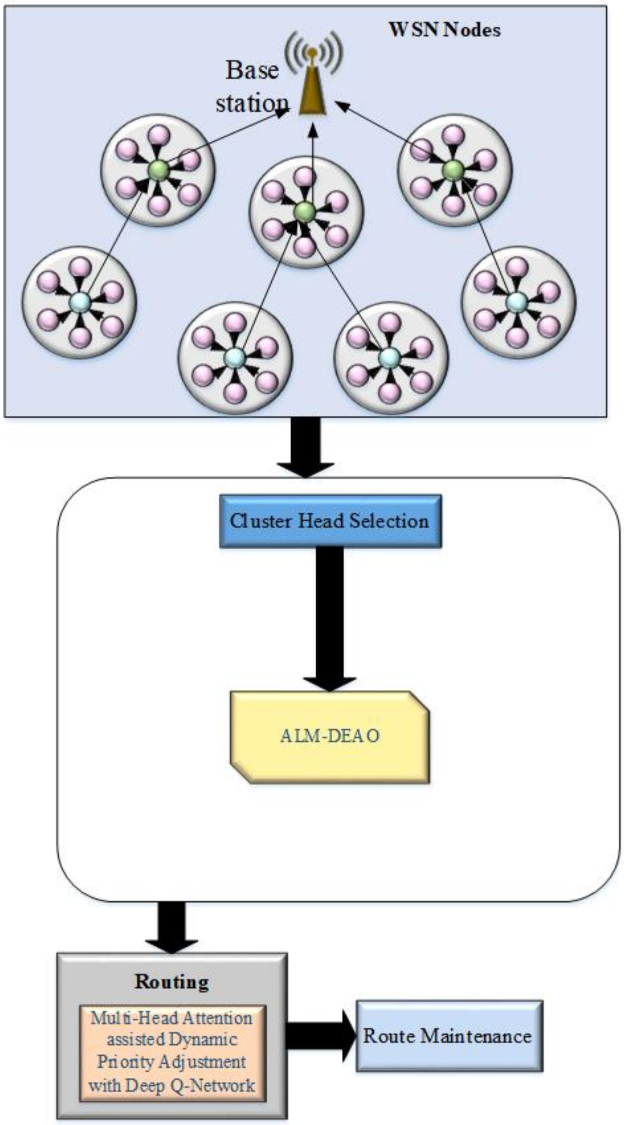


Figure 2 System Model

3.1. Clusters formation by using Fuzzy Enhanced Hierarchical Clustering (FEHC) Algorithm

The FEHC algorithm is selected because it effectively addresses the uncertainty and overlapping characteristics of sensor node distribution in WSN. Unlike conventional clustering models like K-means, fuzzy c-means clustering assigns each node to a single cluster using rigid boundaries. FEHC uses flexible membership values, allowing nodes to belong to numerous clusters with varying levels of confidence. This increases cluster stability, balances cluster sizes, and lowers the likelihood of improper cluster formation. Additionally, FEHC is better suited for dynamic WSN situations since it dynamically adjusts cluster topologies as network conditions change. These advantages result in lower communication overhead, balanced energy consumption, and increased network lifetime, making FEHC a better alternative than standard clustering algorithms for the proposed energy-aware routing system.

3.1.1. Initialization

An initial data (C_0) obtained from the data streams has been utilized to create the initial FHC structure (F_0). There are d_{init} number of $m \times w$ sized windows in this first data (C_0). Therefore, the initial size (C_0) corresponds to $m \times w_{init}$.

3.1.2. Update model

Following the construction of the initial FHC structure (F_0), the update module sequentially processes incoming data (C). The suggested technique aims to capture the dynamic character of the data streams over the procedure of updating the fuzzy hierarchical structure (H). The three submodules that make up the update module, the split submodule, the merge submodule, and the data accommodation submodule, are run sequentially [16]. The data accommodation submodule of the suggested technique computes the centroid for each node $\left(N_l^K \in H^K\right)$ using a fresh set of data. Let's consider C_k. For the k-th data window, compute the ratio of entropies ER_l^k between the node N_l^k as well as its parent node N_p^k as follows. Next, k-th-1 data window, compute the ratio of entropies ER_l^{k-1} between node N_l^{k-1} and its parent node N_p^{k-1} as follows.

$$ER^{k-1} = E_p^{k-1} / E_n^{k-1} \tag{1}$$

Split Submodule: For the set L that includes every leaf node in E^k. Determine the entropies of the node N_l^k in E^k and N_l^{k-1} in E^{k-1} as follows;

$$EC_l = E_l^k / E_l^{k-1} \tag{2}$$

Centroid calculation can be written as,

$$D_j^k = \frac{1}{|N_l|} \sum_{i=1}^{|N_l|} d_{i,j} \tag{3}$$

here, D_j^k is represented by centroid calculation, and $d_{i,j}$ is represented by the count of the matrix. The calculation of member ship equation can be written as,

$$\mu_{i,x}^k = \overline{s_x} * \mu_{i,q}^k, \qquad \mu_{i,y}^k = \overline{s_y} * \mu_{i,q}^k \tag{4}$$

where, $\mu_{i,x}^k$ and $\mu_{i,y}^k$ is represented by a data stream, the $\overline{s_x}$ and $\overline{s_y}$ is multiplied by $\mu_{i,q}^k$, which is represented by the association of the data stream S_i. The entropy of the node can be calculated as,

$$E_l^k = -\sum_j^m \frac{\sum_i^n d_{i,j} \times \mu_j^k}{\sum_{i=1}^n \sum_{k=1}^m d_{i,j} \times \mu_j^k} \log \frac{\sum_i^n d_{i,j} \times \mu_j^k}{\sum_{i=1}^n \sum_{k=1}^m d_{i,j} \times \mu_j^k} \tag{5}$$

During the cluster creation phase, a number of clusters are formed by combining different sensor nodes based on the parameters. After that, CH selection is performed, which is described in the section below.

3.2. CH selected by using Adaptive Levy Mutation based Dynamic Enzyme Action Optimizer (ALM-DEAO)

In this phase, CH is selected based on the input parameters of the sensor nodes, distance between nodes, link stability, residual energy and node density, which is performed by the ALM-DEAO mechanism. The ALM-DEAO algorithm optimally balances global as well as local exploitation in large-scale networks. It ensures high convergence speed and prevents premature entrapment in local optima, drastically prolonging network lifetime compared to standard routing protocols.

Initialization Phase

Both the population size (N) as well as dimensionality (D) of each substrate are specified. Every substrate component is set up using:

$$A_j^{(0)} = LB_d + (UB_d - LB_d).r_{j,d} \tag{6}$$

here, $A_j^{(0)}$ is represented by the value of the d^{th} dimension of the j^{th} substrate at iteration 0, LB_d and UB_d is represented by lower and upper bounds, and $r_{j,d}$ is represented by uniformly distributed random numbers [17].

Adaptive Factor and Enzyme Concentration

Unlike the original EAO, which kept enzyme concentration (EC) constant and grew adaptation factor (AF) linearly utilizing a square root rule, dEAO adjusts these variables dynamically at every iteration t s follows:

$$AF(t) = 0.5 + 0.5.\sin\left(\frac{\pi.t}{t_{\max}}\right) \tag{7}$$

$$EC(t) = 0.3 + 0.2.rand \tag{8}$$

here, $AF(t)$ is represented by adaptive factor at time t, $EC(t)$ is represented by enzyme concentration at time t, and $rand$ is represented by random selection.

3.2.1. Main Search processes

Two potential solutions are produced for every substrate, and levy mutation operation equation can be written as:

$$A_j^{First} = \left(A^{best} - A_j\right) + rand(D).\sin\left(AF.A_j\right) \tag{9}$$

$$q_{best,j}^{t+1} = q_{best,j}^{t} + \theta(j).levy.q_{best,j}^{t} \tag{10}$$

here, A^{best} is represented by the current best substrate, $rand(D)$ is represented by a vector generated randomly, $levy$ is represented by a random number, $\theta(j)$ is represented by the constant of self-adapting variation [18]. The second candidate equation can be written as,

$$Y = A_j + sc_Y.(S_1 - S_2) + ex_Y.\left(A^{best-A_j}\right) \tag{11}$$

$$X = A_j + sc_X.(S_1 - S_2) + ex_X.\left(A^{best-A_j}\right) \tag{12}$$

where, sc_X, ex_X is represented by a random vector, sc_Y, ex_Y is represented by a scalar value. The sine component is not included in this calculation to distinguish between exploitation intensity. These scaling settings affect the depth and direction of the search. After evaluation, the superior of the two is chosen as the second applicant.

3.2.2. Selection and Update

If there is an improvement among the initial and second choices, the superior one, that is, the one with lower fitness, replaces the other. The optimal substrate is updated if it outperforms the global best. The ALM-DEAO selects the best CH based on remaining energy, regional node density, as well as length to the BS. The objective function can be expressed as,

$$Fitness = \alpha\left(\frac{E_i^{res}}{E_{\max}}\right) + \beta\left(\frac{D_i^{local}}{D_{\max}}\right) + \gamma\left(1 - \frac{Dist(i, BS)}{Dist_{\max}}\right) \tag{13}$$

where, E_i^{res} means residual energy of node, D_i^{local} is represented by local node density around node, $Dist(i, BS)$ is represented by Euclidean detachment among the node and BS.

3.3. Energy aware Route Findings by using Multi-Head Attention assisted Dynamic Priority Adjustment with Deep Q-Network (MHA-DPA-DQN)

Sensor nodes deliver data to the appropriate CHs, which aggregate the acquired information before forwarding it to the Base Station (BS). This technique was chosen because, unlike typical static routing algorithms, it is constantly learning and adapting to changing network conditions. As a result, it lowers communication overhead, balances energy consumption, improves routing dependability, and extends the WSN's lifetime.

The MA-DQN agent implements a deep Q-Network with multi-head attention techniques. The attention mechanism enables the network to mimic biological visual attention systems by dynamically weighting various input state variables. The scaled dot-product attention is the foundation of the attention mechanism [19, 20]. The attention output is calculated as follows, given the query Q, key K, and value V matrices:

$$Attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d_K}}\right)V \tag{14}$$

here, $\sqrt{d_K}$ is represented by scaling factor, (Q,K,V) is represented by query, key and value, $soft\max$ is represented by the softmax function. Multi-head attention uses distinct learnt linear projections to carry out h simultaneous attention operations:

$$Multihead(A) = concat\left(head_1,....,head_h\right)W^0 \tag{15}$$

$$head_j = attention\left(AW_j^Q, AW_j^K, AW_j^V\right) \tag{16}$$

where, $\left(AW_j^Q, AW_j^K, AW_j^V\right)$ is represented by linear projection matrices, A is represented by the input value. The followed by dynamic priority adjustment equation can be written as,

$$P_j(t) = \alpha E_j(t) + \beta L_j(t) + \delta Q_j(t) + \gamma D_j(t) \tag{17}$$

where, $E_j(t)$ means residual energy of node j, $L_j(t)$

is represented by link stability, $Q_j(t)$ is represented by query states, $D_j(t)$ is represented by distance factor, and $\alpha, \beta, \delta, \gamma$ is represented by adaptive weighting coefficient. The routing reward function can be written as,

$$R_t = w_1\left(\frac{E_{res}}{E_{\max}}\right) - w_2 O_c - w_3 D_1 - w_4 p_l \tag{18}$$

here, E_{res} means residual energy, O_c is represented by communication overhead, D_1 is represented by transmission delay, p_l is represented by packet loss rate. w_1, w_2, w_3, w_4 is represented by weight parameters.

$$\max = \sum_{t=0}^{T} \gamma^t R_t \tag{19}$$

This reduce communication costs and enhance energy efficient, reliable reading between SNs and BSs. The novelty of the proposed model lies in integrating Multi-Head Attention with DQN for intelligent routing decisions. Unlike conventional routing methods that use fixed metrics, MHA enables the DQN to focus on the most relevant network features dynamically. The DQN learning equation continuously updates routing knowledge based on rewards received from previous transmissions, allowing the network to adapt to changing conditions and discover energy-efficient routes. As a result, the proposed MHA-DPA-DQN achieves improved throughput, reduced communication overhead, balanced energy utilization, and extended network lifetime. Finally output of this stage is the minimum path of base station.

4. Result and Discussion

Table 1: Simulation details

Parameter	Range/value
Number of Sensor nodes	500 nodes
Transmission range	500 m
Simulation time	1000 s
Routing protocol	EACO-R
Simulation area	$200 \times 200 m^2$
Base station position	(100,100)
Packet size	256-1024 bytes
Bandwidth	500 GHz-1000GHz
Metrics	FND, HND, LND, throughput and energy consumption

The suggested system was implemented utilizing MATLAB version of R2024a, as well as results and discussion sections evaluated its performance. First node dead (FND), Half Node dead (HND), Last node dead (LND), throughput and energy consumption are among the performance metrics. The simulation details are exposed in Table 1.

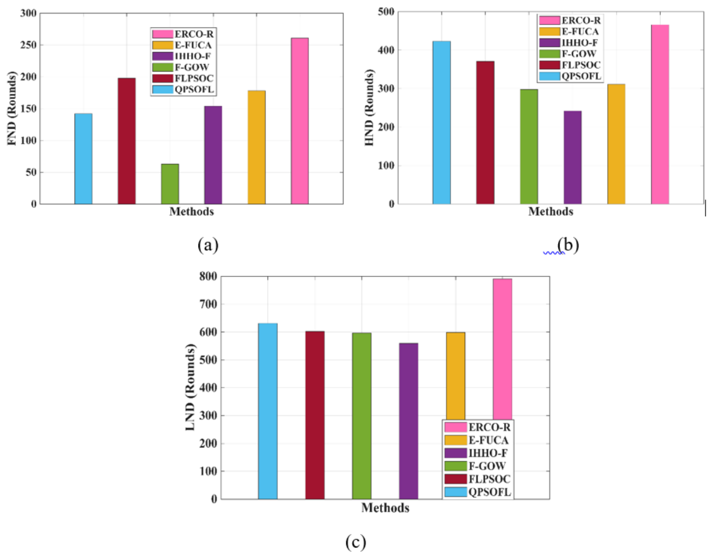
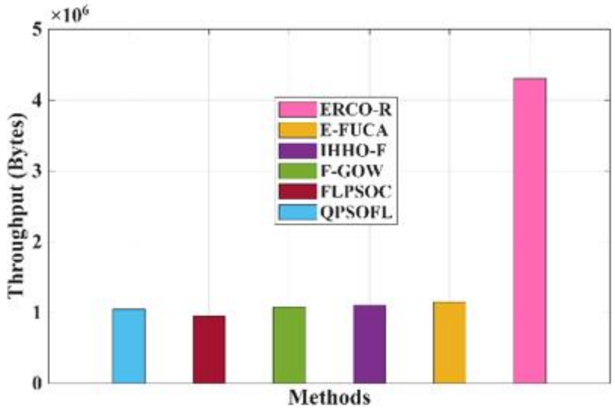
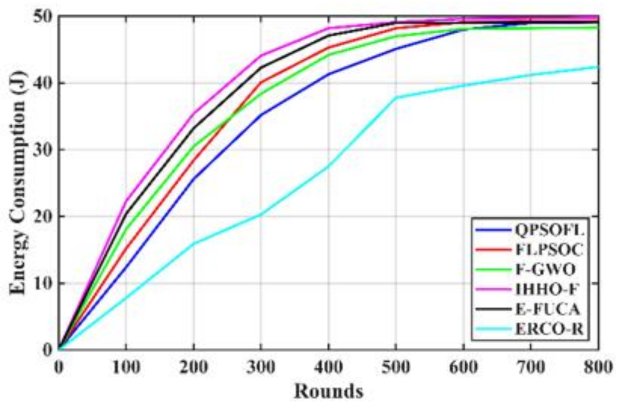


Figure 3 (a) FND, (b) HND and (c) LND Performance Analysis

Figure 3 (a) displays the FND performance analysis of the suggested as well as current models. The suggested model achieved the FND of 261. The proposed model optimally rotates cluster heads based on residual energy, instead of random selection. This prevents nodes with very low batteries from becoming overloaded and ensures that the energy load is evenly distributed across the network. Figure 3(b) displays the HND performance analysis of the proposed and existing models, which achieved the HND of 466. Figure 3(c) shows the LND performance analysis of the suggested and existing models, which achieved the LND of 791. The proposed model considers real-time residual energy and space density when selecting network leaders, minimizing transmission distances and overall power consumption. So the proposed performance is high compared to the other models.



(a)



(b)

Figure 4 (a) Throughput and (b) Energy Consumption

Figure 4(a) displays the throughput performance analysis of the suggested as well as current models. The suggested model achieved a throughput of 4300000 bytes. Because its improved architecture reduces the computational complexity of each operation, it can perform more calculations or data in a second. Figure 4(b) displays the energy consumption performance analysis of the suggested as well as current models. The suggested model achieved the less energy consumption compared to other models. Table 2 and Table 3 display the performance analysis of the suggested and exiting model within the range of 100 to 250.

Table 2 FND, HND, LND Throughput Performance Validation of Proposed and Existing Models Within The range of 100-250 m

Performance/model	FND (Rounds)	HND (Rounds)	LND (Rounds)	Throughput (Bytes)
QPSOFL	142	423	631	1050000
FLPSOC	198	371	602	950000
F-GOW	63	298	596	1080000
iHHO-F	154	242	559	1100000
E-FUCA	178	311	598	1150000
ERCO-R	**261**	**466**	**791**	**4300000**

Table 3 Energy Consumption Performance Validation of Proposed and Existing Models Within the Range of 100-250 m

Rounds	QPSOFL	FLPSOC	F-GOW	iHHO-F	E-FUCA	**ERCO-R**
0	0	0	0	0	0	**0**
100	12.4	15.2	18.1	22.3	20.4	**7.8**
200	25.6	28.4	30.5	35.4	33.2	**15.9**
300	35.2	40.1	38.4	44.1	42.3	**20.3**
400	41.3	45.3	44.2	48.2	47.1	**27.5**
500	45.1	48.2	47	49.1	49	**37.8**
600	48	49.1	48.1	49.6	49	**39.6**
700	49	49.2	48.2	49.7	49.1	**41.2**
800	49.1	49.2	48.3	49.8	49.1	**42.4**

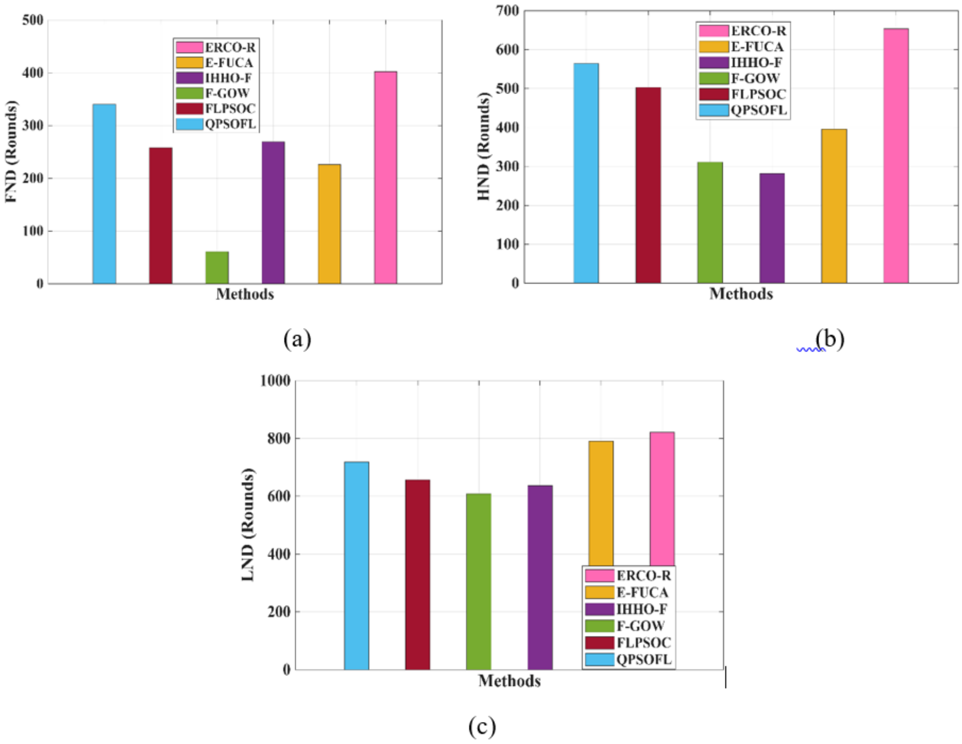
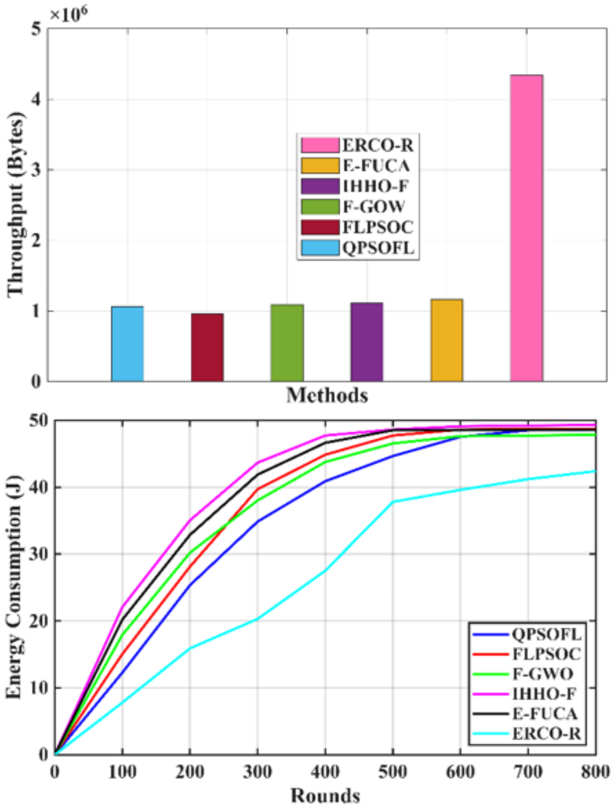


Figure 5 (a) FND, (b) HND and (c) LND Performance Analysis

4.1. Performance analysis

In this section, a number of performance metrics, including FND, HND, LND, throughput and energy consumption, are employed to compare the proposed and existing models. The existing models, such as E-FUCA, AHHO-F, F-GWO, FLPSOC and QPSOFL, use the same environment protocol and parameters, which are implemented and compared with the proposed approach. Two different pathways, 100-250m and 100-200m, are used to communicate the information from the source to the BS. The FND performance analysis of the suggested and existing models is shown in Figure 5 (a). The suggested model attained the FND of 402. The HND performance analysis of the suggested and current model is shown in Figure 5(b), which achieved the HND of 654. The proposed model limits direct long-range transmissions. By utilizing intermediate routing hops, it dramatically lowers communication costs and prevents early energy depletion. The LND performance analysis of the suggested and current models is shown in Figure 5(c). The proposed model attains the LND of 821 (Rounds).



(a) (b)

Figure 6 (a) Throughput and (b) Energy Consumption

The throughput performance study of the proposed and current models is shown in Figure 6(a). The throughput of the suggested model 4343000 (bytes) was attained. The energy consumption performance study of the suggested and current models is shown in Figure 6(b). The energy usage of the suggested model was attained. The proposed model combines algorithmic efficiency and optimized hardware usage. By minimizing unnecessary computations and resource usage, the model can maintain and improve performance while using less power. The performance study of the suggested and current models within the 100–200 range is shown in Tables 4 and 5. The performance evaluation was verified at two base stations, 43.51m and 43.04m, showing great improvements for the proposed model.

Table 4 FND, HND, LND Throughput Performance Validation of Proposed and Existing Models Within A Range of 100-200 m

Performance/model	FND	HND	LND	Throughput
QPSOFL	340	564	719	1060500
FLPSOC	258	503	657	959500
F-GOW	61	311	609	1090800
iHHO-F	269	282	637	1111000
E-FUCA	226	396	791	1161500
ERCO-R	**402**	**654**	**821**	**4343000**

Table 5 Energy Consumption (J) Performance Validation of Proposed and Existing Models Within the Range of 100-200 m

Rounds	QPSOFL	FLPSOC	F-GOW	iHHO-F	E-FUCA	**ERCO-R**
0	0	0	0	0	0	**0**
100	12.2772	15.05	17.921	22.079	20.198	**7.8**
200	25.3465	28.119	30.198	35.05	32.871	**15.9**
300	34.8515	39.703	38.02	43.663	41.881	**20.3**
400	40.8911	44.852	43.762	47.723	46.634	**27.5**
500	44.6535	47.723	46.535	48.614	48.515	**37.8**
600	47.5248	48.614	47.624	49.109	48.515	**39.6**
700	48.5149	48.713	47.723	49.208	48.614	**41.2**
800	48.6139	48.713	47.822	49.307	48.614	**42.4**

4.2. Discussion

The proposed EACO-R protocol performance evaluation shows how well it works to extend the lifetime and operating efficiency of WSNs. The combination of MHA-DPA-DQN, ALM-DEAO and FEHC greatly improved routing stability and energy conservation. In comparison to current techniques, E-FUCA, AHHO-F, F-GWO, FLPSOC and QPSOFL experimental findings show that the proposed model produced reduced FND, HND, LND, throughput and energy consumption. Additionally, the proposed protocol achieved improved throughput, indicating dependable and effective data transfer in dynamic network conditions. The intelligent routing technique increased network lifetime and performance by effectively balancing energy consumption across sensor nodes and reducing communication overhead.

Conclusion

This study introduced an EACO-R protocol for increasing the lifetime and energy efficiency of WSNs operating in dynamic IoT contexts. The suggested framework combines MHA-DPA-DQN for intelligent energy-aware routing, ALM-DEAO for optimal CH selection, and FEHC for balanced cluster formation. The combination of these three approaches ensures dependable data transmission while also allowing for effective load balancing, various routing options, and minimal communication overhead. By accounting for residual energy, node density, connection stability, transmission distance, and network congestion, the proposed routing strategy optimally distributes energy consumption across sensor nodes and eliminates early node failures. When compared to current routing techniques, simulation evaluation shows that the suggested protocol provides better performance in terms of FND, HND, LND, throughput, and overall energy usage. Overall, the proposed EACO-R protocol offers an efficient, scalable, and intelligent routing solution for energy-constrained WSNs, as well as a viable framework for future IoT applications that require dependable and long-lasting wireless connectivity. According to the simulation findings, the suggested model's energy consumption analysis yielded 42.4J, which is low when compared to the current method. In the future, the proposed model will be enhanced by adding security related mechanism and sharing data to base station, with privacy-preserved data.

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