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FIND-ROUTE: Fourier series integrated deep learning model for energy efficient routing in Internet of things-wireless sensor network

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ABSTRACT

The Internet of Things (IoT) relies on wireless sensor networks (WSNs) to transmit data across a wide range of applications. However, the commonly encountered primary challenges in IoT-enabled WSNs are high energy consumption during data transmission, which insists energy optimized routing to prolong the network lifetime. To address these challenges, a novel Fourier series integrated deep learning-based routing (FIND-ROUTE) framework has been proposed for energy-aware communication among IoT nodes in WSN. Initially, a hybrid clustering approach forms an adaptive cluster for efficient data aggregation with reduced energy consumption. After clustering, stable cluster heads (CHs) are elected by a Fourier series-based metaheuristic optimization algorithm for balancing the energy usage with extended network lifetime. Finally, an Intelligent neural network dynamically selects the optimal path and transmits the data efficiently with reduced latency for reliable communication in IoT-WSN. The FIND-ROUTE framework is simulated by using MATLAB, and it is validated by using the WSN-DS dataset. The proposed FIND-ROUTE framework is evaluated based on several parameters, including energy consumption, packet delivery ratio (PDR), network lifetime (NL), time complexity, throughput, number of alive nodes, packet loss ratio (PLR), and space complexity. In comparison, the proposed FIND-ROUTE framework achieves a PDR of 90%, whereas MLBDARP, LQEER, and NBSHO-DRNN achieve 70%, 60%, and 67% respectively.

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1. INTRODUCTION

WSNs are becoming a crucial technology for data collection and transmission across a wide variety of application domains due to the growth of Internet of Things (IoT) devices [1]. In IoT-enabled wireless sensor networks (WSNs), the data must be efficiently transported across multiple access points while maintaining effective communication using the least amount of energy [2], [3]. An energy-aware data collection and communication methods must be developed to reduce the node energy consumption and increase the network lifetime [4], [5].

The low processing power and high energy availability of WSNs necessitate energy-efficient routing methods to increase network longevity [6], [7]. A scalable routing solution is required to process the vast amount of data generated by IoT devices [8], [9]. The IoT-enabled WSN networks manage the various types of nodes using energy-aware routing algorithms which minimize the latency and ensure effective communication [10].

A dramatic increase in multi-objective optimization techniques aims to provide a dependable solution for difficult optimization issues integrated in IoT enabled WSN [11]. These algorithms determine an optimized solution to achieve quality of service (QoS) objectives, increased throughput, energy conservation, PDR, and minimized data gathering delay for network efficiency. In contrast to networks that rely solely on direct connections, WSNs usually use clustering with multilayer topologies to reduce energy usage and offer a more robust network [12], [13].

IoT-enabled WSNs consist of several challenges for energy-efficient data routing because of the dynamic nature of sensor nodes [14]. Due to these dynamics, adaptive routing strategies are essential to effectively manage these shifting network topologies [15], [16]. In addition, the traditional routing systems are inability to manage large amounts of Packet loss, less ideal node selection, nodes with less network lifetime, and increased latency which contradicts the reliable communication of the networks [17], [18]. To address these challenges, a novel FIND-ROUTE framework has been proposed for sustainable data transmission in IoT based WSN environments. The primary goals of the FIND-ROUTE framework are given in the following,

a. The major purpose of this strategy is to construct an energy-optimized data communication in IoT-WSNs to improve network reliability while minimizing latency for seamless communication among dynamic network conditions.
b. The fuzzy C means-balanced iterative reducing and clustering using hierarchies (Fuzzy-BIRCH) clustering algorithm enhances the clustering efficiency by grouping the optimal nodes for minimizing communication overhead in IoT-WSNs.
c. The optimal energy-aware nodes are determined as cluster heads (CHs) using the Fourier series-based firefly optimization algorithm (FSFOA) which enhances the data aggregation to ensure low energy consumption with reliable data delivery among the networks.
d. A synaptic intelligent convolutional neural network (SICNN) determines an optimal routing path for robust data transmission with minimum packet loss.
e. The performance of the FIND-ROUTE framework is evaluated through the network parameters including energy consumption, PDR, network lifetime, time complexity, throughput, number of alive nodes, PLR, and space complexity.

The subsequent sections of the research are organized as: section 2 holds the literature review. Section 3 holds a comprehensive description of the proposed FIND-ROUTE methodology. Section 4 provides the simulation outcomes. The conclusion and the future enhancement are discussed in Section 5.

2. LITERATURE SURVEY

The literature review is primarily focused on machine learning (ML), reinforcement learning (RL), and deep learning (DL) based routing algorithms in IoT-WSNs. Numerous existing approaches that have been suggested for energy-optimized routing in IoT-WSNs have been studied in the literature. In 2023 Seyfollahi *et al.* [19] suggested an energy-optimized routing system of the IoT enhanced by metaheuristics and ML. However, the optimal load balance among sensing devices and energy efficiency are the primary concerns with energy resources in IoT devices. Chandnani and Khairnar [20] suggested an ethical ML-based solution for energy-optimized routing. The MLBDARP model uses ML models which include neural networks (NN) and decision trees (DT) to assess the reliable PDR.

Suresh *et al.* [21] suggested a resource-efficient routing using federated deep reinforcement learning (FDRL) for WSN integrated by the IoT. The suggested FDRL method provides energy-constrained routing and decision-making in a dynamic environment. Shahid *et al.* [22] suggested link-quality-based energy constrained routing (LQEER) is an IoT environment for WSN. The suggested LQEER approach reduces packet loss by integrating energy and network information to identify routes and a cost to determine the best nodes for packet transmission.

Sattibabu *et al.* [23] suggested an enhancement of the performance of IoT-integrated WSN based on federated reinforcement learning (FRL). In comparison to reinforcement learning-based routing (RLBR), the FRL technique improves WSN performance by 30%, increases energy efficiency by 15% to 24%, and increases packet delivery by 13% respectively. Pawar and Jadhav [24] suggested IoT data minimization using a combination of optimization-based topology and DRNN-based detection. The energy of 0.367 J, prediction error of 0.237, delay of 0.595 s, and PDR of 0.469 were all attained by the suggested NBSHO-DRNN approach. Singh *et al.* [25] suggested a IoT-WSN based QoS improvement using edge-enabled multi-objective optimization. In the suggested approach, edge computing increases the scalability and enhances QoS in IoT applications.

According to the literature reviews, existing data routing methods do not account for effective energy characteristics. As a result, the sensor and data connection units of IoT-WSNs require additional energy which is drained and ineffective during data transmission and communication. To address these limitations, a novel FIND-ROUTE methodology is proposed which is an energy-optimized adaptive routing model for IoT-WSNs.

3. THE FIND-ROUTE METHODOLOGY

In this section, a novel FIND-ROUTE framework has been proposed for reliable and energy-optimized data delivery among the intelligent wireless sensor system. Initially, the IoT nodes are organized into clusters using a fuzzy-BIRCH algorithm to manage the network congestion. An FSFO algorithm selects a CHs from the set of clustered nodes based the multi-objective fitness function which reduces the delay and ensures faster data transmission. Finally, the SICNN routes the aggregated data toward the base station which optimizes the consumption of energy and provides reliable data transmission with minimal packet loss in IoT-based WSNs. The overall workflow of the FIND-ROUTE framework is presented in Figure 1.

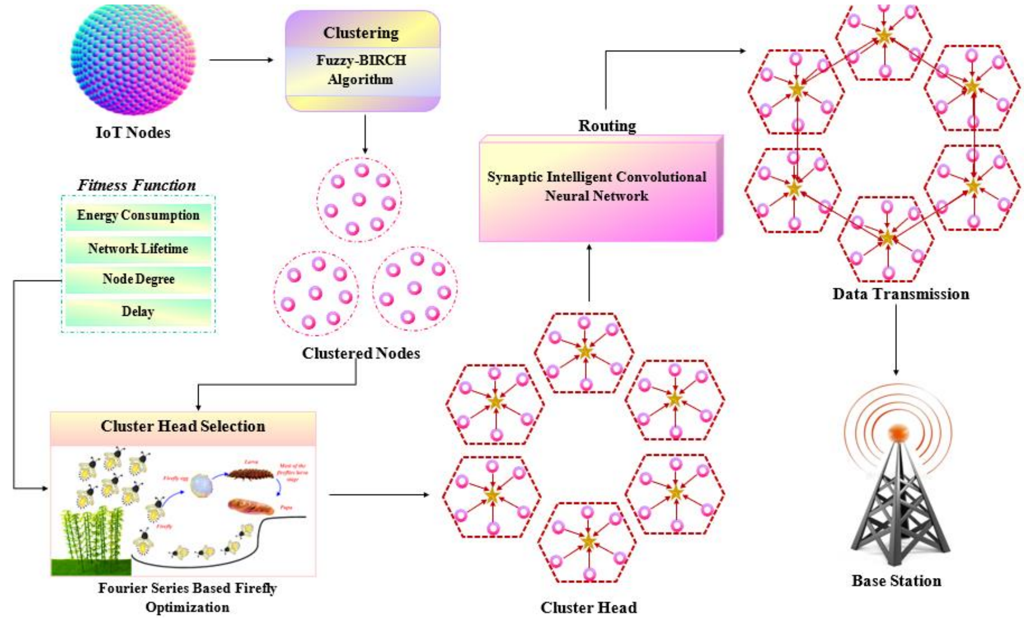


Figure 1. Proposed FIND-route methodology

3.1. Clustering via fuzzy-BIRCH algorithm

Initially, the IoT nodes are organized into clusters using a fuzzy-BIRCH algorithm to manage the network congestion. In BIRCH, a cluster is defined by its cluster features (CFs), and the hierarchical structure of clusters is displayed using a CF tree. To find the cluster centroid, represented by $\{\overrightarrow{X_i}\}$ in BIRCH clustering, where $i = 1,2,\dots,N$, equation (1) applied consecutively.

$$\overrightarrow{X_0} = \frac{\sum_i^N \overrightarrow{X_i}}{N} \tag{1}$$

By choosing the number of clusters, the processed data is separated into discrete subgroups according to specific CFs. Cluster tags are then applied to these subsets to cluster them in an energy-constrained manner. The fuzzy c-means (FCM) divides n vectors into k groups and initializes the affiliation matrix (U) by calculating the clustering center of each group through fuzzy partitioning to minimize the objective function. The class center vector and the affiliation matrix are represented in (2)-(3).

$$C_j = \frac{\sum_{i=1}^N u_{ij}^m . x_i}{\sum_{i=1}^N u_{ij}^m} \tag{2}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_i - c_j\|}{x_i - c_k}\right)^{\frac{2}{m-1}}} \tag{3}$$

where m denotes the number of clusters for clustering, i, and j denote the affiliation of matrix i concerning class cluster j. The objective function is represented in (4).

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \tag{4}$$

Here, c_j denotes the center of class cluster j, $\left\| x_i - c_j \right\|^2$ is the Euclidean distance among the j^{th} selected node and the i^{th} node. The fuzzy partition coefficient (FPC) measures the degree of fuzzy overlap between clusters. It ranges from 0 to 1, indicating energy-efficient clusters with higher values. Therefore, the Fuzzy-BIRCH clustering algorithm enhances the clustering efficiency by grouping the optimal nodes for minimizing communication overhead in IoT-WSNs

3.2. CH selection via Fourier series-based firefly algorithm

The optimal energy-aware nodes are determined as CHs using the FSFOA based on the clustered nodes by Fuzzy-BIRCH which enhances the data aggregation with reliable data delivery among the networks. The brightness of the firefly is influenced by the objective function and it is used to indicate attractiveness of FA implementations. The fitness function including energy consumption, network lifetime, node degree, and delay is represented by the firefly's attractiveness and intelligence in the FA metaheuristics. The minimization of challenges is stated in (5),

$$I(x) = \begin{cases} \frac{1}{f(x)} & , if\ f(x) > 0 \\ 1 + |f(x)| & , Otherwise \end{cases} \tag{5}$$

$f(x)$ represents the objective function value at point x, while $I(x)$ represents attractiveness. Individual attraction decreases the distance from the illumination source due to the brightness.

$$I(r) = \frac{I_0}{1+\gamma r^2} \tag{6}$$

I_0 indicates the brightness at the source, while $I(r)$ defines the brightness at distance r. Additionally, as demonstrated by (7) each firefly individual uses attraction β, which is proportional to the firefly's light intensity and depends on distance.

$$\beta(r) = \frac{\beta_0}{1+\gamma r^2} \tag{7}$$

A random individual i that advances in iteration $t + 1$ toward a new position x_i in the direction of individual j with higher fitness can be found using the following simple FA's search method which is based on (8).

$$x_i^{t+1} = x_i^t + \beta_0 . e^{-\gamma r_{i,j}^2}\left(x_j^t - x_i^t\right) + \alpha^t(k - 0.5) \tag{8}$$

The random number derived from a Gaussian or uniform distribution is represented by κ and ri, where $\boldsymbol{\varphi}$ is the randomization parameter and j represents the displacement of two observed fireflies i and j. The CH selection using FSFOA is presented in Algorithm 1.

Algorithm 1: CH selection via FSFOA

Input: FA parameters and Fourier coefficients
Output: Optimized Cluster Head (CH) nodes
1. Initialize firefly population with positions, fitness, and parameters.
2. Compute fitness of each firefly using fitness parameters.
3. Move fireflies towards brighter ones using:

$$x_i^{(t+1)} = x_i^t + \beta\left(x_j^t - x_i^t\right) + \alpha \sum \left[a_k \cos\left(\frac{2\pi k}{n} t\right) + b_k \sin\left(\frac{2\pi k}{n} t\right)\right]$$

4. Evaluate new positions based on the fitness function.
5. Apply selection criteria to identify CHs.
6. Deploy CHs for efficient communication.

The values for β_0 and α yields satisfactory results for the majority of issues are 1 and [0,1]. Equation (9) is used to compute the Cartesian distance.

$$r_{i,j} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{D} \left(x_{i,k} - x_{j,k}\right)^2} \tag{9}$$

The number of problem parameters is indicated by D. A periodic function's infinite extension in terms of sines and cosines is known as Fourier series analysis. Equation (10) is then used to decompose the continuous function's Fourier series to derive its discrete form.

$$Q_s^{d,s} = a_0 + \sum_{k=1}^{K} \left(a_k cos \frac{2\pi k}{n} m + b_k sin \frac{2\pi k}{n} m \right) \tag{10}$$

The sum of square errors was calculated for each period that was included in the Fourier series. The ideal period (k) for the Fourier series function will be determined using the sum of square errors. An FSFO algorithm selects optimal CHs based on the low energy consumption, delay, and high network lifetime, and node degree which ensures faster data transmission.

3.3. Routing via synaptic intelligent convolutional neural network

The SICNN model determines an optimal routing path for robust data transmission in IoT-WSN. In the SICNN framework, the effect of neural network parameters on energy-aware route selection in IoT-enabled WSN is assessed for reliable data communication among the IoT-WSN networks. The credit assigned to the reduction in performance loss l_μ by the parameter θ_k in the energy-constrained routing scenario which is described in (11).

$$L\left(\theta(t_\mu) - L\left(\theta(t_{\mu-1})\right) = -\sum_k \mathcal{W}_k^\mu\right) \tag{11}$$

A conservative field in calculus is the gradient. This value in the gradient vector field is the route integral along the parameter trajectory from the beginning point $\theta(t_{\mu-1})$ to the destination $\theta(t_\mu)$ which is described in equation (12)-(13).

$$\int_c^{t_\mu} g(\theta(t))d\theta = \int_{t_{\mu-1}}^{t_\mu} g(\theta_t).\theta'(t)\, dt \tag{12}$$

$$L\left(\theta(t_\mu)\right) - L\left(\theta(t_{\mu-1})\right) = \int_{t_{\mu-1}}^{t_\mu} g(\theta_t).\theta'(t)\; dt \tag{13}$$

The comparison between equations (14) and (15) indicates that the path integral of the loss function l_μ may be negative for the parameter θ_k bias. This is required to approximate the previously suggested significant measure $\mathcal{W}_k^\mu$.

$$\int_{t_{\mu-1}}^{t_\mu} g(\theta_t).\theta'(t)\, dt = \sum_k \int_{t_{\mu-1}}^{t_\mu} g_k(t).\theta_k'(t)dt \tag{14}$$

$$\mathcal{W}_k^\mu = \int_{t_{\mu-1}}^{t_\mu} g_k(t).\theta_k'\, dt \tag{15}$$

The performance loss of the prior data can be substituted with a proxy loss from the SI approach using the significance measure $\mathcal{W}_k^\mu$ generated in the preceding section. Where the parameter's position after the optimization in the prior route is shown by $\theta_k'\, dt$, and its regularized strength is indicated in (16).

$$\Omega_k^\mu = \sum_{v<\mu} \frac{\mathcal{W}_k^v}{(\Delta_k^v)^2 + \xi} \tag{16}$$

where the drop of both the currently selected route and the previous route distances are measured by the dimensionless intensity parameter c. The Δ_k^v self-inner product in task v indicates the degree of change in the parameter θ_k. To avoid the computational instability caused by an inadequately tiny denominator, ξ is a constant. Finally, the SICNN routes the aggregated data toward the base station which optimizes the consumption of energy and provides reliable data transmission with minimal packet loss in IoT-based WSNs.

4. RESULT AND DISCUSSION

In this section, the efficacy of the FIND-ROUTE framework and its results are simulated by using MATLAB simulator and it is validated by using WSN-DS dataset. However, the FIND-ROUTE framework is compared against several existing approaches including MLBDARP, LQEER, and NBSHO-DRNN. The performance of the FIND-ROUTE framework is evaluated through the network parameters including energy consumption, PDR, NL, time complexity, throughput, number of alive nodes, PLR, and space complexity.

4.1. Dataset description

The WSN-DS is a dataset for analyzing the security and network efficacy in IoT-WSN. The WSN-DS dataset holds the network features like Node ID, packet size, transmission range, energy consumption, hop count, routing path, and NL. The WSN-DS dataset contains 50,000 records to perform energy efficient routing which is gathered from several sensor nodes. In FIND-ROUTE, the WSN-DS dataset is divided into 80% of training and 20% of testing data for DL-based energy-efficient routing. The simulation output of FIND-ROUTE framework is depicted in Figure 2 and the simulation parameters are shown in Table 1.

The simulation output of the proposed FIND-ROUTE framework is depicted in Figure 2. In this framework, a fuzzy-BIRCH clustering is employed to minimize the redundant data transmission and the FSFOA-based CH selection ensures efficient data aggregation by selecting optimal nodes for communication. An energy-efficient routing is performed by using SICNN which intelligently identifies the most reliable paths for energy-efficient data transmission and communication in IoT-WSN environment. The simulation output demonstrates that the FIND-ROUTE framework provides a robust communication among IoT-WSN environment.

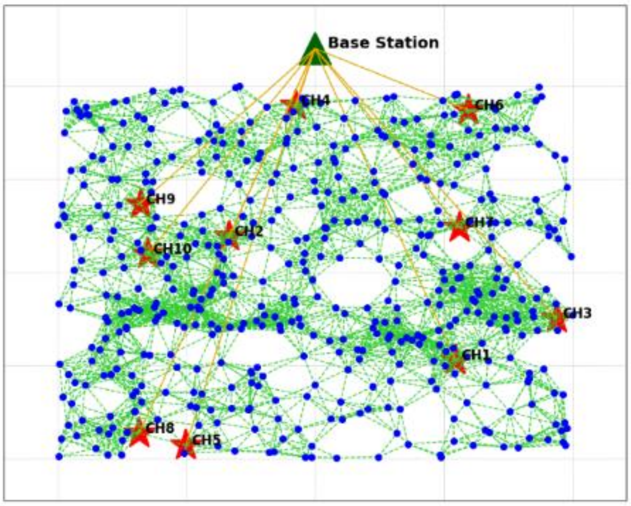


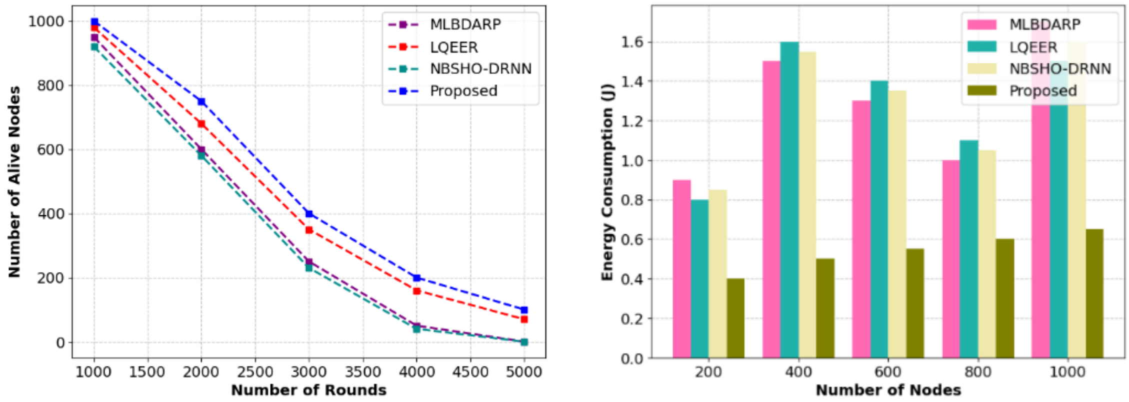
Figure 2. Simulation output of FIND-ROUTE framework

Table 1. Simulation parameters

Parameter	Value
Network area	$1000 \times 1000\ m^2$
Number of nodes	1000 nodes
Initial energy	5J, 50J
Number of clusters	10
Data packet size	500 bytes
Base station location	(250, 875)
Transmission range	250 m
Simulation time	7200 s

4.2. Comparative analysis

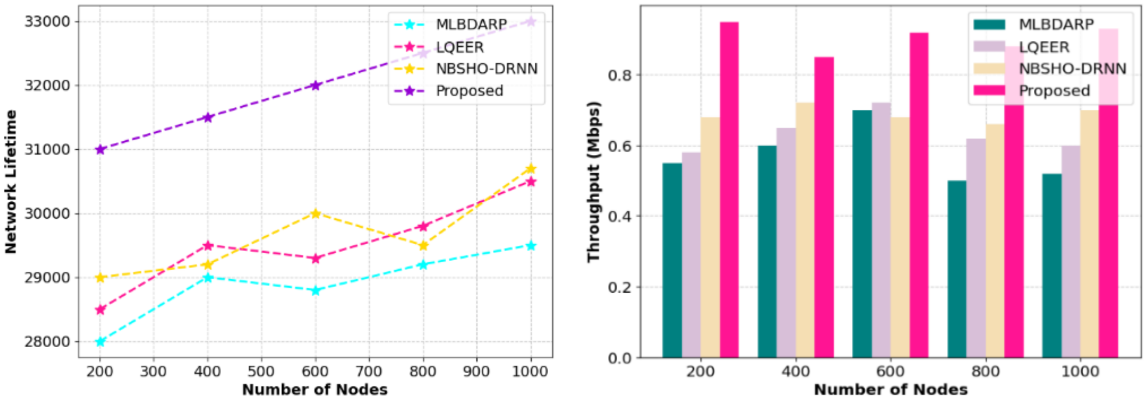
The energy-constrained CH selection and routing in IoT-WSN is analyzed by several network parameters including energy consumption, PDR, number of alive nodes, time complexity, throughput, network lifetime, PLR, and space complexity. Figure 3(a) illustrates the total amount of alive nodes gathered throughout the number of rounds. The proposed FIND-ROUTE framework consistently indicates a large number of alive nodes at each round assessed with existing MLBDARP, LQEER, and NBSHO-DRNN, with values of 970, 650, 300, 120, and 50 respectively. As the rounds increase, it is discovered that the FIND-ROUTE framework outperforms the existing MLBDARP, LQEER, and NBSHO-DRNN algorithms by the total amount of alive nodes available in the entire area. The comparison of energy consumption is shown in Figure 3(b). The FIND-ROUTE framework consumes the least energy across all network sizes ranging from 0.4 J at 200 nodes to 0.65 J at 1000 nodes. Whereas, MLBDARP, LQEER, and NBSHO-DRNN consume higher energy of 1.7 J, 1.5 J, and 1.6 J.



(a) (b)

Figure 3. Comparison of (a) number of alive nodes and (b) energy consumption

Figure 4(a) displays the NL comparison. The FIND-ROUTE framework achieves the highest NL increasing from 31,000 rounds at 200 nodes to 33,000 rounds at 1000 nodes. While, the existing MLBDARP, LQEER, and NBSHO-DRNN reach a maximum of 29,500, 30,500, and 30,700 rounds. The computation of the throughput is based on the large amount of data delivered by the CHs. The comparison results of FIND-ROUTE framework for throughput with algorithms are shown in Figure 4(b). The FIND-ROUTE framework consistently achieves the highest throughput ranging from 0.85 to 0.95 Mbps**,** whereas MLBDARP, LQEER, and NBSHO-DRNN reach a maximum of 0.70 Mbps, 0.72 Mbps, and 0.74 Mbps respectively.

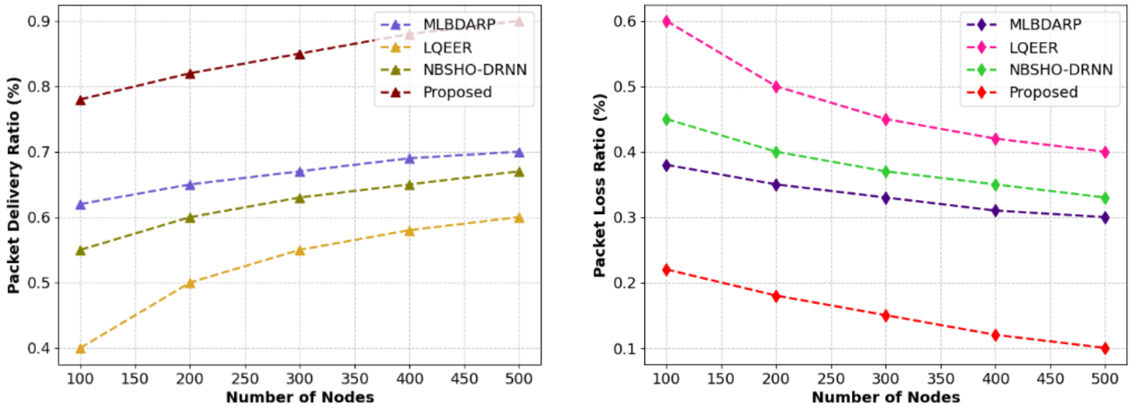


(a) (b)

Figure 4. Comparison of (a) network lifetime and (b) throughput

Figure 5(a) shows PDR which is the relation between data packets successfully broadcast by the transmitter to data transmitted by the receiver at the base station. The PDR for the FIND-ROUTE framework is highest at 90%, whereas MLBDARP, LQEER, and NBSHO-DRNN achieve 70%, 60%, and 67% respectively. Figure 5(b) compares the PLR of the FIND-ROUTE framework with the existing MLBDARP, LQEER, and NBSHO-DRNN methods. The PLR is lowest for the proposed FIND-ROUTE framework at 10%, while MLBDARP, LQEER, and NBSHO-DRNN achieve 30%, 40%, and 33% respectively. As compared to more traditional methods the graph illustrates the extent to which the FIND-ROUTE architecture reduces packet loss. A comparison of the experimental outcomes on several metrics is presented in Table 2.

Figure 6(a) shows the comparison of time complexity for the clustering process using Fuzzy-BIRCH. The fuzzy-BIRCH's time complexity is compared to that of the existing K-Means, PSO-K Means, and DBSCAN clustering algorithms. The Fuzzy-BIRCH method achieves the lowest time complexity ranging from 10 ms to 78 ms as the nodes rises from 20 to 100. In contrast, K-Means, PSO-K Means, and DBSCAN achieve higher time complexities ranges from 85 ms, 92 ms, and 90 ms, respectively. Figure 6(b) shows the space complexity associated with the routing approach. The SICNN's space complexity is compared to that of the existing DQN, LSTM, and DRL routing methods. As the number of nodes rises from 20 to 100, the SICNN approach achieves the lowest space complexity with a range of 6 MB to 60 MB. While, the existing DQN, LSTM, and DRL attains higher space complexities reaching 100 MB, 95 MB, and 85 MB, respectively.

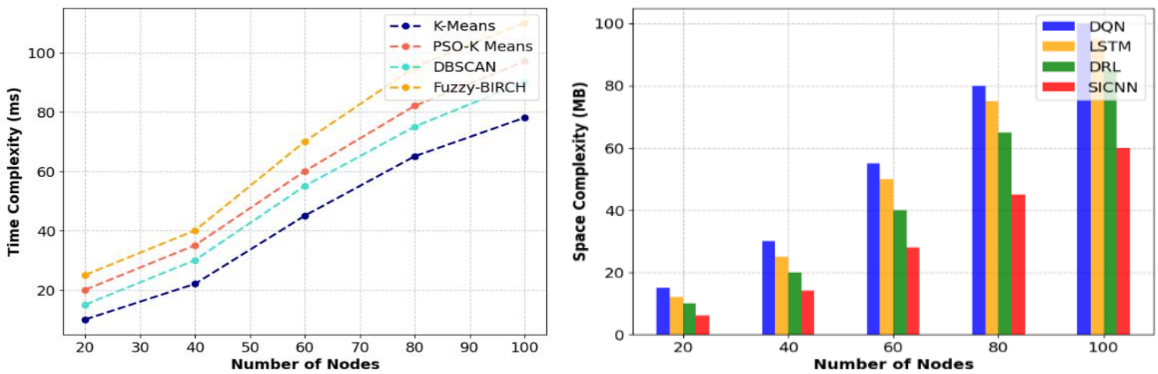


(a) (b)

Figure 5. Comparison of (a) PDR and (b) PLR

Table 2. Experimental result comparison on various metrics

Metric	MLBDARP	LQEER	NBSHO-DRNN	FIND-ROUTE
Number of alive nodes	950	960	940	970
Energy consumption (J)	1.7 J	1.5 J	1.6 J	0.65 J
Network lifetime (rounds)	29,500	30,500	30,700	33,000
Throughput (Mbps)	0.70 Mbps	0.72 Mbps	0.74 Mbps	0.95 Mbps
PDR (%)	70%	60%	67%	90%
PLR (%)	30%	40%	33%	10%



(a) (b)

Figure 6. Comparison of (a) time complexity and (b) space complexity

5. CONCLUSION

In this paper, a novel FIND-ROUTE framework is constructed for energy-aware reliable routing in IoT-WSNs using an intelligent DL network. The FIND-ROUTE framework is simulated by using MATLAB simulator and it is validated by using WSN-DS dataset. The proposed FIND-ROUTE framework is compared against the existing frameworks such as MLBDARP, LQEER, and NBSHO-DRNN regarding the network parameters including energy consumption, PDR, network lifetime, time complexity, throughput, number of alive nodes, PLR, and space complexity. In comparison, the proposed FIND-ROUTE framework achieves a PDR of 90%, whereas MLBDARP, LQEER, and NBSHO-DRNN achieve 70%, 60%, and 67% respectively. However, in terms of energy consumption the FIND-ROUTE framework outperforms the existing methods by consuming the least energy across all network sizes ranging from 0.4 J at 200 nodes to 0.65 J at 1000 nodes. In the future, a lightweight encryption algorithm with authentication layer can be integrated into the FIND-ROUTE framework to strengthen data transmission security in IoT-WSN environments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

I certify that I have explained the nature and purpose of this study to the above-named individual, and I have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

ETHICAL APPROVAL

My research guide reviewed and ethically approved this manuscript for publishing in this journal.

DATA AVAILABILITY

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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