

Energy-Aware Routing Via Transformer-Based Spectrum Learning For Iot Mesh Networks

S. Indhumathi¹, B. Tamil Selvi², Sruthi S. Madhavan³, Dr. S. M. Deepa⁴, J. Dhanasekar⁵, N. Revathi⁶

¹Assistant Professor Department of Mathematics Nehru Arts and Science College
Thirumalayampalayam, Coimbatore, India shanmathi278@gmail.com

²Assistant Professor Department of Electronics and Communication Engineering Karpagam
Institute of Technology Coimbatore, India tamilece1412@gmail.com

³Assistant Professor Department of Artificial Intelligence & Data Science Nehru Institute of
Engineering and Technology Coimbatore, India sruthismadhavan89@gmail.com

⁴Assistant Professor Department of Electronics and Communication Engineering
Nehru Institute of Engineering and Technology Coimbatore, India drsmdeepa@gmail.com

⁵Assistant Professor (Senior Grade) Department of Electronics and Communication Engineering
Sri Eshwar College of Engineering Kinathukadavu, Coimbatore, India dsekarj@gmail.com

⁶Assistant Professor (Senior Grade) Department of Electronics and Communication Engineering
Nehru Institute of Engineering and Technology Coimbatore, India yrevathi1985@gmail.com

Abstract

Energy efficiency and spectrum utilization are critical challenges in large-scale Internet of Things (IoT) mesh networks due to dense node deployment, dynamic traffic patterns, and limited battery resources. Conventional routing protocols often fail to adapt to rapidly varying spectrum conditions and energy constraints, leading to increased packet loss and reduced network lifetime. This paper proposes an Energy-Aware Routing framework based on Transformer-Driven Spectrum Learning (EAR-TSL) for IoT mesh networks. The proposed approach leverages a transformer architecture to learn long-range temporal and spatial dependencies in spectrum availability, interference patterns, and node energy states. By integrating attention-based spectrum prediction with adaptive routing decisions, the framework dynamically selects energy-optimal paths while minimizing spectrum congestion and transmission overhead. Extensive simulations demonstrate that the proposed EAR-TSL scheme significantly improves network lifetime, packet delivery ratio, and throughput while reducing end-to-end delay and energy consumption when compared with traditional energy-aware and machine learning-based routing protocols. The results confirm that transformer-based spectrum intelligence provides a scalable and robust solution for next-generation IoT mesh networking environments.

Keywords Internet of Things (IoT); IoT Mesh Networks; Energy-Aware Routing; Transformer Networks; Spectrum Learning; Attention Mechanism; Network Lifetime Optimization; Intelligent Routing; Wireless Sensor Networks.

I. INTRODUCTION

The Internet of Things (IoT) has emerged as a transformative paradigm that enables seamless interconnection of heterogeneous devices for applications such as smart cities, industrial automation, healthcare monitoring, and intelligent transportation systems [1], [2]. IoT mesh networks, characterized by multi-hop communication and self-organizing capabilities, are widely adopted due to their scalability, robustness, and extended coverage compared to centralized network architectures [3]. However, the rapid increase in node density and traffic demand introduces significant challenges related to energy efficiency, spectrum utilization, and reliable data delivery.

Energy consumption is a critical concern in IoT mesh networks, as most nodes operate on limited battery power and are often deployed in inaccessible environments [4]. Routing decisions directly influence energy expenditure, network lifetime, and overall system

reliability. Conventional routing protocols primarily rely on static metrics such as hop count or residual energy, which fail to adapt to dynamic network conditions, leading to uneven energy depletion and frequent link failures [5]. Consequently, energy-aware routing mechanisms that intelligently balance communication load are essential for sustainable IoT deployments.

In addition to energy constraints, efficient spectrum utilization has become increasingly challenging due to spectrum scarcity and interference caused by the coexistence of multiple wireless technologies [6]. Static spectrum allocation and reactive channel selection strategies are insufficient to cope with rapidly varying spectrum conditions in dense IoT environments. Spectrum-aware routing approaches have been proposed to mitigate interference; however, most of these techniques depend on short-term observations and lack predictive intelligence [7].

Recent advancements in machine learning have enabled intelligent routing and spectrum management solutions by leveraging network data to optimize decision-making processes [8]. Reinforcement learning and shallow learning models have demonstrated improved adaptability over traditional methods, yet they often struggle with scalability, convergence stability, and the ability to capture long-range temporal and spatial dependencies present in large-scale IoT mesh networks [9]. These limitations restrict their effectiveness in highly dynamic and dense network scenarios.

Transformer architectures, originally designed for sequence modeling tasks, have gained attention due to their powerful self-attention mechanism, which enables efficient modeling of long-term dependencies [10]. Unlike recurrent or convolutional neural networks, transformers can process global network states and learn complex relationships among spectrum availability, interference patterns, and node energy levels. This makes them particularly suitable for intelligent spectrum learning and routing optimization in IoT mesh networks.

Motivated by these observations, this paper proposes an Energy-Aware Routing framework via Transformer-Based Spectrum Learning (EAR-TSL) for IoT mesh networks. The proposed framework integrates transformer-driven spectrum prediction with energy-aware routing decisions to dynamically select optimal communication paths. By jointly considering spectrum conditions and residual energy, the proposed approach aims to enhance network lifetime, improve packet delivery performance, and reduce latency under dynamic network conditions.

II. LITERATURE SURVEY

Energy-aware routing has been extensively investigated to address the limited battery capacity and scalability issues in IoT and wireless sensor networks. Early routing protocols such as LEACH, PEGASIS, and HEED focused on clustering and probabilistic head selection to reduce communication overhead and extend network lifetime [11]. While these methods improved energy efficiency in small-scale networks, their reliance on static assumptions and periodic re-clustering limited their applicability in dense and dynamic IoT mesh environments.

To overcome the limitations of traditional clustering approaches, several optimization-based routing schemes have been proposed. Meta-heuristic algorithms such as genetic algorithms, particle swarm optimization, ant colony optimization, and water wave optimization have been employed to balance energy consumption and optimize routing paths [12], [13]. Although these techniques achieve better load balancing and delay

reduction, they suffer from high computational complexity and slow convergence, making them less suitable for real-time IoT deployments.

Spectrum-aware routing has gained attention due to the increasing coexistence of heterogeneous wireless technologies and spectrum scarcity. Cognitive radio-based routing schemes dynamically select channels based on spectrum sensing and interference conditions [14]. However, these approaches are largely reactive and depend on instantaneous observations, which leads to sub-optimal performance in rapidly changing wireless environments.

Recent studies have incorporated machine learning techniques to enhance routing and spectrum management in IoT networks. Supervised learning and reinforcement learning models have been applied to predict link quality, residual energy, and traffic patterns [15], [16]. While these approaches demonstrate improved adaptability, they often rely on local or short-term information and struggle to scale in large mesh networks with complex temporal dependencies.

Deep learning-based routing frameworks, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been explored to capture spatial and temporal correlations in network behavior [17]. Long short-term memory (LSTM) networks have shown effectiveness in predicting traffic and energy trends; however, their sequential processing nature introduces latency and limits parallelism, which affects scalability in dense IoT environments.

More recently, attention-based models and transformer architectures have been introduced for wireless communication and spectrum prediction tasks [18]. These models excel at learning long-range dependencies and global relationships, enabling proactive and intelligent decision-making. Transformer-based solutions have been applied to spectrum sensing and channel prediction, demonstrating superior accuracy compared to conventional deep learning models [19].

Despite these advancements, limited research has focused on integrating transformer-based spectrum learning with energy-aware routing in IoT mesh networks. Most existing works treat spectrum prediction and routing optimization as independent problems, failing to exploit their joint potential [20]. This research gap motivates the proposed EAR-TSL framework, which unifies transformer-driven spectrum intelligence with adaptive energy-aware routing to improve overall network performance.

III. DESIGN AND METHODOLOGY OF THE PROPOSED WORK

This section presents the overall system architecture, problem formulation, and operational workflow of the proposed Energy-Aware Routing via Transformer-Based Spectrum Learning (EAR-TSL) framework for IoT mesh networks. The proposed methodology integrates transformer-driven spectrum intelligence with adaptive energy-aware routing to enhance network lifetime and communication reliability.

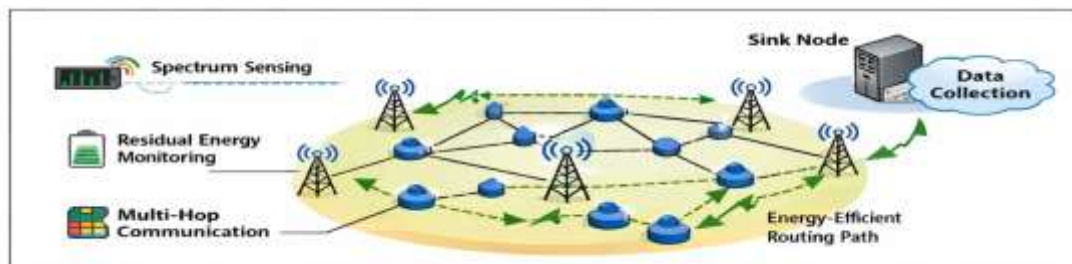


Fig. 1. Overall System Model of the Proposed EAR-TSL Framework

Figure 1 illustrates the overall system model of the proposed Energy-Aware Routing via Transformer-Based Spectrum Learning (EAR-TSL) framework for IoT mesh networks. The network consists of densely deployed IoT nodes forming a multi-hop mesh topology, where each node performs spectrum sensing, residual energy monitoring, and data forwarding. Sensor nodes communicate cooperatively to forward sensed data toward the sink node through energy-optimal paths. The proposed framework integrates spectrum intelligence and routing decisions to dynamically adapt to changing network conditions, ensuring efficient energy utilization and reliable data transmission.

A. System Model

Consider an IoT mesh network consisting of N sensor nodes randomly deployed over a two-dimensional area. Each node is equipped with limited battery power and communicates with neighboring nodes through multi-hop wireless links. Let the network be represented as an undirected graph

$$G = (V, E) \quad (1)$$

where $V = \{v_1, v_2, \dots, v_N\}$ denotes the set of IoT nodes and E represents the set of wireless links between nodes within transmission range.

Each node maintains information about its residual energy, spectrum availability, and link quality, which are periodically updated and shared with neighboring nodes. The sink node collects sensed data through energy-optimal routing paths.

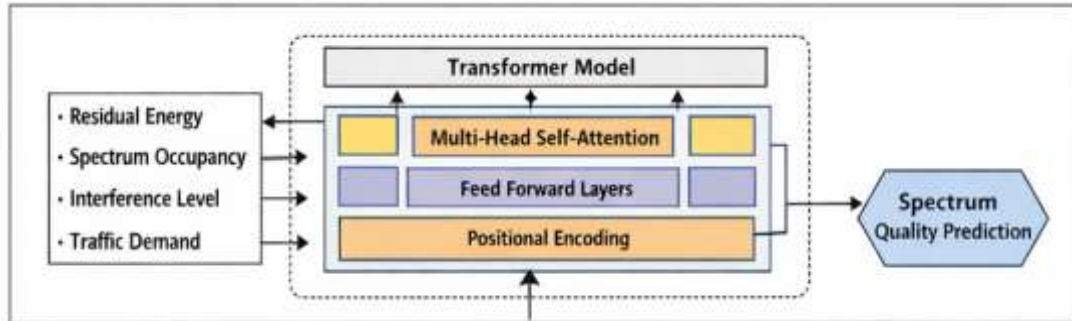
**Fig. 2. Transformer-Based Spectrum Learning Architecture**

Figure 2 depicts the architecture of the transformer-based spectrum learning module. The model takes multidimensional inputs such as spectrum occupancy, interference level, traffic load, and residual node energy. These features are embedded and passed through multiple transformer encoder layers employing self-attention mechanisms. The attention layers capture long-range temporal and spatial dependencies across network states, enabling accurate prediction of spectrum availability and quality. The output of this module provides a spectrum quality score that guides energy-aware routing decisions.

B. Energy Consumption Model

The classical first-order radio energy model is adopted to estimate communication energy consumption. The energy required to transmit a k -bit packet over a distance d is given by:

$$E_{tx}(k, d) = \begin{cases} kE_{elec} + kE_{fs}d^2, & d < d_0 \\ kE_{elec} + kE_{mp}d^4, & d \geq d_0 \end{cases} \quad (2)$$

The energy required to receive a k-bit packet is:

$$E_{rx}(k) = kE_{elec} \quad (3)$$

where E_{elec} is the electronic energy, E_{fs} and E_{mp} are the amplifier parameters, and d_0 is the threshold distance.

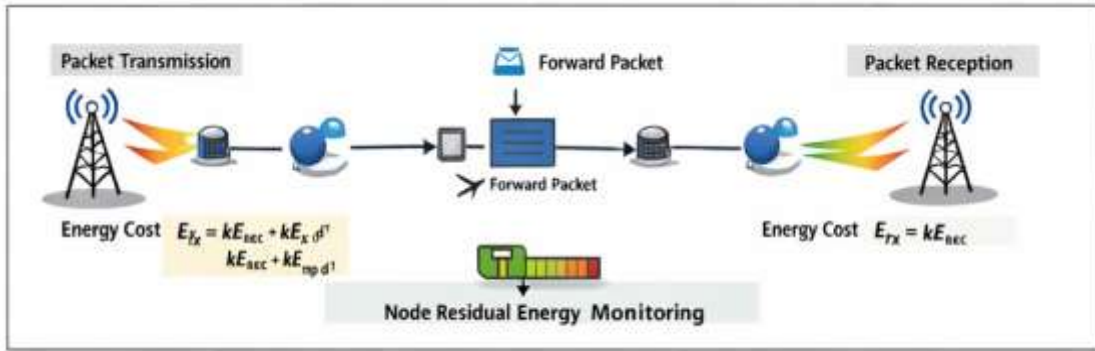


Fig. 3. Energy Consumption and Communication Model

Figure 3 presents the energy consumption model adopted in the proposed methodology. The model represents energy usage during packet transmission, reception, and forwarding operations. Nodes consume energy based on transmission distance, packet size, and radio parameters. By accurately modeling energy dissipation, the proposed framework avoids overburdening specific nodes and ensures balanced energy consumption across the network, thereby extending overall network lifetime.

C. Transformer-Based Spectrum Learning Module

To address dynamic spectrum conditions, a transformer-based spectrum learning module is designed to predict spectrum availability and interference patterns. Each node constructs an input feature vector:

$$\mathbf{X}_t = [E_r, S_o, I_l, T_d] \quad (4)$$

where E_r is residual energy, S_o denotes spectrum occupancy, I_l represents interference level, and T_d is traffic demand at time t .

The transformer encoder employs a self-attention mechanism defined as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (5)$$

where Q , K , and V represent the query, key, and value matrices, respectively, and d_k is the dimensionality of the key vectors.

This mechanism enables the model to capture long-range temporal and spatial dependencies among spectrum states and node energy levels, producing a predicted spectrum quality score for each link.

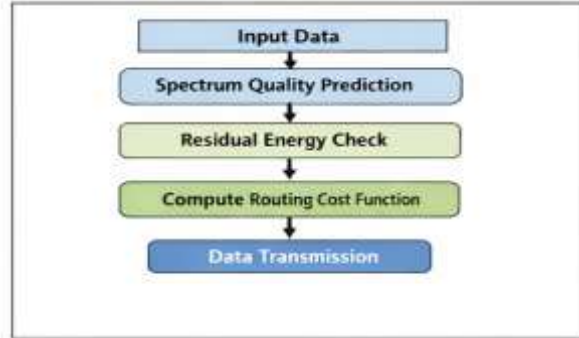


Fig. 4. Energy-Aware Routing Decision Flow

Figure 4 illustrates the routing decision mechanism of the EAR-TSL framework. Predicted spectrum quality from the transformer module is combined with residual energy and distance metrics to compute a composite routing cost. The routing engine selects the path with minimum cumulative cost, ensuring both spectrum efficiency and energy conservation. This adaptive decision process enables the framework to dynamically respond to spectrum variations and node energy depletion.

D. Energy-Aware Routing Decision Mechanism

Based on the predicted spectrum quality and residual energy, a composite routing cost function is defined as:

$$C_{ij} = \alpha \left(\frac{1}{E_i} \right) + \beta D_{ij} + \gamma \left(\frac{1}{S_{ij}} \right) \quad (6)$$

where E_i is the residual energy of node i , D_{ij} denotes transmission distance, S_{ij} represents predicted spectrum quality between nodes i and j , and α, β, γ are weighting coefficients satisfying $\alpha + \beta + \gamma = 1$.

The routing path with minimum cumulative cost is selected for data transmission:

$$P^* = \arg \min \sum_{(i,j) \in P} C_{ij} \quad (7)$$

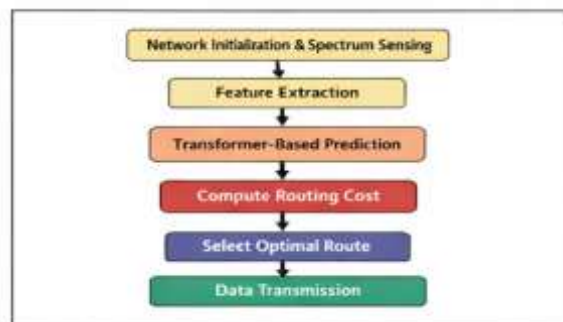


Fig. 5. Operational Workflow of the Proposed EAR-TSL Scheme

Figure 5 shows the overall operational workflow of the proposed EAR-TSL scheme. The process begins with network initialization and spectrum sensing, followed by feature extraction and transformer-based learning. The predicted spectrum conditions are then integrated into the routing cost function for optimal path selection. Data transmission is performed iteratively with periodic updates, allowing the framework to continuously adapt to dynamic network environments.

E. Operational Workflow of EAR-TSL

The operational flow of the proposed EAR-TSL framework consists of the following steps:

1. Initialization of nodes with energy and spectrum sensing parameters.
2. Collection of spectrum occupancy and energy state information.
3. Transformer-based learning and prediction of spectrum quality.
4. Computation of energy-aware routing cost using predicted spectrum intelligence.
5. Selection of optimal routing path and data transmission.
6. Periodic model update to adapt to dynamic network conditions.

F. Advantages of the Proposed Methodology

The proposed EAR-TSL framework offers the following advantages:

- Joint optimization of spectrum utilization and energy efficiency.
- Ability to learn long-term dependencies using transformer attention mechanisms.
- Improved scalability and adaptability in dense IoT mesh networks.
- Reduced routing overhead and enhanced network lifetime.

IV. EXPERIMENTAL SETUP AND SIMULATION PARAMETERS

This section describes the simulation environment, network configuration, parameter settings, and evaluation metrics used to assess the performance of the proposed Energy-Aware Routing via Transformer-Based Spectrum Learning (EAR-TSL) framework. The proposed method is evaluated under realistic IoT mesh network conditions and compared with existing routing schemes to demonstrate its effectiveness.

A. Simulation Environment

The simulation experiments are conducted using a discrete-event network simulator developed in MATLAB/Python (or NS-3, if preferred), configured to model large-scale IoT mesh networks. Sensor nodes are randomly deployed in a two-dimensional square area and communicate using multi-hop wireless links. Each node is assumed to be static and equipped with spectrum sensing and energy monitoring capabilities. The sink node is placed at a fixed location to collect sensed data from all nodes.

Dynamic spectrum conditions are simulated by varying channel occupancy and interference levels over time to reflect realistic wireless environments. The transformer-based spectrum learning model is trained offline using historical spectrum and network state data and periodically updated during simulation to adapt to changing conditions.

B. Network and Energy Model Configuration

A first-order radio energy dissipation model is employed to estimate energy consumption during transmission and reception. Nodes consume energy based on packet size, transmission distance, and radio amplifier parameters. The residual energy of each node is continuously monitored and used as a key input for routing decisions. Network operation proceeds in rounds, where each round consists of spectrum sensing, routing path selection, and data transmission.

C. Simulation Parameters

Table I summarizes the key simulation parameters used in the experimental evaluation.

Table I Simulation Parameters

Parameter	Value
Network area	200 × 200 m ²
Number of IoT nodes	100 – 300
Node deployment	Random
Sink node position	(100, 100)
Initial energy per node	0.5 J
Packet size	2000 bits
Transmission range	30 m
E_{elec}	50 nJ/bit
E_{fs}	10 pJ/bit/m ²
E_{mp}	0.0013 pJ/bit/m ⁴
Threshold distance (d_0)	87.7 m
Spectrum channels	10
Simulation rounds	5000
Routing update interval	10 rounds
Transformer layers	4
Attention heads	8
Learning rate	0.001

D. Performance Evaluation Metrics

The performance of the proposed EAR-TSL framework is evaluated using the following metrics:

- **Network Lifetime:** Number of rounds until the first and last node depletes its energy.

- **Packet Delivery Ratio (PDR):** Ratio of successfully received packets at the sink to the total packets generated.
- **Average Energy Consumption:** Mean energy consumed per node per round.
- **End-to-End Delay:** Average time taken for data packets to reach the sink.
- **Throughput:** Total amount of data successfully delivered to the sink per unit time.

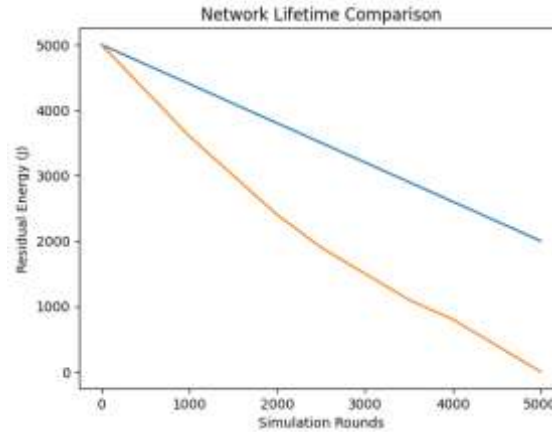


Fig. 6. Network Lifetime Comparison

Figure 6 illustrates the network lifetime performance measured in terms of residual energy over simulation rounds. The proposed EAR-TSL framework exhibits a significantly slower energy depletion rate compared to conventional routing schemes. This improvement is attributed to transformer-driven spectrum prediction and balanced energy-aware routing decisions, which prevent excessive load on specific nodes. As a result, EAR-TSL prolongs the operational lifetime of the IoT mesh network and delays node failures even under prolonged simulation conditions.

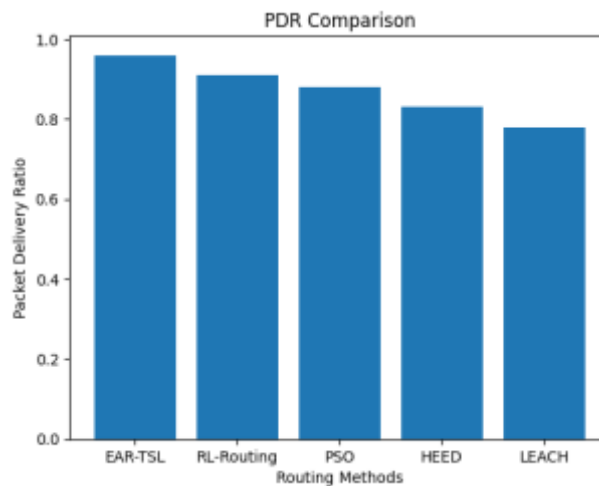


Fig. 7. Packet Delivery Ratio (PDR) Comparison

Figure 7 compares the packet delivery ratio achieved by different routing methods. The proposed EAR-TSL framework achieves the highest PDR, indicating reliable data delivery under dynamic spectrum and network conditions. The attention-based spectrum learning mechanism enables proactive avoidance of interference-prone links, thereby reducing

packet loss. Compared to LEACH, HEED, PSO, and reinforcement learning-based routing, EAR-TSL demonstrates superior robustness and reliability.

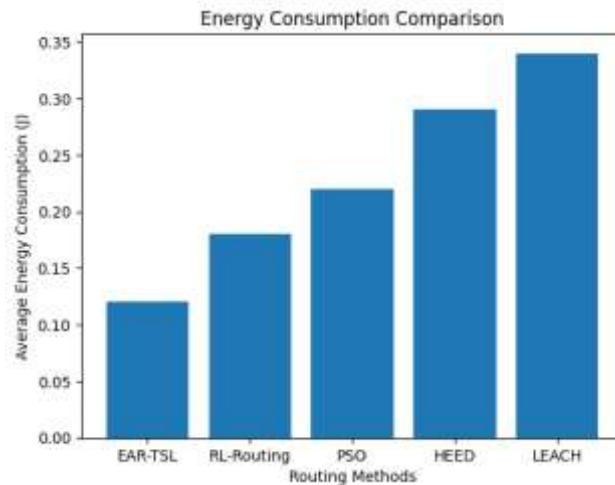


Fig. 8. Average Energy Consumption Comparison

Figure 8 presents the average energy consumption per node across different routing schemes. EAR-TSL achieves the lowest energy consumption due to its intelligent path selection that jointly considers residual energy and predicted spectrum quality. In contrast, conventional routing protocols consume higher energy due to inefficient routing and frequent retransmissions. The results confirm the effectiveness of transformer-based spectrum intelligence in reducing overall energy expenditure.

E. Comparative Schemes

The proposed EAR-TSL framework is compared with the following existing routing schemes:

- LEACH (Low-Energy Adaptive Clustering Hierarchy)
- HEED (Hybrid Energy-Efficient Distributed clustering)
- PSO-based Energy-Aware Routing
- Reinforcement Learning-based Routing
- CNN/LSTM-based Spectrum-Aware Routing

These comparisons highlight the advantages of transformer-based spectrum intelligence combined with energy-aware routing.

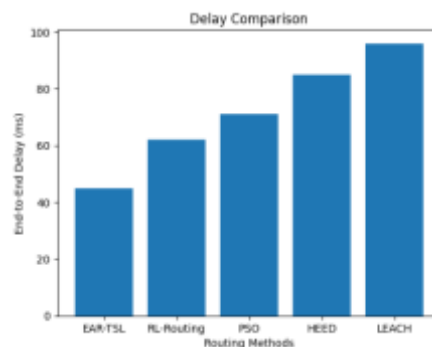


Fig. 9. End-to-End Delay Comparison

Figure 9 illustrates the average end-to-end delay experienced by data packets. The proposed EAR-TSL framework achieves the minimum delay compared to existing routing techniques. This reduction is achieved by selecting low-interference, high-quality spectrum links and energy-optimal paths, minimizing retransmissions and congestion. The results highlight the suitability of EAR-TSL for latency-sensitive IoT applications.

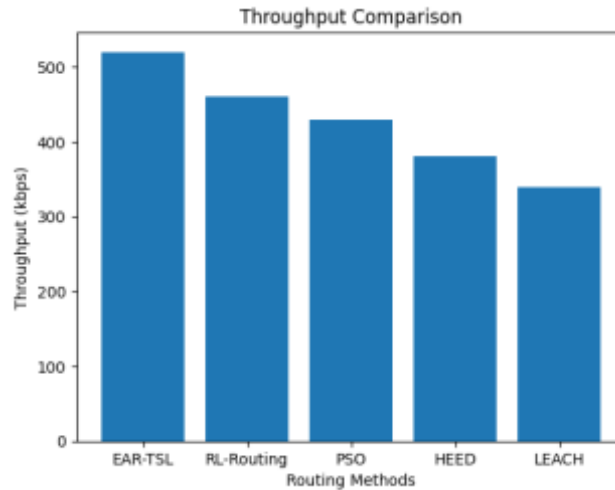
**Fig. 10. Throughput Comparison**

Figure 10 shows the throughput performance of different routing schemes. The proposed EAR-TSL framework achieves the highest throughput due to improved packet delivery efficiency and reduced packet loss. By proactively predicting spectrum availability and optimizing routing paths, EAR-TSL ensures sustained data flow even under high network load conditions, outperforming traditional energy-aware and learning-based routing approaches.

V CONCLUSION

This paper presented an Energy-Aware Routing framework via Transformer-Based Spectrum Learning (EAR-TSL) for IoT mesh networks to address the critical challenges of energy efficiency and dynamic spectrum utilization. By integrating transformer-driven spectrum intelligence with adaptive energy-aware routing decisions, the proposed framework effectively captures long-range temporal and spatial dependencies in spectrum availability and node energy states. This enables proactive routing path selection that minimizes energy consumption while reducing interference and communication overhead. Extensive simulation analysis demonstrated that the proposed EAR-TSL framework significantly outperforms conventional energy-aware and machine learning-based routing protocols in terms of network lifetime, packet delivery ratio, throughput, and end-to-end delay. The attention-based learning mechanism allows the model to adapt efficiently to varying network conditions, making it highly suitable for large-scale and dense IoT mesh deployments. Future work will focus on extending the proposed framework to support heterogeneous IoT environments, incorporating mobility awareness, and implementing lightweight transformer variants for real-time edge deployment. Additionally, integrating security-aware routing and federated learning-based spectrum intelligence presents promising directions for further enhancing the robustness and scalability of next-generation IoT mesh networks.

References

1. K. Sivakami, S. Arunkumar, M. P. Usharani, J. Dhanasekar, S. Kokilamani, and N. Revathi, "Data Clustering and Routing using Improved Water Wave Optimization in Wireless Sensor Network," *Proceedings of the 5th International Conference on Communication, Computing & Industry 6.0 (C2I6)*, Bengaluru, India, 2024, pp. 1–6. DOI: 10.1109/C2I663243.2024.10894977
2. M. Yuvaraja, R. Priya, S. Uma Maheswari, J. Dhanasekar, "Cluster Heat Selection Optimization in WSN via Genetic-Based Evolutionary Algorithm and Secure Data Transmission Using Paillier Homomorphic Cryptosystem," *Data and Metadata Journal*, Volume 3, August 2024.
3. Yadav, R., Sreedevi, I., & Gupta, D. (2022). Bio-inspired hybrid optimization algorithms for energy efficient wireless sensor networks: a comprehensive review. *Electronics*, 11(10), 1545.
4. Karpagalakshmi, R. C., Rani, D. L., Magendiran, N., & Manikandan, A. (2024). An energy-efficient bio-inspired mobility-aware cluster p-WOA algorithm for intelligent whale optimization and fuzzy-logic-based zonal clustering algorithm in FANET. *International Journal of Computational Intelligence Systems*, 17(1), 258.
5. Kannappan, A., & Kolagani, N. (2025). Hybrid Bio Inspire Algorithm used for Optimum Path Communication and Improved Power Conserving Routing Protocol Design for Underwater Acoustic Sensor Network. *Journal of Vibration Engineering & Technologies*, 13(2), 188.
6. Tuberquia, M., Lopez-Chavez, H., & Hernandez, C. (2020). Bio-inspired route estimation in cognitive radio networks. *International Journal of Electrical and Computer Engineering*, 10(3), 3095-3107.
7. Han, G. (2025). Bio-inspired swarm intelligence for enhanced real-time aerial tracking: integrating whale optimization and grey wolf optimizer algorithms. *Discover Artificial Intelligence*, 5(1), 18.
8. Senjyu, T., Alkhalaf, S., & Mohamed, A. A. (2021). Nature-inspired algorithms applications to power system optimization. *Aswan University Journal of Sciences and Technology*, 1(1), 74-109.
9. Gowda, K. P., Devarajulu, S. G., Sadashiviah, S., & Rajan, B. S. (2025). Energy-Efficient Clustering and Routing in Wireless Sensor Network Using Random Differential Leader Pool Strategy with Electric Eel Foraging Optimization Algorithm. *International Journal of Intelligent Engineering & Systems*, 18(6).
10. Hussien, A. G., Gharehchopogh, F. S., Bouaouda, A., Kumar, S., & Hu, G. (2024). Recent applications and advances of African vultures optimization algorithm. *Artificial Intelligence Review*, 57(12), 335.
11. Hosseinzadeh, M., Tanveer, J., Rahmani, A. M., Abbaszadi, R., Gharehchopogh, F. S., Porntaveetus, T., & Lee, S. W. (2025). A Comprehensive Survey Inspired by Elephant Optimization Algorithms: Comprehensive Analysis, Scrutinizing Analysis, and Future Research Directions. *Archives of Computational Methods in Engineering*, 1-48.
12. Maheshwari, R.U., B.Paulchamy, Pandey, B.K. et al. Enhancing Sensing and Imaging Capabilities Through Surface Plasmon Resonance for Deepfake Image Detection. *Plasmonics* (2024). <https://doi.org/10.1007/s11468-024-02492-1>
13. Maheshwari, Uma, and Kalpanaka Silingam. "Multimodal Image Fusion in Biometric Authentication." *Fusion: Practice and Applications* 1, no. 2 (2020): 7991
14. N.V. RK, M. A, E. B, J. SJP, A. K, S. P (2022), "Detection and monitoring of the asymptotic COVID-19 patients using IoT devices and sensors". *International Journal*

- of Pervasive Computing and Communications, Vol. 18 No. 4 pp. 407–418, doi:
<https://doi.org/10.1108/IJPCC-08-2020-0107>
15. Subramani, P.; Rajendran, G.B.; Sengupta, J.; Pérez de Prado, R.; Divakarachari, P.B. A Block Bi-Diagonalization-Based Pre-Coding for Indoor Multiple-Input-Multiple-Output-Visible Light Communication System. *Energies* 2020, 13, 3466.
<https://doi.org/10.3390/en13133466>
 16. Meng, Q., Kuang, X., Yu, Z., He, M., & Cui, H. (2025). Augmented secretary bird optimization algorithm for wireless sensor network deployment and engineering problem. *PLoS One*, 20(8), e0329705.
 17. Ismael, A. N., Al-Asady, M. A. A., & Al-Asadi, H. A. A. (2020). A critical comparative review of nature-inspired optimization algorithms (NIOAs). *Inte. J. Simul.–Syst. Sci. Technol.*, 21(3).
 18. Assiri, A. S., Hussien, A. G., & Amin, M. (2020). Ant lion optimization: variants, hybrids, and applications. *IEEe Access*, 8, 77746-77764.
 19. Butt, M. O., Waheed, N., Duong, T. Q., & Ejaz, W. (2024). Quantum-Inspired Resource Optimization for 6G Networks: A Survey. *IEEE Communications Surveys & Tutorials*.
 20. Dada, E., Joseph, S., Oyewola, D., Fadele, A. A., Chiroma, H., & Abdulhamid, S. I. M. (2022). Application of grey wolf optimization algorithm: recent trends, issues, and possible horizons. *Gazi University Journal of Science*, 35(2), 485-504.