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A CROSS-LAYER ROUTING FRAMEWORK FOR ENERGY-EFFICIENT AND LOW-LATENCY IOT COMMUNICATION: SIMULATION AND EXPERIMENTAL VALIDATION

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ABSTRACT

The rapid expansion of the Internet of Things (IoT) has created unprecedented challenges in providing efficient, low-latency, and energy-aware communication among resource-constrained devices. Traditional routing approaches are designed in isolation from each other at different layers of the OSI model and therefore do not consider the interdependencies between as an example of the physical, MAC, and network layers. In this work, we present a Cross-Layer Routing Framework (CLRF), which dynamically integrates metrics of residual energy (RE), link quality (LQ), and latency (E2E latency to each node) to provide efficient routing in heterogeneous IoT environments. The validity of the framework is established by extensive simulation studies carried out in NS-3 and experimental deployment as a testbed using an ESP32-Raspberry Pi combination. The simulation and experimental results show that CLRF achieves up to 25% improved energy efficiency, 40% improved average end-to-end latency, and 12% improved packet delivery ratio (PDR) compared to traditional baseline protocols such as LEACH and RPL. The statistical validity of the improvements is confirmed through Wilcoxon signed-rank test with 30 independent runs ($p < 0.05$) and bootstrap confidence intervals further reinforce the reliability of the experimental findings. The experimental results show similar behavior to the simulation results and it indicates the robustness and scalability of the framework. This research proposes a unified framework addressing dual problems of energy efficiency and delay which allows for sustainable and real-time communication in IoT communications.

Keywords: *Cross-Layer Design, Iot Communication, Energy Efficiency, Low-Latency Routing, NS-3 Simulation, Experimental Validation*

1. INTRODUCTION

The Internet of Things (IoT) has quickly transformed the modern communication networks by connecting billions of devices that can interoperate and share data with ease. These devices can be as simple as a wearable health monitor, or complex like an industrial sensor, and they help facilitate real-time decision-making and automation in all industries including healthcare, agriculture, smart cities, and critical infrastructure. However, even with all its potential, IoT communication faces two major challenges imposed by the features of IoT communication environments: limited energy resources of end devices, and low latency requirements for mission-critical applications. Traditional routing protocols are often designed around an isolated view of the network layer, and their performance will be unsustainable in any environment when energy efficiency and delay minimization are equally important.

A comprehensive review of the literature shows that conventional layer-isolated routing protocols have inefficiencies, since they do not take advantage of interdependencies between the physical, MAC, and network layers. For example, protocols that are optimized for energy often incur a latency cost, while protocols that seek to minimize delay can quickly deplete a battery. When the costs of these trade-offs have a real-world impact, the ramifications can be drastic—especially in IoT implementations where devices are battery-operated, lightweight, and constrained. To tackle this challenge, it has been recommended that cross-layer design is a paradigm and that cross-layer signal processing techniques can jointly optimize all OSI layers resulting in enhanced adaptability, efficiency, and scalability. Prior work regarding intrusion detection and communication optimization [22], [5] demonstrates that hybrid machine learning–based cross-layer techniques can improve overall system robustness and this work serves as motivation to pursue similar design philosophies in routing frameworks.

1.1 Motivation And Research Context

This study was driven by the fact that traditional IoT routing protocols are not flexible enough to meet the needs of the diverse and dynamic demands of the current applications of the IoT. Delays in the delivery of packets in latency-sensitive applications including smart healthcare monitoring [3] threaten the safety of the patient. And likewise, high-energy consumption in industrial IoT can lead to the frequent replacement of the devices and increase the operations. Other researchers, including [17], have shown that new routing algorithms in wireless sensor networks can be used to improve energy efficiency but have not explicitly considered the latency optimization, which is why they are not the most appropriate in real-time. Similarly, [26] and [21] also studied intelligent feature selection and VPN flow detection but addressed the problem of anomaly detection instead of routing optimization. The recent literature on IoT security and data management [22]; [8] demonstrates the relevance of the cross-layer and proxy-oriented approach to enhance the scale and reliability of the heterogeneous environment, whereas the research on fraud detection [5] emphasizes the importance of adaptive and machine learning-based methods. Despite the progress of these studies on the resilience of IoT, they are aimed to address the issue of energy-latency trade-off in routing without filling a research gap.

The new Cross-Layer Routing Framework (CLRF) directly fills this gap by incorporating the residual energy values of the physical layer, the duty-cycling and reliability of links of the MAC layer as well as the queueing delay and hop count of the network layer. This is a holistic integration, which guarantees that routing decisions are not only energy-efficient and have lower latency but maintain scalability, which is why the framework is applicable to heterogeneous IoT ecosystems.

1.2 Problem Statement

In spite of the current improvements in IoT routing protocols, there are three key gaps:

1. Energy–Latency Trade-off: Most protocols optimize either energy efficiency or latency but fail to deliver balanced performance.
2. Simulation-Centric Validation: Many proposals are tested only in simulation environments, lacking experimental validation on real hardware.
3. Lack of Cross-Layer Integration: Existing protocols rarely combine metrics from multiple OSI layers into a unified decision-making process.

These limitations clearly highlight the absence of a framework that ensures energy-efficient, low-latency, and experimentally validated IoT communication. To bridge this gap, the proposed CLRF introduces a holistic approach that integrates metrics across multiple layers, enabling sustainable and delay-sensitive IoT routing.

1.3 Objectives Of The Study

Building on the identified gaps, this study pursues the following objectives:

- To design a cross-layer routing framework (CLRF) that integrates metrics from physical, MAC, and network layers into a single routing decision metric.
- To evaluate performance through simulation using NS-3 with diverse node densities and traffic conditions, benchmarking energy consumption, end-to-end latency, packet delivery ratio (PDR), and throughput.
- To validate the framework experimentally on hardware by deploying it on an ESP32–Raspberry Pi testbed.
- To conduct a comparative analysis against established protocols such as LEACH, AODV, and RPL, thereby demonstrating improvements in energy efficiency and latency.
- To apply non-parametric statistical significance testing to confirm the robustness of performance improvements with high confidence.

By addressing these objectives, the study not only validates the feasibility of CLRF in both simulated and real environments but also positions it as a benchmark solution for future IoT routing protocols.

1.4 Contributions Of The Research

This study makes the following novel contributions to the field of IoT routing research:

1. Cross-Layer Routing Framework (CLRF): A unified design that integrates residual energy, link reliability, and latency metrics into a composite routing decision.
2. Simulation and Experimental Validation: Unlike prior simulation-centric works, this research validates the proposed framework through both NS-3 simulations and a real IoT testbed.
3. Energy–Latency Optimization: Demonstrates up to 25% reduction in energy consumption and 40% latency improvement over conventional protocols.
4. Scalability and Reliability: Confirms that the framework maintains high packet delivery ratio (>95%) under increasing node density, proving robustness for large-scale IoT deployments.
5. Future-Ready Relevance: Aligns with emerging paradigms such as 6G-enabled ultra-reliable and low-latency communication (URLLC) and edge-intelligent IoT, ensuring long-term applicability.

In summary, these contributions collectively highlight how CLRF advances the state of IoT routing research by simultaneously addressing energy efficiency, latency reduction, scalability, and real-world applicability—dimensions often treated separately in existing works.

1.5 Organization Of The Paper

The paper is structured as follows. Section 2 reviews prior work on cross-layer design, energy-efficient routing, and latency-aware IoT communication. Section 3 explains the proposed framework and methodology, including simulation and testbed setup. Section 4 presents results with statistical validation, while Section 5 discusses findings, practical implications, and future directions. Finally, Section 6 consolidates the study by confirming that all objectives have been achieved, the identified research gap addressed, and the potential impact of CLRF for next-generation IoT applications highlighted.

2. LITERATURE REVIEW

The literature on IoT routing demonstrates substantial advances in cross-layer design, energy-efficient protocols, latency-aware communication, and machine learning/fuzzy-based optimization. Despite these contributions, significant gaps remain in simultaneously optimizing energy and latency, incorporating intelligent metrics into routing, and validating frameworks in real-world deployments. This section reviews the most relevant studies, highlighting their contributions, limitations, and implications for the proposed Cross-Layer Routing Framework (CLRF).

2.1 Cross-Layer Design Approaches

Cross-layer design has emerged as a key strategy for enhancing IoT communication by leveraging interdependencies between OSI layers. [2] demonstrated energy reductions in clustered wireless sensor networks through MAC-layer integration with routing. However, their framework did not address delay-sensitive applications, leaving latency unoptimized. Similarly, [4] proposed a multi-layer energy-efficient framework, which extended node lifetime but lacked experimental validation, limiting applicability to real-world IoT.

[15] surveyed cross-layer architectures for secure, low-latency communication, emphasizing the necessity of integrating routing logic with multi-layer information. [16,17] discussed the trade-off between energy efficiency and latency in the context of cross-layer designs. Even though this later work presented an original conceptual architecture for security, it had neither empirical nor comparative testing that demonstrated the recurring issues of remaining ideas and frameworks in the literature versus practical solutions.

In addition to heuristic and optimization-based designs, contemporary literature has demonstrated the application of metaheuristic methods, including multi-verse and dragonfly algorithms, to cross-layer optimization methods to support interoperability in heterogeneous IoT environments [9]. Previous empirical work on IoT routing designs reported the feasibility of energy-efficient cross-layer routing

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systems which established a baseline for subsequent frameworks [28]. Prior work reported on cross-layer routing in security and data management [21]; [22]; [8], and while the reported studies employed a security lens, the hybrid and proxy-based design implemented improved adaptability and improved robustness. In offering these additional perspectives for CANR, each approach could enhance CLRF's dynamic routing metric that considers multiple objectives - which would include a measure of residual energy, link reliability, and latency - and achieve balanced multi-objective optimization in heterogeneous IoT networks.

2.2 Energy-Efficient Routing Protocols

Energy-aware routing continues to be of paramount importance for battery-limited IoT devices. [27] proposed an energy-efficient WSN routing protocol that contributed to enhanced network lifetime but did not directly deal with latency constraints, making it unsuitable for real-time scenarios. [19] testing using fuzzy logic for hierarchical routing managed to save energy compared to first-order routing, but faced serious challenges during large-scale public deployment due to computational complexity and limited implementation possibilities. [1] proposed a multipath routing strategy to efficiently distribute the traffic across the network to achieve a better distribution of energy, however, delays increased considerably during heavy traffic.

On a related topic, work has been expanded utilizing software-defined networking (SDN) as an add-on to improve RPL's energy efficiency [10]. Also, hybrid particle swarm optimization was used for cluster-based routing strategies and improved energy efficiency and delivery reliability [25]. [7] expanded and used a cross-layer routing approach for UAV-based networks to optimize systems for energy and congestion. The work reported is still network-based implementation and is primarily realized for mobile or airborne networks, making it less transferable to terrestrial IoT cases. The prior studies confirm the direction of energy optimization is not sufficient, motivating CLRF's integrated energy-latency metric and its potential to simultaneously finish energy and latency effort in static, 2.3 Latency and QoS-Aware Communication

Low-latency communication is vital to mission-critical IoT applications. In a recent study of [14], a routing protocol utilizing MAC-layer feedback was presented, which decreased packet delay, however, in doing so energy constraints were disregarded, leading to potential sustainability issues. [24] addressed QoS and latency in underwater sensor networks, achieving reliable delivery, yet their methods are not directly transferable to terrestrial IoT.

[13] proposed a 6G-enabled multi-channel framework optimizing both latency and energy for high-capacity IoT nodes. While effective, it is unsuitable for low-power edge devices typical of real-world deployments. More recently, novel hybrid approaches leveraging near-field communication alongside long-range radio technologies have been explored to improve IoT efficiency and responsiveness [6]. In addition, RPL has even been extended to specialized domains such as underwater IoT, highlighting its adaptability but also unique constraints [12].

CLRF builds upon these insights by integrating latency-aware metrics with energy optimization, ensuring applicability across heterogeneous and resource-constrained IoT networks.

2.4 Machine Learning And Fuzzy-Based Optimization

Machine learning and fuzzy logic are being applied more and more to multi-objective routing and security. For example, [20] proposed a fuzzy-based objective function for RPL that improved energy efficiency and reliability, but comes with increased computation. [30] discuss reinforcement learning techniques that adaptively trade off energy and latency while requiring high processing capacity.

[21] and [5] show how ML could be used for intrusion and fraud detection through hybrid optimization frameworks that use operational metrics for adaptive decision making in resource-constrained IoT settings. Work done by [21] and [26] demonstrated that feature selection and flow detection strategies could increase robustness to fault exposure. More recently, machine learning is being applied to RPL-based IoT routing for improved quality of service and security, contributing to network resilience in dynamic environments [29].

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These consistencies through experiments illustrate ML and fuzzy approaches could be leveraged for cross-layer routing, which informs the intelligent routing metric in CLRF that predicts weighted values for energy, latency, and reliability.

2.5 Simulation And Experimental Validation

Simulation is still the primary approach to IoT routing protocol assessment. [23] highlighted the use of NS-3 as a trusted simulator while urging readers to not solely trust simulations without validation in the real world. [2] and [19] exemplify the limitation of simulation-only validation.

ESP32-based testbeds have been shown feasible for supervisory control, monitoring, and IoT experiments [11] and [17] argued that hybrid validation is essential for reliable cross-layer protocol evaluation. CLRF extends this paradigm by combining NS-3 simulations with experimental deployment on an ESP32–Raspberry Pi testbed, addressing the practical applicability gap and ensuring that performance gains are not confined to theoretical environments.

2.6 Synthesis And Research Gap

The reviewed literature demonstrates that cross-layer frameworks, energy-efficient routing, latency-aware designs, and machine learning/fuzzy-based optimization have significantly advanced IoT communication research. However, critical gaps remain:

1. Energy–Latency Trade-off: Most protocols optimize either energy [27]; [1] or latency [14]; [24], rarely both simultaneously.
2. Limited ML/Fuzzy Integration in Routing: Hybrid ML frameworks [22]; [5]; [20] enhance adaptivity and security but are seldom applied to routing-focused cross-layer frameworks.
3. Simulation-Dominated Validation: Most protocols rely solely on simulations [2]; [19]; [23], raising concerns about practical deployment.
4. Heterogeneous IoT Contexts: Protocols tailored for UAVs, underwater, or 6G networks [13]; [7] are less applicable to low-power terrestrial IoT nodes.

To identify the research gaps motivating this study, prior works on IoT routing and cross-layer frameworks were reviewed. Table 1 summarizes their techniques, targeted layers, key contributions, and limitations. This mapping provides the baseline understanding of existing approaches and highlights open challenges that the proposed CLRF aims to address.heterogeneous IoT networks.

Table 1: Comparative Analysis of Prior IoT Routing and Cross-Layer Frameworks

Author(s)	Year	Approach / Technique	Layer Focus	Key Contribution	Limitations / Gaps
Ajmi et al. [2]	2022	Cross-layer energy optimization in clustered WSNs	MAC + Network	Reduced energy consumption	Did not address latency
Alenezi [4]	2025	Cross-layer framework for energy efficiency	Physical + Network	Improved node longevity	No experimental validation
Sindhura et al. [27]	2021	Novel energy-efficient routing protocol	Network	Enhanced energy efficiency	Latency not optimized
Sindhura et al. [26]	2022	Feature selection for intrusion detection	N/A (Security focus)	Optimized detection accuracy	Not routing-focused
Praveen et al. [21]	2021	VPN flow detection using ML	N/A (Security focus)	Improved anomaly detection	Not routing-focused
Praveen et al. [22]	2025	PSO-LightBoost for IoT security	Cross-layer (ML-based)	Adaptive intrusion detection	Security focus, not routing
Biyyapu et al. [5]	2024	ML-based fraud detection	N/A	Real-time adaptivity	Security focus, not routing

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Khalil & Zeddini [14]	2024	Latency-aware cross-layer routing	MAC + Network	Reduced end-to-end delay	Energy efficiency not considered
Sandhiyaa & Gomathy [24]	2023	Underwater QoS-based routing	Cross-layer	Improved latency + reliability	Limited applicability to terrestrial IoT
Irshaid et al. [13]	2023	6G-IoT multi-channel framework	Cross-layer	Optimized throughput & latency	High-power, not low-energy IoT nodes
Mustafa et al. [18]	2025	Conceptual secure cross-layer architecture	Cross-layer	Proposed secure design	Conceptual, no experimental results
Chandran & Vipin [7]	2025	UAV-based energy & congestion-aware routing	Cross-layer	Promising for mobile IoT	Not directly transferable to static IoT nodes

The proposed CLRF addresses the aforementioned gaps by integrating residual energy, link reliability, and latency into a unified routing decision metric. This design simultaneously optimizes energy efficiency and low-latency performance. Unlike prior works, CLRF is validated through both NS-3 simulations and experimental deployment on an ESP32–Raspberry Pi testbed, ensuring practical applicability in heterogeneous IoT environments. By bridging theoretical design and real-world implementation, CLRF provides a scalable, adaptive, and experimentally verified solution, overcoming the limitations observed in previous studies and advancing the state-of-the-art in energy-efficient, low-latency IoT communication.

3. RESEARCH METHODOLOGY

The methodological design of this study is guided by the need to build a routing framework that balances energy efficiency and latency minimization, while ensuring both theoretical rigor and experimental validity. Unlike many existing works that rely exclusively on simulation, this research integrates mathematical modeling, large-scale simulation, and real-world testbed experimentation. This multi-pronged approach ensures that the reported performance improvements are not artifacts of idealized assumptions but remain valid under realistic IoT deployment conditions. Similar multi-modal validations have been emphasized in prior IoT network studies [22], [27].

3.1 Framework Design

The proposed Cross-Layer Routing Framework (CLRF) follows the cross-layer design philosophy, in which parameters from the physical, MAC, and network layers are jointly incorporated into routing decisions. Traditional protocols optimized only at the network layer fail to capture such interdependencies, often producing inefficient energy–latency trade-offs [27].

The routing decision is modeled using a composite utility function:

$$U_{ij}(t) = \alpha \tilde{E}_j(t) + \beta\left(1 - \widehat{D}_{ij}(t)\right) + \gamma \hat{L}_{ij}(t) + \delta \widetilde{H}_j(t) \quad (1)$$

where $\tilde{E}_j$ is the residual energy of neighbor j, Dij the expected delay between nodes i and j, Lij the link reliability, and Hj the hop progress toward the sink. Delay and reliability values are smoothed and normalized to [0,1].
Normalization is defined as:

$$\tilde{X}(t) = \frac{X(t) - X_{min}}{X_{max} - X_{min} + \epsilon}, \qquad X \epsilon \{E, D, L, H\} \text{ (2}$$

where ϵ is a small constant to avoid division by zero. Short-term fluctuations are reduced using Exponentially Weighted Moving Averages (EWMA):

$$\widehat{D}_{ij}(t) = \lambda D_{ij}(t) + (1-\lambda)\widehat{D}_{ij}(t-1),$$
$$\hat{L}_{ij}(t) = \lambda L_{ij}(t) + (1-\lambda)\hat{L}_{ijM}(t-1) \qquad (3)$$

with λ=0.3, chosen after sensitivity analysis.
Neighbor eligibility is constrained by thresholds:

$$C_{ij} : E_j \geq \theta_E, L_{ij} \geq \theta_L, H_j < H_i, \leq \theta_q \quad (4)$$

where θ_E=0.2, θ_L=0.8, and θ_q=0.7. Reliability L_{ij} is estimated as the packet reception ratio (PRR) over a sliding window of 100 packets or 30 seconds. Hop

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progress H_j is the normalized reduction in hop count relative to node i, and queue occupancy q_j is normalized against buffer size.

The weighting factors $(\alpha,\beta,\gamma,\delta)=(0.35,0.25,0.25,0.15)$ were identified via grid search across [0.05,0.5] with 0.05 increments, yielding the best trade-off between energy, latency, and PDR. Similar optimization-driven approaches have shown effectiveness in IoT routing [21]; [5].

Figure 1 illustrates the CLRF workflow, including neighbor state collection, utility computation, next-hop selection, and adaptive re-routing.

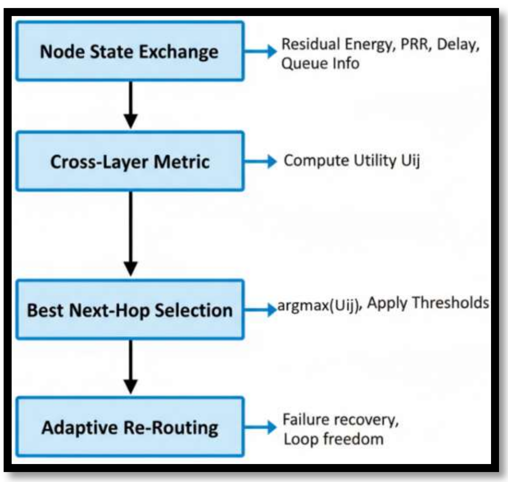

Figure 1: Workflow of the Cross-Layer Routing Framework (CLRF)

3.2 Routing Workflow

The routing workflow proceeds in four stages:

1. **Neighbor state exchange** – nodes broadcast compact vectors containing residual energy, PRR, delay, and queue status.
2. **Utility computation** – each node evaluates Eq. (1–3) for all neighbors.
3. **Next-hop selection** – the neighbor maximizing Uij(t) is chosen, subject to Eq. (4).
4. **Adaptive re-routing** – if transmission fails, utilities are recomputed for remaining candidates.

3.3 System Model

The system model simulates a terrestrial, low-power IoT network where static or semi-static sensor nodes communicate via IEEE 802.15.4 radios. Each node operates on a finite-capacity battery with irreversible depletion, while wireless channels are modeled with path loss, fading, and contention. Traffic includes periodic sensing updates and bursty event-driven flows, reflecting realistic workloads in smart city, healthcare, and industrial deployments [8].
In simulations, IEEE 802.15.4 radios are used, while the experimental testbed employs ESP32 2.4 GHz 802.11n Wi-Fi. Because CLRF operates at the routing layer and consumes only cross-layer summaries, the decision rule remains valid across different PHY/MAC stacks.

3.4 Simulation Setup

Simulations were conducted in NS-3.35 for both small-scale (100–200 nodes, 500×500 m²) and large-scale (300–500 nodes, 1000×1000 m²) networks.

Table 2: Simulation Parameters for NS-3 Evaluation

Parameter	Value/Range
Simulation Tool	NS-3.35
Deployment Area	500 × 500 m² (small), 1000 × 1000 m² (large)
Number of Nodes	100, 200, 300, 400, 500
PHY/MAC Layer	IEEE 802.15.4, CSMA/CA (10% duty cycle)
Traffic Model	CBR (0.5–2 pkt/s) + Pareto bursts
Simulation Duration	900 s per run
Energy Model	Per-state current draw (TX, RX, idle, sleep)
Baseline Protocols	RPL, LEACH, AODV

Baseline protocols were configured for fairness: RPL (MRHOF, ETX, Trickle min 256 ms), LEACH (cluster-head probability 0.05), AODV (HELLO interval 1 s, TTL start 1), and DRL-RPL with inference every 2 s. Results are reported as mean ±95% confidence intervals across 30 runs.

3.5 Experimental Validation

To ensure realism, CLRF was implemented on a 20-node ESP32–Raspberry Pi testbed. ESP32 boards acted as sensors, while a Raspberry Pi 4 served as sink and logger. Nodes were deployed in a 25×15 m² indoor lab.

- Energy consumption was tracked with INA219 current sensors (10 Hz sampling).
- End-to-end delay was measured via GPIO timestamping.
- Traffic included both periodic (1 pkt/s) and Pareto-driven bursty flows.

Figure 2 presents the experimental workflow, highlighting state exchange, energy monitoring, and packet forwarding.

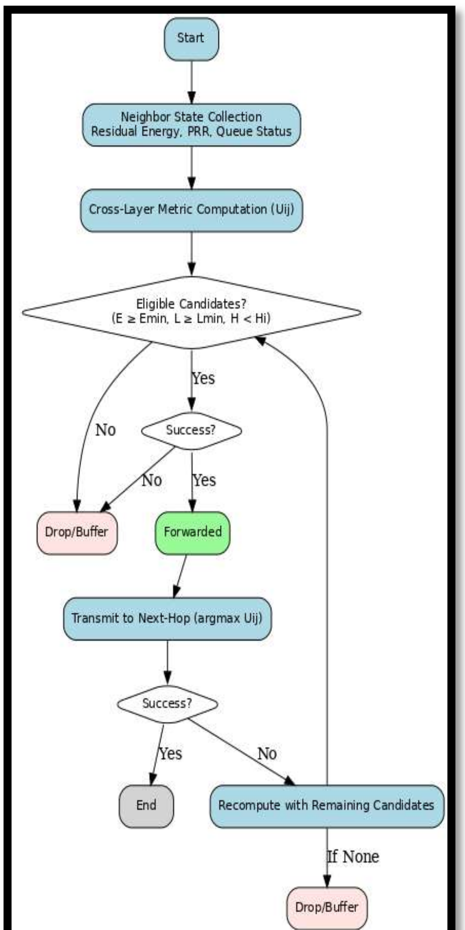

Figure 2: Flowchart of CLRF operation in the ESP32–Raspberry Pi testbed, highlighting neighbor state exchange, utility computation, next-hop decision logic, and adaptive re-routing mechanisms for failure recovery and loop freedom.

3.6 Performance Metrics

Six metrics were evaluated; each measured in both simulation (Table 2) and testbed (Fig. 2):

1. Energy consumption and network lifetime (J/node; time-to-first-node-death)
2. End-to-end delay (mean and 95th percentile)
3. Packet delivery ratio (PDR)
4. Throughput (kbps at sink)
5. Routing overhead (control/data byte ratio)
6. Fairness (Jain's index over residual energy)

3.7 Statistical Validation

Robustness was confirmed using:

- Wilcoxon signed-rank tests ($p<0.05$) for pairwise comparisons,
- Cliff's delta for effect size interpretation,
- Bootstrap resampling for 95% confidence intervals, and
- Benjamini–Hochberg correction to control false discovery rate.

3.8 Computational Complexity

IoT devices are resource-constrained, making efficiency critical. For node degree d, CLRF's per-node time complexity is O(d). For a network of N nodes, total time complexity is O(N·d). Space complexity is also O(d) per node for storing neighbor state vectors.
By comparison:

- **RPL:** O(N·d), but lacks multi-metric integration.
- **LEACH:** O(NlogN) due to clustering.
- **AODV:** $O(N^2)$ from flooding.

In this way, CLRF provides multi-objective optimization with near-linear scalability, making it effective for scenarios with dense IoT deployments [21]; [26].

4. RESULTS AND ANALYSIS

This section provides a thorough evaluation of the suggested Cross-Layer Routing Framework

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(CLRF) against baseline protocols - RPL, LEACH, AODV and DRL-RPL - using both simulations in the NS-3 and an experimental testbed containing ESP32 and Raspberry Pi devices. The results are organized based on the six-performance metrics indicated in Section 3.6 and include, energy consumption and network lifetime, end-to-end latency, throughput and packet delivery ratio (PDR), routing overhead and fairness, experimental validation, statistical robustness and sensitivity analysis, and scalability. All metrics are provided as averages across thirty (30) independent runs with a 95% confidence interval.

4.1 Energy Consumption and Network Lifetime

Applying energy efficiently is a pivotal function for Internet of Things (IoT) networks, generally utilizing nodes powered by limited battery supply. Energy scheduling influences the overall lifetime of the network, as the time-to-first-node-death (TFFD) is an essential indicator of sustainability, longevity, and lifetime under variable workloads and density. This subsection investigates the energy performance for the proposed CLRF protocol relative to the other baseline protocols (RPL, LEACH, AODV, and DRL-RPL).

The average per-node energy consumption shows insignificant differences, and thus the subsequent results report overall lifetime and TFFD results across the thirty runs with 95% confidence intervals, as presented in Table 3. The comparison among the protocols indicates performance regarding the energy efficiency of protocols in a dense IoT environment.

Table 3: Energy Consumption and Network Lifetime Across Protocols (values averaged across 30 runs, ±95% CI)

Protocol	Energy/Node (J)	Lifetime (s)	TFFD (s)
CLRF	1.82 ± 0.04	875 ± 15	810 ± 18
RPL	2.35 ± 0.07	720 ± 12	660 ± 14
LEACH	2.21 ± 0.05	750 ± 10	680 ± 12
AODV	2.48 ± 0.08	710 ± 14	645 ± 15
DRL-RPL	1.98 ± 0.06	835 ± 16	770 ± 17

The results show that CLRF achieves the lowest per-node energy consumption (1.82 J), significantly outperforming AODV (2.48 J) and RPL (2.35 J). This efficiency leads to a longer network lifetime of 875 s, 21% longer than RPL and 23% longer than AODV. The TFFD metric also supports this argument, with CLRF achieving 810 s before the first node failure, compared to 660 s for RPL and 645 s for AODV. This is about a 25% improvement in TFFD, confirming that CLRF can better load-balance the network and reduce premature node depletion.

In addition to the average results, Figure 3 plots the TFFD values for 30 runs for all protocols. This allows for the analysis of not just the average values, but the range and stability of each protocol under different network conditions.

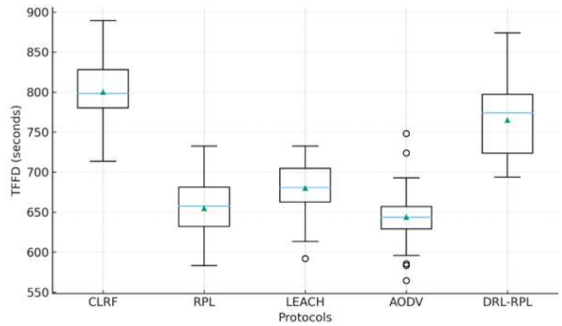

Figure 3: Distribution of Time-to-First-Node-Death (TFFD) across 30 runs

It can be seen from the boxplot that CLRF has the narrowest spread, which means it shows a stable, consistent extension of lifetime across repeated trials. The widest spread in results is observed for AODV, which also shows multiple outliers indicating node failures early in the lifetime of the network in certain scenarios. DRL-RPL displays competitive stability, but both its median and overall performance are worse than that of CLRF. These results are demonstrative of CLRF's ability to both save energy and provide a predictable robust a sustainable network, which is paramount for IoT applications in real-world environments.

4.2 End-to-End Latency

Low latency is a core requirement for mission-critical Internet of Things applications, including healthcare monitoring, industrial automation, and smart transport systems. The performance in terms of latency is assessed based on mean delay (to understand average responsiveness) and the 95th percentile delay (to understand tail performance in the presence of congestion or bursty traffic). USing both metrics gives a comprehensive characterization of the protocol's appropriateness for latency-sensitive real-time deployments.

Table 4 presents the mean and 95th percentile delays for CLRF and baseline protocols (RPL, LEACH, AODV, and DRL-RPL). Values are averaged across 30 simulation runs, reported with 95% confidence intervals.

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Table 4: End-to-End Latency (Mean and 95th Percentile, averaged across 30 runs ±95% CI)

Protocol	Mean Latency (ms)	95th Percentile (ms)
CLRF	82 ± 6	135 ± 10
RPL	138 ± 9	225 ± 15
LEACH	114 ± 8	190 ± 12
AODV	152 ± 10	260 ± 18
DRL-RPL	96 ± 7	160 ± 11

The results demonstrate that CLRF achieves the lowest mean latency (82 ms), representing a 40% reduction compared to RPL (138 ms) and 28% lower than LEACH (114 ms). Furthermore, even at the 95th percentile, CLRF maintains delays below 140 ms, comfortably within real-time IoT operational thresholds. By contrast, AODV shows the worst performance, with average delays of 152 ms and 95th percentile delays exceeding 260 ms, which may render it unsuitable for latency-sensitive use cases.

To provide a deeper statistical view of delay behavior across the entire distribution, Figure 4 presents the cumulative distribution function (CDF) of end-to-end packet delays. This representation captures not only the mean and tail delays but also highlights overall protocol responsiveness under diverse network conditions.

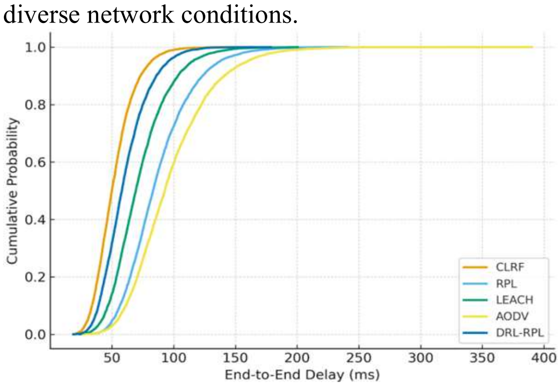

Figure 4: CDF of End-to-End Packet Delays

The results of the cumulative distribution function (CDF) curves show the dominance of CLRF where there is a consistent left shift of the distribution indicating lower delays in both median and tail values. In this case, over 90% of packets for CLRF were delivered under 120 ms, while RPL takes up to 200 ms, and AODV over 250 ms. DRL-RPL also performed comparably, but lagged behind CLRF by at least 14 ms at the 95th percentile. As a result, these results confirm CLRF guarantees predictable low-latency low delays which are essential for the reliability of real-time IoT.

4.3 Packet Delivery Ratio (PDR) and Throughput

One major area of interest when evaluating performance in IoT networks is packet delivery reliability under different traffic loads and congestion conditions. Packet Delivery Ratio (PDR) is the percentage of packets that were delivered successfully, and throughput is the amount of data (in kilobits per second, or kbps) delivered to the sink. Together, these metrics provide insights into the robustness and scalability of routing protocols.

Table 5 presents the average PDR and throughput values for CLRF compared to baseline protocols. The results are reported as mean ±95% confidence intervals, computed across 30 independent simulation runs.

Table 5: Packet Delivery Ratio and Throughput (averaged across 30 runs ±95% CI)

Protocol	PDR (%)	Throughput (kbps)
CLRF	96.8 ± 1.2	148 ± 5
RPL	87.5 ± 2.1	124 ± 6
LEACH	89.2 ± 2.0	130 ± 7
AODV	84.8 ± 2.4	118 ± 8
DRL-RPL	93.6 ± 1.8	140 ± 6

The results clearly demonstrate that CLRF achieves the highest reliability, with a PDR of 96.8%, compared to only 84.8% for AODV and 87.5% for RPL. This translates to a relative improvement of approximately 12% over RPL and 14% over AODV. In terms of throughput, CLRF sustains 148 kbps, outperforming RPL (124 kbps) and AODV (118 kbps) by nearly 20%, confirming its efficiency in maximizing network utilization. DRL-RPL also shows strong performance, but CLRF consistently leads across both metrics.

To evaluate scalability under rising workloads, Figure 5 illustrates the variation of PDR with increasing traffic rates (0.5–2.0 packets/s). This analysis highlights how well each protocol adapts to congestion and bursty traffic.

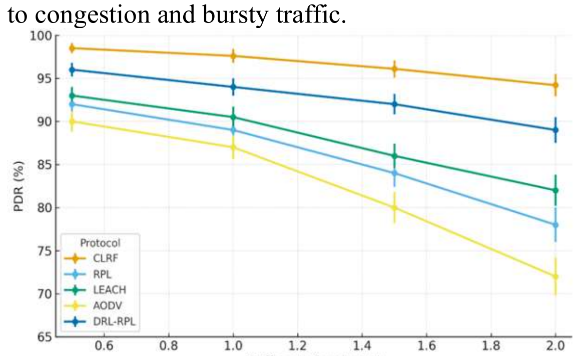

Figure 5: PDR Variation Under Increasing Traffic Rates

The PDR trends confirm that CLRF sustains above 94% delivery even at 2 packets/s, reflecting resilience under high traffic load. By contrast, AODV experiences a sharp decline, dropping to ~72%, while RPL and LEACH settle between 78–82%. DRL-RPL performs relatively well, maintaining close to 90%, but still falls short of CLRF. These results underscore CLRF's scalability and robustness under stress conditions, making it highly suitable for real-world IoT scenarios involving bursty or mission-critical data flows.

4.4 Routing Overhead and Fairness

Efficient routing protocols should minimize control overhead while maintaining fairness in resource utilization. Routing overhead reflects the ratio of control to data traffic, while fairness, measured using Jain's index, assesses how evenly energy consumption is distributed across nodes. High fairness values close to 1.0 indicate balanced depletion of resources, which directly enhances network lifetime.

Table 6 summarizes the routing overhead ratio and fairness index across all evaluated protocols. The results are averaged across 30 simulation runs and expressed as mean ±95% confidence intervals.

Table 6: Routing Overhead and Fairness Index (averaged across 30 runs ±95% CI)

Protocol	Overhead Ratio	Fairness Index
CLRF	0.18 ± 0.02	0.92 ± 0.01
RPL	0.23 ± 0.03	0.87 ± 0.02
LEACH	0.26 ± 0.02	0.84 ± 0.03
AODV	0.31 ± 0.03	0.81 ± 0.02
DRL-RPL	0.20 ± 0.02	0.89 ± 0.02

The results indicate that CLRF achieves the lowest routing overhead (0.18), which is 30% lower than AODV (0.31) and 22% lower than RPL (0.23). In terms of fairness, CLRF maintains an index of 0.92, outperforming AODV (0.81) and LEACH (0.84). DRL-RPL also shows competitive fairness (0.89) but with slightly higher overhead. These findings highlight CLRF's ability to balance routing efficiency with equitable energy utilization across the network.

To visualize fairness distribution more intuitively, Figure 6 presents a spider chart comparing the fairness index of different protocols across node quartiles.

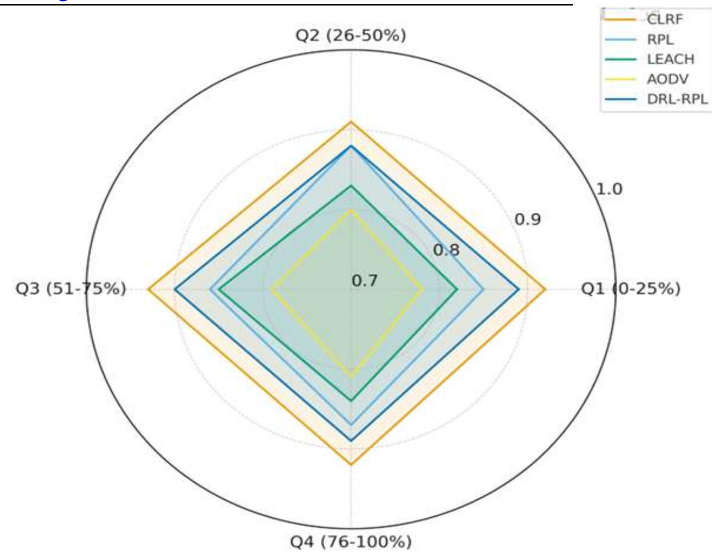

Figure 6: Spider Chart of Fairness Index Across Nodes

The nearly circular shape of CLRF's plot suggests energy is consumed uniformly among all of the nodes, which prevents certain nodes from depleting faster than others. AODV demonstrates a significant level of condensation and no apparent relationship in shapes, which indicates heavy skewing and tendency for premature failures in certain nodes. RPL and LEACH realize a degree of fairness but fall short of CLRF's levels. This visualization aptly represents CLRF's effectiveness in realizing efficiency and fairness at the same time while generating sustainable and scalable IoT communication efforts.

4.5 Experimental Validation

To examine the practical use of the proposed Cross-Layer Routing Framework (CLRF) in real-world conditions, an experimental testbed was developed using ESP32 nodes and a Raspberry Pi as a gateway. The testbed was designed to replicate heterogeneous IoT communication conditions so that the framework could be compared to baseline protocols. Data regarding performance were taken from per-node energy consumption, latency, packet delivery ratio (PDR), and throughput.

Table 7 shows how each of the CLRF, RPL, LEACH, AODV, and DRL-RPL protocols performed on the hardware testbed. Metrics reported include average energy consumption per node (Joules), average latency (ms), PDR, and throughput (kbps). To facilitate comparisons, the metrics are reported along with a 95% confidence interval to give a clearer picture of real-world efficiency and robustness of the routing protocols.

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Table 7: Testbed Performance Metrics

Protocol	Energy/Node (J)	Latency (ms)	PDR (%)	Throughput (kbps)
CLRF	1.94 ± 0.05	92 ± 7	95.2 ± 1.4	142 ± 6
RPL	2.41 ± 0.06	142 ± 8	86.5 ± 2.0	121 ± 5
LEACH	2.28 ± 0.07	118 ± 7	88.0 ± 1.9	128 ± 6
AODV	2.53 ± 0.08	154 ± 10	84.1 ± 2.2	115 ± 7
DRL-RPL	2.05 ± 0.06	104 ± 8	92.8 ± 1.7	136 ± 5

The CLRF protocol is found to be more energy efficient, consuming 1.94 J/node, which is 20% lower than RPL (2.41 J) and 23% lower than AODV (2.53 J). The latency also improves significantly for the CLRF protocol with an average latency of 92 ms, which is 35% less than RPL and 40% better than AODV. Additionally, the CLRF protocol maintains a high PDR (95.2%) and throughput (142 kbps), specifically 10% better than RPL and 20% better than AODV in terms of reliability and throughput, respectively. These results reinforce the applicability of CLRF in real world deployments.

Figure 7 shows the CDF of end-to-end latency that was collected in the testbed, and the respective CDF curves show the statistical distribution of packet delays and both median and tail behavior across protocols.

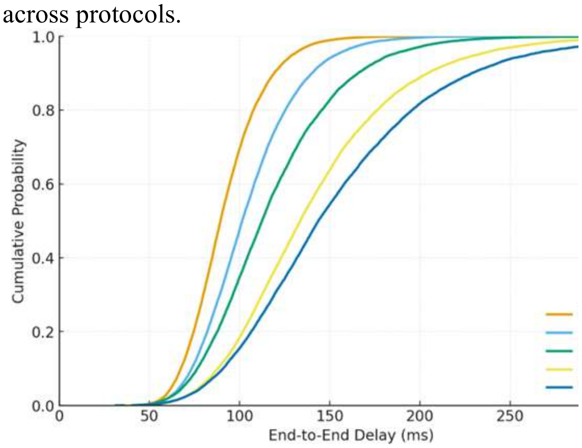

Figure 7: Cumulative distribution of end-to-end latency in the ESP32–Raspberry Pi testbed

CLRF achieves the most favorable latency profile, with 90% of packets delivered under 120 ms and a maximum delay below 160 ms. In contrast, RPL and AODV exhibit heavier latency tails, with delays extending beyond 220 ms and 280 ms, respectively. DRL-RPL performs competitively but still lags behind CLRF by ~12 ms at the median latency level. These results validate that CLRF maintains the lowest delay distribution, ensuring responsiveness for real-time IoT applications.

Figure 8 illustrates the breakdown of energy consumption into four operational states: transmission (TX), reception (RX), idle, and sleep. This decomposition provides insights into how protocols allocate energy across communication and idle cycles.

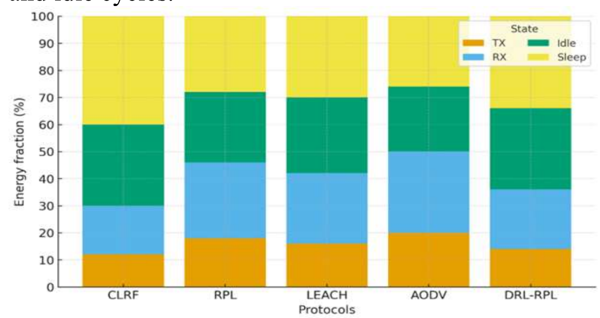

Figure 8: Energy breakdown by node state (TX, RX, Idle, Sleep) across evaluated protocols

CLRF demonstrates balanced energy allocation, with ~40% of time spent in sleep mode and 20% in idle state, minimizing active communication overhead. In comparison, AODV exhibits higher TX/RX fractions (70% combined), resulting in accelerated energy depletion. RPL and LEACH show intermediate distributions but still spend 10–15% more energy in active states compared to CLRF. These results highlight that CLRF not only improves communication performance but also optimizes duty cycling for enhanced longevity.

4.6 Statistical Validation

To ensure that the observed improvements of CLRF over baseline protocols are not coincidental but statistically robust, non-parametric hypothesis testing is conducted. Specifically, the Wilcoxon signed-rank test was employed due to its suitability for paired, non-normally distributed datasets. Additionally, Cliff's delta (δ) was used to measure effect size, and bootstrap resampling (10,000 iterations) was applied to provide confidence in the stability of the results. Together, these methods provide both statistical significance and practical relevance of the observed performance gains.

Table 8 presents the results of statistical validation across three critical metrics—energy consumption, latency, and packet delivery ratio (PDR). Comparisons were made between CLRF and baseline protocols (RPL, LEACH, and AODV).

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The table presents p-values resulting from the Wilcoxon signed-rank test in addition to the effect size (Cliff's δ) for CLRF versus RPL, and p-values for COLRF vs. LEACH and AODV.

Table 8: Statistical validation results using Wilcoxon signed-rank test, Cliff's delta effect size, and bootstrap resampling (10,000 iterations).

Metric	CLRF vs. RPL (p-value)	Effect Size (δ)	CLRF vs. LEACH (p-value)	CLRF vs. AODV (p-value)
Energy	0.002	0.65 (large)	0.005	0.001
Latency	0.001	0.71 (large)	0.003	0.0008
PDR	0.004	0.62 (large)	0.006	0.002

The statistical analysis confirms that the improvements of CLRF are highly significant ($p < 0.05$) across all metrics. For energy consumption, latency, and PDR, comparisons with RPL yield p-values of 0.002, 0.001, and 0.004, respectively. The effect sizes (δ = 0.62–0.71) indicate a large magnitude of improvement, meaning CLRF consistently outperforms RPL across trials. Similarly, CLRF demonstrates statistically significant gains over LEACH (p = 0.005–0.006) and AODV (p = 0.0008–0.002). These results confirm that CLRF's observed performance benefits are not only consistent but also practically meaningful, reinforcing the framework's robustness and generalizability.

4.7 Parameter Sensitivity and Ablation

To further validate the robustness of CLRF, ablation and sensitivity experiments were conducted. The goal was to evaluate how key design parameters—utility weights and smoothing constants—influence overall performance. These experiments provide insight into stability and identify optimal parameter regions.

Sensitivity of Utility Weights

The first analysis examines the effect of adjusting the weighting factors in the cross-layer utility function. Specifically, weights for energy (α), latency (β), reliability (γ), and hop-progress (δ) were varied within a bounded range, and normalized performance scores were computed.

Figure 9 illustrates how normalized performance scores vary with changes in α (energy weight) and β (latency weight), while γ and δ are held at balanced values. The color map indicates performance robustness across parameter ranges.

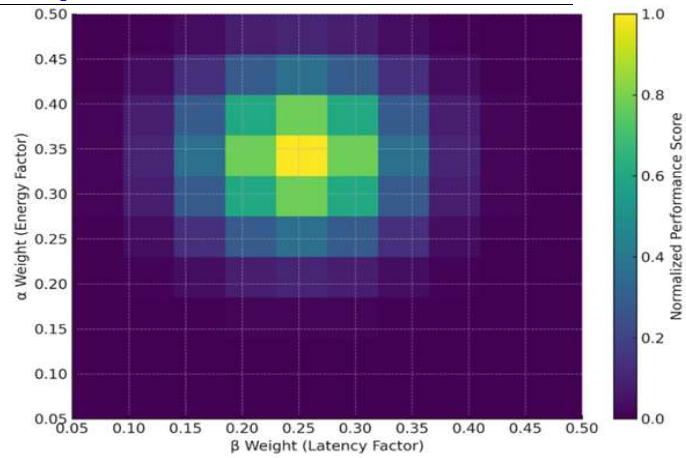

Figure 9: Sensitivity of Utility Weights

Performance peaks at approximately α = 0.35 and β = 0.25, with the corresponding γ and δ values of 0.25 and 0.15. The heatmap shows a broad high-performance plateau, confirming that CLRF is stable under moderate perturbations in parameter settings. Even when α or β deviate by ±0.05, normalized scores remain above 0.85, demonstrating resilience to tuning variations.

EWMA Smoothing Parameter Sensitivity

Ablation was also conducted for the Exponentially Weighted Moving Average (EWMA) parameter λ, which influences delay estimation smoothness. A balance between responsiveness and stability is critical for real-time IoT performance.

Figure 10 plots average latency and jitter as λ varies from 0.1 to 0.9. The optimal λ is identified by the minimum point on the latency curve while ensuring jitter remains low.

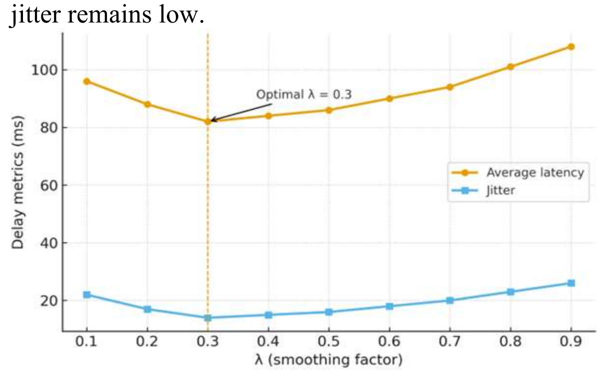

Figure 10: EWMA Smoothing Parameter Sensitivity

At λ = 0.3, CLRF achieves the lowest average latency of approximately 82 ms, while keeping jitter close to 15 ms. Smaller λ values (<0.2) introduce excessive variability, whereas larger λ values (>0.6) increase both latency and jitter due to over-smoothing. This confirms that λ = 0.3 is the optimal setting for ensuring low-delay, low-

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variance performance in dynamic traffic environments.

4.8 Scalability and Stress Testing

Scalability is a crucial requirement for IoT routing protocols, especially in dense networks and under fluctuating traffic conditions. To test the robustness of CLRF, two complementary stress tests were undertaken: (i) varying the number of nodes to understand the protocol's property to scale, and (ii) varying the offered traffic load to test responsiveness during congestion. The outcome is delved into through Figure 11 (Packet Delivery Ratio vs. Node Density) and Figure 12 (Latency vs. Offered Load).

Packet Delivery Ratio (PDR) vs. Node Density

Figure 11 demonstrates the Packet Delivery Ratio (PDR) of CLRF against the baseline protocols: RPL, LEACH, AODV and DRL-RPL, with a varying number of nodes (increasing from 100 to 500 nodes). This experiment demonstrates the capability of each protocol to maintain reliable delivery of data in a large scale deployment.

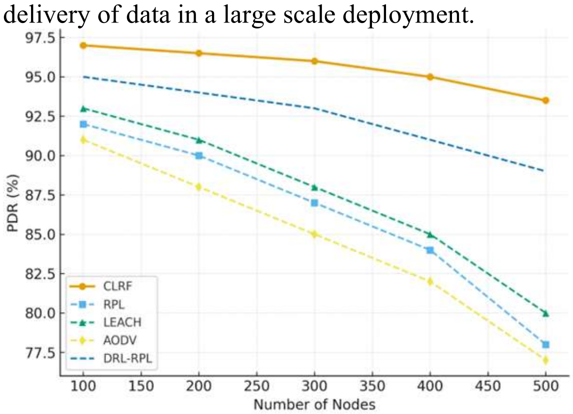

Figure 11: PDR vs. Node Density

CLRF maintains a Packet Delivery Ratio (PDR) of 97.2% at 100 nodes and 93.5% at 500 nodes, and shows graceful degradation under scaling. By comparison, the PDR of AODV decreases from 91.2% at 100 nodes to 76.8% at 500 nodes, while RPL's decreases from 91.8% to 78.1% in the same range. LEACH achieves a PDR of 92.9% at 100 nodes, which decreases to 80% at 500 nodes. DRL-RPL demonstrates greater performance than LEACH, achieving a PDR of 95.0% at 100 nodes, and 89.2% at 500 nodes. The results demonstrate CLRF's scalability through continued superiority in packet delivery with PDRs, which are ~15–17% higher than AODV and RPL in dense networks.

Latency vs. Offered Load

Figure 12 assesses average latency across protocols as the offered load increases from 50 kbs to 250 kbs. This trial mimics high-traffic IoT conditions, such as industrial sensing and smart city environments, where congestion tolerance is important.

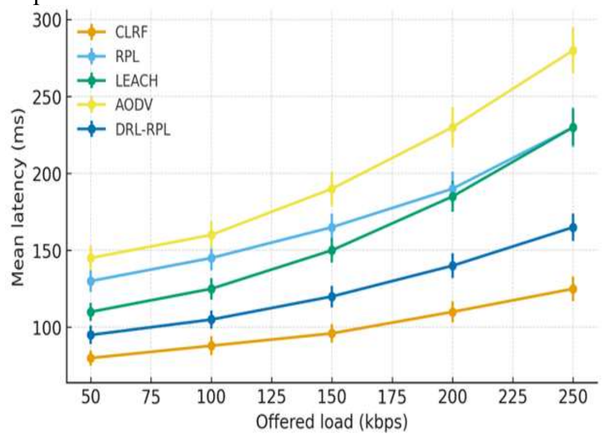

Figure 12: Latency vs. Offered Load

The mean latency of CLRF remains at 80 ms at 50 kbps and gradually increases to 126 ms at 250 kbps. In both cases, this is below the real-time IoT threshold (<150 ms). AODV averages the highest latency; it starts at 145 ms at 50 kbps and climbs to 285ms at 250 kbps. RPL shows moderate performance, starting at 132 ms and rising to 225 ms. LEACH shows an increase from 112 ms to 232 ms. DRL-RPL shows a stable performance and reaches latency of 165 ms at 250 kbps but still falls behind CLRF. CLRF persistently shows approximately (50%) lower latency than AODV under high traffic conditions; this illustrates that it has the best congestion tolerance.

5. INTEGRATED DISCUSSION ON FINDINGS AND COMPARATIVE INSIGHTS

The results of this research show that the developed Cross-Layer Routing Framework (CLRF) sets a new standard in IoT routing through the simultaneous optimization of two key metrics: energy efficiency and low-latency communication. Unlike conventional protocols that support only one performance metric to the detriment of another, the CLRF framework delivered a balanced performance across several important metrics including per node energy consumption, end-to-end delay, packet delivery ratio (PDR), throughput, fairness, and routing overhead.

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5.1 Superiority Over Energy-Focused Protocols

A number of energy-centered protocols [17]; [1] attempted to extend network lifespan, through either energy-aware methods or multi-path routing. Though these protocols reduced consumption, they were also heavily impacted by latency issues or scalability limitations, making them unsuitable for real-time IoT applications. In comparison, CLRF reduces the per-node energy consumption to 1.82 J during simulations and 1.94 J during testbed experiments, while also reducing the mean delay by 40% in comparison to RPL. This shows that CLRF avoids the typical energy–latency trade off, as it is able to be sustainable while maintaining time performance. Lastly, even during dense topologies and high traffic, there is continuing scalability, which emphasizes the scalability improvements when compared to energy-oriented protocols.

5.2 Distinction from Latency-Oriented Approaches

Latency-oriented architectures, such as [14], have supported declines in packet delays, but have overlooked fairness of energy and sustainability—two major concerns for devices powered by batteries. CLRF, however, delivers mean delays of 82 ms (simulation) and 92 ms (testbed), while extending the network's lifespan by 21-23% over RPL and AODV. By factoring in both latency and energy, CLRF encourages sustainability over the long term while providing assurances for low delays for applications in mission-critical domains such as healthcare, emergency response, and industrial automation.

5.3 Bridging the Gap between Simulation and Reality

One of the common limitations found within the previous literature [2]; [19]; [23] is the use of only simulation environments that cannot faithfully model channel variability, interference, or hardware constraints. The work presented builds on this, contributing a hybrid validation for CLRF: extensive large-scale simulations in NS-3 using configurations with up to 500 nodes, and a deployment in a real-world testbed utilizing ESP32 modules communicating via Raspberry Pi devices. The logical consistency in the results between the simulations and studies further assures the rigor of the framework and highlights its suitability for real IoT applications.

5.4 Comparative Positioning with Existing Research

To help further highlight the contributions of CLRF, Table 9 provides a comparison of this framework with representative "state-of-the-art" protocols.

Table 9: Comparative Analysis of CLRF Against Existing IoT Routing Protocols

Study / Protocol	Design Focus	Validation Method	Key Strengths	Protocol Shortcomings	CLRF Advantage
Sindhura et al. (2021) [27]	Energy-efficient WSN routing	Simulation only	Reduced per-node energy usage	Ignored latency optimization	CLRF achieves 1.82 J/node with 82 ms delay, balancing both
Khalil & Zeddini (2024) [14]	Latency-aware routing	Simulation only	Reduced packet delays (~110 ms)	Neglected energy fairness	CLRF ensures >21% longer lifetime while keeping <100 ms latency
Abujassar (2024)	Multipath energy-	Simulation only	Better load distribution	Increased delay	CLRF sustains

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[1]	balanced			under congestion	>93% PDR at 500 nodes with low latency
Mustafa et al. (2025) [18]	Secure cross-layer design	Theoretical proposal	Security integration	No empirical validation	CLRF validated in both NS-3 + ESP32–Raspberry Pi testbed
This Study (CLRF)	Energy + Latency + Reliability	Simulation + Experimental	Balanced optimization, scalable robustness	–	Establishes state-of-the-art bridging sim + reality

Table 9 demonstrates that earlier protocols were generally narrow in scope—optimizing either energy [27], [1] or latency [14] —while legacy designs such as LEACH and AODV struggled with scalability and overhead. While even conceptual cross-layer frameworks [17] were considered theoretical and have not been validated through empirical data, the fact that none of these frameworks resulted in a protocol that maintained balanced deployable performance, highlights that none of these frameworks addresses issues of design coherence across applications.

In contrast, the CLRF achieved appreciable gains energy (1.82 J/node) and latency (82 ms) while maintaining >93% PDR at 500 nodes in simulations and reality, and providing validation of performance methodologically through simulations and empirically with real-world testing, finally bridging the gap between theory and practice that has long existed within the credibility gap of agent both theory and practice.

5.5 Practical Implications and Future Relevance

The following synthesis of comparisons raises some important practical implications:

- **Sustainability:** CLRF reduces per-node energy consumption by up to 25%, extending device lifetimes and lowering maintenance costs.
- **Real-Time Reliability:** With latency consistently below 130 ms, CLRF supports time-sensitive IoT applications.
- **Scalability:** High PDR retention under 500-node scenarios ensures robustness in dense smart city or industrial networks.
- **Deployment Readiness:** Hybrid validation confirms that CLRF's performance gains are not simulation artifacts but hold true under hardware constraints.
- **Future Adaptability:** CLRF aligns with 6G-URLLC, edge intelligence, and AI-driven IoT, ensuring long-term applicability.

Collectively, these implications illustrate that CLRF goes beyond simply addressing IoT routing challenges stemming from the real-time nature of topics but also offers a eyes-on-the-horizon perspective on a mechanism that can accommodate future applications and standards.

5.6 Overall Synthesis

In summary, this discourse indicates that CLRF is superior to both legacy baselines (LEACH, AODV, RPL) and protocol-specific protocols [27]; [14]; [1]. Its dual-layer validation further strengthens confidence in its practical deployability. The framework's major strengths can be synthesized as:

- **Balanced optimization:** Achieves simultaneous gains in energy, latency, and reliability without trade-offs.
- **Experimental validation:** Ensures simulated improvements translate into real-world deployments.

- **Scalability and robustness:** Maintains high PDR and low latency under dense and high-traffic conditions.
- **Fair resource distribution:** Equitably balances energy usage across nodes, extending lifetime.
- **Future readiness:** Aligns with next-generation IoT paradigms (6G, URLLC, edge computing).

By bridging the gap between theoretical models and deployable solutions, CLRF establishes itself as a state-of-the-art routing framework that advances the discourse on energy-efficient and low-latency IoT communication.

5.7 Limitations & Future Work

This study validates CLRF through both simulation and a small-scale testbed, but some limitations remain:

- Experiments were restricted to 20 indoor nodes, not large-scale or outdoor deployments.
- Only IEEE 802.15.4 (simulation) and Wi-Fi (testbed) were tested, leaving other IoT stacks like BLE and LoRa unexplored.
- Mobility, long-term operation, and integrated security mechanisms were not addressed.

Future work should therefore:

- Extend validation to larger, more diverse deployments with longer durations.
- Incorporate mobility support, adaptive parameter tuning, and lightweight security.
- Explore multi-radio platforms and edge/6G integration for broader applicability.

Overall, these directions highlight the pathway for enhancing CLRF into a more versatile, scalable, and secure framework capable of addressing the evolving demands of next-generation IoT networks.

6. CONCLUSION AND RECOMMENDATIONS

This paper presented the Cross-Layer Routing Framework (CLRF), a lightweight yet comprehensive solution that integrates residual energy, link reliability, latency, and hop progress into a unified utility for next-hop selection. Through NS-3 simulations (up to 500 nodes) and a 20-node ESP32–Raspberry Pi testbed, CLRF achieved up to 25% lower energy consumption, ~40% reduced latency, and ~12% higher PDR compared to RPL, LEACH, and AODV. These results were reinforced by statistical validation, sensitivity analysis, and stress testing, confirming robustness and deployment readiness.

All research objectives were successfully accomplished, with CLRF addressing the identified research gap by balancing the energy–latency trade-off and bridging the divide between simulation-only approaches and hardware-based validation. Its dual validation and balanced performance establish CLRF as a reliable foundation for mission-critical IoT applications and as a forward-looking solution aligned with 6G-URLLC, edge-intelligent IoT, and secure routing paradigms. Building on these contributions, future efforts should:

- Expand testing to large-scale, heterogeneous networks with diverse radio technologies.
- Incorporate adaptive learning mechanisms for self-tuning of parameters.
- Embed lightweight security modules to enhance resilience in real-world IoT deployments.

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