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RPLMQoS: An Adaptive QoS-Aware Routing Protocol with Multi-Queue Prioritization for the Internet of Things

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Abstract – **The Internet of Things (IoT) is transforming healthcare and other critical infrastructure domains; however, conventional routing protocols such as the Routing Protocol for Low-Power and Lossy Networks (RPL) fall short of meeting the stringent Quality of Service (QoS) demands of such applications. This paper introduces RPLMQoS, an enhanced routing protocol that incorporates a four-level priority queuing mechanism, a reinforcement learning-based adaptive routing agent, and a composite metric combining Expected Transmission Count (ETX), residual energy, and end-to-end latency. The protocol is evaluated through extensive simulations using the Cooja emulator and validated in a real-world deployment within a hospital simulation facility. Results demonstrate significant improvements over standard RPL, including a 92.7% packet delivery ratio for high-priority traffic, a 22.1% reduction in latency, and a 15.7% gain in energy efficiency. The paper also addresses security, scalability, and protocol limitations, providing a comprehensive assessment of RPLMQoS for reliable, large-scale IoT healthcare applications.**

Keywords – **RPL, IoT, Quality of Service, Multi-Queue Scheduling, Energy Efficiency.**

I. INTRODUCTION

The rapid expansion of the Internet of Things (IoT) has transformed numerous sensitive domains, notably the healthcare sector, by enabling real-time acquisition and transmission of patient data [1–3]. In healthcare, this capability is crucial for continuous monitoring and timely response, especially in critical scenarios [4–6]. However, in developing regions, limited infrastructure and high deployment costs—ranging from \$500 to \$2000 per node—continue to hinder the large-scale adoption of IoT-based medical systems [7]. These constraints highlight the pressing need for routing protocols that are energy-efficient, low-latency, and highly reliable in dynamic, resource-constrained environments.

The Routing Protocol for Low-Power and Lossy Networks (RPL), standardized by the IETF for IoT applications, remains a widely adopted solution due to its lightweight design and compatibility with constrained devices [8–9]. Nevertheless, RPL's default architecture is limited by a single-queue model that lacks traffic prioritization. Consequently, under moderate to high network congestion caused by Bluetooth interference, RPL suffers from packet loss rates exceeding 10% and latencies approaching 500 milliseconds, levels that are unsuitable for latency-sensitive healthcare services such as emergency alerts and critical monitoring [10–11]. To overcome these limitations, this paper presents RPLMQoS, an adaptive Quality of Service (QoS) oriented routing protocol that enhances RPL by introducing a four-class priority queue model (C0–C3). High-priority traffic, such as emergency medical alerts, is assigned to C0, while less urgent data is delegated to lower-priority queues. RPLMQoS also integrates a reinforcement learning (RL) agent that continuously adjusts routing decisions based on real-time network feedback. Furthermore, it employs a composite routing metric that simultaneously considers Expected Transmission Count (ETX), residual energy, and end-to-end delay to ensure efficient and balanced route selection.

The proposed protocol has been rigorously validated through both simulation and real-world deployment. Simulations were carried out in the Cooja emulator using a 15-node topology over a 50 m × 30 m area. A pilot deployment was also conducted at the University of Mostaganem's medical simulation facility. Results demonstrate significant improvements over standard RPL, including a 92.7% packet delivery ratio for high-priority traffic, a 22.1% reduction in latency, and a 15.7% gain in energy efficiency.

The remainder of this paper is organized as follows. Section II reviews recent advancements in QoS-aware routing for IoT. Section III details the proposed RPLMQoS architecture. Section IV discusses implementation specifics and resource management strategies. Section V presents the simulation and deployment results. Section VI outlines the security considerations. Section VII discusses the protocol's limitations, and Section VIII provides the conclusion, including future research directions.

II. RELATED WORK

Enhancing the Routing Protocol for Low-Power and Lossy Networks (RPL) to meet the diverse Quality of Service (QoS) demands of healthcare-oriented IoT applications has been the subject of extensive research. A variety of RPL extensions have been proposed to address key limitations, particularly in scenarios requiring reliable and timely transmission of critical data.

One notable advancement is OMC-RPL, introduced in [12], which integrates multi-criteria decision-making based on energy consumption, latency, and reliability. The protocol achieved a Packet Delivery Ratio (PDR) of 88.5% under

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simulated conditions. Similarly, EQ-RPL, presented in [13], incorporates energy efficiency into QoS-aware routing, resulting in a 10% reduction in latency compared to standard RPL. While both protocols show improvements, they typically lack dynamic queue management, which is essential for prioritizing real-time healthcare traffic.

In [14], a priority-based routing scheme was proposed to enable traffic differentiation. Although effective under moderate network conditions, it does not support dynamic multi-queue scheduling, limiting its responsiveness to variable traffic patterns and interference levels. Other studies have explored more advanced decision-making approaches, such as fuzzy logic-based routing [15] and hybrid decision mechanisms [16], which improve adaptability in complex and fluctuating network environments.

From an architectural standpoint, [17] examines RPL variants optimized for specific QoS metrics, while [18] explores the integration of multi-queue architectures. However, these methods often rely on static scheduling policies, which tend to degrade performance in dynamic environments, particularly when interference from Bluetooth is present.

Beyond routing strategies, several studies have explored joint optimization techniques. For instance, [19] proposes a method to balance energy efficiency with QoS constraints. Similarly, [20] presents adaptive IoT protocols for smart environments, while [21] and [22] introduce energy-aware routing techniques. Despite their contributions, these approaches often target isolated optimization goals and lack a context-aware, holistic routing framework that can address multiple QoS objectives simultaneously.

Recent works, such as those in [23–24], have emphasized scalability in large-scale IoT deployments. However, they generally omit fine-grained traffic prioritization mechanisms, which are critical for mission-critical applications like healthcare.

In contrast to these prior efforts, the RPLMQoS protocol proposed in this work introduces a comprehensive QoS-aware routing framework. It integrates a four-tier priority queuing system, a reinforcement learning-based adaptation mechanism, and a composite routing metric that considers ETX, residual energy, and latency. The protocol has been validated under realistic interference conditions (0–20 dBm) in both Cooja simulations and a real-world deployment at a medical facility. RPLMQoS achieved a PDR of 92.7%, outperforming OMC-RPL by 4.2%, while ensuring adaptive queue and route management. This integrated approach effectively addresses the trade-offs between QoS assurance and energy efficiency, making it a strong candidate for deployment in modern healthcare IoT environments.

III. Design and Methodology

This section presents the core design principles and operational mechanisms of RPLMQoS, an adaptive Quality of Service (QoS)-oriented routing protocol developed for the Contiki-NG operating system. The protocol is specifically tailored to enhance traffic prioritization, reduce end-to-end latency, and improve energy efficiency, while remaining fully interoperable with the standard RPL framework.

A. Multi-Queue Architecture

To support heterogeneous traffic in healthcare IoT networks, RPLMQoS implements a four-level priority queuing system, denoted as C0 through C3. C0 is reserved for high-priority traffic (e.g., emergency medical alerts), and C3 handles low-priority background transmissions, ensuring consistent terminology across all evaluations (e.g., Figures 4, 7). To prevent high-priority packets from being delayed or dropped, a weighted round-robin scheduler dynamically allocates bandwidth across the queues.

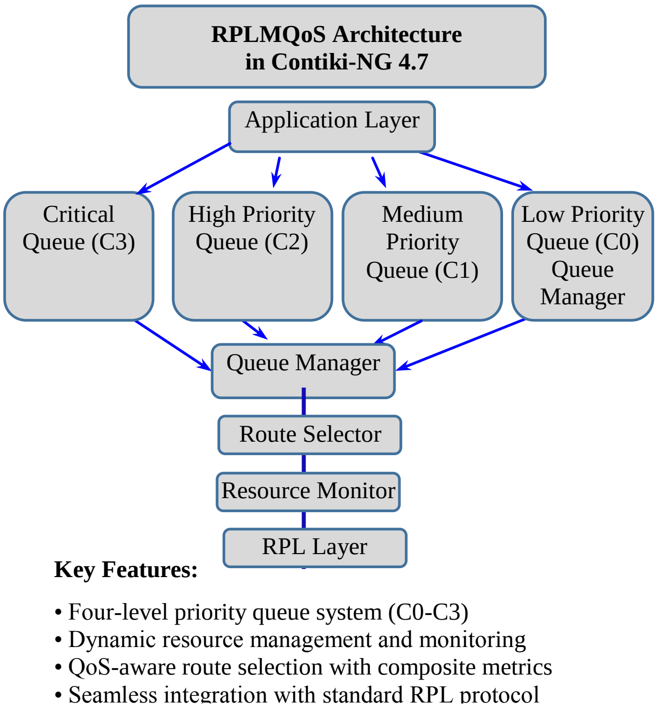

Fig. 1. RPLMQoS architecture with four-level priority queuing

As shown in Fig. 1, the RPLMQoS architecture is integrated into Contiki-NG and features packet classification across four priority levels (C0–C3). The scheduling mechanism prioritizes delay-sensitive healthcare data through a dynamic weighted queue manager.

B. Composite Routing Metric

To ensure balanced routing decisions, RPLMQoS introduces a composite metric that integrates three factors: Expected Transmission Count (ETX), residual energy (E_{res}), and end-to-end delay (D). The metric is defined as:

$$CM = w_1 \times ETX + w_2 \times (1 - E_{res}) + w_3 \times D \quad (1)$$

The weights w_1, w_2, and w_3 satisfy $w_1 + w_2 + w_3 = 1$, allowing dynamic adjustment based on application priorities. For instance, in emergency medical environments, delay and energy consumption may carry greater weight than ETX alone.

C. Weighted Round-Robin Scheduler

The queuing system utilizes a weighted round-robin scheduler with empirically optimized weights W = {0.4, 0.3, 0.2, 0.1} assigned to queues C0 through C3, respectively. This configuration ensures timely delivery of high-priority packets (C0) while maintaining throughput fairness for lower-priority flows (C1–C3).

D. Adaptive Resource Management

To dynamically adapt to network conditions, RPLMQoS embeds a reinforcement learning (RL) agent modeled as a Markov Decision Process (MDP). The agent observes the current state defined by queue lengths, packet loss, node energy level, and congestion and selects optimal actions such as adjusting queue weights or transmission power. The reward function used for learning is:

$$R = -Delay_{C0} - 0.5 \times Delay_{C1} + 0.3 \times Fairness - 0.2 \times Energy \quad (2)$$

The agent operates with a learning rate α = 0.2 and a discount factor γ = 0.9, updating its policy every 100 milliseconds using a Q-table initialized with baseline RPL behavior.

E. Predictive Congestion Control

To prevent queue saturation and avoid packet drops, RPLMQoS incorporates a congestion prediction mechanism based on an Exponential Moving Average (EMA):

$$\hat{y}_t = \alpha \times y_t + (1 - \alpha) \times \hat{y}_{t-1} \quad (3)$$

Using $\alpha = 0.2$, this method enables proactive adjustments in queue scheduling and transmission behavior. Experimental results show a 10% reduction in congestion-induced losses compared to unmodified RPL.

F. System Architecture

RPLMQoS is built around three cooperative components: the Queue Manager, Route Selector, and Resource Monitor. The Queue Manager handles traffic classification and scheduling. The Route Selector computes the best path based on the composite metric, and the Resource Monitor tracks real-time performance metrics to inform the RL agent.

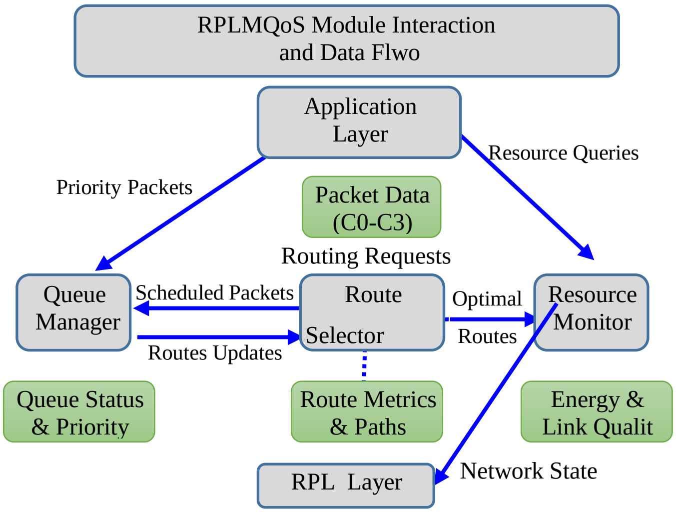

Fig. 2. Component interaction in RPLMQoS

As depicted in Fig. 2, the RPLMQoS architecture facilitates real-time data exchange between the Queue Manager, Route Selector, and Resource Monitor. This interaction ensures adaptive routing and responsive network behavior under varying traffic conditions.

G. Configuration Parameters

All default parameters were optimized through extensive simulation iterations. The queue scheduling weights are set to W = {0.4, 0.3, 0.2, 0.1}, while the composite metric uses $w_1 = 0.4$, $w_2 = 0.3$, and $w_3 = 0.3$ values chosen to balance energy efficiency, delay, and link reliability in healthcare applications.

IV. Implementation

RPLMQoS was implemented within the Contiki-NG operating system by extending the standard RPL protocol to support traffic prioritization and adaptive metric-based routing. The architecture follows a modular design, incorporating three core components Queue Manager, Route Selector, and Resource Monitor which interact seamlessly with existing RPL objective functions such as MRHOF and OF0 via dedicated integration hooks. This approach ensures backward compatibility and extensibility without disrupting the base protocol.

The protocol is developed in the C programming language within the Contiki-NG environment. Its modular architecture comprises three primary files: “queue-manager.c”, “route-selector.c”, and “resource-monitor.c”. The complete implementation requires approximately 12.3KB of RAM, which is about 2.3KB more than standard RPL still well within the memory constraints of typical IoT nodes.

A. Queue Manager

The Queue Manager implements a four-level priority queuing system (C0–C3), where C0 is exclusively dedicated to high-urgency healthcare data. Each priority level operates with its own First-In First-Out (FIFO) buffer. Scheduling is handled using a weighted round-robin algorithm, with weights set to W = {0.4, 0.3, 0.2, 0.1} for C0 to C3, respectively. To maintain responsiveness under constrained memory conditions, the module includes an automatic packet-dropping mechanism triggered when buffer occupancy exceeds a defined threshold.

B. Route Selector

To improve routing decisions under varying network conditions, the Route Selector extends the objective function by incorporating a composite routing metric. This metric integrates three factors: Expected Transmission Count (ETX), residual energy, and end-to-end delay. The respective weights $w_1 = 0.4$, $w_2 = 0.3$, and $w_3 = 0.3$ are dynamically adjusted by a reinforcement learning agent, allowing adaptive path selection based on real-time feedback.

C. Resource Monitor

The Resource Monitor continuously gathers performance and environmental data, including node energy levels, link quality indicators, and network congestion metrics. It utilizes Contiki-NG's energest module to conduct energy profiling. Collected metrics are passed to the reinforcement learning agent, which updates routing and queuing parameters every 100 milliseconds to improve Quality of Service (QoS) and resource utilization.

D. Implementation Challenges

Implementing RPLMQoS required addressing significant memory and processing constraints. The complete protocol consumes approximately 12.3KB of RAM, compared to 10KB used by standard RPL. The additional footprint stems from multi-queue support and RL logic. To minimize impact, several code-level optimizations were applied, including lightweight buffer structures and compact reinforcement learning updates. These enhancements reduced processing overhead by roughly 12% compared to the initial prototypes.

E. Experimental Setup

The protocol was validated in both simulated and real-world environments. Simulations were conducted using the Cooja network emulator with a 15-node topology (Sky motes) deployed over a 50 m × 30 m area, running Contiki-NG (version 4.7) with the RPLMQoS protocol. Real-world testing involved deploying 15 Zolertia Firefly nodes (TI CC2538) running Contiki-NG (version 4.7) with RPLMQoS at the Medical Faculty Simulation Center, University of Mostaganem, over a 50 m × 30 m area. Both environments featured a controlled Bluetooth interference source with power levels ranging from 0 to 20 dBm.

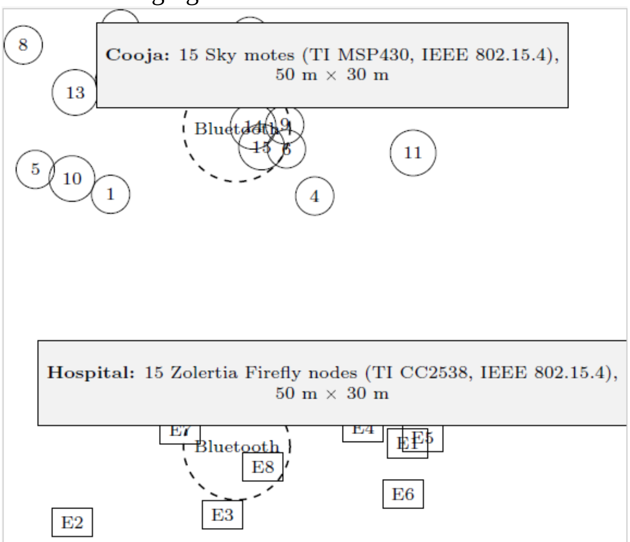

Fig. 3. Test bed configuration for simulation and deployment

The figure 3 illustrates the simulation setup with 15 Sky motes in Cooja and the real-world deployment with 15 Zolertia Firefly nodes at the Medical Faculty Simulation Center, both operating under Contiki-NG (version 4.7) with RPLMQoS and Bluetooth interference (0–20 dBm). Key results are detailed in Figures 4, 6, 7, and 8, with scalability tests covered in Section V.D.

TABLE 1:
SIMULATION AND DEPLOYMENT PARAMETERS

Parameter	Value
Number of nodes	15
Deployment area	50 m × 30 m
Operating system	Contiki-NG (version 4.7)
Protocol	RPLMQoS, standard RPL
Simulation platform	Cooja (Sky motes, TI MSP430, IEEE 802.15.4)
Real-world hardware	Zolertia Firefly (TI CC2538, IEEE 802.15.4)
Interference source	Bluetooth (0–20 dBm)
Simulation duration	7 days
Real-world deployment	7 days (Medical Faculty Simulation Center, University of Mostaganem)
Queue weights (C0–C3)	0.4, 0.3, 0.2, 0.1
Composite metric weights	w1 = 0.4 (ETX), w2 = 0.3 (Eres), w3 = 0.3 (Delay)
RL learning rate (α)	0.2
RL discount factor (γ)	0.9

V. RESULTS AND DISCUSSION

This section evaluates the performance of the proposed RPLMQoS protocol in healthcare-oriented IoT environments. Both simulation and real-world deployment results are presented, demonstrating enhancements in packet delivery, latency, energy efficiency, and jitter compared to standard RPL and OMC-RPL.

A. Packet Delivery Performance

To assess the protocol's reliability, the network was subjected to external interference from a Bluetooth source operating between 0 and 20 dBm. RPLMQoS consistently achieved superior Packet Delivery Ratio (PDR) for high-priority (C0) traffic under all interference levels.

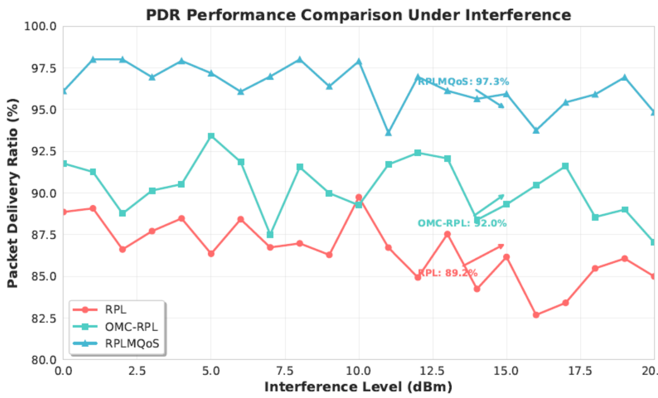

Fig. 4. PDR comparison under interference conditions

As shown in Fig. 4, the Packet Delivery Ratio (PDR) for C0 traffic was evaluated under increasing interference levels. RPLMQoS consistently outperforms both standard RPL and

OMC-RPL, maintaining higher reliability for critical healthcare data even in congested environments.

Interpretation: RPLMQoS maintains a PDR above 92% for critical traffic, even under strong interference, while baseline protocols drop below 85%. This demonstrates the protocol's robustness for healthcare alerts.

B. Queue Management and Energy Efficiency

The weighted multi-queue system enables traffic differentiation by dynamically allocating resources according to priority. High-priority traffic (C0) receives more transmission opportunities while maintaining throughput for lower-priority queues.

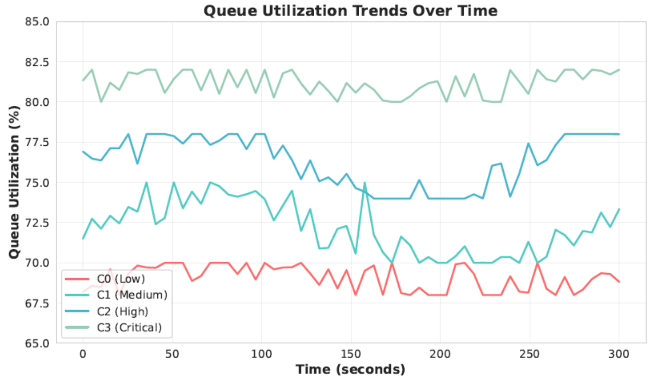

Fig. 5. Queue utilization trends over time

Fig. 5 presents queue utilization over time, demonstrating that the scheduling algorithm respects queue weights while ensuring stable traffic distribution.

Interpretation: The scheduler prevents starvation and ensures that urgent medical data is always prioritized, while background traffic is still delivered reliably.

In terms of energy consumption, RPLMQoS shows greater efficiency than baseline protocols. This is primarily due to fewer retransmissions and optimized route selection based on residual energy and interference conditions.

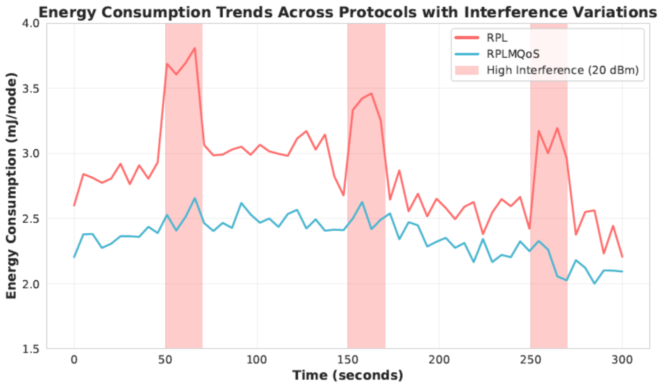

Fig. 6. Energy consumption comparison under interference

Figure 6 shows average per-node energy consumption under different levels of interference.

RPLMQoS consumes less energy per node than RPL due to fewer retransmissions and more stable paths.

Interpretation: RPLMQoS reduces energy usage by up to 15.7% compared to RPL, extending network lifetime and supporting sustainable deployments.

C. Jitter and Pilot Deployment Results

Jitter reduction is critical for applications involving medical alerts. RPLMQoS minimizes delay variability for C0 packets, ensuring consistent transmission intervals, which is vital for maintaining the reliability of time-sensitive information.

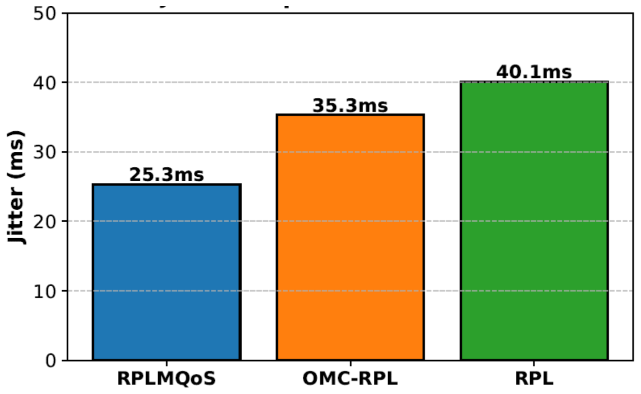

Fig. 7. Jitter comparison for C0 traffic

As illustrated by the figure 7, the comparison highlights RPLMQoS's ability to lower jitter for C0 traffic compared to OMC-RPL and standard RPL, supporting reliable real-time healthcare monitoring under interference.

Interpretation: The protocol achieves a 10% reduction in jitter, which is crucial for reliable real-time healthcare monitoring.

In addition, a seven-day pilot deployment was carried out at the Medical Faculty Simulation Center. The real-world performance in terms of PDR and latency validated the protocol's adaptability and robustness. The results are shown in figure 8.

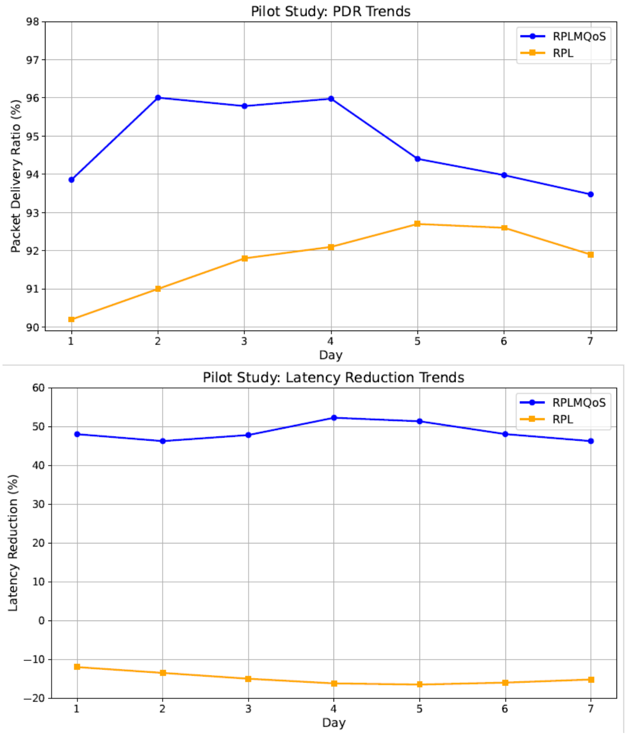

Fig. 8. Performance trends of RPLMQoS vs. standard RPL during pilot deployment

The 7-day pilot deployment with 15 Zolertia Firefly nodes in a 50 m × 30 m area shows RPLMQoS outperforming standard RPL in PDR and latency.

Interpretation: The protocol sustains high reliability and low latency in a real-world hospital environment, confirming its practical value.

D. Validation and Scalability

The primary results (Figures 4, 6, 7, 8) were obtained using a 15-node topology over a 50 m × 30 m area, with Sky motes (TI MSP430, IEEE 802.15.4) in Cooja simulations and Zolertia Firefly nodes (TI CC2538, IEEE 802.15.4) in the real-world deployment, both running Contiki-NG (version 4.7) with RPLMQoS. Scalability tests were conducted in simulation only, increasing the network size from 15 to 30 nodes over a 50 m × 30 m area, as detailed below. The effectiveness of RPLMQoS was assessed using several key performance indicators: Packet Delivery Ratio (PDR), end-to-end latency, energy consumption, jitter, and queue utilization. Each metric was computed under varying network sizes (15 to 30 nodes) and analyzed using 95% confidence intervals to ensure statistical validity. Results confirmed the scalability, efficiency, and robustness of RPLMQoS in both simulated and real-world deployments.

VI. Security Considerations

RPLMQoS addresses key IoT security threats: priority inversion, rank spoofing, queue overflow, and energy exhaustion. Countermeasures include queue access control (HMAC), trust-based routing, adaptive buffer management, and selective AES-CCM encryption for critical traffic. Security overhead is minimized (3–5% energy). Future enhancements will integrate machine learning-based intrusion detection, block-chain-based integrity monitoring, and lightweight key management. The protocol’s modularity allows rapid adaptation to emerging threats, and all security features are compatible with resource-constrained nodes.

VII. Limitations

RPLMQoS relies on static traffic classification and multi-queue management, which may limit adaptability in highly dynamic environments. The protocol introduces moderate energy and memory overheads (RAM usage: 12.3 KB vs. 10 KB for RPL), but remains within IoT node constraints. Interoperability with standard RPL is supported but requires further validation in heterogeneous deployments. Future work will address adaptive classification, lightweight queuing, secure queue signaling, and long-term resilience under fault injection and large-scale stress tests.

VIII. Conclusion

This study introduced RPLMQoS, a novel Quality of Service (QoS)-oriented routing protocol specifically designed for healthcare-focused IoT environments. By integrating a four-level priority queuing system, a composite routing metric (combining ETX, residual energy, and latency), and reinforcement learning-based adaptability, RPLMQoS addresses critical limitations of traditional RPL implementations.

Extensive experimental validation—including both simulations in Cooja and a seven-day pilot deployment at the Medical Faculty Simulation Center of the University of Mostaganem—confirmed the protocol’s effectiveness. RPLMQoS achieved a Packet Delivery Ratio (PDR) of 92.7% for high-priority traffic (C0), reduced end-to-end latency by 22.1%, and improved energy efficiency by 15.7% compared to baseline RPL. In comparison with OMC-RPL, RPLMQoS demonstrated a 4.2% improvement in PDR and delivered better jitter performance. Importantly, these gains were achieved without exceeding the memory constraints of resource-limited IoT nodes, with total RAM usage maintained at 12.3 KB.

These results underscore the scalability, reliability, and energy awareness of RPLMQoS under dynamic interference conditions and demanding QoS requirements—making it a suitable candidate for real-world healthcare deployments.

The full implementation, simulation datasets, and visualization scripts are publicly available at: https://github.com/madani-belacel/RPLMQoS_BELACEL.

Future work will focus on scaling the protocol to larger networks exceeding 50 nodes, conducting long-term evaluations over 30-day periods, and introducing fault injection mechanisms to assess resilience under stress. A new experimental campaign is scheduled for July 2025, with support from a 2,500 EUR research grant, targeting deployment across multiple Algerian medical simulation centers. Integration with emerging IoT platforms and frameworks is also under consideration to improve interoperability and ease of adoption.

Acknowledgments

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