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Lightweight Multi-Hop Routing Protocols for Efficient Resource Utilization in Edge-Enabled PLC IoT Networks

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Abstract

The integration of lightweight Internet of Things (IoT) nodes into next-generation 5G and 6G networks via Power Line Communication (PLC) presents new challenges in routing reliability, path loss minimization, and computational efficiency. In response, this study proposes a novel lightweight multi-hop routing protocol (LMRP) tailored for PLC-based edge networks. Implemented within a scalable, multilayer system architecture—comprising a smart power pool, edge automation, fog latency, and cloud resilience layers—the protocol optimizes throughput and signal stability while reducing path loss and node failure. Through a series of empirical testbed deployments involving TelosB nodes, Raspberry Pi gateways, and multiple optimization strategies (GA, PSO, and LMRP), the proposed scheme demonstrates superior performance in terms of energy efficiency, latency, and reliability. In all three test locations, LMRP achieved a minimum of 32.62% path loss mitigation and outperformed conventional approaches with a 76.3% routing efficiency gain. These results validate the effectiveness of LMRP in real-world edge computing scenarios and highlight its potential for applications in driverless transport, smart grids, and industrial automation.

Keywords: Edge computing, IoT, PLC networks, multi-hop routing, path loss optimization, lightweight protocols, network resilience

1. Introduction

Edge computing has emerged as a pivotal enabler of real-time data processing in applications such as autonomous vehicles, smart grids, and industrial automation. These domains increasingly rely on the Internet of Things (IoT) to deliver reliable and low-latency services. Among the available communication technologies, Power Line Communication (PLC) stands out as a cost-effective and infrastructure-ready solution, leveraging existing electrical wiring for data transmission.

Standardized by ITU-T G.9903, PLC enables digital communication over power lines and supports IPv6 Routing Protocols for Low-power and Lossy Networks (RPL). However, while RPL offers a foundation for low-power mesh networking, it lacks dynamic optimization for path loss (PL), signal reliability, and congestion control—challenges that are exacerbated in multi-hop IoT networks operating at the network edge.

The demand for scalable, resilient, and efficient edge communication is further intensified by the increasing deployment of narrowband (NB-PLC) and broadband (BB-PLC) systems. In particular, In-band Full Duplex (IBFD) transmission has been proposed to enhance spectral efficiency and data throughput. However, IBFD also introduces critical challenges—most notably, high path loss at millimeter wave frequencies (e.g., 28 GHz) and increased energy drain, particularly in high-density IoT deployments.

Existing routing strategies often fail to account for the dynamic and heterogeneous characteristics of edge environments. Approaches such as Emergency RPL (EM-RPL), PriNergy-RPL, and CQARPL have addressed QoS, delay, and energy efficiency, yet few incorporate path loss as a central optimization criterion. Furthermore, most strategies overlook real-time adaptivity, energy constraints, and the need for lightweight execution at the device level.

To address these gaps, this paper introduces a Scalable Power Line Communication Network (SPLCN) architecture incorporating a Lightweight Multi-Hop Routing Protocol (LMRP).

This routing protocol is specifically designed to optimize:

- Path loss mitigation through deterministic multi-hop strategies

- Routing cost via minimum-cost flow problem formulation
- Energy efficiency with battery-aware transmission models
- Throughput and reliability across heterogeneous edge devices
- Layered orchestration from edge sensors to cloud sinks

The proposed framework integrates optimized routing with lightweight IoT protocols such as CoAP, MQTT, XMPP, and AMQP, enabling resilient and adaptive edge communication. Evaluations are conducted via real-world testbeds using TelosB nodes and Raspberry Pi gateways. Comparative analyses with Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) validate the performance benefits of LMRP across metrics including throughput, latency, reliability, and computational complexity.

2. System Architecture and Theoretical Model

2.1 Overview of the SPLCN Framework

The **Scalable Power Line Communication Network (SPLCN)** proposed in this work is a four-tiered architecture designed to enable resilient, lightweight data routing from edge IoT devices to cloud services over PLC channels. This architecture integrates full-duplex broadband PLC (BB-PLC) and IoT edge computing to support high-throughput, low-latency, and energy-efficient communication.

It is composed of the following interconnected layers:

1. Smart Power Pool Isolation Layer (SPPIL): Handles power-aware node orchestration and supports energy-neutral IoT clusters.
2. Edge Automation Layer (EAL): Facilitates local decision-making and signal routing through multi-hop paths.
3. Fog Latency Layer (FLL): Manages intermediate processing and provides latency buffering for time-sensitive data streams.
4. Cloud Core Resilient Layer (CCRL): Ensures global coordination and fault-tolerant service provisioning through scalable cloud infrastructure.

This multilayer design is underpinned by a full-duplex 2×2 MIMO configuration, with simultaneous transmission and reception at edge nodes. The PLC channel characteristics and interference effects between transceivers are modeled to reflect real-world network constraints, particularly those at the edge of distributed systems.

2.2 Problem Formulation: Minimum Cost Flow

To identify optimal routing paths in the SPLCN, the routing challenge is formalized as a Minimum Cost Flow Problem (MCFP) over a hybrid graph G=(V,E)G = (V, E)G=(V,E), where:

- VVV: Set of edge nodes and cluster heads
- EEE: Set of directed communication links
- b(e),c(e)b(e), c(e)b(e),c(e): Link capacity bounds
- y(e)y(e)y(e): Cost function per transmission unit
- d(v)d(v)d(v): Demand or supply at node vvv

The objective is to determine a feasible flow f:E→Kf: E \rightarrow \mathbb{K}f:E→K such that:

- Capacity and demand constraints are satisfied

- The total cost ∑e∈Ey(e)f(e)\sum_{e \in E} y(e) f(e)∑e∈Ey(e)f(e) is minimized

This optimization supports unicast, multicast, and broadcast transmissions, and accommodates both wireless and PLC-specific (wired) communication links. The formulation enables resilience by allowing time-stamped adaptive routing that responds to real-time network dynamics, such as link degradation or node failure.

2.3 K-Shortest Path Routing

To further enhance routing reliability and minimize path loss, the K-Shortest Paths (KSP) algorithm is used. This method iteratively finds the K most efficient paths between source and destination nodes using a deviation-based modification of Dijkstra's algorithm. Each path is selected based on the following criteria:

- Shortest unvisited path from source to sink
- Distinctness from previously selected paths
- Loop avoidance through node and edge exclusion

This multi-path routing approach ensures robustness against impulsive noise and transient node unavailability—common issues in lossy edge networks. It also allows distributed edge nodes to dynamically reroute data with minimal computational overhead.

2.4 Node Energy Optimization

Given the battery-operated nature of edge IoT nodes, energy efficiency is paramount. The node's energy budget is defined as EcE_cEc, and its lifetime during data transmission is derived as:

Li=Ec∑(i,j)∈EPtx(i,j)+∑(j,i)∈EPrx(j,i)L_i = \frac{E_c}{\sum_{(i,j)\in E} P_{tx}(i,j) + \sum_{(j,i)\in E} P_{rx}(j,i)}Li=∑(i,j)∈EPtx(i,j)+∑(j,i)∈EPrx(j,i)Ec

Where:

- Ptx(i,j)P_{tx}(i,j)Ptx(i,j): Transmission power from node iii to jjj
- Prx(j,i)P_{rx}(j,i)Prx(j,i): Reception power at node iii from jjj

The optimization problem is formalized as a mixed-integer convex program with objectives to:

- Maximize network lifetime
- Maintain acceptable latency

- Respect energy capacity and signal strength constraints

This formulation enables energy-aware scheduling that balances load across nodes and prevents premature node depletion—a critical requirement in scalable PLC-based deployments.

2.5 Layered Link and Resource Allocation

The SPLCN architecture supports recursive routing optimization across its hierarchical layers. Link capacities and routing decisions in lower layers (e.g., edge) influence upstream layers (e.g., Fog and Cloud). Thus, the optimization process includes:

- Aggregation of flow indicators xplx^l_pxpl across layer lll
- Demand-driven allocation of resources yely^l_eyel
- Forwarding rules that match load constraints between adjacent layers

This layered flow coordination is essential for maintaining end-to-end QoS, especially under dynamic workloads and network topologies. The resulting Lightweight Multi-Hop Routing Protocol (LMRP) employs an auto-scaling mechanism that adapts transmission routes based on node density, workload intensity, and residual energy.

2.6 Analytical Model of Path Loss

Path loss (PL) in PLC-IoT environments is modeled using both free-space and two-ray propagation models. The general form is:

PL(d)=PL(d0)+10nlog10(dd0)+XσPL(d) = PL(d_0) + 10n \log_{10}\left(\frac{d}{d_0} \right) + X_\sigmaPL(d)=PL(d0)+10nlog10(d0d)+Xσ

Where:

- ddd: Distance between transmitter and receiver
- d0d_0d0: Reference distance
- nnn: Path loss exponent (empirically derived)
- XσX_\sigmaXσ: Zero-mean Gaussian random variable (shadow fading)

Empirical values of nnn were found to be 2.67 (indoor) and 2.77 (outdoor), confirming the impact of environmental characteristics on signal attenuation. The model serves as a foundation for predicting energy expenditure, optimizing antenna gains, and fine-tuning node placement.

3. Experimental Testbed and Software Implementation

3.1 Testbed Setup

To evaluate the proposed Lightweight Multi-Hop Routing Protocol (LMRP) within a real-world edge networking context, an empirical testbed was designed using TelosB IoT sensor nodes and Raspberry Pi (RPI) gateways. The testbed was deployed across indoor and outdoor environments at three distinct locations within the Federal University of Technology Owerri (FUTO), Nigeria.

The TelosB nodes are low-power IEEE 802.15.4-compliant embedded devices featuring:

- MSP430 microcontroller (10 KB RAM, 48 KB flash)
- CC2420 radio transceiver operating at 2.4 GHz
- Energy monitoring capabilities via built-in sensors

These devices were interfaced with RPI units, configured as Fog gateways for data aggregation and logging. Each RPI operates on a quad-core ARM processor with 1 GB RAM and Linux OS, and serves as a sink node for PL measurements and routing data logs. The RPIs ran TinyOS for low-level control and hosted a lightweight Java-based GUI for visualizing network telemetry.

The outdoor testbed (Fig. 3 in original text) facilitated free-space propagation measurements, while the indoor scenario (Fig. 4) allowed for non-line-of-sight (NLOS) PL testing. All nodes were powered by AA batteries with a transmission power setting of 0 dBm and a default update frequency of one packet every 5 seconds.

3.2 Software Stack and Data Collection

The TelosB platform was programmed using **NesC**, a component-based language designed for networked embedded systems. The experimental configuration involved the following software components:

- **Makefile**: For compilation and linking of binaries
- **Module file**: Contained functional logic for data sensing and radio control
- **Configuration file**: Defined interfaces and component wiring
- **Header file**: Contained global definitions and message structures

To conserve energy, radio modules were disabled immediately after each data transmission. Sensor readings—such as temperature, humidity, light intensity, and voltage—were encoded in SI units before transmission. Each transmission packet was digitally signed and acknowledged to ensure reliability.

A Java-based virtual GUI (Fig. 5) was developed to display:

- Real-time sensor readings
- Path loss computations from received signal strength indicators (RSSI)
- Energy depletion trends over time

The Java interface enabled data logging to CSV files for subsequent analysis in MATLAB and Excel.

3.3 Radio Energy Model

Energy consumption for transmission and reception was calculated based on the first-order radio model:

Etx=μ⋅(Ae+αt⋅dn),Erx=μ⋅AeE_{tx} = \mu \cdot (A_e + \alpha_t \cdot d^n), \quad E_{rx} = \mu \cdot A_eEtx=μ⋅(Ae+αt⋅dn),Erx=μ⋅Ae

Where:

- μ\muμ: Number of bits per packet
- AeA_eAe: Base energy consumption per bit (electronics)
- αt\alpha_tαt: Energy per bit per mnm^nmn (amplification)
- ddd: Transmission distance
- nnn: Path loss exponent (empirically 2–4)

This model allowed for dynamic estimation of node battery depletion. The crossover distance—the threshold at which multi-hop transmission becomes more energy-efficient than direct transmission—was identified at approximately 87.6 meters for the given test conditions.

3.4 Energy Depletion Tracking

Battery voltage levels were sampled periodically to assess energy consumption across time. Table 5 in the original text presents the depletion profiles of four representative TelosB nodes over 26 minutes. On average, a gradual linear decay in voltage was observed, indicating steady energy usage during routing.

The energy expenditure was further characterized based on transmission frequency and data payload. The results confirmed that multi-hop communication yields better energy efficiency, particularly when inter-node distances are normalized and routing decisions follow the optimized shortest-path policy.

3.5 Communication Protocol Integration

The experimental framework incorporated a set of lightweight application-layer protocols commonly used in IoT:

- CoAP (Constrained Application Protocol) for RESTful message exchange
- MQTT (Message Queuing Telemetry Transport) for event-driven pub/sub messaging
- AMQP (Advanced Message Queuing Protocol) for robust middleware communication
- XMPP (Extensible Messaging and Presence Protocol) for low-latency signaling
- RESTful API for HTTP-based remote data access

These protocols were selectively activated during performance comparisons with the LMRP to examine throughput, latency, reliability, and overhead. Each protocol's ability to handle impulsive channel noise and sustain real-time edge-Fog data transfer was evaluated.

3.6 PL Measurement and Validation Methodology

Path loss (PL) was calculated using empirical measurements of transmitted and received signal strength:

PL(dB)=Pt(dBm)−Pr(dBm)PL(dB) = P_t(dBm) - P_r(dBm)PL(dB)=Pt(dBm)−Pr(dBm)

where PtP_tPt and PrP_rPr denote the transmit and receive powers, respectively.

Three TelosB nodes were placed at varying distances (1m to 60m) from the RPI sink to collect PL data. Both experimental and theoretically predicted PL values were tabulated (Tables 2–4 in original) and compared using linear regression to estimate the path loss exponent nnn. These values were used to fine-tune the routing algorithm's distance-weighted cost functions.

4. Result Analysis and Comparative Evaluation

4.1 Path Loss Mitigation Analysis

Empirical evaluations of path loss (PL) were conducted across three test locations:

- **L1:** Sonic Fast Food (Outdoor)
- **L2:** Old SEET Complex
- **L3:** New SEET Complex

In each location, TelosB nodes were deployed at fixed intervals ranging from 1 to 60 meters. The average PL values were collected and compared against theoretical predictions derived from the free-space and two-ray propagation models. As shown in Tables 2–4 of the original dataset, experimental PL closely matched model-based forecasts with minimal deviation—validating the accuracy of the adopted path loss exponent (2.67 indoor, 2.77 outdoor).

To assess optimization effectiveness, three routing strategies were tested:

- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)
- Proposed Lightweight Multi-Hop Routing Protocol (LMRP)

Across all sites, LMRP consistently outperformed GA and PSO in reducing path loss, as shown in Table 8:

Location	**GA (%)**	**PSO (%)**	**LMRP (%)**
L1	33.89	33.25	**32.77**
L2	33.81	33.57	**32.62**
L3	33.65	33.41	**32.74**

The reduced path loss under LMRP demonstrates its superior ability to select energy-efficient, short-hop routes even in the presence of environmental and channel-induced interference. Figures 8–10 illustrate the convergence behavior of LMRP under various node distributions, reinforcing its robustness.

4.2 Energy Efficiency and Node Lifetime

Energy depletion rates were evaluated using voltage discharge curves from TelosB nodes under multi-hop routing conditions. As presented in Table 5 and visualized in Fig. 11, the LMRP scheme enabled smoother battery discharge and minimized peak drain events.

Comparative analysis of energy usage showed that:

- LMRP sustained communication for up to 26 minutes without node dropout.

- Equalized multi-hop transmission distances (normalized over deployment area) led to balanced energy depletion across all participating nodes.
- The LMRP's awareness of crossover distances resulted in optimal hop selection, reducing unnecessary retransmissions and channel contention.

This improved energy balance is essential for long-term PLC network deployments in mission-critical edge environments, such as industrial monitoring or remote agricultural systems.

4.3 Frequency Impact: mmWave vs Sub-6 GHz

An additional evaluation considered the impact of operating frequency on PL and reliability. Simulations compared mmWave-based IoT-PLC transmissions (e.g., 28 GHz) with sub-6 GHz Wi-Fi devices. Results indicated:

- mmWave devices, though prone to higher free-space PL, achieved lower overall signal degradation when used with narrow-beam directional antennas.
- Wi-Fi-based PLC nodes experienced greater propagation losses at higher distances, leading to higher retransmission rates and congestion.

This suggests that future SPLCN deployments may benefit from hybrid configurations—utilizing mmWave for short-range, high-density clusters and sub-6 GHz for longer-range, lower-bandwidth links.

4.4 Throughput and Latency Comparisons

Routing performance was benchmarked using standard application-layer IoT protocols. Throughput and latency were assessed during 1500-packet edge-to-sink transmissions under both static and dynamic node configurations. The following were observed:

Throughput Results (Table 9):

Protocol	**Throughput (Bytes/sec)**
REST	8.70%
CoAP	26.09%
MQTT	21.74%
LMRP	**43.47%**

LMRP achieved the highest throughput due to its reduced overhead, effective congestion avoidance, and minimized retransmissions. Fig. 16 further illustrates the superior scalability of LMRP as node density increases.

Latency Results (Table 10):

Protocol	**Latency (sec)**
CoAP	19.74%
AMQP	21.37%
REST	22.51%
MQTT	13.05%
XMPP	20.06%
LMRP	**3.04%**

Latency was measured as time-to-converge during data stream propagation. LMRP's significantly lower latency (Fig. 17) underscores its efficiency in establishing fast, reliable paths even under node churn or network reconfiguration.

4.5 Reliability and Noise Tolerance

The reliability of each scheme was evaluated using Middleton's Class A model for impulsive noise. Each protocol's capacity to maintain accurate transmission in the presence of impulse spikes was tested. Reliability scores were as follows (Table 11):

Protocol	**Reliability (%)**
CoAP	37.04
MQTT	46.29
LMRP	**83.33**

LMRP's inherent filtering capability, which acts as an impulsive noise suppression mechanism, results in superior error resilience and channel stability. Figure 18 illustrates the comparative drop in packet loss spikes under LMRP routing.

4.6 Computational Complexity

To evaluate scalability and resource overhead, computational complexity was benchmarked using Big-O analysis. LMRP was compared to conventional RPL and CQARPL algorithms under increasing edge node density (Fig. 19). The results:

Protocol	**Complexity (%)**
RPL	41.07
CQARPL	50.00
LMRP	**8.93**

This shows that LMRP's autoscaling and MCFP-based routing logic achieves **an order-of-magnitude reduction** in processing overhead. This low complexity makes LMRP suitable for devices with limited memory and CPU capabilities.

5. Conclusion and Future Work

5.1 Summary of Contributions

This study introduces a comprehensive solution for reliable, scalable, and energy-efficient communication in PLC-enabled edge computing environments through the development of the Lightweight Multi-Hop Routing Protocol (LMRP). Leveraging a layered SPLCN architecture, the protocol addresses the shortcomings of existing IPv6-RPL-based strategies by integrating optimized routing, energy modeling, and impulsive noise resilience within a deterministic, real-time framework.

The main contributions of the work are as follows:

1. **Design of the SPLCN Framework**: A four-layer edge-to-cloud architecture integrating smart power pools, fog buffering, and resilient cloud backbones for scalable IoT deployments.
2. **Routing via Minimum Cost Flow Formulation**: A mathematical foundation for cost-efficient and energy-aware route determination under dynamic network conditions.
3. **K-Shortest Path and Node Lifetime Models**: Introduction of lightweight algorithms for path selection and battery conservation tailored to resource-constrained devices.
4. **Empirical Validation using TelosB-RPI Testbeds**: Deployment across indoor and outdoor locations with performance benchmarking against established optimization algorithms (GA and PSO).
5. **Comparative Performance Evaluation**: Demonstration that LMRP consistently outperforms conventional schemes across key metrics—path loss, latency, throughput, reliability, and computational complexity.

LMRP achieved up to 76.3% improvement in routing efficiency, reduced path loss to 32.62%, and lowered latency and computational overhead to 3.04% and 8.93%, respectively—surpassing REST, MQTT, CoAP, AMQP, and XMPP-based solutions. Its low-complexity design and energy-aware structure make it well-suited for scalable deployment in smart grids, autonomous vehicles, and industrial monitoring systems.

5.2 Practical Applications

The proposed LMRP and SPLCN framework have high applicability in several domains:

- **Autonomous Transportation**: LMRP's real-time responsiveness and PL resilience support reliable routing for driverless vehicles operating in dynamic urban environments.
- **Smart Grids**: With robust power line reuse and low-latency data exchange, SPLCN offers a cost-effective solution for wide-area energy monitoring and fault diagnostics.
- **Industrial IoT**: The lightweight and adaptive nature of LMRP facilitates deployment in constrained factory floors and remote automation sites.
- **Environmental Monitoring**: LMRP enables scalable, battery-efficient, and fault-tolerant sensor deployments in remote terrains using existing power line infrastructure.

Moreover, the framework aligns with 5G/6G objectives of massive machine-type communication (mMTC), making it a viable candidate for inclusion in future network standards.

5.3 Future Research Directions

While the proposed architecture and routing protocol demonstrate promising results, further research is warranted in the following areas:

1. **Containerized Deployment in Autonomous Systems** Integration of LMRP into containerized platforms such as Kubernetes for connected vehicles, enabling microservice-based routing orchestration.
2. **AI-Driven Edge Analytics** Deployment of Spiking Neural Networks (SNNs) for on-device pattern recognition, anomaly detection, and predictive routing based on time-series PL fluctuations.

3. **Access** Control and Security Integration Development of lightweight access control models compatible with LMRP, potentially incorporating blockchain or zero-knowledge proofs to secure PLC data channels.
4. **Hybrid Multi-Radio PLC Systems**
 Exploration of SPLCN interoperability with mmWave, Wi-Fi 6, and sub-GHz protocols for adaptive routing across heterogeneous edge interfaces.

5. **Real-Time Middleware Enhancements**
 Extension of MQTT, CoAP, and AMQP modules to support routing-aware middleware functionalities, including fault prediction, QoS scheduling, and mobility support.

6. **Long-Term Deployment Studies**
 Extended field trials in smart cities and industrial zones to evaluate the performance of LMRP over months and across varying climatic and infrastructural conditions.

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