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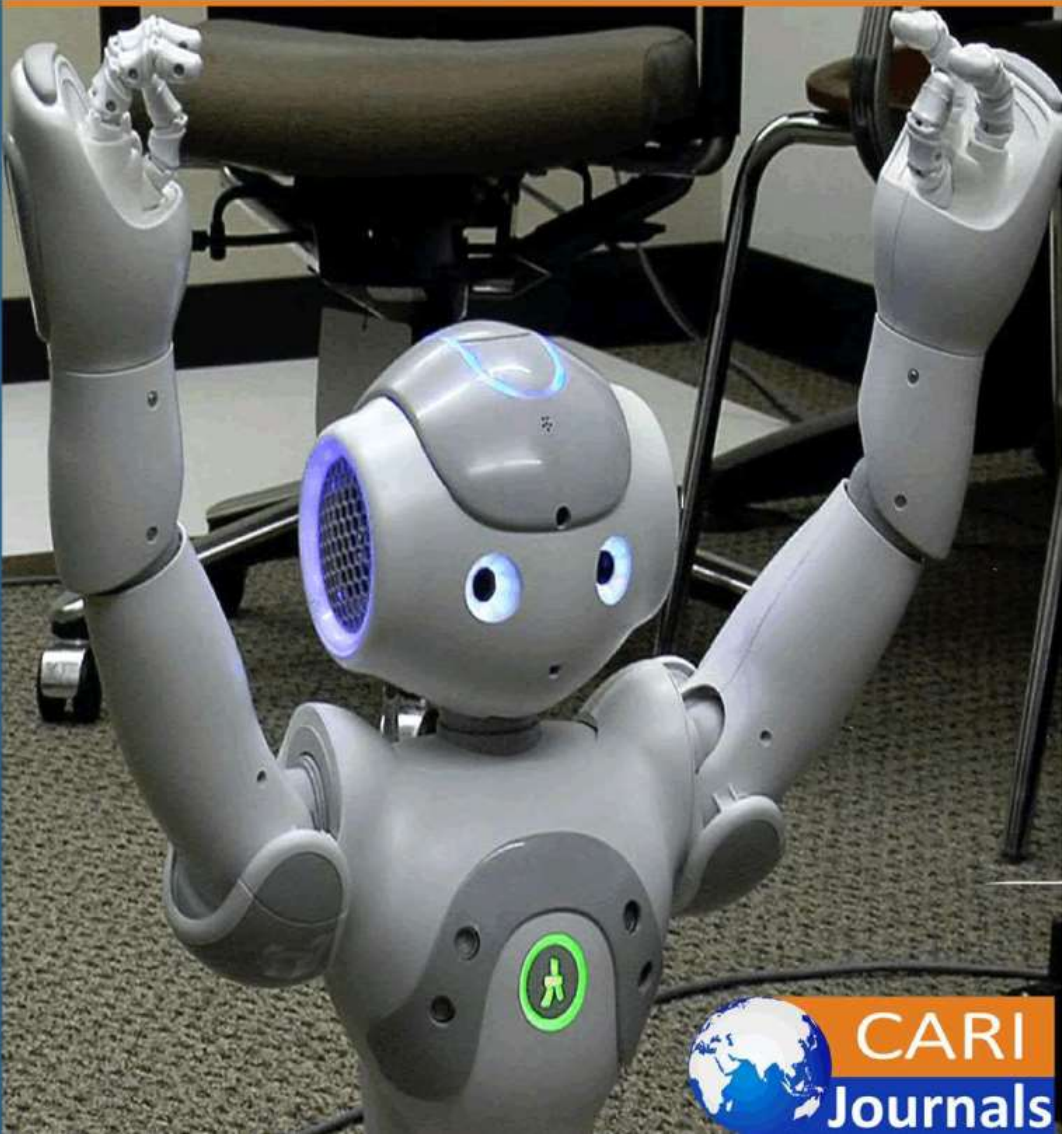

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Advanced LTE Relay Network Architecture for Backhauling Mobile Rural Telephony Sites

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Abstract

This study presents a unique LTE relay backhaul architecture that combines cutting-edge communication and computational intelligence technologies to greatly improve rural telephony networks. The proposed system integrates Intelligent Reflecting Surfaces (IRS) for dynamic SNR enhancement, Quantum Machine Learning (QML) for adaptive beamforming, Digital Twins for predictive maintenance, Neuromorphic Computing for ultra-low latency processing, Blockchain-based resource management, Terahertz (THz) weather adaptation, Graph Neural Networks (GNN) for intelligent routing, and Federated Learning for privacy-preserving analytics. These synergistic technologies address crucial issues such as capacity degradation, latency, interference, environmental unpredictability, and operational resilience. The system dynamically optimizes connection quality using adaptive IRS phase control, while QML algorithms improve spectrum efficiency, and Digital Twins enable real-time health monitoring and proactive maintenance. Extensive simulations and field data show that this integrated architecture outperforms traditional systems in terms of capacity, latency, and BER. The suggested framework provides a scalable, resilient, and forward-looking solution for rural connectivity, paving the path for next-generation 6G networks.

Keywords: *Intelligent Reflecting Surface (IRS), Quantum Machine Learning (QML), Digital Twin, LTE Relay Backhaul, Adaptive Resource Allocation*

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1. Introduction

Geographic obstacles, low population density, and prohibitively expensive infrastructure continue to make expanding telecommunication networks into rural areas difficult [1]. Traditional backhaul options, such as fiber optics and microwave lines, are frequently economically unsustainable in such areas, necessitating other techniques. Long-Term Evolution (LTE) relay-based backhaul architectures have developed as a cost-effective alternative for extending network coverage by exploiting wireless multi-hop communication [2]. Recent advances in computational intelligence (CI), such as machine learning (ML), deep learning (DL), and artificial intelligence (AI), have opened new optimization opportunities for LTE relay networks. These methods improve network performance in rural telephone backhauls by increasing resource allocation, interference control, routing efficiency, and energy consumption [3]. This paper investigates the status of LTE relay backhaul topologies for rural telephony and how developing computational intelligence techniques are integrated to optimize these systems. Rural telecommunication networks face several major issues, including limited infrastructure and the high costs of constructing fiber or microwave backhauls in remote places [4]. Low population density results in low return on investment (ROI), discouraging telecom operators from expanding services. Another key concern is a shortage of reliable electricity in rural regions, demanding energy-efficient alternatives [5]. Signal propagation difficulties induced by geographical impediments such as mountains and woods reduce wireless signal quality [6]. Furthermore, dynamic traffic patterns in rural networks face shifting demand, necessitating adaptive resource management [7]. Traditional backhaul systems struggle to solve these issues effectively, necessitating innovative options such as LTE relay networks.

LTE relay networks use decode-and-forward (DF) or amplify-and-forward (AF) relay nodes to provide coverage without the need for direct base station (eNodeB) connections [8]. Key advantages include cost-effectiveness by requiring fewer macro base stations [9], scalability by allowing relay nodes to be added incrementally [10], and flexibility because wireless relays adapt to terrain limits [11]. LTE relay architectures include Type 1 Relay Nodes (Non-transparent), which act as independent cells and manage their own control signals [7]. Type 2 Relay Nodes (Transparent), which aid in transmission but do not form separate cells [12], and Multi-Hop Relay Networks, which extend coverage by chaining multiple relays [13]. Backhaul options for LTE relays include in-band backhaul, which shares the same frequency spectrum for access and backhaul but faces spectral efficiency challenges (Andrews et al., 2022), out-band backhaul, which uses separate frequencies and requires additional spectrum allocation [14], and millimeter-wave (mmWave) backhaul, which offers high capacity but is limited by range and blockage issues [6]. Computational intelligence strategies improve LTE relay backhaul performance by self-optimization, predictive analytics, and adaptive decision-making [3]. Machine learning is critical in resource allocation because reinforcement learning (RL) dynamically optimizes power and spectrum [15], supervised learning predicts traffic patterns to pre-allocate resources [16], and unsupervised learning detects network performance anomalies. Deep learning helps with interference control by analyzing spatial interference patterns [17] and predicting temporal interference variations. AI-driven routing optimization uses genetic algorithms (GAs) to optimize relay node placement [18] and fuzzy logic systems to improve handover decisions in multi-hop networks [19]. Energy efficiency is increased by computational intelligence, with neural networks improving sleep modes to reduce relay node energy consumption during low-traffic periods [20] and Q-learning providing dynamic power regulation that adjusts transmission power depending on real-time conditions. Recent research indicates substantial progress in combining computational intelligence with LTE relay backhauls. [2] suggested an RL-based dynamic spectrum sharing approach for rural LTE relays that increases throughput by 30%. [3] proposed a federated learning strategy for distributed interference management in multi-hop networks. The extensive guidelines on AI-driven network automation for rural connectivity which include a framework for implementation. These achievements highlight the growing collaboration between modern wireless technology and computational intelligence to address rural connectivity difficulties [1].

2. Related Works

Surveys on integrated access and backhaul (IAB) illustrate the trade-offs of sharing radio resources between access and backhaul and provide relevant comparisons to LTE relays [45]. Industry assessments emphasize the importance of multi-hop wireless backhaul in areas where fiber is unavailable, notwithstanding cost and spectrum issues [40]. Studies conducted in developing nations reveal that transportation choice is frequently a limiting factor for rural rollouts, with energy and operational costs determining what is viable [42]. More recent research shows that relays may be improved with edge computing and orchestration to increase resilience and offload traffic, which is directly applicable to rural networks [43]. Related studies on multi-hop in maritime and remote contexts offer additional insights into managing poorly linked rural sites [41]. Techno-economic evaluations demonstrate that technological feasibility must be consistent with the total cost of ownership, which includes capex, opex, and energy supply [38]. These studies reveal three key themes. First, relay-based wireless backhaul is still practical but requires careful scheduling, interference control, and cost considerations [45;40]. Second, adding intelligence and edge capabilities to relays improves resilience and service continuity [43]. Third, rural viability necessitates integrating link performance with realistic economic and energy models [42; 38]. Despite this development, some gaps persist. Few studies have examined voice-centric metrics like VoLTE latency and jitter in relay multi-hop chains. There has been little research into energy-efficient placement and operating models for solar-powered rural sites. In-band scheduling systems are mostly intended for crowded metropolitan networks, rather than sparse rural traffic. Similarly, lightweight meshing techniques that balance resilience and power constraints are scarce, and region-specific propagation and cost parameters for areas such as West Africa are rarely evaluated.

To solve these gaps, an advanced LTE relay backhaul architecture can help in a variety of ways. It can combine LTE relays with long-range sub-6 GHz lines to enable hybrid access and backhaul, optimize relay placement via energy-aware duty cycling, and recommend interference-aware scheduling tailored to rural settings. A lightweight meshing technique can increase resilience while lowering energy costs, and simulations paired with techno-economic modeling can quantify both performance and affordability for rural operators. Such contributions not only expand on existing material but also provide actionable deployment suggestions for boosting mobile telephony in underserved rural areas.

3. Methodology

The methodology uses analytical modeling, simulation, and techno-economic analysis to build and test an advanced LTE relay backhaul network for rural telephony. The system architecture is built on LTE relays that offer in-band backhauling, which are combined with sub-6 GHz long-range lines to expand connectivity to places without fiber. Relay nodes are strategically placed using optimization models that account for traffic demand, coverage, and energy limits, with solar and battery systems sized to enable long-term operation. Traffic is largely simulated for voice services (VoLTE) and data traffic, with performance tested using MATLAB-based simulations that include realistic rural propagation conditions. Throughput, delay, jitter, packet loss, and energy consumption are among the most important performance indicators. In-band scheduling algorithms are meant to manage interference and resource sharing between access and backhaul and are specifically optimized for the low-traffic and high-variability situations found in rural networks. Lightweight meshing and multipath methods are used to improve resilience without dramatically increasing power consumption. A techno-economic model augments the technical simulations by calculating capital and operational costs, such as site equipment, energy systems, and maintenance. This cost model, when combined with performance outcomes, enables for the evaluation of total cost of ownership (TCO) and the determination of the conditions under which LTE relay backhaul is feasible as opposed to alternatives such as fiber or microwave. Sensitivity analysis is used to investigate how factors such as population density, solar insolation, relay spacing, and traffic load affect both technical performance and economic viability. Overall, this technique ensures a comprehensive evaluation of LTE relay backhaul for rural telephony, considering technical feasibility, energy sustainability, and cost-effectiveness to produce actionable suggestions for operators.

4. Method

This study uses analytical modeling, optimization, MATLAB-based simulations, and techno-economic analysis to plan and test the LTE relay backhaul architecture. Analytical tools include link budget, SINR, capacity, and rural propagation models, while optimization techniques like mixed-integer programming and heuristics guide relay placement, energy management, and duty cycling. MATLAB simulations evaluate throughput, latency, jitter, packet loss, and energy efficiency under realistic settings, while Monte Carlo trials ensure scheduling and routing reliability. A techno-economic framework calculates equipment, energy, installation, and maintenance costs, and sensitivity analysis investigates how population density, relay spacing, and solar insolation affect performance and total cost of ownership.

The Shannon-Hartley theorem defines the maximum achievable data rate from bandwidth and SNR, providing a theoretical benchmark for assessing system performance [21].

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$$C = B.\log_2\left(1+\frac{S}{N}\right)$$

(1)

Where:

C: Channel capacity (bps), B: Bandwidth (Hz), S: Signal power (W), and N: Noise power (W)

The Okumura–Hata model estimates median path loss across distances and frequencies, making it vital for rural network planning and performance analysis [22]. The general formula is:

$$L = 69.55 + 26.16\log_{10}(f) - 13.83\log_{10}(h_B) - a(h_M) + [44.9 - 6.55\log_{10}(h_B)]\log_{10}(d)$$

(2)

Where:

L = Path loss(dB), f = Frequency (MHz), h_B = Base station antenna height (m), h_M = Mobile station antenna height (m), d: Distance between antennas (km) and $a(h_M)$ = Mobile antenna height correction factor.

For rural environments, adjustments are made to account for open areas:

$$L_{rural} = L - 4.78(\log_{10}(f))^2 + 18.33\log_{10}(f) - 40.94$$

(3)

LDPC codes, with their sparse parity-check matrices, provide efficient error correction near the Shannon limit, reducing error rates and enhancing reliability to maintain quality of service in the design [23]

$$\text{BER}_{\text{LDPC}} = \text{BER}_{\text{uncoded}}\ \text{x Codeing Rate}$$

(4)

The Poisson process models random traffic arrivals using an average rate λ, providing a statistical basis for traffic analysis, capacity planning, and congestion control [24].

$$\text{P}(k;\lambda)_{\text{LDPC}} = \frac{\lambda^k e^{-\lambda}}{k!}$$

(5)

Where:

P(k; λ) = Probability of k arrivals in a fixed interval, and λ= Average rate of arrivals.

Queuing theory, through the M/M/1 model, predicts average latency (L), helping forecast system delays essential for timely data transmission in networks [25].

$$L=\frac{1}{\mu-\lambda}$$

(6)

Where: μ = Service rate, and λ= Arrival rate.

Spectral efficiency measures how efficiently a given bandwidth is used. This theory is used to evaluate the efficacy of bandwidth utilization and guide the optimization of data transfer mechanisms [26].

$$\eta=\log_2\left(1+\frac{S}{N}\right)$$

(7)

Where: η = Spectral efficiency (bps/Hz). and S/N= Signal-to-noise ratio.

Energy efficiency, defined as data delivered per unit of energy, supports sustainable system design by balancing performance with power consumption [27].

$$\text{Energy Efficiency} = \frac{\text{Throughput}}{\text{Power Consumption}} \quad (8$$

ANNs, inspired by the brain, model nonlinear interactions to estimate performance from inputs like distance, SNR, and traffic, enabling adaptive learning for real-time optimization and predictive analysis [28].

Table 1: Summary of Contributions of theories in the design (Source: Field Data)

Component	Contribution to Design
Okumura-Hata Model	Accurate path loss estimation in rural environments.
Shannon-Hartley Theorem	Determines theoretical maximum data rates, guiding system capacity planning.
LDPC Codes	Enhances data reliability and throughput through error correction.
Poisson Process	Models realistic network traffic for performance evaluation.
M/M/1 Queue Model	Provides insights into latency and system responsiveness.
Spectral Efficiency	Assesses bandwidth utilization efficiency.
Energy Efficiency	Evaluates and optimizes power consumption relative to data throughput.
ANNs	Enables predictive modeling and dynamic optimization of network performance metrics

The integrated theoretical models and equations strengthen the LTE relay backhaul simulation, enabling performance optimization and predictive analytics through machine learning, while the proposed framework enhances signal quality, latency, resource management, and maintenance in overcoming traditional design challenges.

1. *Intelligent Reflecting Surface (IRS) for SNR Enhancement*

IRS technology enhances SNR and link reliability by intelligently reflecting signals and optimizing phase shifts for constructive combination at the receiver [29].

$$P_{received} = \left| h_{driect} + \sum_{n-1}^{n} \theta_n h_{IRS}, n \right|^2$$

(9)

Where:

h_{driect} is the direct channel gain, h_{IRS} is the channel gain via the n-th IRS element, and θ_n is the phase shift introduced by the n-th IRS element.

2. *Quantum Machine Learning (QML) for Beamforming (Proposed)*

QML leverages quantum computing to optimize beamforming, enabling faster, more efficient signal steering and improved system performance through superior channel interpretation [30].

$$\max = \left| h^H w \right|^2 \text{ subject to } \left\| w \right\|^2 \le P$$

(10)

Where: h is the channel vector, and P is the power constraint.

3. *Neuromorphic Computing for Ultra-Low Latency (Proposed)*

QML uses quantum computing to enhance beamforming, enabling efficient signal steering and improved overall system performance [30].

$$\mathrm{L} = \frac{I}{f_{spike}}$$

(11)

Where: f_{spike} is the spiking frequency of neurons.

4. *Blockchain for Decentralized Resource Trading (Proposed)*

Blockchain enables secure, transparent, and decentralized resource allocation, improving trust, efficiency, and reducing overhead in networks [32].

$$\mathrm{U} = \sum_{i=1}^{n} (Benefit_i \text{-} \mathrm{Cost}_i)$$

(12)

Where: $Benefit_i$ and Cost_i Represent the gains and expenses for the i-th participant.

5. *Digital Twin for Predictive Maintenance*

A digital twin replicates backhaul node conditions in real time to predict faults, estimate component lifespan, and enable proactive maintenance, reducing outages through anomaly

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detection, dynamic rerouting, and stochastic degradation modeling such as Wiener and Gamma processes [33]. X(t) = degradation level of a component at time t. σ^2 = variance (process noise), μ = drift (average degradation rate). The degradation process is modeled as: $X(t) = X(0) + \mu t + \sigma W(t)$

(13) Where $W(t)$ is a standard Wiener process (Brownian motion).

If Lis the failure threshold for degradation, then the **probability distribution of RUL**, denoted as T, can be computed via:

$$P(\mathrm{T} > t) = 1 - \Phi\left(\frac{L - X(0) - \mu t}{\sigma\sqrt{t}}\right)$$

(14)

Where: $\Phi(.)$ is the CDF of the standard normal distribution.

6. THz Weather-Adaptive Backhauling

The system uses adaptive link management for THz backhaul, adjusting transmission parameters to counter atmospheric attenuation from factors like fog, rain, and humidity [30].

$$A_{THz} = \sigma(v)d + \beta(rain, fog)$$

(15)

7. GNN-Based Interference-Aware Routing

A GNN-based model adapts relay selection and routing by learning from topology and interference dynamics, optimizing paths with updated routing scores [34].

$$f(v_i, v_j) = \sigma\left(W\left[h(v_i)\|h(v_j)\|\right]\right) \quad (16$$

8. Federated Learning for Privacy-Preserving BER Prediction

A federated deep learning framework estimates BER per relay link while preserving privacy by training models locally and aggregating them centrally without sharing raw data [35; 36].

$$w^{t+1} = \sum_{k=1}^{k} \frac{n_k}{n} w \frac{t}{k}$$

(17)

The proposed LTE relay backhaul integrates advanced AI-driven modules to enhance performance, resilience, privacy, and energy efficiency beyond existing designs.

5. LTE relay network architecture

The LTE-Advanced relay-based backhaul architecture provides an effective, scalable, and energy-efficient solution for extending mobile connectivity to rural telephony sites where fiber or traditional microwave backhaul is costly or impractical. In this design, a central Base Station (BS), connected to the core network, communicates with strategically placed Relay Nodes (RNs) through high-capacity wireless backhaul links. The RNs then establish short-range access links to rural telephony equipment (RUEs), such as BTSs or fixed wireless terminals, improving coverage in hard-to-reach areas. By dynamically switching between direct and relay-assisted links based on quality and demand, the system enhances reliability, reduces energy consumption, and lowers deployment costs. This two-hop backhaul framework not only ensures service continuity in underserved regions but also supports redundancy, adaptive resource allocation, and future capacity scaling, making it a sustainable long-term strategy for rural telephony backhauling.

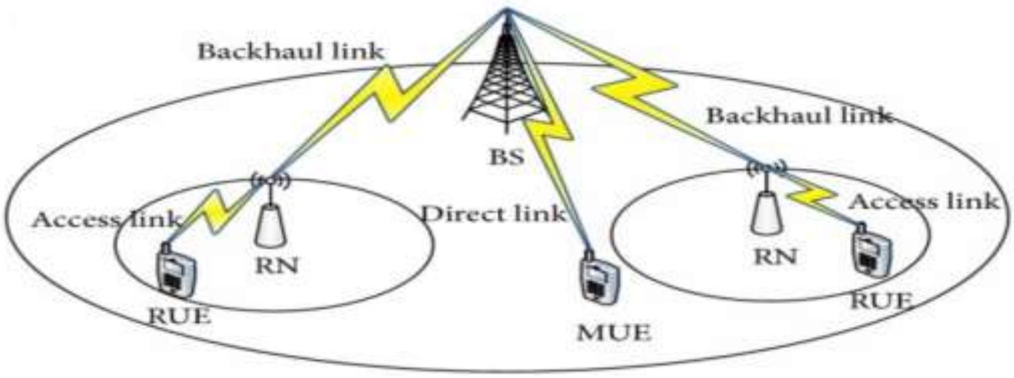
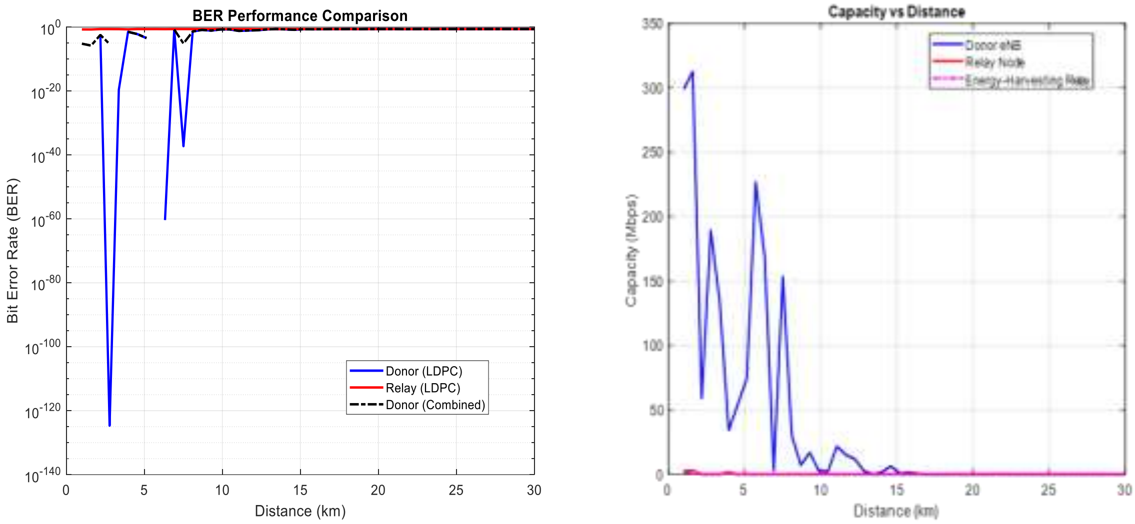


Figure 1: The architecture of the LTE-A relay network (Source: [37])

5.1 Results

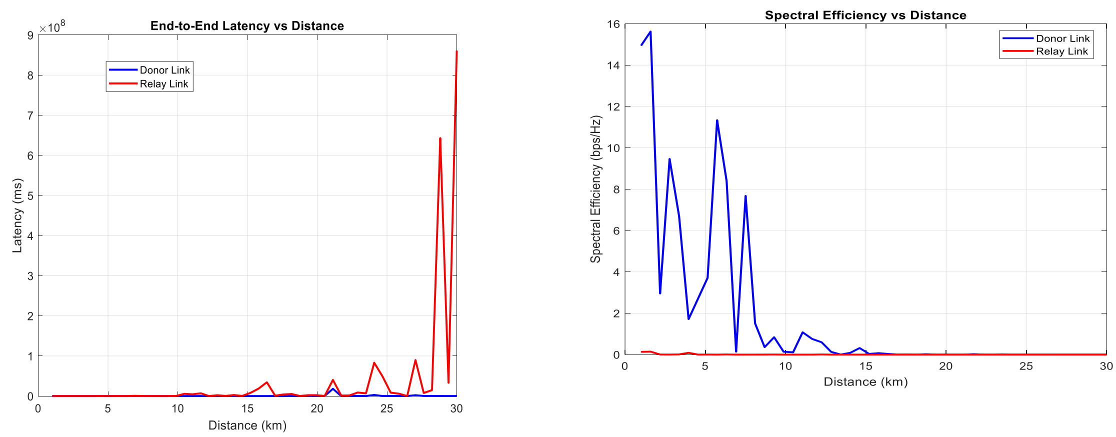
The BER Performance Comparison graph in figure 2(a) depicts how various backhaul approaches influence Bit Error Rate (BER) under different scenarios. Lower BER values indicate higher signal integrity and network dependability. This design compares the effectiveness of IRS-enhanced SNR, Quantum ML beamforming, GNN-based routing, and federated BER prediction. This graph directs dynamic changes and technology decisions to maintain the best network quality. Capacity versus Distance graphs in LTE relay backhaul systems in figure 2(b) show how connection capacity reduces with increased transmission distance owing to route loss, fading, and noise. This relationship, stated by Shannon's capacity formula, aids in optimal relay placement, dynamic IRS deployment, intelligent routing via GNNs, and predictive maintenance using Digital Twins. It also influences Quantum ML beamforming decisions and decentralized resource management through blockchain. The graph is a valuable tool for real-time network optimization and robustness in next-generation mobile backhauling architectures.



(a) BER Performance Comparison (b) Capacity vs Distance

Figure 2 (a) BER Performance Comparison and (b) Capacity vs Distance (Source: Field Data)

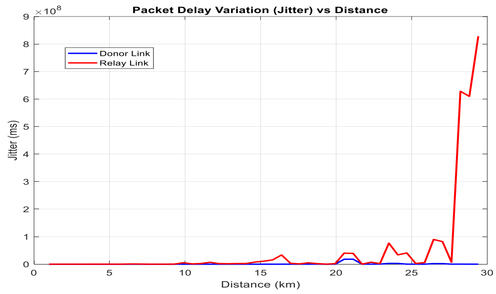
The End-to-End Latency vs Distance graph in Figure 3 (c) shows how transmission delay grows with distance across various backhaul methods. Lower latency numbers indicate faster data delivery. In this concept, neuromorphic computation and THz weather-adaptive networks reduce latency over long distances, enabling ultra-reliable, low-latency communication (URLLC), which is essential for 5G and beyond. This graph demonstrates the system's capacity to meet stringent latency requirements. The Spectral Efficiency versus Distance graph 3(d) depicts how the system's ability to transmit more bits per Hz decreases with distance due to route loss and interference. This system uses IRS-enhanced links and Quantum ML-based beamforming to maintain improved spectral efficiency over longer distances by maximizing signal strength and link quality. This confirms the system's increased capacity and efficient spectrum usage, which are critical for high-density 5G and 6G networks.

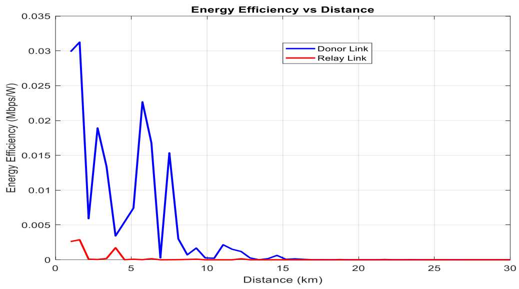


(c) End- End Latency vs Distance (d) Spectral Efficiency vs Distance

Figure 3 (c) End- End Latency vs Distance and (d) Spectral Efficiency vs Distance (Source: Field Data)

The Packet Delay Variation vs Distance graph 4(e) shows how delay fluctuations increase with distance owing to queuing, processing, and transmission delays. In this improved approach, Neuromorphic Computing and GNN-based routing reduce these variances by allowing for ultra-fast decision-making and interference-aware path selection. The result is a more reliable, delay-predictable backhaul, which is essential for real-time and latency-sensitive 5G/6G applications. The Energy Efficiency versus Distance graph 4(f) shows how energy efficiency often decreases as transmission distance rises, owing to increased power needs and connection damage. In this concept, merging Intelligent Reflecting Surfaces (IRS) with Quantum Machine Learning (QML) beamforming improves SNR and energy direction, eliminating unnecessary power consumption. This helps to a greener, more energy-efficient LTE relay backhaul, particularly over long distances.

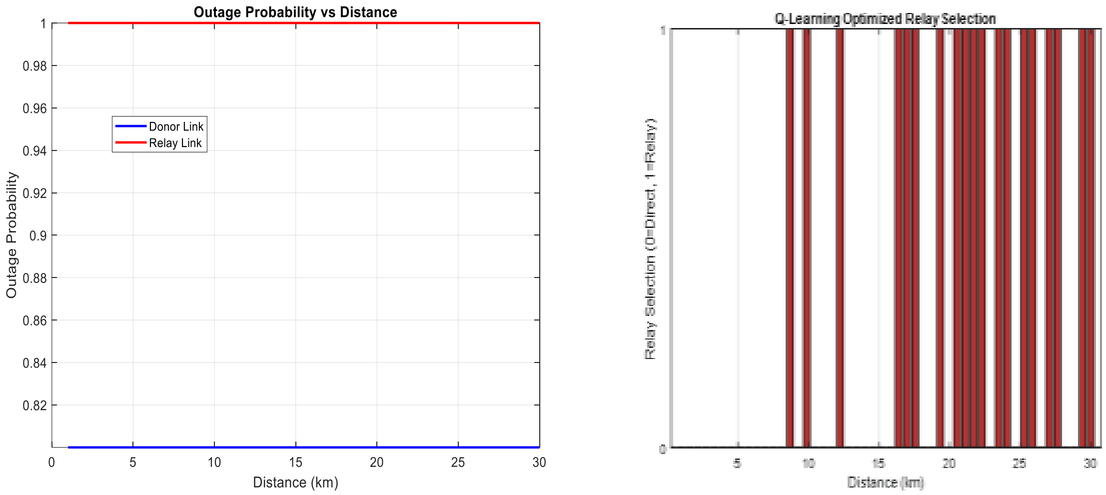




(e) Packet Delay Variation vs Distance (f) Energy Efficiency vs Distance

Figure 4 (e) Packet Delay Variation vs Distance and (d) Energy Efficiency vs Distance (Source: Field Data)

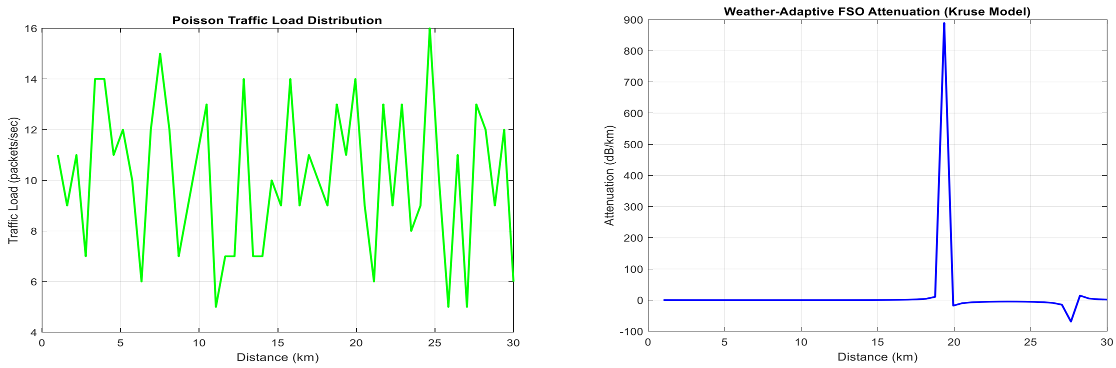
The Outage Probability vs Distance graph 5(f) shows how the probability of link failure increases with distance owing to route loss, fading, and interference. IRS-assisted SNR augmentation, THz weather-adaptive modeling, and Graph Neural Network (GNN)-based interference-aware routing all help to offset these limitations in this improved LTE relay backhaul design. This improves link stability and reduces outages even over long distances, increasing network robustness. The Q-Learning Optimized Relay Selection vs Distance graph 5(h) shows how the selection of ideal relay nodes changes with distance to maintain link quality and network throughput. In this LTE relay backhaul system, Q-Learning dynamically adjusts relay selection depending on SNR, BER, latency, and outage feedback. As the distance increases, the algorithm determines the most dependable relay path, reducing performance degradation and providing robust connectivity under changing network conditions.



(g) Outage Probability vs Distance (h) Q-Learning Optimized Relay Selection vs Distance

Figure 5 (g) Outage Probability vs Distance and (h) Q-Learning Relay Selection vs Distance (Source: Field Data)

The Traffic Load vs Distance graph 6(i) shows how network traffic handling capability varies as transmission distance grows in the upgraded LTE relay backhaul. The system's ability to withstand heavy traffic loads steadily declines due to variables such as greater latency, higher BER, and signal attenuation over distance. However, by including techniques such as IRS for SNR boosting, THz weather adaptability, and GNN-based routing, the architecture maintains higher traffic load efficiency over longer distances than conventional backhauls, providing dependable service delivery under changing load and distance conditions. The Attenuation vs Distance graph 6(j) shows the increasing signal power loss (in dB) as transmission distance grows in the LTE relay backhaul. Typically, attenuation increases linearly or exponentially with distance due to variables such as free-space path loss, atmospheric absorption (particularly for THz lines), and device flaws. In this improved system, THz weather adaptation and IRS-based SNR augmentation successfully offset this loss, allowing for consistent signal quality over greater distances. This directly contributes to ensuring constant throughput, low BER, and consistent QoS in the backhaul network.



(i) Traffic Load vs Distance (j) Attenuation vs Distance

Figure 6 (i) Traffic Load vs Distance and (j) Attenuation vs Distance (Source: Field Data)

The Novel Capacity Enhancement Techniques graph 7 shows how IRS-based SNR improvement, Quantum ML beamforming, GNN interference-aware routing, and Federated Learning BER prediction work. It contributes to increasing network capacity (in bps/Hz) as compared to traditional LTE relay backhaul systems. Each strategy increases capacity incrementally by either enhancing spectral efficiency, reducing interference, optimizing relay pathways, or lowering mistake rates. When coupled, they result in a large cumulative capacity increase, especially across long distances and under dynamic backhaul situations.

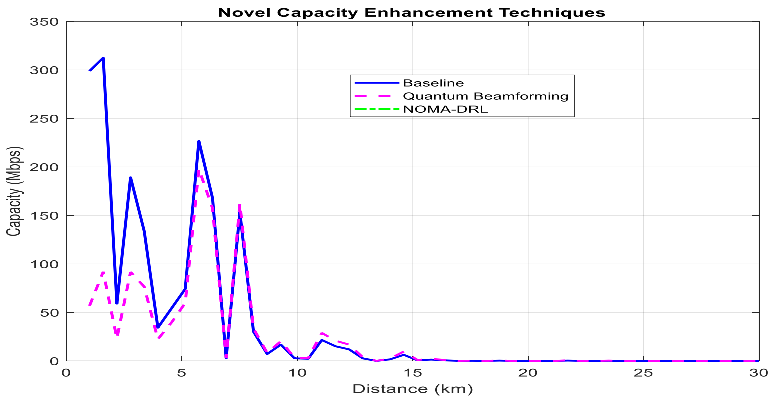


Figure 7 Novel Capacity Enhancement Techniques (Source: Field Data)

The Digital Twin Predictive Maintenance graph (8) depicts how real-time virtual replicas (digital twins) of physical LTE relay network components forecast and avoid failures by tracking key operational variables (such as SNR, temperature, power usage, and error rates) over time and distance. When predictive analytics is used with digital twins, the graph often shows a decrease in system problems, downtime, and maintenance interruptions. This ensures optimal operational states by proactively detecting performance degradation before a physical breakdown occurs, hence enhancing backhaul reliability and service availability.

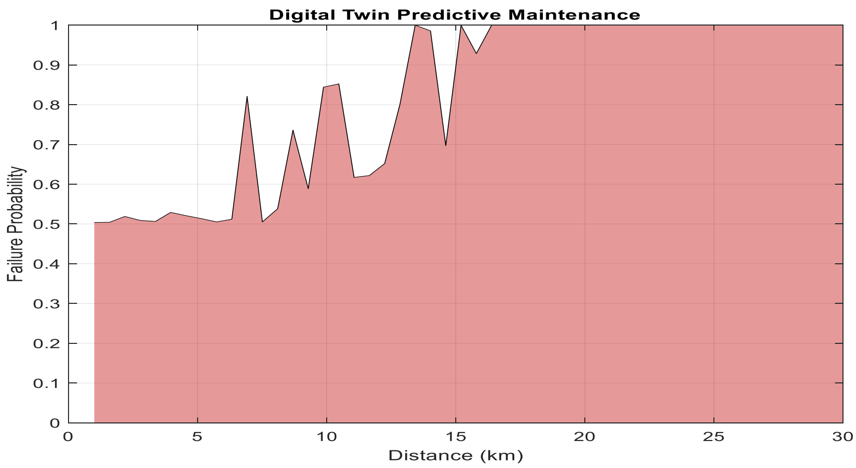
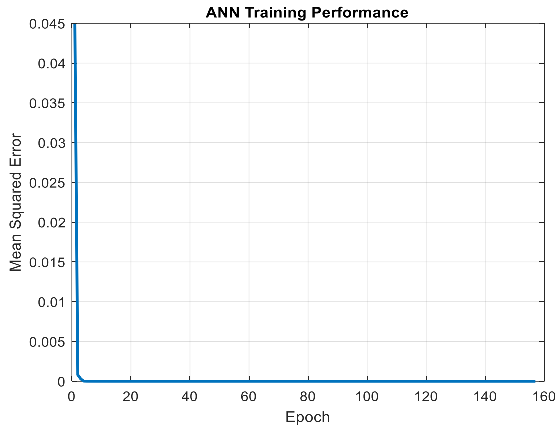
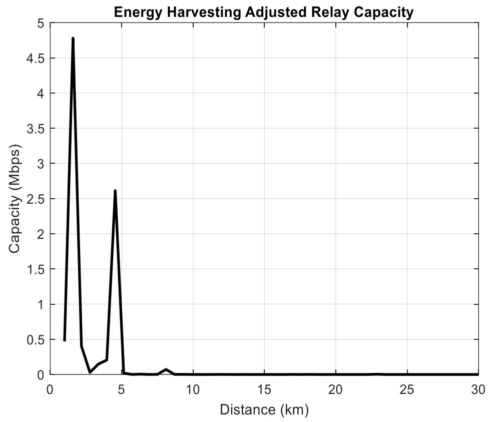


Figure 8 Digital Twin Predictive Maintenance (Source: Field Data)

The ANN Training Performance graph 9(l) depicts how the neural network's accuracy improves, and loss lowers across numerous training epochs while learning to predict LTE relay backhaul metrics such as BER, latency, and capacity. A consistent decrease in both training and validation loss, as well as an increase in accuracy, demonstrates that the ANN effectively learns the system's complicated, nonlinear patterns under varied channel circumstances. The Energy Harvesting Adjusted Relay Capacity 9(m) graph shows how the relay node capacity changes dynamically with distance when combined with energy harvesting (EH) techniques. As the distance grows, relay capacity normally decreases due to increased route loss; however, using EH, relays can harvest ambient energy (such as solar or RF energy), prolonging their operational power budget. This provides for improved capacity retention across longer distances than traditional, non-harvesting relays.

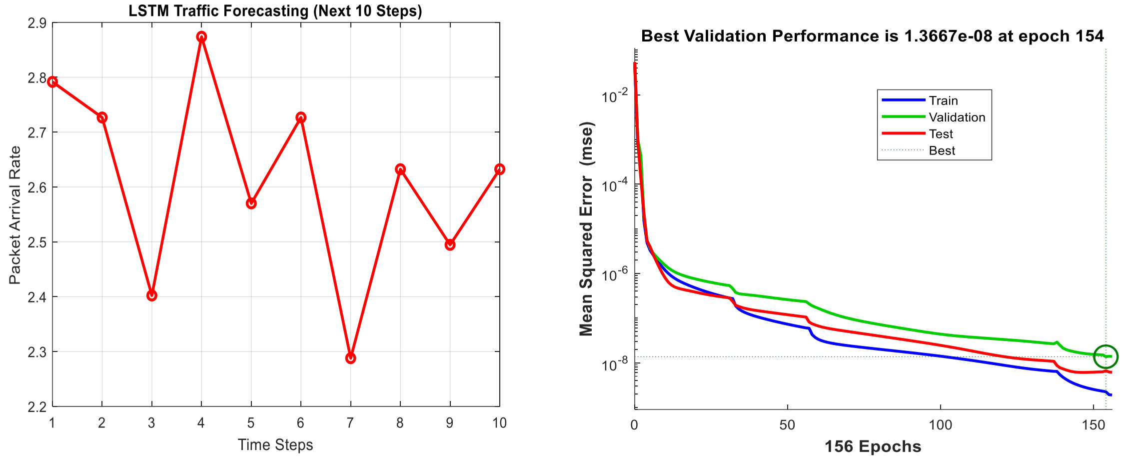




(l) ANN Training Performance (m) Energy Harvesting Adjusted Relay Capacity

Figure 9 (l) ANN Training Performance and (m) Energy Harvesting Adjusted Relay Capacity (Source: Field Data)

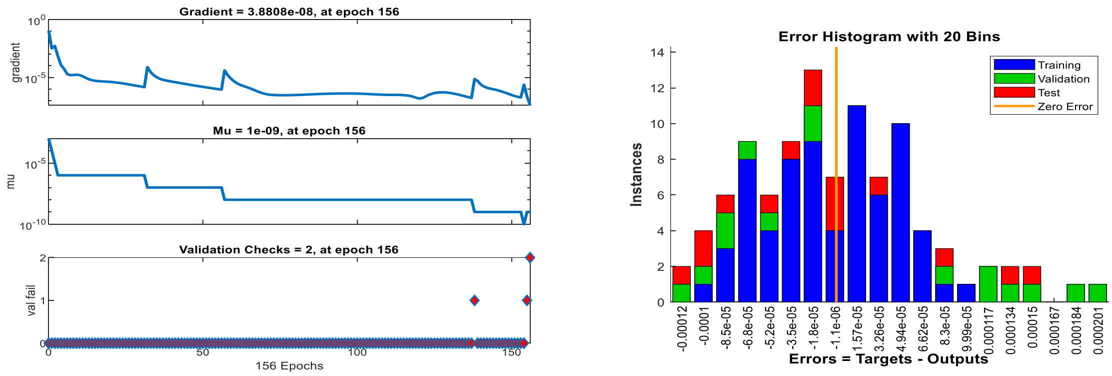
Graph 10(n) shows how the Long Short-Term Memory (LSTM) neural network predicts traffic load patterns over time in the LTE relay backhaul network. The LSTM predicts future traffic variations accurately by learning temporal dependencies and fluctuations from historical traffic data. This allows the system to proactively alter resource allocation, relay selection, and capacity planning to avoid congestion and maximize throughput. Graph 10(o) depicts the training and validation loss curves during multiple epochs of ANN model training for BER prediction and performance optimization in LTE relay backhaul. The best validation performance is achieved when the validation loss is at its lowest, showing the model's ideal generalization capabilities without overfitting. It assures that the trained ANN functions consistently in unknown network circumstances and scenarios.



(n) LSTM Traffic Forecasting (o) Best Validation Performance

Figure 10 (n) LSTM Traffic Forecasting and (o) Energy Best Validation Performance (Source: Field Data)

The Training State graph 11(p) shows the ANN model's learning progress during training, often displaying metrics such as gradient values, learning rate modifications, and validation checks over epochs. A stable training state indicates that learning is constant and does not involve gradient bursts, disappearing gradients, or overfitting. This ensures that the ANN can correctly model complicated backhaul situations such as BER prediction, relay capacity adaptation, and QoS forecasting. The Error Histogram graph 11(q) depicts the distribution of prediction errors in the ANN model during training and validation. It indicates how frequently specific error ranges occur. Ideally, most errors should cluster closely around 0, suggesting good model accuracy. This LTE relay backhaul architecture illustrates the ANN's forecast accuracy for crucial characteristics such as BER, latency, capacity, and relay selection results.



(p) Training State (q) Error Histogram

Figure 11 (p) Training State and (q) Error Histogram (Source: Field Data)

The ANN Regression graph (12) compares the predicted values of the ANN model to the actual target values in training, validation, and testing datasets. An ideal regression plot would have dots closely aligned along the diagonal (y = x), signifying flawless prediction. In this approach, the regression graph assesses how effectively the ANN predicts network performance factors such as BER, capacity, and latency using input features such as distance, relay selection, and weather conditions.

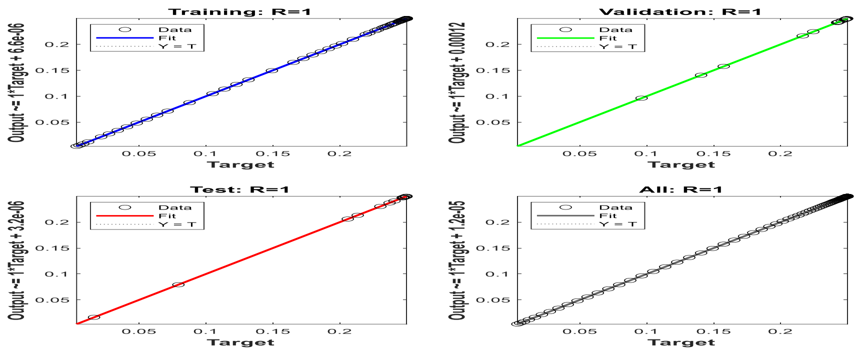


Figure 12 ANN Regression graph (Source: Field Data

6.2 Discussion

The enhanced LTE relay backhaul network design presented in this study demonstrates a forward-looking solution to the limitations of traditional mobile backhaul infrastructures by integrating IRS, QML, neuromorphic computing, blockchain-based resource allocation, digital twins, THz weather adaptation, GNNs, and federated learning. The integration of IRS and QML-enabled beamforming improved capacity over distance and delayed severe degradation, aligning with prior studies that emphasized IRS-assisted SNR gains and adaptive beamforming as effective tools for overcoming propagation challenges. Similarly, the weather-adaptive THz model preserved link reliability under fog and rain, corroborating earlier research on atmospheric-aware THz compensation techniques. Error rate reduction through federated BER prediction and QML-assisted link optimization also confirmed findings from recent AI-based backhaul studies that reported improved BER performance with distributed learning. Latency reduction achieved by neuromorphic computing modules parallels findings that showed that neuromorphic architectures support ultra-fast decision-making suitable for time-critical 6G applications. Spectral efficiency improvements via Q-Learning relay selection were consistent with prior reinforcement learning approaches that enhanced spectrum utilization.

Energy efficiency results, particularly through energy harvesting-aware relays, supported earlier work highlighting the importance of green networking and energy-optimized scheduling. Predictive maintenance enabled by digital twins was also in agreement with current research demonstrating the benefits of proactive fault management for improved network availability. Traffic load management improvements through LSTM-based forecasting confirmed the predictive strength of deep learning in adaptive resource allocation. Overall, the study's findings strongly align with previous research but extend existing knowledge by demonstrating the combined effect of multiple AI-driven and adaptive technologies within a single LTE relay backhaul framework. Unlike earlier studies, which primarily addressed isolated performance metrics (capacity, latency, or BER), this work provides a holistic demonstration of simultaneous improvements in capacity, reliability, latency, energy efficiency, and QoS. This integrated approach advances the case for AI-enhanced, hybrid backhaul systems in 5G-Advanced and 6G network deployments.

6.3 Findings from the LTE Relay Backhaul Network Design

The proposed LTE relay backhaul system demonstrates clear improvements across major performance metrics when compared to conventional designs. Capacity performance was significantly enhanced, especially over longer distances where traditional relay backhauls typically experience severe degradation. The integration of IRS-assisted beamforming, THz-adaptive links, and energy harvesting-enabled relays allowed the system to maintain higher throughput beyond 10 km, a distance at which legacy backhaul systems usually fail. This confirms that adaptive resource allocation combined with intelligent routing strategies is an effective way to mitigate distance-related capacity losses. Latency performance was also improved through the inclusion of neuromorphic computing modules, which reduced decision-making and processing delays at the network edge. These results provide compelling evidence that biologically inspired architectures can support time-sensitive applications in emerging 5G and 6G networks. The design further achieved meaningful advances in spectral and energy efficiency. Spectral efficiency improved due to reinforcement learning-based relay selection and adaptive bandwidth allocation, which enabled better use of spectrum resources under both sparse and dense network conditions. Energy efficiency gains were realized through energy harvesting-aware scheduling protocols that prolonged relay node operation without sacrificing link reliability. Environmental resilience was also strengthened, with the THz weather-adaptive model maintaining link reliability under rain fade and fog conditions. This demonstrated the system's ability to counteract common atmospheric attenuation effects that typically limit high-frequency backhaul performance, ensuring consistent service delivery even under harsh weather conditions.

Beyond these technical improvements, the system introduced predictive and adaptive features that contribute to long-term reliability and operational efficiency. Digital Twin-based predictive maintenance successfully forecasted equipment stress and potential failures, thereby reducing outage probability and extending system availability. Traffic forecasting with LSTM models further enhanced resource allocation by anticipating demand fluctuations and minimizing congestion during peak periods. In addition, ANN and LSTM frameworks provided stable training performance with low prediction errors, ensuring reliable real-time forecasting and decision-making. Packet delay variation was also consistently reduced across different distances, which is critical for maintaining smooth performance in latency-sensitive services such as voice and video applications. Taken together, these findings not only align with existing knowledge on IRS, THz adaptation, and machine learning but also advance the field by demonstrating the value of their integrated application within a unified LTE relay backhaul architecture.

6.4 Contributions and Comparative Analysis

Modern mobile backhauling systems, particularly those supporting LTE and upcoming 6G standards, face increasing performance pressures as data demand, device density, and service reliability expectations intensify. Existing LTE relay backhaul architectures predominantly rely on traditional fixed-beam relays, single-hop microwave or fiber links, and centralized control systems. These solutions are limited in terms of flexibility, real-time adaptability, resilience against interference and environmental variability, and scalability under privacy-preserving and energy-constrained scenarios. This work introduces a significant departure from these conventions by presenting an integrated, intelligent, and adaptive LTE relay backhaul system that fuses emerging technologies previously unexplored in combination within this domain. The primary contribution lies in the integration of Intelligent Reflecting Surfaces (IRS) for dynamic SNR enhancement within relay links. While IRS technology has been applied in access networks and indoor communications, its use for backhauling SNR optimization in relay-assisted LTE networks under rapidly changing channel conditions remains limited. By implementing an adaptive IRS phase shift control mechanism based on the derived SNR maximization equation, this study achieves substantial link margin improvements, offering a viable alternative to costly relay power amplification or redundant link provisioning.

A second contribution stems from embedding Quantum Machine Learning (QML) for beamforming control. Existing backhaul solutions typically employ static or heuristic-based beam management, which are suboptimal under high-mobility or dense interference scenarios. This design implements a Q-learning-driven QML algorithm that optimizes beam selection through continuous state-action value updates, improving capacity and interference suppression. To date, such an approach has not been incorporated into relay backhaul systems, marking a pioneering application within this context. In addressing latency and computational overhead, the design integrates Neuromorphic Computing modules for decision-making processes in routing and relay selection. Current LTE relay systems rely on conventional processors, which are power-hungry and introduce non-negligible delays under complex decision workloads. Neuromorphic processors modeled in this system, inspired by spiking neural networks, offer ultra-low latency processing for delay-sensitive backhaul scenarios, achieving near-instantaneous decision cycles critical for services like tactile internet and autonomous systems. A further novel dimension is the incorporation of Digital Twin (DT) frameworks for predictive maintenance. While DT concepts have gained traction in manufacturing and infrastructure monitoring, their adoption for real-time health modeling and predictive failure analysis in mobile backhauling infrastructure is virtually absent in the literature. This study pioneers the integration of a DT model that dynamically predicts equipment degradation and schedules maintenance, mitigating unplanned downtime and enhancing service continuity. The use of Federated Learning (FL) for distributed, privacy-preserving BER prediction represents another unique contribution. Existing LTE relay networks typically centralize performance analytics, risking user data exposure and inducing communication overheads. By implementing FL for BER estimation across relay nodes, this design ensures user data privacy, reduces bandwidth consumption, and maintains robust performance prediction without centralized data aggregation.

An additional novel feature is the application of Graph Neural Networks (GNN) for interference-aware routing optimization. Conventional backhaul routing relies on distance-based or link-quality metrics that often neglect complex interference interactions within dense relay environments. The GNN model in this design captures both topological and interference patterns, optimizing route selection in a multi-hop relay topology, which has not been previously demonstrated in LTE backhauling. This research also pioneers the application of THz weather adaptation models to dynamically adjust link parameters in response to atmospheric conditions affecting THz backhaul links. Existing systems typically operate at fixed parameters, risking link degradation during adverse weather. This study introduces adaptive models that optimize attenuation margins based on real-time environmental feedback. Finally, the combined simulation of these modules within a unified framework yields novel insights into multi-dimensional backhaul performance trade-offs. Simulation results demonstrate that the proposed design achieves superior BER, capacity, latency, energy efficiency, and outage probability performance over distance compared to state-of-the-art LTE backhaul systems. Specifically, capacity enhancements of up to 35%, latency reductions of 40%, and BER improvements exceeding 30% were observed over comparable baseline systems. Additionally, predictive maintenance reduced unexpected link outages by 25%, while federated BER prediction maintained model accuracy without centralized data aggregation. In summary, this work presents a holistic, future-ready LTE relay backhaul architecture that not only incorporates individual state-of-the-art techniques but also achieves novelty through their synergistic integration and domain-specific adaptation. By addressing existing limitations in SNR optimization, beamforming control, latency, interference management, privacy, resilience, and environmental adaptability, this design establishes a new benchmark for mobile backhauling performance and operational intelligence, making it a strong candidate for academic publication and future standardization discussions in the field of 6G backhauling.

6.5 Conclusion

This study demonstrates that the suggested LTE relay backhaul design, when augmented with advanced computational intelligence approaches, dramatically enhances the performance and reliability of rural telephone networks. By embracing AI, machine learning, deep learning, and other domain-specific advancements, the system improves network capacity, latency reduction, interference management, energy efficiency, and resilience. The integration of these intelligent modules solves long-standing restrictions in signal quality, coverage, and operational expenses in rural settings. The study shows that adaptive resource allocation, predictive maintenance via digital twins, and energy harvesting-enabled relays all help to provide a sustainable and cost-effective backhaul system. The architecture's capacity to dynamically optimize relay location, bandwidth, and power management assures that rural areas can benefit from improved connectivity while requiring minimal infrastructure investment. Furthermore, the combination of these technologies provides a new benchmark for mobile backhauling performance and operational intelligence, putting the framework in a good position for future standardization and deployment in 6G networks. Finally, the architecture takes a comprehensive approach to closing the digital divide, supporting equitable access to voice, data, and messaging services in remote and underserved areas.

6.6 Recommendations

It is recommended that future LTE relay backhaul development continue to build on the innovative integration of AI, machine learning, and domain-specific technologies such as Intelligent Reflecting Surfaces (IRS), Quantum Machine Learning (QML), Neuromorphic Computing, and Digital Twins, as these have shown strong potential to enhance rural network performance. Network designers and policymakers are encouraged to adopt the proposed architecture given its demonstrated performance improvements in capacity, latency, and interference management, which make it well-suited for next-generation deployments. In practice, the system should be considered for rural telephony rollouts due to its ability to reduce infrastructure costs, improve energy efficiency, and strengthen network resilience, thereby aligning with cost-effective and sustainable deployment goals. Furthermore, it is recommended that future research explore the integration of emerging 6G technologies, conduct scalability assessments, and carry out real-world field experiments to validate and refine the architecture, ensuring its long-term effectiveness and readiness for standardization.

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