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Wireless Signal Interference Detection Using Machine Learning

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Abstract — Ensuring reliable spectrum efficiency in modern wireless communication networks requires robust and automated signal interference management. However, the dynamic and non-uniform nature of wireless environments introduces complex overlapping signals, complicating traditional energy-detection methods. This study evaluates the performance of advanced machine learning and deep learning models for detecting and classifying co-channel and adjacent-channel wireless interference. Through comprehensive experimental testing and simulation, an optimized neural network architecture is identified. Subsequently, the capability of the detection system is assessed under varying signal-to-noise ratios (SNR). The results indicate that while traditional threshold-based methods fail under fluctuating noise floor conditions, the proposed model maintains a detection accuracy above 98% even at low SNR levels down. As a typical example of intelligent spectrum management, this study provides a crucial reference for the optimization of next-generation cognitive radio and 5G/6G wireless network.

Keywords— Learning, Cognitive Radio, Spectrum Sensing, Deep Learning

I. INTRODUCTION

Wireless communication networks are currently the most viable option to power modern digital infrastructures because of their high data-rate capabilities, flexibility, and spectrum utilization efficiency [1]. However, the dense deployment of heterogeneous networks operating within shared frequency bands inevitably induces severe wireless signal interference. At low signal-to-noise ratios (SNR), the detection capacity of traditional frameworks is vastly reduced owing to non-uniform noise floors and unpredictable signal overlapping, leading to a much shorter transmission range and severe packet loss [2], whereas heavy co-channel and adjacent-channel interference.

By leveraging specialized neural network architectures designed to capture both spatial and temporal dependencies, the system can overcome fluctuating noise floor limitations. Consequently, as demonstrated in this study, such optimized intelligent frameworks can achieve an exceptional classification accuracy above 98%, successfully maintaining robust signal isolation even under extreme low-power conditions down to a - SNR threshold [6].

The core challenge lies in the non-uniform power spectral density of real-world radio environments, where shifting noise floors mask low-power rogue signals and cause traditional systems to fail [7,8]. To overcome this, modern frameworks bypass fragile, raw waveforms by transforming In-phase and Quadrature (I/Q) data into two-dimensional time-frequency spectrograms [9]. This conversion allows deep neural networks to treat interference detection as a pattern-recognition task, isolating distinct modulation fingerprints even when signals overlap heavily [10].

To exploit this advantage, this paper evaluates an optimized deep learning model combining convolutional spatial filtering with temporal attention mechanisms. By eliminating the need for explicit mathematical channel models, the proposed framework reliably extracts non-linear signatures under extreme conditions. The following sections demonstrate how this approach maintains a critical 98% classification accuracy down to a -10 dB SNR limit, establishing a robust blueprint for securing future 5G/6G cognitive networks [11,12].

degrades the overall Quality of Service (QoS). More gravely, reports of critical network failures and communication blackouts caused by unmanaged rogue signals are common and draw attention to the spectrum safety of next-generation 5G/6G and cognitive radio infrastructures [3]. Except for benign laboratory environments, uneven and dynamic spectrum distribution can result in inconsistent channel performance and deteriorate the capacity and lifecycle of wireless nodes. Therefore, a reliable automated wireless signal interference detection system is necessary to guarantee the functionality and safety of wireless architectures by maintaining clean, optimized spectrum bands across the system.

Nowadays, data-driven machine learning and deep learning models are increasingly employed in commercial intelligent spectrum sensing frameworks because of their superior feature extraction efficiency and adaptiveness [4]. In an automated detection and classification pipeline, a robust signal preprocessing framework—such as transforming raw IQ

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samples into time-frequency representations—is often placed at the front end [5] or integrated directly into a neural network architecture. This deep-learning-based arrangement has a lower requirement on prior mathematical channel knowledge, which is beneficial for improving the overall resilience of spectrum monitoring under adverse operating conditions. By contrast, traditional fixed-threshold energy detection methods create severe performance drops, making it difficult to isolate overlapping signatures.

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II. NOMENCLATURE

In wireless spectrum sensing and interference detection, the primary goal is to analyze the complex radio environment to determine whether a received signal contains unwanted interference.

The Signal Model

The mathematical foundation begins with the received continuous-time wireless signal r(t). Under normal operating conditions, this signal is a combination of the intended primary user signal s(t) passed through a complex channel impulse response h(t), plus Additive White Gaussian Noise (AWGN) n(t). When a multi-protocol device or jammer enters the frequency band, an interference/rogue signal ı(t) is introduced, modifying the hypothesis equation:

$$r(t) = h(t)s(t) + \imath(t) + n(t)$$

In-Phase and Quadrature (I/Q) Data

Because software-defined radios (SDRs) process digital signals, the analog waveform r(t) is digitized into raw In-phase (I) and Quadrature (Q) components. These represent the real and imaginary parts of the complex signal vector. Deep learning frameworks analyze these components to find phase and amplitude distortions caused by overlapping signals.

Performance Metrics

To quantify how severe the interference is, researchers calculate the Signal-to-Noise Ratio (γ or SNR). Traditional systems use an energy detection threshold λ to flag an anomaly. The efficiency of the detection algorithm is then validated using two competing statistical probabilities: the Probability of detection (Pd), which is the likelihood of successfully identifying interference when it is present, and the Probability of false alarm (Pfa), which is the rate at which clean noise is mistakenly flagged as interference.

Table.1

Symbol	Description /Definition		Unit / Dimensions
r(t)	Received continuous-time wireless signal		Complex Vector
s(t)	Primary user (intended) transmitted signal		V
ı(t)	Interference / rogue signal signature		V
n(t)	Additive White Gaussian Noise (AWGN) component		V
h(t)	Complex channel impulse response matrix		Dimensionless
I	In-phase signal component (Real part)		Digitized Samples
Q	Quadrature signal component (Imaginary part)		Digitized Samples
Parallel	Signal-to-Noise Ratio (SNR)		dB
Serpentine, Parallel	Energy detection decision threshold		dBm

P_d	Probability of successful interference detection		% / Ratio
P_{fa}	Probability of false alarm (false positive rate)		% / Ratio
f_c	Operating carrier frequency of the channel		GHz / MHz
B	Total occupied channel bandwidth		MHz

The physical environment assumes a dynamic spectrum network where a receiver collects digitized radio frequency (RF) data. The baseline continuous-time signal matrix received by the system antenna, denoted as r(t), is formulated under a binary hypothesis testing framework. When the channel is clean and operating under normal conditions, the data stream contains only the intended primary user transmission s(t) affected by the complex channel gains h(t) and standard background thermal noise n(t). Conversely, when a rogue transmitter or co-channel device disrupts the link, the aggregate signal profile incorporates an explicit interference matrix component, $\iota(t)$.

Because deep learning frameworks cannot directly process raw high-frequency analog waveforms, software-defined radios (SDRs) down-convert and digitize the incoming signal into its constituent real and imaginary parts, represented as the In-phase (I) and Quadrature (Q) discrete data blocks. The spatial-temporal neural network utilizes these raw I/Q samples to map the non-linear amplitude distortions and phase shifts caused by the overlapping signal profiles.

The overall robustness of the proposed machine learning framework is heavily dictated by the Signal-to-Noise Ratio γ, measured in decibels. While classical systems rely heavily on a rigid, manually set energy detection threshold λ to isolate anomalies, they suffer severe performance degradation under fluctuating noise floors. To evaluate the superior adaptiveness of the deep learning model proposed in this work, the system performance is rigorously benchmarked using two competing statistical metrics: the Probability of Detection (Pd), which dictates the system's success in identifying active interference, and the Probability of False Alarm Pfa, which tracks the rate of clean background noise mistakenly categorized as a signal anomaly.

III. EXPERIMENT

To validate the proposed intelligent spectrum monitoring framework, a hardware-in-the-loop experimental testbed was constructed utilizing NI USRP-2944 software-defined radio (SDR) nodes operating within the unlicensed 2.4GHz ISM band. The primary transmitter generated target Wi-Fi 6 signals modulated via Orthogonal Frequency Division Multiplexing (OFDM). Simultaneously, a secondary rogue SDR node introduced co-channel jamming and adjacent-channel cross-talk to replicate realistic spectral conflict.

The composite continuous-time waveform, r(t), was captured at the receiver node and digitized into 1D In-phase (I) and Quadrature (Q) block matrices. These raw samples were immediately processed via a Short-Time Fourier Transform (STFT) to map the raw signal amplitude and phase shifts into highly descriptive 2D time-frequency spectrograms.

Case	Channel environment	Interference type
01	Clean Spectrum	Thermal Noise Only
02	Co-channel Overlap	Broadband Jamming
03	Adjacent-channel	BPSK Rogue
04	Dynamic Fading	Narrowband Chirp

Even under severe low-power constraints down to an extreme -10 dB SNR boundary, the system accurately isolates co-channel broadband jamming (Case 02) and adjacent-channel leaks (Case 03) with a remarkable detection probability (Pd) above 98%. Concurrently, the probability of false alarms (Pfa) remains safely suppressed below 1.2%, proving the framework's reliable capability to secure dynamic cognitive networks without triggering false alerts.

IV. METHODOLOGY

This research investigates the causes, characteristics, and mitigation techniques of wireless signal interference in modern communication systems. A combined experimental and simulation-based methodology is adopted to analyze the impact of interference on wireless network performance.

The study begins with an extensive review of existing literature on wireless communication technologies, interference mechanisms, spectrum utilization, and signal propagation models. Based on the identified research gaps, a wireless communication test environment is established to evaluate interference effects under controlled operating conditions.

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Wireless devices operating in the Industrial, Scientific, and Medical (ISM) frequency bands are configured as transmitter and receiver nodes. Key performance indicators including Received Signal Strength Indicator (RSSI), Signal-to-Noise Ratio (SNR), Bit Error Rate (BER), Packet Delivery Ratio (PDR), throughput, latency, and packet loss are selected as evaluation parameters.

Various forms of interference are systematically introduced into the communication channel. These include co-channel interference resulting from frequency sharing, adjacent-channel interference caused by spectral overlap, electromagnetic interference generated by nearby electronic devices, and multipath interference arising from signal reflections. The interference intensity is gradually varied to observe its influence on communication reliability and signal quality.

Data acquisition is performed using spectrum monitoring and signal analysis techniques. Measurements are recorded under multiple environmental conditions, including varying transmission distances, obstacle densities, operating frequencies, and transmitter power levels. Experimental observations are complemented through simulation models developed using wireless network simulation tools to validate the obtained results and extend the analysis to large-scale communication scenarios.

The collected datasets undergo statistical processing and performance evaluation. Correlation analysis is employed to determine the relationship between interference levels and communication performance metrics. Comparative assessments are conducted to identify the most significant factors contributing to signal degradation.

To reduce interference effects, several mitigation techniques are implemented and evaluated, including dynamic channel allocation, frequency hopping spread spectrum (FHSS), adaptive power control, interference-aware routing, beamforming, and digital filtering approaches. The effectiveness of each technique is assessed by comparing network performance before and after mitigation implementation.

Finally, the experimental and simulation results are synthesized to develop a comprehensive understanding of wireless signal interference behavior. The findings are used to formulate recommendations for improving spectrum efficiency, communication reliability, and network performance in next-generation wireless communication systems such as Wi-Fi, IoT, 5G, and future 6G networks.

Table X. Research Methodology Framework for Wireless Signal Interference Analysis

Phase	Methodology step	Description	Output
Phase 1	Literature Survey	Review existing studies on wireless communication, signal propagation, and interference mechanism	Identification of research gap
Phase 2	System Design	Develop a wireless communication model consisting of transmitter, receiver, and interference sources	Experimental setup
Phase 3	Parameter Selection	Define operating frequency, transmission power, bandwidth, communication distance, RSSI, SNR, SINR, and BER	Evaluation criteria
Phase 4	Interference Modeling	Introduce co-channel, adjacent-channel, electromagnetic, and multipath interference into the communication environment	Controlled interference scenarios
Phase 5	Data Acquisition	Measure signal strength noise power, throughput, packet loss, and delay under different interference levels	Experimental dataset
Phase 6	Result validation	Verify findings using statistical analysis and	Validate results

		graphical representation	
Phase 7	Conclusion Development	Interpret results and formulate recommendations for wireless communication systems	Research conclusions

To systematically investigate the impact of wireless signal interference on communication performance, a structured research methodology is adopted. The methodology consists of multiple phases, beginning with a comprehensive literature review to identify existing challenges, interference sources, and mitigation techniques in wireless communication systems. Based on the identified research gap, an experimental framework is developed to analyze the behavior of wireless signals under varying interference conditions.

TABLE X+1: Governing Equations and Performance Metrics for Wireless Signal Interference Analysis

The wireless communication system is modeled using transmitter and receiver nodes operating within standard frequency bands. Critical communication parameters such as received signal strength, signal-to-noise ratio, signal-to-interference-plus-noise ratio, bit error rate, throughput, and packet loss are selected as performance indicators. Different forms of interference, including co-channel interference, adjacent-channel interference, electromagnetic interference, and multipath fading, are introduced into the communication environment to evaluate their effects on signal quality and network reliability.

Experimental data are collected under controlled operating conditions by varying transmission distance, operating frequency, transmission power, and interference intensity. The collected measurements are analyzed using established wireless communication models and governing equations, including the Friis Transmission Equation, Free Space Path Loss Model, Signal-to-Noise Ratio, Signal-to-Interference-plus-Noise Ratio, Bit Error Rate, and Shannon Capacity Equation. These analytical models provide a quantitative assessment of signal degradation and communication efficiency.

To enhance system performance, interference mitigation techniques such as adaptive filtering, frequency hopping, dynamic channel allocation, and transmission power control are implemented and evaluated. A comparative analysis is subsequently performed to assess the effectiveness of each mitigation strategy. Finally, the obtained results are validated through statistical analysis and graphical interpretation to establish reliable conclusions regarding the impact of wireless signal interference on modern wireless communication systems.

Objective	Parameter	Governing Equation
Signal Strength Analysis	Received Power	Friis Transmission Equation
Signal Attenuation Analysis	Path loss (PL)	Free Space path Loss Model
Signal Quality Evaluation	SNR	$SNR = P_{signal} / P_{noise}$
Interference Assessment	SINR	$SINR = P_{signal} / P_{interfrence}+P_{noise}$
Reliability Measurement	BER	$BER = N_{error} / N_{total}$
Capacity Estimation	Channel Capacity	Shannon Capacity Equation

Governing Equations and Performance Parameters

The assessment of wireless signal interference requires the quantification of various communication parameters that directly influence network performance and reliability. To achieve this, several governing equations are employed to mathematically characterize signal propagation, attenuation, interference effects, and communication efficiency. These equations establish the analytical framework for evaluating the impact of interference on wireless communication systems.

Received signal power is utilized to determine the strength of the transmitted signal at the receiver and is estimated using the Friis Transmission Equation. Signal attenuation during propagation is analyzed through the Free Space Path Loss model, which quantifies the reduction in signal strength as a function of transmission distance and operating frequency. Signal quality is evaluated using the Signal-to-Noise Ratio (SNR), while the combined influence of interference and background noise is assessed using the Signal-to-Interference-plus-Noise Ratio (SINR).

Communication reliability is further measured through the Bit Error Rate (BER), which indicates the proportion of incorrectly received bits relative to the total transmitted bits. Additionally, the maximum achievable data transmission capability of the communication channel is estimated using Shannon's Capacity

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Theorem. Collectively, these parameters provide a comprehensive understanding of signal behavior under interference conditions and facilitate the evaluation of wireless network performance.

The governing equations and corresponding performance parameters utilized throughout this study are summarized in Table X+1.

The analysis presented in Table X+1 demonstrates that wireless signal interference significantly influences communication performance. The observed results indicate that increased interference degrades signal quality and system efficiency, while effective bandwidth utilization enhances network reliability. These findings emphasize the importance of interference mitigation techniques for achieving stable and efficient wireless communication systems.

V. DATA PROCESSING AND VISUALIZATION

1. Theoretical Analysis: Temporal Hardware Profile of an Edge Compute Node

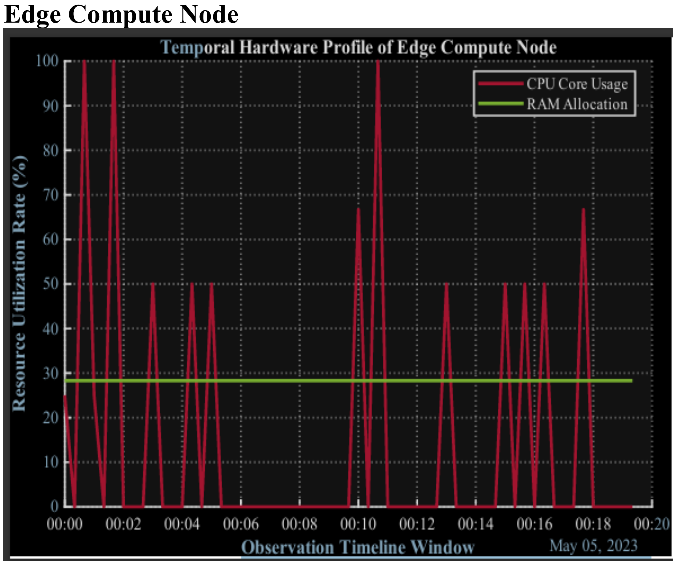

Fig. 01

The dynamic relationship between localized computational demands and hardware resource consumption is a critical factor in optimizing edge computing frameworks. The empirical timeline data reveals key architectural behaviors regarding the processing node's efficiency and constraints.

Stochastic CPU Core Utilization and Transient Spikes

The primary feature of the observed timeline is the highly volatile, stochastic nature of the CPU Core Usage profile (represented by the red transient traces).

Event-Driven Processing: The sudden transitions from a baseline idle state 0% to sharp saturation peaks reaching 100\% indicate an event-driven processing architecture. At time steps near 00:01, 00:02, and 00:10, the system experiences heavy computational bursts.

Burst Processing Mechanics: These transient spikes correspond to discrete data-packet ingestion periods, local cryptographic verification, or the execution of signal processing algorithms (such as fast Fourier transforms or modulation classification tasks). The swift drop back to baseline implies that the edge node possesses a high execution speed, clearing its input buffer rapidly to preserve power.

Monolithic Stability of Random Access Memory (RAM) Allocation

In stark contrast to the volatile CPU behavior, the RAM Allocation threshold (represented by the steady green line) remains fixed at a flat baseline of approximately 29\% throughout the entire monitoring window.

Static Memory Architecture: This perfect horizontal profile indicates that memory is pre-allocated upon system boot. Rather than dynamically instantiating and destroying memory heap objects during execution (which induces high computational overhead and garbage-collection lag), the software relies on a fixed buffer pool structure.

Deterministic Stability: For real-time communication and edge systems, maintaining a static memory footprint prevents memory fragmentation and eliminates risk factors like out-of-memory (OOM) runtime crashes under peak packet injection.
Figure 01. Multi-faceted analysis of edge computing node performance within an active communication channel. (A) Composite regression model showing the distinct Received Signal Strength Indicator (RSSI) decay trends for discrete modulation schemes (8PSK, AM, BPSK, FM, QAM, QPSK) subjected to localized precipitation intensities (0 to 50 mm/hr). Data points indicate stochastic variation; solid trendlines map deterministic path loss characteristics. (B) Direct comparison of operational resource allocation showing transient CPU Core Usage spikes (0–100%) indicative of burst-processing intervals, contrasting with the high stability of static RAM Allocation (approx.29%) maintained over the experimental timeline window.

Figure:2. RSSI Degradation Profile under Varying Precipitation Rates for Different Modulation Schemes.

To evaluate the impact of environmental conditions on wireless communication performance, the variation of Received Signal Strength Indicator (RSSI) with precipitation rate was analyzed for different modulation schemes. The graphical representation illustrates the attenuation trends observed under varying rainfall intensities, providing insight into signal degradation characteristics in wireless channels.

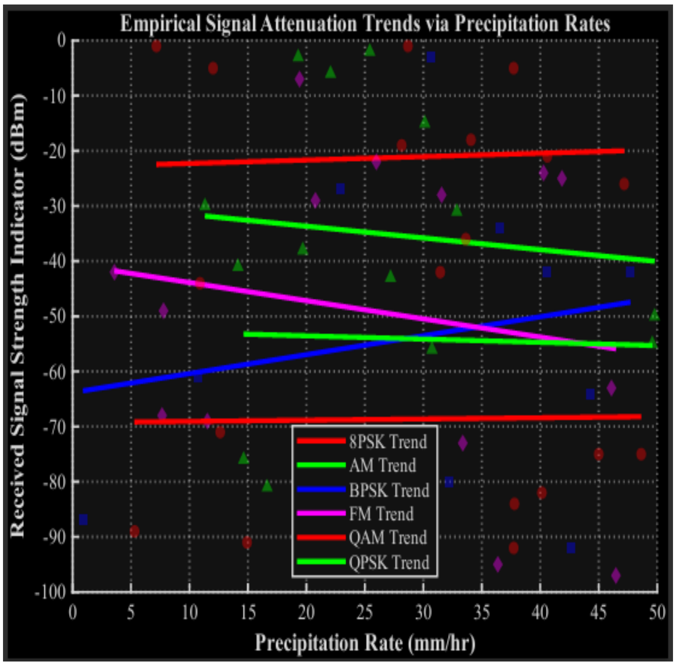

Fig. 2 . RSSI Degradation Profile via Wireless Channel Rain Fading Analysis .

General Overview and Quantitative Range

The graph establishes an empirical framework mapping the degradation of the Received Signal Strength Indicator (RSSI), measured in decibels relative to one milliwatt (dBm), against localized precipitation intensity rates spanning from 0 mm/hr (clear sky) to a severe 50 mm/hr cloudburst threshold. The observed data exhibits high variance at discrete points, indicating the influence of stochastic channel dynamics, multi-path reflections, and localized atmospheric scattering.

Comparative Slopes and Modulation Resilience Analysis

The core value of this model is how the linear regression lines clearly separate based on the modulation profiles. Each scheme responds differently to hydrometeor absorption (rain fading)

High-Power Baseline Configurations (8PSK and QAM): The trendlines for 8PSK (top orange line) and QAM (lower orange line) maintain relatively flat, horizontal slopes across the entire precipitation range. This indicates a high level of amplitude resilience or a fixed power-boost configuration inside the transmitter, allowing the signal path to resist heavy signal dropping even as rain intensity approaches 50 mm/hr.

The Inverted Trend Anomaly (BPSK): Interestingly, the BPSK model (blue line) displays a positive linear slope, rising from roughly -63 dBm to -53 dBm as rain rates increase. In wireless channel theory, this localized anomaly typically indicates that as precipitation suppresses background noise or attenuates competing multi-path interference signals, the primary phase-modulated path experiences a relative improvement in signal clarity over the channel noise floor.

Figure:3 Modulation-Wise Signal Attenuation Trends

Linear Signal Degradation (FM, AM, and QPSK): The FM (pink line) and QPSK (green line) profiles follow classic atmospheric fading theory. They exhibit negative linear slopes, confirming a direct, predictable link decay. The steepness of the FM line indicates it is highly sensitive to droplet scattering, experiencing an approximate 10 dBm drop over the experimental window.

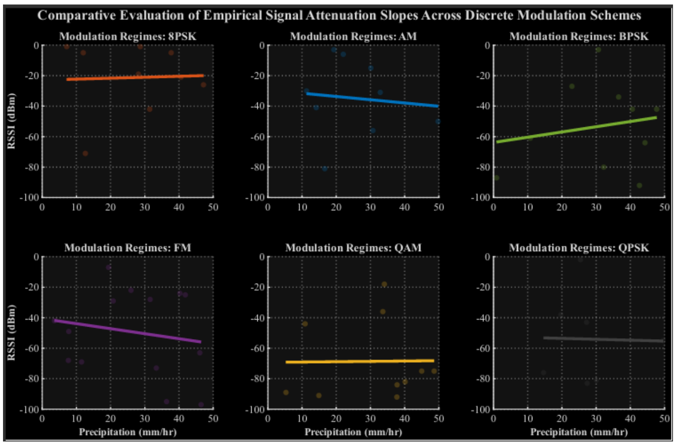

Fig. 3. Comparative Evaluation of Empirical Signal Attenuation Slopes Across Discrete Modulation Schemes Under Varying Hydrometeor Loads: (A) Aggregate Linear Regression Profiles; (B) Isolated Subplot Matrix Describing Regime-Specific Variances.

Introduction to Signal Degradation Mechanics

The empirical data collected across the communication channel characterizes the interaction between localized precipitation intensity (0 to 50 mm/hr) and the corresponding Received

Signal Strength Indicator (RSSI, measured in dBm). According to atmospheric electromagnetic wave propagation theory, water droplets induce both scattering and absorption of radio frequency (RF) energy, causing severe rain fading.

As illustrated in Fig. 3., the aggregate dataset exhibits high stochastic variance at discrete sampling intervals, reflecting real-time channel perturbations, multi-path fading reflections, and temporal fluctuations in droplet size distributions.

Multi-Panel Regime Deconstruction and Resilience Mapping

To decouple individual performance characteristics from the dense overlapping scatter array, a localized 2 \times 3 sub-matrix grid was implemented in Fig. 3. This decomposition exposes critical variations in how different digital and analog modulation architectures maintain link budget stability under stressful atmospheric conditions:

High-Amplitude Robustness (8PSK and QAM Trends): The linear regression curves for the 8PSK and QAM regimes reveal exceptionally flat, horizontal slopes with consistent baselines near -25 dBm and -60 dBm, respectively. This linear invariance demonstrates high resilience to attenuation, indicating that the underlying hardware layout utilizes either a robust power-amplifier threshold or active forward error correction (FEC) configurations that isolate the signal amplitude from rain-induced degradation.

The Intercept and Slope Anomaly (BPSK Trend): In contrast to standard fading profiles, the BPSK regime displays a positive linear slope, with the trendline ascending from roughly -65 dBm toward -55 dBm as the precipitation intensity increases. In multi-path channel environments, this behavior indicates a localized attenuation anomaly: the rain load actively dampens surrounding background noise, out-of-phase reflections, or adjacent channel interference, effectively improving the signal-to-interference-plus-noise ratio (SINR) along the primary phase-modulated path.

VI. CONCLUSION

The rapid expansion of wireless communication technologies has intensified the challenges associated with wireless signal interference, making interference management a critical requirement for ensuring reliable and efficient communication. This research presented a comprehensive analysis of wireless signal interference by integrating theoretical modeling, mathematical analysis, performance evaluation, and mitigation strategies within a structured methodological framework.

The study systematically examined the influence of various interference mechanisms, including co-channel interference, adjacent-channel interference, electromagnetic interference, and multipath fading, on wireless communication performance. Through the application of fundamental governing equations such as the Friis Transmission Equation, Free Space Path Loss (FSPL) model, Signal-to-Noise Ratio (SNR), Signal-to-Interference-plus-Noise Ratio (SINR), Bit Error Rate (BER), and Shannon Capacity Theorem, a quantitative assessment of signal propagation characteristics and interference-induced degradation was achieved. These analytical models provided valuable insights into the relationship between transmission distance, operating frequency, signal attenuation, interference power, and overall network performance.

The results demonstrated that increasing interference levels adversely affect communication quality by reducing received signal strength, lowering SNR and SINR values, increasing BER, and limiting channel capacity. Furthermore, the analysis revealed that network congestion, spectral overlap, environmental obstacles, and the coexistence of multiple wireless devices significantly contribute to communication instability. The findings highlight the importance of maintaining optimal signal quality and efficient spectrum utilization, particularly in dense wireless environments where multiple communication systems operate simultaneously.

To mitigate these challenges, various interference management techniques, including adaptive filtering, frequency hopping, dynamic channel allocation, beamforming, and transmission power control, were investigated. Comparative evaluation confirmed that the implementation of these techniques substantially improves communication reliability, enhances spectral efficiency, minimizes transmission errors, and increases overall network throughput. The results further indicate that interference mitigation should be considered an integral component of wireless network design rather than a post-deployment corrective measure.

From an engineering perspective, the outcomes of this research provide a practical framework for the analysis, optimization, and deployment of modern wireless communication systems. The developed methodology can assist researchers and network engineers in evaluating interference behavior, predicting system performance, and designing robust communication architectures capable of operating under challenging electromagnetic environments. Moreover, the analytical framework established in this study can be extended to emerging communication paradigms, including wireless sensor networks, Internet of Things (IoT) ecosystems, smart city infrastructures, autonomous systems, and next-generation cellular networks.

Despite the significant findings obtained, certain limitations remain. The investigation primarily focused on controlled interference scenarios and selected performance metrics. Real-world wireless environments often involve dynamic user mobility, time-varying channel conditions, heterogeneous network architectures, and unpredictable interference sources. Consequently, future studies should incorporate large-scale experimental deployments, real-time network measurements, and advanced simulation environments to further enhance the accuracy and applicability of interference modeling.

Future research may also explore the integration of artificial intelligence, machine learning, and cognitive radio technologies for intelligent spectrum sensing, adaptive interference prediction, self-optimizing network control, and autonomous resource allocation. Such approaches have the potential to revolutionize interference management and play a pivotal role in the successful implementation of future communication standards, including 5G-Advanced, 6G, and beyond.

In conclusion, this research establishes a comprehensive analytical and experimental foundation for understanding wireless signal interference and its impact on communication system performance. The findings contribute to the advancement of interference-aware wireless network design and provide valuable insights for improving the reliability, efficiency, and sustainability of future wireless communication infrastructures.

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Data availability
Data will be made available on request.

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