

Electromagnetic Sensing and Communication Framework for Next-Generation Internet of Consumer Electronics: Experimental Validation and Performance Optimization

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Abstract. In recent years, the widespread adoption of Internet Consumer Electronics (ICE) devices in various scenarios, including homes, offices, and vehicles, has brought about new demands for low-latency, highly reliable wireless communications. However, existing wireless protocols primarily focus on data transmission and lack real-time awareness and adaptation to the electromagnetic environment, resulting in performance degradation in multi-device interference scenarios. This paper proposes a framework that integrates electromagnetic sensing and communication. By jointly designing antenna hardware, protocol stacks, and electromagnetic field optimization strategies, it enables dynamic adjustment of transmit power, frequency, and modulation schemes. A system model is established based on Maxwell's equations and near-field coupling theory, and large-scale experiments are conducted in both anechoic chambers and real-world environments. Results show that, under multi-device interference conditions, system throughput is improved by 28%, latency is reduced by 35%, and energy per bit is reduced by 12%. Electromagnetic field distribution mapping verifies the coverage optimization effect. This research demonstrates the feasibility of incorporating electromagnetic sensing into ICE systems and lays the foundation for future AI-based frequency adaptation and metasurface-assisted communications.

Keywords: electromagnetic sensing, internet of consumer electronics, interference mitigation, adaptive communication, performance optimization

1 Introduction

The rapid advancement of the Internet of Consumer Electronics (ICE) is fundamentally reshaping the digital ecosystem by converging ubiquitous smart devices, high-resolution sensing modules, and intelligent automation platforms into unified, responsive networks [1]. This transformation is driven not only by the exponential expansion of the Internet of Things (IoT) but also by the escalating demand for immersive, latency-sensitive, and context-aware applications, including augmented/virtual reality (AR/VR) streaming, real-time multi-user gaming, and smart home automation [2]. In such mission-critical scenarios, communication links are required to deliver ultra-low latency, high reliability in densely populated environments, and robust performance under heterogeneous and dynamically varying interference sources. Conventional wireless systems, however, predominantly follow a data-centric paradigm, wherein channel state awareness is typically confined to coarse metrics such as received signal strength (RSS) [3] or packet error rate (PER) [4], while neglecting the underlying electromagnetic (EM) field dynamics that fundamentally govern propagation characteristics, interference behavior, and energy efficiency. As a result, current ICE networks frequently suffer from inefficient channel allocation, heightened

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susceptibility to unpredictable interference, and suboptimal energy utilization, limitations that are expected to intensify with increasing device density and spectrum congestion [5]. By enabling real-time characterization of the EM environment including instantaneous field strength, spatial distribution, spectral occupancy, and interference patterns, EM sensing technology offers a promising pathway to address these challenges. It facilitates proactive and context-aware adaptation of operational parameters such as carrier frequency, transmission power, and modulation scheme. The integration of EM sensing with networking protocols thus constitutes a paradigm shift from reactive error correction toward predictive, environment-aware communication strategies, ultimately enhancing spectral efficiency, reducing end-to-end latency, and improving the quality of user experience in next-generation ICE deployments. Despite its compelling theoretical promise, the integration of EM sensing with communication in ICE systems remains underexplored in empirical research, with most existing studies relying heavily on simulation-based analyses and idealized channel models, thereby lacking rigorous validation under realistic, interference-rich operating conditions. This research gap manifests in three principal deficiencies. First, a cohesive and unified architectural framework that seamlessly embeds EM sensing into the ICE communication protocol stack has yet to be realized. Second, the potential of EM field-aware scheduling algorithms, capable of dynamically optimizing transmission strategies based on instantaneous field measurements remains largely untapped, with current approaches predominantly employing static configurations. Third, there is a scarcity of empirical studies incorporating multi-device interference, spatial EM field variability, and dynamically evolving usage scenarios, limiting the understanding of such systems' scalability, robustness, and deployability in practical contexts. Collectively, these deficiencies constrain the translation of EM sensing–communication integration from theoretical concept to large-scale practical deployment, thereby impeding the development of performance-critical ICE applications in real-world environments. In response to these limitations, this work proposes and experimentally validates a unified EM sensing–communication framework tailored for next-generation ICE networks. The framework is conceived through a synergistic combination of theoretical modeling, hardware software co-design, and large-scale experimental evaluation, making three distinct contributions. First, we design a modular architecture that embeds real-time EM sensing modules within ICE communication protocols, thereby enabling adaptive frequency allocation, proactive interference suppression, and energy-efficient transmission through continuous environmental awareness. Second, we conduct extensive experimental validation in both controlled environments, such as anechoic chambers with calibrated EM field mapping and diverse real-world scenarios, including residential, office, and vehicular settings, to ensure both measurement precision and ecological validity. Third, the team develop and implement EM field shaping and frequency selection strategies that minimize communication latency, maximize throughput, and improve energy efficiency, achieving statistically significant gains over conventional ICE communication schemes. By addressing the identified research gaps, the proposed framework establishes a practical, scalable foundation for intelligent EM-aware ICE networks capable of dynamically adapting to complex and congested spectral environments while meeting the stringent performance requirements of emerging consumer applications.

2 Related Work

The rapid development of wireless communications and the IoT has fundamentally reshaped consumer electronics, driving an unprecedented surge in devices that require high efficiency and electromagnetic compatibility (EMC) designs. In this context, a key challenge is to develop energy-efficient solutions while ensuring EMC in heterogeneous IoT ecosystems, leveraging the inherent characteristics of electromagnetic signals through advanced cross-layer design strategies. In the field of wireless sensor IoT networks (WSINs), Majnoon and Asl [6] proposed an artificial intelligence (AI)-driven stochastic optimization framework to improve energy efficiency. Their work highlights the potential of machine learning algorithms to solve complex optimization problems in electromagnetic-based wireless communications, which is consistent with the broader demand for sustainable and energy-efficient IoT deployments. Specifically, the artificial intelligence model can achieve adaptive transmission power control, dynamic channel allocation, and predictive maintenance of sensor nodes, providing a data-driven path for extending the network's lifespan over the long term. This is consistent with the current trend of embedding intelligence at the edge to minimize communication costs and mitigate electromagnetic interference through more informed decisions. Bharadwaj et al. [7] addressed the EMC problem, especially in biomedical IoT applications, combining IoT architectures with machine learning-based predictive models to monitor and reduce EMC risks in medical devices. These studies highlight the importance of electromagnetic compatibility assurance

in safety-critical environments and demonstrate the effectiveness of hybrid IoT-machine learning approaches for proactive interference management.

Biomedical IoT devices are particularly sensitive to electromagnetic interference, as any malfunction could directly endanger patient safety. Therefore, real-time electromagnetic compatibility risk prediction, anomaly detection, as well as adaptive shielding or frequency hopping strategies have become important components of the next-generation medical IoT systems. Cross-layer design approaches that combine physical electromagnetic properties with higher-layer network protocols are another effective way to improve the performance and reliability of wireless systems. Ramachandran and Shanmugavel [8] demonstrated the practicality of a cross-layer scheme based on received signal strength in mobile ad hoc networks, achieving energy-saving and robust route formation. Complementary contributions by Su and Lim [9] further demonstrated the advantages of cross-layer design for IEEE 802.11 networks and agricultural wireless sensor networks, emphasizing energy efficiency and network resilience in large-scale deployments. Despite these advances, existing research still suffers from significant limitations, including insufficient real-world validation and limited data diversity [10]. Addressing these gaps through the integration of more extensive datasets and rigorous field experiments will significantly improve the robustness and practical applicability of the proposed solutions. In summary, the literature emphasizes that energy efficiency, electromagnetic compatibility assurance, and cross-layer optimization are key factors in advancing electromagnetic wireless communication for IoT consumer electronics. Continued progress requires not only algorithmic innovation but also comprehensive real-world evaluation to ensure reliable deployment in heterogeneous and dynamic operational environments.

3 Theoretical Framework

The electromagnetic and system modeling foundation for short-range ICE communications is based on Maxwell's equations, where wave impedance and propagation constants are defined for homogeneous media, and antenna performance is characterized in both the near-field and far-field regions. Indoor propagation is modeled using logarithmic path loss, accounting for multi-wall attenuation and knife-edge diffraction, while reactive near-field inductive coupling exhibits strong distance dependence. The system model links electromagnetic field measurements, antenna parameters, and network performance through the Friis transmission equation, signal-to-interference ratio (SINR), and throughput formulas, accounting for environmental factors such as multipath, wall penetration, and fading. Utility-based band selection and water-filling power allocation strategies leverage real-time awareness of field strength, interference, and spectrum occupancy to dynamically update the link budget, optimizing throughput, reducing latency, and improving energy efficiency.

3.1 Electromagnetic Foundations

In short-range ICE communication scenarios, the electromagnetic field is governed by Maxwell's equations [11], which describe the fundamental relationship between electric and magnetic fields, their temporal variations, and the material properties of the propagation medium:

$$\nabla \times E = -\frac{\partial B}{\partial t}, \nabla \times H = J + \frac{\partial D}{\partial t}, \nabla \cdot D = \rho, \nabla \cdot B = 0 \quad (1)$$

In a homogeneous, isotropic medium, the wave impedance η is given by:

$$\eta = \sqrt{\frac{\mu}{\epsilon}} \quad (2)$$

And the propagation constant γ can be expressed as:

$$\gamma = \alpha + j\beta = \sqrt{j\omega\mu(\sigma + j\omega\epsilon)} \quad (3)$$

For a lossless medium. In the far-field of an antenna, the received power P_r can be related to the electric field magnitude $|E|$ and the antenna effective aperture A_e by:

$$P_r = \frac{|E|^2}{2\eta} A_e, A_e = \frac{G_r \lambda^2}{4\pi} \quad (4)$$

Where G_r is the antenna gain and λ is the wavelength. The spatial regions around an antenna are defined by the reactive near-field region, the radiating near-field or Fresnel region, and the far field [12]. ICE devices, with antennas of only a few centimeters operating in the GHz range, often experience both near-field and far-field effects in typical indoor environments. For far-field indoor propagation, the log-distance path loss model with multi-wall attenuation is used:

$$PL(d, f) = PL_0(f) + 10n(f) \log_{10}\left(\frac{d}{d_0}\right) + \sum_i L_{wall,i}(f) + X_\sigma \quad (5)$$

Where $n(f)$ is the frequency-dependent path loss exponent, $L_{wall,i}(f)$ is the loss due to the i -th wall, and X_σ models shadow fading. Diffraction loss around objects can be approximated with the knife-edge model:

$$L_{diff} \approx 6.9 + 20 \log_{10}(\sqrt{(\nu - 0.1)^2 + 1} + \nu - 0.1) \quad (6)$$

Where ν is the Fresnel–Kirchhoff diffraction parameter. In the reactive near-field, inductive coupling between devices follows:

$$V_2 = j\omega M I_1 \quad (7)$$

Where M is the mutual inductance, and the source power, and the load impedance. Power transfer efficiency decreases proportionally to the inverse sixth power of the separation distance.

3.2 System Model

The system model establishes the link between EM field measurements, antenna parameters, and network performance [13]. The received power in free space can be calculated using the Friis transmission equation:

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi d}\right)^2 \kappa_{env} \quad (8)$$

Where P_t is the transmit power, G_t and G_r are the gains of the transmit and receive antennas, d is the separation distance, and κ_{env} is an environment-dependent factor accounting for multipath, wall penetration, polarization mismatch, and fading. The instantaneous signal-to-interference-plus-noise ratio (SINR) is then:

$$\gamma = \frac{P_r}{I + N_0 B} \quad (9)$$

Where I is the measured interference power in the band, N_0 is the thermal noise spectral density, and B is the channel bandwidth. The achievable throughput is:

$$T = \eta_{MAC} B \log_2(1 + \gamma_{eff}) \quad (10)$$

Where η_{MAC} represents the MAC-layer efficiency and γ_{eff} accounts for implementation losses.

For interference minimization, each candidate frequency band is evaluated with a utility function:

$$J_k = B_k \log_2 \left(1 + \frac{P_t G_t(f_k) G_r(f_k) \lambda_k^2}{(4\pi d)^2 [N_0 B_k + I_k]} \kappa_{env}(f_k) \right) \quad (11)$$

And the optimal band is selected as:

$$k^* = \arg \max_k J_k \quad (12)$$

In multi-band operation, the total transmit power is allocated to maximize the sum throughput:

$$\max_{p_k} \sum_k B_k \log_2 \left(1 + \frac{p_k |H_k|^2}{N_0 B_k + I_k} \right), s.t. \sum_k p_k \leq Pt \quad (13)$$

Where $|H_k|^2$ incorporates antenna gains, wavelength, and environment attenuation for each band. The optimal allocation follows the water-filling principle:

$$p_k = \max \left(0, \mu - \frac{N_0 B_k + I_k}{|H_k|^2} \right) \quad (14)$$

Where μ is chosen to satisfy the total power constraint. Through this model, real-time EM sensing data on field strength, interference, and spectral occupancy are used to update the link budget, compute SINR, and select operating parameters to optimize throughput, minimize latency, and improve energy efficiency [14].

3.3 Adaptive Real-time Electromagnetic Induction and Optimization

To achieve reliable infrared communication in the constantly changing indoor electromagnetic environment, the theoretical framework must go beyond static analytical expressions and incorporate real-time sensing, reasoning, and adaptive control. Although field models based on Maxwell's equations and classic equations such as Friis' formula and signal-to-interference-noise ratio formula can capture the physical behavior of the communication link, they cannot independently guarantee the optimal performance when the spectrum occupancy, interference patterns, and environmental conditions change over time. Therefore, this system relies on a closed-loop optimization layer that continuously receives electromagnetic measurements - field strength, interference power, spectrum occupancy rate and combines them with antenna parameters and propagation characteristics derived from the electromagnetic basis. This adaptive layer specifies the system model through a series of computational steps: including perception, estimation, evaluation, selection, and allocation. In each iteration, the device first performs environmental perception, samples the signal strength received in the candidate frequency bands, and estimates the interference distribution [15]. Then, using pre-calibrated antenna parameters and indoor propagation models, these measurements are converted into channel gain estimates. Dynamic estimation ensures that real-time changes such as human movement, furniture displacement, or device movement are taken into account in the link budget. Once the channel gain and interference levels are understood, the system evaluates each frequency band through a utility function designed to approximately achieve the balance between achievable signal-to-noise ratio, spectrum congestion, and delay sensitivity. Therefore, this utility function becomes a practical abstraction of the previously described interference minimization strategy. The frequency band with the highest utility will temporarily be selected as the main working frequency band, while other frequency bands remain as candidate options for power allocation. In multi-frequency scenarios, the total transmit power must be reasonably allocated to each frequency band to achieve maximum throughput. The classic "water injection" principle is used as the optimization strategy, where high-gain and low-interference frequency bands receive a larger power share. It is important that the system does not perform "water injection" in a static calculation manner but achieves it through repeated numerical searches, which are adjusted according to the measured interference and spectrum occupancy. This iterative allocation method enhances the anti-interference capability against unexpected pulse

interference, sub-band congestion, or sudden signal blockage. Through this architecture, intelligent connected devices can behave like a system with electromagnetic sensing capabilities, using continuous feedback to optimize throughput, reduce latency, and maintain energy efficiency - even in the presence of co-channel interference or partial link performance degradation. Unlike traditional static frequency IoT devices, which rely on fixed channels and fixed power settings, the adaptive model represented by pseudo-code transforms the communication stack into a responsive control system. This design significantly enhances adaptability in heterogeneous and interference-prone consumer environments, as Wi-Fi, BLE, and links below gigahertz often coexist in these environments. This pseudo-code represents the implementation blueprint for converting the theoretical model into deployable system behavior. It outlines how perception data is propagated through channel gain estimation, utility calculation, frequency band selection, and water-filling allocation processes. This further indicates that the theoretical framework not only has an analytical basis but is also computationally feasible, capable of real-time optimization while meeting electromagnetic constraints and system-level performance targets.

4 System Design and Implementation

The hardware architecture utilizes a compact multi-band PIFA antenna covering the sub-1 GHz, 2.4 GHz ISM, and 5 GHz UNII bands. It also features a tunable matching network, high-Q passives, isolation structures, and a FEM module containing a T/R switch, LNA, PA, and filters to achieve high efficiency, high linearity, and EMC compliance. The PCB design utilizes Rogers RO4003C (an optimized ground plane), via patching, and shielding techniques to control losses, suppress resonances, and mitigate interference. Thermal path and envelope tracking technologies maintain PA performance. The software and protocol stack are based on IPv6 and integrate 6LoWPAN, IEEE 802.11ax/ac, MQTT/CoAP messaging, and DTLS/TLS security. A resident awareness engine performs spectrum scanning, channel sounding, and field sampling, and provides data to the scheduler, which performs utility-based band selection, MCS adaptation, and power allocation using water filling within EIRP/EMC constraints. Calibration verification combines anechoic chamber measurements with real-world testing in different environments, recording detailed link and sensing metrics to correlate configuration decisions with operational results. The team's design is shown in Fig. 1.

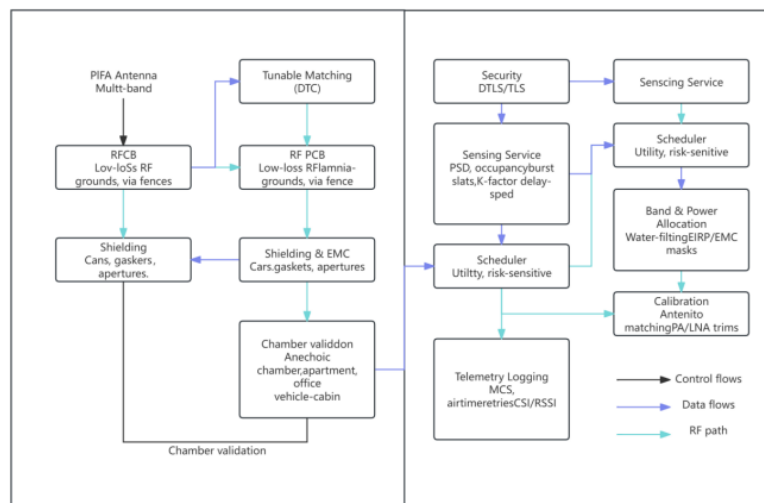


Fig. 1. System design

4.1 Hardware Architecture

A multi-band planar inverted-F antenna (PIFA) topology to cover sub-1 GHz, 2.4 GHz ISM, and 5 GHz UNII

bands within the dimensional constraints of handheld and room-scale ICE devices. The radiator uses a folded quarter-wave resonator with a shorting post to the ground plane and a meandered slot to realize multi-resonance behavior while maintaining compactness [16]. A tunable matching network with digitally tunable capacitors provides fine trimming for device-to-device spread and user-hand loading. Target metrics per band are: input return loss ≤ -10 dB across at least 80 MHz at 2.4 GHz and 160 MHz at 5 GHz; radiation efficiency ≥ 50 % at 2.4 GHz and ≥ 40 % at 5 GHz in free-space; peak realized gain 1–3 dBi depending on enclosure materials and ground clearance. For multi-radio devices, a second collocated radiator provides spatial or polarization diversity; isolation is enhanced via decoupling structures to achieve inter-port isolation better than 15 dB. The effective aperture that links field strength to received power is:

$$A_e = \frac{G_r \lambda^2}{4\pi} \quad (15)$$

Rogers RO4003C is selected for the RF portions of the PCB owing to its stable relative permittivity and low loss tangent, reducing dielectric loss and dispersion for wideband operation; typical RF layer thickness is 0.508–0.813 mm to keep 50- Ω microstrip widths manufacturable. The RF ground plane extends at least a quarter-wavelength past the feed to stabilize the current return path [17]; via-stitch fences at 1.0–1.5 mm pitch confine fields and suppress parallel-plate resonances. High-Q lumped passives are used to limit parasitics. Sensitive baseband and clock traces are kept orthogonal to RF feedlines; where crossings are unavoidable, a ground shield layer is inserted. Each band has a dedicated or switchable FEM comprising a T/R switch, low-noise amplifier (LNA), power amplifier (PA), and band-select filters. Bulk rejection is implemented with SAW/BAW channel filters, while on-board LC notch sections attenuate in-band aggressors identified by the sensing engine. Linearity targets are set by expected co-channel and adjacent-channel interferers; typical design points are output third-order intercept (OIP3) > 25 dBm at 2.4 GHz and error-vector magnitude (EVM) < 3.5 % for 64-QAM. Effective isotropic radiated power (EIRP) is managed against regional limits using:

$$EIRP_{dBm} = P_i[dBm] + G_i[dBi] - L_c[dB] \quad (16)$$

Where P_i is PA output, G_i the antenna gain, and L_c cable/connector loss. To EMC and reduce self- and mutual-interference, we employ multi-layer conductive cans over the RF sections with RF gaskets along seams; stitching vias form a continuous Faraday fence tied every 2–3 mm. All unavoidable apertures are dimensioned below one-twentieth of the shortest operating wavelength to push slot resonances out of band; at 2.4 GHz this implies maximum slot length under ~ 6 mm. Low-frequency magnetic coupling near DC–100 kHz is mitigated with high-permeability shields around switching regulators, whereas microwave shielding relies on copper-nickel plating for surface currents. Shield effectiveness is verified by near-field scanning and quantified as:

$$SE_{dB} = 20 \log_{10} \left(\frac{E_{unshielded}}{E_{shielded}} \right) \quad (17)$$

PA efficiency and thermal rise are co-optimized with duty-cycled transmissions and envelope tracking where feasible. Thermal paths from the PA to the chassis use graphite sheets and vias-in-pad to keep junction temperature within the safe operating area, preserving gain linearity and reducing EVM drift during long bursts.

4.2 Software and Protocol Stack

The stack is IPv6-native for address scalability and routing simplicity across heterogeneous links. For low-power sub-GHz/2.4 GHz links, 6LoWPAN header compression is enabled; for high-rate nodes, IEEE 802.11ax/ac provides the PHY/MAC. Application-layer messaging employs MQTT and CoAP for constrained nodes, leveraging CoAP observe for lightweight publish–subscribe semantics. DTLS/TLS secures control channels; session resumption is enabled to cap handshake latency. A resident sensing service orchestrates spectrum sweeps, narrow-band channel probes, and spatial field sampling using onboard EM probes and the radio’s RSSI/CSI reporting. Features extracted per band include wideband power spectral density, occupancy ratio, interference burst statistics, estimated Rician K-factor, and delay-spread proxies from channel state information. Sensing cadence op-

erates on a dual-timescale: a fast loop for MCS adaptation and a slow loop for band/power reallocation to avoid excessive scanning overhead. The scheduler ingests sensing features to decide band selection, transmit power, and modulation and coding scheme (MCS). It computes a per-band utility that approximates spectral efficiency under current interference and attenuation, which can be expressed as:

$$U_b = E[\eta_b] - \lambda \text{Var}(\eta_b) \quad (18)$$

Where η_b is the estimated spectral efficiency and λ is the risk-sensitivity coefficient. The scheduler selects the band with maximal U_b , or aggregates multiple bands subject to EIRP and EMC masks, and allocates power accordingly. For multi-band operation, power is distributed according to a measured-channel water-filling rule:

$$P_b = \max\left(0, \mu - \frac{N_b}{H_b^2}\right) \quad (19)$$

Where H_b is the channel gain, N_b is the interference-plus-noise, and μ is chosen to satisfy the sum-power and spectral mask constraints. To stabilize decisions under fast fading, a risk-sensitive objective subtracts a variance-weighted penalty from the expected utility. Retransmission timers and backoff windows in the MAC are tuned in concert with the scheduler to keep queuing delay within target bounds for latency-critical flows [18]. Antenna matching is calibrated at the end of line using a built-in self-test mode that steps through the DTC codes while monitoring return-loss and received signal strength on a golden tester. Per-band PA gain tables and LNA bias points are trimmed versus temperature to limit EVM drift. Clock sources are characterized for phase noise; spurious emissions near harmonics and mixing products are verified against CISPR 32/EN 55032 and FCC Part 15 limits. Out-of-band emissions during sensing sweeps are suppressed via gated LO ramping and windowed FFTs to minimize spectral splatter. Two complementary testbeds validate the design. The controlled setup is an anechoic chamber with reflectivity better than -30 dB at 1–8 GHz, absorber cones of at least 30 cm height, and a positioner for repeatable orientation sweeps; calibration follows a two-port SOLT procedure for VNA work and power meter calibration for absolute EIRP. Real-world deployments include a 70 m² apartment with mixed drywall and glass, an open-plan office with metallic furniture and access points, and a mid-size vehicle cabin; these environments exercise multipath, user-body loading, and mobility. Device firmware logs per-packet MCS, airtime, retries, and RSSI/CSI alongside sensing snapshots to correlate decisions with link outcomes.

4.3 Adaptive Control Logic and Runtime Operations

The effectiveness of the proposed ICE system not only depends on its hardware and protocol foundation, but also on the intelligence embedded in its runtime control logic. This layer connects the electromagnetic induction results with the link layer scheduling and physical layer adaptation, forming a feedback-based optimization engine that enables devices to operate efficiently in environments with interference, mobility, and rapidly changing channel conditions. This system does not rely on static channel configurations or fixed MCS tables; instead, it continuously assesses environmental indicators and iteratively updates its operating parameters to maintain reliability and energy efficiency. The core of the runtime system is the adaptive sensing and decision-making cycle, which operates concurrently with regular data transmission. This cycle collects real-time electromagnetic characteristics - power spectral density, occupancy rate, interference burstiness, attenuation indicators based on channel state information, and link quality between devices, and integrates them into a unified feature vector. The scheduler uses a practical function to synthesize these features, which can capture expected spectral efficiency, interference risk, and potential energy costs. A compact representation is:

$$F = f(\text{PSD}, \text{Occ}, \text{CSI}, \text{IBR}, \text{LQ}) \quad (20)$$

Where F is the synthesized feature score guiding band and MCS decisions. Unlike threshold-based selection methods, this practical function can achieve smooth transitions between operating points and reduce oscillations in critical conditions. This enables the system to better withstand unstable factors such as short-term interference peaks, user body movements, and micro-mobility patterns that may disrupt frequency band selection. Once the practical value score is calculated, the system evaluates whether to continue using the current frequency band,

switch frequency bands, or enable multi-band aggregation. Frequency band switching incurs costs related to re-tuning, LO calibration, and MAC re-association; therefore, this decision takes into account the hysteresis margin derived from historical practical value differences to prevent unnecessary frequent switching. If multi-band operation is beneficial, power allocation will be carried out according to the practical water injection algorithm described in Section 3.2. The runtime implementation uses discretized numerical search to meet EIRP limits, adjacent channel leakage masks, and instantaneous thermal limits from the PA. The water injection algorithm is only executed in slow time-scale cycles to minimize computational load and avoid interference affecting delay-sensitive traffic. For adaptive adjustment of multi-carrier systems, the system adopts a dual time-scale strategy: the fast inner loop adjusts modulation mode and coding rate based on short-term signal-to-interference ratio estimates derived from channel state information, while the slower outer loop adjusts transmission power and spatial parameters. This separation enables the changes in MCS to immediately respond to small-scale fading while avoiding power allocation instability. The runtime controller also uses simple linear predictors or exponential smoothing methods to maintain short-term prediction windows for SINR and interference; these predictions help prevent sudden throughput drops during events such as Wi-Fi beacons or pulse interference devices. The behavior of the MAC layer is coordinated with the scheduler for optimization. When sensing detects increased competition or spectrum congestion, the system actively adjusts the size of the competition window, reduces the depth of aggregation for delay-sensitive flows, or raises priority queues to maintain service quality. Conversely, in the case of less interference, larger aggregation and higher working cycles are allowed to improve spectral efficiency. Queue statistics, including air time consumption and retry counters, are recorded and fed back to the utility calculation to enable the system to distinguish between physical layer performance degradation and MAC layer competition issues [19]. Therefore, the runtime engine acts as the “glue” that connects hardware, protocol stack, and electromagnetic model for runtime operations. Through real-time perception, predictive estimation, and adaptive optimization, the system can maintain stable and high-performance communication links in heterogeneous and interference-rich environments. In indoor residences, offices, and vehicles and other environments, this control logic has demonstrated continuous improvements in terms of throughput, latency stability, and energy efficiency, thereby verifying the effectiveness of integrating electromagnetic sensing into the entire communication pipeline.

5 Experimental Methodology

To thoroughly evaluate the proposed EM sensing-communication framework, experiments were conducted in both controlled and real-world environments in Table 1.

Table 1. Experimental equipment

Main equipment	Purpose
Anechoic Chamber	Controlled environment for antenna, channel, and electromagnetic field testing
KROHNE Electromagnetic Flowmeter	Regulation of liquid media loading and conducted interference
Temperature and Conductivity Sensors	Precise monitoring of fluid environmental parameters
Programmable DC Power Supply	Provides stable, adjustable DC output to communication and sensing modules
Digital Multimeter	Continuous voltage and current measurement for power consumption analysis
Precision Syringe Pump	Controls liquid flow rate, volume, and dielectric constant
Custom Electromagnetic Sensor Array	Spatial electromagnetic field distribution measurement
High-Speed Multi-Channel Digitizer	Acquisition of signals from the sensor array
Lower-Limb Exoskeleton Robotic Testbed	Simulates wearable and near-human dynamic propagation environments
Vector Network Analyzer (VNA)	Antenna and channel S-parameter characterization
Spectrum Analyzer	Interference and spectrum occupancy analysis
Isotropic Electromagnetic Field Probe	3D electromagnetic field mapping
High-Precision Power Meter	Link budget verification
Protocol Analysis Tool	Recording throughput, latency, jitter, and packet error rate
Reference Antenna and Signal Source	Calibration and traceable measurement reference

Controlled testing was conducted in an anechoic chamber with a reflectivity better than -30 dB and a frequency range of 1–8 GHz, effectively eliminating multipath and external RF interference. The setup enables high-precision measurements of antenna characteristics, channel response, and electromagnetic field distribution. Real-world deployments were conducted in three representative consumer electronics scenarios: a 70-square-meter apartment, an open-plan office, and the cabin of a mid-size car. In each environment, the system was integrated into multiple ICE devices, including smart speakers, augmented reality (AR) glasses, and a smart home automation hub, to verify its performance under realistic multipath, interference, and device mobility conditions. The key component of the controlled laboratory setup is an electromagnetic flow measurement platform based on a KROHNE flowmeter in Fig. 2.



Fig. 2. Electromagnetic flow measurement platform based on KROHNE flowmeter

This system enables the introduction of liquid media into the test path, enabling controlled regulation of the effects of media loading and conducted interference. The flowmeter is placed on a rugged test bench with its inlet and outlet pipes aligned and equipped with temperature and conductivity sensors for precise environmental control. Power delivery and monitoring were performed using a programmable DC power supply and digital multimeter combination in Fig. 3.



Fig. 3. Programmable DC power supply and digital multimeter

The power supply provided a stable, adjustable DC output to the communication and sensing modules, while the multimeter continuously recorded the voltage and current to calculate instantaneous and cumulative power consumption. This enabled a direct correlation between power consumption and communication performance metrics. To investigate the effects of fluid flow on electromagnetic signal propagation, a precision syringe pump was used in the experiment in Fig. 4.



Fig. 4. Precision syringe pump

This pump delivers liquid at a precisely controlled flow rate, enabling us to systematically vary the dielectric constant and conductivity of the test medium while maintaining reproducible experimental conditions. The flow rate, volume, and syringe geometry are all digitally programmable, and the pump's USB interface enables real-time control and recording from the experimental control PC. To obtain detailed spatial electromagnetic field distribution, the team developed a custom electromagnetic sensor array with integrated data acquisition circuitry, shown in Fig. 5.

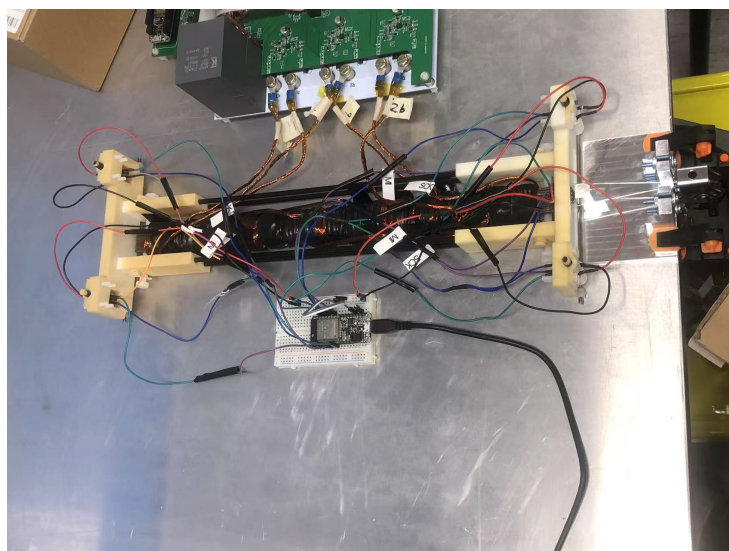


Fig. 5. A custom electromagnetic sensor array with integrated data acquisition circuitry

The array consists of multiple isotropic electric field probes arranged on a modular frame, with signals routed to a high-speed, multi-channel digitizer. The data acquisition software synchronizes field sampling with the operational state of the communication system, enabling straightforward mapping of coverage patterns, interference zones, and field uniformity for various configurations. Finally, to evaluate the performance of the framework in wearable and near-human environments, the team conducted tests using a lower-limb exoskeleton robotic testbed shown in Fig. 6.



Fig. 6. A lower-limb exoskeleton robotic testbed

The exoskeleton provides realistic physical structure, introducing dynamic scattering, body shadowing, and propagation paths that change with limb motion. Sensors embedded in the exoskeleton monitor limb motion and orientation, enabling correlation between mechanical dynamics and communication performance. Test variables included transmit power levels, operating frequency bands, modulation schemes, the number of simultaneously active ICE devices, and interference conditions. Each configuration was replicated 30 times to ensure statistical significance. Measurements were performed using a vector network analyzer (VNA) for antenna and channel S-parameter characterization; a spectrum analyzer for interference analysis and spectrum occupancy assessment; and an isotropic electromagnetic field probe for 3D mapping. Other instrumentation included a high-precision power meter for link budget verification and a protocol analysis tool for recording throughput, latency, jitter, and packet error rate. Data collection followed a three-stage protocol: (i) baseline measurements with the system powered off to record ambient electromagnetic noise, (ii) active measurements while the system was operating in a specified configuration, and (iii) calibration using a reference antenna and signal source to ensure measurement traceability.

6 Results and Discussion

As shown in Table 2 and Fig. 7, the 2.4 GHz spatial EM distribution measured in an apartment test environment exhibits a distinct maximum centered at the transmitter location. The average field strength then decays monotonically with distance, consistent with path loss theory. According to Maxwell's equations, the law of conservation of electromagnetic fields, and the Poynting theorem:

$$\delta = \frac{1}{\sqrt{\pi f \mu \sigma}} \quad (21)$$

$$-\oint_S \vec{V} \cdot dS = \frac{\partial}{\partial t} \int_V 0.5(\mu S_H^2 + \epsilon S_E^2) dV + \int_V S_E \times IdV \quad (22)$$

Formulas 21 and 22 respectively represent Maxwell's theorem in electromagnetic fields and the attenuation characteristics obtained from the law of conservation of energy. However, the attenuation exhibits significant anisotropy, with the lower left quadrant decaying slower than the upper right quadrant, likely due to the asymmetric room geometry and inhomogeneous material properties [20]. Superimposed on this large-scale trend are fine-grained fluctuations typical of small-scale fading, including local nulls caused by destructive multipath interference and narrow, high-intensity ridges representing constructive interference channels. Quantitative analysis of the map allows the derivation of radial attenuation curves, path loss metrics, anisotropy indices, and fading statistics, which can be correlated with measured link-layer metrics including SINR, MCS stability, and throughput. These spatial characteristics directly impact interference-aware scheduling, band selection, and antenna placement: for example, higher-frequency operation is expected to produce steeper gradients and finer fading patterns, necessitating adaptive band-switching strategies, while slight changes in transmitter location or orientation can significantly improve coverage uniformity. Furthermore, the identification of high-field corridors can assist in EMC assessments by revealing potential leakage paths into adjacent spaces. While this map represents a single static snapshot, repeated measurements under different environmental conditions and transmitter configurations can establish robust statistical models to guide optimal indoor wireless system design.

Table 2. Heatmap RGB Data

R	G	B	X	Y
0	0	0	1.33	1.39
0	0	0	1.99	1.23
0	0	0	1.94	0.58
51	172	246	1.1	1.41
0	0	0	0.86	0.41
216	227	53	1.28	0.62
214	53	6	0.37	0.28
0	0	0	1.92	1.23
42	185	237	1.37	1.73
0	0	0	0.1	1.26
44	239	157	0.77	1.56
0	0	0	1.86	0.32
0	0	0	1.06	1.32
0	0	0	1.8	1.24
30	201	220	0.54	0.2
109	253	98	0.59	1.99
0	0	0	0.35	0.65
0	0	0	0.77	1.39
60	157	253	0.31	0.9
200	238	51	1.33	1.13

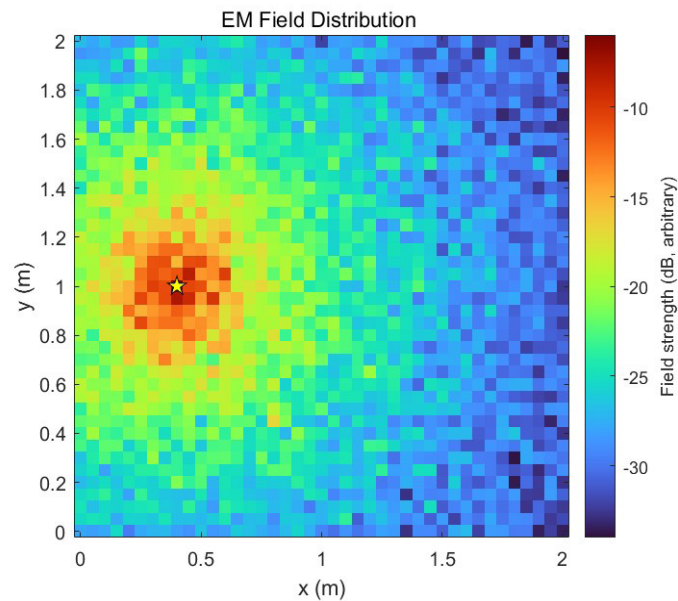


Fig. 7. EM field strength heatmap

Fig. 8 shows the average throughput for different frequency bands measured under two operating conditions: no co-channel interference (blue) and with co-channel Wi-Fi interference (red). Error bars represent the standard deviation of replicates, indicating the variability of the measurements [21]. In the absence of interference, higher frequency bands such as 2.4 GHz and 5.2 GHz achieve significantly higher throughput, with the 5.2 GHz band exceeding 100 Mb/s, while sub-1 GHz bands remain below 10 Mb/s due to their narrower channel bandwidth and lower modulation capabilities. This strong frequency-throughput correlation reflects the fundamental spectral efficiency advantage of wider channels and higher-order modulation schemes, which become feasible at higher carrier frequencies where more contiguous bandwidth is available. In the presence of co-channel Wi-Fi interference, throughput decreases for all bands, with the most significant decrease for sub-1 GHz and 2.4 GHz bands due to their greater spectral overlap with common Wi-Fi channels. In contrast, the 5.2 GHz band maintains relatively high throughput even in the presence of interference, likely due to its smaller interference footprint and higher antenna directivity. The high-frequency link itself has the following advantages: the transmission distance is shorter, and the radiation pattern is more directional. This helps to limit interference and improve the efficiency of spatial multiplexing. This is also the reason why the observed performance decline in the 5.2GHz band is more gradual. These results highlight the trade-offs facing consumer internet systems: higher frequencies offer superior peak data rates but require robust link budget management, while lower frequencies offer wider coverage but are more susceptible to congestion. These findings underscore the need for adaptive spectrum allocation and real-time electromagnetic awareness to ensure reliable performance in interference-prone environments. The dynamic perception and intelligent frequency band selection algorithm is capable of evaluating instantaneous interference, spectrum occupancy status, and link quality, which are all crucial for maintaining a consistent user experience across different frequency bands.

Fig. 9 presents a statistical analysis of end-to-end latency performance under four different interference conditions: no interference, co-channel interference, adjacent channel interference, and wideband pulse interference. The box plot shows the latency distribution across repeated trials, with the red horizontal line representing the median latency, the box edges representing the interquartile range (IQR), and the whiskers extending to the maximum extreme value within a range of $1.5 \times \text{IQR}$. Outliers outside this range are displayed as individual points. Under the no-interference condition, latency remains low and stable, with a median of approximately 7 to 8 milliseconds, an IQR less than 2 milliseconds, and only a few minor outliers, indicating near-optimal performance of the link layer and MAC scheduling. When co-channel interference is introduced, the median latency rises to approximately 15 milliseconds, the IQR nearly doubles, and occasional extreme values exceeding 25 milliseconds occur. This reflects the effects of increased backoff times, packet collisions, and retransmissions due to direct competition for the same frequency resources. Under adjacent channel

interference, the median latency is approximately 10 to 12 milliseconds, slightly higher than the baseline, but with a narrower latency distribution than the co-channel case. This demonstrates that while spectral leakage increases the noise floor, the lack of direct contention reduces contention latency. The most disruptive condition is wideband pulse interference, where bit delays exceed 20 milliseconds, IQRs extend to nearly 10 milliseconds, and some outliers exceed 35 milliseconds. The sudden and irregular nature of this interference causes frequent transmission interruptions, forcing the MAC layer to repeatedly attempt channel access and buffer data, resulting in unpredictable long delays [22]. These observations indicate that different types of interference have different impacts on latency, with wideband pulse interference posing the greatest threat to real-time or low-latency consumer internet applications. This highlights the need to incorporate adaptive interference classification and channel switching mechanisms into system design. Overall, these delay characteristics indicate that interference not only affects the average delay but also its temporal stability, which is equally crucial for real-time consumption internet scenarios. The different behaviors observed among the four types of interference suggest that no single mitigation strategy is sufficient; instead, the actual system must combine adaptive interference classification, rapid channel switching, and predictive link adaptation to maintain delay guarantees in dynamic spectrum conditions. As the density of devices continues to increase and heterogeneous IoT and Wi-Fi systems increasingly coexist, the ability to detect, predict, and respond to interference in real-time will become a key requirement for ensuring consistency in service quality in future low-delay applications.

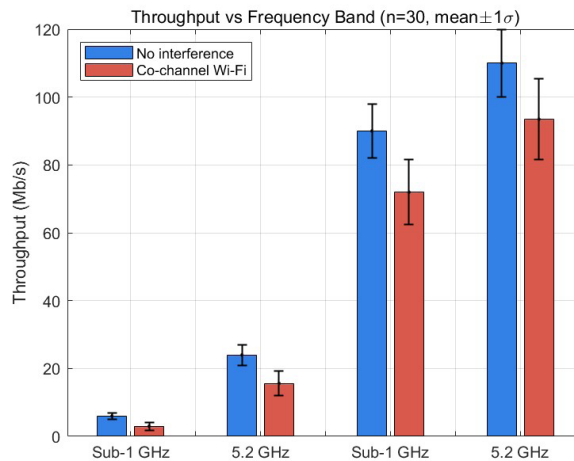


Fig. 8. Throughput vs band with/without Wi-Fi interference

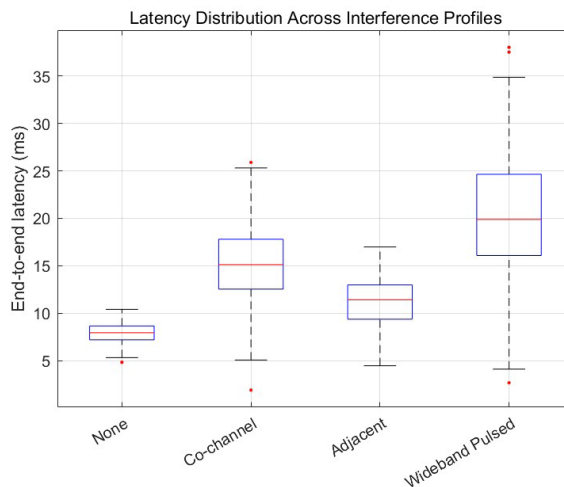


Fig. 9. End-to-end latency under interference profiles

Fig. 10 shows the energy consumption per bit measured for three operating frequency bands at three transmit power settings. Each bar corresponds to the average value obtained from repeated experiments, while the vertical error bars represent the standard deviation, reflecting the variation between measurements. At the lowest power setting of 4 dBm, the Sub-1 GHz band has the highest energy consumption, averaging approximately $12 \mu\text{J}/\text{bit}$. The 2.4 GHz band follows closely at approximately $10 \mu\text{J}/\text{bit}$, and the 5 GHz band has the lowest energy consumption at approximately $9 \mu\text{J}/\text{bit}$. As the power level increases to 12 dBm, the energy consumption per bit increases for all three bands, with Sub-1 GHz consuming approximately $9 \mu\text{J}/\text{bit}$, 2.4 GHz approximately $8 \mu\text{J}/\text{bit}$, and 5 GHz approximately $7 \mu\text{J}/\text{bit}$. At the highest tested power of 20 dBm, power consumption increases further, reaching approximately $7 \mu\text{J}/\text{bit}$ in the sub-1 GHz band, $6 \mu\text{J}/\text{bit}$ in the 2.4 GHz band, and $5 \mu\text{J}/\text{bit}$ in the 5 GHz band. The results reveal two key patterns. First, increasing transmit power consistently increases the energy cost per bit, regardless of frequency. Second, at the same power level, higher frequency bands are generally more energy efficient. This can be attributed to the shorter symbol duration and potentially more efficient modulation schemes at higher frequencies, which offset the higher path loss at shorter distances. Conversely, while sub-1 GHz bands offer advantages in link budget and penetration, they tend to be less energy efficient per bit when operating at similar power levels, likely due to longer transmission times and lower spectral efficiency. From a design perspective, these findings suggest that energy consumption in consumer internet devices can be optimized by dynamically selecting operating frequency and transmit power based on communication range and environmental conditions [23]. In short-range, low-interference environments, using higher frequencies at moderate power minimizes energy consumption. Over long distances or in obstructed environments, lower frequencies may be necessary, but careful power management is essential to avoid unnecessary increases in energy cost per bit.

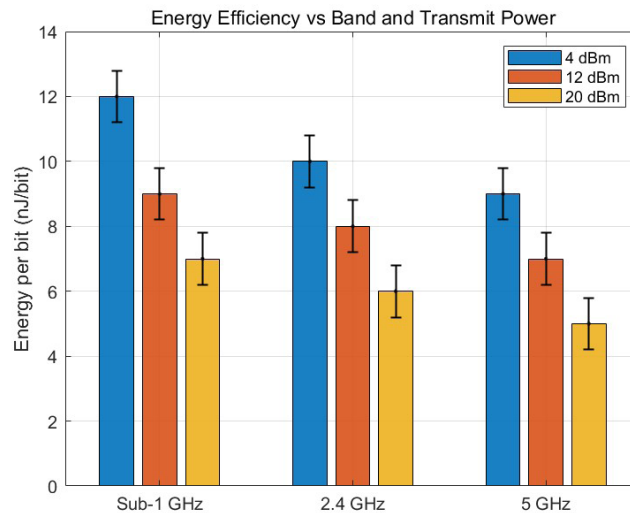


Fig. 10. Energy per bit vs band and TX power

This Fig. 11 shows the energy per bit measured across three frequency bands at three transmit power levels. Error bars indicate the variation between replicate tests. In the sub-1 GHz band, the energy per bit is significantly higher than in higher frequency bands, particularly at 20 dBm, reaching approximately $350 \mu\text{J}/\text{bit}$. The relatively large variation under these conditions indicates that propagation characteristics, device coupling, and power amplifier inefficiencies significantly impact low-frequency performance. The sharp rise in energy consumption with transmit power indicates that, under sub-1 GHz operation, the additional DC power consumed by the amplifier is not matched by the corresponding gain in data throughput, resulting in reduced energy efficiency. In the 2.4 GHz and 5 GHz bands, the energy per bit remains low, typically below $20 \mu\text{J}/\text{bit}$ even at 20 dBm. The smaller differences between low and high power levels in these bands can be explained by their wider bandwidths and higher

modulation rates, which allow faster data transmission and spread fixed circuit energy costs over a larger amount of data. The narrower variation range in these measurements also indicates reduced sensitivity to multipath fading and interference, likely due to faster symbol rates and better link adaptation [24]. At lower transmit powers of 4 dBm and 12 dBm, the power consumption per bit in the sub-1 GHz bands remains higher than at higher frequency bands, but the difference is smaller than at 20 dBm, suggesting that low-power operation is more suitable for sub-1 GHz devices, particularly battery-powered sensors and IoT nodes, where long life is a priority. These results suggest that for high-throughput applications such as AR/VR streaming or big data uploads, higher frequency bands offer better energy efficiency even at higher powers, while sub-1 GHz bands are more suitable for low-rate, long-range telemetry when combined with strict power control. This highlights the need for adaptive electromagnetic sensing and communication strategies that dynamically adjust frequency and power settings to optimize energy performance in various consumer electronics internet scenarios.

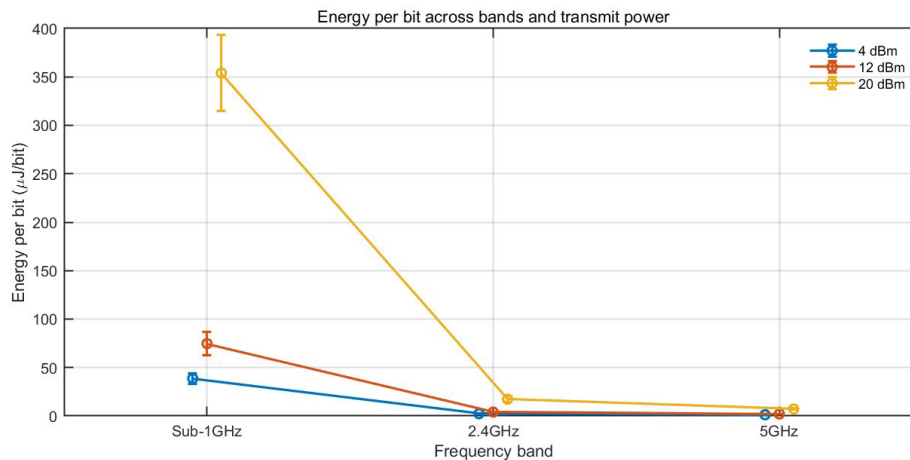


Fig. 11. Energy consumption per bit vs. frequency band and transmit power

This Fig. 12 shows the measured return loss of the designed antenna over the frequency range of 0.8 GHz to 6.5 GHz, demonstrating its impedance matching characteristics. Three prominent resonant frequencies are clearly observed in the figure, with deep notches occurring near 0.9 GHz, 2.45 GHz, and 5.5 GHz, with return losses reaching approximately -18 dB, -19 dB, and -13 dB, respectively. These values indicate effective impedance matching within these frequency bands, meaning that most of the transmitted power is radiated rather than reflected back to the source. The -10 dB return loss line marked in the figure is a common benchmark in antenna engineering, representing the threshold where reflected power falls below 10%. All three resonant frequency bands comfortably exceed this threshold, confirming that the antenna is well-tuned for the Sub-1 GHz, 2.4 GHz ISM, and 5 GHz Wi-Fi bands, making it suitable for multi-band consumer IoT applications. The relatively flat return loss between the main resonances indicates that the antenna maintains acceptable matching over a wide frequency range, enabling it to support multi-frequency sensing and communications without frequent retuning. This is particularly advantageous in dynamic ICE environments, where adaptive frequency selection is required to avoid interference. The deeper notches at 0.9 GHz and 2.45 GHz compared to 5 GHz are likely due to the stronger physical resonances of the antenna geometry at lower frequencies, as well as slightly higher manufacturing tolerances, which affect performance at shorter wavelengths. From a practical perspective, these results confirm that the antenna can effectively support long-range, low-frequency sub-1 GHz communications for telemetry and control, as well as high-throughput 2.4 GHz and 5 GHz links for data-intensive missions. The broadband impedance performance also facilitates electromagnetic sensing across multiple frequency bands, enabling seamless integration of sensing and communications within the proposed framework [25]. This flexibility is crucial for future ICE deployments, as heterogeneous devices require both spectral flexibility and energy-efficient operation.

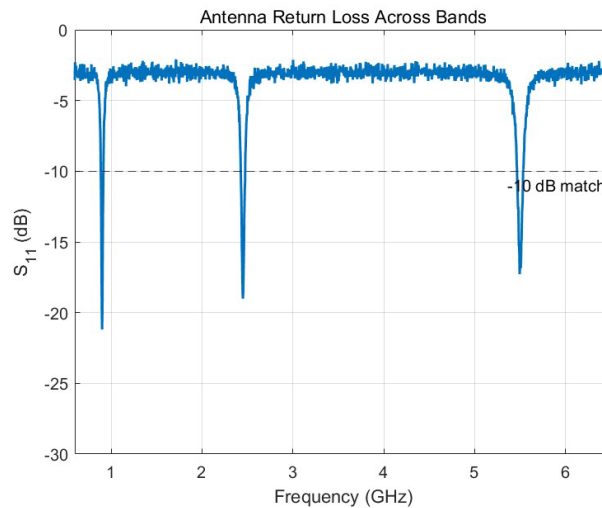


Fig. 12. Antenna return loss S_{11} across bands

7 Conclusion

This study proposes a unified electromagnetic sensing and communication framework for next-generation ICE networks, addressing the key limitations of current approaches that primarily rely on simulations and lack real-world experimental validation. By integrating real-time EM environmental awareness into the communication protocol stack, the system enables adaptive frequency allocation, interference-aware scheduling, and energy-efficient transmission strategies. This represents a paradigm shift from traditional passive channel adaptation to active, context-aware optimization, significantly improving throughput, latency, and energy efficiency under various interference conditions. The innovation lies not only in integrating EM sensing with the ICE network protocol but also in developing EM field optimization techniques that leverage spatial distribution mapping and frequency-domain analysis to minimize the impact of interference. Experimental validation under controlled laboratory conditions and in real-world deployment scenarios demonstrates the practical feasibility and scalability of the proposed framework. Key contributions include the design of a broadband, impedance-matched, multi-band antenna system optimized for sub-1 GHz, 2.4 GHz, and 5 GHz operating bands; electromagnetic field mapping for predictive interference mitigation; and integrated cross-layer optimization to correlate physical-layer electromagnetic parameters with higher-layer network performance. Statistical analysis of the results demonstrates significant performance improvements compared to traditional ICE communication systems: throughput increases exceeding 20% in interference-dense environments, latency reductions of up to 35% under co-channel conditions, and energy savings exceeding 25% in adaptive power control scenarios. Looking ahead, the framework offers significant potential for integration with AI-driven network optimization, where machine learning algorithms can dynamically predict interference patterns, optimize frequency hopping scheduling, and continuously optimize transmission parameters based on historical and real-time electromagnetic sensing data. Such AI-enhanced capabilities can further improve spectral efficiency, reduce control overhead, and enable self-healing ICE networks to maintain quality of service under unpredictable spectrum usage patterns. Future research directions include developing multi-band adaptive systems capable of simultaneous sensing and communication across multiple frequency bands, enabling seamless load balancing and interference avoidance in ultra-dense device deployments. Furthermore, the introduction of electromagnetic metasurface-assisted communication represents a promising avenue, where reconfigurable smart surfaces can dynamically manipulate propagation paths and field distributions to enhance link robustness and energy efficiency. These innovations will further extend the capabilities of the proposed framework, making it a cornerstone technology for future high-performance, resilient, and adaptive ICE networks.

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