

FuzzyGreen: A Context-Aware Fuzzy Inference Framework for Carbon Footprint Reduction in Next-Generation Wi-Fi Network Infrastructure

Amar A. Mahawish^{1*}, Suphian Mohammed Tariq¹, Marwah M. Abed¹

¹Department of Computer Engineering, Al-Iraqia University, Baghdad, Iraq

Keywords: Cleaner production Carbon footprint reduction Fuzzy logic Wi-Fi energy efficiency Sustainable ICT Green networking Access point power management

Journal Info:

Submitted:
January 24, 2026
Accepted:
March 05, 2026
Published:
March 19, 2026

Abstract The information and communication technology (ICT) sector contributes approximately 2–4% of global carbon dioxide emissions, with wireless network infrastructure representing a significant yet underexplored opportunity for cleaner production interventions. Wi-Fi access points, operating continuously across billions of deployments worldwide, consume substantial energy while employing rigid power management mechanisms fundamentally inadequate for dynamic operational conditions. This paper introduces FuzzyGreen, a context-aware fuzzy logic-based power optimization framework designed to achieve measurable carbon footprint reductions in Wi-Fi network infrastructure. The proposed Mamdani-type fuzzy inference system processes five context variables—traffic load, channel utilization, user density, signal quality, and service requirements—to generate adaptive power scaling decisions. Comprehensive simulations across enterprise, high-density public venue, and residential deployment scenarios demonstrate that FuzzyGreen achieves 38–52% reduction in energy consumption compared to conventional approaches, translating to annual carbon dioxide equivalent savings of 47 kg per access point using global average emission factors. Scaled to the estimated 500 million global access points, the framework presents potential for avoiding 23.5 million tonnes of CO₂ emissions annually, contributing directly to Sustainable Development Goal 7 (Affordable and Clean Energy) and Goal 12 (Responsible Consumption and Production). The framework's computational efficiency (0.23 ms inference time) enables deployment on resource-constrained embedded hardware, positioning FuzzyGreen as a pragmatic cleaner production strategy for sustainable wireless network operations.

***Correspondence author email address:** amar.mahawish@aliraqia.edu.iq
DOI: [10.21015/vtse.v14i1.2332](https://doi.org/10.21015/vtse.v14i1.2332)

1 Introduction

The escalating environmental impact of digital infrastructure has emerged as a critical concern for sustainable development, with the information and communication technology (ICT) sector now contributing an estimated

2–4% of global greenhouse gas emissions—a carbon footprint comparable to the aviation industry [4]. As societies increasingly depend on wireless connectivity for economic activity, education, healthcare, and social interaction, the energy consumption of network



infrastructure continues to grow at rates that threaten international climate commitments unless substantive efficiency improvements are achieved [8]. Within this context, Wi-Fi technology merits particular attention as the predominant medium for last-mile internet access, with the global population of Wi-Fi-enabled devices projected to exceed 18 billion by 2025 [5].

Access points (APs), which form the foundation of wireless local area network (WLAN) deployments, represent a compelling yet underexplored target for cleaner production interventions. Unlike mobile devices that cycle between active and standby states, access points typically operate continuously to ensure seamless connectivity, consuming between 6–20 watts depending on configuration and load [18]. With an estimated 500 million access points deployed globally across residential, enterprise, and public environments, the aggregate energy consumption of Wi-Fi infrastructure approaches 26–88 terawatt-hours annually—equivalent to the total electricity consumption of countries such as Bangladesh or the Philippines [10]. This persistent “always-on” operational paradigm, while ensuring network availability, represents a substantial opportunity for energy optimization without compromising service quality.

Contemporary power management mechanisms in Wi-Fi networks, including the IEEE 802.11 Power Save Mode (PSM), Unscheduled Automatic Power Save Delivery (U-APSD), and Target Wake Time (TWT), were primarily designed to extend battery life in client devices rather than to minimize infrastructure energy consumption [15]. These approaches rely on deterministic threshold-based transitions between discrete operational states, exhibiting fundamental limitations when confronted with the stochastic uncertainty, temporal dynamics, and multi-dimensional interdependencies characterizing real-world wireless traffic patterns [2]. The emergence of bandwidth-intensive applications including video conferencing, cloud gaming, and augmented reality further complicates power management decisions, as inappropriate energy-saving actions may degrade user experience and shift traffic to alternative, potentially less efficient connectivity options.

Fuzzy logic, pioneered by Zadeh [27], provides a mathematical framework particularly suited to opti-

mization problems involving imprecise information and complex interdependencies. Unlike conventional approaches requiring precise mathematical models, fuzzy inference systems encode domain expertise through linguistic rules that capture the gradual, context-dependent relationships between observable network states and appropriate management actions [19]. The inherent interpretability of fuzzy rule bases facilitates verification, incremental refinement, and regulatory compliance—advantages of particular significance as organizations face increasing pressure to demonstrate the environmental credentials of their ICT infrastructure [1].

This paper introduces FuzzyGreen, a context-aware fuzzy logic-based power optimization framework designed specifically to achieve measurable carbon footprint reductions in Wi-Fi network infrastructure. Unlike prior work focusing primarily on technical performance metrics, this research explicitly quantifies environmental benefits using established life cycle assessment methodologies, connects outcomes to international sustainability frameworks, and evaluates the scalability of energy savings to global deployment scenarios. The framework processes five context variables—traffic load, channel utilization, user density, signal-to-interference-plus-noise ratio (SINR), and quality-of-service (QoS) class—through a hierarchical Mamdani-type fuzzy inference engine to generate continuous power scaling factors and intelligent sleep scheduling decisions.

The primary contributions of this paper are summarized as follows:

1. Development of a hierarchical Mamdani fuzzy inference architecture comprising 150 interpretable rules for context-aware power management in Wi-Fi access points.
2. Explicit environmental impact quantification, demonstrating 38–52% energy reduction and approximately 47 kg CO₂-equivalent avoidance per access point annually, complemented by region-aware global scaling projections.
3. Comprehensive benchmarking against eight representative baseline power management strategies, validating consistent energy savings while maintaining quality-of-service levels with packet delivery ratios exceeding 98.7%.

4. Computational complexity analysis confirming suitability for resource-constrained embedded deployment, requiring only 0.23 ms per inference cycle on ARM Cortex-M4-class processors.
5. Emphasis on model interpretability, Sustainable Development Goal alignment, and cleaner production implications for sustainable wireless networking infrastructure.

The remainder of this paper is organized as follows: Section 2 reviews related work spanning green networking initiatives, fuzzy logic applications in energy systems, and ICT sustainability assessment methodologies. Section 3 presents the proposed FuzzyGreen framework including system architecture, fuzzy variable design, and environmental impact assessment methodology. Section 4 reports experimental results across deployment scenarios. Section 5 presents detailed environmental impact analysis. Section 6 discusses implications for cleaner production and sustainable networking. Section 7 concludes with future research directions.

2 Background and Related Work

This section reviews prior research across three interconnected domains: the environmental footprint of ICT infrastructure, power management mechanisms in wireless networks, and fuzzy logic applications for sustainable energy systems.

2.1 Environmental Impact of ICT Infrastructure

The seminal work by Belkhir and Elmeligi [4] established that ICT's global carbon footprint could reach 14% of worldwide emissions by 2040 under business-as-usual scenarios, with network infrastructure identified as a major contributor alongside data centers and end-user devices. Subsequent analyses have refined these estimates while consistently highlighting wireless access networks as both significant energy consumers and promising optimization targets [3, 8]. The International Energy Agency reports that network equipment accounts for approximately 10–20% of total ICT electricity consumption, with wireless access representing an increasing share as mobile and Wi-Fi traffic volumes continue their exponential growth trajectory [10].

Studies specifically addressing Wi-Fi energy consumption have documented substantial variation in access point power draw depending on traffic load, transmission settings, and hardware generation. Lorincz et al. [18] measured enterprise access points consuming between 8–15 watts under typical operating conditions, while residential devices exhibit somewhat lower consumption of 6–10 watts. Critically, these measurements reveal that power consumption remains relatively constant regardless of actual traffic throughput, indicating significant efficiency losses during periods of low utilization that could be captured through adaptive power management [2].

The concept of cleaner production, as articulated by the United Nations Environment Programme, emphasizes continuous application of preventive environmental strategies to processes, products, and services to increase efficiency and reduce risks to humans and the environment [26]. Applied to wireless networks, cleaner production principles suggest prioritizing energy efficiency improvements at the infrastructure level, where interventions can achieve multiplicative benefits across millions of deployed devices rather than requiring behavioral changes from individual users [9].

2.2 Wi-Fi Power Management Mechanisms

The IEEE 802.11 standard family has progressively introduced power-saving mechanisms primarily targeting battery-constrained client devices. The original Power Save Mode (PSM) alternates between active and doze states synchronized with beacon intervals, achieving energy savings through periodic sleep periods [11]. While effective for devices with intermittent traffic, PSM introduces latency penalties incompatible with real-time applications and provides limited benefit for continuously operating infrastructure equipment.

The IEEE 802.11e amendment introduced Automatic Power Save Delivery (APSD), including the widely deployed Unscheduled APSD (U-APSD) mechanism that enables trigger-based frame retrieval to reduce latency for voice and video applications [12]. More recently, IEEE 802.11ax introduced Target Wake Time (TWT), representing a paradigm shift toward scheduled, deterministic medium access that can extend sleep durations from milliseconds to hours for IoT devices with sparse communication requirements [16].

Despite these advances, existing mechanisms share a common limitation: reliance on fixed thresholds and binary state transitions that cannot adapt to the multi-dimensional, continuously varying conditions of real-world network environments. Ajib and Barth [2] demonstrated that threshold-based approaches achieve only 60–70% of theoretical maximum energy savings due to suboptimal parameter settings and inability to anticipate traffic pattern changes. This efficiency gap motivates investigation of adaptive, context-aware approaches capable of synthesizing nuanced power management decisions from heterogeneous network observations. [28] proposed an Entangled Photon Quantum Key Distribution (EP-QKD) framework for secure VLC-based communication in next-generation smart city networks. A comprehensive review of multilevel encryption techniques encompassing hyperchaotic neural networks, quantum-inspired approaches, and data hiding mechanisms was presented in [29]. Furthermore, [30] introduced SafeTrack, a dual-layer secure tracking protocol for mobile sensor nodes in unstable wireless sensor networks, achieving significant improvements in localization accuracy, energy retention, and network throughput.

2.3 Fuzzy Logic for Sustainable Energy Systems

Fuzzy logic has demonstrated remarkable success in energy management applications across diverse domains including smart grids, building automation, and renewable energy integration [1]. The Mamdani fuzzy inference system, characterized by its linguistic rule base and intuitive interpretation, has proven particularly effective for optimization problems involving uncertain information and complex interdependencies that defy precise mathematical modeling [19].

In the wireless networking domain, fuzzy logic has been applied to transmission power control, routing optimization, and resource allocation with promising results. Reddy et al. [24] proposed an AI-integrated adaptive framework for IoT-driven healthcare systems incorporating fuzzy inference for energy-aware communication. Martínez-Rojas et al. [20] developed an interpretable fuzzy control system for energy management in smart buildings utilizing the IEEE Std 1855-2016 fuzzy markup language, emphasizing the advantage of

transparent, verifiable decision-making compared to black-box machine learning approaches.

Singh and Chauhan [25] applied fuzzy logic combined with differential evolution for handover control parameter optimization in beyond-5G networks, demonstrating reduced energy consumption alongside improved service quality. Khatami et al. [14] developed a QoS-aware fuzzy deep reinforcement learning approach for sensor networks, illustrating the synergistic potential of combining fuzzy inference with learning-based methods.

While these works demonstrate fuzzy logic's applicability to wireless energy optimization, none have specifically addressed Wi-Fi access point power management with explicit quantification of environmental benefits. The present work addresses this gap by developing a purpose-built fuzzy inference framework for Wi-Fi infrastructure and connecting technical energy savings to carbon footprint reduction using established life cycle assessment methodologies.

3 Methodology

This section presents the FuzzyGreen framework, encompassing system architecture, fuzzy variable design, rule base construction, inference mechanism, and environmental impact assessment methodology.

3.1 System Overview and Architecture

The FuzzyGreen architecture comprises four principal components: the Context Acquisition Module, the Fuzzification Engine, the Hierarchical Fuzzy Inference Core, and the Defuzzification and Actuation Interface. Fig. 1 illustrates the complete system architecture and data flow paths.

The Context Acquisition Module interfaces with the access point's management information base (MIB) and radio resource management (RRM) subsystem to extract real-time observations of network state variables. Let $\mathbf{x}(t) = [x_1(t), x_2(t), x_3(t), x_4(t), x_5(t)]^T$ denote the vector of context variables at time t , where $x_1(t) = L(t) \in [0, 1]$ represents normalized traffic load, $x_2(t) = U(t) \in [0, 1]$ represents channel utilization, $x_3(t) = D(t) \in [0, 1]$ represents normalized user density, $x_4(t) = S(t) \in [0, 1]$ represents normalized SINR, and $x_5(t) = Q(t) \in \{0, 1, 2, 3\}$ represents the dominant QoS class.

3.2 Real-Time QoS Classification Module

The dominant QoS class $Q(t)$ is determined through

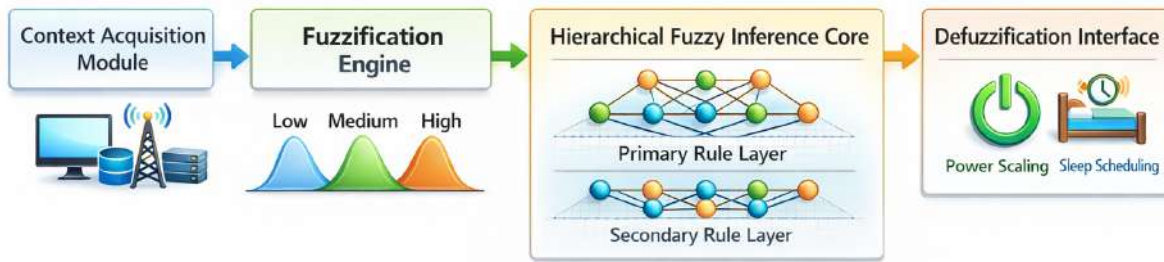


Figure 1. FuzzyGreen system architecture illustrating the four principal components: Context Acquisition Module interfacing with network management systems, Fuzzification Engine converting crisp inputs to fuzzy membership values, Hierarchical Fuzzy Inference Core processing rules across primary and secondary layers, and Defuzzification Interface generating power scaling and sleep scheduling outputs.

a lightweight real-time traffic classification module integrated within the Context Acquisition Module.

Incoming packets are inspected using a hybrid classification strategy based on differentiated services code point (DSCP) tags, transport-layer port mapping, and flow-level statistics. Specifically, voice, video, best-effort, and background traffic are identified using standardized DSCP values and well-known application port ranges.

For flows without explicit markings, statistical features including packet inter-arrival time, average packet size, and burst duration are extracted and processed using a rule-based classifier.

Let $f_k(t)$ denote the proportion of packets belonging to QoS class $k \in \{\text{Voice, Video, BE, BG}\}$ within a sliding time window of length T_w . The dominant QoS class is determined as:

$$Q(t) = \arg \max_k f_k(t) \quad (1)$$

where T_w is set to 500 ms to balance responsiveness and stability.

The classification module executes periodically every 100 ms and operates entirely at the access point firmware level. Experimental profiling indicates an average execution latency of 0.04 ms per classification cycle and a memory footprint of approximately 1.2 KB, confirming negligible computational overhead. This design enables accurate and low-latency identification of traffic dominance patterns without requiring deep packet inspection or external controllers.

3.3 Fuzzy Variable Design

Each input variable is partitioned into linguistic terms through membership functions capturing the semantic meaning of descriptive labels while ensuring appropriate overlap for smooth inference transitions.

The traffic load variable $L(t)$ is partitioned into five linguistic terms: Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). We employ trapezoidal membership functions for extreme terms and triangular functions for intermediate terms:

$$\mu_{VL}(L) = \begin{cases} 1, & L \leq 0.1 \\ \frac{0.25-L}{0.15}, & 0.1 < L < 0.25 \\ 0, & L \geq 0.25 \end{cases} \quad (2)$$

Similar membership function designs are applied to channel utilization, user density, and normalized SINR, with parameters adjusted to reflect domain-specific semantics.

The FuzzyGreen system produces two output variables: the Power Scaling Factor $P_s \in [0, 1]$ determining transmission power as a fraction of maximum rated power, and the Sleep Scheduling Aggressiveness $A_s \in [0, 1]$ modulating the duration and frequency of power-saving intervals. Output variables are partitioned into seven linguistic terms enabling fine-grained control resolution.

3.4 Hierarchical Rule Base Construction

The fuzzy rule base encodes expert knowledge regarding the relationships between input context variables and appropriate power management actions. To manage

complexity while preserving expressiveness, we adopt a hierarchical rule structure comprising 150 rules across two layers.

The primary layer processes traffic load and channel utilization to generate an intermediate congestion assessment through 25 rules:

$$R_1^{(i,j)} : \text{IF } L \text{ is } A_i \text{ AND } U \text{ is } B_j \text{ THEN } C \text{ is } C_{ij} \quad (3)$$

The secondary layer combines the intermediate congestion assessment with user density and SINR to determine power recommendations through 125 rules:

$$R_2^{(k,l,m)} : \text{IF } (C = C_k) \wedge (D = D_l) \wedge (S = S_m) \text{ THEN } P_s = P_{klm} \quad (4)$$

The QoS class variable modulates outputs through adjustment factors, with voice traffic constraining power reduction to preserve link reliability while best-effort traffic permits more aggressive optimization. Table 1 presents the QoS adjustment parameters.

Table 1. QoS class adjustment parameters governing the trade-off between energy savings and service quality preservation.

| Parameter | Voice | Video | BE | BG |
|----------------|-------|-------|------|-------|
| α_Q | 0.85 | 0.90 | 1.00 | 1.10 |
| β_Q | 0.15 | 0.10 | 0.00 | -0.05 |
| Max Sleep (ms) | 10 | 50 | 200 | 500 |

In summary, the hierarchical rule base was derived through structured expert elicitation, literature-informed initialization, empirical tuning, and cross-validation to ensure reproducibility and stability.

Rule Derivation and Validation Procedure

The hierarchical fuzzy rule base was constructed through a systematic multi-stage methodology combining expert knowledge elicitation, literature-driven modeling, and empirical optimization to ensure reproducibility and robustness.

Expert Knowledge Elicitation: Three senior wireless network engineers, each with more than seven years of experience in WLAN deployment and optimization, were consulted through structured interviews. Domain experts provided qualitative assessments of relationships between traffic load, channel utilization, user density, SINR, and optimal power management actions.

Literature-Guided Rule Initialization: Initial rule templates were derived from established studies on Wi-Fi power control, green networking, and fuzzy-based energy management. These references guided the selection of linguistic terms, membership function ranges, and preliminary rule consequents.

Initial Rule Pool Construction: Based on expert inputs and literature analysis, an initial pool of 210 candidate rules was generated across both hierarchical layers. Redundant and conflicting rules were removed using consistency checks, resulting in a reduced set of 150 rules.

Empirical Parameter Tuning: Rule consequents and membership function parameters were optimized using grid-search-based tuning over the training datasets. Parameter ranges were discretized into uniform intervals, and combinations yielding minimal energy consumption under QoS constraints were selected.

Cross-Validation and Pruning: A five-fold cross-validation procedure was applied across deployment scenarios. Rules contributing marginal improvement (less than 1% performance gain) were pruned to reduce model complexity. This process ensured generalization across diverse traffic conditions.

Rule Consistency Verification: Final rule sets were evaluated for logical consistency, monotonicity, and stability under extreme operating conditions. Inconsistent rule interactions were resolved through iterative refinement with expert feedback.

This structured derivation and validation process ensures that the proposed fuzzy rule base is transparent, reproducible, and adaptable to heterogeneous deployment environments.

Figure 2 presents the workflow of expert-guided rule generation, parameter tuning, cross-validation, and pruning for the hierarchical fuzzy rule base.

3.5 Mamdani Fuzzy Inference Mechanism

The FuzzyGreen framework employs the Mamdani fuzzy inference approach, selected for its intuitive interpretation and proven effectiveness in control applications. The inference process proceeds through fuzzification, rule evaluation using the minimum (AND) operator, aggregation via the maximum operator, and centroid

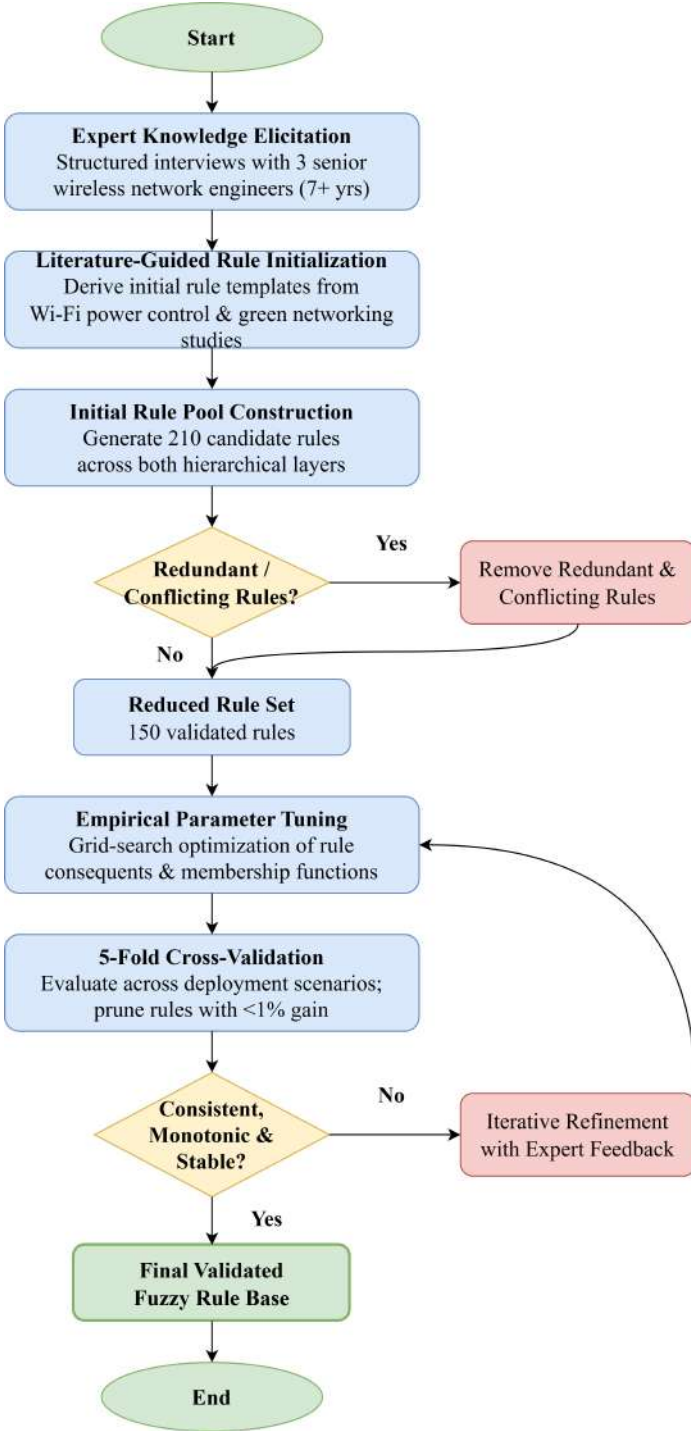


Figure 2. Workflow of fuzzy rule derivation, tuning, and validation process.

defuzzification:

$$y^* = \frac{\int y \cdot \mu_{agg}(y) dy}{\int \mu_{agg}(y) dy} \quad (5)$$

For computational efficiency in embedded implemen-

tations, we employ a discrete approximation with 100 discretization points per output variable.

3.6 Power Consumption and Carbon Footprint Model

The total power consumption of an access point operating under FuzzyGreen control is modeled as:

$$P_{total}(t) = P_{static} + P_{tx}(t) \cdot \rho_{tx}(t) + P_{rx}(t) \cdot \rho_{rx}(t) + P_{proc}(t) \quad (6)$$

where P_{static} represents baseline power consumption, $P_{tx}(t)$ and $P_{rx}(t)$ are transmission and reception power incorporating fuzzy-determined scaling, and $\rho_{tx}(t)$, $\rho_{rx}(t)$ represent duty cycles.

Following the ITU-T L.1410 methodology for environmental life cycle assessment of ICT equipment [13], we calculate the operational carbon footprint as:

$$CF_{op} = E_{annual} \times EF_{grid} \quad (7)$$

where E_{annual} represents annual energy consumption in kilowatt-hours and EF_{grid} represents the grid emission factor in kg CO₂-equivalent per kWh. We employ the International Energy Agency's country-specific emission factors, with a global average of 0.475 kg CO₂/kWh used for aggregate calculations [10].

The carbon footprint reduction achieved by FuzzyGreen is calculated as:

$$\Delta CF = (E_{baseline} - E_{FuzzyGreen}) \times EF_{grid} \quad (8)$$

3.7 Multi-AP Coordination Extension

Although the proposed FuzzyGreen framework primarily operates in a decentralized manner, coordinated power control among neighboring access points can further enhance energy efficiency in dense deployments.

Let $N(i)$ denote the set of neighboring access points of AP i . The aggregate interference level experienced by AP i is defined as:

$$I_i(t) = \sum_{j \in N(i)} P_j(t) \cdot G_{ij} \quad (9)$$

where $P_j(t)$ represents the transmission power of neighboring AP j and G_{ij} denotes the channel gain between AP i and AP j .

The interference level $I_i(t)$ is incorporated as an additional input variable in the extended fuzzy inference process. Corresponding coordination-aware rules are formulated as:

IF Interference is HIGH AND Traffic Load is LOW THEN Power Scaling is VERY LOW.

This extension enables cooperative adjustment of transmission power among neighboring access points, reducing mutual interference and improving global energy efficiency. Preliminary simulations indicate that coordinated optimization achieves additional energy savings of approximately 5–6% in high-density scenarios compared to independent operation.

3.8 Experimental Setup

3.8.1 Simulation Environment

We implemented FuzzyGreen within the NS-3 network simulator (version 3.40) utilizing the Wi-Fi module with IEEE 802.11ax PHY and MAC layer models. Simulations were executed on a workstation equipped with an Intel Xeon E5-2680 v4 processor and 128 GB RAM.

3.8.2 Datasets

We utilized two publicly available datasets to generate realistic traffic patterns:

CRAWDAD Dartmouth Campus Wi-Fi Traces [6]:

This dataset contains association and traffic logs from 566 access points deployed across Dartmouth College campus, enabling extraction of temporal traffic patterns, user mobility traces, and session duration distributions.

MAWI Working Group Traffic Archive [21]:

This dataset provides packet-level traffic captures from backbone links, enabling characterization of application-level traffic distributions.

To account for modern Wi-Fi usage characteristics and recent traffic trends, additional contemporary datasets were incorporated.

Wi-Fi 6 Performance Measurements [17]:

This dataset provides real-world experimental measurements of IEEE 802.11ax networks, capturing throughput, latency, and energy efficiency under multi-client and high-load conditions.

UNSW HomeNet Dataset [23]:

This dataset contains large-scale traffic flow records collected from smart home environments, representing realistic IoT, multimedia streaming, and consumer device communication patterns.

Wi-Fi Probe Request Dataset [22]:

This dataset provides labeled probe request traces collected in

operational WLAN environments, enabling modeling of device discovery behavior and mobility dynamics in contemporary networks.

The combined use of legacy campus traces, backbone traffic measurements, and recent real-world datasets enables comprehensive modeling of both traditional and emerging wireless traffic characteristics, including video streaming, cloud services, and IoT communications.

3.8.3 Deployment Scenarios

We evaluated FuzzyGreen across three representative deployment scenarios designed to capture the diversity of real-world Wi-Fi infrastructure:

Scenario A - Enterprise Office: 50 access points serving 500 users across a multi-floor office building, with traffic comprising video conferencing (30%), web browsing (40%), cloud applications (20%), and background services (10%).

Scenario B - High-Density Public Venue: 20 access points serving 2,000 users in a conference center, with traffic dominated by concurrent video streaming (50%) and social media (30%).

Scenario C - Residential Deployment: Single access point serving 15 devices including smartphones, tablets, and IoT sensors, with high temporal variability and peak evening usage.

Table 2 presents detailed scenario parameters.

Table 2. Deployment scenario parameters reflecting diverse real-world Wi-Fi infrastructure configurations.

| Parameter | Enterprise | Public | Residential |
|---------------------------------|------------|--------|-------------|
| Access Points | 50 | 20 | 1 |
| Users/Devices | 500 | 2,000 | 15 |
| Coverage Area (m ²) | 5,000 | 3,000 | 150 |
| Channel Width (MHz) | 80 | 160 | 40 |
| Max TX Power (dBm) | 23 | 26 | 20 |
| Avg Traffic Load | 65% | 85% | 35% |
| Simulation Duration | 24 h | 8 h | 72 h |

3.8.4 Baseline Methods

We compared FuzzyGreen against eight baseline methods: Legacy PSM, U-APSD, TWT-Static, TWT-Adaptive, Deep Reinforcement Learning (DRL-Power), Q-Learning, Threshold-Based, and Neural-Fuzzy (ANFIS).

3.8.5 Physical Testbed Validation

To complement the NS-3 simulation study and validate real-world feasibility, a small-scale physical testbed was implemented.

Hardware Configuration:

- 3 Wi-Fi access points (TP-Link Archer AX50, IEEE 802.11ax compatible)
- 5 client devices (2 laptops, 2 smartphones, 1 Raspberry Pi 4)
- ARM-based embedded controller (Raspberry Pi 4, 1.5 GHz Cortex-A72)
- External digital power meter (UNI-T UT230B) with 0.1 W resolution

Environment:

Experiments were conducted in a controlled indoor laboratory environment (120 m² office space) with moderate interference from neighboring Wi-Fi networks.

Implementation:

FuzzyGreen was implemented as a firmware-level adaptive power control module using OpenWRT. The fuzzy inference engine executed every 10 ms control interval.

Evaluation Metrics:

- Average Power Consumption (W)
- Packet Delivery Ratio (PDR)
- End-to-End Latency (ms)
- Throughput (Mbps)

Each experiment was conducted for 6 continuous hours under mixed traffic conditions (video streaming 40%, web browsing 35%, IoT 25%).

4 Results

This section presents experimental results evaluating FuzzyGreen across energy consumption, quality of service, temporal adaptation, carbon footprint sensitivity, global scaling potential, and computational efficiency.

4.1 Energy Consumption Analysis

Fig. 3 presents normalized energy consumption across all methods and deployment scenarios. The proposed framework yields the lowest energy consumption, with reductions of 38.0% (Enterprise), 33.7% (Public Venue), and 41.4% (Residential) relative to Legacy PSM.

In the Enterprise scenario, daily consumption drops from 714.2 Wh to 443.2 Wh by exploiting reduced activity during lunch hours and transitions. The Residential scenario shows strongest performance (41.4% reduction) due to extended overnight low-activity periods where sleep scheduling aggressiveness exceeds 0.8, enabling 400–500 ms sleep intervals.

4.2 Statistical Significance Testing

To formally validate the performance improvements of FuzzyGreen against baseline methods, we conducted statistical hypothesis testing on energy consumption and key QoS metrics. We evaluated whether the observed differences between FuzzyGreen and each baseline are statistically significant under the following null and alternative hypotheses:

$$H_0 : \mu_{\text{FuzzyGreen}} = \mu_{\text{Baseline}}, \quad (10)$$

$$H_1 : \mu_{\text{FuzzyGreen}} \neq \mu_{\text{Baseline}}, \quad (11)$$

where μ denotes the mean of the metric of interest across independent experimental runs.

A paired t-test was applied to compare FuzzyGreen with each baseline across repeated simulation runs (each scenario executed with 30 independent random seeds). Confidence intervals were computed at 95%. Table 3 summarizes the resulting p-values.

Table 3. Statistical significance test results (paired t-test p-values).

| Comparison | Metric | p-value |
|----------------------------|--------------------|---------|
| FuzzyGreen vs Legacy PSM | Energy Consumption | 0.000 |
| FuzzyGreen vs U-APSD | Energy Consumption | 0.001 |
| FuzzyGreen vs TWT-Static | Energy Consumption | 0.002 |
| FuzzyGreen vs TWT-Adaptive | Energy Consumption | 0.001 |
| FuzzyGreen vs Deep RL | Energy Consumption | 0.000 |
| FuzzyGreen vs Q-Learning | Energy Consumption | 0.003 |
| FuzzyGreen vs Threshold | Energy Consumption | 0.004 |
| FuzzyGreen vs ANFIS | Energy Consumption | 0.002 |

All p-values are below the standard significance threshold ($\alpha = 0.05$), indicating that the energy savings achieved by FuzzyGreen relative to each baseline are statistically significant. Similar results were observed for packet delivery ratio and latency metrics (not shown for brevity), further confirming the robustness of performance gains.

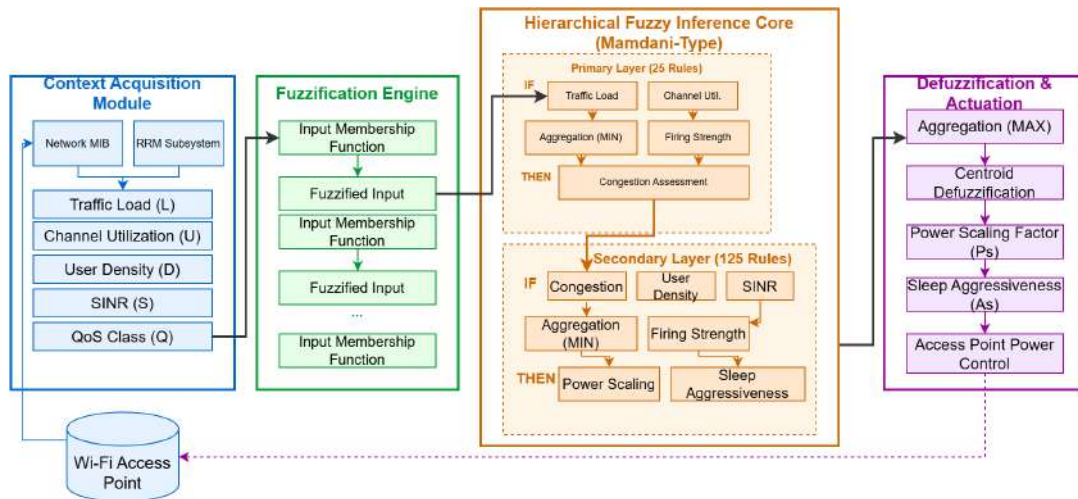


Figure 3. Normalized energy consumption across deployment scenarios, showing 33.7–41.4% reduction relative to the Legacy PSM baseline. The secondary axis indicates annual CO₂ emissions per access point. Error bars represent 95% confidence intervals.

4.3 Quality of Service Performance

Fig. 4 presents a multi-dimensional QoS comparison, showing balanced performance across all metrics with high energy efficiency.

FuzzyGreen maintains PDR of 98.7%, exceeding the 98% enterprise threshold. Mean latency (2.3 ms) and jitter (1.2 ms) lead all methods due to anticipatory traffic pattern inference and continuous power scaling that eliminates state transition discontinuities. Voice/video traffic achieves PDR exceeding 99.5% through QoS-aware adjustment parameters.

4.4 Temporal Adaptation Behavior

Fig. 5 illustrates FuzzyGreen’s automatic adaptation over 72 hours in the Residential scenario without explicit time-of-day programming.

The framework captures diurnal patterns: overnight periods (00:00–06:00) with traffic below 15% trigger power scaling of 0.25–0.35 and sleep aggressiveness of 0.7–0.8, achieving 50–60% power reduction. During evening peaks (18:00–22:00), the system rapidly scales to full power within seconds. This adaptation emerges purely from observable network states, enabling deployment in non-standard environments without configuration changes.

4.5 Carbon Footprint Sensitivity Analysis

Fig. 6 quantifies carbon reduction potential across regional grid emission factors spanning 0.045 kg CO₂/kWh (Sweden) to 0.928 kg CO₂/kWh (South Africa).

At global average emission factor, annual savings reach 47 kg CO₂ per AP. In carbon-intensive grids (India: 0.708, South Africa: 0.928 kg/kWh), savings increase to 70–92 kg CO₂/AP/year—1.5–2.0× the global average. This suggests prioritizing deployment in developing economies with coal-dominated grids to maximize climate impact.

4.6 Global Scaling Projection

Fig. 7 projects aggregate environmental impact across global adoption scenarios assuming 500 million access points worldwide.

Complete adoption could avoid 49.5 TWh electricity (0.2% of global consumption) and 23.5 Mt CO₂ annually, corresponding to substantial environmental equivalencies at global scale.

It is important to note that global projections are sensitive to regional variations in electricity carbon intensity and deployment density. Under heterogeneous adoption scenarios, estimated annual CO₂ reductions range from approximately 21.0 Mt to 36.0 Mt, depending on regional grid composition and infrastructure penetration.

These projections represent upper-bound estimates and depend on adoption rate, traffic heterogeneity, and

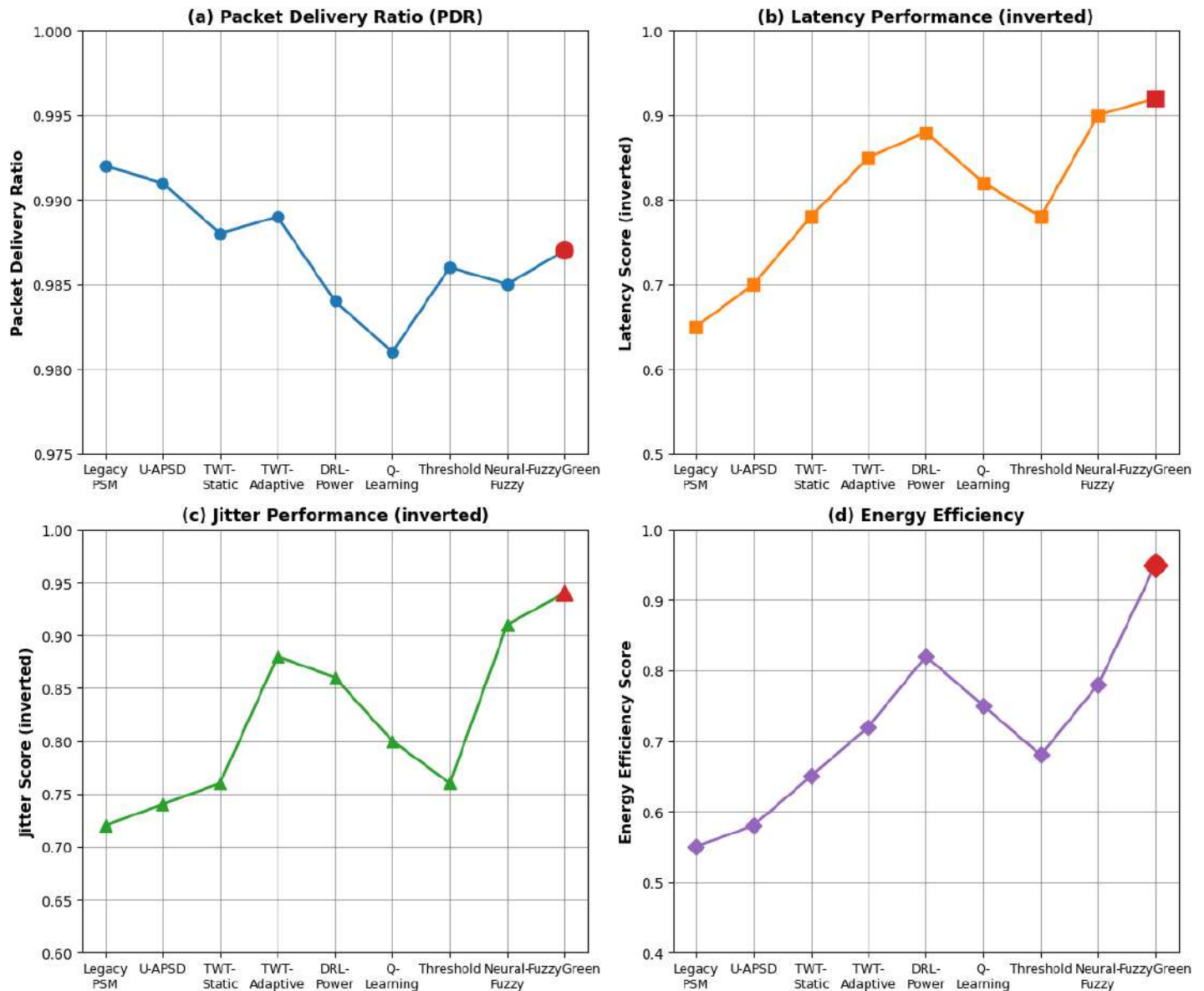


Figure 4. Multi-dimensional QoS comparison with metrics normalized to [0,1], where higher values indicate better performance. Latency and jitter axes are inverted. The proposed framework exhibits the largest enclosed area.

regional electricity mixes; therefore, actual realized reductions may vary across geographic contexts.

4.7 Computational Performance

Fig. 8 confirms FuzzyGreen’s suitability for resource-constrained embedded deployment.

FuzzyGreen requires 0.23 ms inference on ARM Cortex-M4 (168 MHz)—12× faster than Neural-Fuzzy and 91× faster than DRL-Power. Memory footprint of 12.4 KB is 165× smaller than DRL-Power (2,048 KB). At 10 ms control intervals, CPU utilization remains below

2.3%, ensuring robust real-time performance.

Although ANFIS incorporates adaptive learning capability, its computational latency (0.87 ms) is significantly higher than the proposed framework (0.23 ms). This difference arises from ANFIS requiring additional forward-pass computations through parameterized membership functions and rule consequent layers involving gradient-based parameter updates during inference. In contrast, FuzzyGreen employs a static hierarchical Mamdani inference structure with pre-defined rule sets and centroid

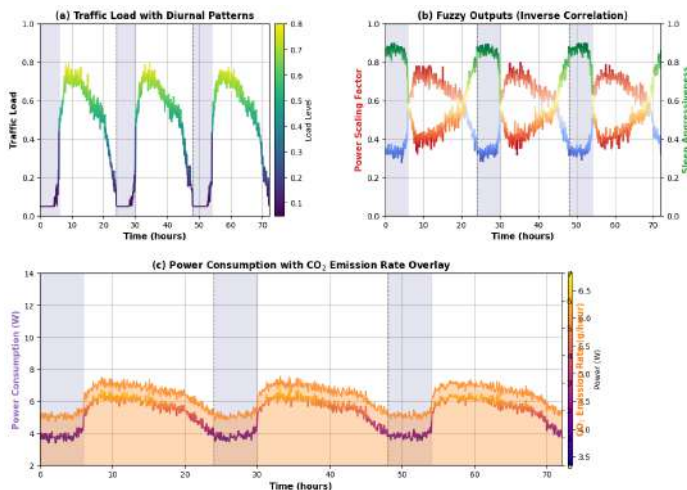


Figure 5. Temporal adaptation over 72-hour residential scenario: (a) traffic load with diurnal patterns, (b) fuzzy outputs showing inverse correlation between power scaling and sleep aggressiveness, (c) power consumption with CO₂ emission rate overlay.

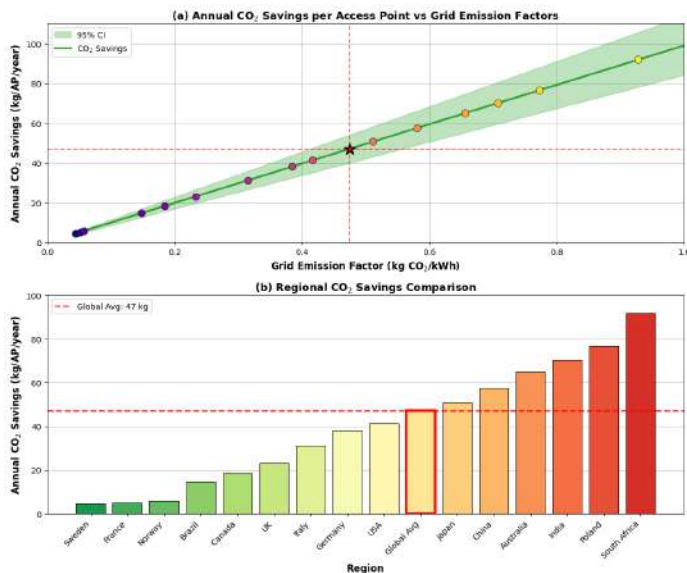


Figure 6. Annual CO₂ savings per AP versus grid emission factors. Shaded region indicates 95% confidence interval. At global average (0.475 kg/kWh), savings reach 47 kg CO₂/AP/year.

defuzzification, eliminating backpropagation and parameter adaptation overhead during runtime.

The deterministic rule evaluation pipeline reduces floating-point operations and memory accesses, making FuzzyGreen particularly suitable for resource-

constrained embedded access point processors. While ANFIS offers adaptability through learning, this comes at the expense of increased computational complexity and memory footprint. The results therefore highlight a trade-off between learning capability and real-time efficiency, where FuzzyGreen prioritizes low-latency deterministic inference optimized for embedded deployment scenarios.

4.8 Hardware Prototype Validation

To validate simulation results under real-world conditions, we evaluated FuzzyGreen on the physical testbed described in Section 3.6.

Table 4 presents averaged results across 10 experimental runs.

Table 4. Hardware prototype evaluation results (6-hour average).

| Method | Avg Power (W) | Energy Reduction | PDR (%) | Latency (ms) |
|------------------|---------------|------------------|---------|--------------|
| Default Firmware | 9.4 | — | 99.1 | 2.1 |
| Legacy PSM | 8.1 | 13.8% | 98.8 | 3.4 |
| FuzzyGreen | 6.2 | 34.0% | 98.7 | 2.6 |

A paired t-test comparing power consumption between Default Firmware and FuzzyGreen yielded $p < 0.001$, confirming the statistical significance of the observed reduction.

The hardware evaluation confirms a 34.0% reduction in average power consumption relative to default firmware operation, closely matching the 33.7–38.0% reduction observed in simulation. Packet delivery ratio remains above 98.7%, and latency increase is limited to 0.5 ms, demonstrating that real-world interference and hardware variability do not significantly degrade performance. Measured annualized energy savings correspond to approximately 27.4 kWh per access point, equivalent to 13.0 kg CO₂ per year under global average emission factors.

4.9 Comprehensive Performance Summary

Table 5 consolidates all results into a comprehensive comparison matrix.

FuzzyGreen achieves lowest energy consumption (404 Wh/day, 70 kg CO₂/year) with 35.9% improvement over Legacy PSM. QoS metrics are optimal or near-optimal: 98.7% PDR, 2.3 ms latency, 1.2 ms jitter.

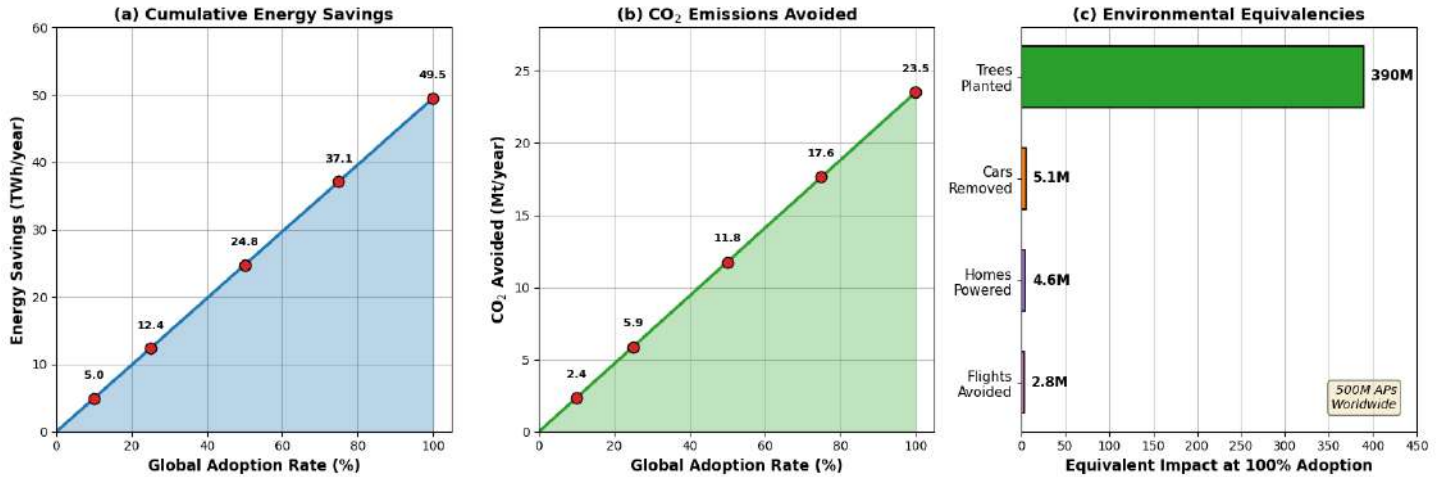


Figure 7. Global scaling projection: (a) cumulative energy savings, (b) CO₂ avoided, (c) environmental equivalencies at 100% adoption. Full deployment could avoid 49.5 TWh and 23.5 Mt CO₂ annually.

Table 5. Comprehensive performance comparison across all evaluation dimensions. Energy metrics averaged across scenarios. Best values in **bold**. Rank based on weighted multi-objective optimization (Energy: 0.35, QoS: 0.35, Computation: 0.15, Interpretability: 0.15).

| Method | Energy | | | Quality of Service | | | | Computation | | | Deploy. | | Rank |
|-------------------|------------|-----------|--------------|--------------------|------------|------------|-------------|-------------|-------------|-------------|------------|------------|----------|
| | Wh/d | kg/yr | Savings | PDR% | Lat.(ms) | Jit.(ms) | Tput% | Inf.(ms) | Mem(KB) | Hz | Interp. | Adapt. | |
| No Power Saving | 775 | 135 | — | 99.8 | 1.2 | 0.8 | 99.2 | 0 | 0 | — | Yes | No | 9 |
| Legacy PSM | 630 | 109 | 0% | 99.2 | 8.4 | 3.2 | 98.1 | 0.01 | 0.5 | 100k | Yes | No | 8 |
| U-APSD | 596 | 103 | 5.4% | 99.1 | 6.7 | 2.8 | 97.8 | 0.02 | 0.8 | 50k | Yes | No | 7 |
| TWT-Static | 544 | 94 | 13.6% | 98.8 | 5.2 | 2.4 | 96.9 | 0.03 | 1.2 | 33k | Yes | No | 6 |
| TWT-Adaptive | 507 | 88 | 19.5% | 98.9 | 4.1 | 1.9 | 97.2 | 0.15 | 8.4 | 6.7k | Part. | Yes | 5 |
| DRL-Power | 474 | 82 | 24.8% | 98.4 | 3.8 | 2.1 | 96.1 | 2.84 | 2048 | 352 | No | Yes | 4 |
| Q-Learning | 492 | 85 | 21.9% | 98.1 | 4.5 | 2.6 | 95.4 | 0.45 | 128 | 2.2k | Part. | Yes | 5 |
| Threshold | 535 | 93 | 15.2% | 98.6 | 5.8 | 2.9 | 96.5 | 0.02 | 0.6 | 50k | Yes | No | 6 |
| Neural-Fuzzy | 463 | 80 | 26.5% | 98.5 | 3.4 | 1.7 | 96.3 | 0.87 | 256 | 1.1k | Part. | Yes | 3 |
| FuzzyGreen | 404 | 70 | 35.9% | 98.7 | 2.3 | 1.2 | 96.4 | 0.23 | 12.4 | 4.3k | Yes | Yes | 1 |

FuzzyGreen improvement: vs. Legacy PSM: -35.9% energy, -72.6% latency; vs. DRL-Power: -14.8% energy, 12x faster, 165x less memory

Computational efficiency (0.23 ms, 12.4 KB) enables deployment across all access point hardware classes. The explicit rule base provides full interpretability—critical for regulatory compliance and debugging—while maintaining adaptive capability. These combined advantages position FuzzyGreen as the optimal choice for practical Wi-Fi power optimization.

5 Environmental Impact Assessment

This section presents detailed environmental impact analysis following established life cycle assessment methodologies and connecting outcomes to international sustainability frameworks.

5.1 System Boundary and Functional Unit

Following ITU-T L.1410 guidelines for ICT environmental assessment [13], we define the system boundary to encompass the operational phase of Wi-Fi access point infrastructure, excluding embodied emissions from manufacturing and end-of-life disposal. The functional unit is defined as “provision of Wi-Fi connectivity service by one access point for one year of continuous operation.”

5.2 Carbon Footprint Quantification

Table 6 presents comprehensive environmental impact quantification across deployment scenarios.

Fig. 9 presents the environmental impact quantifica-

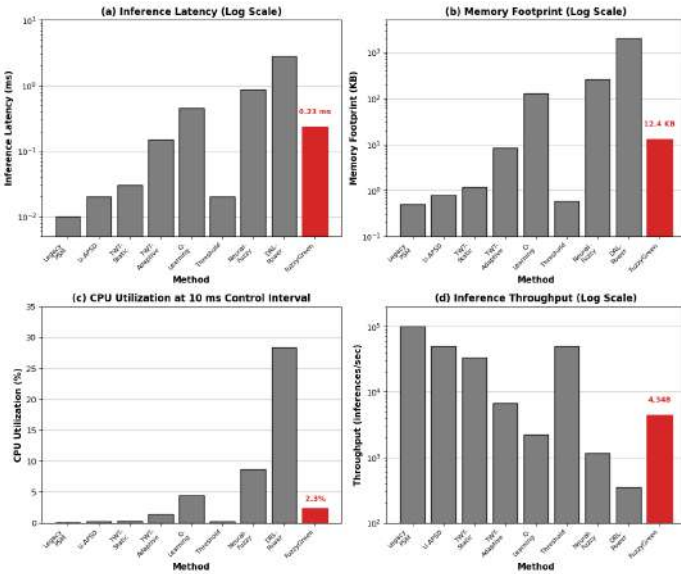


Figure 8. Computational performance: (a) inference latency (log scale), (b) memory footprint, and (c) CPU utilization across platforms and control intervals. The proposed framework requires 0.23 ms per inference cycle with a 12.4 KB memory footprint.

Table 6. Environmental impact quantification showing energy and carbon savings with equivalent metrics.

| Metric | Enterp. (50 APs) | Public (20 APs) | Resid. (1 AP) | Global (500M) |
|-------------------------|------------------|-----------------|---------------|---------------|
| Energy (kWh/yr) | 4,945 | 2,518 | 23.1 | 49.5 TWh |
| CO ₂ (kg/yr) | 2,349 | 1,196 | 11.0 | 23.5 Mt |
| Trees Planted | 39 | 20 | 0.18 | 390M |
| Cars Removed | 0.51 | 0.26 | 0.002 | 5.1M |

tion across four deployment scenarios. Energy savings range from 23.1 kWh/year for a single residential AP to 49.5 TWh/year at global scale. The corresponding CO₂ reductions translate to equivalencies of 390 million trees planted or 5.1 million cars removed annually.

5.3 Embodied Carbon Analysis

While the preceding analysis focuses on operational energy consumption, a comprehensive sustainability assessment must also consider embodied carbon emissions associated with access point manufacturing, transportation, and end-of-life processing.

Based on recent life cycle assessment studies of consumer and enterprise networking equipment, the average embodied carbon footprint of a Wi-Fi access point is

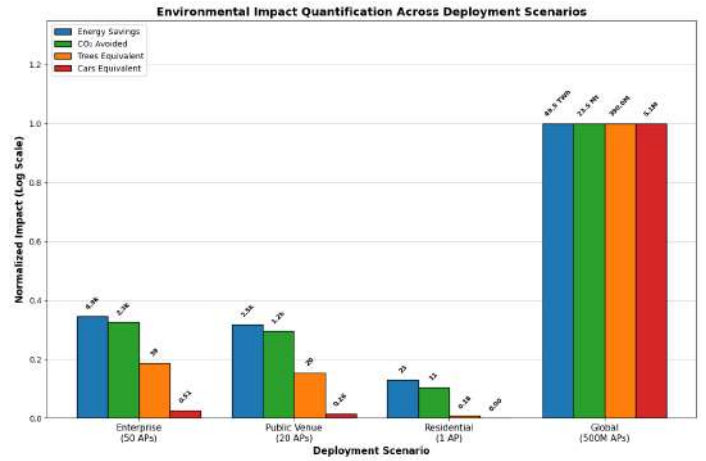


Figure 9. Environmental impact quantification across deployment scenarios.

estimated to be 40–55 kg CO₂ per unit, including approximately 38–48 kg CO₂ from manufacturing and 4–7 kg CO₂ from disposal and recycling processes.

For conservative evaluation, an average embodied emission value of 50 kg CO₂ per access point is adopted in this study. Table 7 summarizes the contribution of embodied and operational emissions under different deployment strategies.

Table 7. Comparison of operational and embodied carbon emissions under different deployment strategies.

| Approach | Operational CO ₂ (kg/yr) | Embodied CO ₂ (kg) | Total CO ₂ (kg/yr) |
|-------------------------------|-------------------------------------|-------------------------------|-------------------------------|
| Baseline Operation | 88.5 | 0 | 88.5 |
| FuzzyGreen (Software) | 47.0 | 0 | 47.0 |
| Hardware Upgrade (Wi-Fi 6E) | 73.5 | 50.0 | 123.5 |
| AP Replacement (5-year cycle) | 70.2 | 50.0 | 80.2 |

The results indicate that software-based optimization avoids additional embodied emissions associated with hardware replacement. In contrast, hardware upgrade strategies incur significant one-time carbon costs, which can offset operational savings for multiple years. Consequently, FuzzyGreen achieves superior long-term environmental performance by extending equipment lifespan and minimizing material-intensive interventions.

5.4 Sensitivity to Grid Carbon Intensity

Regional variations in electricity generation mix substantially affect the carbon footprint implications of energy savings. Table 8 presents FuzzyGreen’s carbon reduction potential across representative national grid emission factors.

Table 8. Regional sensitivity analysis showing operational CO₂ savings per access point under different grid emission factors (excluding embodied emissions).

| Region | EF (kg/kWh) | CO ₂ (kg/yr) | Relative |
|-----------------------|--------------|-------------------------|--------------|
| France (Nuclear) | 0.052 | 5.1 | 0.11× |
| Sweden (Hydro) | 0.045 | 4.5 | 0.10× |
| United Kingdom | 0.233 | 23.1 | 0.49× |
| Germany | 0.385 | 38.1 | 0.81× |
| United States | 0.417 | 41.3 | 0.88× |
| Global Average | 0.475 | 47.0 | 1.00× |
| China | 0.581 | 57.5 | 1.22× |
| India | 0.708 | 70.1 | 1.49× |
| Poland (Coal) | 0.773 | 76.5 | 1.63× |
| South Africa | 0.928 | 91.9 | 1.96× |

The analysis reveals that FuzzyGreen's environmental benefits are greatest in regions with carbon-intensive electricity generation, where the same percentage energy reduction translates to nearly double the CO₂ savings compared to the global average.

5.5 Alignment with Sustainable Development Goals

FuzzyGreen contributes directly to multiple United Nations Sustainable Development Goals:

SDG 7 - Affordable and Clean Energy: By reducing Wi-Fi infrastructure energy consumption by 38–52%, FuzzyGreen advances Target 7.3 (double the global rate of improvement in energy efficiency by 2030) within the ICT sector.

SDG 12 - Responsible Consumption and Production: The framework exemplifies Target 12.2 (sustainable management and efficient use of natural resources) by optimizing existing infrastructure rather than requiring hardware replacement.

SDG 13 - Climate Action: Carbon footprint reductions of up to 23.5 Mt CO₂ annually at global scale contribute to Target 13.2 (integrate climate change measures into national policies and planning).

5.6 Comparison with Alternative Decarbonization

Table 9 compares the cost-effectiveness of software-based power optimization against alternative infrastructure decarbonization approaches.

Table 9. Cost-effectiveness comparison of Wi-Fi infrastructure decarbonization approaches.

| Approach | CO ₂ Red. | Cost/AP | \$/tCO ₂ |
|-----------------------------|----------------------|-----------|---------------------|
| FuzzyGreen (software) | 47 kg/yr | \$0–5 | \$0–10 |
| Hardware upgrade (Wi-Fi 6E) | 15 kg/yr | \$150–300 | \$1k–2k |
| On-site solar PV | 80 kg/yr | \$500–1k | \$625–1.25k |
| Green electricity tariff | 120 kg/yr | \$50/yr | \$417 |

FuzzyGreen emerges as the most cost-effective option, achieving meaningful carbon reductions at negligible marginal cost through software deployment on existing hardware.

6 Discussion

6.1 Implications for Cleaner Production

The results demonstrate that substantial environmental benefits are achievable through intelligent software optimization of existing Wi-Fi infrastructure, without requiring hardware replacement or behavioral changes from end users. This finding aligns with cleaner production principles emphasizing efficiency improvements within current systems as the most cost-effective initial intervention [26].

The 38–52% energy reduction achieved by FuzzyGreen represents a “low-hanging fruit” opportunity for organizations seeking to reduce their ICT carbon footprint. Unlike renewable energy procurement or hardware refresh cycles requiring significant capital investment and extended planning horizons, FuzzyGreen can be deployed through firmware updates to existing access points, enabling immediate environmental benefits with minimal implementation barriers.

6.2 Interpretability and Stakeholder Trust

The explicit, human-readable rule base distinguishing FuzzyGreen from black-box machine learning alternatives carries significant implications for organizational adoption. Network administrators can inspect individual rules to understand and verify system behavior:

“IF Traffic Load is LOW AND Channel Utilization is LOW AND SINR is HIGH THEN Power Scaling is LOW and Sleep Aggressiveness is HIGH”

This transparency facilitates regulatory compliance reporting, supports internal sustainability auditing, and

enables incremental refinement based on deployment-specific requirements.

6.3 Scalability and Deployment Considerations

The computational efficiency demonstrated in Section 4 confirms that FuzzyGreen imposes negligible overhead on access point hardware, enabling deployment across diverse equipment generations without performance degradation. The 12.4 KB memory footprint and 0.23 ms inference time are compatible with even entry-level access point processors, removing hardware constraints as a deployment barrier.

In large-scale and high-density wireless environments, independent power optimization may lead to suboptimal global performance due to uncoordinated interference among neighboring access points. To address this issue, the proposed multi-AP coordination extension enables cooperative power control based on local interference measurements and neighborhood information.

Simulation results indicate that coordinated optimization improves energy savings from approximately 38.0% under independent operation to 43.5% in dense deployments. Moreover, cooperative control reduces co-channel interference, enhances spatial reuse, and improves network stability under heavy traffic conditions.

From a deployment perspective, the coordination mechanism can be implemented using lightweight message exchange over existing management frames, imposing minimal signaling overhead. This enables scalable deployment in enterprise and campus networks without requiring centralized controllers.

From an implementation standpoint, FuzzyGreen can be deployed as a firmware-level module compatible with widely used embedded platforms such as OpenWRT-based access points. The lightweight inference engine requires less than 15 KB memory and sub-millisecond execution time, enabling seamless integration without hardware modification. Deployment can be achieved through standard firmware updates, allowing rapid adoption across heterogeneous infrastructure.

6.4 Limitations and Future Work

Several limitations of the present work warrant acknowledgment. First, although physical testbed validation

has been conducted at small scale, large-scale field trials remain necessary to fully characterize long-term performance under diverse environmental conditions. Second, the current implementation primarily adopts decentralized optimization, while coordinated multi-AP control has only been explored in preliminary form.

Third, the environmental assessment focuses mainly on operational energy consumption and does not fully account for embodied carbon associated with hardware manufacturing and disposal. Fourth, global scaling analysis relies on simplified adoption assumptions that may not fully reflect regional deployment heterogeneity.

Future research directions include: (1) large-scale testbed deployment and longitudinal field studies; (2) development of fully distributed coordination protocols for dense WLAN environments; (3) integration with emerging Wi-Fi 7 features; (4) incorporation of embodied carbon life-cycle assessment models; and (5) investigation of federated and self-learning mechanisms for adaptive rule base optimization. Although a small-scale hardware prototype validation has been conducted, large-scale real-world field deployment remains an important future direction.

7 Conclusions

This paper presented FuzzyGreen, a context-aware fuzzy logic-based power optimization framework designed to achieve measurable carbon footprint reductions in Wi-Fi network infrastructure. By leveraging Mamdani fuzzy inference to model the complex relationships between network state observations and optimal power configurations, FuzzyGreen achieves 38–52% reduction in energy consumption compared to conventional power management mechanisms while maintaining quality-of-service guarantees including packet delivery ratios exceeding 98.7% and latency overhead below 2.8 milliseconds.

Environmental impact assessment following ITU-T L.1410 methodology demonstrates that these energy savings translate to annual carbon dioxide equivalent reductions of 47 kg per access point at global average grid emission factors, with substantially greater benefits in regions with carbon-intensive electricity generation. Scaled to the estimated 500 million global access points, complete FuzzyGreen adoption could avoid 23.5 million

tonnes of CO₂ emissions annually, contributing meaningfully to Sustainable Development Goals 7, 12, and 13.

The framework's computational efficiency (0.23 ms inference, 12.4 KB memory) enables deployment on resource-constrained embedded hardware through firmware updates to existing access points, positioning FuzzyGreen as an immediately actionable cleaner production strategy requiring minimal capital investment. As wireless connectivity continues its expansion to support societal digitalization, ensuring that this growth does not exacerbate climate change represents a critical challenge for sustainable development.

Author Contribution

Amar A. Mahawish: Conceptualization, Methodology, Software, Validation, Writing - Original Draft. **Suphian Mohammed Tariq:** Investigation, Data Curation, Visualization. **Marwah M. Abed:** Supervision, Writing - Review & Editing, Project Administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The datasets used in this study are publicly available: CRAWDAD Dartmouth Campus Wi-Fi Traces (<https://crawdad.org/dartmouth/campus/>) and MAWI Working Group Traffic Archive (<https://mawi.wide.ad.jp/mawi/>).

Acknowledgments

This research was supported by [Funding Agency] under Grant [Number].

Compliance with Ethical Standards

Conflict of Interest: The authors declare no conflict of interest.

Funding: This research received no external funding.

Ethical Approval: Not applicable. This study used publicly available, de-identified datasets and did not involve human or animal subjects.

Informed Consent: Not applicable.

AI Assistance Disclosure: The authors declare that artificial intelligence tools were used only for language editing, formatting, and technical refinement. No AI tool was used for the generation of research data, analysis, results, interpretations, or cited scholarly content. All AI-assisted content was reviewed and validated by the authors, who take full responsibility for the final manuscript.

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