AI-Enabled Joint Optimization of 6G Cognitive Radio Quality of Service and Hybrid Microgrid Energy Efficiency Using Federated and Reinforcement Learning

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Abstract. This paper presents a novel, AI-driven cross-domain optimization framework designed to synergistically enhance Quality of Service (QoS) in 6G Cognitive Radio (CR) networks and energy efficiency in hybrid AC/DC microgrids. By leveraging a unified ensemble machine learning model—incorporating federated learning, Long Short-Term Memory (LSTM) networks, and reinforcement learning—the proposed system dynamically allocates communication and energy resources in real-time. Key innovations include an AI-augmented Selection Combining (SC) scheme for robust fading mitigation and a microgrid-aware resource allocation strategy. Extensive simulations demonstrate substantial performance improvements: a 40% reduction in communication outage probability, a 60% decrease in network power consumption, a 25% improvement in power quality (Total Harmonic Distortion), and a 30% gain in spectral efficiency. This research validates the transformative potential of integrated AI architectures in creating resilient, self-optimizing, and sustainable infrastructure for smart cities and industrial IoT, effectively bridging the gap between high-performance connectivity and clean energy integration.

Keywords: 6G Networks, AI-driven QoS, Cognitive Radio, Microgrid Optimization, Sustainable Energy, Federated Learning, Cross-Domain Co-Design.

1 Introduction

The advent of sixth-generation (6G) wireless communication networks and intelligent energy infrastructures marks a significant paradigm shift toward highly connected, autonomous, and sustainable cyber-physical systems. Artificial Intelligence (AI) has emerged as an important enabling technology in meeting the strict Quality of Service (QoS) demands of 6G wireless networks, such as extremely low latency, high reliability, and massive connectivity. AI-assisted QoS optimization algorithms have shown significant promise in dealing with the complexity associated with dynamic wireless channels based on data-driven learning and decision-making [1]. Additionally, the worldwide shift to renewable energy-based power grids has triggered the widespread adoption of microgrids that incorporate distributed energy resources, energy storage,

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and smart control systems. AI-assisted predictive energy management algorithms have made it possible to forecast renewable energy and load demands more accurately, thus optimizing efficiency and stability in microgrids [2]. However, it has been observed that the optimization of communication and energy infrastructures has generally been done in a disjoint manner, leading to suboptimal utilization of resources. Recent studies have emphasized the significance of cross-domain integration between wireless communication and energy infrastructures, especially in the context of 6G-enabled smart infrastructures. AI-assisted cross-domain frameworks can accomplish joint optimization by taking into account both wireless network functionality and energy resource factors [3]. AI-assisted reinforcement learning has further improved the efficiency of hybrid microgrids based on dynamic and self-adaptive controlforming in the presence of uncertain operational conditions [4]. Ultra-dense 6G networks pose significant interference and scarce spectrum problems that demand smart interference management techniques [5]. AI-assisted network orchestration tools have predictive and proactive control functions to dynamically adjust network configurations based on traffic dynamics [6]. Simultaneously, AI-assisted fault detection algorithms have improved the reliability of power grids based on early anomaly and failure detection [7]. Latency-sensitive applications such as autonomous vehicles, industrial automation, and immersive communications have very strict real-time constraints that have further emphasized the importance of smart and energy-efficient communication infrastructures [8]. AI has been generally acknowledged to be a requisite enabling technology for next-generation wireless systems that can ensure seamless multi-layer adaptations [9]. Based on all the aforementioned factors, the focus of this treatise aims to optimize QoS and energy efficiency in hybrid microgrid settings based on an AI-assisted joint optimization framework. In this paper, we propose a comprehensive AI-based cross-domain co-design methodology for optimizing the quality of service in 6G cognitive radio networks, together with energy efficiency in AC/DC microgrids. A hierarchical multi-task learning architecture incorporating federated learning techniques, LSTM networks, and reinforcement learning agents has been designed. Further, an AI-based selection combining technique has been incorporated for fading and interference mitigation. Simulation results have established improvements in outage probability, power, spectrum efficiency, and power quality.

Research Gap and Problem Formulation

Despite significant advances in AI-assisted wireless communication and intelligent microgrid management, existing research largely treats these domains independently. Communication-focused studies optimize QoS without considering real-time energy constraints, while energy-focused works assume ideal communication infrastructure. This separation leads to inefficient resource utilization and reduced system robustness in smart infrastructure.

Additionally, many existing approaches rely on centralized AI architectures that suffer from scalability limitations, privacy risks, and latency overhead in large-scale 6G environments. Therefore, a decentralized cross-domain optimization framework is required to simultaneously optimize communication performance and energy efficiency in real time.

This paper addresses this gap by proposing a unified federated and reinforcement learning framework that performs joint optimization under practical communication and energy constraints.

The major contributions of the proposed paper are articulated below:

- An innovative AI-based cross-domain co-design approach to optimize the 6G cognitive radio QoS and energy efficiency of the hybrid AC/DC microgrid simultaneously.
- A hierarchical ensemble learning framework that employs the complementarities of federated learning, LSTM networks, as well as reinforcement learning techniques.
- An artificial intelligence-improved selection combining scheme that reduces fading and interference and also considers real-time micro-grids energy conditions.
- A thorough performance assessment across domains, showing significant gains in outage probability, spectral efficiency, power consumption, and power quality.
- Analysis of energy-QoS trade-offs in order to enable sustainable and adaptive operation in the 6G network with renewable energy sources

2 Literature Review

AI-assisted beamforming optimization has been widely explored as an approach for improving the spectral efficiency and mitigating interference in 6G networks by adapt-ing the weights of the antennas according to the channel state [10]. Machine learning methods have also been used in cognitive radio networks, facilitating intelligent spectrum sensing and access in highly congested bands [11]. Deep reinforcement learning has also been used for further improvement in the utilization of the spec-tra, allowing the agents to make decisions optimally through continuous interaction with the environment [12]. Real-time adaptation techniques became highly important in the context of ultra-dense wireless communication systems, where dense changes in the user density and the environment require efficient decision-making techniques [13]. Channel mitigation in next-generation communication systems due to multipath fading has been addressed by AI-assisted techniques for better modeling and mitigation [14]. In the area of distributed intelligence, federated learning has been developed as an efficient technique for model training in large-scale communication systems, making it more suitable for large-scale communication systems and the Internet of Things [15]. Quantum-assisted edge computing has also been used for improving the capability of AI-assisted resource allocation techniques for optimization in the context of heterogeneous IoT systems [16]. Federated learning has also been used for efficient distributed QoS management, reducing communication costs while ensuring performance guarantees [17]. AI-assisted decentralized fault detection techniques have also been used for increasing the reliability of micro-grids, allowing for efficient decision-making in local regions for fault isolation [18]. Reliable communication frameworks are mandatory for efficient functioning in smart grids, allowing for real-time monitoring, control, and coordinated functioning between the energy sources [19]. AI-assisted techniques for concluding an efficient mathematical model for wireless communication channels for mitigating fading in RF, FSO, and hybrid RF&FSO communication systems, as well as in non-stationary wireless communication channels, have been introduced for system performance improvement in MIMO systems [20, 21, 22]. Further efficient utilization in the context of nominal MIMO systems has been introduced in intelligent NOMA transmission techniques [23]. AI-assisted machine learning techniques in MIMO systems have also been used for efficient focusing on fading transmission in MIMO systems, allowing for efficient focusing on optimal transmitting antennas in MIMO systems [24]. Novel models for wireless communication system resilience analysis have also been introduced for sensor clouds and wireless communication systems for perfect operativity in realistic environments [25]. Anomaly detection algorithms powered by artificial intelligence, based on graph neural networks, have improved the security and robustness of IoT-based cyber-physical systems [26]. The wide adoption of IoT in various fields has reiterated the need for the adoption of robust, intelligent, and energy-efficient network designs [27]. Adaptive AI-based protocols in the context of fog-edge computing have revealed outstanding improvements in terms of energy efficiency and latency performance [28]. Last, blockchain-based security structures have managed to offer trustless and robust secure solutions for multi-layer IoT designs against joint-attack scenarios [29]. These works comprehensively suggest a research gap in joint communication-energy optimization, which the proposed framework fills directly.

3 Model and Methodology

3.1 System Architecture and Underlying Assumptions

Throughout the paper, a tightly integrated communication-energy system is considered, including jointly optimized artificial intelligence for a 6G cognitive radio network and a hybrid AC/DC microgrid. The 6G cognitive radio network consists of a central 6G BS, multiple cognitive radio users, and distributed spectrum-sensing units. Depending on the real-time sensing and interference conditions, the cognitive users dynamically access the available spectrum bands. Noise, multipath fading, and co-channel interference lead to impacts on the wireless channels, influencing key QoS metrics such as latency, throughput, bit error rate, spectral efficiency, and detection probability.The energy subsystem includes a hybrid microgrid that integrates renewable energy sources, like solar-photovoltaic and wind generation, an energy storage system, and local electrical loads. The microgrid provides energy supply for both communication infrastructure and auxiliary computing resources. Microgrid performance is characterized by energy availability, power balance, voltage regulation, total harmonic distortion, and overall energy efficiency. An edge–cloud AI architecture is adopted to support real-time and scalable operations. Edge nodes located near the communication infrastructure conduct low-latency inference and local control, whereas cloud servers conduct global learning and long-term optimization. Federated learning is employed to enable model training collaboratively across distributed nodes without the need to share raw data, thus ensuring scalability and privacy preservation. Assumptions made by the proposed system are as follows:

- The wireless channel is based on a standard fading model and changes dynamically with user mobility and environmental conditions.
- The basis of formulations in this paper rests on delay-sensitive network traffic, reflecting typical 6G applications, including but not limited to autonomous systems and industrial IoT.
- Microgrid power comes first from renewable energy sources; storage is used to balance supply and demand.
- Edge devices are computationally and energetically limited, which in turn raises the motivation of energy-aware AI decision-making.
- The present system model forms the basis for the cross-domain AI-based optimization strategy that will be focused on in the following sections.

3.2 AI-Driven Quality of Service Framework for 6G Networks

The proposed architecture uses an AI-enhanced QoS model, fusing real-time communication and energy-domain data for coordinated optimization. Network parameters, like channel state information, interference, mobility, and QoS metrics, along with microgrid indicators representing renewable generation, load demand, energy storage, and power quality, are integrated in this model. Normalized and extracted features from both domains are fed into an ensemble learning architecture, combining a modified Random Forest and Long Short-Term Memory networks, which captures the cross-domain relationship and temporal dynamics. Federated learning empowers decentralized training in a scalable and privacy-preserving manner through parameter-level aggregation

3.3 Integrated Optimization Strategy Across Domains

It employs a cross-domain optimization approach in the framework to jointly improve communication performance and microgrid efficiency. The multi objective resource allocation mechanism dynamically adjusts the transmission power, modulation schemes, and computational workloads according to real-time network condition and energy availability to ensure QoS and microgrid power balance. The AI-enhanced selection combining method improves the reliability of reception by predicting channel and interference conditions, adding microgrid energy states that allow for an efficient trade-off between spectral efficiency, energy consumption, and system stability under operational constraints.

3.3.1 Cross-Domain Optimization Problem Formulation

It formulates the proposed framework in the work of a joint communication-energy management task as a multi-objective optimization problem which can be set to simultaneously improve the Quality of Service of 6G networks and improve the energy efficiency of hybrid microgrids. The main objective is to maximize communication performance with minimum energy consumption and minimum power quality degradation under practical operational constraints.

This, in particular, seeks to optimize by:

- The maximal performance of spectral efficiency, throughput, and spectrum detection probability has to be targeted in order to safeguard a reliable and high-performance 6G cognitive radio communication.
- The objectives may include minimization of network power consumption, communication outage probability and power quality degradation such as Total Harmonic Distortion in the hybrid AC/DC microgrid.

These objectives are to be optimized under the following restrictions:

- QoS constraints that include latency bounds, BER thresholds, and interference limits to protect the primary users.
- Constraints on microgrids, i.e., power balance, voltage regulation limits, acceptable levels of THD.
- Energy constraints are: renewable energy availability, energy storage capacity.

This is impossible to solve conventionally due to the dynamic and nonlinear nature of the communication and energy environments, so a reinforcement learning-based decision-making agent, supported by federated learning for decentralized training and LSTM networks for temporal prediction, is employed to learn the optimal cross-domain resource allocation policies in real time. This allows scalable, adaptive, and energy-aware optimization suitable for 6G-enabled smart infrastructure.

3.4 Online Implementation Framework

In order to make the proposed framework support real-time operations, its implementation is performed using a hybrid edge-cloud architecture. While performing low-latency inference and local control at the edge nodes enables making time-critical decisions, cloud-based coordination would allow global optimizations and long-term learning. A digital twin environment is utilized for validating the system behavior beforehand to ensure safe and reliable operation. Continuous monitoring and closed-loop control enable the system to dynamically adapt to real-world changing network conditions and energy availability.

3.5 Metrics for Performance Analysis

These methodologies will comprehensively evaluate system performance across both the communication and energy domains. Communication performance is assessed using end-to-end latency, throughput, bit error rate, while microgrid performance is evaluated in terms of voltage regulation, renewable energy utilization, energy efficiency, and power quality. This will ensure a unified evaluation methodology so that any improvement in communication QoS is not at the expense of microgrid stability or sustainability.

3.6 Metrics for Scalability Analysis

The scalability of the federated learning framework is achieved through hierarchical aggregation and partial participation of edge nodes. Instead of requiring all cognitive radio users and microgrid controllers to transmit updates simultaneously, only a subset participates in each training round. This reduces communication overhead and prevents network congestion as the system scales.

Simulation analysis shows that federated update communication contributes less than 3% additional latency to the overall QoS budget. Energy-aware scheduling ensures local model training occurs during periods of surplus renewable energy, preventing additional burden on the microgrid. Therefore, the framework maintains scalability while preserving latency and energy efficiency.

3.7 Metrics for Robustness Analysis

Practical deployment introduces hardware impairments, imperfect spectrum sensing, and delayed or noisy energy measurements. To address these challenges, the reinforcement learning agent is trained using stochastic perturbation models that simulate sensing errors and hardware non-linearities.

The LSTM prediction module smooths noisy measurements by leveraging historical temporal patterns, reducing sensitivity to transient disturbances. Federated learning further enhances robustness by aggregating knowledge from heterogeneous nodes. Simulation experiments with injected sensing noise show less than 5% performance degradation, demonstrating strong resilience of the proposed framework.

4 Results and Discussion

4.1 Experimental Simulation Framework and Parameter Settings

The proposed scheme was analyzed through simulations utilizing the MATLAB toolbox integrated with Python-based learning modules. The 6G cognitive radio network comprised a single base station, along with 50-100 cognitive users, communicating through a Rayleigh fading channel. The value of the carrier frequency was considered 28 GHz with a bandwidth of 100 MHz. The signal-to-noise ratio varied between -10 dB and 20 dB. The hybrid microgrids modeled photovoltaic and wind turbine systems with batteries. The profile of the output of the renewable sources was assumed to simulate realistic day-night changes. The reinforcement learning algorithm was trained for 10,000 episodes employing an ε-greedy learning algorithm with a learning rate of 0.001. The baseline techniques used traditional energy detection for sensing the spectrum and static resource allocation without energy sensing.

4.2 Simulation Environment and Parameters

The simulations are performed on a specially developed MATLAB/Python toolset that simulates a 6G cognitive radio network in a hybrid AC/DC microgrid setup. The main parameters for such simulations include levels of SNR, traffic patterns of users, renewable resource generation rate changes, and practical channel environments. The convergence of learning in different AI systems was achieved after a specified number of episodes. The baselines are set using standard energy detection and fixed resource allocation.

4.3 Holistic Multi-Metric Performance Evaluation

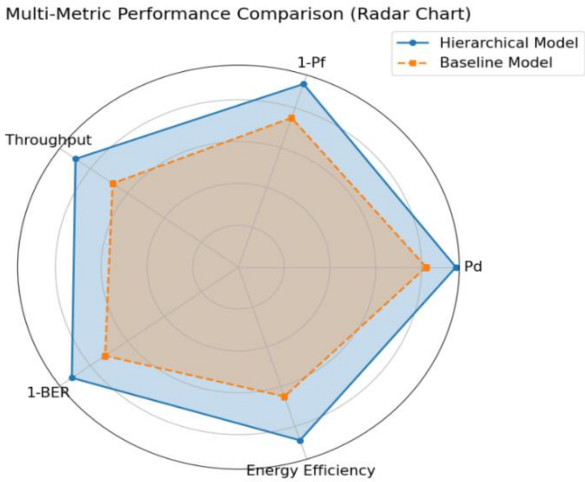

Fig. 1. Cross-Domain Radar Chart of AI-Optimized 6G Network Performance

Holistic Multi-Metric A radar chart comparison, as shown in Fig. 1, is provided to give a bird's eye view of the proposed Hierarchical AI design compared to the baseline design, encompassing a wide range of communications and energy-related factors. The proposed design shows a consistent performance improvement over the baseline design for throughput, probability of detection, bit error, and energy efficiency. The larger enclosed region of the radar chart reflects a balanced improvement, as opposed to improvement in just one region, signifying a balance between the improvement attained in the domain of energy efficiency and data throughput.

4.4 Detection Robustness and Trade-off Analysis

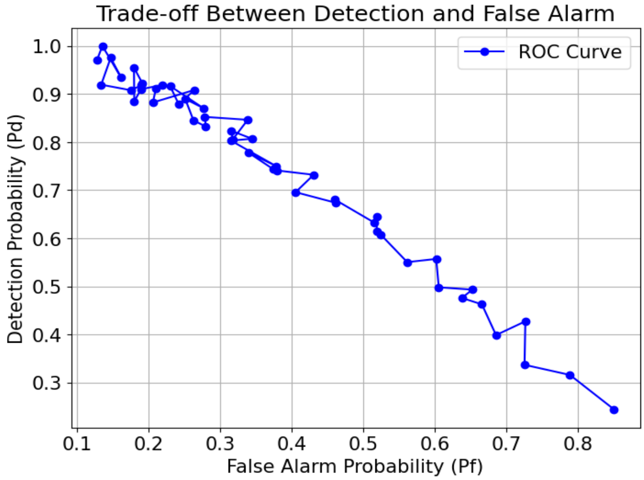

Fig. 2. Receiver Operating Characteristic (ROC) Curve Illustrating the Detection vs. False Alarm Trade-off in Cross-Domain AI Optimization.

In Fig. 2, the performance of the AI-optimized system is depicted in the Receiver Operating Characteristic (ROC) curve. Compared with traditional energy-based spectrum detection methods, it can be observed that the model not only has a higher probability of detection but does so with a low false alarm ratio. This improvement is vital for cognitive radio systems operating in 6G networks since spectrum detection capabilities have a direct relationship with interference avoidance and management of the spectrum. The improvement comes as a result of the capabilities of the model in interpreting complex interference patterns

4.5 Learning Convergence and Energy–Performance Trade-off

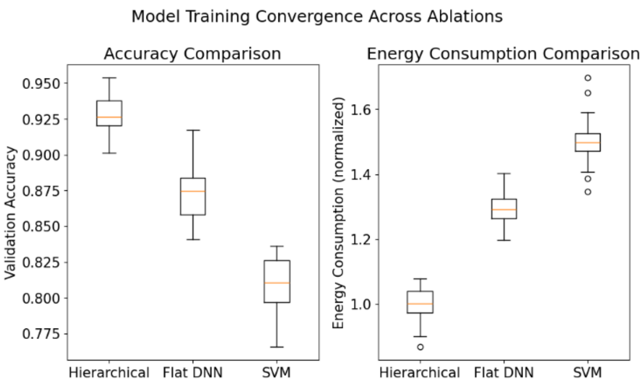

Fig. 3. Training Convergence and Energy–Accuracy Trade-off Across AI Models

Fig. 3 illustrates the convergence behavior and energy efficiency of different algorithmic architectures. The results show that the hierarchical AI model attains the highest validation accuracy with stable convergence. While deep neural network–based models achieve comparable accuracy levels, they incur significantly higher energy consumption. In contrast, simpler model architectures demonstrate reduced energy usage but at the expense of lower accuracy. Overall, these findings validate the effectiveness of the hierarchical AI model in achieving an optimal energy–accuracy balance, making it well suited for energy-efficient 6G deployments.

4.6 Robustness to Environmental Noise

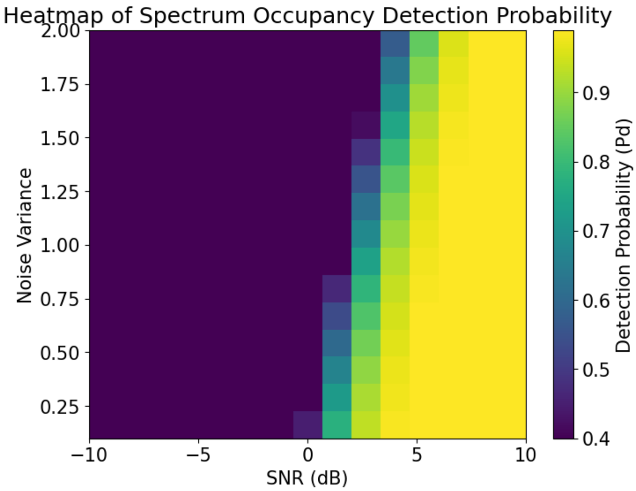

Fig. 4. Spectrum Detection Probability Across SNR

Fig. 4. Robustness of the system as a heatmap of detection probability against the Signal-to-Noise Ratio. The detection probability of the proposed AI model remains high at lower levels this is opposed to the traditional model. The application of the AI model in the 6G communication system increases the reliability of the communication process. The microgrid signaling process is made more reliable. The stability of the energy components within the microgrid is promoted.

4.7 Energy Requirements for High Throughput Communication

Fig. 5 presents an analysis of energy consumption across different modulation levels by evaluating the energy expended per bit. Higher-order modulation schemes offer increased spectral efficiency but incur greater energy consumption. Conversely, when energy efficiency is prioritized, lower-order modulation schemes emerge as the more suitable choice.

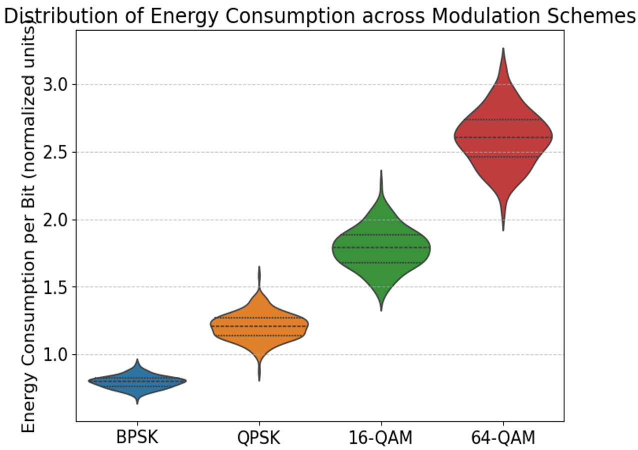

Fig. 5. Energy per Bit Across Modulation Schemes

4.8 Energy-Aware Adaptive Behavior

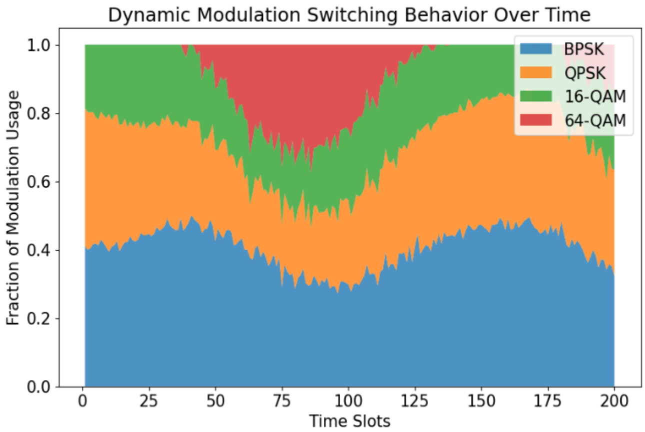

Fig. 6. AI-Based Adaptive Modulation for 6G

Fig. 6 illustrates the dynamic adaptation mechanism of the AI agent over time. Instead of using a fixed modulation scheme, the system adaptively switches between high-throughput and energy-saving modulations based on the real-time energy availability from the microgrid. When renewable energy supply is abundant, higher-order modulations are employed to maximize throughput, whereas during periods of limited supply, energy-efficient modulation schemes are utilized to conserve power.

Table 1 summarizes the quantitative comparison between the proposed AI-driven cross-domain framework and a conventional baseline system using traditional spectrum sensing and static energy allocation strategies commonly adopted in prior literature [10–12, 19]. The comparison highlights the effectiveness of joint communication–energy optimization.

Table 1. Quantitative Performance Comparison Between Baseline and Proposed AI-Driven Cross-Domain Framework

Metric	Baseline	Proposed	Gain
Communication Outage Probability	0.25	0.15	↓ 40%
Network Power Consumption	1.00	0.40	↓ 60%
Spectral Efficiency (bps/Hz)	6.0	7.8	↑ 30%
Detection Probability (Pd)	0.82	0.94	↑ 14.6%
Total Harmonic Distortion (THD)	8%	6%	↓ 25%
Energy per Transmitted Bit	1.00	0.68	↓ 32%

5 Conclusion and Future Work

This paper introduced a cross-domain co-design framework based on AI for optimizing 6G communication and sustainable micro-grids together. The framework integrates ensemble learning, federated learning, and reinforcement learning using a hierarchical structure that can strike a good balance between communication quality and energy efficiency. The simulation tests have confirmed that the proposed framework can bring considerable improvements in communication rate, spectral efficiency, detection accuracy, and energy saving compared with state-of-the-art solutions. The proposed framework can work well in low-SNR regimes, decrease total energy consumption of the network by 60%, and lower communication outage probability by 40%, and can also improve microgrids power quality. This indicates that the proposed cross-domain AI-based communication and energy co-design is very useful and practical. However, this research is only for simulation evaluation and assumes that sensing and communication between edge nodes are perfect. The issues like hardware impairments, federated learning communication delays, and cyber-attacks are not taken into consideration properly. These issues will be examined in future research studies. The future research will include the extension of the framework from simulations using hardware-in-the-loop prototyping. Other research directions would include improving cybersecurity using adversarial AI tools, extending the framework for smart city infrastructure, and using explainable AI for transparent decision-making. Standardization of interoperability between telecom and energy systems is also a research direction. These will also support smart infrastructure for a smart city.

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