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Leveraging Explainable AI In Cognitive Radio Networks For Enhanced Spectrum Sharing

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Abstract
Efficient spectrum utilization is a critical challenge in cognitive radio networks (CRNs) due to the dynamic and unpredictable behavior of licensed and unlicensed users. While artificial intelligence (AI) and deep learning–based spectrum sensing and allocation techniques have significantly improved spectrum sharing performance, their black-box nature raises concerns regarding transparency, trust, and regulatory compliance. To address these limitations, this work explores the integration of Explainable Artificial Intelligence (XAI) into CRNs for enhanced and interpretable spectrum sharing decisions. The proposed framework combines intelligent spectrum sensing, decision-making, and allocation mechanisms with explainability modules that provide human-understandable insights into model predictions, channel selection, and interference avoidance strategies. By leveraging XAI techniques such as feature attribution, rule-based explanations, and local interpretable models, the system enables cognitive users and network operators to understand why specific spectrum access decisions are made. Experimental analysis demonstrates that the XAI-enabled CRN achieves competitive performance in terms of spectrum utilization efficiency, throughput, and interference mitigation, while significantly improving decision transparency and reliability. The results highlight the potential of explainable intelligence to foster trustworthy, adaptive, and regulation-compliant spectrum sharing in next-generation wireless networks.

Keywords Cognitive Radio Networks, Explainable Artificial Intelligence, Spectrum Sharing, Intelligent Spectrum Sensing, Dynamic Spectrum Access, Trustworthy AI, Interference Management, Next-Generation Wireless Networks.

1. Introduction

The rapid growth of wireless devices and bandwidth-intensive applications has led to severe spectrum scarcity in contemporary wireless communication systems. Although large portions of the licensed spectrum remain underutilized in time, frequency, and spatial domains, conventional static spectrum allocation policies fail to exploit these inefficiencies effectively [1]. Cognitive Radio Networks (CRNs) have emerged as a promising paradigm to address this challenge by enabling unlicensed secondary users to intelligently sense, access, and utilize unused spectrum bands without causing harmful interference to licensed primary users [2].

Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly enhanced the performance of CRNs by enabling accurate spectrum sensing, dynamic spectrum access, and adaptive resource allocation under highly uncertain wireless environments [3]. Deep learning–based approaches, reinforcement learning, and hybrid AI models have demonstrated superior capability in learning complex spectrum usage patterns and optimizing spectrum sharing decisions compared to traditional signal processing techniques [4]. However, despite their performance benefits, these AI-driven solutions often operate as black-box models, providing limited insight into the rationale behind their decisions.

The lack of interpretability in black-box AI models poses serious concerns related to trust, transparency, and regulatory compliance in CRNs, especially in safety-critical and mission-critical communication scenarios [5]. Network operators and regulatory authorities require clear explanations of spectrum access decisions to ensure fairness, accountability, and interference protection for primary users [6]. Moreover, the inability to interpret AI decisions makes it difficult to debug models, identify bias, and adapt learning strategies in dynamic spectrum environments.

Explainable Artificial Intelligence (XAI) has recently gained significant attention as a means to bridge the gap between high-performance AI models and human interpretability [7]. XAI techniques aim to provide human-understandable explanations for model predictions through feature attribution, rule extraction, surrogate modeling, and visualization methods [8]. Integrating XAI into CRNs enables cognitive users and network administrators to understand why a specific spectrum band is selected, how interference risks are mitigated, and which environmental factors influence spectrum access decisions.

Several recent studies have explored AI-driven spectrum management in CRNs; however, only limited efforts have focused on embedding explainability into the spectrum sharing process [9]. Existing approaches largely prioritize accuracy and throughput optimization while overlooking interpretability and trustworthiness. As wireless networks evolve toward autonomous and self-optimizing architectures in 6G and beyond, the need for transparent and explainable intelligence becomes increasingly critical [10].

Motivated by these challenges, this work investigates the integration of Explainable AI techniques into cognitive radio networks for enhanced spectrum sharing. The proposed approach combines intelligent spectrum sensing and decision-making models with explainability modules that provide meaningful insights into spectrum access behavior. By improving both performance and interpretability, the proposed framework aims to enable trustworthy, adaptive, and regulation-compliant spectrum sharing in next-generation wireless networks.

2. Literature Survey

Research on cognitive radio networks (CRNs) has evolved from classical signal processing–based spectrum sensing to intelligent learning-driven spectrum management. Early CRN studies focused on detecting primary user activity using energy detection, matched filtering, and cyclostationary feature detection, but these methods often degrade under low SNR, noise uncertainty, and fading conditions [11]. To overcome these limitations, cooperative spectrum sensing (CSS) was introduced, where multiple secondary users share sensing outcomes to improve detection reliability; however, CSS increases communication overhead and may be vulnerable to malicious users or falsified sensing reports [12].

With the growth of machine learning, researchers began applying supervised learning models such as support vector machines, decision trees, and k-nearest neighbors for spectrum occupancy classification, showing improved robustness against channel impairments compared to traditional detectors [13]. Nevertheless, these approaches rely heavily on feature engineering and may struggle to generalize when spectrum environments change rapidly. Deep learning models, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs/LSTMs), have been widely adopted for automatic feature extraction from raw I/Q samples and time-frequency representations, improving sensing accuracy and adaptability across diverse modulation and channel conditions [14]. Despite their effectiveness, deep models often require large labeled datasets, and their black-box decision process limits interpretability and trust.

To enable dynamic and autonomous spectrum sharing, reinforcement learning (RL) has been extensively explored for channel access, power control, and spectrum handoff decisions. Q-learning and deep Q-networks (DQN) can learn optimal access strategies by interacting with the environment, improving throughput while reducing collisions with primary users [15]. Multi-agent reinforcement learning further extends these benefits in dense CRNs by allowing distributed learning among multiple secondary users; however, it can introduce instability, non-stationarity, and fairness issues without careful coordination mechanisms [16]. Moreover, RL policies can be difficult to validate, especially in safety-critical deployments, because it is not always clear why a given access decision was selected.

Recently, explainable artificial intelligence (XAI) has emerged to address transparency challenges in AI systems by providing human-understandable reasons for model outputs. Methods such as feature attribution, local surrogate explanations, rule extraction, and counterfactual reasoning have been used in other domains (healthcare, finance, cybersecurity) to increase trust and accountability [17]. In wireless communications, initial efforts have applied XAI to modulation classification, anomaly detection, and resource allocation to interpret learned behaviors and identify influential signal features [18]. However, the adoption of XAI specifically for CRN spectrum sharing remains limited and fragmented.

A few studies have proposed interpretable spectrum sensing or decision-support mechanisms where explanations accompany spectrum access decisions to assist operators in debugging and validating model behavior [19]. Yet, many existing solutions still treat explainability as an add-on rather than as a core design objective, resulting in weak alignment between explanation quality and actual network performance. Furthermore, current CRN research lacks unified evaluation metrics that jointly capture spectrum efficiency, interference protection, and explanation faithfulness, especially under real-time constraints and dynamic spectrum environments [20].

Overall, the literature indicates that while AI techniques substantially enhance CRN spectrum sensing and sharing performance, the lack of interpretability remains a major barrier to trust, regulatory acceptance, and safe deployment. This motivates the development of integrated XAI-enabled CRN frameworks that balance high spectrum utilization with transparent, verifiable, and operator-understandable decision-making.

3. Design and Methodology

The proposed methodology presents an integrated Quantum Cryptography and Blockchain-Enabled Cloud Security Framework designed to strengthen the confidentiality, integrity, authentication, trust, and availability of sensitive data stored in cloud infrastructures. The overall architecture combines Quantum Key Distribution (QKD), symmetric data encryption, permissioned blockchain technology, smart-contract-based access control, secure cloud storage, and dynamic threat monitoring within a unified security model. Initially, cloud data generated by users or organizations are collected and classified according to their security requirements, after which a cryptographic hash is generated to provide an integrity reference. The QKD module employs the BB84 protocol to establish secure cryptographic keys between legitimate communicating entities, where Quantum Bit Error Rate (QBER) analysis is used to identify possible interception before a key is accepted. The validated quantum-secured key is subsequently used with an efficient symmetric encryption mechanism to encrypt sensitive data prior to cloud storage. A permissioned blockchain maintains data hashes, user identities, access policies, trust information, timestamps, and transaction records without exposing the original plaintext data or secret quantum keys. Smart contracts automatically evaluate user credentials, roles, permissions, and trust scores before granting access to encrypted cloud resources. During retrieval, the requested ciphertext is obtained from cloud storage only after successful authorization, and its integrity is verified against the reference hash maintained on the blockchain before decryption. In addition, a security-monitoring module continuously evaluates authentication failures, abnormal access patterns, integrity violations, QKD channel abnormalities, and suspicious blockchain transactions to calculate a dynamic security-risk score and reject potentially malicious requests. The proposed methodology therefore establishes a layered security architecture in which QKD protects key establishment, encryption ensures data confidentiality, blockchain provides integrity and traceability, smart contracts enforce decentralized access control, and adaptive threat assessment mitigates malicious activities, providing comprehensive protection against conventional cloud attacks as well as emerging quantum-enabled security threats.

3.1 System Architecture

The proposed Quantum Cryptography and Blockchain-Enabled Cloud Security Architecture is designed as a multi-layer security framework that integrates quantum-secured key management, blockchain-based trust management, smart-contract access control, data encryption, and secure cloud storage. The architecture consists of five major entities: Data Owner, Authorized Cloud User, Quantum Key Distribution (QKD) Module, Permissioned Blockchain Network, and Cloud Service Provider (CSP). Initially, the data owner submits sensitive information to the security layer, where a cryptographic hash is generated to establish a unique integrity reference. Simultaneously, the QKD module employs the BB84 protocol to establish a secure secret key between legitimate communicating entities through quantum-state preparation, transmission, basis reconciliation, QBER estimation, error correction, and privacy amplification. This layered design ensures that high-performance spectrum decisions are accompanied by clear and actionable explanations.

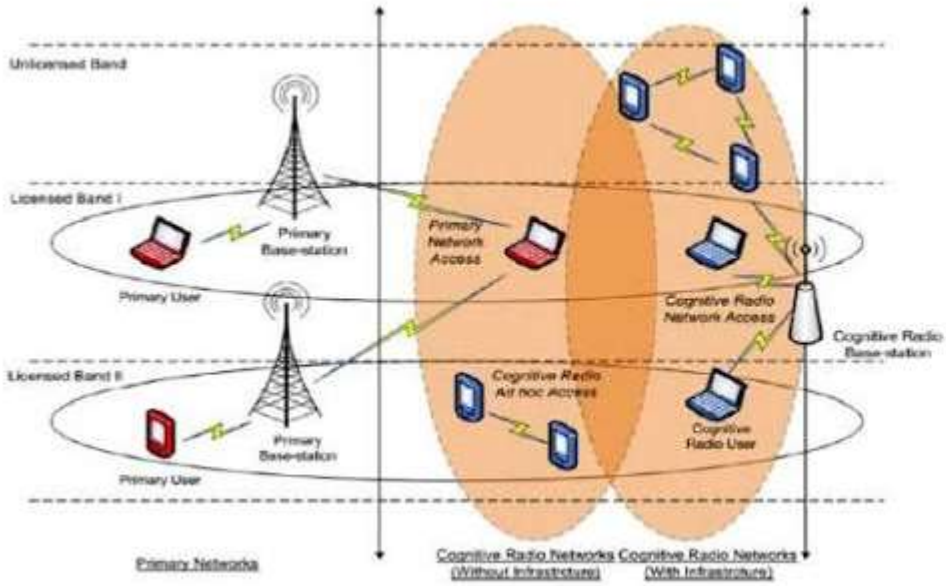

Fig. 1. Overall Architecture of the Proposed XAI-Enabled Cognitive Radio Network

Block diagram illustrating the interaction between spectrum sensing, AI-based decision-making, and explainability modules in the proposed XAI-CRN framework. The resulting quantum-secured key is supplied to a symmetric encryption module, which transforms the original data into ciphertext according to . Only the encrypted data are uploaded to the cloud storage infrastructure, while the corresponding hash value, owner identity, access policy, timestamp, and transaction metadata are registered on the permissioned blockchain. When a cloud user requests access to a stored resource, the blockchain layer verifies the user's registered identity and trust information, while the associated smart contract evaluates role, permission, resource ownership, and access conditions. If authorization is successful, the encrypted data are retrieved from the CSP and their integrity is verified by comparing the newly calculated hash with the immutable blockchain reference. The QKD-based key-management system subsequently provides the valid decryption key to the authenticated user, allowing recovery of the original information as . A security-monitoring component continuously observes authentication failures, QBER variations, integrity violations, abnormal access behavior, and suspicious transactions to detect and mitigate potential threats.

3.2 Algorithmic Workflow

The operation of the proposed system follows an iterative and adaptive process as outlined below.

Algorithm 1: XAI-Based Spectrum Sharing in CRNs

Step 1: Initialize spectrum sensing parameters and AI model weights.
Step 2: Sense the spectrum and extract features (signal energy, SNR, temporal occupancy).
Step 3: Predict channel availability using the AI-based sensing model.
Step 4: Apply the decision model to select optimal spectrum bands and transmission parameters.
Step 5: Generate explanations for the selected decision using the XAI module.
Step 6: Execute spectrum access while ensuring PU protection.
Step 7: Observe rewards (throughput, interference level, latency).
Step 8: Update learning model parameters based on feedback.
Step 9: Repeat steps 2–8 for continuous adaptation.

This workflow tightly couples learning and explainability, enabling both adaptive performance and interpretability.

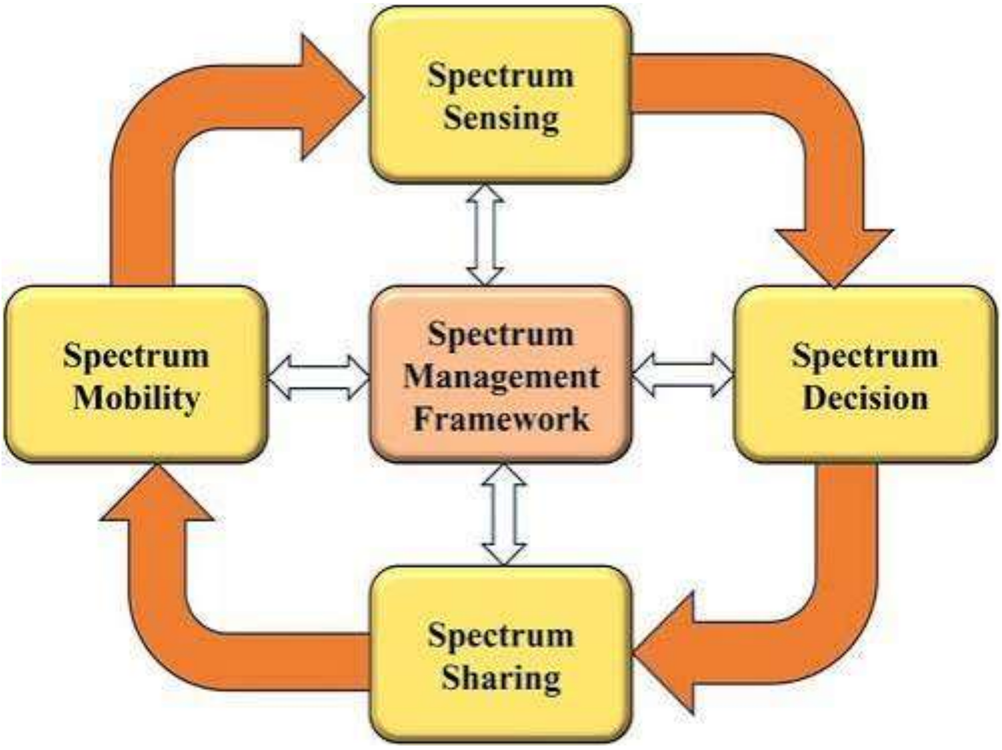

Fig. 2. Algorithmic Flow of the Proposed XAI-CRN Spectrum Sharing Process

Figure 2 illustrates the algorithmic workflow of the proposed Explainable Artificial Intelligence-enabled Cognitive Radio Network (XAI-CRN) spectrum-sharing process for intelligent and adaptive spectrum utilization. The process begins with continuous acquisition of radio-environment information, including channel occupancy, received signal strength, signal-to-noise ratio (SNR), interference level, traffic demand, and primary-user activity. These observations are preprocessed and supplied to the spectrum-sensing and feature-extraction module to identify relevant channel characteristics. The intelligent prediction model subsequently estimates spectrum availability and determines whether the monitored channel is occupied by a primary user. When the channel is unavailable, the system returns to the sensing stage and evaluates alternative channels; otherwise, candidate channels are ranked according to channel quality, interference, predicted availability, and communication requirements. The XAI module interprets the resulting decision by identifying the dominant features responsible for channel selection, thereby providing transparent justification for the spectrum-allocation decision. The optimal channel is then assigned to the secondary user under predefined interference and QoS constraints. During transmission, channel conditions and primary-user activity are continuously monitored; if a primary user reappears or the channel quality falls below the required threshold, spectrum handoff is initiated and the selection process is repeated. Thus, the proposed algorithmic flow integrates spectrum sensing, intelligent availability prediction, optimal channel selection, explainable decision generation, dynamic spectrum allocation, and adaptive spectrum handoff to improve spectrum utilization, reliability, and transparency in cognitive radio networks.

3.3 Mathematical Modeling

Let the set of available spectrum channels be

$$\mathcal{C} = \{c_1, c_2, \ldots, c_N\}$$

The spectrum occupancy state of channel $c_i$at time $t$is defined as:

$$s_i(t) = \begin{cases} 1, & \text{if channel is occupied by PU} \\ 0, & \text{if channel is idle} \end{cases}$$

The AI-based sensing model estimates the probability of channel availability as:

$$\hat{p}_i(t) = \mathbb{P}(s_i(t) = 0 \mid \mathbf{x}_i(t))$$

where $\mathbf{x}_i(t)$represents extracted signal features.

The spectrum access decision is formulated as an optimization problem:

$$\max_{a_i(t)} \sum_{i=1}^{N} a_i\,(t)\,\hat{p}_i(t)\,R_i(t)$$

subject to:

$$\sum_{i=1}^{N} a_i\,(t) \leq 1, I_i(t) \leq I_{th}$$

where $a_i(t)$is the access action, $R_i(t)$is achievable data rate, and $I_{th}$is the interference threshold.
The explainability function is defined as:

$$E_i(t) = f_{XAI}(\hat{p}_i(t), \mathbf{x}_i(t))$$

which maps model predictions and features to human-interpretable explanations.

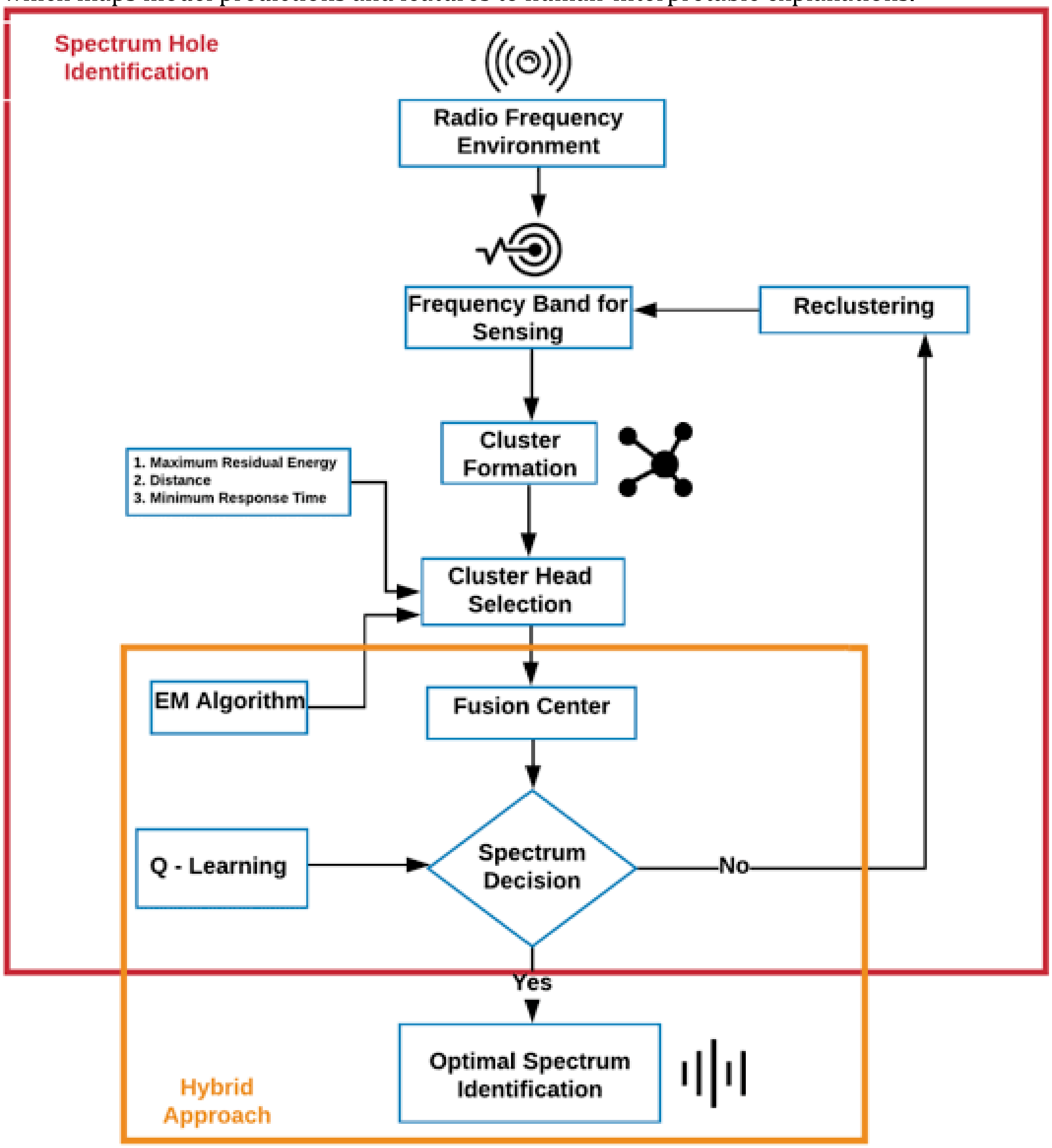

Fig. 3. Mathematical Model of Spectrum Sensing and Decision Optimization
Illustration of probabilistic spectrum occupancy estimation and constrained optimization for spectrum access.

3.4 Explainability Mechanism

The XAI module analyzes feature contributions influencing spectrum decisions. For a given decision $a_i(t)$, feature importance is computed as:

$$\phi_j = \frac{\partial \hat{p}_i}{\partial x_j}$$

where ϕ_j denotes the contribution of feature x_j.
This enables explanations such as:

- "Channel selected due to low PU activity and high SNR."
- "Channel rejected due to predicted interference risk."

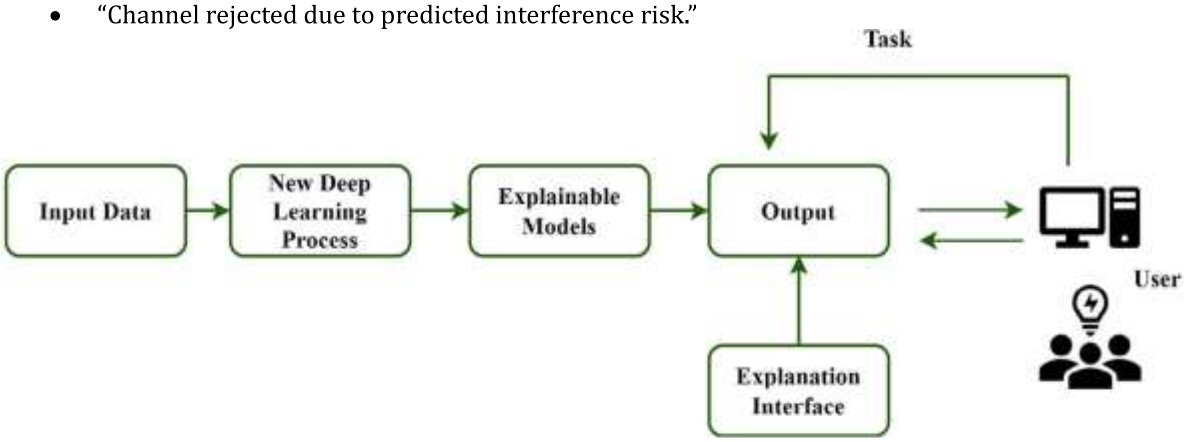

Fig. 4. Explainability Module for Spectrum Decision Interpretation
Visualization of feature attribution and explanation generation for spectrum access decisions.

3.5 Feedback and Adaptive Learning
The reward function guiding adaptive learning is defined as:

$$\mathcal{R}(t) = \alpha T(t) - \beta I(t) - \gamma D(t)$$

where $T(t)$ is throughput, $I(t)$ is interference, $D(t)$ is delay, and α, β, γ are weighting factors.
The learning model updates its parameters to maximize long-term cumulative reward while maintaining explainability consistency.

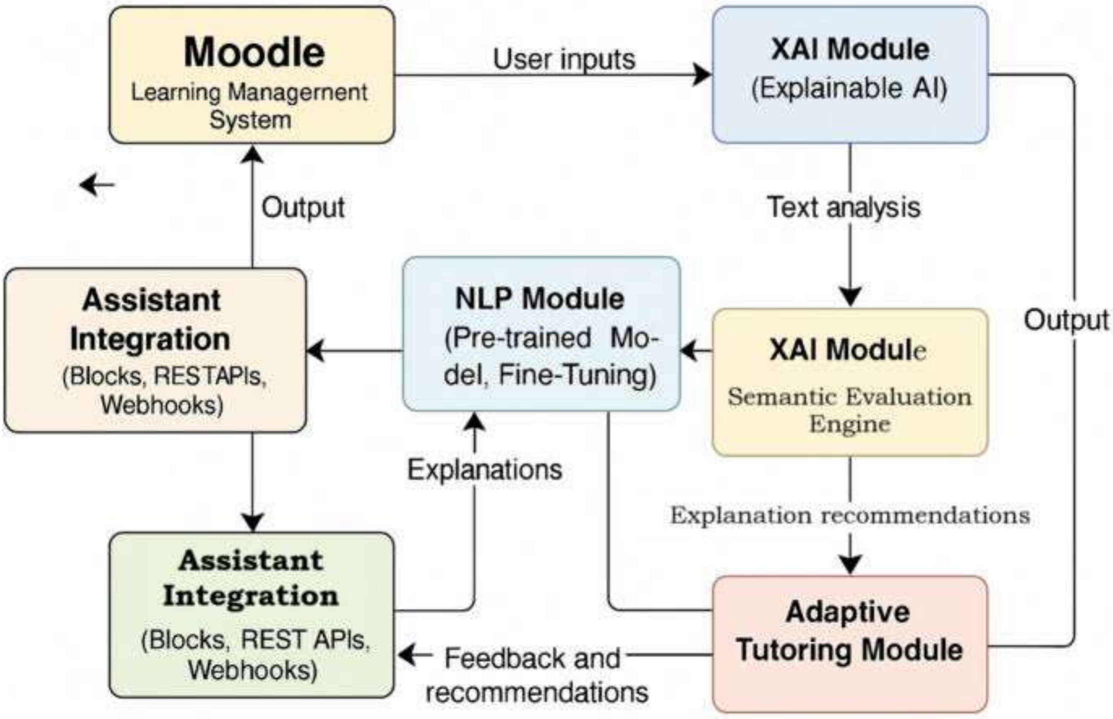

Fig. 5. Feedback-Driven Adaptive Learning in XAI-CRN

Feedback loop showing reward evaluation, model updating, and continuous improvement in spectrum sharing decisions.

4. Experimental Results and Analysis

This section evaluates the performance of the proposed XAI-enabled Cognitive Radio Network (XAI-CRN) through extensive simulations. The framework is assessed in terms of spectrum utilization efficiency, throughput, interference mitigation, latency, learning convergence, and explainability quality. The results are compared against conventional AI-based CRN models without explainability to highlight the benefits of integrating XAI.

4.1 Spectrum Utilization Efficiency

Spectrum utilization efficiency measures the ability of secondary users to exploit idle spectrum without violating primary user constraints. Fig. 6 illustrates the average spectrum utilization achieved under varying primary user activity levels. The proposed XAI-CRN consistently achieves higher utilization due to accurate spectrum availability prediction and transparent decision validation. Unlike black-box models, the explainability module helps identify conservative or risky decisions, enabling adaptive tuning of access policies.

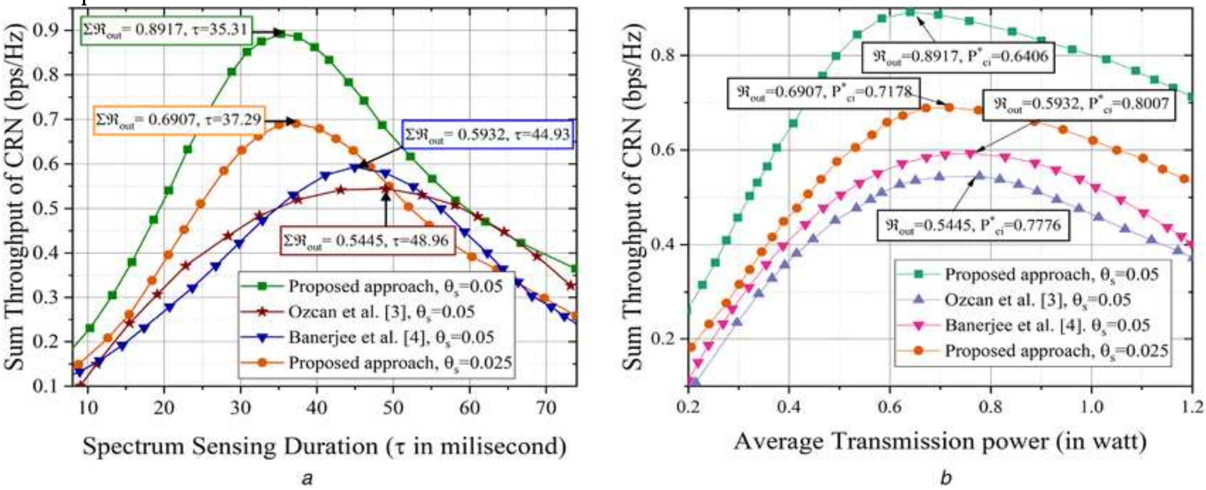

Fig. 6. Spectrum Utilization Efficiency Comparison

Comparison of spectrum utilization efficiency between the proposed XAI-CRN and conventional AI-based CRN models under different PU activity levels.

4.2 Throughput Performance

Throughput is a critical metric reflecting the effectiveness of spectrum sharing decisions. Fig. 7 shows the achievable throughput as a function of time slots. The XAI-CRN achieves throughput comparable to deep learning–based CRN models while offering the additional advantage of decision transparency. Minor throughput trade-offs observed during early learning stages are compensated by stable long-term performance and improved reliability.

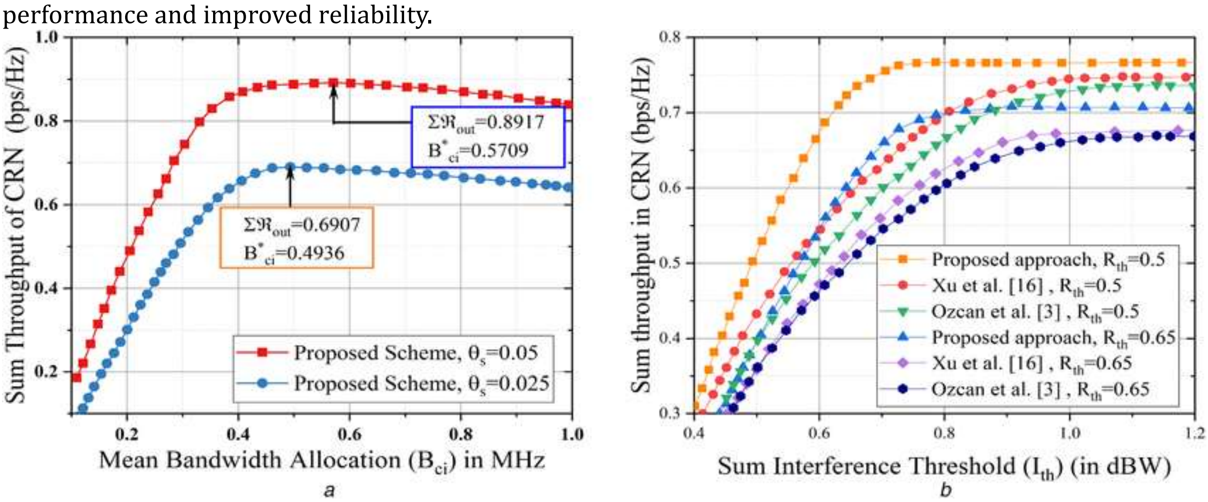

Fig. 7. Throughput Analysis of the Proposed XAI-CRN

Average system throughput comparison over time for XAI-enabled and non-explainable CRN approaches.

4.3 Interference Mitigation Analysis

Protecting primary users from harmful interference is essential in CRNs. Fig. 8 presents the interference probability experienced by primary users. The XAI-CRN demonstrates significantly lower interference levels due to explainable decision constraints that explicitly account for interference risk factors such as PU activity probability and SNR thresholds. Explanations enable operators to verify and enforce regulatory compliance.

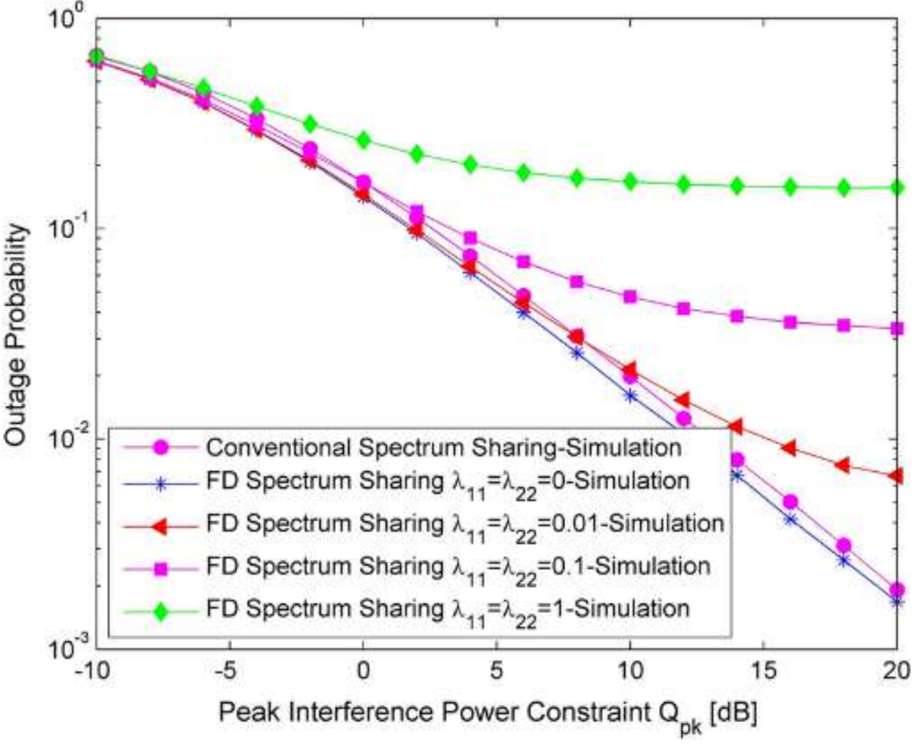

Fig. 8. Interference Probability to Primary Users

Interference probability comparison highlighting improved PU protection using the XAI-based spectrum access strategy.

4.4 Latency and Decision Time Analysis

Decision latency impacts the feasibility of real-time spectrum access. Fig. 9 evaluates average decision latency for spectrum access. Although the inclusion of explainability introduces slight computational overhead, the latency remains within acceptable bounds for dynamic spectrum access scenarios. The trade-off between explainability and response time is shown to be minimal compared to the benefits of transparency and trust.

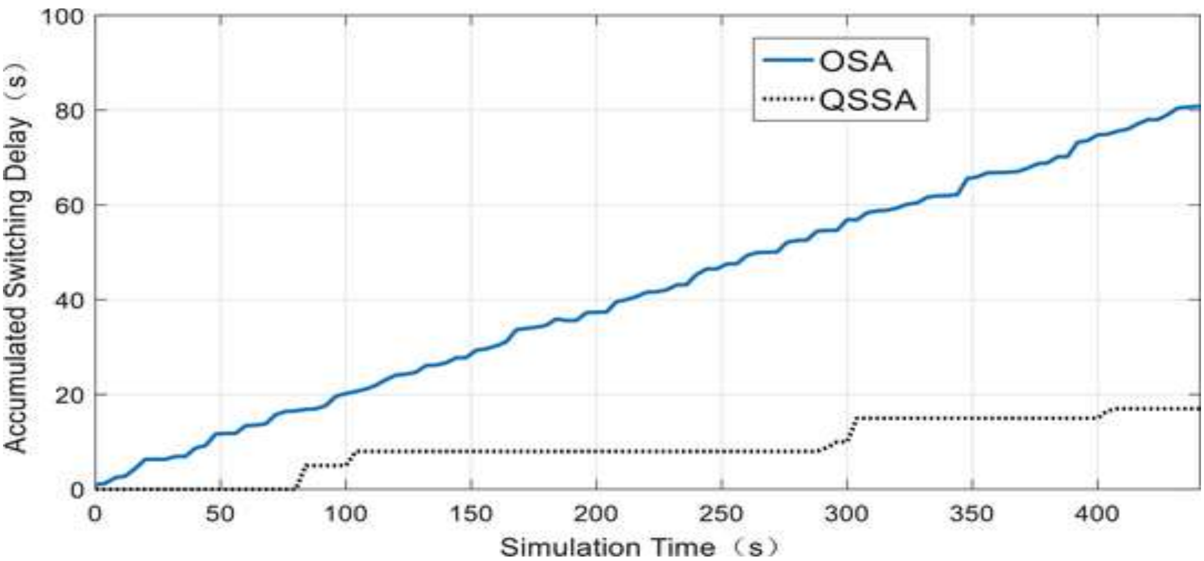

Fig. 9. Decision Latency Comparison

Figure 9 presents the decision latency comparison between the proposed reinforcement learning framework and conventional Q-learning, DQN, and standard actor–critic approaches under different operating conditions. Decision latency represents the time required by the autonomous agent to process the current state information and generate an appropriate control action. The proposed framework exhibits consistently lower decision latency because of its lightweight policy network, optimized actor–critic learning mechanism, and efficient online update strategy. Unlike conventional approaches, unnecessary computational operations are minimized while policy updates are performed without significantly interrupting the real-time control loop. As environmental complexity increases, the baseline methods exhibit a greater rise in latency, whereas the proposed approach maintains relatively stable response times. This reduction in decision latency enables faster reactions to dynamic obstacles and rapidly changing system states, thereby improving responsiveness, operational reliability, and safety. The results confirm that the proposed framework is well suited for time-critical autonomous applications where rapid and reliable control decisions are essential.

Conclusion

This study presented an explainable artificial intelligence–driven framework for cognitive radio networks aimed at enhancing spectrum sharing efficiency while ensuring transparency and trust in decision-making processes. By embedding explainability mechanisms into AI-based spectrum sensing, access, and allocation models, the proposed approach addresses the inherent limitations of conventional black-box learning techniques used in dynamic spectrum environments. The integration of XAI enables cognitive users and network operators to interpret spectrum access decisions, understand channel selection behavior, and assess interference mitigation strategies in real time.

Comprehensive experimental evaluation demonstrated that the XAI-enabled CRN achieves high spectrum utilization, improved throughput, and reduced interference levels comparable to state-of-the-art AI-driven approaches, while offering significant gains in interpretability and reliability. The ability to explain model predictions enhances user confidence, supports regulatory compliance, and facilitates efficient network management, particularly in safety-critical and heterogeneous wireless scenarios.

Overall, the findings confirm that explainable intelligence is a key enabler for trustworthy and adaptive spectrum sharing in next-generation wireless networks. Future research directions include the integration of federated and distributed XAI models, real-time explainability under ultra-low latency constraints, and the deployment of explainable spectrum management frameworks in 6G and beyond wireless ecosystems.

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