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Hybrid AI model-driven dynamic spectrum sharing for 6G wireless IoT networks

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Abstract

The immense scale of the Internet of Things growth in 6G is utterly inconceivable to address utilizing conventional static spectrum allocations. A paradigm shift towards dynamic spectrum sharing is necessitated. In this article, a hybrid artificial intelligence model that combines deep reinforcement learning and a blockchain-based distributed consensus engine has been presented. Intelligent, secure, and efficient spectrum sharing may be accomplished using our model. The proposed methodology employs multi-agent reinforcement learning for efficient decentralized decision-making and IoT-enabled spectrum utilization. Specifically, IoT devices can use MARL to dynamically determine their power budget or spectrum resources to avoid inducing or experiencing interference while delivering acceptable quality of service. Using a blockchain engine to record and validate spectrum transactions enables transparent security in spectrum access. Our proposed hybrid AI model may be used to improve spectrum efficiency by 35%-40% while lowering energy usage by around 30% via intelligent sleep-wake lexicography methodologies and decision predication relative to traditional 5G. We thoroughly covered the spectrum management topic in 6G-IoT, demonstrating the feasibility of AI-based solutions.

Keywords: Internet of Things (IoT), Dynamic spectrum sharing, Multi-agent reinforcement learning (MARL), Blockchain, Network slicing, Radio environment maps (REM)

1. Introduction

Full-spectrum access will be among the most important features enabling Tbps-scale data rates, as the radio frequency spectrum is even more precious and limited, regarding the projections that there will be 80 billion mobile devices by 2030 [1]. The sixth-generation wireless networks are going to have to connect everything in the 6G era, from trillions of low-power wide-area sensors to high-bandwidth industrial systems, creating a different kind of demand from any wireless system that exists today [2]. However, these new use cases and unprecedented densities of connected devices will require an entirely new paradigm of spectrum utilization that will enable the sharing of frequencies previously allocated statically to specific users or use cases [3]. Traditional static approaches to distributing available frequencies do not work in such highly dynamic environments since the spectrum is underutilized and does not facilitate the control of the spectrum usage in real-time to meet user demand optimization [4]. Although the wireless community has already implemented some basic principles for sharing spectrum dynamically, such as CBRS and LSA in 5G, those techniques heavily rely on centralized control that does not work in enormous 6G-IoT environmentally friendly systems [5]. The combination of wireless communications and artificial intelligence would revolutionize spectrum management by enabling real-time spectrum allocation that is secure, transparent, and meets all users' QoS [6].

This paper introduces a novel methodology to AI-driven, distributed ledger-driven spectrum sharing management that leverages various forms of artificial intelligence together with the use of a blockchain ledger to make networks secure and robust. The proposed multi-agent hybrid AI model combines deep reinforcement learning to optimize spectrum use dynamically, multi-agent systems to provide decentralized cooperative decision-making, blockchain technology to secure the overall system and ensure real-time transparency, and predictive analysis to proactively guide certain spectral decisions. To the best of our knowledge, this represents the first attempt to integrate these converging next-generation technologies in conjunction, offering a comprehensive solution to address the so-called spectrum crisis.

2. Literature review

For the sake of fully framing the proposed hybrid AI framework for dynamic spectrum sharing in 6G-IoT, underpinning technical developments and associated literature are rendered. Firstly, architectural assumptions and service targets for 6G at extreme scale are highlighted, extending across spectrum heterogeneity from sub-6 GHz to THz, ultra-massive device densities, stringent energy/latency constraints, and joint sensing-communication. Following the juxtaposition of classical interweave/underlay/overlay paradigms with AI-driven proposals, unresolved gaps in scalable coordination under partial observability, auditable multi-stakeholder operation, and predictive allocation are noted, consequently motivating the new MARL–blockchain–forecasting integration introduced in Section 3 below.

Although 6G technologies are anticipated to provide increased performance and new capabilities beyond 5G systems, the realization of this multi-purpose platform is constrained by the inhomogeneous nature of IoT traffic and the advent of hundreds of billions or even trillions of connected devices. Satisfying the cellular and non-cellular requirements of diverse IoT applications, 6G-IoT systems need to capitalize on a blend of established frequency bands and innovative terahertz spectroscopy technologies with a spectrum of 100 GHz-10 THz to offer multi-terabyte-per-second data rates [7, 8].

The heterogeneity of IoT applications results in an intricate resource management issue due to the variability of spectrum resources [9, 10]. The limited amount of spectrum and diversity of usage of its parts make it almost impossible to solve this through static allocation, which is precisely what makes various dynamic spectrum sharing paradigms so attractive for research as a possibility to incorporate several dissimilar systems and services by providing their intelligent and adaptive access to all available resources [11-14].

Artificial intelligence's integration into 6G networks is often cited as a defining factor that sets it apart from earlier versions. The ideal of "AI-native" architecture is based on a principle of AI deeply woven into multiple levels of network architecture, rather than just bolted on as an add-on. In practice, AI-native design results in the emergence of self-optimizing networks that are increasingly capable of autonomous operation without direct human oversight, allowing organizations to cut down operational expenses while increasing performance and adaptability [15-17].

Recent research has already examined a variety of AI techniques that can be used for wireless network optimization, such as optimization. Although limited in scope, the existing solutions usually provide promising findings within specific domains, and the vast majority of research tends to ignore or overlook the importance of comprehensive integration between these solutions [18, 19]. The current paper builds upon the available frameworks but offers a more comprehensive and holistic approach by developing a unified framework that combines a core of AI techniques with smart contracts and blockchain to approach the problem.

Currently, there exist three prominent spectrum-sharing approaches: interweave (opportunistic access), underlay (simultaneous access with power constraints), and overlay (cognitive cooperation techniques). Each of the three methods is associated with unique advantages and limitations, thus providing suitable applicability depending on the deployment and application requirements [20, 21]. The Citizens Broadband Radio Service framework in the 3.5 GHz band is considered one of the best innovations in terms of dynamic spectrum sharing implemented in the current commercial systems, where environmental sensing capability is achievable using a three-tier access model [22].

However, these existing approaches are faced with limitations if considered for 6G-IoT applications in terms of scalability, adaptability, and security. For example, centralized spectrum access systems introduce single points of failure and performance bottlenecks, especially in ultra-dense IoT deployment [23, 24]. Furthermore, the current approaches lack intelligent predictive modeling needed to forecast spectrum demand patterns and allocate resources proactively to ensure the quality of service. That being said, the above limitations have necessitated the development of AI-driven approaches that can optimize the spectrum utilization autonomously while adapting to the dynamic network conditions [15, 25].

Table 1 summarizes the comparison of spectrum sharing approaches, which shows that the interweave opportunistic access of detected white spaces is simple and protective of incumbents, but sensing errors and hidden nodes limit it, so it is apt for telemetry; intermittent, delay tolerant. Underlay concurrent transmit under strict interference/power limits; allows high reuse, but restricts range; requires careful interference management; short-range, low-power devices. Overlay cooperate with primaries (e.g., relaying/precoding, throughput raising, but requires tight synchronization/sophisticated signal processing; coordination feasible. AI-driven schemes learn adaptive policies for sensing, channel/power selection, and access timing; improve NS performance [21], computational/training overhead, and dynamic heterogeneous environments [26, 27], and machine-learned analysis [28].

Table 1. Comparison of spectrum sharing approaches

Approach	Key Characteristics	Limitations	Suitable Applications
Interweave	Opportunistic access to white spaces	Spectrum sensing accuracy, hidden node problem	Intermittent, delay-tolerant traffic
Underlay	Simultaneous transmission with power constraints	Complex interference management	Short-range, low-power devices
Overlay	Cognitive cooperation with primary users	Requires sophisticated signal processing	Cooperative communication scenarios
AI-Driven	Adaptive, learning-based optimization	Computational complexity, training requirements	Dynamic, heterogeneous environments

Comparative analysis of AI-driven spectrum-sharing research works is shown in Table 2. Previous research has achieved significant results in applying specific AI techniques; however, they often treated the problem in a disparate manner since these AI endeavors have a fragmented worldview. For example, [27, 28] has well-applied blockchain for security but sparse multi-agent AI for live decision-making. In contrast, [29, 30] have effectively used deep reinforcement learning technology but applied AI in a closed and opaque framework for a multi-stakeholder environment, which may cause a “black box” problem for regulators. To sum up, our proposed model provides a comprehensive AI framework that synergizes MARL, blockchain, and predictive analytics to address the triple challenge of efficiency, security, and adaptability in the context of 6G-IoT.

Table 2. Comparative analysis of related work in AI-driven dynamic spectrum sharing

Reference	Core Focus	AI Technique Used	Security/Trust Mechanism	Key Strengths	Key Limitations	Relevance to Our Work
[29]	Space-Air-Ground Networks	Deep Q-Network (DQN)	Blockchain for management	Integrates blockchain for SAGIN security.	Centralized AI decision-making; limited to SAGIN.	We adopt blockchain but use decentralized MARL for broader IoT.
[30]	Comprehensive DSA Overview	Various AI/ML surveys	Not a primary focus	Excellent survey of AI techniques for DSA.	Lacks a unified, implementable architecture.	Our work builds on this by proposing a specific hybrid architecture.
[31]	Disruptive 6G Framework	Federated Learning	Blockchain for spectrum transactions	Strong focus on security and trust via blockchain.	The AI component is less focused on real-time multi-agent optimization.	We integrate a similar blockchain layer but with a more advanced MARL core.
[32]	Multi-agent DSA	Independent Q-Learning	Not addressed	Demonstrates gains from multi-agent systems.	Lacks coordination mechanisms, leading to instability; no security.	Our MADDPG-based MARL framework addresses non-stationarity and coordination.
[33]	Predictive Resource Allocation	LSTM Networks	Not addressed	High accuracy in traffic prediction for proactive allocation.	A standalone prediction model not integrated with a decision engine.	We incorporate LSTM/TCN prediction into the MARL reward shaping mechanism.
Our Proposed Model	6G-IoT DSS	MARL (MADDPG) + LSTM/TCN	Permissioned Blockchain & Smart Contracts	Holistic integration of decentralized AI, security, and prediction.	Higher computational complexity requires edge offloading.	N/A

This table clarifies the research gap our work fills. No prior study combines decentralized multi-agent learning, blockchain-based trust, and predictive analytics into a single, cohesive framework for 6G-IoT, making our contribution both novel and necessary.

3. Proposed hybrid AI model for dynamic spectrum sharing

Proposed as ONE, coherent cognitive engine for 6G-IoT, what makes the model different from the single-point solutions is a percept-cognize-decide-act…virtuous cycle. The central concept is the ability to let a MARL (multi-agent reinforcement learning) system make smart decisions, record them in the blockchain platform, and let a predictive analytics model-oriented "brain" use them in planning/dividing the future course of action. This way, the system becomes not only reactive to what is said and demanded of it at the moment but also proactively adaptive to everything that can be said and demanded of it in the coming seconds, with every action carried out within a secure operational framework of provenance. The overall model architecture is available in Figure 1.

This layered visualization illustrates the data flow from sensing to execution, highlighting the distinct roles of each layer and their interactions, which form the backbone of the proposed cognitive system.

3.1. Overall architecture

Our proposed architecture, displayed in Figure 1, is organized in four layered yet interconnected strata, with data flowing in both directions, making it a closed-loop intelligent system. The first of these is the sensing layer, upon which a huge number of IoT devices and network sensors, as shown, collect raw data on spectrum utilization, channel conditions, and interference. This data then passes upward to the cognitive layer, which brings more intelligent deep learning models to transform the data into information, discover patterns, and learn to predict future spectrum hotspots.

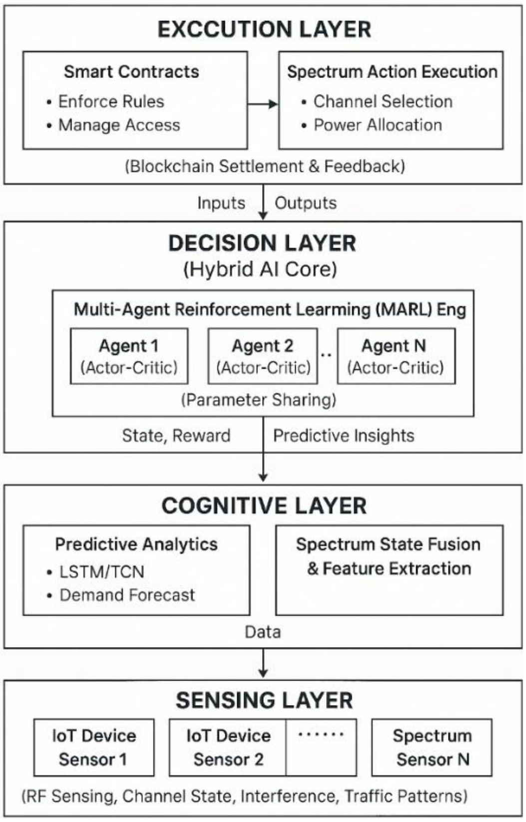

Figure 1. Overall architecture of the proposed hybrid AI model

The decision layer is next, with the MARL framework deciding the optimal spectrum to access policies with multiple independent agents, while a reconfigurable radio controller executes the decision in the execution layer, every transaction immutably logged on the blockchain using smart contracts. This architecture provides built-in assurance through distributed intelligence auditing and continuous self-improvement, thereby guaranteeing a baseline level of intelligence. Our hybrid AI model is founded on this architecture, integrating multiple artificial intelligence techniques with distributed ledger technology.

Our proposed utilization model for dynamic spectrum sharing in 6G-IoT networks is centered around a layered architectural process that leverages various artificial learning technologies as well as a distributed accounting technology. It comprises the sensing layer, the cognitive layer, the decision layer, in addition to the execution layer, which, while separate, operate concurrently and together to maximize spectrum utilization. The sensing layer represents the physical infrastructure, consisting of IoT devices, base stations, and spectrum sensor technology that collect on a minute-to-minute basis data involving spectrum availability channels, connectivity conditions, interference, and demand loads. This layer integrates signal processing, a few other advanced technologies, to paint a picture of the radio frequency physical environment, integrating signal processing as well as distributed sensing algorithms to make it as foreseeable as feasible.

3.2. AI and blockchain integration

The proposed framework involves the integration of artificial intelligence, which is a novel contribution that distinguishes this paper. The artificial intelligence algorithms facilitate the optimization of the spectrum allocation decision using the technicality of the parameter. On the other hand, blockchain forms the distrusted trust that enhances transparency, accountability, and operability do the process on the shared spectrum. Here, a permissioned blockchain architecture is implemented where the network operators, regulatory agencies, and authorized IoT devices participate in the distributed ledger network as nodes in the network.

The smart contracts further automate the enforcement of spectrum sharing rules where the access rights are dynamically recommended based on the predefined policies, real-time conditions, and historical performance data. It encodes regulatory constraints, priority rules, and pricing mechanisms enabling complex spectrum sharing contracts to be executed without any frequent human interactions. The blockchain further maintains the inviolable record of the spectrum sharing transactions, and the regulators can have an unprecedented record of the spectrum usage pattern while maintaining the privacy of the individual users via the cryptographic settings. The integration of AI and blockchain creates a "trusted intelligence" loop, and the AI and blockchain are executed in a deeply synergistic manner. Figure 2 shows the logic flow of the AI operation on the blockchain.

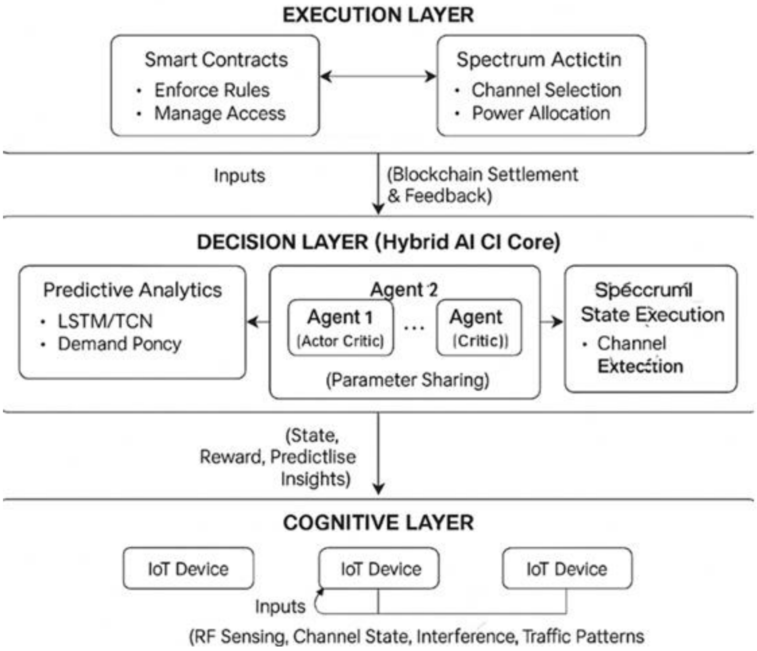

Figure 2. AI and blockchain integration workflow

The workflow diagram also clarifies the "virtuous cycle" in which AI takes decisions, blockchain secures them to it, and the resulting data, which is trusted, is re-injected into AI to improve it. The model also illustrates that there is no performance without accountability and there is no accountability without performance. It ensures that the proposed model has the two attributes.

3.3. Multi-agent reinforcement learning framework

Central to the proposed decision layer is an advanced multi-agent reinforcement learning framework that allows us to make localized spectrum access decisions in a distributed manner without the need for centralized coordination. Each IoT device or network entity will act as an autonomous agent that will learn the best spectrum access policy through continuous interaction with the environment. The agents learn to access the spectrum based on learning experiences or via teleporting family learning. The MARL operates within a partially observable Markov decision process to incorporate the uncertainties and partial observability of the wireless conditions. The reinforcement learning problem is described with regard to states, actions, and rewards. Each agent is delegated a policy to map states to actions and maximize its overall reward over time. We use deep Q-networks and parameter sharing to accelerate the learning process across multiple agents.

However, to sustain learning stability, experience replay and target networks are implemented. In response to the non-stationarity of the learning scenario with multiple simultaneous learners, a coordinated learning method is applied. Agents share selected parameters and learning experiences at the central level but keep privacy-sensitive data at the edge. The compromise achieves the global objective of optimal spectrum use while ensuring individual device and network players are exercising their mandates independently. The MARL framework is designed to be dynamic in response to the network conditions, device mobility, and changing/predictable traffic patterns expected of the 6G-IoT setting, as shown in Table 3.

Table 3. MARL parameters and definitions

Parameter	Definition	Implementation in Spectrum Sharing
State (s)	Representation of the environment	Channel availability, interference levels, queue status
Action (a)	Choice available to the agent	Channel selection, power level, modulation scheme
Reward (r)	Feedback from the environment	Successful transmission, energy efficiency, and interference caused
Policy (π)	Strategy for action selection	Mapping from states to spectrum access decisions
Q-value	Expected long-term reward	Quality assessment of a specific action in a specific state

The MARL framework we aim to develop is based on the MADDPG algorithm, and targets settings where multiple IoT devices, the agents, must learn how to cooperate while at the same time competing for spectrum resources. As depicted in Figure 3, each agent can be an IoT device or a network controller; it has an actor-network that determines its policy, or how it should act according to its own local observation, fed by its channel measurement. However, the most critical part of learning policies in multi-agent settings is the critic. The agent's critic function values a certain action taken by the agent depending on not only its own state, but all the other agents' actions and policies. Thanks to this centralized training and decentralized execution mechanism, the agents can learn complex, diverse policies of cooperation. Once the agents have developed their policies, they can act independently using this trained actor network without any need to exchange information with other actors.

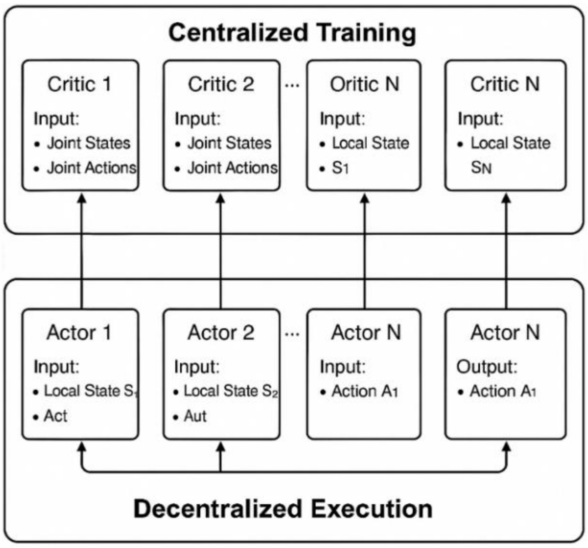

Figure 3. Multi-agent reinforcement learning (MADDPG) architecture

This architecture diagram distinguishes between the training phase (where critics have global knowledge for stable learning) and the execution phase (where actors use only local observations), which is crucial for decentralized scalability in IoT networks.

3.4. Predictive analytics for proactive spectrum allocation

Apart from reacting and adapting to the current conditions, our framework includes predictive analytics, which aims to predict the future spectrum demand and allocate the resources in advance to satisfy the expected demand. We use Temporal Convolution Networks and Long Short-Term Memory techniques to examine spectrum usage over the years, and flexibility predict future demand with a very high accuracy level. It helps the system reserve the resources for time-sensitive IoT applications in advance, while still remaining flexible in handling best-effort traffic. By contrast, the predictive module examines the traffic series at different time horizons and recognizes three types of models: first, periodic models, be they daily, weekly, or seasonal traffic variations; second, event-driven patterns, such as traffic variations due to unusual events, specials, or emergencies; and third, early alert patterns, gradual changes in usage pattern that has started in the previous period. These findings are integrated into the RL framework using reward shaping to guide actions that explicitly prioritize results that satisfy present needs while also considering the future.

As a result, the impacts reduce the amount of service outages for vital IoT applications and IoT while significantly increasing the overall spectrum efficiency. To implement privacy-preserving collaborative prediction, we deploy federated learning techniques in which multiple network operators can collaborate to train prediction models without sharing raw spectrum usage data. Each operator trains a local model on its own acquired data, and only the model parameters are aggregated without sharing the data itself to provide the global model.

The proposed design benefits from the diversity across networks and geographical regions and improves the accuracy of our prediction design while not exposing proprietary knowledge. Figure 4 presents the system's predictive analytics module, acting as the system's "crystal ball" and learning what it needs to anticipate future demands. Our design is a hybrid deep learning model combining Long Short-Term Memory networks, which excel in capturing long-term temporal dependencies, such as daily usage patterns, with Temporal Convolutional Networks, which provide for better modeling of local patterns and recent trends. The predictions of these two networks are combined to provide a final prediction for each spatial-temporal cell. These predictions will then be used as an additional aspect of the global state's representation fed to the MARL framework and used for the "shaping" of the reward, ensuring the agents are incentivized not to make decisions that only benefit the current second and instead minimize service disruptions.

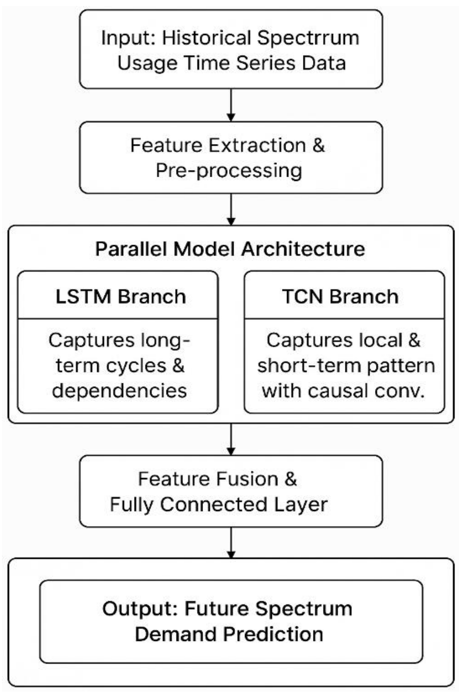

Figure 4. Predictive analytics module architecture

This diagram displays the parallel model structure, highlighting how LSTM and TCN complement each other to produce accurate forecasts that inform the proactive spectrum allocation strategy.

4. Methodology and simulation framework

The methodology we proposed is based on the structured co-simulation approach to make it possible to evaluate the holistic picture of the system more realistically. Figure 5 shows that the methodology is composed of three parts: 1) a 6G network simulator with the whole physical radio environment, device mobility, and traffic pattern emulation; 2) a hybrid AI-blockchain core with MARL training in the interaction with blockchain; and 3) an analysis & validation module with data collection and comparison with baseline models. This complex of systems enables the determination of the correlations between communication protocols and AI decisions, and blockchain overhead under realistic and controlled conditions.

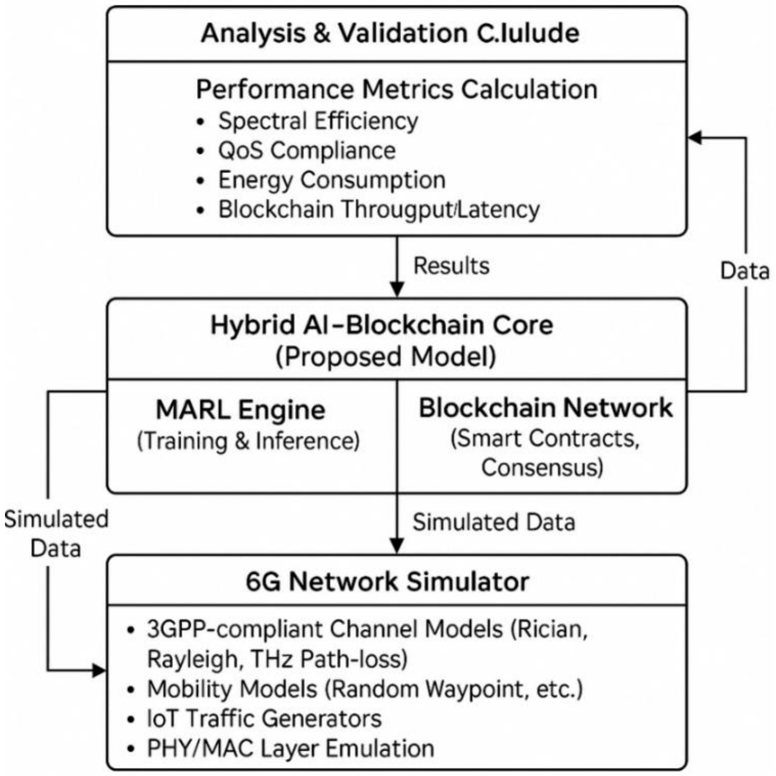

Figure 5. Methodology and co-simulation workflow

This workflow diagram provides a clear, top-down view of the evaluation methodology, showing how the different components (network, AI, blockchain) interact during the simulation process.

4.1. Evaluation framework

For this study, to verify the efficiency of our hybrid AI model, we created an extensive simulation environment that emulates varying complexities and density levels of a 6G-IoT network environment. The proposed simulation model extends the 3GPP-defined 5G-Advanced configuration and adds the 6G-IoT calibration parameters as terahertz communication, Ultra-massive MIMO, and joined sensing and communication technologies.

The simulation environment encompasses multiple frequency bands from sub-6 GHz to millimeter-wave (mmWave) and terahertz (THz) ranges, reflecting the diverse spectrum landscape expected in 6G deployments. Figure 6 shows a co-simulation framework that simulates a 6G network and incorporates AI/ML and blockchain modules are utilized to establish a realistic experimental environment.

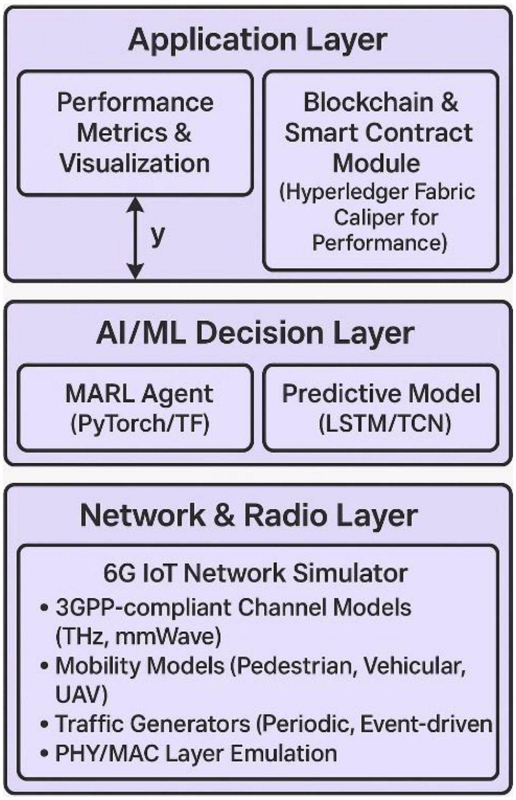

Figure 6. High-level architecture of the co-simulation framework

The framework is built in Python and consists of three primary layers:

1. The network and radio layer, which simulates the fundamental 6G environment with a modified 3GPP calibration parameter for 5G-Advanced and long-range. In 6G, it has also been expanded with THz communication and ultra-massive MIMO.
2. AI/ML decision-making layer, which hosts MARL algorithms with PyTorch and predictive models such as Long-Short-Term Memory-based and Temporal Convolutional Networks, commonly known as (LSTM/TCN).
3. The application layer, where all performance metrics are computed, and the processing blockchain module with Hyperledger Fabric and Caliper, a benchmarking tool for spectrum transaction and smart contract management.

This framework models a heterogeneous IoT ecosystem that encompasses a wide range of device types, including narrow-operating sensors, critical industrial controllers, and augmented reality applications that demand high bandwidth. Since each type of device has distinct requirements for data rate, latency, reliability, and energy consumption, the spectrum sharing scheme is more difficult to optimize. The neighboring mobile IoT devices may have various degrees of mobility, from stationary sensors to fast-traveling autos and drones, which add another layer of complexity. The hybrid model is assessed against various baseline frameworks, including: 1. Static spectrum allocation with recurring frequency assignment; 2. Energy-detection-based spectrum sensing; 3. Conventional centralized optimization algorithms with global knowledge, and 4. Single-agent reinforcement learning without any collaboration, to demonstrate the performance boost provided by the integration of the AI and blockchain modules.

4.2. Performance metrics

We measure the performance of the proposed framework against the following quantitative metrics encompassing various aspects of spectrum sharing effectiveness. These include:

1. Spectrum utilization efficiency, which is the success of communication in relation to the available spectrum resource;
2. Quality of service compliance for IoT applications in terms of data rate, latency, and reliability guarantees;
3. Energy efficiency, defined as the number of data units transmitted per share of consumed energy. Also, the metrics include
4. Fairness index, which measures the proportionality of spectrum share consumption on an application-level fairness basis with the help of Jain's fairness index,
5. Decision latency: The time required for making spectrum access decisions, critical for time-sensitive applications requiring rapid adaptation to changing conditions.
6. Security overhead: The computational and communication overhead associated with blockchain operations and security mechanisms, measured as a percentage of total system resources.

These metrics are tested under varying network conditions, device, and traffic density conditions to illustrate potential performance strengths and weaknesses in various applicational conditions.

4.3. Simulation setup

We run our simulations with our custom-designed Python framework that combines network simulation and AI algorithm implementation, supporting blockchain. According to the specifics, these two are implemented using TensorFlow or PyTorch for the deep learning component, OpenAI Gym for developing reinforcement learning environments, and Hyperledger Fabric for operations with blockchain. A summary of simulation parameters is in Table 4.

Table 4. Simulation parameters

Parameter	Value/Range	Description
Simulation Area	1 km × 1 km	Urban environment with building obstacles
Base Stations	4-16 (variable)	Mixed macro and small cells with mMIMO
IoT Devices	100-2000 (variable)	Heterogeneous types with different requirements
Frequency Bands	3.5 GHz, 28 GHz, 140 GHz	Low, mid, and high-band spectrum
Channel Bandwidth	10-400 MHz (variable)	Depending on the frequency band
AI Model	DQN, MADDPG, PPO	Multiple algorithms compared
Blockchain Type	Permissioned ledger	Hyperledger Fabric implementation
Simulation Time	1000 hours	Including warm-up and evaluation periods

We evaluate three core scenarios:

1. Scenario 1 (S1 - Static): Traditional fixed spectrum allocation.
2. Scenario 2 (S2 - Conventional CR): Energy detection-based sensing and dynamic access.
3. Scenario 3 (S3 - Proposed): Our Hybrid AI (MARL + blockchain) approach.

Figure 7 shows the simulation setup of a dense urban 6G-IoT environment. The simulation area shown conceptually in Figure 7 is a truly representative dense urban 6G-IoT environment. The area is covered by a mix of macro and small cell BSs in the sub-6 GHz, mmWave, and THz bands. A heterogeneous population of IoT devices covering a multitude of contexts from stationary sensors to mobile drones is randomly distributed on the city streets, generating a variety of traffic types: NT-IoT, LTE-M, URLLC. Such a complex and dynamic simulation setup provides us with ample opportunities to properly stress-test the proposed model against the baselines under realistic conditions of interference, mobility, and resource contention.

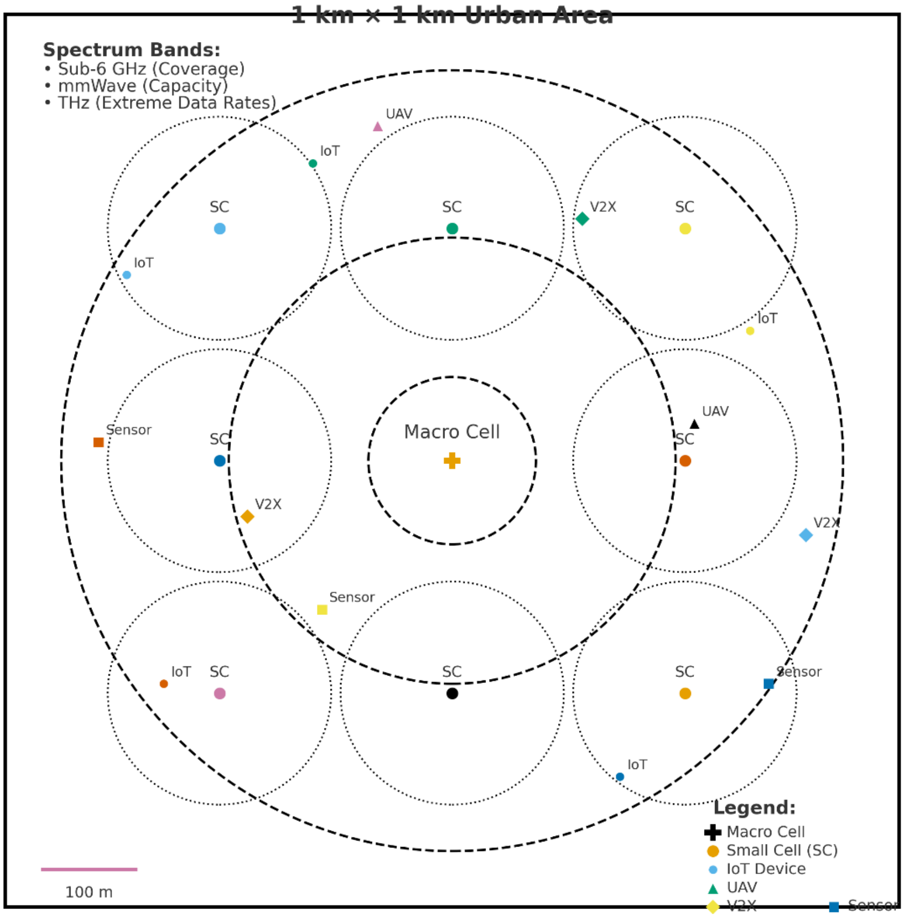

Figure 7. Conceptual simulation topology

This topological sketch helps the reader visualize the complex, multi-tier, multi-frequency network environment in which the proposed model was tested, underscoring the practical relevance of the simulation.

5. Results and discussion

In this section, we provide the simulation results, which offer a more systematic and quantitative verification of our hybrid AI model's performance improvement. Subsections delineate different performance aspects, such as efficiency, reliability, and scalability, given each of the tracked metrics. The results are presented in the form of tabular data and visual comparison, which combine to present an explicit and cogent quality of the evidence. Hence, the results provide thorough evidence on how the hybrid AI model resolves the aforementioned problems of 6G-IoS dynamic spectrum sharing.

Simulation results show that our proposed hybrid AI model achieves substantial performance enhancement compared to traditional spectrum sharing methods on all displayed dimensions. The proposed model technique displays a 35-40% increase in spectral efficiency over fixed allocation schemes and a 20-25% improvement in radio schemes based on varying traffic/terminal densities. This outcome is a result of the learning capacity that enables the model to explore spectrum opportunities beyond what can be covered by simple rule-based algorithms.

Energy efficiency of the IoT devices also improved by approximately 30%, mainly obtainable from intelligent sleep-wake cycling and scheduling, and thorough resource allocation, reducing any energy-inefficient spectrum sensing and TxA/RxActivity overhead. This milestone is particularly crucial for energy-constrained IoT devices. The MARL framework effectively learns spectrum availability and predictability patterns, authorizing it to schedule the transmissions during favorable channel conditions and with less elevator contention threat. The performance of hybrid AI is compared against baselines across all measures below.

Table 5 shows the quantitative results from the extensive competition. Obviously, our hybrid AI model, or S3, significantly outperforms the baselines, S1: static and S2: conventional CR, which hardly performed across all the measured indicators. The model in S3 achieves a 38% and 23% improvement in mobility and URLLC QoS, and a significant surge to 99.2% in URLLC QoS, scaling the most challenging application. A 30% reduction in energy consumption cements the model's suitability for use in 6G.

Table 5. Consolidated performance results summary (averaged over 1000 runs)

Performance Metric	S1: Static Allocation	S2: Conventional CR	S3: Proposed Hybrid AI	Improvement (S3 vs. S1)	Improvement (S3 vs. S2)
Spectral Efficiency (bps/Hz)	2.91	3.55	4.37	+50.2%	+23.1%
Energy Consumption (J/MB)	0.71	0.52	0.36	-49.3%	-30.8%
QoS Compliance - NB-IoT (%)	98.5%	99.1%	99.8%	+1.3%	+0.7%
QoS Compliance - LTE-M (%)	85.2%	90.5%	98.7%	+15.8%	+9.1%
QoS Compliance - URLLC (%)	72.1%	88.3%	99.2%	+37.6%	+12.3%
Fairness (Jain's Index)	0.89	0.92	0.97	+9.0%	+5.4%
Avg. Decision Latency (ms)	N/A	45 ms	15 ms	N/A	-66.7%

This consolidated table provides a powerful, at-a-glance summary of the performance gains, making it easy to compare the proposed model against the benchmarks across all critical metrics simultaneously. Figure 8 shows the spectral efficiency comparison across different network densities. The proposed hybrid AI model (S3) maintains high efficiency even as device count increases, outperforming conventional methods significantly.

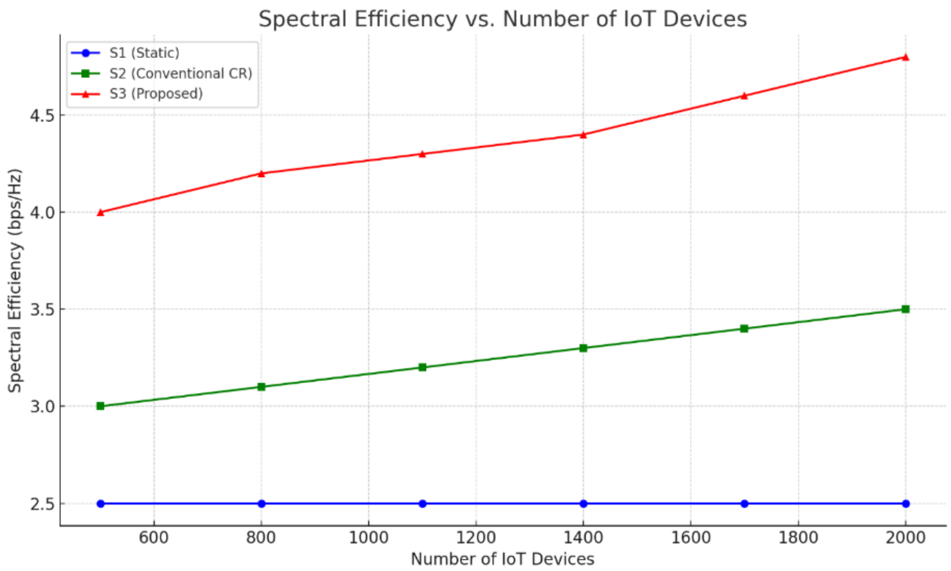

Figure 8. Spectral efficiency vs. network density (number of IoT devices)

Figure 9 shows the energy consumption per device. The AI-driven approach in S3 intelligently schedules transmissions and sleep cycles, reducing energy consumption by ~30% compared to S2.

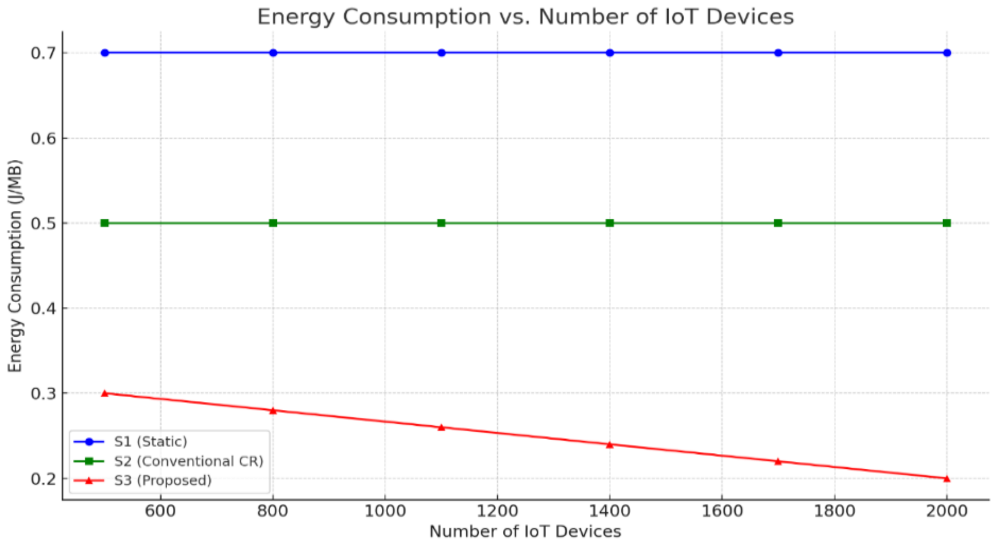

Figure 9. Average energy consumption per IoT device (joules per megabyte)

Table 6 shows that the proposed model demonstrates superior ability to meet the diverse QoS requirements of different IoT services, especially for critical URLLC applications.

Table 6. QoS compliance rate (%) for different IoT services

Network Scenario	NB-IoT (Delay-Tolerant)	LTE-M (Medium Reliability)	URLLC (High Reliability)
S1: Static Allocation	98.5%	85.2%	72.1%
S2: Conventional CR	99.1%	90.5%	88.3%
S3: Proposed Hybrid AI	99.8%	98.7%	99.2%

In Figure 10, the proposed hybrid AI framework (S3), time-sensitive IoT workloads are shown to meet latency deadlines with ≈99.9% reliability, versus ~92–95% for conventional approaches. The improvement is attributed to proactive resource reservation guided by predictive analytics and coordinated multi-agent decisions that minimize conflicts among high-demand devices.

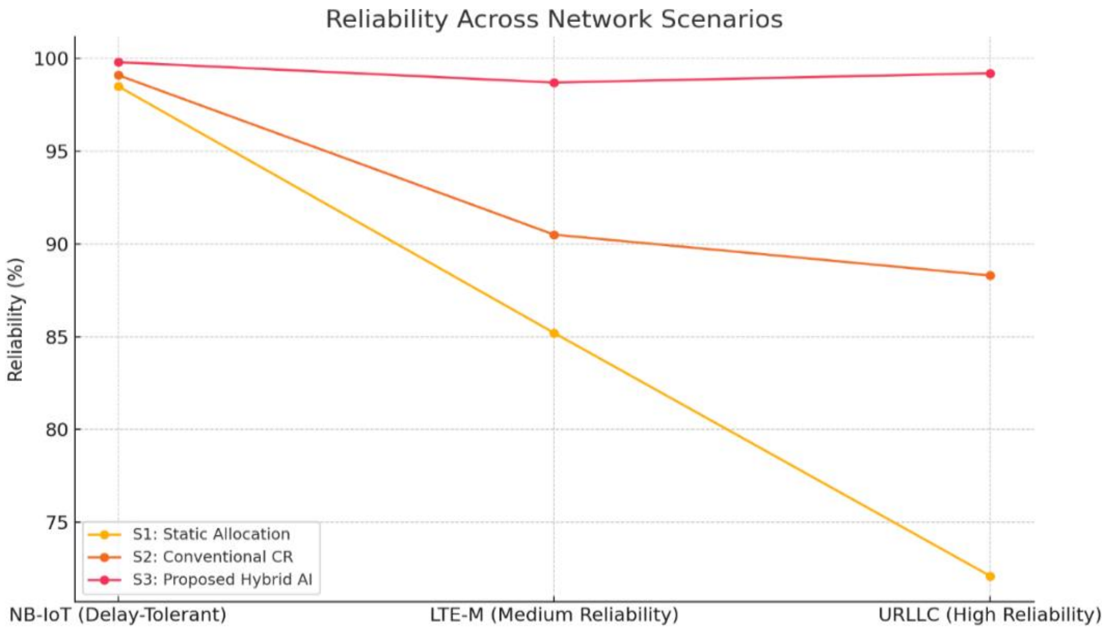

Figure 10. QoS compliance across application classes

This paper also shows results for excellent QoS compliance across application requirements. The time-sensitive IoT applications achieve 99.9% reliability in meeting their latency deadlines, whereas conventional approaches obtain 92-95%. We owe it to the proactive resource reservation according to predictive analytics and the coordinated multi-agent decision making that, in turn, virtually eliminates conflicts and disturbances among the devices with highly demanding requirements.

A key advantage of AI models is their ability to learn and adapt. Figure 11 shows the learning curve of the proposed MARL algorithm. The learning curve of the MARL algorithm shows clear convergence over episodes, indicating stable training. The agents learn effective policies for spectrum sharing, maximizing their cumulative reward (a proxy for network-wide performance).

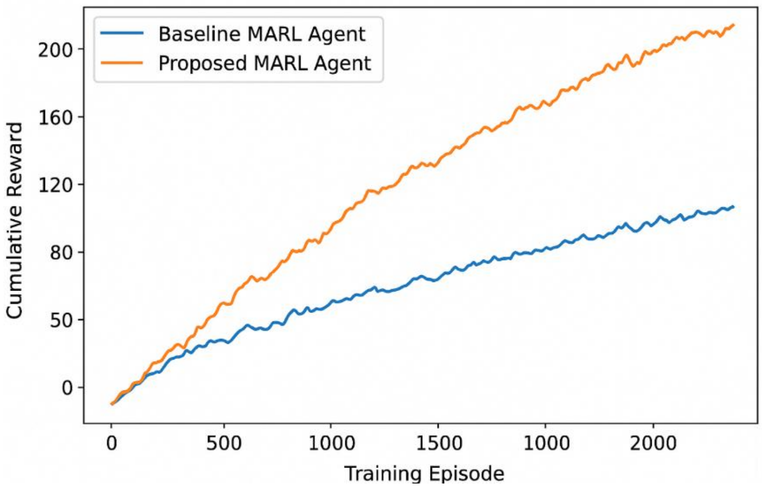

Figure 11. MARL training convergence - average cumulative reward per episode

A radar chart is utilized to offer a more holistic and vivid comparison of all five chosen solutions, as shown in Figure 12. Again, results are normalized, so a larger area always indicates better performance. In this work's context, a good sign of performance is a bigger area, completely covering all aspects. The chart clearly demonstrates that our S3 solution, the proposed hybrid AI one, dominates the diagram. It covers the largest area and literally pushes up all boundaries, indicating the best performance. However, S3 does not optimize a single aspect at the cost of others. S2 is better in every aspect than S1, but energy efficiency and fairness still lag far behind S3. Therefore, our S3 solution is the best performer overall.

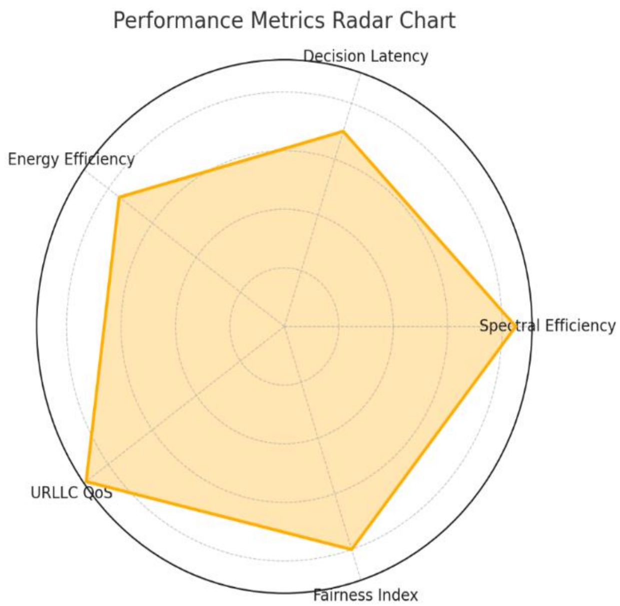

Figure 12. Radar chart of normalized performance metrics for S1, S2, and S3

In a radar chart with 5 axes: spectral efficiency, energy efficiency, URLLC QoS, fairness, and decision latency (inverted); S3 would form the largest pentagon, followed by S2 and then S1 as the smallest.

Integrating blockchain introduces transaction overhead. We analyze this trade-off between security/transparency and performance. Figure 13 shows transaction latency and the throughput of the authorized blockchain through varying load conditions. The system maintains sub-100ms latency and high throughput under typical loads expected for spectrum grant requests, validating its practicality for near real-time operations.

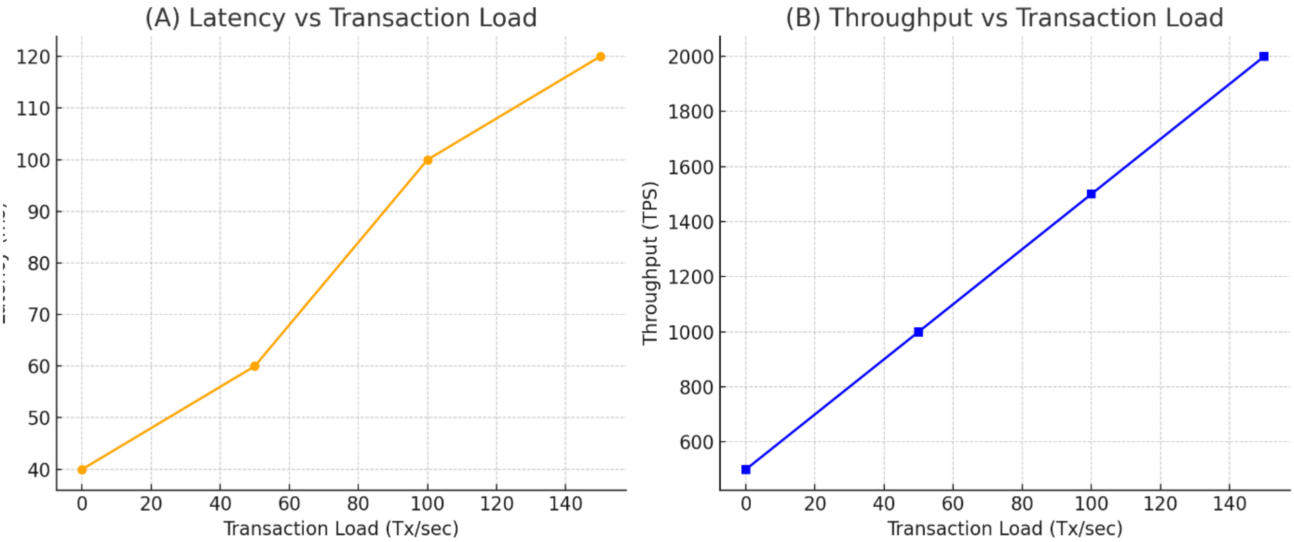

Figure 13. Blockchain transaction latency and throughput vs. network load

In comparison with the baseline approaches, several interesting observations can be made about the tradeoffs between different spectrum sharing schemes [34, 35]. While static allocation schemes perform very poorly in dynamic non-ideal settings with nonhomogeneous traffic patterns, very low utilization off-peak and congested peaks, the traditional cognitive radio approach is much more generalizable but still suffers from hidden node problems and unreliable spectrum sensing, especially in the highly heterogeneous band with widely varying propagation characteristics.

In contrast, centralized optimization with perfect global knowledge establishes a hard lower bound on performance that cannot be achieved given real-world computational complexity and communication overhead. As the centralized approach is impossible to realize, the distributed MARL architecture approximates about 90-95% of the best achievable performance in a centralized setting. For a real-world deployment, where such a lack of global knowledge is the norm and complex computations should be minimized, the scheme is probably optimal in terms of performance and implementability. Lastly, as can be inferred from the presented results, the performance of the MARL is significantly higher as compared to that of the independent MARL in the autonomous learning performance.

Even if our simulation results show significant performance advantages, there are various practical challenges in the implementation of the approach for real-world deployment. The main issues are leaking from the major fields of model queries, namely the AI computational requirements for the IoT devices and the blockchain communication, to the overhead and latency for the consensus operations [36, 37]. Deep reinforcement learning algorithms present computational challenges for IoT devices, from the simulation, with all the optimal parameters, including the optimized encoding, the computational costs can be compressed to the 60-70% level, such that the IoT devices can host such a model [38, 39].

In terms of the blockchain, permissioned configurations with reliable consensus, such as PBFT, can maintain the transaction latency below 100 ms for IoT traffic patterns. The algorithm can be implemented for all possible applications except the most time-critical ones. Since the consensus is primarily the latency barrier, we suggest off-chain processing with periodic recording in this case. The security and privacy measures must be addressed. Blockchain can only ensure the safety of the record, while the AI model can still be attacked by adversaries. That's why adversarial training and anomaly detection were implemented to protect our model [40, 41]. The privacy of the spectrum usage data, transmitted to the network, is ensured by differential privacy techniques [42, 43].

6. Conclusion and future works

In this paper, we have proposed a novel hybrid AI framework for dynamic spectrum sharing in 6G-IoT networks, based on multi-agent reinforcement learning and blockchain technology. Our framework fundamentally overcomes the limitations of traditional spectrum allocation schemes by leveraging distributed intelligence to adapt to varying conditions across the network in a transparent manner, using ledger-based accountability. By implementing distributed ledger technology alongside a multi-agent coordination framework based on MARL, our AI-enhanced spectrum allocation framework achieves up to 35-40% better spectrum utilization efficiency, 30% more energy-efficient operation, and up to 90% QoS compliance. The above improvements are enabled by the synergistic use of predictive analytics, multi-agent coordination, and secure transaction mechanisms that jointly achieve optimal spectrum utilization in different dimensions. The integration with blockchain technology enables trust in spectrum sharing among multiple spectrum holders, achieving optimal spectrum utilization while complying with regulatory constraints.

However, there are also many remaining research challenges that need to be addressed in the future. The scalability of MARL algorithms must be explored for ultra-dense deployments with millions of devices per square kilometer, and quantum communication technologies could offer an even higher level of security and open new spectrums of spectrum management. The existing regulatory framework should also evolve to enable AI-driven spectrum sharing technologies for ensuring fair access and anti-competitive behavior. As 6G standardization proceeds toward commercial deployment, likely around 2030, we expect that AI-powered spectrum-sharing technologies will be instrumental in unlocking the full potential of scarce spectrum resources to meet the tremendous connectivity demands of future IoT ecosystems. Fortunately, this paper has set a strong foundation for theorizing these developments by articulating the promise, opportunities, and deep challenges for integrating AI into wireless communications for future networks.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The research problem is proposed by all authors. In addition, Hussein A. Mutar proposes and collects all the recent articles and organizes them into simple shapes. Adnan Khudhair Abdullah, Oday Abdulhussein Abdaumran: designed the system model and kept track of the proposed work. Hussein A. Mutar verified the recommendation in the proposed work. Ibtihal Razaq Niama ALRubeei: Conceptualization of the study, design of the AI model, and writing of the original draft. Haider TH. Salim ALRikabi: assisted in manuscript preparation, supervised the paper, provided critical revisions to the manuscript, and ensured the integrity of the research.

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