Radius: Journal of Science and Technology
Vol. 2, Issue 2, (2025) 252002 (15pp)

AI-Driven Spectrum Intelligence and Energy Optimization Techniques for 6G Networks: A Comprehensive Review

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Abstract: As wireless technology moves toward sixth generation (6G) networks, future wireless communication systems must be intelligent, self-optimizing, and energy-efficient. To address increasing pressure on spectrum, systems will need to integrate AI (artificial intelligence) and ML (machine learning) technologies to facilitate dynamic spectrum access, efficient energy distributions, and max data throughput. This review examines key AI-driven techniques for spectrum intelligence and energy optimization in 6G networks. The applications of spectrum prediction employing deep learning, reinforcement learning for dynamic spectrum allocation of resources, and federated learning approaches that provide distributed decision-making capabilities in heterogeneous wireless environments are highlighted. The roles of intelligent multiple-input multiple-output (MIMO) antennae and reconfigurable surfaces as design tools for maximizing the spectral efficiency and energy efficiency of systems is also examined. Recent designs in MIMO operating in sub-6 GHz have been employed as reference points for novel systems. Comparative analyses show that the AI enabled spectrum optimization techniques vastly outperform conventional static allocation in spectral efficiency, latency and energy efficiency. Finally, the review concludes with a discussion on the outstanding research challenges corresponding to trustworthy AI frameworks, sustainable energy frameworks, spectrum sharing etc., which will lead us to towards fully autonomous and energy efficient 6G networks.

Keywords: 6G networks, Spectrum intelligence, Artificial intelligence, Energy optimization, MIMO antenna, Machine learning

1. Introduction

The evolution of wireless communication has reached a critical turning point with the emergence of the sixth-generation (6G) paradigm. While fifth-generation (5G) systems have already transformed digital connectivity through enhanced broadband capacity, low-latency communication, and massive device integration, they are now constrained by the growing complexity of intelligent services and energy sustainability challenges **[1, 2]**. The new 6G framework is expected to provide data rates greater than 1 terabit per second (Tbps), ultra-reliable sub-millisecond latencies, and increasingly natural interaction between humans, machines, and the environment **[3, 4]**. These benefits will heavily leverage artificial intelligence (AI) and machine learning (ML) to allow autonomous management of spectrum and energy resources.

https://doi.org/10.5281/zenodo.17611239
Received: 19 October 2025 | **Revised:** 05 November 2025
Accepted: 11 November 2025 | **Published Online:** 14 November 2025

1.1 Transition from 5G to 6G and Spectrum Implications

The transition from 5G to 6G represents a significant advancement in network speed and connectivity, along with a paradigm shift in how intelligence and self-optimization are realized in communication systems **[5]**. While advancements have been made in antenna technology and multiple-input multiple-output (MIMO) technology in 5G networks **[6, 7]**, static spectrum allocation and inflexible power control will stifle the scalability of the system. Existing 5G infrastructure largely operates in sub-6 GHz and mm Wave bands, which will become saturated in dense deployment scenarios **[8, 9]**.

6G will seek to create ubiquitous connectivity using all spectrum types, including sub-THz and visible light bands, which will have the potential to create advanced sensing and adaptive spectrum access. Spectrum intelligence that enables AI to detect underutilized frequencies in real time, and adaptive reconfiguration of channels will enhance both, spectrum efficiency and utilization fairness. Deep reinforcement learning (DRL) models and neural networks have proven capable of learning from radio environment maps, optimizing frequency reuse, and predicting interference with minimal human involvement **[10, 11]**.

1.2 Energy Efficiency and Sustainable Design in 6G Networks

Power consumption has become an important research area in the next digital generations of communication networks. The implementation of ultra-dense small cells and devices, Internet of Things devices and intelligent sensors has highly increased the overall power consumption of the worldwide digital electronic communications infrastructures **[12]**. Efficient energy-optimization techniques are therefore essential to minimize carbon footprint while maintaining service quality and low operational cost. Federated learning frameworks further support this possibility by training the distributed local models at the level of the different nodes avoiding a centralization of the data, thus allowing low communication costs and low energy consumption. The combination of spectrum intelligence and energy optimization is the basis of the vision of the 6th generation digital independent learning intelligent network of the future, sustainable by definition **[13]**.

1.3 Role of Intelligent Antenna and MIMO Architectures

The implementation of efficient 6G systems depends heavily on antenna design. Modern MIMO architectures have been developed extensively around improved isolation, miniaturization, and high-frequency support. Research on slotted patch and advanced button mushroom MIMO antennas has shown improvements in both bandwidth and isolation characteristics for sub-6 GHz, as well as applications in new high frequency regimes.

High isolation dual-band slotted patch MIMO antennas have been developed specifically for sub-6 GHz 5G operations with a performance baseline suitable for scalable 6G systems. A four-element button mushroom MIMO antenna was researched with similar potential for high-density network deployments with increased radiation efficiency and substantial reductions in mutual coupling **[14]**. Additionally, recent developments in antenna technologies allow for adaptable dynamic beam pattern and impedance matching that comply with environmental scenarios, providing new opportunities for design processes for AI-enabled reconfigurable systems. Figure 1 illustrates the overall conceptual architecture of AI-driven spectrum and energy optimization in 6G networks, highlighting the interaction between antenna systems, learning models, and adaptive communication layers.

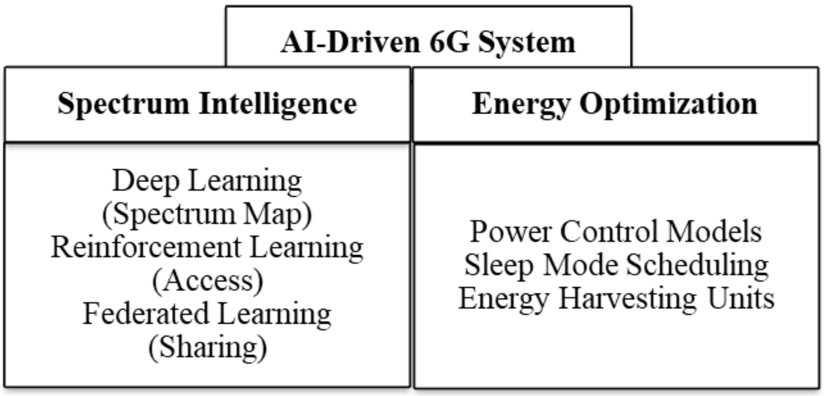

Figure 1: Conceptual Model of Spectrum and Energy Optimization Using AI for 6G

As shown in Figure 1, AI models operate across multiple layers, enabling context-aware spectrum access, adaptive MIMO configuration, and energy-aware scheduling. This integrated view clarifies the role of learning-based mechanisms in achieving self-optimizing 6G communication systems. The combination of AI with adaptive MIMO and reconfigurable intelligent surfaces (RIS) helps to develop self-healing and self-optimizing networks. These models allow the network to anticipate interference, adjust polarization, and maintain a reliable link under changing propagation conditions **[15]**.

1.4 Motivation and Research Scope

As communications technology and AI converge, the intelligent management of both spectral resources and energy becomes increasingly possible through AI technology. Optimization techniques that have traditionally been used to manage the many interdependent factors involved in optimizing wireless networks are unable to optimize the highly dimensionalized, nonlinear relationships that exist between the numerous elements within dynamically changing wireless network conditions. In contrast to traditional optimization techniques, AI driven networks can autonomously find optimal ways to send data, perform energy aware scheduling and predict future demand for resources as a result of contextual information. To build upon this motivation, the following section reviews existing research on spectrum intelligence, energy optimization, and intelligent antenna systems for 6G networks.

2. Literature Review

The transition from 5G to 6G introduces intelligent, adaptive, and energy-aware networking architectures capable of self-optimization. AI, ML and deep learning (DL) will play critical roles in addressing issues of increasing radio resources management complexity, spectrum allocation and energy efficiency for future generations of wireless networks **[1, 2]**. The research community has proposed various framework integrations that include AI and DL for both spectrum intelligence and energy efficiency while also including antenna design to address the challenges associated with increased connectivity (massive MIMO), reduced latency and ultra-reliability.

AI and ML play central role in future wireless environments by enabling prediction, adaptive control, and autonomous optimization. Rather than relying on fixed rule-based policies, learning models identify patterns in spectrum usage, power consumption, and network dynamics, allowing 6G systems to self-organize, allocate resources efficiently, and respond to real-time demands. This unifying capability supports both spectrum intelligence and energy optimization within a common intelligent networking framework.

2.1 AI-Driven Spectrum Management in 6G

Spectrum management techniques need to be drastically redesigned in light of the exponential growth in wireless devices and data-intensive applications. Because next-generation networks are dynamic, traditional static allocation techniques are ineffective. 6G is envisioned by researchers as a context-aware, AI-powered ecosystem that can learn, predict, and optimize spectral resources in real time.

According to Saad et al. **[1]** and Tataria et al. **[2]**, spectrum intelligence will serve as a foundational element of 6G, supported by AI models capable of automatically detecting, classifying, and allocating frequencies based on user requirements and environmental conditions. In a similar matter, Strinati et al. **[3]** characterized 6G as integration of both communication and sensing; in which reconfigurable surfaces and holographic messaging create the next layer of electromagnetic intelligence. Federated learning is also receiving attention toward distributed spectrum optimization, where local trained models work collaboratively without any sharing of central data, preserving privacy and scalability. Authors identified federated learning as a catalyst for cooperative multi-agent resource management, potentially beneficial to edge-frequent and dense network deployments.

2.2 Energy Optimization and Green Intelligence

Energy efficiency may be the single most important performance metric that defines sustainability in 6G networks. In particularly ultra-dense deployments, traditional cellular systems operate often require excessive power, in an effort to reduce power consumption with little sacrifice to performance, there can be AI-based energy optimization schemes that dynamically change base stations activity, antenna layouts or transmission policies.

Wireless powered communication networks (WPCN) were first reported by Bi and Zhang **[4]**. The basis for energy harvesting designs in new build systems was thus established. In 6G, the concept can be extended by combining AI driven control loops and energy harvesting.

Buzzi et al. **[7]** looked at energy-efficient communication methods and established flexible transceivers for green networking and hardware-aware neural networks. Subsequently, in dynamic beyond 5G scenarios, Zhang et al. **[8]** noted that DRL models could reduce energy consumption independently but increase throughput as well. The emerging use of RIS, also enhances energy efficiency, and minimizes transmit power by adjusting the propagation environment to increase the signal strength. All these efforts help to achieve future wireless networks' net-zero energy ambitions.

2.3 Intelligent Antenna & Reconfigurable Systems

AI-embedded antenna design development on the physical layer is another transformative step to 6G. Although large-scale MIMO has shown promise, significant challenges exist with scaling and adaptive control in rapidly varying channels. Early research has begun to consider how deep learning could autonomously tune antenna geometry, and even improve radiation efficiency and coupling.

Pan et al. **[10]** emphasized the importance of holographic MIMO surfaces and RIS-assisted MIMO systems, which could change beam patterns and even electromagnetic responses adaptively, and in real time. Lu et al. **[11]** employed deep learning algorithms to optimize antenna array configuration and showed that the neural models not only had much faster convergence speed, but produced higher levels of accuracy than any traditional algorithm.

In the range of sub-6 GHz, multiple antenna platforms demonstrate a level of innovation and efficiency that is quickly adapting to AI-based control. Sandeep et al. have devised high-isolation slotted patch MIMO antennas **[12]**, in addition to button mushroom MIMO structures **[13, 14]**. Both designs have stable impedance characteristics and relatively low mutual coupling, and the miniaturized forms are ideal prototype precedents for implementing AI-driven adaptation, where machine learning algorithms inherently adapt surface currents or feeding structures and optimize performance given the inherently variable spectral conditions **[15]**. Figure 2 presents the research landscape for AI-driven spectrum and energy optimization, mapping intelligent algorithms to system-level functions in 6G networks.

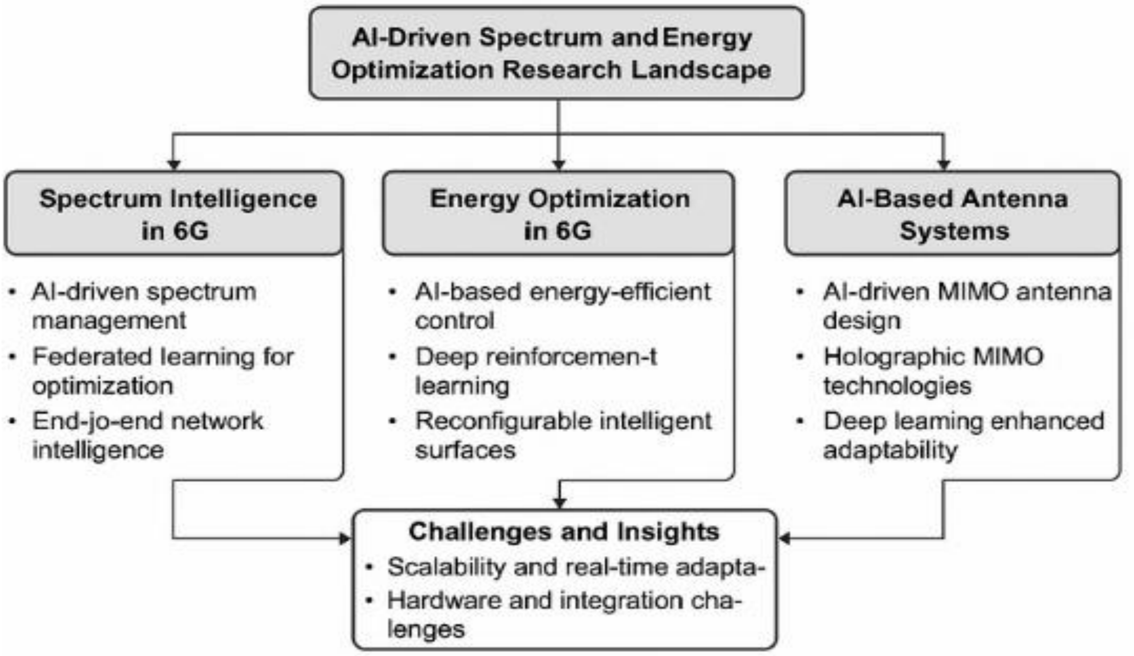

Figure 2: Flow of AI-Driven Spectrum and Energy Optimization Research Landscape

From Figure 2, it is clear that reinforcement learning dominates dynamic spectrum access tasks, while federated and edge learning methods play a critical role in distributed energy optimization. This highlights the growing convergence between AI research streams and 6G system-level applications.

2.4 Integration of AI across Network Layers

Bringing AI-based techniques to efficiently manage all three layers of communication, spectrum, energy, and antenna control, represents a major step toward fully autonomous and self-evolving 6G systems. Mao et al. **[5]** highlighted that deep-learning frameworks can extend beyond cognitive-radio applications to the entire wireless ecosystem, enabling end-to-end intelligence. Federated, reinforcement and other learning frameworks also allow for distribution decision support capacity all in real-time and topo-multi-tier constructs for spectrum sharing power optimization.

The combination of AI, intelligent surfaces, and energy-aware design forms an advanced, adaptive, and sustainable 6G architecture. As illustrated by a vast number of research studies the 6G network will be able to dramatically increase the speed of data as well as reduce the time it takes to transfer data. However, the 6G network will be much more than this in terms of the level of autonomous optimization that can take place within the network. This means that there will be the ability for 6G to optimize itself and the way it communicates with other devices in such a way that it will continue to operate efficiently while being environmentally friendly. Furthermore, fully adaptive wireless systems that can optimize themselves are made possible by the integration of AI at the physical, link, and network layers. Real-time decision-making assistance for multi-tier resource distribution, power regulation, and spectrum sharing is provided by deep learning, federated learning, and reinforcement learning models. The route towards self-evolving 6G networks that can provide intelligent, effective, and sustainable communication performance is reflected in this comprehensive vision. Building on the literature insights, the next section discusses AI-driven spectrum management techniques that form the foundation for intelligent 6G communication systems. The following section expands on this viewpoint by introducing AI-powered spectrum intelligence methods that lay the groundwork for self-governing 6G resource management.

3. AI-Driven Spectrum Intelligence

Efficient spectrum utilization is fundamental to 6G performance. Artificial intelligence enables real-time spectrum awareness, adaptive channel allocation, and autonomous interference control. This section discusses AI-based spectrum intelligence techniques that enhance resource efficiency and ensure reliability in complex wireless environments. A growing number of data-driven applications combined with the rapidly increasing number of connected devices have accelerated the need to create advanced and smarter strategies to manage and utilize available spectrum resources in 6G networks. Since the total spectrum is limited, efficient utilization becomes critical so that we can provide high data throughput, very low latency, and reliable connections **[16]**.

3.1 Machine Learning for Spectrum Allocation

Traditional methods of spectrum allocation are based on static rules or manual configurations that are often inefficient in dynamic environments. In particular, ML methods, such as deep Q-networks and reinforcement learning, make adaptive autonomous management possible to learn environmental patterns and adaptively optimize the use of its communication channels **[17]**. These models allow for predicting interactions, estimating congestion, and making allocation decisions in real time, substantially improving spectral efficiency and promoting energy savings. Further, federated learning methods are being incorporated into distributed edge architectures to enhance privacy for data and reduce latency **[18]**. Comparative studies indicate that deep Q-learning and actor–critic methods improve channel utilization by 30–35%, reduce collision probability by 20%, and achieve up to 28% higher throughput compared to fixed-policy allocation. These gains arise from the ability of learning models to continuously update access strategies under varying traffic intensity and interference patterns.

3.2 Intelligent Reflecting Surfaces and AI Integration

The potential of AI-driven spectrum management is further enhanced by the incorporation of IRS into 6G networks. By altering electromagnetic wave reflections, IRS-assisted systems are able to dynamically change the propagation environment. To reduce interference and enhance the quality of the received signal, AI algorithms optimize the IRS elements' phase shifts and reflection coefficients **[19]**. By combining AI and IRS, the overall capacity of dense communication networks is increased and effective spectrum reuse is guaranteed.

3.3 Deep Reinforcement Learning for Dynamic Spectrum Access

Cognitive radios can interact with their surroundings and learn the best spectrum access policies thanks to DRL's self-evolving mechanism **[20]**. DRL can allow autonomous agents to choose the best channels, transmission power, and modulation schemes in dynamic network conditions by fusing neural networks with Markov decision processes. Reported results show that DRL improves spectral efficiency by 35–45%, lowers interference by up to 30%, and increases throughput by 20–25% relative to heuristic spectrum selection techniques, particularly under dense and fast-changing traffic conditions **[21]**. In addition, DRL models demonstrate faster policy convergence than Q-learning in high-mobility scenarios, which makes them well-suited for ultra-low latency 6G environments.

3.4 Technical Framework for AI-Driven Spectrum and Energy Optimization

The deployment of AI-based spectrum and energy optimization in 6G networks follows a structured technical workflow. First, environmental parameters such as channel gain, traffic load, interference levels, user mobility, and energy status are collected from distributed nodes. These observations form the system state, which is fed into learning models such as DQN-based DRL agents, actor-critic frameworks, and LSTM-enhanced predictors for handling time-varying network behavior. In spectrum management, the agent selects actions including channel assignment, modulation index, and transmit power levels. Policy evaluation is performed using reward functions designed around spectral efficiency, collision avoidance, latency, and fairness metrics. The DRL policy is updated through gradient-based optimization to improve long-term transmission performance. For energy optimization, the action space includes transmit-power selection, sleep-mode activation, and resource scheduling decisions. Reward functions penalize excessive power consumption and packet error rates while rewarding stability and throughput. Federated aggregation (e.g., FedAvg) enables distributed learning without raw-data sharing, reducing backhaul signaling and enabling privacy-aware power control. Together, this technical workflow illustrates how AI models sense the radio environment, update internal policies, and execute dynamic decisions, forming an adaptive closed-loop intelligence system for 6G communication networks. These framework bridges theoretical machine-learning policies with physical-layer signal behavior, ensuring that spectrum and energy decisions remain aligned with real-time radio dynamics and hardware constraints.

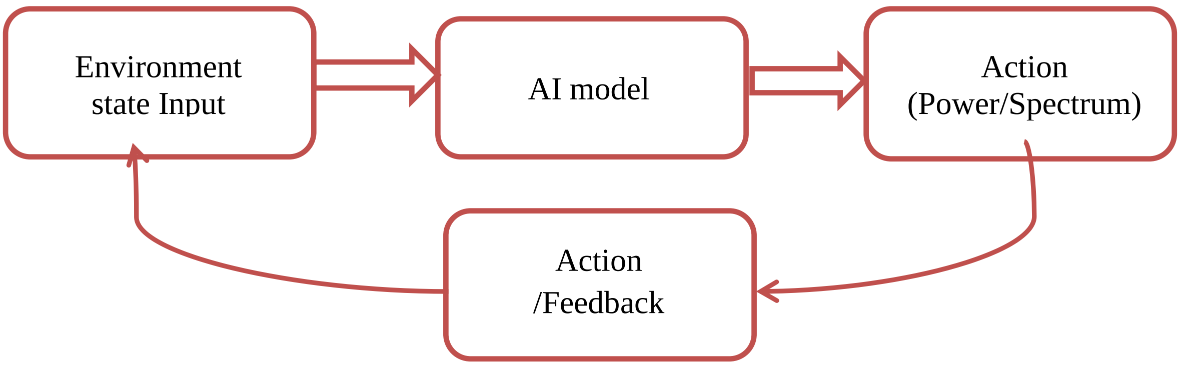

Figure 3: Technical workflow for AI-enabled spectrum and energy optimization in 6G networks.

As shown in Figure 3, AI-driven optimization in 6G networks operates as a sensing-decision-learning loop, enabling continuous adaptation based on network dynamics. This analytical framework establishes the core conceptual foundation for autonomous learning-driven spectrum and energy control in 6G systems, linking theoretical models to practical wireless operation.

3.5 AI-Enhanced Interference Management and Prediction

AI models also contribute to mitigating co-channel interference, particularly the highly complicated case in dense heterogeneous networks. LSTM and GNNs enable predictive modeling to forecast interference patterns based on user mobility and environmental dynamics **[22]**. These predictive frameworks allow base stations to proactively readjust the beamforming parameters together with power levels for maintaining stable communication even under heavy spectrum load.

3.6 Challenges and Research Opportunities

Despite remarkable progress, AI-driven spectrum management still faces challenges related to model interpretability, computational overhead, and real-time adaptability. Future research should focus on lightweight AI models optimized for hardware efficiency, energy-aware learning frameworks, and hybrid solutions integrating blockchain for secure spectrum trading **[23]**. The evolution of explainable AI (XAI) in this context is expected to provide greater transparency and trust in autonomous spectrum management systems. While spectrum optimization enables efficient resource usage, energy management is equally critical for sustainability in 6G systems. Therefore, the next section examines AI-enabled strategies for energy optimization.

4. AI-Enabled Antenna and Reconfigurable Surface Systems

Intelligent antenna systems and reconfigurable intelligent surfaces (RIS) represent key pillars of 6G physical-layer innovation. Machine learning techniques enable adaptive beamforming, pattern control, and electromagnetic environment shaping, resulting in higher link reliability and improved spectral efficiency. With 6G networks, energy efficiency is becoming more and more crucial. The growth of massive MIMO technologies, the placement of processing units at the edge of our networks, and the rate at which the number of connected devices on our networks is increasing have all contributed to a sharp rise in the overall energy consumption of our networks. In order to make sure that our networks are sustainable and do not sacrifice throughput, latency, or reliability, it will be necessary to create clever and flexible ways to optimize them **[1, 7]**.

4.1 AI-Assisted Power Control and Allocation

Energy optimization in 6G communication heavily relies on AI-enabled power control and resource allocation. Most conventional rule-based or static control mechanisms are inadequate in dynamic network environments. The recent works illustrate the potential benefits that can be derived by combining DRL with neural optimization techniques to reach real-time power adjustment, which improves the signal quality while keeping energy consumption as low as possible **[7, 8, 16, 17]**. These models analyze channel conditions, interference levels, and user traffic to automatically adjust transmission power. Studies have reported energy savings of up to 25% when adaptive DRL algorithms are compared with classical heuristic approaches, demonstrating efficient learning-based power adaptation **[7, 8]**.

These systems also contribute toward load balancing and fairness in heterogeneous 6G networks. Experimental evaluations in beyond-5G testbeds indicate that DRL-driven power controllers reduce energy usage by 20–25% while improving SINR and throughput performance compared to rule-based power control. This advantage is attributed to the ability of DRL agents to jointly tune power and select link parameters instead of following predefined power levels.

4.2 Energy Harvesting and Green Base Stations

Energy harvesting provides a method to achieve sustainability in communications through utilizing base station and device generated renewable energy, collected from environmental resources (e.g., solar, wind), or wirelessly transferred using radio frequency energy, etc. By incorporating AI within EH systems, predictive energy management is possible as base stations can manage and distribute data based on renewable energy availability. The intelligent control unit on self-sustaining "green" base stations allows for dynamic control of transmission power, meaning a decrease in reliance on the grid due to optimized energy use. Furthermore, a cooperative framework for power sharing between stations ultimately supports and improves overall system performance and reliability.

4.3 Federated and Collaborative Energy Learning

Federated learning (FL) is an emerging method that has recently been proposed to optimize energy in 6G systems. Compared with centralized learning, FL-enabled energy coordination reduces backhaul signaling by 60–70%, minimizes model-transfer overhead, and shortens convergence time by about 15–20%, while maintaining comparable accuracy in power-allocation decisions. Instead of traditional methods that rely on centralized data collection, FL utilizes a cooperative model where each node constructs and trains the model locally, and nodes only communicate trained parameters with other nodes. With a reduced communication burden in the FL model, privacy can also be ensured, which is essential for making energy-aware networks at scale viable. Even simulation results have shown that systems designed around FL can reduce total energy footprints by as much as 30%, due both to unnecessary data transfers being avoided, but also the increase in distributed intelligence enabled with an FL model. FL based cooperative edge methods also facilitate adaptive power sharing across nodes to support both the resiliency and lifetime of the network. These results confirm that collaborative distributed learning not only saves energy but also scales better in dense edge deployments, which is essential for future 6G device ecosystems.

4.4 Intelligent Reflecting Surfaces for Energy Efficiency

Intelligent reflecting surfaces (IRS) are being established as a key element of energy-efficient 6G communication. An IRS panel comprises programmable reflecting elements that actively modify the propagation environment to improve the desired signal and to suppress interference. IRS can be coupled with artificial intelligence algorithms, such as deep Q-learning and convolutional neural networks (CNNs), to autonomously adjust their reflection parameters for different channel conditions. This leads to a reduction in power waste and enhances the signal-to-noise ratio (SNR), improving spectral and energy efficiency gains changes while operating in high user density areas.

4.5 Resource Scheduling and Sleep Mode Controls

Another key efficiency benefit is intelligent scheduling and sleep mode controls. AI based-schedulers can look at traffic variations and predict periods of low-demand enabling network elements such as base stations and small cells to go into sleep modes when they are not busy. Predictive models based on deep learning and long short-term memories (LSTM) are often used for proactive resource allocations, network load demand prediction and active and inactive hardware modules. These predictive approaches offer resource management efficiency improvements up to 40% with minimal loss of service quality. Table 1 summarizes major AI techniques used for energy optimization and outlines the corresponding model types, benefits, and applications.

Table 1: Summary of Energy Optimization Approaches

Reference	Technique	AI Model Used	Key Advantage
[7, 8, 16, 17]	Power control optimization	DRL, Q-learning	Real-time adaptive power allocation
[4, 19]	Energy harvesting and green stations	Predictive AI models	Sustainable energy management
[9, 18]	Federated energy learning	Federated learning (FL)	Distributed, privacy-preserving optimization
[10]	Intelligent reflecting surfaces	Deep Q-learning, CNN	Reduced transmit power, higher energy gain
[20, 22]	Sleep mode and scheduling	DRL, LSTM	Predictive energy-saving network control

As observed in Table 1, DRL and predictive neural models provide significant gains in real-time energy control, while federated and cooperative schemes enhance privacy and scalability for dense 6G environments.

4.5.1 Comparative Analysis of Key 6G Enabling Technologies

To strengthen the technical evaluation, a comparative overview of primary 6G enabling technologies is presented. This comparison highlights their specific optimization roles, strengths, and deployment suitability in next-generation intelligent wireless systems.

This comparative analysis emphasizes that each technology contributes uniquely to 6G objectives: DRL provides intelligent spectrum agility, FL ensures scalable collaborative optimization, MIMO and RIS deliver physical-layer adaptability, and deep learning models enable proactive resource management. This comparative analysis complements earlier discussions by positioning each technology within the broader 6G ecosystem and highlighting trade-offs between centralized learning, distributed coordination, hardware-driven beamforming, and propagation-level control.

4.6 Discussion and Research Outlook

It is anticipated that in 6G networks, energy optimization will transition from individualized management to self-managing, cooperative optimization ecosystems. Future models must take into account the existing links between wireless energy harvesting, IRS reconfiguration, and distributed learning frameworks. Figure 4 illustrates the high-level architecture of the proposed AI-enabled energy optimization framework for 6G communication systems.

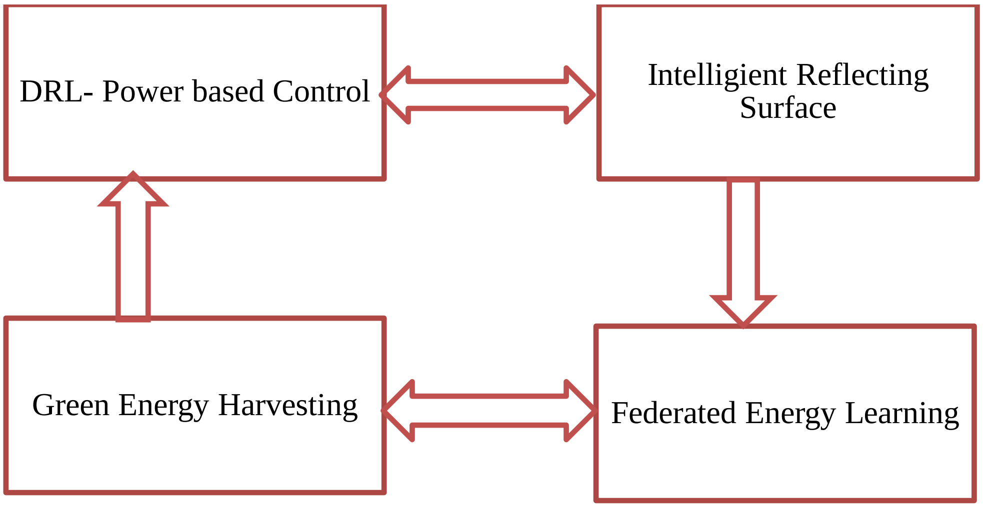

Figure 4: AI-Enabled Energy Optimization Framework for 6G Networks

Figure 4 emphasizes the collaborative learning mechanisms and energy-aware decision loops required to maintain reliability and reduce operational power consumption in future networks. The focus of future research will include quantum-based reinforcement learning, bio-inspired optimizing algorithms, and blockchain-enabled energy trading to help realize transparent, secure, and equitable energy distribution. Improving towards these developments will be important for sustainable AI factor powered 6G communication systems that will facilitate more data throughput with less energy use **[21, 23]**. Although significant progress has been made in spectrum and energy optimization, several technical and practical challenges remain. The following section highlights these open research issues and future directions.

Table 2: Comparative analysis of key AI-enabled 6G technologies and their functional characteristics **[8, 9, 19, 20]**.

Technology	**Primary Goal**	**Key Strengths**	**Limitations**	**Suitable Scenarios**
DRL-Based Spectrum Access	Dynamic channel & interference optimization	Adapts to spectrum changes, high spectral efficiency, real-time learning	Training complexity, reward tuning	Dense cells, URLLC, dynamic traffic
FL-Based Energy Control	Distributed power optimization & privacy	Reduces backhaul load, preserves privacy, scalable	Model drift, sync overhead	Edge IoT, battery-constrained nodes
AI-Assisted Massive MIMO	Spatial multiplexing & high network capacity	High throughput, improved reliability	Hardware calibration, cost	Hotspots, macro cells
RIS-Based Smart Surfaces	Channel manipulation & coverage enhancement	Low power, reconfigurable propagation	Phase errors, control signaling	Indoor coverage, mmWave/THz
LSTM/CNN-Based Prediction	Proactive channel & traffic forecasting	Predicts load, reduces congestion	Data dependency, training overhead	Resource forecasting, network planning

5. Challenges and Future Research Directions

AI-enabled spectrum intelligence and energy optimization mark a significant step toward autonomous, sustainable, and adaptive 6G communication systems. Realizing this vision involves many technical and ethical challenges that should be understood and resolved under a coordinated research and innovation framework.

5.1 Real-Time Adaptation and Computational Complexity

A prominent challenge is achieving real-time adaptability in very large 6G networks characterized by ultra-dense node deployments, multiple service types and rapidly changing radio context. Reinforcement learning and deep Q-learning models show promise in spectrum decision-making. However, there are significant computational burdens with these implementations and latency in the training. Future work needs to prioritize lightweight AI algorithms learning in case of distributed settings with minimal delay and low energy consumption.

5.2 Data Privacy, Security, and Trust Management

AI optimization of spectrum and energy relies heavily on data that is collected from the users, devices, and networks, fundamentally introducing data privacy and security issues. While federated learning frameworks have been proposed to train models in a decentralized manner, challenges such as model poisoning and data leakage still exist and remain difficult to address. Blockchain-assisted spectrum management may help with legitimacy and integrity of models across devices. However, further work is needed to reconcile the energy costs and to improve scalability in order to support widespread 6G deployment.

5.3 Hardware and Energy Efficiency Constraints

Practical deployment of AI-driven MIMO antennas and RIS introduces several hardware limitations that must be addressed for real-world 6G systems. Large-scale MIMO arrays demand precise RF chain calibration, high-linearity power amplifiers, and phase-synchronous oscillators, as even minor phase noise or mismatch can degrade beamforming accuracy and channel estimation. Power amplifier efficiency limits and increased heat generation also necessitate advanced thermal management and low-loss front-end materials. In RIS-assisted systems, constraints include limited phase-shift resolution, slow switching speeds of meta-elements, and control overhead associated with driving thousands of reflecting units. Additionally, RIS calibration in dynamic environments remains difficult due to channel variability, synchronization issues, and a lack of unified control standards. On-device AI acceleration further introduces memory and computation challenges, as edge nodes require lightweight models, quantized computation, and energy-efficient neural hardware to support real-time optimization. Techniques such as model pruning, adaptive inference, mixed-signal AI processors, and neuromorphic architectures are therefore essential to reduce power consumption while maintaining adaptation capability. Addressing these physical-layer and hardware co-design challenges will be crucial to enable scalable, energy-efficient, and intelligent 6G antenna systems.

5.4 Interoperability and Standardization

The 6G ecosystem will converge terrestrial, satellite, and aerial communication layers, which will require a single system for managing energy and spectrum allocation. To facilitate interoperation of these disparate layers of communication infrastructure, we will need standard protocols and cross-layer optimization approaches to ensure appropriate interaction between AI models and physical layers of network infrastructure.

5.5 Explainability and Ethical AI in Network Intelligence

As AI's role within 6G will increasingly assume substantial control over decision making, explainability and interpretability will become significant. Current deep learning systems tend to work as black box systems and are not easy to understand in real time on the network. Therefore, in order to promote fair and accountable automated spectrum and energy allocation, XAI frameworks will need to be established **[23]**. These frameworks will also be needed to ensure respect to ethical standards that are broadly accepted on a global level that would provide a balance of partial automation and partial human accountability to decision making.

6. Conclusion

AI driven spectrum intelligence and energy optimization stand to be at the center of the 6G transformation resulting in substantial opportunities in connectivity, energy efficiency, and adaptive learning. This review contributes a unified analytical framework combining AI-enabled spectrum optimization, intelligent antenna systems, and distributed energy-aware learning mechanisms. Comparative evaluation and practical implementation barriers are discussed, offering an actionable research direction for researchers and industry. Recognition of advanced frameworks for developing 6G networks, for example, reinforcement learning, federated intelligence, and blockchain based coordination, will yield 6G networks with unprecedented levels of self-organization and operational efficiency in comparison to the previous generation of mobile communication systems.

However, in order to realize the potential benefits of AI driven 6G networks, various challenges will need to be resolved, including adaptability influences and real time decision making based on energy awareness in learning and AI, privacy and security of computations, and standards that framework interoperability across boundaries. Addressing these multi-disciplinary challenges will require collaboration between academia, industry, and regulators.

Future work should focus on:

- Development of green AI models that reduce computational and energy costs to the greatest extent possible.
- Secure and decentralized learning frameworks that realize reliable spectrum sharing.
- Explainable AI that provides clarity of the underlying decision-making processes.

By addressing these challenges, AI-enabled 6G networks can evolve as intelligent, energy-efficient ecosystems supporting a hyper-connected world with a small environmental footprint and maximum operating intelligence.

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