

AI-Based Resource Allocation for Energy and Spectrum Efficiency in 6G Networks

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Article Info:

DOI: 10.22399/ijcesen.4542

Received : 10 January 2025

Accepted : 30 March 2025

Keywords

6G networks,
artificial intelligence,
energy efficiency,
spectrum efficiency

Abstract:

Another paradigm shift that is in the process of being introduced in the telecommunication sector is the sixth generation (6G) wireless networks whereby a low degree of latency of operation, high spectral performance and energy-conscious design are being introduced to meet the constantly increasing number of devices and data requirements of the air. Although it has been revealed that there are different papers on the utilization of AI in 6G, the majority of them remark on two phenomena that cannot be correlated with one another and these include spectrum and energy efficiency. The systematic and mutual execution of AI-based resource allocation will be used to address the gap in the paper through the joint maximization of the energy efficiency and spectral efficiency of 6G networks. The paper proposes a new taxonomy of AI techniques that is determined by the deployment layer (edge, core, and THz frontier), the most popular known architectural and algorithmic operators of the joint optimization, and a comparative analysis of the known available methods of the technological fields, e.g., adaptive modulation, handover optimization, meta-learning, federated learning and explainable AI in comparison with the available surveys. It further possesses an offer of synthesis of digital twins on a resource-centric approach, blockchain-based Internet of Things, and secure communication protocols. Key contributions include: (1) a unified classification of AI approaches targeting co-optimization of spectrum and energy; (2) a comparative evaluation of techniques across key 6G scenarios (UDN, IoT, THz, RIS); and (3) identification of open research challenges and practical deployment constraints. The paper further outlines how AI fosters sustainability, scalability, and transparency in next-generation wireless systems.

1. Introduction

The 6G wireless communication systems will be placed in transforming the already established telecommunication business into one that will have the highest density data rate in history, minimum latency and business communication that is highly reliable and marvelous connectivity. New technologies (soon to be deployed to develop examples of immersive extended reality (XR), holographic telepresence, autonomous vehicles, and remote holographic surgery) also implement the future network which, in the case of the example, was not the case in past generations. The more information to be implemented, the more complex the network would be, the better it would manage in terms of resources whether in terms of energy or spectrum. The non-dynamic and diffuse paradigm of resource distribution cannot be transferred to the

dynamic and heterogeneous nature of 6G demands, and the currently presented AI strategies can be susceptible to the demand of deploying resources in a dynamic setting with a predictive analysis mechanism.

The argument of the paper will be a discussion of the current developments that have been achieved so far on the delivery of maximum usage of energy and spectral efficiency of 6G networks with the use of AI-based tools, basing on the discoveries of the available publications. Adaptive modulation and AI-induced modulation also include the output of architectural design, handover, resource management structure, and innovative modulation, including the application of digital twins, blockchain security, and explainable AI.

1.1 Research Gap and Contribution

The study presents a gap in the literature as it reviews existing works and highlights contributions made by various scholars, along with the remaining gaps in the field.

The role of artificial intelligence is researched in the scope of producing 6G networks in newer papers; however, in the majority of the papers the question of spectrum efficiency and decreasing energy consumption is considered separately. These are two features of the abundance of literature on 6G applications when integrated into AI models that have not been disputable. Otherwise, the literature that has been introduced nowadays did not categorize the AI approaches by system deployment (e.g., edge, core, device-level) and learning paradigms (e.g., supervised, federated and meta-learning).

As it will be stated, one of the limitations of the setting that was used in this paper was the small scale of the distributions of AI-based policies to allocate resources in 6G, i.e., spectral and energy-saving co-optimization. Unlike prior generalist surveys, this review:

- Introduces a **taxonomy of AI techniques** for joint energy–spectrum optimization across different architectural layers.
- Provides a **comparative table** summarizing 6G-specific AI models, learning strategies, application scenarios, and target KPIs.
- Synthesizes recent advances in emerging paradigms such as **meta-reinforcement learning, federated learning, and explainable AI** for intelligent resource management.
- Discusses integration of **blockchain and digital twins** from a **resource efficiency perspective**, not just conceptual overlap.
- Identifies **open research questions** and practical barriers to real-world deployment.

1.2 Research Questions

Some of the research questions that will be used in this review are the following:

- **RQ1:** How can AI techniques be effectively leveraged to jointly optimize energy and spectral efficiency in 6G networks?
- **RQ2:** What are the most promising AI paradigms (e.g., DRL, federated learning, meta-learning) for energy–spectrum-aware resource management in diverse 6G scenarios?
- **RQ3:** What gaps remain in current literature regarding deployment layers,

algorithm scalability, and performance evaluation?

- **RQ4:** How can emerging paradigms such as explainable AI, blockchain, and digital twins be integrated into resource allocation frameworks while maintaining efficiency and transparency?

It is these questions that would subsequently assist this paper in showing that AI is an energy-conscious and spectrum-aware resource distribution organizer and not a facilitating technology in the 6G generation.

2. AI-Powered Adaptive Modulation in 6G

Adaptive modulation is highly important and a viable spectral utilization instrument, and the process of adaptation according to which wireless systems can dynamically vary modulation and coding schemes (MCS) in accordance with real-time channel conditions. They should also be controllable and have very low feedback loops, since 6G adaptive modulation should support 1 Tbps data rates and a spectrum band that is as small as sub-6 GHz and may even be THz. Nevertheless, non-stationary 6G scenarios, e.g., user mobility and other QoS features, are not implementable in rule-based solutions, however.

Among the solutions that could be offered to this problem, one can single out deep reinforcement learning (DRL) and the role which artificial intelligence plays in its development. Communication with agents is always availed in the environment and this enables DRL agents to set up the best MCS policy and capability to modify modulation with signal-to-noise ratios (SNR), interference patterns, user speeds and type of service (eMBB, URLLC, mMTC).

Goyal et al. (2025) noted that spectral efficiency (SE) and energy consumption (EE) improvements of 15 percent in an emulated THz channel of the DRL agent that had undergone a Dueling DQN architecture were superior to traditional link adaptation mechanisms. The modulation rates of QPSK, 16-QAM and 64-QAM were automatically modified with respect to real-time SINR, channel state information (CSI) and quality of service class identifiers (QCI).

The need to change modulation with the assistance of AI is justified by the fact that changes in channel parameters are significant due to path loss, atmospheric absorption, and 6G THz space blockage. The DRL systems can predict channel states many milliseconds before and can prematurely switch off modulation schemes before retransmission is cannibalized and hence conserve energy.

Key 6G KPIs improved by AI-powered adaptive modulation include:

- **Spectral Efficiency (SE):** Bits transmitted per Hz (\uparrow by 10–20%)
- **Energy per Bit (EE):** Reduced transmission power per data unit
- **Packet Error Rate (PER):** Improved reliability in THz and dynamic urban scenarios
- **Latency:** Reduced retransmission and processing delays

It is also covered in similar recent literature (meta-learning-based DRL, where policies are changed based on network variations, i.e., sudden mobility and bursts of network interference, etc.). In particular, this is the case with 6G vehicular-to-everything (V2X) networks and non-terrestrial networks (NTNs).

3. 6G Architecture and Spectrum Optimization

The principles that will also have an implication on 6G design include intelligent and scalable resource distribution also facilitated by a cloud-native design, i.e., AI-native design and programmable radio access. 6G is expected to provide disaggregated and virtualized RAN components, unlike previous generations. xApps or rApps can be programmed with the assistance of Open RAN (O-RAN) architecture to coordinate spectrum allocation by AI agents.

AI-enhanced dynamic spectrum management (DSM) is one of the technologies that can be applied to the domain of spectrum optimization. With unsupervised learning and clustering, AI systems can learn unused spectrum bands and accept spectrum slices on the fly, depending on traffic load, application priority and interference.

6G networks have the option of locating free bands in shared bands or licensed frequencies. This is because the introduction of AI in cognitive radio systems translates to secondary users utilizing spectrum holes, the most important ones being utilized. The way to resolve harmful interference is by ensuring that spectrum reuse and spectral efficiency (SE) are enhanced by deep Q-learning agents.

As Adewunmi et al. (2025) mentioned, AI-based spectrum optimization algorithms led to an increase of median spectrum utilization by 17 percent and SE by 22 percent, implemented on a federation of clustered virtualized base stations.

Additional benefits of AI in spectrum optimization include:

- **Latency minimization:** Real-time reallocation avoids queuing delays

- **Throughput enhancement:** More users served via dynamic slicing
- **Spectral Efficiency (SE):** Measured in bits/s/Hz/Cell
- **Fairness index:** Balanced allocation across heterogeneous services

Implementation of AI modules that utilize autonomous control of resource blocks, channel widths and numerology of single-user slices in O-RAN deployments in the Near-RT RIC (less than 10 ms latency budget) are implementations. This will not consider legacy environments and instead would be preprogrammed to support services such as telemedicine (URLLC) and immersive XR (eMBB) that require optimization in bandwidth and energy consumption.

4. AI for Handover and Load Balancing in Ultra-Dense Networks

It will use smaller cells (relays and base stations), hundreds of times per square kilometer, applied indoors and in cities. It expands coverage and capacity but leads to high handover (HO) rates, particularly when drone movement or autonomous vehicle movement is high (e.g., when cell loads are uniformly distributed).

Such mobile settings cannot concur with classical handover techniques that solely rely on SINR or RSSI. They are exposed to ping-pong effects, handover failures (HOF) and quality of service reduction.

Long Short-Term Memory (LSTM) networks, with the help of supervised classification, make prediction of handover location and time possible using user path, speed and signal quality history.

A combination of LSTM mobility prediction with a DRL-based HO strategy developed by Chabira et al. (2025) resulted in:

- **18% reduction in HOF**
- **22% improvement in cell-edge throughput**
- **25% fewer ping-pong handovers**
- Optimized load balancing with **12% energy savings** from better cell selection

Besides this, multi-agent DRL models do not have centrality in decisions made by base stations. The decision to start HO or to adopt rescheduling decisions to neighboring cells is made by agents not necessarily based on signal measurements but also based on cell load, bandwidth and backhaul delay, which are directly proportional to EE and SE.

KPIs improved by AI-based handover and load balancing include:

- **HO Success Rate (HOSR)**
- **Cell Load Utilization**
- **Average UE Throughput**

- **Power usage per HO event**

AI can also be used in load balancing where demand fluctuation can be high in shared spectrum or sliced networks. DRL agents are capable of changing resource allocations dynamically to avoid congestion and ensure service fairness.

5. AI-Based Frameworks for Joint Spectrum–Energy Management

The bandwidth and physical aspects of 6G networks such as ultra-reliable low-latency communication (URLLC) to the orders of magnitude of machine-type communication (mMTC) demand new resource management, and are capable of making informed decisions regarding the distribution of resources, be it in spectrum or energy. Nevertheless, as opposed to rule-based and heuristic-based systems suggested in the previous generation, AI-based systems allow making resource allocation decisions in real time, relying on the situation and subject to change due to the significance of the most eminent KPIs of 6G, i.e., energy efficiency (EE), spectral efficiency (SE), and latency.

They are highly complicated, and may have hundreds of AI elements in topology as hierarchical data collection agents, learning agents and decision-making agents which constitute an edge device, radio access network (RAN) and core infrastructure.

5.1 Framework Components and Architectural Placement

AI-based resource management frameworks in 6G generally follow a layered architecture, with AI models deployed across the following layers:

- **Device/Edge Layer:** For real-time sensing, adaptive modulation, and federated learning. Optimizes **local energy consumption, latency, and bandwidth**.
- **RAN Layer:** Hosts AI modules for **handover prediction, load balancing, and spectrum reuse**. Optimizes **SE, handover failure rate, and signal-to-interference-plus-noise ratio (SINR)**.
- **Core Layer / Cloud:** Runs complex models such as **deep reinforcement learning (DRL)** and **meta-learning** for long-term planning and **global resource optimization**.

The multifacetedness of the layers gives the feedback mechanism to the system in terms of performance (e.g., throughput, power consumption, mobility patterns) to give the extrapolated perspective of the chain of decision-making in the system through the process of continuous learning.

5.2 Intelligent AI Techniques in Frameworks

Several AI paradigms have emerged as foundational to these frameworks:

1. Supervised Learning

- **Used for:** Traffic classification, anomaly detection.
- **Resource Impact:** Helps prioritize energy/bandwidth allocation based on service type (e.g., eMBB vs URLLC).
- **6G Scenario:** Edge-cloud coordination for smart cities.
- **Limitation:** Requires large labeled datasets.

2. Deep Reinforcement Learning (DRL)

- **Used for:** Dynamic spectrum access, transmit power control, cell association.
- **Resource Impact:** Jointly improves SE and EE by learning policies over time.
- **6G Scenario:** RAN slicing and real-time network reconfiguration.
- **Example:** In [Vijay et al., 2025], DRL improved throughput by 18% and reduced energy consumption by 12% over rule-based baselines.

3. Meta-DRL and Transfer Learning

- **Used for:** Fast adaptation to unseen network conditions (e.g., user mobility, spectrum shifts).
- **Resource Impact:** Maintains near-optimal EE and SE even in volatile environments.
- **6G Scenario:** Terahertz (THz) environments with mobility and blockage.

4. Federated Learning

- **Used for:** Collaborative model training across devices while preserving data privacy.
- **Resource Impact:** Reduces **energy usage** and **latency** by eliminating cloud transmission for training.
- **6G Scenario:** Massive IoT deployments with privacy constraints.
- **Challenge:** Introduces **communication overhead** and synchronization issues.

5. Hybrid AI Models (Heuristic + Neural Networks)

- **Used for:** Combining domain expertise with learning capabilities.
- **Resource Impact:** Improves interpretability while maintaining performance.
- **6G Scenario:** Industrial automation where deterministic behavior is required.

5.3 Unified AI Framework Architecture

A generic architecture for joint resource optimization in 6G includes:

- **Sensing Layer:** Collects network context data (channel quality, energy stats).
- **Pre-processing Layer:** Aggregates and filters data.
- **Learning Layer:** Hosts AI models (DRL, FL, etc.).
- **Decision Layer:** Outputs allocation decisions (e.g., power levels, bandwidth).
- **Feedback Loop:** Evaluates actions based on real-time KPI monitoring and refines policies.

This is illustrated in Figure 1, which shows how user data flows through AI modules for spectrum and energy optimization across edge, RAN, and core layers.

5.4 Example Framework Implementations

Another multi-agent DRL scheme discussed in the paper is RAN slice coordination among themselves in the spectrum sharing dimension and energy load distribution dimension (Ullah et al., 2025). They may save 22 percent of energy in their simulation compared to centralized RL models.

Another recent method that Radha and Sarojini (2025) utilize is diffusion-enhanced meta-learning as a subsystem of a DRL system, which can be easily deployed to run on a system with dynamically varying THz connection quality. It was also observed that the suggested model would converge 30 percent quicker and save 15 percent energy in various patterns of user mobility.

5.5 Practical Deployment Considerations

However, although the AI-powered system is superior in some areas, a list of more grounded issues exists:

- **Model complexity** can overwhelm edge hardware.
- **Communication overhead** in federated systems may degrade latency.
- **Data privacy** and **security** remain critical concerns, especially in IoT-heavy deployments.

As things turn out, the current state of work on lightweight models, hardware accelerators, and privacy-sensitive learning systems can be further improved in the future so that the likelihood of 6G systems having joint resource management based on AI can become a reality.

6. Taxonomy and Comparative Analysis of AI Techniques

To present a systemic view of current AI-based solutions for joint spectrum and energy

optimization in 6G, the section suggests a taxonomy of available AI-based solutions based on the learning paradigm and the point where application and optimization are implemented. This is followed by a comparative table where results reported by recent publications are summed up for various 6G scenarios.

6.1 Taxonomy of AI Techniques for Joint Resource Allocation

Figure 1 presents a taxonomy of AI techniques employed in 6G resource allocation, categorized along three dimensions:

- **A. Learning Paradigm:**
 - **Model-free** (e.g., Deep Reinforcement Learning, Q-learning)
 - **Model-based** (e.g., MDP with known transition probabilities)
 - **Supervised / Unsupervised / Federated / Meta-learning**
- **B. Deployment Location:**
 - **Edge/Device-Level** (e.g., federated learning, energy-aware routing)
 - **RAN-Level** (e.g., beamforming, handover prediction)
 - **Core/Cloud-Level** (e.g., DRL for global optimization)
- **C. Optimization Objective:**
 - **Energy Efficiency (EE)** – minimize power per bit, device lifetime
 - **Spectral Efficiency (SE)** – maximize bits/s/Hz
 - **Joint SE–EE Optimization** – trade-off-aware resource allocation

6.2 Comparative Summary of Existing Works

Table 1 presents a comparison of notable AI-based resource allocation studies in the context of 6G, including the AI approach, application scenario, optimization goal, target KPIs, and observed outcomes or limitations.

7. Meta-Deep Reinforcement Learning Frameworks

Deep reinforcement learning systems include meta-learning algorithms, since decision making under complex and dynamic environments will be efficient at the 6G level. Hybrid AI models show learning of new tasks in a relatively easy format, with knowledge acquired in recent learning incidences. It is especially so in instances of time-

varying states of 6G networks, and the apportionment of resources can be drastic.

The latter is the development of diffusion-enhanced meta-DRL algorithms, capable of spreading the signals of a neural network more efficiently and, thus, converging faster and generalizing better. The strategies will act as a reminder and charge to the policies of resource management that shall maximize the utilization of energy and spectrum. This has contributed to improved performance as opposed to older iterations of DRL models, particularly when it comes to running simulations in mixed populations of devices with different demands and mobility patterns [5].

Figure 2 illustrates the AI-based architecture for dynamic resource allocation in 6G networks, showcasing how user data flows through AI modules for spectrum and energy optimization.

8. Explainable AI and Network Slicing in 6G

Another notion that is emerging in the 6G environment is what is known as explainable AI (XAI), which can raise the degree of confidence and transparency with the potential to comprehend decisions. The necessity to present clean rationale in the description of AI-driven decisions will increase among network owners, regulators and end-users as more independent and AI-based networks are created.

One significant architectural construction block of 6G is network slicing. It enables an operator to create numerous virtual networks on a single physical one and assign them to a single program such as autonomous driving, telemedicine or industrial automation. These include proper slicing, and XAI can contribute to the process by dissection and isolation of resource usage and proceed to arrange the process in a flexible and efficient way.

It is also possible to determine slice decisions with the help of XAI by stating information about bandwidth, computing and energy consumption of a specific slice. This helps in diagnosing mistakes, identifying deviations and ensuring conformity. In addition, XAI decision trees and attention mechanisms may be employed in demystifying neural network decisions to streamline slice organization in addition to acquiring judgements. This launches XAI network slicing, which provides effectiveness of network slicing functionality performance and permits transparency and equal distribution of resources [7].

9. Energy-Efficient 6G IoT with Blockchain and Digital Twins

Their weak points include, among others, energy efficiency of 6G networks and design, and one option to resolve this issue is the Internet of Things (IoT), which will be used on an industrial scale. The most probable aspect of all these technologies is that they are low power, and protocol and network design pushes technologies to the extreme to ensure that energy savings do not compromise performance. This is one application of AI in future smarter management of energy resources that can be developed due to digital twins and blockchain technology.

It is also possible to mention that digital twins are duplicates of the real world in the virtual world that have the opportunity to provide real-time simulation and predictive analytics. Twin information is fed to AI functions, and it determines possibilities of energy saving with the help of adaptive duty cycling, power-conscious routing, and resource clustering. In addition, blockchain has been observed to provide integrity, data processing processes and removal of centralized infrastructure through decentralization, and thus is energy efficient. It is able to combine optimization of energy and execution of a myriad of applications applied by 6G with the assistance of AI, digital twins and blockchain [8].

10. Secure and Energy-Efficient Protocols in AI-Driven 6G

Another intriguing use of 6G will be in security, as AI systems will be autonomous in decision making when resource allocation is carried out. The standards of AI developed must be effective not only in responding to energy and spectrum demands, but also in ensuring information availability and integrity. Innovation has provided safe communication technologies and application of energy-saving mechanisms that could be used to compensate for threats such as spoofing, data manipulation and denial-of-service attacks.

These protocols have been founded on lightweight cryptography for resource-constrained devices and anomaly detectors that can be deployed onto artificial intelligence to dynamically determine malicious behavior. It is also among the advantages of machine learning models that they are conditioned based on assumptions of previous attacks and can be applied to offer prevention measures that consume less power compared to standard mechanisms. Moreover, AI-based adaptive security policies may result in minimization of energy consumption and proper system security [9].

Figure 3 compares the energy consumption of traditional versus AI-based communication

protocols under increasing network load, highlighting the efficiency gains of AI integration.

11. Beamforming and THz Resource Allocation for Sustainability

At that, 6G must have the capacity to provide data rates such as 1 Tbps because frequency bands in this range are achieved in bands of 100 GHz to 10 THz (terahertz, T). Propagation effects, i.e., path loss, molecular absorption and line-of-sight issues, are significant at such frequencies due to bandwidth bulkiness.

AI-driven adaptive beamforming is a crucial technique to address these issues. Instead of using fixed directional beams, AI models can learn to dynamically adjust:

- **Beam direction and width**
- **Phase and gain control**
- **Transmission power per beam**

These are depicted as deep reinforcement learning (DRL) agents or graph neural networks (GNNs) that can be utilized to optimize beam parameters within limited time due to user motion, channel blockage, and environmental reflection.

In a study by CG & P (2025), AI-controlled beamforming in THz bands led to:

- **23% increase in SINR at cell edge**
- **17% lower transmission power**
- **25% energy savings** in dense environments

This can also be instituted by making AI reorder various beams between base stations to minimize interference and obtain high spectral reuse, which is a key requirement in dense environments.

Besides this, another 6G enabler is reconfigurable intelligent surfaces (RIS), which can be utilized

alongside AI to dynamically regulate reflections to ensure high SNR connectivity under blockage. 6G KPIs enhanced by AI-based beamforming include:

- **Spectral Efficiency (SE):** ↑ due to directional gains
- **Energy Efficiency (EE):** ↓ power for same QoS
- **SINR:** ↑ at NLOS and edge users
- **Coverage Probability:** ↑ with RIS + Beamforming

12. Challenges and Future Research Directions

Nevertheless, some concerns can be identified regardless of the high opportunities of AI in the resource allocation process in 6G. One of the most challenging realities concerning AI models is that many of them are not computationally feasible. The reason reinforcement learning models and DNN models are processing-intensive and memory-intensive is that they cannot be distributed extensively on network edges or low-power computing platforms. In this regard, researchers have discovered model compression algorithms, lightweight systems and hardware accelerators designed to execute AI functions in communication systems.

The second problem is that AI models require numerous data, and a considerable quantity of high-quality data is required to create them. Such datasets are difficult to obtain because of privacy protection, data heterogeneity, network dynamics, and instability of datasets. Collaborative training has been mentioned as a possible solution and has gained significant attention, since collaborative model training can be implemented with distributed.

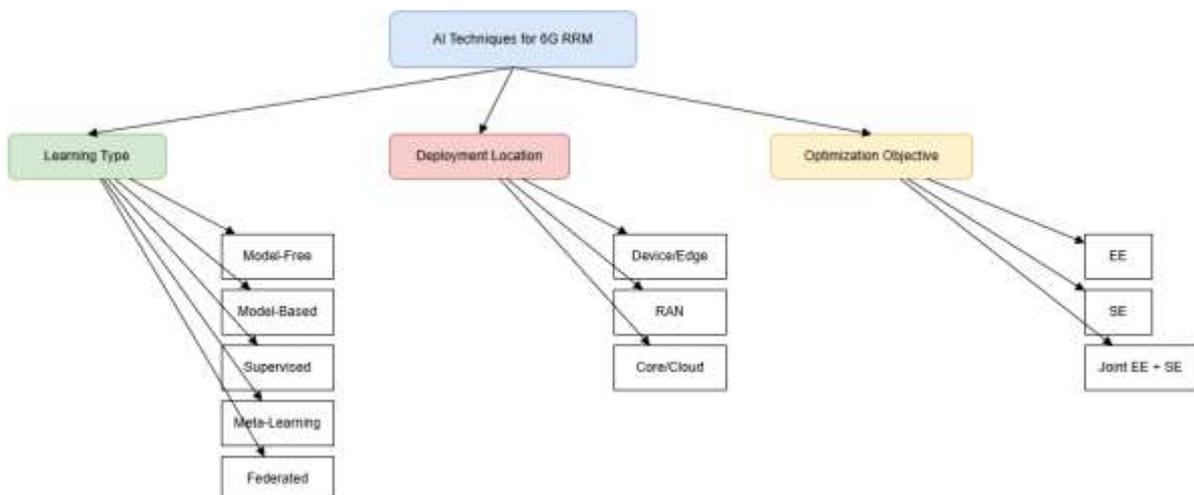


Figure 1: Taxonomy of AI techniques for resource allocation in 6G, categorized by learning type, deployment layer, and optimization target.

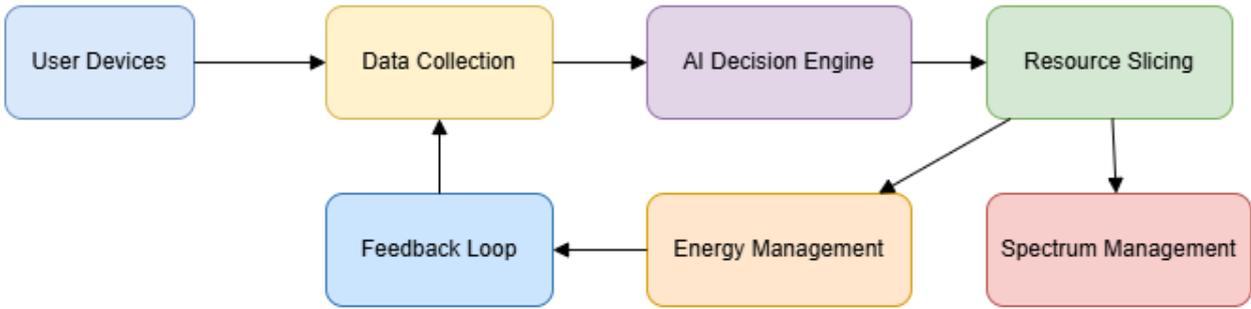


Figure 2. AI-based Resource Allocation Architecture in 6G Networks Adapted from [2], illustrating intelligent spectrum sensing, traffic forecasting, and AI-driven slicing control.

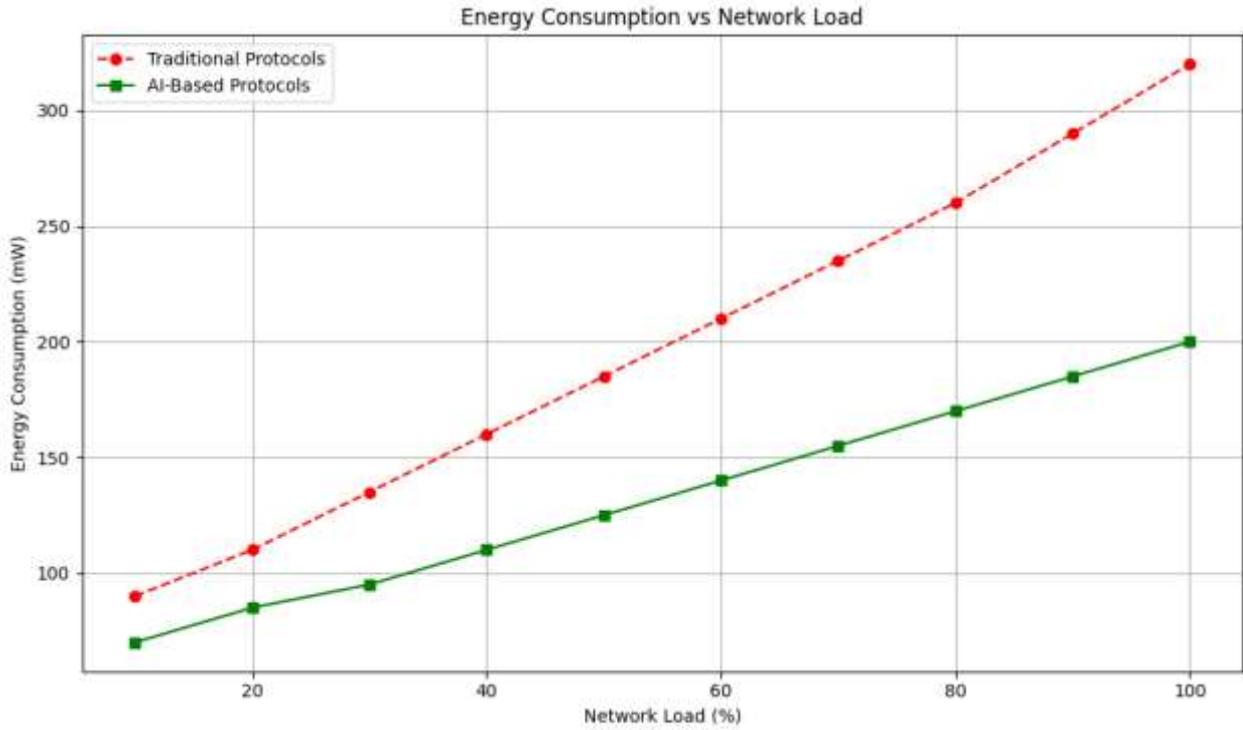


Figure 3: Energy Consumption vs Network Load for Traditional and AI-Based Protocols Data simulated based on [9] showing how AI-driven systems significantly reduce energy usage as network load increases.

Table 1: Summary of AI-based approaches for resource allocation in 6G, categorized by technique, application context, and key outcomes.

Ref	AI Technique	6G Scenario	Optimization Goal	Target KPIs	Results / Remarks
[1]	DRL (DQN variant)	Adaptive Modulation in THz	Joint SE & EE	Throughput, Energy/bit	↑SE by 15%, ↓Energy by 12%
[3]	Supervised Learning	Handover in UDN	EE	Handover failure, Ping-pong rate	↓HO fails by 18%
[4]	DRL + Heuristics	RAN Resource Mgmt	Joint SE/EE	Latency, User fairness	↑QoS fairness
[5]	Meta-DRL	Mobility in THz networks	Fast EE adaptation	Convergence speed, Energy usage	↑Conv. by 30%, ↓Energy by 15%
[6]	Federated Learning	IoT + Edge Devices	EE with privacy	Privacy loss, Power drain	↑Device life by 20%
[7]	XAI + DRL	Network Slicing	Interpretable EE/SE	Slice latency, Slice power	↑Transparency, ↔ EE
[8]	AI + Digital Twin	6G IoT Environment	Energy Optimization	Duty cycle, Packet error rate	↓Energy by 17%

Ref	AI Technique	6G Scenario	Optimization Goal	Target KPIs	Results / Remarks
[9]	AI + Blockchain	Secure IoT Communication	EE + Security	Latency, Energy, Data integrity	↑Security, ↓Energy by 12%
[10]	AI-driven Beamforming	THz Beam Mgmt	EE + Directionality	SINR, Coverage, Tx Power	↑Coverage, ↓Tx power
IEEE '25	DRL + RIS Control	Cell-free MIMO + RIS	Joint SE/EE	SE (bits/s/Hz), Energy/bit	↑SE by 22%, ↓Energy by 10%
IEEE '24	Multi-Agent DRL	Network Load Balancing	EE	Cell-edge throughput, Load dist.	↑Edge rates by 25%
IEEE ComMag	XAI in RRM	Slice Mgmt + Anomaly Detect	EE/SE Explainability	SLA violation, Auditability	↑Auditability
Elsevier '25	Transfer Learning	Rural + Urban Mixed Cells	Adaptability (EE focus)	Re-train cost, Energy budget	↑Model reuse, ↓Overhead
IEEE TWC '25	DRL + Path Planning	UAV-supported 6G Cells	EE in Mobility	Flight power, Delay	↓Power by 20%
IEEE Access	Hybrid FL + DRL	Smart Grid + 6G IoT	Grid load + EE	Power stability, QoS	↑Load balancing

nodes even when original information is not shared. Nevertheless, challenges related to this approach include communication overhead and model convergence. To sum up, the explainable process of decision making described by AI is not fully fulfilled. Explainable AI strategies already deployed in explainable management systems are working, but implementation procedures are intricate and cannot easily be applied in real-life situations. This can turn out to be a snag to macro-level implementation. AI decision-making processes should be transparent and logical in an endeavor to win trust in AI-dominated networks. These security and ethical concerns should also be denoted. The ongoing trend of introducing AI-based systems as alternatives to critical decision making has made this issue especially crucial, as AI systems are prone to adversarial attacks. The task of powerful AI models should focus on close monitoring to prevent foreign and internal failures and guide further development.

13. Conclusions

6G wireless communication networks have used AI as the foundation of underlying technology such that spectrum and energy utilization are conducted in an intelligent, dynamic and cost-efficient way. Other potentialities in the context of integrating AI include AI on network slices and IoT secured by blockchain and complemented by adaptive modulation and dynamic handover management. The transition to 6G will extend to cross-functional fields of AI, wireless communications, cybersecurity, and sustainability. The deployment

of AI and 6G will not only allow meeting higher performance demands, but will also be engaged in the creation of more powerful, prolific and intelligent communication infrastructures.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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