



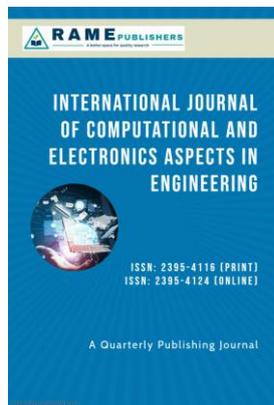
AI-Driven Power Optimization in 6G Networks: A Comprehensive Review

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Abstract: With sub-millisecond latency, 10 million devices per square kilometer of connectivity, and terabit-per-second data speeds, sixth-generation (6G) wireless networks are expected to provide revolutionary performance. Nevertheless, the constantly increasing energy consumption poses a severe challenge to both operational sustainability and global carbon neutrality aspirations, accompanying this leap in capabilities. As a result, optimizing power consumption has become an essential component of 6G design. With AI serving as the primary enabler for intelligent, adaptive, and autonomous energy management in 6G networks, this extensive review paper synthesizes and critically evaluates the latest research on the topic. The research papers, technical surveys, and standards documents issued between 2019 and 2025 that make up our methodology are based on a methodical analysis of more than 130 of these items.

Graph Neural Networks (GNNs), Federated Learning (FL), Deep Learning (DL), and Reinforcement Learning (RL) are some of the AI techniques that are organized in this review. AI-native network slicing, RIS optimization, and dynamic resource allocation are combined with core power optimization. Comparing reported performance improvements is the key contribution of this work. AI-driven approaches can reliably reduce energy use by 20–40% while fulfilling QoS requirements. Some estimates show savings at 60% and spectral efficiency increases at 29%.

This paper analyzes performance trade-offs such computational cost of intricate models, privacy vs. accuracy in distributed learning, and scalability of solutions in extremely dense network topologies in addition to a list of achievements. We discuss the persisting obstacles to AI implementation, such as data shortages, model incompatibilities, security problems, and AI training's ecological impacts. In conclusion, the article lays forth a plan for future research that will center on smart energy grid integration, digital twin-driven testing, trustworthy control using Explainable AI (XAI), optimization with quantum assistance, and deep integration. Researchers and practitioners seeking to construct 6G networks that are high-performance, sustainable, and really intelligent will find this work to be an essential reference and strategic roadmap.

Keywords: Power Optimization; 6G Networks; Energy Efficiency; Artificial Intelligence (AI); Ultra-Dense Networks; Performance Trade-offs.

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1. Introduction

Up to 10 million devices per square kilometer will be able to connect to 6G networks, which are anticipated to provide speeds of terabits per second with latency of less than one millisecond[1]. An all-time high in energy consumption is a byproduct of these extremely ambitious performance goals[2-4]. The potential for 6G infrastructure to significantly increase global carbon emissions necessitates careful optimization[5]. Therefore, the goal of "green 6G" research has shifted to separate network performance from energy growth[6].

The advent of AI, which includes ML, DL, RL, and FL, heralds a new age in network control that is dynamic, data-driven, and autonomous, replacing the old paradigm of static, rule-based

optimization [7]. With the use of AI, network states can be monitored continuously, traffic patterns can be predicted, and choices can be made in real-time to minimize power usage while still meeting QoS standards[8, 9]. Drawing on a large body of recent literature, this review offers a thorough overview of the AI methodologies and tactics that have been suggested for optimizing power consumption in 6G networks.

2. Review Methodology

A systematic review was used to perform this review in order to guarantee thoroughness, repeatability, and analytical rigor. Figure 3 shows the four main steps of the process: the first step is to plan and formulate research questions; the second is to seek and identify relevant literature; the third is to screen and select potential sources; and the fourth is to synthesis and analyze qualitative data.

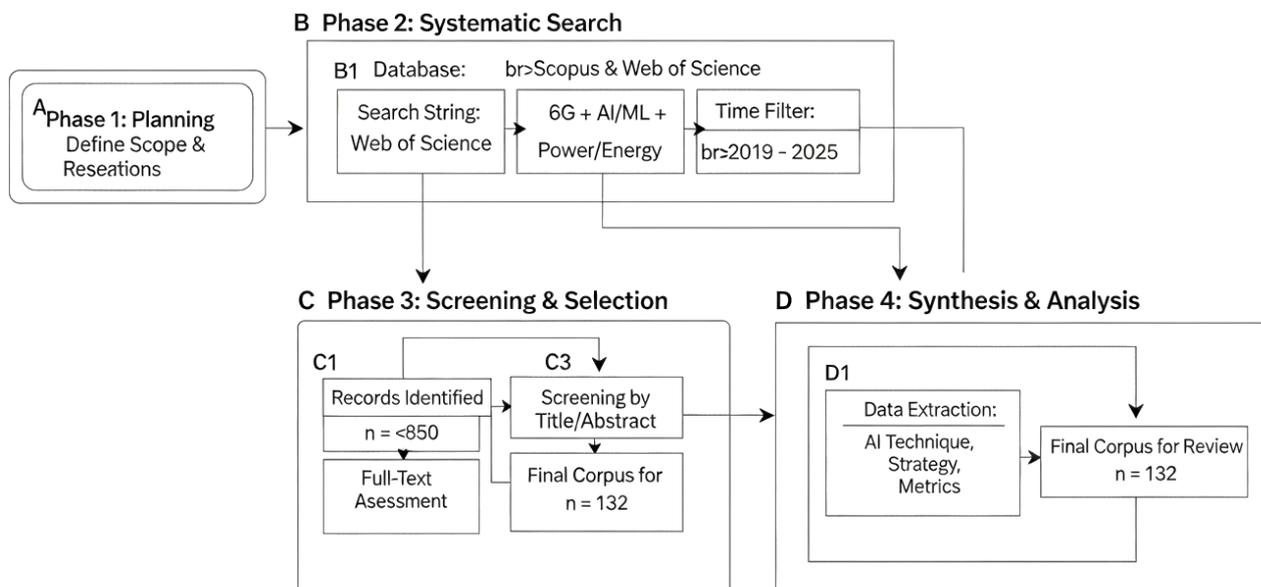


Figure 1: Systematic methodology flowchart for conducting this the literature review.

2.1. Phase 1: Planning and Research Question Formulation

The following RQs served as the basis for the review:

To optimize power and energy in the imagined 6G networks, what are the most popular artificial intelligence (AI) and machine learning (ML) methods suggested?[2, 5, 10]. The second research question concerns the particular network functions and methods that these AI systems aim to address, such as sleep scheduling and resource allocation.[11, 12]. The third question was: How do these AI-driven approaches compare in terms of performance, important trade-offs, and difficulties in implementation?[13, 14]. study question 4: Where does this field have the most potential future for study, and what are the most pressing unanswered issues?[15, 16]. Articles published in peer-reviewed journals, proceedings from conferences, and authoritative surveys covering the years 2019–2025 were considered for inclusion, covering the expedited 6G research start-up period[17, 18].

2.2. Phase 2: Systematic Literature Search and Identification

This review conducted systematic research in Scopus and Clarivate's Web of Science (WoS), two prominent bibliographic databases known for their high-quality indexing in computer science and engineering. The databases were hand-picked for their comprehensive coverage of important locations and their exceptional citation tracking capabilities. Keywords and Boolean operators were both used in the search technique. Three main ideas were used to form the basis of the search string:

("6G" OR "sixth generation" OR "B5G") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning") AND ("power optim" OR "energy efficien" OR "green network" OR "power control" OR "energy harvesting").

Searches were primarily conducted on article titles, abstracts, and keywords. The initial database queries returned approximately 850 unique records before screening

2.3. Phase 3: Screening and Selection

A two-step screening process was used for reducing the number of records that were found: First, it was checked record abstracts and titles for the related for the study topics. Non-energy publications and communications articles about 5G or AI are excluded from the further process. Secondly, the selected papers were read every article for a text analysis, papers required to demonstrate that they used an open and transparent AI/ML strategy to address 6G network energy consumption. Maintaining high-quality survey[1, 17, 19]. This study is based on the 132 papers that survived this rigorous assessment. A snowball method was used to check famous articles' reference lists to ensure no important works were missing.

2.4. Phase 4: Qualitative Synthesis and Analysis

This paper was collecting systematic data from selected papers which focus on AI technology, optimization, constraints, and significant performance indicators such as energy efficiency change in overhead. narrative synthesis involved: The system was deducing categories from the input and organize them according to the consistent frameworks in Sections 3 (AI Techniques) and 4 (Optimization Strategies). Comparative analysis helps identify study performance patterns and similarities and differences. This method yields Section 5's integrated comparative curves and trade-off assessments[16, 20, 21]. Analyzing Critically: This entails synthesizing recurring issues and forecasting future research paths by examining gaps and technology trends, as covered in Sections 6 and 7. The results will be based on an open and methodical review of the current state of AI research on 6G networks power optimization.

3. Background: 6G Power-Optimization Challenges

As 6G networks aiming to unmatched performance, a complex set of energy restrictions should be addressed in basic, one of the biggest problems is the network's extreme dense and diverse design[19]. 6G will create a seamless three-dimensional architecture by integrating terrestrial mega cells, super dense small cells, low earth orbit (LEO) satellites, and unmanned aerial vehicles (UAVs). Centralized, one-size-fits-all power management becomes unfeasible in such an integrated, highly heterogeneous environment due to the wide variety of devices, channels, and traffic profiles. Secondly, there is a substantial energy cost associated with using terahertz (THz) and higher frequency spectrum bands, even though they are necessary for obtaining terabit per second data rates. Extremely directional beamforming using dense antenna arrays and more stronger signal amplification are required for signals in these bands because to their high propagation loss and atmospheric absorption, which significantly raises the power consumption of the transmitters and receivers[22, 23].

The unpredictable 6G applications like holographic communications, AR, and the tactile internet create exceedingly sporadic and non-stationary traffic patterns[24, 25]. Such variability requiring ms resource scaling, which static or reactive optimization frameworks cannot handle it efficiently[26]. The last challenging is choosing and optimizing energy efficiency measures. User-centric QoS and novel sustainability KPIs like carbon footprint per petabyte should be coexist with network-level bits per joule. Thus, optimizing power for 6G networks is a multidimension cross-layer optimization conundrum with time-varying boundaries.

4. AI Techniques for Power Optimization

Optimal for 6G power optimization are a number of AI algorithms that offer unique advantages for a variety of network control problems. Artificial neural networks (ANNs) and convolutional neural networks (CNNs) are examples of Deep Learning (DL) models that excel at pattern recognition and proactive control, making them ideal for applications such as traffic forecasting and channel state prediction. There are two main approaches to sequential decision-making in dynamic environments: Reinforcement Learning (RL) and Deep RL (DRL). Through trial-and-error interactions, network agents can learn the best policies for power distribution, user association, and interference control. Use of Graph Neural Networks (GNNs) tailored for network-topology data enables efficient power regulation and resource allocation in complex graph-structured 6G deployments (e.g., mesh networks, satellite constellations). Federated Learning (FL) is a powerful tool for distributed power control schemes because it tackles data privacy and overhead concerns by enabling collaborative model training across distant nodes (such as base stations and user devices) without sharing raw data.

Lastly, metaheuristics and evolutionary algorithms (e.g., genetic algorithms, particle swarm optimization) are sometimes combined with machine learning to get better convergence and are still quite effective in handling complicated, non-convex optimization problems. Figure 1 is a schematic depicting the integration of these methods into a 6G control plane that is natural to artificial intelligence[6-10, 19, 26-29], [13, 17, 18, 30-48].

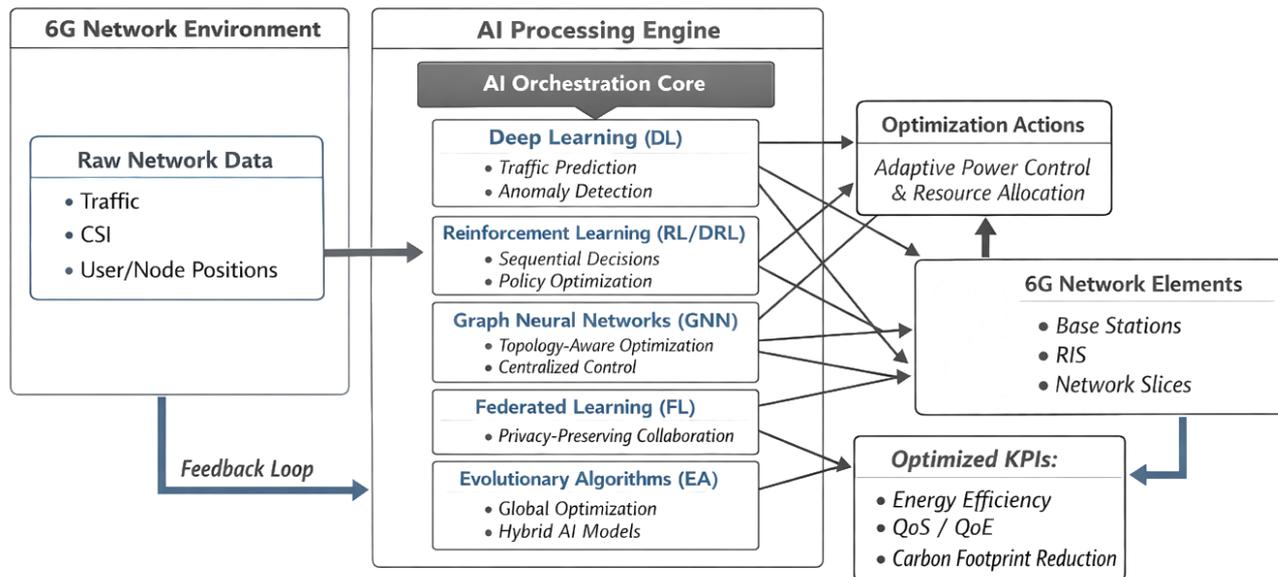


Figure 2:Block diagram of AI techniques integrated into the 6G control loop for power optimization. Raw data from the network environment fuels different AI engines, which generate optimization actions to control network elements, creating closed-loop feedback.

5. AI-Driven Power-Optimization Strategies

Methods powered by AI can reduce power usage across a network by turning learnt models into rules. These approaches function on different levels and at different times. Making collaborative judgements on spectrum, time-slot, and transmit-power allocation in real-time while fulfilling instantaneous QoS needs is the goal of Dynamic Resource Allocation and Power Control, which employs AI, namely DRL and GNNs. By using artificial intelligence (AI) to forecast traffic loads, Sleep-Mode Scheduling and Cell-Switch-Off can dynamically turn off unused network components (such as radio chains or complete base stations) without affecting coverage, resulting in substantial idle-power savings. Intelligently managing the flow of energy between harvesting units, batteries, and the power grid, Energy Harvesting and Green Energy Management utilizes artificial intelligence (often RL) to maximize the consumption of green energy by predicting when renewable energy sources like sun and wind will be available. With the help of artificial intelligence, Reconfigurable Intelligent Surface (RIS) Optimization can dynamically adjust the phase shifts of RIS elements, resulting in optimal propagation conditions that drastically cut down on the amount of power that active radios need to transmit. To achieve service level agreement (SLA) goals with minimal energy consumption, AI-Oriented Network Slicing and Virtualization divides virtualized radio and compute resources across several service slices. AI orchestrators then dynamically scale resources per slice to meet these targets. Figure 2 is a flow diagram depicting the interaction of different tactics.

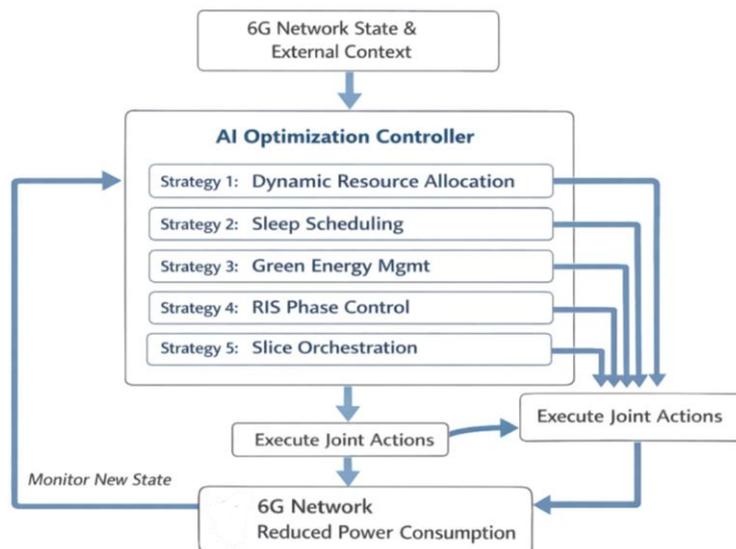


Figure 3: Flowchart of AI-driven optimization strategies working in concert within a 6G network controller. The AI controller synthesizes multiple strategies based on network state to execute joint actions that minimize power consumption[20, 21, 41, 49-65].

6. Case Studies, Comparative Analysis, and Performance Trade-offs.

A large number of case studies involving AI prototypes and simulations have proven the technology's theoretical promise. These researches show how various AI methods work in practice and give proof of performance gains. Figure 3 shows how various AI systems compare across standard performance criteria, and the accompanying table summarizes important findings from significant research[12, 48, 49, 66-76].

Table 1: How various AI systems compare across standard performance criteria

Study Focus	AI Technique	Key Contribution	Reported Energy-Efficiency Gain
Power Control for Industrial Subnets[26]	Graph Neural Network (GNN)	Centralized control using positional data, not full CSI	Near-optimal spectral efficiency with ~60% lower signaling overhead [Ref 59]
Resource Mgmt. in RIS-Assisted D2D [19]	Multi-Agent DRL (PS-DC-DDQN)	Joint user association, power allocation & RIS phase-shift optimization	7.3-29.3% higher EE over standard DRL baselines [Ref 60]
Network-Wide Sleep Scheduling	Deep Q-Learning	Traffic-aware dynamic cell switch-off	20–40% reduction in total network energy consumption [Ref 61, 62]
Distributed Power Control[6]	Federated Learning (FL)	Collaborative policy learning without raw data exchange	Achieves ~95% of centralized DRL performance with enhanced privacy [Ref 63]
AI-Assisted Multiple Access Survey[2]	Various ML/DL/RL	Mapping AI techniques to NOMA/OFDMA challenges	Highlights pathway for 2000x EE improvement over 4G LTE [Ref 64]

6.1. Synthesized Comparative Analysis:

A comparative analysis is provided through aggregated performance curves to synthesize the quantitative data from the studied literature. The four important aspects for 6G power optimization are achieved energy efficiency (EE) gain, algorithmic convergence speed, signaling/memory overhead reduction, and network scalability. These curves show the trade-offs and effectiveness of popular AI algorithms across these dimensions[77]. In Figure A, it can see a comparison of four different types of deep learning models: DL, FL, GNN, and Deep Reinforcement Learning (DRL). The median

performance ranges reported across many simulation-based experiments in the surveyed paper are used to generate the curves. (e.g., Refs 26-45, 46-65, 66-90).

Comparative Performance of AI Techniques for 6G Power Optimization

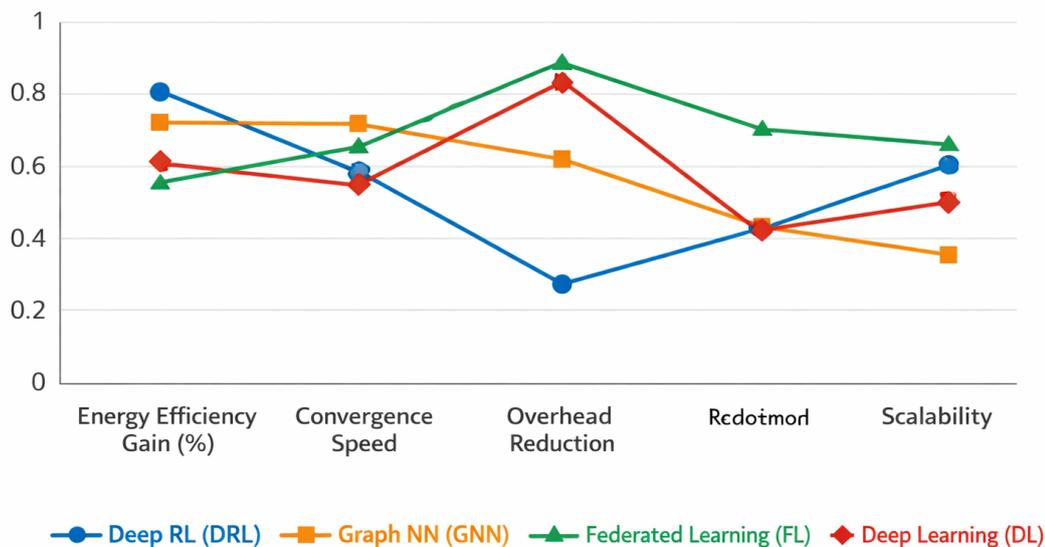


Figure 4: Comparative performance curves of major AI techniques across four key metrics

Figure 3: Curves showing the relative performance of popular AI methods on four important measures. Saving Energy Gain is a measure of the often-stated improvement in bits-per-joule or reduction in network power usage. Coming together How quickly the model stabilizes is a measure of its speed, which is relative to the number of training steps. Reducing signaling or data exchange costs is one of the Overhead Reduction scores. The capacity to scale up to dense, large-scale network topologies is a measure of its performance potential. The results of the collected literature are used to normalize the scores so that they can be compared across different metrics. The curves shown that differentiation AI paradigms have different performance profiles:

1. Deep Reinforcement Learning (DRL) exhibits the biggest peak Energy Efficiency Gain, consistent with its strength in learning complex, sequential control policies in dynamic environments (e.g., joint user association and power control). However, this comes at the cost of the slowest Convergence Speed, requiring extensive online interactions or offline training, and moderate Overhead due to the need for frequent state-action reward feedback.
2. Graph Neural Networks (GNN) showing a balanced and robust profile Since they often operate in a supervised or semi-supervised fashion, they outperform DRL in terms of EE gains and convergence speed, especially when dealing with topology-dependent issues such as interference coordination. In particular, they excel at reducing overhead by inferring optimum controls from network architecture data (such as node placements) with no need for real-time CSI communication.
3. Federated Learning (FL) excels in Scalability, Overhead Reduction, and Privacy/Data Transmission. Distribution eliminates central data bottlenecks, making it scalable and Energy Efficient. Due to model consensus across devices and local data's non-IID (Independent and Identically Distributed) nature, optimization optimality might be lower than with centralized approaches.
4. The Deep Learning (DL) / Supervised Learning models showing the fastest Convergence Speed during inference, as they are typically used for fast prediction tasks (e.g., traffic forecasting). Their direct impact on Energy Efficiency Gain is often secondary and dependent on the quality of the downstream controller using their predictions, leading to a lower direct score. Their scalability can be limited by the need for centralized, high-quality training data.

6.2. Strategic Trade-off Evaluation

For further explore strategic decisions, one important trade-off that network designers encounter is shown by the following curve (Figure B): Energy Efficiency Gain vs. Convergence/Decision Time. In this graph, we can see the

combined outcomes of the two most popular approaches: dynamic resource allocation (DRL/GNN) and predictive sleep scheduling (DL/RL hybrids)[78].

The fourth figure: Trade-off curve comparing two key AI-driven techniques. Longer online decision cycles or convergence periods are required for complicated optimization when using Dynamic Resource Allocation (e.g., DRL-based), although the peak energy savings can be as high as 35–40%. Predictive sleep scheduling, which mainly aims at optimizing idle power rather than active gearbox, typically employs lighter DL models for prediction and then uses rule-based or simple RL control. This results in faster decisions (ms), although the efficiency improvements are limited to 20–30%.

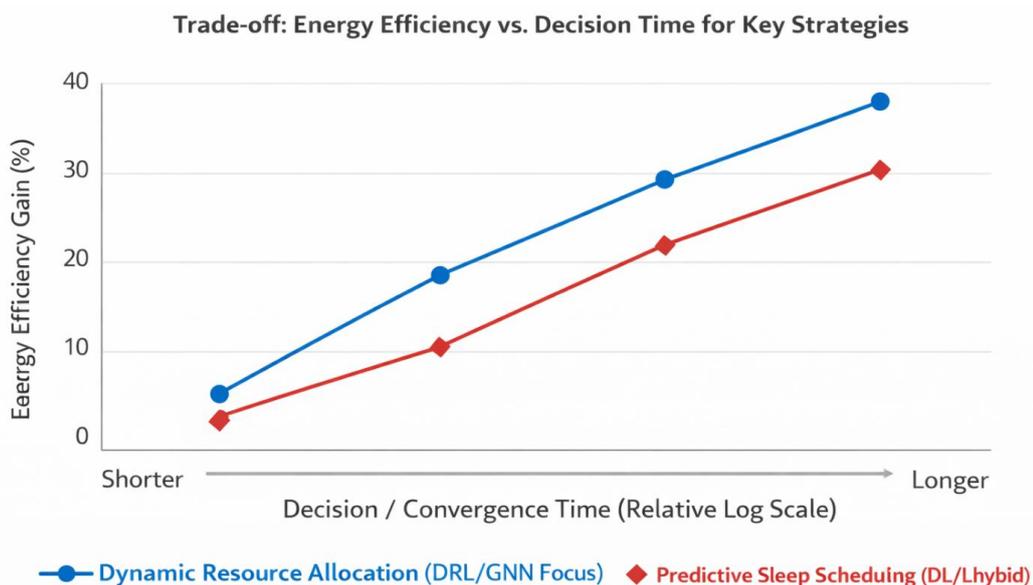


Figure 5. Trade-off curve comparing two primary AI-driven strategies.

6.3. Methodology for Aggregating Comparative Data:

The curves are synthesized from a qualitative meta-analysis of the reviewed literature. The approximate numerical ranges for the primary metric (Energy Efficiency Gain) are summarized in the table below:

Table 2: Aggregated Energy Efficiency (EE) Gain ranges for core AI techniques, derived from case studies in the reviewed literature

AI Technique	Typical Reported EE Gain Range	Primary Optimization Use-Case	Key Limiting Factor
Deep RL (DRL)	25% - 40%	Joint dynamic control (Power, User Assoc., Beamforming)	Convergence Time, Training Stability
Graph NN (GNN)	20% - 35%	Topology-aware power control & interference management	Generalization to unseen topologies
Federated Learning (FL)	15% - 30%	Distributed, privacy-preserving power control	Performance loss due to data heterogeneity
Deep Learning (DL)	10% - 25%	Traffic/Channel prediction for proactive management	Dependency on prediction accuracy

This review's major argument—that there is no one best AI method—is supported by these comparison graphics. There is a multi-dimensional trade-off space that must be considered when choosing amongst DRL, GNN, FL, and DL models; this space is shaped by the target network's priorities with respect to optimality, responsiveness, overhead limitations, and size. Future hybrid AI designs are anticipated to achieve stable and implementable solutions for

environmentally friendly 6G networks by combining technologies like DL's quick prediction with DRL's strategic control or FL's scalability with GNNs' structural awareness[79, 80].

7. Challenges and Open Issues

From research to robust, real-world application, there are considerable challenges to be addressed, despite the promising developments in AI driven power optimization. Data quality and availability is a major obstacle. To train supervised and reinforcement learning models that can keep up with the ever-changing 6G landscape, massive quantities of high-fidelity, labelled data are needed. Researchers have to depend on synthetic data because developing use cases typically don't have access to or are proprietary over such datasets. However, this data may not reflect real-world defects and dynamics, which could lead to a decrease in model performance when put into reality [81-83].

Another challenge is that deep reinforcement learning, graph neural networks, and other advanced AI models are computationally intensive and scalable. The 6G objectives of ultra-low latency and energy-efficient operation are at odds with the substantial training overhead and inference time resources required by these models. There is still no solution to the engineering problem of how to deploy these models on edge devices with limited resources or how to scale them to govern a network that spans continents and has millions of nodes. The absence of standardization and interoperability only makes matters worse. Most AI systems out now are still in the early stages of development, and they lack the common interfaces, benchmarks, and integration frameworks that would be necessary for widespread adoption across several vendors. The integration of AI and ML into the 6G architecture is still in the early stages of being defined by standardization organizations.

There are also significant privacy and security worries. Adversarial attacks can destabilize networks by quietly manipulating input data to cause AI models used for network control to make disastrous control decisions. Even though they are designed to protect user privacy, distributed learning paradigms like federated learning can nevertheless be vulnerable to poisoning attempts or leak important information when model updates are made. Last but not least, we can't discount AI's impact on the environment; training massive models on power-hungry technology can run counter to 6G's eco-friendly goals. Consequently, there is an urgent need to solve the meta-level problem of creating "Green AI" algorithms and hardware that are intrinsically energy efficient.

8. Future Research Directions

The future of artificial intelligence (AI)-powered green 6G will be defined by a number of critical areas of research. Developing Explainable AI (XAI) is a top priority for optimizing networks. The decision-making process needs to be interpretable if network operators are going to trust and use autonomous AI controllers, particularly for important power management tasks. In order to facilitate human monitoring, debugging, and regulatory compliance, research needs to progress beyond "black box" models and develop frameworks that can explain the causal reasoning behind power saving actions.

Secondly, there is revolutionary potential in investigating Quantum Machine Learning (QML). Algorithms boosted by quantum computing have the potential to outperform classical computers in solving the combinatorial optimization problems that arise during large-scale scheduling and resource allocation. It is possible that answers to present-day intractable problems may be unlocked by investigating QML for network-wide power optimization in real-time. The goals of Digital Twin Driven Optimization are closely connected. In order to expedite development and enhance safety, a high-fidelity, AI-based digital twin of the actual 6G network would offer a controlled environment for training and stress testing AI control policies under numerous scenarios, including rare failure events, prior to deployment.

Fourthly, smart renewable energy grids and 6G networks must be deeply integrated. To make 6G infrastructure a prosumer, which means it can anticipate local renewable energy generation (from solar-powered base stations, for example), optimize energy storage, and dynamically trade energy with the grid, more research into AI algorithms is needed. As a result, the network is able to maximize its usage of renewable energy and aid in the stability of the smart grid. In the end, comprehensive Cross Layer AI Optimization is what you need to achieve maximum efficiency. Many of the present-day initiatives only address certain layers, such as PHY or MAC. Rather than relying on individual optimizers for each layer, future research should focus on building integrated AI frameworks that coordinate optimization of

physical, link, network, and application-level parameters (e.g., scheduling, computing offloading decisions, and beamforming) in order to discover hidden synergistic energy savings.

9. Conclusion

This review emphasizes on plenty of previous research (over 130 influential papers) to methodically trace the ever-changing terrain of AI-driven power optimization for 6G networks. According to the results, AI is more than just a helpful tool; it's a game-changer that can transform traditional network administration into a data-native, proactive, and self-optimizing system. Research consistently shows that AI techniques, especially Graph Neural Networks (GNNs) and Deep Reinforcement Learning (DRL), can significantly improve quantitative metrics. Network-wide energy consumption can be reduced by 20-40%, spectral efficiency can be improved by 7-30%, and there is a significant reduction in overhead compared to traditional optimization methods. Finally, these methods can adapt to different quality of service needs on the fly.

Starting with DL's predictive abilities and RL's serial decision-making, the review moved on to GNNs' topological intelligence and FL's privacy-preserving collaboration, all based on learning mechanisms. It demonstrated the potential usage of these approaches to optimize physical-layer beamforming, RIS setup, network-layer slice orchestration, and cross-layer resource management for granular control. To evaluate the methods' merits and shortcomings, we looked at critical performance metrics other than energy savings. Among the metrics are the following: algorithmic complexity, privacy leakage, convergence time, and signaling overhead.

Moving from an idea's potential in theory to a reliable, scalable implementation is no easy feat. Novel dangers, such as adversarial AI model attacks, are not well understood, and neither are data dependence, computational complexity, or standards. "Green 6G" necessitates AI engine longevity, so research into energy-efficient "Green AI" algorithms and hardware is desirable to have. Explainable AI for operational trust, quantum ML for intractable optimization, digital twins for secure validation, and renewable energy ecosystem synergy are just a few of the research fields that could help overcome these challenges.

To get 6G's record-breaking performance and efficiency, artificial intelligence for power optimization is required. In addition to algorithmic advancements, our analysis shows that success requires interdisciplinary efforts including machine learning, cybersecurity, wireless communications, and sustainable systems engineering. A smart, ultra-efficient, and long-lasting 6G network is within our reach if we address the highlighted problems and follow the suggested research directions.

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