The survey of AI-Empowered Energy Efficiency Optimization in Ultra-Dense 6G Edge Networks

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Abstract

This paper conducts a comprehensive investigation into the energy efficiency optimization driven by artificial intelligence in ultra-dense 6G edge networks, providing reference methods for key challenges such as high energy consumption, dynamic resource management, and multi-objective trade-offs. Traditional methods often lack adaptability and real-time performance, prompting the exploration of advanced artificial intelligence technologies, including deep reinforcement learning (DRL), federated learning (FL), graph neural networks (GNN), and long short-term memory (LSTM) networks. Although challenges such as training complexity, data dependence, and device heterogeneity still exist, these methods show great potential in reducing energy consumption while maintaining service quality. We propose a closed-loop framework that integrates DRL for real-time control, FL for privacy-preserving distributed optimization, GNN for topology-aware resource allocation, and LSTM for time-flow prediction. Additionally, we have identified key future research directions, such as algorithm lightweighting, multi-objective dynamic optimization, cross-domain integration, and standardization efforts. By combining the most advanced artificial intelligence technologies with emerging 6G requirements, this work provides a roadmap for achieving sustainable, intelligent, and energy-efficient 6G networks, ultimately advancing the global green communication goal.

Keywords

6G network; UDN; Edge computing; AI; deep reinforcement learning; Green communication.

1. Introduction

With the rapid development of technology, networks have evolved from 5G to 6G. The UDN and Multi-access Edge Computing (MEC) requirements are two core directions in future communication technologies. Their deep integration will enable new intelligent, low-latency, and high-reliability applications. However, ML tasks incur massive computational burdens and energy costs[1]. The high energy consumption of 6G networks, including ultra-dense base stations, terahertz communication, and distributed AI computing, increases carbon emissions and operational costs, conflicting with global carbon neutral and green communication. Addressing these issues requires intelligent energy-saving technologies, renewable energy integration, and efficiency optimization. The fusion of AI and mobile networks enables dynamic and automated network configuration[1]. AI plays a crucial role in 6G edge networks through adaptive decision-making, intelligent resource allocation, and distributed learning, effectively optimizing energy efficiency.

Existing energy efficiency optimization methods reduce network energy consumption but face limitations. Even with sufficient energy, unlicensed spectrum band contention creates spectrum scarcity issues[2]. Task offloading lowers terminal energy consumption but suffers from wireless channel instability, unbalanced edge server loads, and backhaul bottlenecks, potentially reducing efficiency or causing energy transfer problems. In contrast, AI offers superior energy efficiency optimization. Machine learning enables dynamic network adaptation, providing real-time management solutions[3]. AI has significant advantages in improving energy efficiency through intelligent resource allocation and adaptive management, which is why an increasing number of researchers are focusing on AI-based solutions to address the energy challenges of 6G.

This paper first introduces the basic background knowledge of UDN and edge computing, emphasizing their crucial role in achieving high-performance and low-latency 6G communication systems. Subsequently, the paper systematically classifies and analyzes these methods based on the existing learning framework of artificial intelligence-driven approaches, including DRL, FL, GNN, and LSTM. Additionally, from the perspective of deployment, these methods are categorized into centralized optimization, distributed collaboration, and lightweight edge deployment strategies, each of which is applicable to different network scenarios and resource constraints. To provide practical insights, the paper also examines several typical case studies, demonstrating how these artificial intelligence technologies have successfully been applied to optimize the energy efficiency of real-world or simulated 6G edge networks. Finally, this paper identified the key challenges and proposed future research directions. Compared with existing reviews, it is more instructive in terms of the depth of technology integration and the feasibility of implementation. Below is the flowchart of this article.

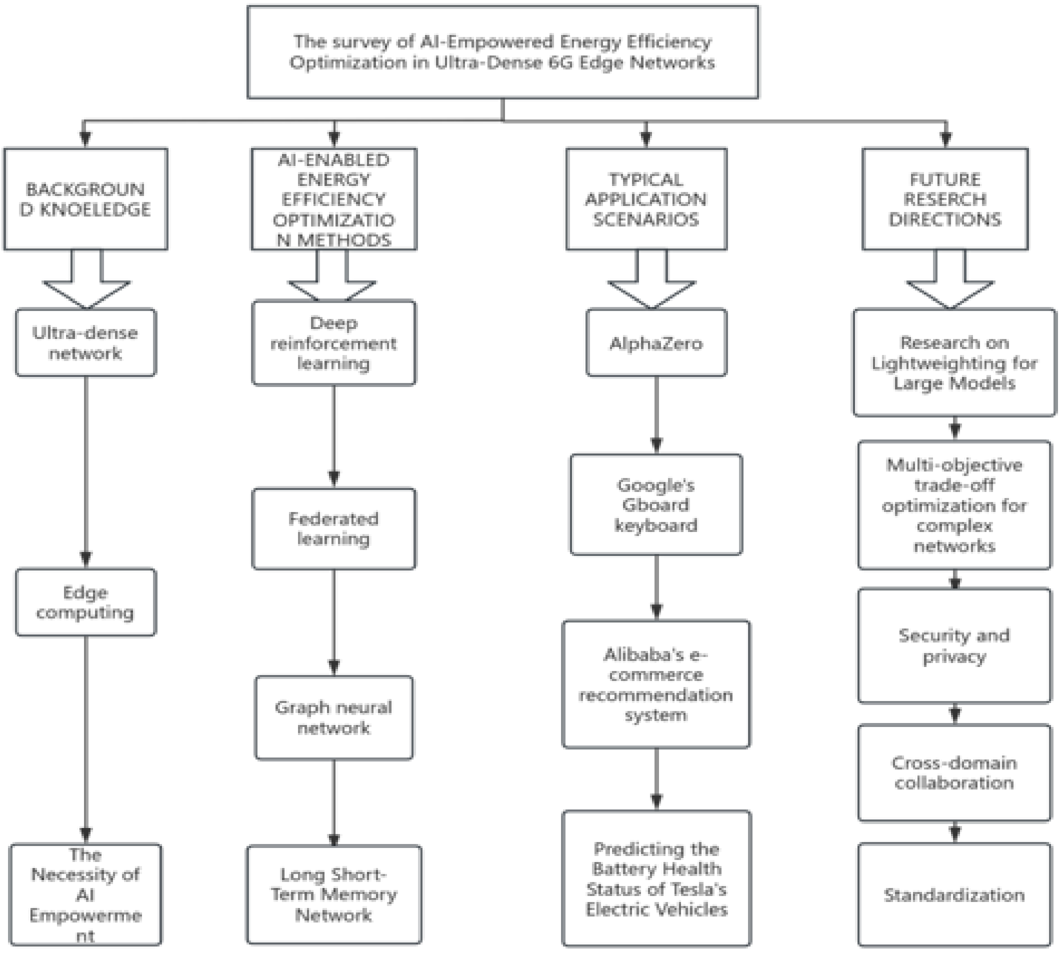

Figure 1. Flowchart

2. Background Knoeledge

2.1. UDN

UDN is one of the key technologies in 6G and future communication networks. By significantly increasing the deployment density of low-power small base stations within a unit area, it achieves significant improvements in network capacity, spectral efficiency, and coverage. Just like Ultra Dense Heterogeneous Networks, which involve densely deployed small cells overlaying traditional macro cellular networks, will be an enabling solution for extremely high data rate communications [4]. The core idea is to utilize spatial multiplexing gain, shorten the distance between users and access nodes, reduce interference, and improve signal quality. UDN faces challenges such as inter-cell interference management, mobility management, and backhaul resource optimization. It requires the combination of intelligent collaboration, dynamic resource allocation, and network virtualization to achieve efficient networking and provide ultra-high-speed and ultra-low latency communication services for high-density user scenarios.

2.2. Edge computing

To reduce network and service latency, edge computing has been proposed to offload part of the workload generated by mobile users to nearby edge servers with sufficient resources[5]. Edge Computing is a distributed computing paradigm that moves data processing, storage, and application services from the cloud to the network edge, thereby reducing data transmission latency, lowering bandwidth consumption, and enhancing real-time performance. Its core concept is local processing, and it is suitable for scenarios such as IoT, autonomous driving, and industrial internet that are sensitive to latency. Edge computing can significantly reduce data transmission delay and return energy consumption by sinking computing tasks to the edge of the network close to the data source and combining them with the deployment of high-density base stations in the 6G UDN, so as to jointly optimize network energy efficiency and achieve low-power, responsive green communication.

2.3. The Necessity of AI Empowerment

In ultra-dense 6G networks and edge computing, traditional optimization methods have shortcomings such as insufficient adaptability and low computational efficiency. In contrast, technologies based on artificial intelligence offer more flexible solutions. The introduction of AI technology offers a brand-new approach to solving these problems. Its powerful data-driven learning ability, environmental adaptability, and intelligent decision-making advantages enable precise perception, dynamic prediction, and autonomous optimization of network energy consumption. Through AI algorithms such as deep learning and reinforcement learning, 6G networks can break through the limitations of traditional static optimization models, ensuring service quality while significantly reducing energy consumption and meeting the development needs of green communication. AI-enabled energy efficiency optimization not only improves the efficiency of network resource utilization but also provides a sustainable intelligent solution for the massive device connections and diverse business scenarios in the 6G era and is a key technical path for promoting the efficient and low-carbon operation of 6G networks.

3. AI-Enabled Energy Efficiency Optimization Methods

I have summarized four AI-enabled methods for energy efficiency optimization (Table 1), which are listed in the table below. AI technology offers diverse solutions for the energy efficiency optimization of 6G ultra-dense networks. However, it is necessary to balance the algorithm complexity, real-time performance, and multi-objective optimization capabilities according to specific scenarios in order to achieve an efficient and green 6G network.

Table 1. The classification of AI-Enabled Energy Efficiency Optimization Methods

Method	Application Scenarios	Advantage	Disadvantage	Reference
Deep reinforcement learning	Base station sleep strategy, resource allocation	Dynamic environmental adaptability and long-term energy efficiency optimization	High training complexity and action space explosion	[6][7][8]
Federated learning	Distributed energy efficiency optimization (such as the MUSIC architecture)	Privacy protection, low communication cost	Device heterogeneity and slow convergence speed	[9][10][11]
Graph neural network	Network topology optimization	Handling complex topological relationships	High data dependency and long training time	[12][13][14]
Long-short term memory network	Traffic and Energy Consumption Prediction	Strong ability in modeling time series data	A large amount of historical data is required.	[15][16][17]

3.1. DRL

Energy efficiency optimization based on deep reinforcement learning is a method that teaches optimal energy-saving strategy through the dynamic interaction between the agent and the environment. Its core idea is to model the energy consumption problem as a Markov decision process and use deep neural networks to approximate the value function or policy function, thereby achieving autonomous decision-making in high-dimensional state and action spaces. For example, in ultra-dense networks, DRL can minimize the long-term cumulative energy consumption while meeting quality of service constraints by dynamically controlling the sleep/activation mode of base stations[6] or adjusting resource allocation parameters. Deep Reinforcement Learning (DRL) demonstrates significant advantages in handling nonlinear and time-varying problems by integrating domain expertise. The article [7] shows that deep reinforcement learning has demonstrated unique advantages in 6G energy efficiency optimization, dynamically optimizing resource allocation, complex trade-offs between energy consumption and latency through autonomous decision-making mechanisms, and providing intelligent solutions for ultra dense networking and new businesses such as holographic communication. The article [8] proposes a DRL deployment framework based on the MEC-O-RAN unified architecture. Through innovative methods such as multi-time-scale coordination, asynchronous request prediction, incremental learning, and simulation migration training, it addresses the challenges of dynamic adaptability, heterogeneous topology generalization, and real-time convergence faced by DRL in 6G network energy efficiency optimization. This significantly enhances the intelligence level of resource allocation and energy consumption management and also verifies its efficiency and feasibility in practical scenarios such as task offloading and network slicing.

DRL has significant advantages in 6G energy efficiency optimization. It learns the optimal energy-saving strategies through the dynamic interaction between intelligent agents and the environment and can achieve dynamic and autonomous decision-making in complex environments. However, its practical application faces some limitations, including long convergence time, sensitivity to environmental changes, and the need for high-precision simulation to ensure safe exploration. Future progress needs to address these challenges by enhancing the generalization ability in heterogeneous networks, reducing training costs through incremental learning, and integrating hierarchical coordination of multi-agent systems to improve the scalability and robustness in actual 6G deployments.

3.2. FL

In 6G networks, FL employs distributed collaborative training models without the need for data sharing, thereby significantly reducing communication energy consumption, decreasing latency, enhancing privacy protection, and supporting large-scale device connections. Its advantages lie in reducing data transmission costs through local computing and parameter aggregation, and meeting the efficient, low-latency and privacy requirements of 6G[9]. The article[10] proposes a federated clustering algorithm based on conditional reversible neural networks. By using a global encoder to map client data into a Gaussian distribution and leveraging a generative model to learn latent features, it achieves efficient clustering of heterogeneous data while protecting data privacy, thereby enhancing the accuracy and efficiency of the federated learning model. This method demonstrates significant advantages in 6G energy efficiency optimization, as it can reduce communication costs through precise distributed resource allocation and dynamic clustering, and adapt to non-independent and identically distributed data environments. The article [11] proposes the FedAssist framework, which optimizes the application of FL in non-independent identically distributed surface electromyography data through local and global two-level preheating strategies, significantly improving the collaborative learning efficiency and model robustness of AI prostheses. This method demonstrates unique advantages in 6G energy efficiency optimization, reducing data transmission requirements through distributed training, lowering communication energy consumption, and protecting user privacy.

FL demonstrates significant advantages in 6G energy efficiency optimization, including reducing communication energy consumption, lowering latency, enhancing privacy protection, supporting massive device connections。 It also adapts well to non-independent and identically distributed data environments, as evidenced by innovations like the federated clustering algorithm based on conditional reversible neural networks [10], which improves model accuracy through latent feature learning, However, FL still faces challenges such as asynchronous communication, privacy security risks, and convergence. In the future, with the optimization of algorithms and the development of 6G technology, FL is expected to achieve more efficient energy efficiency optimization in areas such as intelligent edge computing and semantic communication. However, its large-scale deployment still requires solving the problem of coordinated management of computing and communication resources.

3.3. GNN

Graph neural networks provide innovative methods for energy-saving optimization in 6G networks. This method models base stations, users, and devices as graph data, where nodes represent network entities and edges represent communication or interference relationships. Through the message passing mechanism, graph neural networks can aggregate neighborhood information, simultaneously learn the topological features and dynamic traffic patterns of the network space, and achieve collaborative optimization of the overall network energy consumption. The article[12] introduces GNN as a network interpreter in 6G networks, which can efficiently handle non-Euclidean space data and is particularly suitable for modeling complex network topologies. This enables intelligent resource allocation, network management and signal processing in 6G energy efficiency optimization. Its advantages include high adaptability to dynamic networks, low computational cost, and the potential to enhance overall energy efficiency. The article[13] proposes a digital twin-driven service self-healing mechanism based on GNN. It achieves precise network performance prediction and anomaly detection through a dynamic graph attention network and optimizes service deployment using a deep graph matching algorithm, thereby significantly enhancing the energy efficiency and load balancing capabilities of 6G edge networks. The article[14] proposes a multi-path routing algorithm based on GNN. By using GNN to model the dynamic topology and traffic characteristics of low-orbit satellite networks, it achieves non-intersecting link path planning and dynamic traffic allocation, thereby significantly improving throughput, reducing latency, enhancing the generalization ability for any orbital constellation, and optimizing energy efficiency without the need for repeated training in 6G networks.

GNN has significant advantages in 6G energy efficiency optimization. It can achieve intelligent resource allocation, adaptive network management, and precise performance prediction with low computational overhead, which is demonstrated in applications such as digital twin-driven self-healing and multi-path routing in satellite networks. However, its reliance on high-quality graph representations and potential scalability challenges in ultra-large-scale networks are still its limitations. Future progress may focus on enhancing real-time adaptability, integration with other artificial intelligence technologies, and application expansion in the emerging 6G architecture.

3.4. LSTM

The 6G energy efficiency optimization based on the LIME-Series prediction model integrates interpretable AI and time series prediction to intelligently analyze the impact of network parameters on energy consumption and predict future states, achieving dynamic energy-saving regulation. This model not only ensures service quality but also can accurately predict energy consumption trends and provide transparent decision-making basis, significantly improving the energy utilization efficiency of ultra-dense networks. This article [15] presents two lightweight variants of LSTM. By fixing the gate parameters and simplifying the memory unit structure, the number of parameters is significantly reduced, while maintaining performance comparable to that of the standard LSTM and significantly lowering computational costs. This efficient characteristic makes it more suitable for deployment on resource-constrained edge devices in 6G networks. By reducing model complexity and accelerating the training process to optimize energy efficiency, while maintaining the ability to process time-series data, it provides a feasible solution for real-time energy-saving computing in 6G scenarios. The article[16] proposes a model based on CNN-LSTM, which is used for channel estimation in 6G networks assisted by RIS-NOMA. It significantly improves the accuracy and robustness of channel prediction, thereby optimizing the energy efficiency and performance of 6G networks. The article[17] proposes a fusion-separation deep neural network based on 1D CNN-LSTM, which is applied to the 6G ultra-large-scale MIMO hybrid beamforming system. The core function of LSTM is to capture the time-series characteristics of channel state information. Combined with the spatial feature extraction ability of CNN, it significantly reduces the computational complexity of traditional iterative algorithms while maintaining a frequency spectrum efficiency close to the optimal level.

LSTM demonstrates significant advantages in 6G energy efficiency optimization, capable of accurately predicting energy consumption trends through time series modeling and dynamically adjusting network parameters, thereby enhancing the energy utilization efficiency of ultra-dense networks. However, LSTM still has issues with high model complexity and long training time. Although lightweight variants alleviate some computational burdens by fixing gate parameters and simplifying the structure, they may still face challenges when processing ultra-large-scale real-time data. In the future, LSTM needs to further optimize its architecture to balance energy efficiency and real-time performance and explore integration with new neural networks to better adapt to the high mobility, low latency, and ultra-high energy efficiency requirements of 6G networks.

4. Typical Application Scenarios

4.1. AlphaZero

The DRL framework of AlphaZero provides innovative ideas for the energy efficiency optimization of 6G networks. Its core concept is a pure self-bidding intelligent evolution mechanism. In the simulation environment, the DRL agent continuously attempts actions such as base station sleep and power adjustment, receives real-time feedback on network energy efficiency, and ultimately autonomously learns the optimal energy-saving strategy. Similar Monte Carlo tree search of AlphaZero can accelerate strategy exploration, while the value network can predict the long-term energy efficiency benefits of different configurations. This data-driven optimization method without prior knowledge is particularly suitable for complex and dynamic interference management and multi-objective trade-off problems in 6G ultra-dense networks, providing an adaptive solution for green communication.

4.2. Google's Gboard keyboard

When Google's Gboard keyboard optimizes the input prediction model through FL, its distributed training mechanism contributes to the energy efficiency optimization of mobile devices. This solution allows user devices to train the model locally and only upload encrypted model parameters instead of the original data, significantly reducing the data transmission energy consumption required by traditional cloud training. This localized processing reduces network load and cloud computing pressure, enabling devices to maintain high performance while reducing communication energy consumption, providing an important reference for the energy efficiency optimization of distributed AI in the 6G era.

4.3. Alibaba's e-commerce recommendation system

Alibaba's e-commerce recommendation system utilizes GNN to model the complex relationships among users, products, and merchants. By conducting efficient local graph computations, it reduces redundant data transmission and significantly lowers the cloud computing energy consumption required by traditional centralized recommendation algorithms while enhancing the recommendation accuracy. Its distributed inference architecture based on GNN only needs to aggregate neighbor information within the product relationship subgraph, avoiding the high energy consumption problem of global data traversal. This provides a low-power and highly scalable solution for edge AI services (such as real-time personalized recommendations) in the 6G era.

4.4. Predicting the Battery Health Status of Tesla's Electric Vehicles

Tesla uses LSTM networks to analyze the time-series data of vehicle batteries. By capturing the long-term degradation patterns of battery performance, it achieves precise health status predictions. This technology predicts and regulates charging and discharging strategies in a predictive manner, reducing unnecessary energy consumption, extending battery life, and avoiding energy loss caused by excessive charging, providing an intelligent solution for the green energy management of electric vehicles.

In the energy efficiency optimization of 6G networks, technologies such as DRL, federated learning, GNN, and LSTM each have their own advantages and complement each other. These technologies jointly form a closed-loop energy efficiency optimization system for 6G: DRL is responsible for real-time control, federated learning solves the problem of data islands, GNN handles spatial correlation, and LSTM captures time dependence. Ultimately, in scenarios such as ultra-dense networking and edge computing, AI-native green communication is achieved.

5. Future Research Directions

The rapid development of ultra-dense 6G networks and AI-driven communication technologies presents both opportunities and challenges in optimizing energy efficiency. To address these challenges, future research should focus on the following key directions (Figure 2)

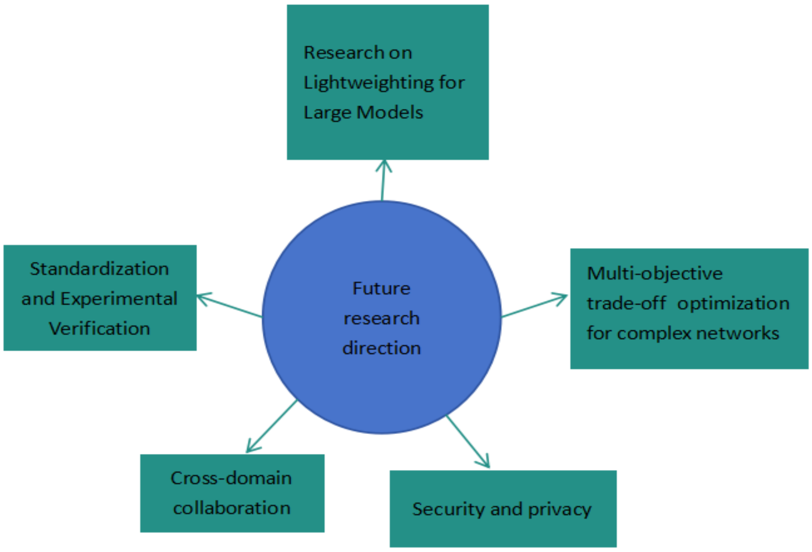

Figure 2. Future research direction

5.1. Research on Lightweighting for Large Models

Deploying large-scale artificial intelligence models in 6G networks presents significant energy efficiency challenges, as their computational intensity conflicts with the strict latency and resource limitations of edge devices. Advanced lightweight techniques, such as structured pruning, reduce the model size while maintaining extremely high accuracy, thus solving this problem. These methods work in conjunction with neural architecture search for hardware optimization topologies and knowledge extraction for compact model training. When integrated with 6G energy-saving technologies, lightweight models can enhance system efficiency. Future progress depends on the collaborative design of hardware algorithms, including adaptive lightweighting through reconfigurable intelligent surfaces, energy-aware NAS for Pareto-optimal architectures, and carbon-efficient sparse MoE training for non-IID FL. As the fundamental pillar of 6G edge intelligence, lightweight large-scale models can sustainably deploy immersive AI services while meeting the strict energy targets of the next-generation network.

5.2. Multi-objective trade-off optimization for complex networks

The 6G network faces the challenge of jointly optimizing multiple performance indicators. The optimization of one indicator often leads to a decrease in another indicator. It must address the complex interactions among the competing key performance indicators. Emerging artificial intelligence-driven methods have achieved dynamic Pareto optimal trade-offs among these indicators by continuously adapting to the real-time network status. For example, in the scenario of collaborative deployment of ultra-dense networks and intelligent reflectors, multi-objective optimization can enable joint decision-making on base station sleep, resource allocation, and interference management, ensuring user experience while maximizing energy efficiency. Research in this direction will also provide theoretical support and algorithmic guarantees for 6G green and low-carbon, high-performance communication.

5.3. Security and privacy

With the widespread application of AI technology in 6G networks, security and privacy issues have become increasingly prominent. Future research needs to focus on defense mechanisms against attacks to ensure the robustness of AI models. The frequent synchronization of massive data, the limited communication and computing resources, as well as the concerns of data security and privacy hinder the construction of digital twins of IIoT devices by the edge servers[18]. In federated learning, how to achieve trustworthy collaborative learning while protecting user data privacy and improving model performance is a significant challenge. Moreover, researching the application of technologies such as differential privacy and homomorphic encryption in distributed optimization will provide new solutions for security and privacy protection.

5.4. Cross-domain collaboration

The integration of AI with emerging communication technologies will bring revolutionary breakthroughs to 6G networks. Future research can explore the application of AI in areas such as reconfigurable intelligent surfaces (RIS), terahertz communication, and quantum computing. Machine learning can consider multiple performance metrics simultaneously and finds suboptimal solutions during dynamic adjustments to ensure that the system maintains good performance across various application scenarios[19]. For instance, using AI to optimize the reflection parameters of RIS to reduce energy consumption, or enhancing the transmission efficiency of terahertz channels through machine learning. Cross-domain collaborative research not only requires technological integration but also needs to address the compatibility and standardization issues between different technologies.

In order to promote the implementation of AI-enabled energy efficiency optimization technologies in actual networks, future research needs to strengthen standardization efforts. This includes establishing unified evaluation metrics and testing frameworks, as well as deploying and validating the performance of AI algorithms in real scenarios. Through large-scale experiments and simulations, algorithm parameters can be further optimized to ensure their reliability and scalability in complex environments. Moreover, collaboration among industry, academia, and research institutions will accelerate the transformation of technology from theory to practice.

6. Conclusion

This paper systematically investigates the application and challenges of artificial intelligence technologies in the energy efficiency optimization of ultra-dense 6G edge networks. It deeply analyzes the unique advantages of AI methods such as deep reinforcement learning, federated learning, and graph neural networks in dynamic resource allocation, privacy-preserving distributed optimization, and topology-aware energy efficiency improvement. It also reveals the key issues such as training complexity, real-time performance, and multi-objective trade-offs. By constructing a closed-loop optimization framework, the paper not only provides multi-scenario AI solutions for 6G networks, including dynamic base station sleep and edge task scheduling, but also proposes future research directions such as algorithm lightweighting, cross-domain technology integration, and standard verification. This study provides key technical paths for the subsequent development of 6G green communication. The AI-enabled collaborative optimization approach and typical application scenarios proposed in this paper can effectively guide researchers in balancing multiple dimensions such as energy efficiency, latency, and service quality, and promote the transition of 6G networks from theoretical innovation to practical deployment.

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