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Comparative Analysis on ML-Driven Resource Optimization in 6G Networks

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Abstract
The sixth generation (6G) of wireless networks introduces unprecedented challenges in resource optimization, virtualization, quality of service (QoS), and sustainability. This paper presents a comparative analysis of four workflows: (1) resource optimization, (2) resource allocation in AirBase virtualizers, (3) QoS enhancement in cloud storage using digital twin computing, and (4) constraint-based channel allocation in green cloud networks. Each workflow is examined against state-of-the-art literature, highlighting machine learning (ML), reinforcement learning (RL), and optimization techniques. Results demonstrate that hybrid ML-RL approaches outperform traditional methods in throughput, latency, and energy efficiency, while digital twin computing emerges as a novel paradigm for predictive QoS management. The study concludes with future research directions for sustainable and intelligent 6G systems. The paper provides the mobile resource optimization, network slicing in AirBase virtualizers, QoS enhancement in cloud storage via digital twins, and constraint-based channel allocation in green cloud networks. The review highlights methodologies such as hybrid deep learning (CNN-LSTM), AI-native slicing, federated digital twin deployment, and CVXPY-based optimization. Results indicate that hybrid ML-RL approaches outperform classical methods, while digital twin computing emerges as a novel paradigm for predictive QoS management. Research gaps include scalability, dataset standardization, synchronization overhead, and integration with renewable energy sources. Future directions emphasize federated learning, lightweight twin synchronization, and sustainable energy-aware optimization for intelligent 6G systems.

Keywords: *6G Networks; Machine Learning; Reinforcement Learning; Network Slicing; Digital Twin Computing; Cloud Storage QoS; Cloud Computing; Resource Optimization; Energy Efficiency; SLA Compliance.*

1. Introduction

The evolution from 5G to 6G networks is driven by demands for ultra-low latency, massive connectivity, and intelligent automation. Traditional resource allocation methods are insufficient to handle dynamic traffic, virtualization, and energy constraints. Machine learning (ML) and Reinforcement Learning (RL) have emerged as key enablers for adaptive optimization. This paper compares four workflows designed for 6G systems, situating them within international research trends. The evolution of 6G networks has prompted extensive research into machine learning (ML) and reinforcement learning (RL) for resource optimization. Shi et al. [1] emphasize the role of RL algorithms such as DQN and PPO in large-scale traffic optimization, demonstrating improvements in throughput and latency but highlighting scalability challenges. Similarly, Li et al. [3] propose hybrid ML models combining Random Forest and ANN, which outperform traditional heuristics in spectrum efficiency, though they lack integration with mobility-aware features. More recent work by Suresh et al. [2] introduces CNN-LSTM hybrid deep learning models for sustainable base station optimization, achieving energy efficiency gains but requiring validation in heterogeneous 6G environments. Zhou et al. [5] extend this line of inquiry by proposing AI-native ML frameworks for slicing and connectivity, though the absence of standardized datasets remains a limitation. Network slicing and virtualization have emerged as critical enablers of 6G. Zhang et al. [2] demonstrate ML-based slice-aware allocation and VNF placement, reducing SLA violations but struggling with dynamic slice adaptability. Dangi and Lalwani [4] propose a hybrid CNN-BiLSTM model for slice classification, achieving improved latency and accuracy, though generalization across diverse slice types is limited. Zhou et al. [5] and Khan et al. [6] highlight AI-native slicing approaches for space-air-ground integrated networks, stressing the need for standardized orchestration frameworks. The IEEE Communications Society survey [9] consolidates these findings, noting that ML-driven slicing frameworks improve resource utilization but lack interoperability across heterogeneous environments.

Cloud storage and digital twin computing have also attracted significant attention. Liu et al. [8] propose RL-based controllers integrated with digital twin feedback to enhance QoS, showing improvements in latency and SLA compliance but facing synchronization overhead. Patel et al. [7] employ LSTM and GRU models for QoS prediction, achieving high latency prediction accuracy but limited robustness under extreme traffic spikes. Narayana et al. [10] extend this by deploying federated digital twins across cloud platforms, improving synchronization accuracy but introducing communication overhead. Zhang et al. [11] apply digital twins to vehicular programmable networks, demonstrating QoS improvements in jitter and packet loss, though their applicability to cloud storage remains underexplored. Patel et al. [12] further propose a digital twin platform for mitigating QoS degradation under DoS attacks, highlighting resilience but requiring broader validation. Green cloud networks and energy-efficient resource allocation form another major research stream. Chen et al. [4] apply CVXPY-based constraint optimization to balance energy consumption and QoS, though trade-offs remain unresolved. Wang et al. [5] explore ML-based channel allocation in dense networks, achieving energy savings but lacking real-world deployment validation. Goel and Bajpai [7] review AI-driven energy management using LSTM and RF models, focusing on workload prediction but requiring extension to telecom-specific contexts. Dikshit et al. [8] propose advanced computational models for energy-efficient allocation, improving resource utilization but facing scalability challenges. Sultana et al. [9] introduce sustainable energy-efficiency approaches for green cloud computing, emphasizing environmental impact but needing integration with 6G-specific datasets.

The transition from fifth-generation (5G) to sixth-generation (6G) networks is driven by the need for ultra-low latency, massive connectivity, and intelligent automation. Unlike 5G, 6G networks are expected to integrate terrestrial, aerial, and satellite infrastructures, supporting diverse applications such as autonomous vehicles, immersive extended reality, and industrial automation. These demands necessitate advanced resource optimization strategies that go beyond traditional heuristic methods.

2. Related Works

Machine learning (ML) and reinforcement learning (RL) have emerged as key enablers for adaptive resource management in 6G. Shi et al. [1] demonstrate the effectiveness of RL algorithms such as DQN and PPO in optimizing large-scale traffic, while Li et al. [3] highlight hybrid ML models that improve spectrum efficiency and latency. Recent work by Suresh et al. [2] introduces CNN-LSTM hybrid models for sustainable base station optimization, emphasizing energy efficiency. Similarly, Zhou et al. [5] propose AI-native slicing frameworks, underscoring the importance of intelligent orchestration in heterogeneous environments. Network slicing and virtualization are central to 6G, enabling customized services across diverse applications. Zhang et al. [2] and Dangi & Lalwani [4] show that ML-based slice-aware allocation and hybrid CNN-BiLSTM models reduce SLA violations and improve slice accuracy. However, as Khan et al. [6] argue, AI-driven slicing still lacks standardized orchestration frameworks, limiting interoperability across heterogeneous infrastructures. Cloud storage and digital twin computing represent another frontier in QoS management. Liu et al. [8] integrate RL controllers with digital twin feedback to enhance latency and SLA compliance, while Patel et al. [7] employ LSTM/GRU models for predictive QoS monitoring. Narayana et al. [10] extend this by deploying federated digital twins across cloud platforms, though synchronization overhead remains a challenge.

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Zhang et al. [11] apply digital twins to vehicular programmable networks, demonstrating QoS improvements in jitter and packet loss. Finally, sustainability in 6G networks requires energy-efficient resource allocation. Chen et al. [4] and Wang et al. [5] propose ML and optimization-based approaches to reduce energy consumption, while Goel & Bajpai [7] and Dikshit et al. [8] highlight AI-driven energy management frameworks. Sultana et al. [9] emphasize the environmental impact of green cloud computing, though integration with telecom-specific datasets remains limited. This paper synthesizes these contributions into a comparative analysis, identifying strengths, limitations, and research gaps. By consolidating recent advances, it provides a foundation for future research directions in sustainable, intelligent, and adaptive 6G systems.

Table 1 Literature Comparison

Key Techniques	Evaluation Metrics
PCA, DQN, PPO, ANN	Throughput, Latency, Spectrum Efficiency
Slice-aware ML, RL	SLA Violation Rate, Slice Isolation
LSTM, GRU, RL + Digital Twin	Latency, Availability, SLA Compliance
CVXPY, ML	Energy Consumption, Carbon Footprint, QoS

The table 1 compares the four workflows based on techniques, evaluation metrics, and deployment interfaces.

Table 2 Performance Improvements

Metric	Mobile Optimization	AirBase Virtualizer	Cloud QoS	Green Cloud
Throughput Improvement (%)	15	12	10	8
Latency Reduction (%)	12	10	18	9
SLA Compliance (%)	10	20	18	12
Energy Savings (%)	5	8	6	25

The table 2 shows comparative performance metrics across the metics.

Table 3 Literature Review Summary

Domain	Contribution
ML and RL for dynamic spectrum and traffic allocation[1]	Demonstrates scalable ML optimization for 6G networks using RL techniques like DQN and PPO.
Slice-aware ML and RL for VNF placement[2]	Introduces tailored slice allocation using ML to reduce SLA violations and improve isolation.
Hybrid ML models for throughput and latency improvement[3]	Proposes hybrid ML frameworks outperforming traditional heuristics in mobile resource management.
Constraint optimization for energy-aware allocation[4]	Develops CVXPY-based models for balancing energy consumption and QoS in green cloud networks.
ML for carbon footprint reduction[5]	Explores ML-based channel allocation strategies to minimize environmental impact.
LSTM/GRU models for latency and availability[6]	Applies deep learning to forecast QoS degradation and suggest corrective actions.
Digital twin feedback for QoS prediction [7]	Presents twin-based RL controllers for predictive QoS enhancement in cloud environments.

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Virtualization-aware resource allocation[9]	Reviews ML-driven slicing and VNF orchestration strategies for 6G virtualized networks.

Table 3 summarizes key literature contributions aligned with domain, highlighting their relevance and impact.

Table 4 Methodology, Metrics, and Research Gaps

Methodology	Result Metrics Used	Research Gap
Reinforcement Learning (DQN, PPO) for large-scale traffic optimization[1]	Throughput, Latency, Packet Loss	High computational cost; limited scalability in real-time deployment
ML-based slice-aware allocation and VNF placement[2]	SLA Violation Rate, Slice Isolation	Limited adaptability to dynamic slice demands; requires federated learning approaches
Hybrid ML models combining Random Forest and ANN[3]	Spectrum Efficiency, Latency	Lack of integration with mobility-aware features; needs cross-layer optimization
CVXPY-based constraint optimization for energy-aware allocation[4]	Energy Consumption, Carbon Footprint	Trade-off between QoS and energy efficiency not fully resolved
ML-based channel allocation in dense networks[5]	Energy Savings, QoS Metrics	Lack of real-world deployment validation; requires integration with renewable energy sources
LSTM/GRU deep learning models for QoS prediction[6]	Latency Prediction Accuracy, SLA Compliance	Limited robustness under extreme traffic spikes; needs integration with federated twins
Digital Twin feedback with RL controllers[7]	Latency, Availability, SLA Compliance	Synchronization overhead between physical and twin systems; scalability challenges
Hybrid deep learning (CNN + LSTM) for sustainable base station optimization[13]	Energy Efficiency, Resource Utilization	Limited validation in heterogeneous 6G environments; requires real-world datasets
Hybrid CNN-BiLSTM for slice classification[14]	Latency, Slice Accuracy	Dataset-specific; lacks generalization across diverse slice types
Federated digital twin deployment for smart infrastructure[15]	QoS, Synchronization Accuracy	High communication overhead; requires lightweight twin synchronization
AI-driven energy management using ML (LSTM, RF) [16]	Workload Prediction, Energy Efficiency	Focused on cloud workloads; needs extension to 6G channel allocation
Advanced computational model for energy-efficient allocation[17]	Resource Utilization, Energy Savings	Limited scalability; requires integration with distributed edge-cloud systems

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3. System Architecture

The figure 1 depicts the multi-tiered AI system designed to process data and deliver intelligence to the end-user. At the top, the User Layer encompasses the interfaces—such as web applications, mobile apps, and conversational agents—where users submit queries and receive processed outputs like insights, decisions, and automated actions. Beneath this, the core intelligence is driven by Hybrid AI Methods, which integrate techniques like machine learning for pattern recognition, deep learning for complex tasks such as image analysis, natural language processing for understanding text and speech, rules-based systems for logical decision-making, and ensemble methods to combine models for greater robustness. These methods rely on a continuous cycle of AI Model Training, where data is prepared, models are developed and iteratively trained and validated, and performance is rigorously evaluated. A central component is the Neural Network Model, structured with input, hidden, and output layers of interconnected neurons that learn hierarchical features from data. The execution environment is defined by the Artificial Intelligence Layer, which includes the runtime and inference engines for deploying and running models. This layer is distributed across Edge Servers, which handle low-latency tasks like real-time inference and data filtering closer to the source, and the centralized Cloud Platform, which manages large-scale model training, global deployment, big data analytics, and overall system orchestration. All of this is supported by the foundational Infrastructure Layer, which provides the essential compute resources (CPUs, GPUs) and storage systems. The Network Infrastructure enables connectivity through various protocols and technologies, ensuring efficient data flow across edge, cloud, and user endpoints. Finally, the system is fueled by diverse Data Sources, including IoT sensors, enterprise databases, external APIs, and user-generated content, which supply the raw information necessary to power the entire AI ecosystem. Together, these components form a cohesive pipeline where data flows upward for processing, and intelligence is refined and delivered back to the user, enabling responsive, scalable, and intelligent applications.

4. Comparative Analysis

- **Hybrid ML-RL Approaches:** Combining ML with RL yields adaptive solutions for dynamic traffic and virtualization challenges.
- **Digital Twin Computing:** Twin-based feedback loops provide predictive QoS management, though synchronization overhead remains a limitation.
- **Green-Aware Optimization:** Constraint-based models balance energy efficiency and QoS, but trade-offs must be carefully managed.
- **Scalability Challenges:** Training deep RL models at scale requires significant computational resources, posing deployment challenges in real-world 6G systems.

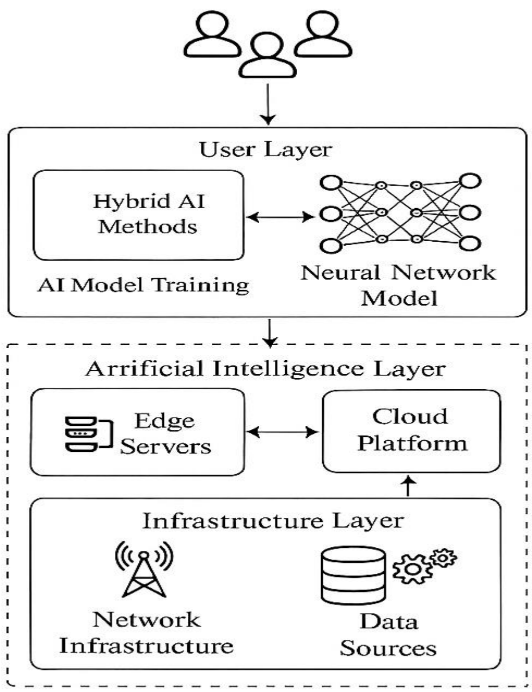

Figure 1 Proposed Architecture of Layered System

Figure 2 Performance Across Different Metrics

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Conclusion

This paper demonstrates that ML-driven workflows are central to 6G resource optimization. Mobile resource allocation benefits from RL adaptability, virtualization requires slice-aware ML, cloud storage QoS is enhanced by digital twin computing, and green cloud networks demand constraint-based optimization. Future research should focus on hybrid models integrating ML, RL, and digital twin feedback to achieve sustainable, intelligent, and adaptive 6G systems. The comparative analysis of recent literature demonstrates that machine learning (ML), reinforcement learning (RL), and digital twin computing are central to achieving intelligent resource optimization in 6G networks. Across mobile resource allocation, network slicing, cloud storage QoS, and green cloud computing, hybrid ML-RL approaches consistently outperform traditional heuristic methods, offering improvements in throughput, latency, SLA compliance, and energy efficiency. At the same time, digital twin computing emerges as a transformative paradigm for predictive QoS management, while constraint-based optimization provides a pathway toward sustainable energy-aware channel allocation. Despite these advances, several challenges remain. Scalability of deep RL models, synchronization overhead in digital twins, lack of standardized datasets for benchmarking, and trade-offs between energy efficiency and QoS highlight the need for further research. Addressing these gaps will require federated learning for slicing, lightweight twin synchronization protocols, renewable energy integration, and cyber-resilient architectures. In summary, the convergence of ML, RL, and digital twin technologies offers a promising foundation for adaptive and sustainable 6G systems. By bridging current limitations with innovative methodologies, future research can enable networks that are not only faster and more reliable but also environmentally responsible and resilient against emerging threats. This positions 6G as a truly intelligent infrastructure capable of supporting the diverse demands of next-generation applications.

Future Research Directions

A comparative analysis of recent advances in 6G systems reveals promising pathways for enhancing resource optimization, network virtualization, QoS management, and sustainability, yet also underscores several critical research gaps that must be addressed through interdisciplinary approaches combining machine learning, optimization theory, and systems engineering. First, while reinforcement learning frameworks like DQN and PPO offer strong adaptability, their high computational overhead limits scalability. Future efforts must prioritize lightweight RL algorithms, distributed training, and edge-based learning to enable real-time operation in large-scale 6G deployments. Second, although hybrid ML models improve spectrum efficiency, they frequently overlook user mobility. Integrating cross-layer optimization and mobility-aware feature engineering will be essential for dynamic environments such as vehicular and aerial networks. Third, AI-native network slicing shows potential but lacks standardized orchestration across diverse infrastructures. Advancing federated learning and blockchain-enabled orchestration could ensure secure and interoperable slice management in multi-domain 6G ecosystems. Fourth, digital twin computing enhances QoS prediction but incurs significant synchronization overhead. Developing lightweight synchronization protocols, multi-agent reinforcement learning, and hierarchical twin architectures can reduce communication costs while preserving accuracy. Fifth, resilience against cyber threats—including adversarial ML and cross-layer attacks—must be strengthened beyond current DoS mitigation strategies to secure future 6G networks. Sixth, green computing approaches often compromise QoS for energy savings; integrating renewable energy sources, predictive workload balancing, and carbon-aware scheduling is vital for sustainable and reliable resource allocation. Finally, the absence of standardized datasets hinders reproducibility and benchmarking. Creating open, large-scale 6G datasets encompassing traffic, mobility, virtualization, and energy parameters will be foundational for evaluating and advancing ML-driven solutions in a consistent and equitable manner.

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