Center of Artificial Intelligence

REVIEW ARTICLE

AI-driven Optimization Techniques in Next Generation Wireless Communication Networks and Systems

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Article Info.

Article history:

Received: 07/11/2025

Accepted: 11/12/2025

Published: 26/01/2026

Abstract

This research addresses the core challenge of optimizing next-generation wireless networks, including 5G, 6G, and future generations. It focuses on improving resource allocation, power control, interference management, traffic prediction, and mobility management using artificial intelligence techniques. The approach combines a structured survey with an analytical review of supervised and unsupervised learning, deep learning, reinforcement learning, evolutionary algorithms, and hybrid models, supported by case studies and experimental evaluations. The key findings show that AI-based schemes consistently outperform traditional heuristic and static methods. They enable real-time, data-driven decision-making, resulting in higher throughput, lower latency, better energy efficiency, and more effective interference management. This work has significant implications for ultra-dense and heterogeneous networks, particularly in supporting autonomous systems, smart cities, and immersive multimedia services. Its main contributions are combining AI methods for wireless optimization and outlining future directions in explainable AI, federated learning, and AI-native architectures.

Keywords: AI; 6G; Optimization; Wireless Communication; Machine Learning.

1. Introduction

Wireless communication networks have evolved rapidly, transitioning from legacy systems to fifth-generation (5G) networks and now progressing toward sixth-generation (6G) and beyond. These emerging networks are expected to deliver substantial improvements in data rates, latency, capacity, and connectivity density, enabling advanced applications such as autonomous vehicles, extended reality (XR), massive Internet of Things (IoT), and real-time holographic communications [1] - [3].

The growing complexity of future wireless environments necessitates new approaches to network design and management that go beyond traditional optimization techniques. Key challenges include dynamic resource allocation, interference management, energy efficiency optimization, and the provision of adaptive quality-of-service (QoS) guarantees [4], [5]. The rapid proliferation of connected devices and heterogeneous services places unprecedented pressure on network resources, rendering static or heuristic optimization methods increasingly ineffective in highly dynamic scenarios [6].

Moreover, the deployment of ultra-dense networks, integrated space–air–ground–sea communication architectures, and advanced paradigms such as network slicing introduces large-scale, nonlinear, and highly dynamic optimization problems [7], [8]. In this context, artificial intelligence (AI) has emerged as a key enabling technology for next-generation wireless systems by providing data-driven, adaptive, and scalable optimization capabilities [9], [10]. Techniques, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), enable networks to learn from environmental observations, predict traffic and mobility patterns, and autonomously optimize operational decisions in real-time [11], [12].

This paper investigates AI-driven optimization methods for next-generation wireless networks. It addresses fundamental optimization challenges in 5G and 6G systems, reviews state-of-the-art AI techniques, examines practical applications in resource allocation, power control, interference mitigation, and mobility management, and discusses performance gains, limitations, and system integration considerations. In addition, recent developments and representative case studies are surveyed, with particular emphasis on scalable, secure, and distributed AI-enabled optimization solutions for future wireless networks [13], [14].

2. Overview of Next Generation Wireless Networks and Systems

Next-generation wireless networks, encompassing 5G, 6G, and future communication systems, represent a fundamental transformation in wireless network design, architecture, and operational capabilities. These systems are engineered to accommodate the rapid growth in connectivity demands and to support emerging services that require ultra-high data rates, ultra-low latency, and massive device connectivity [15], [16]. As a result, next-generation networks depart significantly from traditional cellular paradigms, introducing new architectural concepts and performance objectives that form the basis for AI-driven optimization techniques.

2.1. Key Characteristics and Requirements

Next-generation wireless networks aim to deliver ubiquitous connectivity with significantly enhanced performance metrics. Core requirements include extremely high data rates, where 6G systems are envisioned to achieve peak rates in the terabit-per-second range, end-to-end latencies on the order of one millisecond or below, ultra-high reliability, massive connectivity to support billions of IoT devices, and improved energy efficiency to ensure sustainable network operation [16]-[18]. In addition, these networks are expected to provide flexible and differentiated quality-of-service (QoS) guarantees to accommodate a wide range of services, from mission-critical communications to immersive multimedia applications [19].

Emerging use cases such as augmented reality (AR), virtual reality (VR), extended reality (XR), holographic communications, autonomous systems, and smart city infrastructures impose stringent and often conflicting requirements on network capacity, responsiveness, and adaptability [20], [21]. These demands exceed the capabilities of conventional radio access and core network architectures, necessitating novel deployment models, intelligent control mechanisms, and advanced resource management strategies [22].

2.2. Architectural Innovations

To satisfy these stringent requirements, next-generation wireless networks adopt innovative architectures that integrate diverse technologies across multiple layers. Ultra-dense networks (UDNs), characterized by dense deployments of small cells, enhance spatial reuse and network capacity while reducing transmission distances and improving energy efficiency [23]. Furthermore, the integration of space-air-ground-sea communication platforms enables seamless global connectivity by interconnecting terrestrial networks with satellites, high-altitude platforms, unmanned aerial vehicles, and maritime communication nodes [24], [25].

Network slicing is another defining architectural feature, allowing a shared physical infrastructure to be partitioned into multiple virtual networks tailored to specific applications and service requirements. This capability supports differentiated service levels and customized resource allocation policies, thereby improving overall network utilization and operational flexibility [26].

In addition, cloud-native designs and edge computing paradigms are increasingly incorporated to move computation and intelligence closer to end users. This reduces latency, supports real-time analytics, and enables localized decision-making. However, the distributed nature of cloud-edge architectures significantly increases the complexity of resource orchestration and coordination, creating new challenges for efficient and scalable network optimization [27], [28].

2.3. Optimization Challenges in Next-Generation Networks

The scale and heterogeneity of next-generation wireless architectures introduce a wide range of optimization challenges. Resource allocation must dynamically adapt to fluctuating traffic demands, user mobility patterns, and diverse service requirements across multiple network slices and access technologies [29]. At the same time, effective interference management in ultra-dense and multi-tier network deployments is critical for maintaining signal quality and achieving high spectral efficiency [30].

Energy efficiency represents another major concern, as the proliferation of network nodes and infrastructure elements increases operational costs and environmental impact. Achieving sustainable operation while meeting strict QoS constraints requires intelligent power control, traffic-aware sleep scheduling, and coordinated network management strategies [18], [22]. Moreover, the strong interdependence among distributed network components demands coordination mechanisms that are scalable, adaptive, and capable of operating under incomplete or imperfect information [27].

Traditional optimization approaches, which typically rely on static models and simplified assumptions, are often ill-suited for such highly dynamic and complex environments. Consequently, the characteristics of next-generation wireless networks strongly motivate the adoption of data-driven and learning-based optimization techniques. These challenges set the stage for AI-driven approaches, which are discussed in subsequent sections to demonstrate their potential in enhancing network efficiency, reliability, and adaptability.

3. AI Techniques Applied to Wireless Network Optimization

The growing complexity and dynamic nature of next-generation wireless communication networks necessitate optimization strategies that extend beyond traditional model-based algorithms. Artificial intelligence (AI) techniques play a critical role in addressing these challenges by enabling data-driven, adaptive, and scalable optimization solutions [15], [16]. This section presents an overview of major AI techniques applied to wireless network optimization, including machine learning, deep learning, evolutionary algorithms, and hybrid approaches, emphasizing their principles and relevance to wireless systems.

3.1. Machine Learning Methods

Machine learning (ML) forms the foundation of many AI-driven optimization frameworks in wireless networks and encompasses supervised, unsupervised, and reinforcement learning paradigms, each suited to different optimization tasks [17].

3.1.1. Supervised learning relies on labeled datasets to predict or classify network parameters such as traffic demand, modulation schemes, and anomaly detection. Algorithms, including support vector machines (SVMs), random forests, and neural networks, have demonstrated strong capability in capturing nonlinear relationships within wireless network data [18].

3.1.2. Unsupervised learning extracts latent structures from unlabeled data and is widely used for user clustering, traffic pattern discovery, and anomaly detection. Techniques such as k-means clustering and principal component analysis (PCA) are effective for dimensionality reduction and pattern recognition in large-scale network datasets [19].

3.1.3. Reinforcement learning (RL) addresses sequential decision-making problems by enabling agents to learn optimal policies through interaction with the environment. RL has proven particularly effective for adaptive resource allocation, power control, and handover management in dynamic wireless environments [20].

3.1.4. Deep reinforcement learning (DRL) integrates deep neural networks with RL to handle high-dimensional state and action spaces, making it well-suited for ultra-dense networks and complex 5G/6G scenarios [21].

3.2. Deep Learning Architectures

Deep learning (DL), a subset of ML, employs multi-layer neural networks to model hierarchical and nonlinear relationships in wireless network data. Architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are widely used for channel estimation, beamforming, signal detection, and mobility prediction [22]. CNNs excel at extracting spatial features from channel state information, while RNNs, particularly long short-term memory (LSTM) networks, are effective for modeling temporal dependencies in traffic and mobility patterns [23]. Despite their strong performance, DL models require substantial computational resources and large datasets, motivating the adoption of distributed and edge-based learning paradigms in wireless systems [24].

3.3. Evolutionary and Swarm Intelligence Algorithms

Evolutionary algorithms and swarm intelligence techniques, inspired by biological and social behaviors, offer robust solutions for nonlinear and multi-objective optimization problems common in wireless networks [25].

Genetic algorithms (GAs) utilize selection, crossover, and mutation mechanisms to explore large solution spaces for scheduling, routing, and resource allocation. Particle swarm optimization (PSO) leverages collective intelligence to refine candidate solutions for power control and interference mitigation. Ant colony optimization (ACO) applies a communication principle to routing and path optimization in distributed networks [26]. Although these approaches can escape local optima, they often involve trade-offs in convergence speed and computational complexity.

3.4. Hybrid AI Methodologies

Hybrid AI methodologies combine complementary AI techniques to exploit their respective strengths while mitigating individual limitations. For example, integrating reinforcement learning with genetic algorithms enhances the balance between exploration and exploitation in dynamic resource management scenarios [27]. Similarly, combining deep learning for feature extraction with evolutionary algorithms for optimization enables efficient handling of high-dimensional inputs while achieving near-optimal solutions [28].

Federated learning further supports collaborative model training across distributed edge nodes without sharing raw data, preserving privacy and reducing communication overhead. This capability is particularly important for decentralized 5G and emerging 6G architectures [29]. Overall, hybrid and distributed AI strategies provide scalable, resilient, and privacy-aware optimization solutions for future wireless networks [30].

Overall, AI techniques have truly revolutionized optimization in next-generation wireless networks. While machine learning and deep learning offer powerful tools for predictive and adaptive optimization, evolutionary algorithms continue to be effective for tackling complex nonlinear challenges. Therefore, hybrid and distributed AI strategies present scalable, privacy-conscious, and resilient optimization solutions that meet the demanding requirements of future wireless systems. The next section will delve into specific wireless optimization issues where these AI-driven techniques have been successfully implemented.

Figure 1 presents a high-level overview of the major AI techniques applied in wireless network optimization, including machine learning, deep learning, reinforcement learning, and evolutionary algorithms, and illustrates their relationships to key network functions.

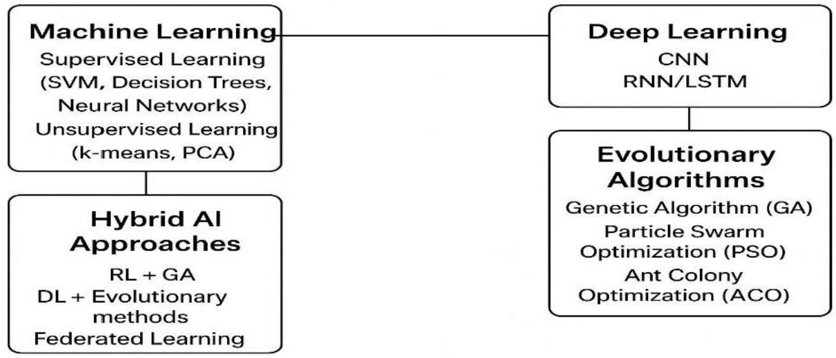

Fig. 1**.** Overview of AI Techniques Applied in Wireless Network Optimization

It highlights how these techniques enable intelligent, adaptive, and data-driven optimization across tasks such as resource allocation, interference management, power control, and traffic prediction in next-generation wireless networks.

Table 1 highlights how different AI techniques target specific wireless optimization tasks, ranging from traffic forecasting and resource allocation to interference mitigation and routing, by exploiting their distinct learning or search mechanisms.

Table 1: AI Techniques and Their Applications in Wireless Optimization

AI Technique	**Description**	**Wireless Network Optimization Tasks**	**Advantages**	**Limitations**
Supervised Learning	Training from labeled data	Traffic forecasting, modulation classification	Accurate prediction with labels	Requires large labeled datasets
Unsupervised Learning	Finds patterns without labels	User clustering, anomaly detection	Works with unlabeled data	May need parameter tuning
Reinforcement Learning	Learning via interaction with the environment	Dynamic resource allocation, power control, and handover	Adaptive, real-time optimization	High training time, complex
Deep Learning (CNN)	Models spatial features	Beamforming, channel estimation	Handles high-dimensional data	Computationally intensive
Deep Learning (RNN)	Models temporal dependencies	Traffic prediction, mobility modeling	Models sequences well	Needs lots of training data
Genetic Algorithms	Evolution-inspired search	Scheduling, routing optimization	Good global search ability	Slow convergence
Particle Swarm Opt.	Swarm-intelligence-based search	Power control, interference mitigation	Simple, efficient search	May get trapped in local optima
Hybrid Methods	Combines multiple AI techniques	Complex multi-objective optimizations	Balances strengths	Increased model complexity

Each technique offers notable advantages, such as accurate prediction, real-time adaptation, or strong global search capability, while also presenting limitations like data requirements, computational cost, or convergence challenges, underscoring the need for careful method selection and hybrid approaches in practical deployments.

4. Optimization Problems in Wireless Networks Addressed by AI

Next-generation wireless networks present complex optimization challenges related to resource utilization, service quality, and energy sustainability. AI techniques are increasingly applied due to their ability to model nonlinear interactions, adapt to dynamic environments, and operate in real time [31].

4.1. Resource and Spectrum Allocation

Efficient spectrum allocation is essential for maximizing capacity in dense and heterogeneous networks. Reinforcement learning and deep learning approaches dynamically adapt channel assignments and bandwidth allocation based on real-time network feedback, outperforming traditional heuristic methods [32]. AI-enabled cognitive radio systems further improve spectral efficiency by allowing intelligent access to underutilized spectrum [33].

4.2. Power Control and Energy Efficiency

AI-driven power control strategies optimize transmit power to reduce energy consumption while maintaining QoS requirements. Reinforcement learning enables real-time energy-aware decisions, while ML-based traffic prediction supports sleep-mode scheduling for base stations and small cells [34].

4.3. Interference Mitigation and Beamforming Optimization: In ultra-dense and multi-tier networks, AI techniques improve interference coordination and beamforming design. CNN-based models optimize beam patterns, while RL frameworks dynamically adjust power and beam configurations in massive MIMO and millimeter-wave systems [35].

4.4. Network Traffic Prediction and Load Balancing: Accurate traffic prediction using RNNs and LSTM networks enables proactive load balancing and congestion avoidance. AI-assisted handover optimization further enhances user experience in dense small-cell deployments [36].

4.5. Mobility Management and Handover Optimization: AI-based mobility management leverages reinforcement learning and predictive analytics to enable seamless handovers under varying mobility conditions, reducing latency and handover failures in vehicular and high-speed scenarios [37].

Table 2 shows that different AI techniques are mapped to specific wireless optimization problems, such as using reinforcement learning and deep learning for dynamic resource and spectrum allocation, or evolutionary and swarm-based algorithms for power control and interference mitigation. Each problem–technique pairing exploits the strengths of a given AI method, for example, sequence models like LSTM for traffic prediction, and clustering methods for load balancing and anomaly detection.

Table 2. Wireless network optimization problems with AI techniques applied to address them

Optimization Problem	AI Techniques Applied	Description and Benefits	Typical Applications and Key Outcomes
Resource and Spectrum Allocation	Reinforcement Learning (RL), Deep Learning (DL), Supervised Learning	RL adapts to real-time network states to allocate spectrum dynamically. DL predicts traffic for proactive allocation. Supervised learning classifies channel quality.	Dynamic channel assignment, bandwidth allocation, and cognitive radio networks result in improved throughput and spectrum efficiency
Power Control and Energy Efficiency	RL, Evolutionary Algorithms (GA, PSO), Deep Learning	RL facilitates adaptive power adjustment. Evolutionary algorithms optimize power levels for global energy savings. DL predicts load to manage sleep modes.	Energy-aware base station management, interference reduction, load-adaptive power control, and achieving reduced operational costs and emissions
Interference Mitigation and Beamforming	Deep Learning (CNN), RL, Swarm Intelligence (Particle Swarm Optimization, Ant Colony Optimization)	CNNs optimize beam patterns; RL tunes power and beamforming dynamically; swarm algorithms help find optimal interference mitigation schemes.	Enhanced signal quality, reduced interference in MIMO and millimeter-wave systems, improving capacity and reliability
Network Traffic Prediction and Load Balancing	Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Unsupervised Learning (Clustering)	RNN/LSTM models predict traffic patterns for better load distribution; clustering groups users/devices for efficient resource use.	Congestion control, load balancing in dense small-cell networks, improving QoS and reducing packet loss
Mobility Management and Handover Optimization	RL, Supervised Learning, Predictive Analytics	RL models learn best handover policies; supervised models classify mobility patterns; predictive analytics anticipate user movement.	Reduced handover failures, seamless connectivity in high-speed scenarios such as vehicular networks, and improved user experience
Anomaly Detection and Fault Diagnosis	Unsupervised Learning, Supervised Learning, Hybrid Models	Unsupervised techniques detect unknown faults; supervised models classify known fault types; hybrids combine strengths.	Network fault management, security anomaly detection, and maintaining network health and resilience

Overall, the table emphasizes that no single AI approach is sufficient; instead, selecting or combining techniques depends on the problem's structure, real-time constraints, and scalability requirements.

5. Case Studies and Applications

Practical deployments demonstrate that AI-driven optimization significantly improves performance, adaptability, and reliability in 5G and emerging 6G networks [38].

Reinforcement learning has been successfully applied to dynamic spectrum allocation in ultra-dense 5G small-cell networks, achieving notable gains in spectral efficiency compared to heuristic approaches [39]. Deep learning-based beamforming optimization using CNNs has also shown near-optimal performance in massive MIMO systems [40].

Federated learning has emerged as a key enabler for distributed optimization in 6G smart cities and edge computing environments, enabling privacy-preserving model training and efficient resource coordination [41]. AI-driven network slicing further supports immersive services such as holographic communications by dynamically allocating radio and computing resources in real time [42].

Table 3 illustrates diverse real-world AI-driven wireless network optimization case studies from organizations like Vodafone, AT&T, Ericsson, and Huawei, showcasing applications, such as traffic prediction, anomaly detection, handover optimization, and energy reduction using techniques like machine learning, deep reinforcement learning, and federated learning. These cases demonstrate measurable outcomes, including reduced RF interference, improved network visibility, faster fault resolution, and up to 15% energy savings, particularly in high-density environments like churches, smart cities, and 5G deployments. Overall, the table underscores AI's practical impact on enhancing reliability, efficiency, and scalability across telecom operators and emerging 6G scenarios

Table 3. AI-driven wireless network optimization case studies

Case Study / Organization	**Problem Focus**	**AI Techniques Used**	**Key Results and Outcomes**	**Impact and Significance**
Vodafone	Network traffic prediction, resource allocation	Machine learning (ML) algorithms	Improved traffic forecasting, adaptive bandwidth allocation	Reduced network congestion, enhanced QoS, and user experience
AT&T	Anomaly detection, network failure prediction	Deep learning (DL) models	Early fault detection minimized service interruptions	Improved network reliability and operational resilience
Wi-Fi Network Performance (High-density deployment)	Throughput maximization, frame size, & CW optimization	Generative AI (GAN, VAE), Deep Reinforcement Learning (DRL)	An efficient frame configuration reduces traffic congestion	Enhanced throughput in dense environments, adaptive channel access
6G Network Optimization (Smart Cities)	Distributed resource management, load balancing	Federated learning, Reinforcement Learning	Efficient network slicing and edge resource allocation	Preserved user privacy, optimized resource usage
Autonomous Vehicle Networks	Handover optimization, latency reduction	Deep RL, Predictive Analytics	Reliable seamless connectivity during high-speed mobility	Critical improvement for vehicular communication safety
Industrial IoT (Energy Optimization)	Energy-efficient power control in distributed base stations	ML and predictive modeling	Balanced power consumption with optimal energy use	Sustainable operation for rural IoT networks

6. Challenges and Future Directions

Despite the significant advances in AI-driven optimization for next-generation wireless networks, several critical challenges hinder large-scale real-world deployment, particularly in safety-critical and ultra-reliable 6G systems. One major issue is scalability; AI models need to function seamlessly across vast, diverse networks that include billions of devices, various network slices, and distributed edge-cloud setups. Training and deploying these models demand a lot of computational power and communication resources, which can lead to delays and increased energy use, definitely not what we want for the performance goals of future wireless systems.

On top of that, the quality and availability of data are significant roadblocks. AI models rely on large, representative datasets, but getting these can be tricky due to privacy issues, incomplete data, or ever-changing network conditions. Another challenge is model interpretability. Many AI methods, especially deep learning models, act like black boxes, making it tough for network operators to grasp or trust the automated decisions made in critical situations. Security and robustness are also concerns, as adversarial attacks, model poisoning, and data manipulation can seriously undermine network reliability and integrity if AI-driven control loops are compromised [43].

Looking ahead, research is shifting towards creating explainable and trustworthy AI frameworks that offer clear, verifiable, and auditable decision-making processes for network optimization. Explainable AI techniques are set to be crucial for ensuring regulatory compliance and building operator confidence in managing networks autonomously. Additionally, federated and decentralized learning models are emerging as promising ways to tackle privacy and data governance issues, enabling collaborative model training across distributed edge nodes without the need to share raw data. This method not only cuts down on communication overhead but also boosts privacy protection. Another key area to explore is creating AI-native network architectures, where intelligence is woven right into communication protocols, radio access networks, and core network functions. These architectures allow for networks that can self-optimize, self-heal, and self-configure, adapting on their own to changing environments and service needs. Merging AI with new technologies like digital twins, quantum-safe cryptography, and semantic communications is also set to significantly improve network resilience and performance. Together, these research paths aim to position AI as a core element of future wireless systems, paving the way for scalable, secure, and smart communication infrastructures for beyond-6G applications [44], [45].

7. Conclusion

AI-driven optimization techniques hold transformative potential for next-generation wireless communication networks and systems by enabling intelligent, adaptive, and efficient resource management. This paper has explored key AI methods, their applications in addressing fundamental wireless optimization problems, and demonstrated their impact through diverse case studies. While challenges remain in scalability, interpretability, and security, ongoing research in explainable AI, federated learning, and AI-native network design charts a promising path forward. The continued convergence of AI and wireless technologies is poised to facilitate the realization of ambitious 5G/6G performance targets and unlock new use cases in smart cities, autonomous systems, and beyond. Future efforts will focus on developing robust, trustworthy, and scalable AI frameworks tightly integrated with evolving wireless architectures to fully harness the benefits of AI-driven optimization in next-generation networks.

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