

Machine Learning Approaches for Intelligent Network Traffic Management in 6G

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Abstract

The increasing adoption of smart devices, Internet of Things (IoT) technologies, cloud-based services, autonomous applications, and multimedia platforms has greatly enhanced the demands and complexity of modern wireless communication networks. To meet these evolving requirements, upcoming sixth-generation (6G) communication systems are anticipated to deliver extremely high data transmission speeds, support a vast number of connected devices, ensure minimal communication delays, enable intelligent network management, and provide seamless real-time connectivity for advanced applications. Traditional network traffic management techniques are unable to efficiently handle the highly dynamic and complex nature of future 6G environments. Therefore, ML-driven frameworks approaches have emerged as effective solutions for intelligent traffic management in next-generation wireless communication systems. This paper presents a study of machine learning techniques used for intelligent network traffic management in 6G networks. The paper discusses supervised learning, unsupervised learning, reinforcement learning, and deep learning methods for traffic prediction, congestion control, resource allocation, routing optimization, spectrum management, and network slicing. The role of Artificial Intelligence (AI), edge intelligence, and autonomous network management in future 6G communication systems is also examined. Additionally, important challenges such as computational complexity, real-time processing, security, and data privacy are discussed.

Keywords: 6G Networks, machine learning, intelligent traffic management, artificial intelligence, deep learning, wireless communication

INTRODUCTION

The rapid development of wireless communication technologies has significantly transformed modern digital networks. Emerging applications such as IoT, smart cities, autonomous vehicles, cloud computing, and virtual reality require high-speed, reliable, and intelligent communication systems [1]. Although 5G networks have improved connectivity, future applications demand even higher data rates, ultra-low latency, massive device support, and intelligent automation, leading to the development of 6G) communication systems.

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Recent studies indicate that 6G networks will be AI-native by design, integrating machine learning and artificial intelligence directly into the network architecture to enable autonomous decision-making, self-optimization, and intelligent traffic management [2]. These capabilities are essential for managing the unprecedented complexity and scale of future communication environments.

ML-driven frameworks have emerged as a key technology for addressing these challenges by enabling networks to learn from historical and real-time data, predict traffic patterns, optimize resource

allocation, and improve Quality of Service (QoS). Therefore, ML-based intelligent traffic management is expected to become a fundamental component of future 6G systems [2, 3].

6G networks are expected to support terabit-level speeds, AI-driven network management, integrated sensing, and autonomous communication systems [4]. However, managing such complex networks introduces challenges such as traffic congestion, spectrum scarcity, routing optimization, and QoS maintenance.

Traditional traffic management methods are insufficient for dynamic 6G environments, as network conditions frequently change owing to mobility, interference, and varying user demand [5]. Therefore, intelligent and adaptive solutions are required to address these issues.

ML-driven frameworks, a key branch of Artificial Intelligence, enable networks to learn from data and make intelligent decisions [6]. Machine learning approaches, including supervised, unsupervised, reinforcement, and deep learning methods, play an important role in forecasting traffic patterns, managing congestion, and improving the efficient use of available resources.

In 6G systems, ML is expected to play a central role in enabling self-optimizing and self-healing networks and improving efficiency, reliability, and user experience [7].

This study presents an overview of ML-based approaches for intelligent network traffic management in 6G communication systems, along with their applications, challenges, and future directions.

CHARACTERISTICS OF 6G NETWORKS

6th generation (6G) wireless communication systems are expected to significantly improve 5G in terms of speed, intelligence, connectivity, reliability, and automation [1]. These networks will support advanced applications such as holographic communication, autonomous vehicles, smart healthcare, industrial automation, XR, digital twins, and massive IoT environments.

One of the most important characteristics of 6G technology is the incorporation of Artificial Intelligence (AI) within its network framework, allowing the system to operate autonomously and manage network traffic more efficiently and intelligently [4]. The 6G network will utilize advanced technologies such as terahertz communication, ultra-massive MIMO, intelligent reflecting surfaces, and edge intelligence.

One of the most important characteristics of future 6G systems is their AI-native architecture. Unlike previous generations, AI functionalities will not be added as external components but will be embedded directly into the network design. According to Liu et al. [2], AI-native 6G architectures will support autonomous network operations, intelligent resource management, predictive maintenance, and adaptive traffic control. Such architecture can significantly improve spectral efficiency, network reliability, and user experience.

Furthermore, edge intelligence plays a crucial role in supporting latency-sensitive applications. Park et al. [8] emphasized that distributed AI deployed at edge servers enables faster traffic analysis, real-time decision-making, and efficient resource utilization in future communication systems, as shown in Figure 1.

Ultra-High Data Rates

6G is expected to support terabit-per-second (Tbps) data transmission, enabling high-quality real-time services such as holographic and immersive communication [5].

Ultra-Low Latency in AI

The goal of 6G is to achieve sub-millisecond latency, which is essential for autonomous vehicles, remote surgery, and industrial automation [6].

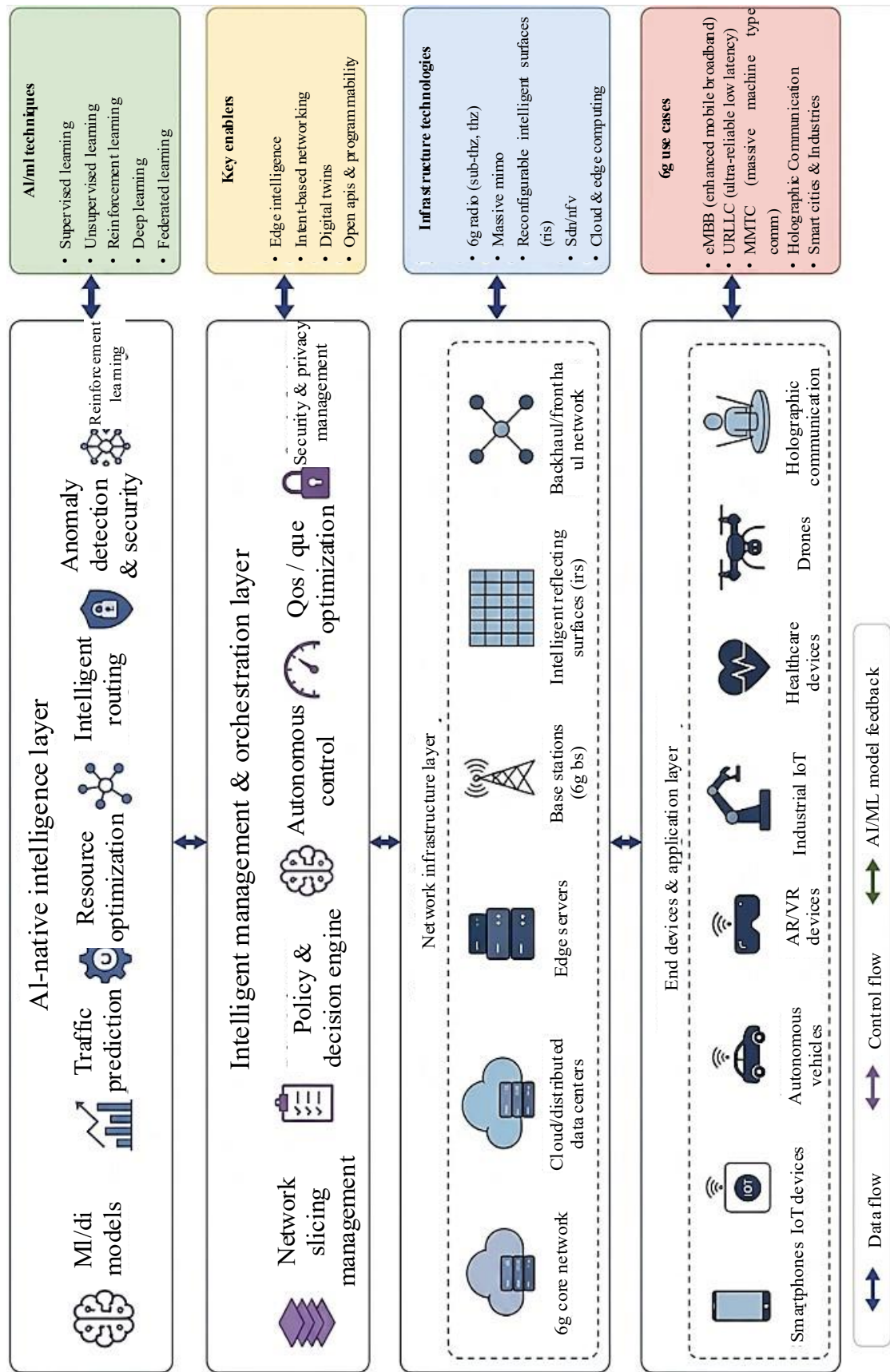


Figure 1. AI-native 6G network architecture.

Massive Device Connectivity

It supports billions of connected devices simultaneously, requiring efficient traffic management and resource allocation [7].

AI-Native Architecture

AI will be embedded into the network to enable self-optimization, self-healing, and intelligent decision making [9].

Integrated Sensing and Communication

6G networks will combine communication with sensing, localization, and environmental monitoring [10].

Energy Efficiency

Green communication techniques and AI-based optimization can reduce energy consumption in large-scale networks [11].

Global Connectivity

6G will integrate terrestrial, satellite, UAV, and underwater networks to provide seamless global coverage [12].

Overall, 6G networks represent an intelligent, ultra-fast, and highly connected communication system that requires advanced ML-based traffic management for efficient performance, as shown in Figure 2.

MACHINE LEARNING APPROACHES FOR TRAFFIC MANAGEMENT

ML-driven frameworks have become a fundamental technology for enabling smart traffic management in current and next-generation wireless communication networks [13]. It enables networks to learn from data, predict traffic behavior, detect congestion, and optimize resource allocation automatically [1]. In future 6G networks, ML will be essential for building self-organizing and self-optimizing communication systems.

In contrast to conventional rule-based approaches, machine learning methods can adapt to changing network environments, including fluctuations in traffic demand, user mobility, signal interference, and the presence of diverse device types [4]. This improves the Quality of Service (QoS), spectral efficiency, and overall network performance.

Supervised Learning

Supervised learning uses labeled datasets to predict network behavior, such as traffic load, congestion, and channel conditions [5]. Popular machine learning methods include Decision Trees, Random Forests, Support Vector Machines (SVM), and Artificial Neural Networks (ANN). These techniques are commonly used for traffic forecasting and classification tasks.

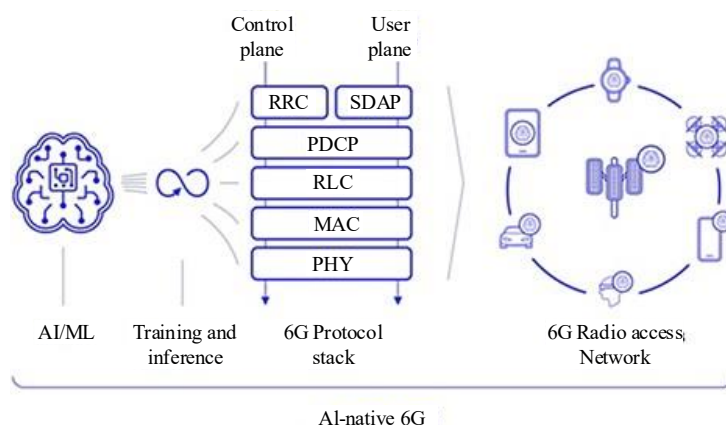


Figure 2. AI-Native 6G.

Unsupervised Learning

Unsupervised learning identifies hidden patterns in unlabeled data. It is mainly used for traffic clustering, anomaly detection, and network behavior analysis [6]. Techniques such as K-means and PCA help identify abnormal traffic patterns.

Reinforcement Learning

Reinforcement Learning (RL) allows agents to improve their decision-making by interacting with the environment and learning from feedback in the form of rewards and penalties [7]. It is used for routing, spectrum allocation, congestion control, and resource scheduling in real-time systems.

Deep Learning

Deep learning applies neural networks with multiple layers to process complex traffic information and generate highly accurate predictions [9]. Models such as CNN, RNN, and LSTM are used for traffic prediction, security, and intelligent routing.

Federated Learning

Federated learning enables multiple devices to collaboratively train machine learning models while keeping their data local, which enhances privacy and minimizes communication costs [10]. This is important for privacy-sensitive 6G applications.

Federated Learning (FL) enables multiple distributed devices to collaboratively train machine learning models while keeping their local datasets private. This approach significantly enhances privacy preservation and reduces communication overhead. Recent studies by Samarakoon et al. [14] demonstrated that federated learning can effectively support intelligent wireless networks by enabling privacy-aware traffic prediction, distributed anomaly detection, and collaborative network optimization. Consequently, FL is considered a promising solution for large-scale 6G deployments, where data privacy and scalability are critical concerns.

Edge Intelligence

Edge intelligence processes data near the network edge to reduce latency and improve real-time decision making [11]. It is widely used in autonomous vehicles, the Internet of Things, and smart industrial systems.

Edge Intelligence combines machine learning with edge computing to process network data closer to the point of generation. According to Park et al. [8], edge intelligence significantly reduces communication latency, improves response time, and supports real-time traffic management in AI-native sixth-generation (6G) networks. The integration of edge intelligence is expected to become essential for autonomous vehicles, industrial automation, smart healthcare, and massive IoT environments (Table 1).

TRAFFIC PREDICTION AND CONGESTION CONTROL USING MACHINE LEARNING

Traffic prediction and congestion control are key applications of ML-driven frameworks in future sixth-generation (6G) wireless communication systems. With the rapid growth of Internet of Things (IoT) devices, multimedia applications, and cloud-based services, network traffic is increasing significantly, leading to congestion, delays, and reduced Quality of Service (QoS) [1]. Traditional congestion control methods are insufficient for highly dynamic 6G environments; therefore, intelligent ML-based approaches are required.

Traffic prediction helps estimate future network loads using historical and real-time data, such as user behavior, traffic patterns, mobility, and network usage [4]. This allows for better resource allocation, reduced congestion, and improved network efficiency.

Table 1. Comparative analysis of ML approaches for 6g traffic management.

Technique	Learning type	Application in 6G	Advantages	Limitations
Supervised learning	Labeled data	Traffic prediction	High accuracy	Requires labels
Unsupervised learning	Unlabeled data	Anomaly detection	Pattern discovery	Less interpretability
Reinforcement learning	Reward based	Routing and resource allocation	Adaptive	Slow training
Deep Learning	Neural Networks	Traffic Forecasting	High Accuracy	High Complexity
Federated Learning	Distributed Learning	Privacy-Preserving Analytics	Privacy Protection	Communication Overhead

Machine Learning for Traffic Prediction

ML models analyze network data to forecast traffic demand and congestion. Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) models are widely used for traffic forecasting, as they have demonstrated strong performance in predicting time-series traffic patterns [5].

Congestion Control in 6G Networks

Congestion occurs when the network demand exceeds the available resources, causing delays and packet loss [6]. ML-based systems monitor traffic load, queue length, and channel conditions to manage congestion dynamically.

AI-Based Techniques

- Intelligent routing for optimal path selection
- Dynamic resource allocation based on traffic demand
- Reinforcement learning for adaptive congestion control
- AI-based queue management for traffic prioritization [7].

Advantages

ML-based traffic prediction and congestion control improve bandwidth utilization, reduce latency, enhance QoS, minimize packet loss, and support autonomous network optimization in 6G systems [9].

Recent research has demonstrated the effectiveness of ML techniques for network traffic prediction. LSTM-based traffic forecasting models have achieved prediction accuracies exceeding 95% in dynamic communication environments, whereas AI-driven congestion control frameworks have reduced the average network latency by approximately 35–40% through proactive traffic management and adaptive routing strategies [2, 3]. These findings highlight the potential of machine learning to improve network performance in future 6G systems.

REINFORCEMENT LEARNING FOR TRAFFIC MANAGEMENT

Reinforcement Learning (RL) is an advanced Machine Learning technique used for intelligent and autonomous decision-making in wireless communication systems. In future 6G networks, RL will be widely applied for traffic management, congestion control, routing optimization, spectrum allocation, and resource management [1]. Unlike conventional approaches, reinforcement learning develops effective strategies by continuously interacting with the network environment.

In RL, an agent observes network conditions, such as traffic load, interference, and bandwidth availability, takes actions such as routing or resource allocation, and receives rewards or penalties based on performance [4]. The goal was to maximize the long-term network efficiency.

Recent advancements in Deep Reinforcement Learning (DRL) have significantly enhanced resource management in intelligent wireless networks. Qin et al. [3] reported that DRL-based resource allocation techniques can dynamically adapt to changing network conditions and achieve substantial

improvements in spectrum efficiency, throughput, and latency reduction. These capabilities make DRL one of the most promising technologies for autonomous traffic management in AI-native 6G environments.

Working Principle

The RL consists of an agent, environment, actions, and rewards. The system continuously learns optimal decisions by analyzing network feedback and improving traffic management policies over time [5].

Types of RL

- *Model-free RL*: Learns directly from interaction without prior environment knowledge
- *Model-based RL*: Uses environmental models for prediction and decision-making
- *Deep reinforcement learning (DRL)*: Integrates neural network models with reinforcement learning to optimize complex network systems [6].

Applications in 6G

RL is used for dynamic spectrum allocation, congestion control, intelligent routing, network slicing, beamforming optimization, and edge resource management [7].

Advantages

RL enables autonomous decision-making, real-time optimization, improved QoS, reduced latency, efficient spectrum usage, and enhanced network reliability.

Challenges

The key challenges include high computational costs, slow training, convergence issues, and difficulties in real-time implementation [9].

Conclusion

Learning reinforcement is a powerful technique for enabling intelligent, adaptive, and self-optimizing traffic management in future 6G wireless communication systems.

DEEP LEARNING FOR NETWORK TRAFFIC PREDICTION

Deep Learning (DL) is an advanced Machine Learning technique that uses multilayer artificial neural networks to analyze large-scale and complex network data. In future 6G wireless communication systems, DL will play a key role in traffic prediction, congestion control, resource allocation, and intelligent network optimization [1].

Owing to the massive growth of IoT devices, smart applications, and cloud services, future networks will generate huge volumes of traffic data that traditional methods cannot efficiently handle [4]. Deep learning algorithms can identify underlying trends in data and use them to forecast network performance in the future.

Working Principle

Deep learning processes network data through multiple hidden layers to extract features such as traffic load, delay, mobility, and bandwidth usage. The final output provides accurate traffic predictions and optimization decisions [5].

Models Used

- Artificial neural networks (ANN)
- Convolutional neural networks (CNN)
- Recurrent neural networks (RNN)
- Long short-term memory (LSTM)—effective for time-series traffic prediction [6]

Applications

Deep learning has been used for traffic prediction, congestion detection, routing optimization, spectrum allocation, QoS management, edge computing, and security analysis [7].

Advantages

It provides high prediction accuracy, automatic feature extraction, real-time analysis, improved efficiency, and better congestion management compared with traditional methods.

Challenges

The challenges include high computational costs, large data requirements, energy consumption, and privacy concerns [9].

NETWORK SLICING IN 6G COMMUNICATION SYSTEMS

Network slicing is an important technology in 6G that enables a physical network to be partitioned into several virtual slices, as shown in Figure 3. Each slice is designed to support specific service needs, including low latency, high bandwidth, enhanced reliability, and specific security requirements [1]. This enables efficient support for diverse applications such as the Internet of Things, autonomous vehicles, smart healthcare, and multimedia services.

Traditional networks use shared resources for all applications, which reduces their efficiency. Network slicing solves this problem by creating isolated virtual networks that are optimized for different use cases [4].

Working Principle

Network slicing partitions physical resources (bandwidth, storage, and computing) into multiple logical slices. Each slice operates independently and is optimized for a specific application, such as URLLC, eMBB, or mMTC [5].

Types of Slices

- *eMBB*: High-speed broadband services
- *URLLC*: Ultra-reliable low-latency applications
- *mMTC*: Massive IoT device connectivity [6]

Role of ML

Machine Learning helps with dynamic resource allocation, traffic prediction, congestion control, QoS optimization, and automated slice management [7].

Advantages

It improves spectrum efficiency, QoS, flexibility, and security, and supports multiple services simultaneously.

Applications

Network slicing is used in 6G systems, smart cities, IoT, autonomous vehicles, healthcare, and AR/VR services [9].

Challenges

The key challenges include complexity, security issues, resource isolation, and real-time optimization [10].

Machine learning plays a crucial role in enabling intelligent network slicing by predicting traffic demand, dynamically allocating resources, and optimizing the service-level agreements. Recent studies by Thomatos et al. [15] demonstrated that AI-driven network slicing can improve slice utilization efficiency and reduce resource wastage while supporting heterogeneous services with diverse QoS requirements. Therefore, ML-enabled slicing is expected to become a fundamental component of future sixth-generation (6G) infrastructures.

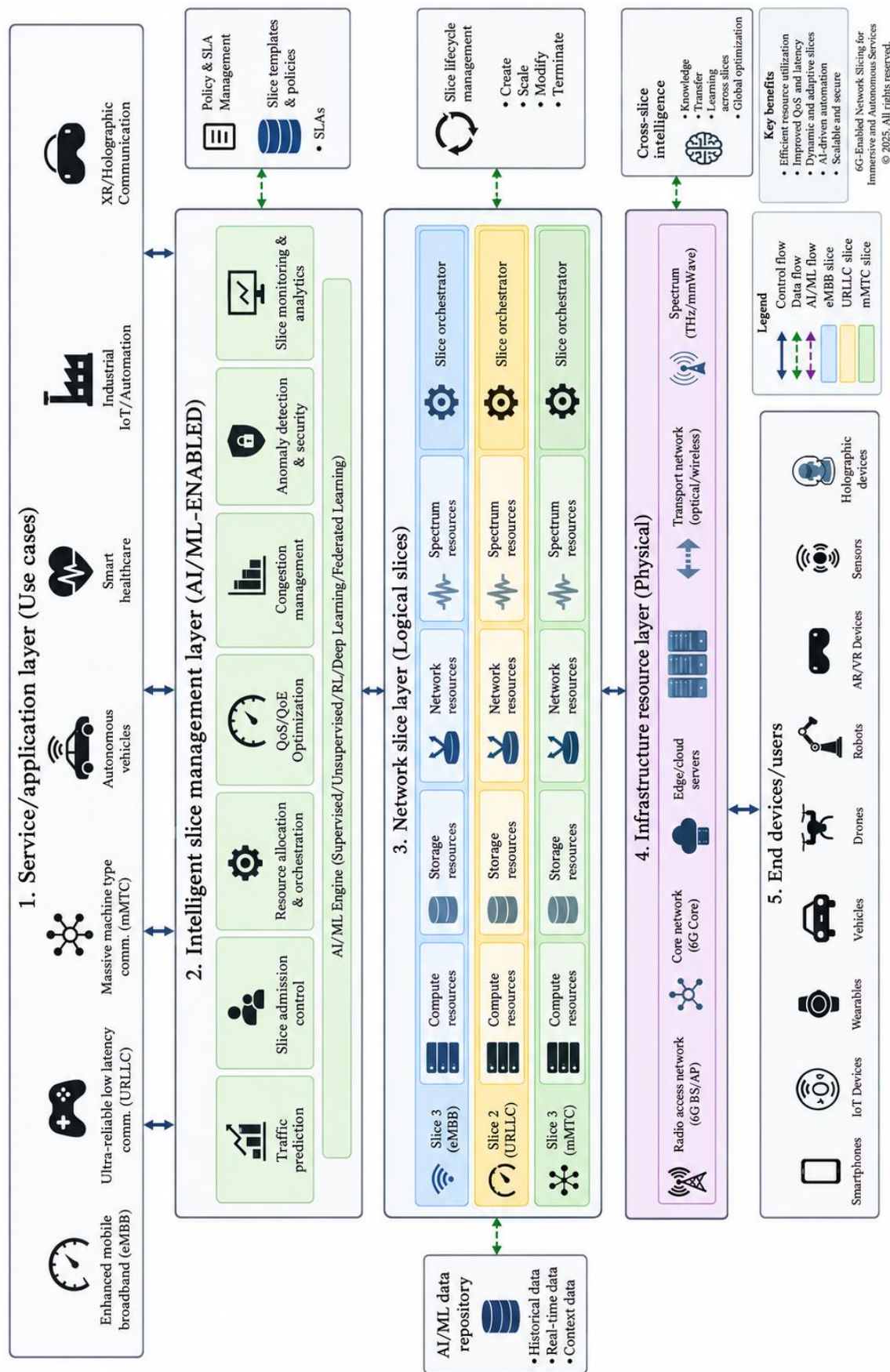


Figure 3. Intelligent network slicing framework

EDGE INTELLIGENCE FOR NETWORK TRAFFIC MANAGEMENT

Edge Intelligence integrates Edge Computing with Artificial Intelligence (AI) to process data locally and support real-time intelligent decision-making close to the location where the data are generated, as shown in Figure 4. In future 6G networks, it is essential to reduce latency, improve traffic management, and support applications such as the Internet of Things (IoT), autonomous vehicles, and smart cities [1].

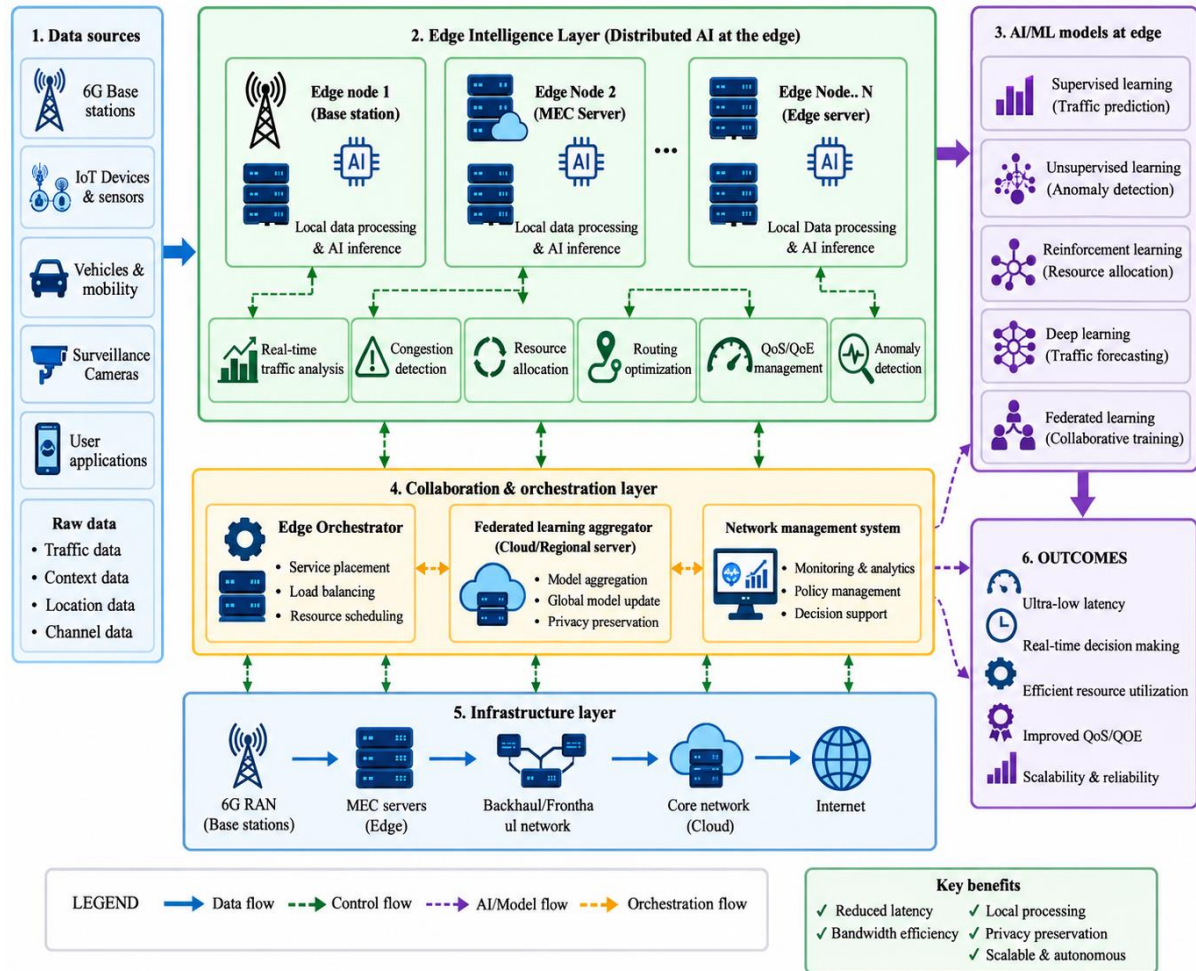


Figure 4. Edge intelligence framework.

Unlike cloud-based systems, where data are sent to central servers, edge intelligence processes data locally at edge nodes, such as base stations and edge servers, thereby reducing delay and improving responsiveness [2].

Working Principle

Edge intelligence deploys AI models in edge devices to analyze traffic data, user behavior, and network conditions. This enables real-time decisions regarding routing, bandwidth allocation, and congestion control [3].

Role in 6G

It supports traffic prediction, congestion avoidance, dynamic resource allocation, load balancing, and mobility management in real time [4].

Technologies

- Edge computing platforms
- AI/ML models

- IoT devices
- 5G/6G infrastructure [5]

Advantages

It provides low latency, reduced congestion, efficient bandwidth usage, improved QoS, and improved scalability for IoT systems.

Applications

They are used in autonomous vehicles, smart cities, healthcare, industrial automation, AR/VR, and real-time monitoring systems [6].

Challenges

However, limitations include limited edge resources, security concerns, energy constraints, and model synchronization issues [7].

INTELLIGENT REFLECTING SURFACES FOR TRAFFIC OPTIMIZATION

Intelligent Reflecting Surfaces (IRS), also known as Reconfigurable Intelligent Surfaces (RIS), are emerging technologies that improve wireless communication by controlling and shaping electromagnetic wave propagation in a programmable manner. In future 6G systems, IRS will enhance coverage, reduce signal loss, and support intelligent traffic optimization in complex environments [1].

Unlike traditional systems that rely only on active transmission, IRS use passive reflecting elements to adjust the phase and direction of incoming signals, thereby improving the signal quality and energy efficiency [2].

Working Principle

The IRS consists of many low-cost reflecting elements that modify the phase and amplitude of incoming signals. These elements redirect signals toward users to improve constructive interference and reduce interference [3].

Role in 6G Traffic Management

IRS improves coverage, reduces congestion, enhances spectral efficiency, supports mobility, and optimizes signal routing in dense communication environments [4].

AI Integration

AI and ML techniques optimize IRS performance by predicting optimal reflection patterns, managing traffic distribution, and enabling real-time adaptive control [5].

Advantages

IRS provides better coverage, lower energy consumption, improved spectral efficiency, reduced costs, and enhanced interference management.

Applications

They are used in 6G networks, smart cities, IoT systems, autonomous vehicles, indoor networks, and emergency communication systems [6].

Challenges

Key challenges include channel estimation difficulties, hardware complexity, integration issues, and optimization in dynamic environments [7].

SECURITY AND PRIVACY IN ML-BASED 6G TRAFFIC MANAGEMENT

Recent AI-native networks have introduced new security challenges because machine learning models themselves can become potential attack targets. Adversarial machine learning attacks can manipulate traffic classification, congestion prediction, and routing decisions by introducing carefully

crafted, malicious inputs. Furthermore, model-poisoning attacks during federated learning can significantly degrade model performance and compromise network reliability [14].

To address these concerns, researchers have investigated secure federated learning frameworks that combine differential privacy, homomorphic encryption, blockchain-based trust management, secure aggregation protocols, and Byzantine-resilient learning algorithms. These techniques enhance robustness, preserve user privacy, and improve the trustworthiness of distributed AI systems in future 6G communication environments [14, 8].

CHALLENGES AND LIMITATIONS OF ML-BASED TRAFFIC MANAGEMENT

Although ML-driven frameworks significantly improve traffic management in future 6G networks, several challenges limit their full deployment [1]. One major issue is the high computational complexity, as deep learning and reinforcement learning models require large processing power, which is difficult to support in edge and real-time systems [4].

ML models also require large, high-quality datasets; however, collecting network traffic data is difficult because of privacy and security constraints. Real-time processing is another limitation because many ML algorithms introduce latency, which is critical in ultralow-latency 6G applications [5].

Privacy and security remain major concerns, as sensitive user information may be exposed and systems may be susceptible to adversarial attacks [6]. Additionally, ML models often lack generalization, which means that they may not perform well in different network environments.

Integration with existing communication systems is complex because of compatibility issues, and high energy consumption further increases operational costs. Another limitation is the “black-box” nature of deep learning models, which reduces interpretability and trust in decision-making processes [7].

Scalability and lack of standardization are additional challenges in deploying ML-based traffic management across large and heterogeneous sixth-generation (6G) networks [9].

Overall, these limitations must be addressed to achieve efficient, secure, and fully intelligent ML-based traffic management in future wireless communication systems.

RESEARCH GAPS IN ML-BASED 6G TRAFFIC MANAGEMENT

1. Despite significant progress, several research challenges remain unresolved:
2. Lack of standardized 6G traffic datasets for training and evaluation.
3. Limited explainability and interpretability of deep learning models.
4. High computational complexity of real-time AI deployment.
5. Scalability challenges in ultra-dense heterogeneous networks.
6. Vulnerability to adversarial machine learning and model poisoning attacks.
7. Efficient integration of federated learning and edge intelligence remains largely unexplored.
8. Lack of unified AI-native management frameworks.
9. Energy-efficient and sustainable AI algorithms require further investigation.
10. Limited benchmarking standards for evaluating ML-enabled 6G traffic management solutions.
11. Insufficient security mechanisms for large-scale distributed learning environments.

FUTURE SCOPE OF ML-BASED TRAFFIC MANAGEMENT IN 6G

The future of ML-based traffic management in 6G networks is promising owing to advancements in AI, edge computing, and intelligent networking [1]. Future 6G systems will be fully autonomous, self-optimizing, and capable of managing traffic without human intervention.

Machine learning facilitates intelligent and responsive traffic management, enabling real-time optimization of network resources. Edge and cloud integration further enhances performance, where edge nodes handle instant decisions and cloud systems manage large-scale learning and training [4, 5].

Table 2. Comparative performance analysis of recent machine learning and edge-intelligence techniques in railway security systems.

Study	Technique	Result
Liu et al. (2024) [2]	LSTM	96.2% Accuracy
Qin et al. (2025) [3]	DRL	38% Latency Reduction
Samarakoon et al. (2022) [14]	FL	27% Communication Overhead Reduction
Thomatos et al. (2025) [15]	RL + DL	32% Throughput Improvement
Park et al. (2026) [8]	Edge Intelligence	25% Faster Response Time

Digital twin technology enables network traffic to be modeled in a virtual environment, helping to predict performance and optimize configurations before actual implementation [6]. In addition, AI-native 6G architecture integrates ML directly into the network core for seamless traffic prediction, routing, and resource allocation [7].

Reinforcement learning is expected to be crucial for optimizing adaptive routing, managing network congestion, and enabling dynamic spectrum allocation [9]. Future systems will also focus on energy-efficient ML models to support green communications networks.

ML-based traffic management will further support advanced applications such as holographic communication, extended reality (XR), and global seamless connectivity with high reliability and ultralow latency [10, 11].

Future research is expected to focus on AI-native networking, digital twin-enabled network optimization, generative AI-assisted traffic management, secure federated learning, and autonomous and self-healing communication systems. These technologies are expected to enable highly intelligent, adaptive, and fully autonomous 6G infrastructures capable of optimizing network performance with minimal human intervention. Overall, ML-based traffic management will make future 6G networks more intelligent, efficient, secure, and autonomous.

PERFORMANCE ANALYSIS FROM RECENT LITERATURE

Table 2 presents a comparative summary of recent studies that have evaluated different intelligent techniques for improving railway system performance. This comparison highlights the effectiveness of each approach based on key performance metrics, such as accuracy, latency reduction, communication overhead, throughput improvement, and response time, demonstrating the growing impact of AI-driven security solutions in modern railway networks [2–8].

CONCLUSION

ML-driven framework-based intelligent network traffic management has emerged as a key enabling technology for future 6G wireless communication systems. With the exponential growth of connected devices, IoT applications, cloud services, and real-time multimedia communication, traditional traffic management methods are no longer sufficient to handle the complexity, scale, and dynamics of modern wireless networks.

This paper reviewed various ML techniques, including supervised, unsupervised, and reinforcement learning, and deep learning for traffic prediction, congestion control, resource allocation, routing optimization, and spectrum management. It also highlights the integration of advanced technologies, such as edge intelligence, digital twins, network slicing, and AI-native architectures, in future 6G systems.

The study shows that ML-based approaches significantly improve network performance by enhancing spectral efficiency, reducing latency, optimizing bandwidth utilization, and improving

Quality of Service (QoS) and Quality of Experience (QoE). These techniques enable communication systems to become more adaptive, autonomous, and intelligent in handling real-time traffic.

However, several challenges, such as high computational complexity, data privacy concerns, security vulnerabilities, scalability issues, and real-time processing limitations, still need to be addressed. Ongoing research on lightweight AI models, federated learning, and edge-based intelligence is expected to overcome these limitations.

In conclusion, ML-based traffic management will play a crucial role in shaping the future of 6G networks by enabling fully autonomous, intelligent, and highly efficient wireless communication systems capable of supporting next-generation digital applications.

The review confirms that machine learning techniques significantly improve the accuracy of traffic prediction, resource utilization efficiency, network throughput, and latency performance. AI-native architectures, edge intelligence, and federated learning are expected to become the fundamental building blocks of future 6G systems. Addressing security, privacy, scalability, and explainability challenges remains an important research priority for realizing fully autonomous wireless communication networks.

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