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Article

# Artificial Intelligence-Driven Assessment and Performance Evaluation of Fifth-Generation (5G) Wireless Communication Networks

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**Abstract:** The rapid evolution of Fifth Generation (5G) wireless communication has introduced new challenges in monitoring and optimising network performance due to increasing traffic demand, heterogeneous applications, and complex network architectures. This study assessed the role of artificial intelligence (AI) in 5G network performance using a review research approach. The review focused on eight major performance assessment areas, namely intelligent (Key Performance Indicator) KPI monitoring, predictive performance forecasting, QoE-centric (Quality of Experience) assessment, Automated Root Cause Analysis (ARCA), Radio Access Network (RAN) Optimization and self-tuning, network slicing performance assurance, energy efficiency assessment, and Digital Twin simulation for what-if testing. The work made use of recent peer-reviewed studies, gotten from reputable databases, including IEEE Xplore, SpringerLink, MDPI, Elsevier ScienceDirect, ACM Digital Library, and other credible publishers. From the reviewed studies, it was observed that AI techniques such as machine learning, deep learning, random forest, XGBoost, convolutional neural networks, long short-term memory networks, reinforcement learning, and digital twin technology can improve 5G network monitoring, intelligent decision-making, predictive maintenance, resource allocation, traffic management, energy efficiency, and network optimisation. The findings further revealed that AI enhances service reliability, reduces operational costs, minimizes latency, improves throughput, and supports proactive network management while ensuring compliance with Quality-of-Service requirements. From the results, it was concluded that AI is an essential technology for the performance assessment and optimization of modern 5G networks. This study will benefit telecommunication service providers, network engineers, researchers, government regulators, equipment manufacturers, and end users by demonstrating how AI can be applied to enhance the performance, quality of service, and sustainability of 5G communication networks.
**Keywords:** Artificial intelligence, 5G network, Congestion analysis, Deep learning, Random Forest, Signal quality assessment

## 1. Introduction

Wireless communication systems have reached several major milestones, especially within the last decade, and are considered among the fastest dynamically growing technologies. The transition from one generation to the next typically lasts about ten years. The latest generation deployed is 5G, and a massive increase in the number of connected devices has been observed (Lassoued and Boujnah, 2026). As the telecommunications industry continues to advance, the integration of cutting-edge technologies and the intricate interactions among network components present considerable challenges for network troubleshooting. Software testing is a critical phase in telecommunications that ensures the quality, functionality, and reliability of network products. It involves executing network systems to identify defects, bugs, errors, issues, or unmet requirements, collectively referred to as 'faults' (Myers et al., 2011). Therefore, it can be said that adding LLMs to 5G/6G brings another layer of intelligence, as they can support natural language tools for network management, easier troubleshooting, automatic policy creation, and better interaction between people and networks. These models can read complex network logs, create simple reports, assist in planning, and make network control more user-friendly through conversation (Mani et al., 2023; Long et al., 2025; Usman et al., 2025). According to recent studies, 5G networks are required to serve 10 to 100 times more cellular devices compared to previous generations. In this direction, Internet of Things (IoT) analytics estimates that the number of connected devices will reach 40 billion by 2030 (Lorincz et al., 2024; Lassoued and Boujnah, 2025). The emergence of 5G technology marks a significant milestone in developing telecommunication networks, enabling exciting new applications such as augmented reality and self-driving vehicles. However, these improvements bring an increased management complexity and a special concern in dealing with failures, as the applications 5G intends to support heavily rely on high network performance and low latency. Thus, automatic self-healing solutions have become effective in dealing with this requirement, allowing a learning-based system to automatically detect anomalies and perform root cause analysis (RCA) (Hasan et al., 2024). 5G wireless networks are complex, leveraging layers of scheduling, retransmission, and adaptation mechanisms to maximize their efficiency. But these mechanisms interact to produce significant fluctuations in uplink and downlink capacity and latency. This markedly impacts the performance of real-time applications, such as video conferencing, which are particularly sensitive to such fluctuations, resulting in lag, stuttering, distorted audio, and low video quality (Yi et al., 2023).

Advances in industrial 5G communication technologies and robotics create new possibilities while also increasing the complexity and variability of networked control systems. The additional throughput and lower latency provided by 5G networks enable applications such as teleoperation of machinery, flexible reconfigurable robotic manufacturing cells, or automated guided vehicles (Zhang et al., 2020). These use cases are set up in dynamic network environments where communication latency and jitter become critical factors that must be managed. Despite the advancements in 5G technologies, such as ultra-reliable low-latency communication (URLLC), adaptive control strategies such as reinforcement learning (RL) remain critical to handle unpredictable network conditions and ensure optimal system performance in real-world industrial applications (Gilerson et al., 2025). The 5G and Beyond 5G (B5G) networks are designed to serve different types of users, i.e., verticals, with a plethora of different services, achieving higher performance in terms of latency, throughput, and reliability, fostering the digital transformation of vertical industries (GSMA, 2021). As a result of this, it is important to know that accurate forecasting of data traffic assumes a critical role in the administration of 5G networks, as it allows for optimal routing, detection of network anomalies, and improved management of network resources (Lykakis et al., 2025). Also, network traffic prediction is an important network monitoring method, which is widely used in network resource optimization and anomaly detection. However, with the increasing scale of networks and the rapid development of 5th generation mobile networks (5G), traditional traffic forecasting methods are no longer applicable (Wu and Wu, 2024). Considering the importance of reliable 5G network services, at any given time, the assessment of the performance of 5G networks became necessary; hence, the need for this work.

## 2. Methodology

This study adopted the review research method involving the systematic identification, selection, evaluation, and synthesis of existing scholarly literature to provide a comprehensive understanding of a research problem. The review method was considered appropriate because the study sought to examine how artificial intelligence has been applied in assessing and improving the performance of modern 5G communication networks as observed in some recent previous works. In this, relevant materials or sources were obtained through systematic searches of reputable academic databases, including IEEE Xplore, SpringerLink, MDPI, Elsevier ScienceDirect, ACM Digital Library, Wiley Online Library, and other credible publishers. Also, the sources used in this work were peer-reviewed journal articles and conference papers published between 2024 and 2026 in order to ensure that the review reflected recent developments in artificial intelligence and 5G technologies, while selected earlier publications were retained where they provided important background or foundational information. Also, the literature selection focused on studies addressing AI applications in key areas of 5G performance assessment, including intelligent (KPI) monitoring, predictive performance forecasting, Quality of Experience (QoE)-centric assessment, automated root cause analysis

(RCA), RAN optimization and self-tuning, network slicing performance assurance, energy efficiency assessment, and digital twin simulation for what-if testing. Also, the information extracted from each selected study included the research objective, methodology, artificial intelligence techniques employed, major findings, and conclusions. The reviewed studies were critically analysed according to the specific performance assessment areas to identify common trends and practical applications, which formed the basis for discussing how AI contributes to intelligent network monitoring, predictive analysis, resource optimization, and energy-efficient operation of modern 5G communication systems.

### *2.1 Literature Search Strategy*

A structured literature search was conducted to identify relevant studies on the application of artificial intelligence to 5G network performance assessment and optimization. The search was conducted using IEEE Xplore, SpringerLink, ScienceDirect, ACM Digital Library, Wiley Online Library, MDPI, and other relevant scholarly sources. The search combined keywords and Boolean operators related to the study objectives. The principal search terms included "artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" AND "5G network" OR "5G wireless" AND "network performance" OR "performance assessment" OR "performance evaluation" OR "network optimization." Additional searches were conducted using combinations of terms related to the eight identified areas, including "KPI monitoring," "traffic prediction," "Quality of Experience," "root cause analysis," "RAN optimization," "network slicing," "energy efficiency," and "digital twin."

### *2.2 Eligibility Criteria*

Studies were considered eligible when they directly examined the application of artificial intelligence, machine learning, deep learning, reinforcement learning, or related intelligent techniques to 5G or beyond-5G network performance assessment, monitoring, prediction, optimization, assurance, or simulation. The review primarily considered studies published between 2024 and 2026 to reflect recent developments in the field. Journal articles and relevant conference papers were considered, while publications that did not address AI applications in 5G network performance or that focused exclusively on unrelated communication technologies were excluded. Earlier publications were retained only where they provided important background or foundational information relevant to the study.

### *2.3 Screening and Selection Procedure*

The identified publications were screened in stages. First, retrieved records were examined based on their titles and abstracts to remove studies that were clearly outside the scope of the review. Duplicate records were subsequently identified and removed. The remaining studies were subjected to full-text assessment against the predefined eligibility criteria. Studies that did not provide sufficient information on AI techniques, 5G network performance, or one of the identified performance assessment areas were excluded. The complete identification, screening, eligibility, and inclusion process was documented using a PRISMA 2020 flow diagram. PRISMA 2020 provides a structured framework for transparently reporting how studies are identified, screened, assessed for eligibility, and included in a review.

### *2.4 Data Extraction*

Information was systematically extracted from each eligible publication using a structured data-extraction framework. The extracted information included the authors and publication year, research objective, network environment, AI or machine learning technique employed, data or evaluation approach, performance indicators considered, major findings, limitations, and the contribution of the study to 5G network performance assessment. The extracted studies were subsequently grouped according to the eight major areas identified in this study: intelligent KPI monitoring, predictive performance forecasting, QoE-centric assessment, automated root cause analysis, RAN optimization and self-tuning, network slicing performance assurance, energy efficiency assessment, and digital twin simulation for what-if testing.

### *2.5 Quality Assessment of the Selected Studies*

The selected publications were critically assessed according to their relevance to the research objectives, clarity of methodology, description of the AI technique employed, adequacy of performance evaluation, clarity of reported findings, and relevance to 5G network performance assessment. Studies providing clear methodological descriptions and direct evidence of AI application to 5G network performance were given greater emphasis during the synthesis. This process helped to reduce reliance on studies with limited methodological information and improved the consistency of the evidence used in the review.

### *2.6 Data Synthesis and Analysis*

A thematic synthesis approach was used to analyse the selected literature. The studies were organized according to the eight performance assessment areas identified from the literature. Within each category, studies were compared according to their objectives, AI techniques, performance indicators, application environments, and major findings. Common patterns, differences, advantages, and limitations were identified across the studies. The synthesis was primarily qualitative because the reviewed studies differed substantially in their datasets, experimental environments, AI algorithms, performance indicators, and evaluation procedures. The results were therefore integrated narratively rather than statistically pooled through meta-analysis.

### *2.7 PRISMA Reporting*

The literature identification and selection process were reported in accordance with the PRISMA 2020 reporting framework. A total of 73 records were identified and downloaded from the selected academic databases and other relevant scholarly sources. During the screening process, 7 duplicate records were identified and removed, leaving 66 unique records for further assessment. The remaining records were screened based on their titles, abstracts, and relevance to the research objectives. Following the screening and eligibility assessment, 20 records were excluded, resulting in 46 studies that were retained and included in the final review and reference list. The PRISMA approach was used to improve transparency in reporting the identification of records, removal of duplicates, screening, eligibility assessment, and final inclusion of relevant studies.

## 3. Results and Discussion

The following sections present the major areas in which artificial intelligence (AI) is applied for assessing the performance of 5G networks.

### *3.1. Intelligent KPI Monitoring*

A Key Performance Indicator (KPI) is a measurable value used to evaluate how effectively a system, organization, or process is achieving its objectives. In the context of 5G networks, KPIs are specific performance metrics used to assess the health, efficiency, and quality of the network such as throughput, Latency, Packet Loss Rate, Signal, Network Availability, Call Drop Rate. Intelligent Key Performance Indicator (KPI) monitoring is one of the most important applications of artificial intelligence (AI) in assessing the performance of fifth-generation (5G) mobile networks. AI-driven KPI monitoring continuously analyses essential performance indicators such as Signal-to-Interference-plus-Noise Ratio (SINR), throughput, latency, jitter, packet loss, and handover success rate. Machine learning models, particularly long short-term memory networks and autoencoders, learn the normal operational patterns of these indicators from historical and real-time network data. Once trained, these models can instantly detect abnormal deviations that may indicate equipment malfunction, radio interference, congestion, or unexpected traffic surges. Rather than waiting for service failures to occur before initiating corrective actions, AI identifies early warning signs and alerts network operators before users experience noticeable service degradation. This proactive capability significantly improves network reliability, reduces downtime, shortens fault detection time, and enhances the Quality of Experience (QoE) for end users.

Panek et al. (2024) investigated the role of automatic performance assessment in achieving autonomous mobile network management. The aim of the study was to identify the limitations of existing manual network monitoring systems and propose an AI-based framework capable of continuously assessing network performance without human intervention. The authors adopted a review and conceptual framework supported by AI-driven network management principles and machine learning techniques for automated KPI analysis. Their findings revealed that traditional network management remains largely reactive, whereas AI-based KPI monitoring enables continuous performance evaluation, early anomaly detection, and predictive maintenance. The study concluded that automated KPI monitoring is a fundamental requirement for realizing fully autonomous 5G and future 6G networks.

In the work by Alfonso et al. (2024), who proposed an adaptive end-to-end monitoring framework for heterogeneous 5G and beyond networks, their primary aim of the research was to develop a monitoring system capable of evaluating network performance across multiple domains while improving fault detection and localization. The researchers designed and evaluated an adaptive monitoring architecture that integrates network telemetry, real-time KPI collection, and intelligent monitoring mechanisms within heterogeneous 5G environments. The results show that adaptive KPI monitoring significantly improves network observability and enhances overall performance assessment compared with conventional monitoring approaches. The authors concluded that intelligent monitoring frameworks are essential for supporting reliable and scalable 5G network operations.

According to Luo et al. (2024), in their work focusing on overcoming an intelligent model capable of detecting abnormal behaviour across multiple network KPIs simultaneously, using a Temporal Fusion Transformer integrated with probabilistic forecasting techniques to analyse multivariate KPI time-series collected from large-scale operational communication networks, AI-based intelligent KPI monitoring significantly improves the early identification of abnormal network conditions, thereby allowing network administrators to detect faults before they affect service quality. The study concluded that Transformer-based monitoring models provide an effective solution for autonomous performance assessment in future 5G and beyond communication networks. This is also in conformation with the results by Alimohammadi et al., (2024).

### *3.2. Predictive Performance Forecasting*

Predictive performance forecasting is the process of using artificial intelligence (AI), machine learning (ML), and statistical forecasting techniques to analyze historical and real-time performance data in order to predict the future state of a system. It helps identify potential performance degradation, resource demands, and operational issues before they occur, enabling proactive optimization and informed decision-making. Machine learning and deep learning models, including Transformer networks, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models, analyse historical datasets alongside contextual information such as weather conditions, user mobility, special events, and application usage trends. These models learn complex temporal patterns and generate accurate predictions of future congestion, cell overload, throughput reduction, latency increase, and Quality of Experience (QoE) degradation. For example, an AI model may predict that a particular 5G cell serving a commercial district will experience heavy traffic during evening hours due to increased user activity. Such predictions allow network operators to proactively allocate additional radio resources, optimise load balancing, adjust beamforming parameters, or activate neighbouring cells before congestion occurs. As a result, predictive performance forecasting enhances network efficiency, improves resource utilisation, minimises service interruptions, and supports autonomous network management.

In the study by Wu and Wu (2024), which aimed to develop an intelligent prediction model capable of forecasting network traffic accurately while maintaining low computational complexity for real-time 5G applications, it was reported that the proposed model, which was evaluated using real-world 5G traffic datasets and compared with existing traffic prediction methods, showed higher prediction accuracy and lower computational overhead than conventional forecasting models. The model effectively predicted future traffic patterns, enabling proactive resource allocation, congestion avoidance, and improved network performance.

In the same way, Petrella, Miozzo, and Dini (2024) investigated the application of distributed artificial intelligence for mobile traffic prediction at the network edge to support proactive resource management in 5G networks. The aim of the study was to develop an AI-based traffic forecasting framework that performs accurate predictions while reducing communication overhead and preserving data privacy through distributed learning. The results revealed that the distributed deep transfer learning model achieved prediction accuracy comparable to centralized models while significantly reducing communication costs and improving scalability. The authors concluded that distributed AI-based predictive performance forecasting provides an efficient and scalable solution for autonomous 5G and beyond network optimization by enabling intelligent resource management before performance degradation occurs.

According to Yuliana et al. (2024), in their study, which investigated the application of machine learning for predicting base station traffic and throughput using hourly Key Performance Indicator (KPI) data in 5G mobile networks and which employed several supervised machine learning algorithms to analyse hourly KPI datasets collected from operational cellular base stations, it was stated that the machine learning models accurately predicted future traffic demand and throughput variations, enabling network operators to anticipate congestion and optimise resource allocation before service degradation occurred. The authors concluded that AI-driven predictive performance forecasting based on hourly KPI analysis provides an effective tool for improving network planning, enhancing Quality of Service (QoS), and enabling autonomous management of modern 5G networks.

### *3.3. Quality of Experience (QoE)-centric Assessment*

Quality of Experience (QoE)-centric assessment is an emerging AI-driven approach that focuses on evaluating 5G network performance from the perspective of the end user rather than relying solely on technical performance indicators. Traditional network assessment methods primarily measure Quality of Service (QoS) metrics such as throughput, latency, packet loss, and Signal-to-Interference-plus-Noise Ratio (SINR). Although these metrics provide valuable information about network conditions, they do not always reflect the actual experience of users during activities such as video streaming, online gaming, video conferencing, or Voice over Internet Protocol (VoIP) communication. AI techniques, including regression models, Random Forest, XGBoost, and Artificial Neural Networks (ANNs), analyse historical network measurements alongside user feedback and application performance data to determine how variations in network KPIs affect user satisfaction. For example, machine learning algorithms can predict video buffering events, streaming interruptions, and gaming delays before users notice service degradation. By continuously learning from real-time network conditions, AI enables operators to identify areas where users experience poor service despite acceptable technical KPIs. This user-centered assessment allows network engineers to optimise network resources based on actual customer experience rather than infrastructure performance alone.

Wang et al. (2024) carried out a study that was aimed at developing an intelligent routing strategy capable of improving end-user experience rather than relying solely on conventional Quality of Service (QoS) metrics. The researchers designed a machine learning-based routing model that continuously analysed application KPIs alongside real-time network conditions to determine the routing path that would provide the highest QoE. It was observed from the result that the proposed QoE-oriented routing strategy significantly improved user satisfaction, reduced service interruptions, and enhanced application performance under varying network conditions. The authors concluded that integrating AI with QoE assessment provides a practical solution for intelligent network optimization in 5G and beyond communication networks.

According to Ullah et al. (2024), who investigated AI-enabled Quality of Experience-aware mobility management in heterogeneous 5G cellular networks, an AI-based QoE-aware framework significantly reduced unnecessary handovers, minimized latency, improved throughput, and increased user satisfaction across heterogeneous 5G environments. The authors concluded that incorporating AI-driven QoE assessment into mobility management enhances overall network performance and provides a more user-centric approach to evaluating 5G service quality.

Mihailović et al. (2024) proposed a hybrid analytical framework for evaluating the Quality of Experience (QoE) of enhanced Mobile Broadband (eMBB) services in standalone (SA) 5G networks. It was discovered that the AI technique accurately identified QoE degradation even when conventional QoS metrics indicated acceptable network performance. The authors concluded that integrating AI-assisted QoE evaluation with network KPIs provides a more reliable assessment of user experience in modern 5G networks. In the same way, Dobreff et al. (2024) investigated an

AI-enabled framework for QoE-aware network slice placement and resource allocation in 5G networks. The results demonstrated that AI technology improved user QoE and network resource utilization compared with conventional slice allocation methods. The authors concluded that AI-driven QoE-aware resource management enhances service quality and supports efficient operation of future 5G networks. Vishwanath et al. (2025) investigated the use of federated deep reinforcement learning to improve Quality of Experience (QoE) in Mobile Edge Computing (MEC) environments supporting 5G services. The results showed that AI has the capability to improve QoE, reduce response time, and achieve better resource utilization than existing offloading methods. Long and Wang (2025) carried out research with the aim of improving users' Quality of Experience by dynamically allocating network resources according to application requirements. The researchers implemented an Adaptive Reinforcement Learning-based Network Slicing (ARL-NS) framework and evaluated its performance using VR/AR applications over simulated 5G networks and reported that reinforcement learning enables intelligent QoE-centric resource allocation and enhances user satisfaction in AI-enabled 5G networks.

### *3.4. Automated Root Cause Analysis*

Automated Root Cause Analysis (ARCA) is defined as the process of using artificial intelligence (AI), machine learning (ML), and data analytics to automatically identify, analyze, and determine the underlying causes of faults, failures, or performance degradation in a system without requiring extensive manual investigation. It is a critical AI-enabled capability that helps network operators quickly identify the underlying causes of performance degradation in complex 5G environments. Due to the large number of interconnected network components, including gNodeBs, core networks, edge computing platforms, and network slices, a single service disruption may generate thousands of alarms and performance logs within a short period. Artificial intelligence combines anomaly detection algorithms, Graph Neural Networks (GNNs), Bayesian inference models, and correlation analysis to process alarms, network logs, performance counters, and telemetry data simultaneously. Rather than treating alarms as isolated events, AI recognises patterns and dependencies across different network elements to determine whether performance degradation originates from hardware failure, radio interference, software malfunction, congestion, configuration errors, or backhaul limitations. For instance, when users experience increased latency and reduced throughput within a specific coverage area, AI can automatically correlate radio signal degradation, traffic congestion, and equipment alarms to identify the primary fault responsible for the service disruption. This significantly reduces the Mean Time to Repair (MTTR), enabling engineers to restore network services much faster than traditional manual diagnostic approaches.

In the work by Isaac et al. (2025), who investigated the application of machine learning and generative AI for automated fault detection and root cause analysis in the 5G packet core, it was reported from the findings that the proposed framework accurately classified faulty network frames and substantially reduced manual troubleshooting effort while improving diagnosis efficiency. The authors concluded that combining machine learning with generative AI provides an effective approach for intelligent fault diagnosis and autonomous 5G network management.

Similarly, Wankvar and Witayangkurn (2025) investigated automated root cause analysis of network failures in IP/MPLS networks using machine learning and case-based reasoning. The results showed that the AI technology can accurately identify the originating fault among cascading network alarms and significantly reduced troubleshooting time compared with manual diagnosis. It was concluded that integrating machine learning with case-based reasoning improves automated fault diagnosis and can be extended to intelligent management of 5G and future communication networks.

Yi et al. (2025) carried out research work aimed to identify the actual causes of QoE degradation by correlating physical-layer, transport-layer, and application-layer events. The researchers collected extensive measurements from commercial and private 5G networks and built an automated causal analysis tool capable of tracing performance anomalies to their source. Their results showed that automated cross-layer RCA enables faster troubleshooting and more reliable performance optimization for AI-enabled 5G networks. In the work, Leveraging Multi-Agent Framework for Root Cause Analysis, by Fu et al. (2025), it was reported that the proposed multi-agent framework achieved higher diagnostic accuracy and faster fault localization than conventional single-model RCA approaches.

The authors concluded that collaborative AI agents provide a scalable and explainable solution for automated root cause analysis and have strong potential for deployment in autonomous 5G and cloud-native network management systems.

### *3.5. Radio Access Network (RAN) Optimization and Self-Tuning*

RAN Optimization and Self-Tuning is the application of artificial intelligence (AI), machine learning (ML), and automation techniques to continuously monitor, analyze, and optimize the performance of the Radio Access Network (RAN) while automatically adjusting network parameters to adapt to changing traffic conditions, user mobility, and environmental factors. The 5G radio access network consists of numerous interconnected base stations (gNodeBs), massive multiple-input multiple-output (Massive MIMO) antennas, beamforming technologies, and spectrum management mechanisms that operate in highly dynamic environments. Artificial intelligence, particularly deep reinforcement learning (DRL), Deep Q-Networks (DQN), and Multi-Agent Reinforcement Learning (MARL), continuously interacts with the network environment to identify the most effective configuration strategies. These intelligent agents analyse network performance indicators such as throughput, latency, Signal-to-Interference-plus-Noise Ratio (SINR), handover success rate, and spectral efficiency before adjusting parameters including transmission power, beamforming direction, scheduling policies, and handover thresholds. These adaptive capabilities ensure that network resources are utilised efficiently while maintaining consistent service quality Hole et al. (2026).

Long and Wang (2025) investigated the application of artificial intelligence for adaptive network optimization in immersive virtual reality (VR) and augmented reality (AR) services over 5G networks. The aim of the study was to develop an intelligent reinforcement learning framework capable of dynamically allocating network resources according to changing service demands. The researchers proposed an Adaptive Reinforcement Learning-based Network Slicing (ARL-NS) algorithm and evaluated its performance under different traffic conditions in a simulated 5G environment. The results showed that artificial intelligence reduced latency, improved bandwidth utilization, and increased Quality of Experience (QoE) compared with conventional resource allocation methods. The adaptive learning capability enabled the network to respond effectively to dynamic traffic variations while maintaining stable service quality. The authors concluded that reinforcement learning provides an effective AI solution for adaptive optimization of 5G network resources.

Senthil et al. (2025) investigated the application of deep reinforcement learning (DRL) for adaptive handover optimization in 5G mobile networks. The aim of the study was to improve network performance by dynamically selecting optimal handover decisions according to changing user mobility and radio conditions, in which the researchers developed an Advanced Handover Optimization (AHO) framework based on Deep Q-Network (DQN) reinforcement learning and evaluated its performance using a simulated 5G environment. The results showed that the deep reinforcement learning-based framework significantly reduced unnecessary handovers, improved throughput, minimized latency, and enhanced overall Quality of service (QoS) compared with conventional handover algorithms. The authors concluded that deep reinforcement learning provides an effective AI-driven approach for adaptive network optimization in next-generation 5G systems. Vishwanath et al. (2025) did a work aimed at optimizing network performance by dynamically distributing computational tasks while maximizing Quality of Experience (QoE), which involved the integration of federated learning with deep reinforcement learning to enable intelligent decision-making across distributed edge nodes. The authors concluded that AI-driven adaptive optimization significantly enhances network efficiency and supports autonomous management of next-generation 5G infrastructures. Hole et al. (2026) investigated the application of Deep Reinforcement Learning (DRL) for adaptive optimization in Reconfigurable Intelligent Surface (RIS)-assisted 5G Multiple-Input Single-Output (MISO) networks. It was reported that the DRL framework enhanced spectral efficiency, signal quality, and network capacity while reducing computational complexity compared with conventional optimization methods. They added that adaptive learning capability enabled the system to respond effectively to changing channel conditions without requiring continuous manual parameter tuning. They concluded that deep reinforcement learning offers an efficient AI-driven solution for adaptive network optimization in future intelligent 5G systems. Also, Gilerson et al. (2025) investigated the application of reinforcement learning (RL) for adaptive control and optimization of 5G-enabled networked systems operating under variable communication delays. The results demonstrated that incorporating realistic 5G latency into the training process significantly improved the robustness and adaptability of the reinforcement learning controller. The researchers concluded that reinforcement learning provides an effective AI-driven approach for adaptive optimization of 5G-enabled networked systems, particularly in applications requiring real-time communication and autonomous decision-making.

### *3.6. Network Slicing Performance Assurance*

Network slicing performance assurance is the process of continuously monitoring, evaluating, and optimizing the performance of individual network slices to ensure that each slice consistently meets its predefined service-level agreements (SLAs), Quality of service (QoS), and application-specific performance requirements. Network slicing is a key feature of 5G technology that enables a single physical network infrastructure to support multiple virtual networks, each designed to meet the specific requirements of different applications and services. AI machine learning techniques such as Convolutional Neural Networks (CNNs), Random Forest, XGBoost, and traffic classification algorithms can continuously monitor network slices and identify variations in service performance. These models classify different traffic types and evaluate whether each slice is meeting its predefined Quality of Service (QoS) and Quality of Experience (QoE) objectives. For instance, AI can detect if an Ultra-Reliable Low-Latency Communication (URLLC) slice begins to exceed its required latency threshold, allowing the system to automatically prioritise resources and restore compliance with the agreed service level. As reported by Long and Wang (2025) in the work entitled "AI-Driven 5G Network Optimization for Immersive Educational VR/AR Applications in Mobile Learning Environments," it was stated that the AI-driven framework can reduce end-to-end latency, improve bandwidth utilization, and enhance users' Quality of Experience (QoE) compared with conventional slicing methods. The authors concluded that reinforcement learning provides an effective solution for intelligent network slicing performance assurance in next-generation 5G systems. Khan et al. (2025) examined the application of machine learning techniques for intelligent resource allocation and performance assurance in 5G network slicing. The authors observed that AI-based resource orchestration significantly improved throughput, reduced latency, and increased network utilization while maintaining service isolation among network slices. It was authors concluded that machine learning enables autonomous network slicing management and improves the operational efficiency of 5G communication systems. Also, Shah et al. (2024) investigated Artificial Intelligence-enabled orchestration for adaptive resource management in 5G network slicing. The aim of the study was to improve the performance of heterogeneous network slices by applying deep reinforcement learning for dynamic resource allocation. The researchers developed an AI-based orchestration framework capable of continuously monitoring traffic demands and reallocating radio and computing resources according to slice requirements. The results demonstrated that the proposed framework achieved higher resource efficiency, lower latency, and improved SLA satisfaction compared with conventional static allocation methods. The authors concluded that AI-driven orchestration provides an effective mechanism for assuring network slicing performance in modern 5G systems. Similarly, Conţu et al. (2025) investigated the application of machine learning-assisted resource monitoring for automated network slice creation and performance assurance in 5G networks. The results demonstrated that the machine learning-assisted monitoring approach enabled proactive resource allocation, reduced manual intervention, and ensured better compliance with Service Level Agreements (SLAs). The authors concluded that integrating AI into network slice orchestration significantly enhances performance assurance and supports autonomous management of modern 5G networks. Thomatos et al. (2025) presented a comprehensive survey of artificial intelligence methods across the entire network slice life cycle, including slice design, admission, orchestration, monitoring, assurance, optimization, and termination. The review showed that AI significantly improves network slicing performance by enabling proactive SLA assurance, intelligent resource orchestration, traffic prediction, and adaptive slice management. The study further identified reinforcement learning and deep learning as the most promising techniques for autonomous network slicing because they continuously adapt to changing network conditions while maintaining Quality of service (QoS) and Quality of Experience (QoE). It was concluded in the work that AI-driven automation is fundamental to achieving reliable and scalable network slicing in future 5G and 6G communication systems.

### 3.7. Energy Efficiency Assessment

"Energy efficiency assessment" is defined as the systematic process of measuring, analyzing, and evaluating how effectively a network or system utilizes energy while maintaining the required level of performance and service quality. Energy efficiency assessment has become an essential aspect of evaluating the performance of modern 5G networks because of the increasing number of base stations, massive MIMO (Multiple Input, Multiple Output) antennas, edge computing nodes, and connected Internet of Things (IoT) devices. Although 5G provides significantly higher data rates and lower latency than previous generations, these capabilities also lead to increased energy consumption across the network infrastructure. Artificial intelligence techniques like Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), and predictive machine learning models can continuously monitor network utilisation and make intelligent energy management decisions. These algorithms learn the traffic behaviour of different cells throughout the day and determine the most appropriate periods to activate or deactivate radio units, carriers, antennas, or entire base stations without affecting users' Quality of Service (QoS). For example, during periods of low network activity, AI can place selected radio components into sleep mode while automatically reactivating them when traffic demand begins to increase. Ezzeddine et al. (2024) conducted a comprehensive review of Artificial Intelligence (AI)-based techniques for improving the energy efficiency of 5G networks. The aim of the study was to examine how AI technologies can reduce energy consumption in 5G systems while maintaining important network performance indicators such as Quality of Service (QoS), Quality of Experience (QoE), throughput, and latency. The review showed that AI techniques enable intelligent management of network resources by dynamically switching base stations and radio units on or off according to traffic demand, predicting future network loads, optimizing resource allocation, and improving sleep-mode scheduling. The authors concluded that integrating AI into 5G network management significantly enhances energy efficiency, reduces operational costs and carbon emissions, and supports the development of sustainable and autonomous next-generation wireless communication systems. Lassoued and Boujnah (2026) presented a comprehensive review of energy-efficient techniques for 5G networks, with particular emphasis on the integration of artificial intelligence for sustainable network operation. The authors adopted a review research methodology by examining recent studies on AI-assisted radio resource management, massive MIMO, sleep-mode mechanisms, traffic prediction, machine learning, and deep reinforcement learning for energy optimization. The review found that AI-based techniques enable intelligent prediction of traffic demand, dynamic allocation of radio resources, and adaptive activation or deactivation of network components according to real-time network conditions. The researchers concluded that artificial intelligence is becoming a fundamental technology for achieving sustainable and energy-efficient 5G and beyond-5G networks, particularly when combined with advanced radio technologies and intelligent network management. Lazrek et al. (2025) investigated the use of artificial intelligence (AI)-driven dynamic discontinuous reception to improve energy efficiency in 5G networks. The aim of the study was to reduce the power consumption of User Equipment (UE) while maintaining acceptable network performance. The researchers reported that AI techniques reduce energy consumption while maintaining low latency and reliable communication performance. The adaptive mechanism responded effectively to varying traffic loads, providing better energy savings than conventional DRX schemes. The authors concluded that AI-driven adaptive sleep scheduling is an effective solution for improving energy efficiency in 5G networks. Maiwada et al. (2024) conducted a literature review on energy efficiency in 5G systems. The aim of the study was to examine recent techniques for reducing energy consumption in 5G networks while maintaining network performance. The results showed that artificial intelligence, particularly machine learning and reinforcement learning, plays an important role in optimizing network resources, predicting traffic demand, and reducing the energy consumption of 5G infrastructure without compromising Quality of Service (QoS). They concluded that AI-enabled energy management is essential for developing sustainable and green 5G communication systems. Okpara et al. (2024) studied the use of machine learning to improve the energy efficiency of the 5G Radio Access Network (RAN). The results showed that the machine learning model effectively identified low-traffic periods during which network resources could be managed more efficiently, leading to reduced energy consumption without significantly affecting Quality of Service (QoS). The researchers stated that intelligent machine learning techniques can enhance the energy efficiency of 5G radio access networks and contribute to sustainable wireless communication systems. According to Ichimescu et al. (2024) in the reviewed work, “Energy

Efficiency for 5G and Beyond 5G: Potential, Limitations, and Future Directions." Artificial Intelligence, particularly reinforcement learning and machine learning, enables dynamic base station management, intelligent traffic prediction, and adaptive resource allocation, resulting in significant energy savings without degrading network performance. The authors concluded that AI-driven optimization is one of the most promising approaches for achieving sustainable and energy-efficient operation in future 5G and beyond-5G networks. In the same way, Lorincz et al. (2024) reviewed the role of network slicing in improving the energy efficiency of 5G networks. The aim of the study was to examine how intelligent network slicing techniques can minimize energy consumption while maintaining Quality of service (QoS) for different 5G applications. The study, which adopted a review research method, showed that artificial intelligence enables dynamic slice management by allocating resources according to traffic demand, activating energy-saving mechanisms during low network utilization, and maintaining Service Level Agreements (SLAs). The authors concluded that integrating AI with network slicing significantly improves the energy efficiency and sustainability of 5G networks while ensuring reliable service delivery.

### *3.8. Digital Twin Simulation for What-If Testing*

Digital Twin Simulation for What-If Testing is defined as the use of a virtual replica (digital twin) of a physical system or network to simulate, analyze, and evaluate the effects of different operational scenarios before implementing changes in the real environment. Digital twin simulation is an advanced AI-enabled approach that supports the assessment and optimisation of 5G network performance through the creation of a virtual replica of the physical network. As 5G infrastructures become increasingly complex, testing new configurations, deploying additional base stations, or introducing new services directly on operational networks may result in service disruptions, increased costs, and operational risks. A digital twin integrates real-time network telemetry, traffic statistics, radio propagation information, user mobility patterns, and infrastructure data to create an accurate virtual representation of the operational 5G network. Artificial Intelligence models, including machine learning algorithms, deep neural networks, and predictive analytics, continuously synchronise the virtual environment with the physical network and evaluate the impact of proposed changes. In the work by Garcia et al. (2025), who investigated the application of artificial intelligence (AI)-enhanced Digital Twin technology for testing and evaluating complex engineering systems, AI-enhanced digital twins accurately predicted system behaviour, improved decision-making, and supported reliable what-if analysis by evaluating different operational conditions before implementation. The conclusion by the authors was that AI-powered digital twins provide an effective platform for predictive testing, performance optimization, and risk reduction, making the technology highly suitable for future intelligent communication networks, including 5G and beyond. Mahomed and Saha (2025) studied the integration of digital twin technology with 5G networks to support real-time simulation, intelligent network planning, and predictive performance evaluation in smart city environments. The aim of the study was to examine how 5G connectivity enhances digital twin applications by enabling continuous data synchronization, real-time monitoring, and AI-assisted decision-making. The research showed that AI-enabled digital twins allow network operators to perform what-if simulations by evaluating different deployment scenarios before implementation. The conclusion by the authors was that integrating AI-driven digital twins with 5G provides an effective framework for predictive network management and continuous performance optimization in next-generation communication systems. Aben-Athar et al. (2025) developed a Network Digital Twin (NDT) framework for intelligent route optimization in 5G/Beyond-5G transport networks. The researchers designed an experimental platform that synchronized a digital twin with the physical transport network and integrated a Graph Neural Network (GNN) to predict latency and recommend optimal routing strategies for different network slices and reported that the proposed network digital twin accurately predicted network latency for Ultra-Reliable Low-Latency Communications (URLLC) and enhanced mobile broadband (eMBB) services, allowing operators to evaluate multiple routing scenarios before implementation. The conclusion by the authors was that Digital Twin technology combined with Artificial Intelligence provides an effective framework for predictive network planning and performance optimization in future 5G and beyond-5G networks. According to Huang (2025), in their work, which investigated the application of Digital Twin Networks (DTNs) for enabling intelligent self-evolution in future wireless communication systems, AI-enabled DTN improved network efficiency, reduced operational risks, and enhanced service reliability through continuous prediction and optimization. The conclusion by the authors was that Digital Twin technology is a key enabler for intelligent planning, simulation, and performance assessment in future 5G and 6G communication networks. Li et al. (2025) reviewed the integration of Generative Artificial Intelligence (GenAI) with Network Digital Twins (NDTs) for intelligent mobile network management. The aim of the study was to examine how generative AI enhances digital twins by enabling accurate network modeling, predictive simulation, and what-if analysis for 5G and future 6G networks. The review showed that generative AI significantly improves the capability of digital twins to simulate different network scenarios, predict network behaviour, evaluate resource allocation strategies, and optimize network performance before real-world implementation. The authors concluded that AI-powered network digital twins provide an effective framework for intelligent planning, risk reduction, and continuous optimization of next-generation wireless communication networks.

## 4. Conclusion

This study investigated the recent developments in the application of artificial intelligence for assessing and improving the performance of 5G communication networks using the review research method. The review identified eight major areas: intelligent KPI monitoring, predictive performance forecasting, QoE-centric assessment, automated root cause analysis, RAN optimization and self-tuning, network slicing performance assurance, energy efficiency assessment, and digital twin simulation. The reviewed studies demonstrate that machine learning, deep learning, reinforcement learning, and digital twin technologies can support intelligent and data-driven 5G network management. The findings indicate that AI improves anomaly detection, traffic prediction, resource allocation, fault diagnosis, user experience, network optimization, and energy efficiency. Digital twins also provide opportunities for what-if testing and safer network planning. In all, it can be said that AI enables more proactive and increasingly autonomous management of 5G networks. However, effective implementation of AI-driven 5G performance assessment requires reliable data, appropriate model selection, adequate computational resources, security, explainability, and continuous adaptation to changing network conditions. Future studies should therefore focus on real-world validation, robust and explainable AI models, and the integration of AI with emerging 5G and 6G technologies. From the results, it can be concluded that AI is an essential technology for the performance assessment and optimization of modern 5G networks, providing intelligent, proactive, and efficient approaches to network monitoring and management. This study will benefit telecommunication service providers, network engineers, researchers, government regulators, equipment manufacturers, and end users by demonstrating how AI can be applied to enhance the performance, quality of service, and sustainability of 5G communication networks.

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