Connecting The Dots

How AI Supercharges Wi-Fi and 5G Connectivity

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1. Introduction

The wireless medium has emerged as the primary means of internet access for modern users. Whether engaging in video calls with family, conducting online searches, or streaming content, most individuals depend on WiFi or cellular networks for their connectivity.

With the continuous increase in the number of devices connected to the internet, there is a corresponding demand for higher bandwidth and reduced latency. This shift has introduced greater complexity into wireless networks, such as WiFi and 5G. As a result, consumers now anticipate minimal downtime and swift resolutions to any network issues or performance challenges. In this landscape, artificial intelligence (AI) plays a vital role by providing operators with the necessary tools for more effective network management, allowing them to address these escalating demands and enhance the overall connectivity experience.

At its core, a positive customer experience is built upon an efficient and secure network infrastructure. This paper examines how AI can improve the efficiency of wireless networks and its essential contribution to the development of future connectivity solutions, such as autonomous vehicles and smart cities. By leveraging AI technologies, we can establish more reliable, responsive, and secure network systems that not only fulfill current requirements but also facilitate innovative applications that transform our interactions with technology and the world around us.

2. The Role of AI in Network Management

Artificial Intelligence (AI) can significantly enhance the performance, efficiency, and capabilities of each layer in both WiFi and 5G networks. By integrating AI into the various layers of network architecture, operators can optimize operations, improve service quality, and respond more effectively to user demands.

2.1. Physical Layer (Layer 1)

2.1.1. WiFi

In the context of WiFi networks, researchers have increasingly explored the application of AI and machine learning techniques to enhance performance at the transport and link layers. A key area of interest is dynamic radio resource optimization, where AI is used to make more intelligent decisions regarding channel selection, transmission parameters, and congestion control to improve overall throughput and latency.

Unlike 5G, the IEEE 802.11 WiFi standards have not historically incorporated AI/ML into their MAC or transport layer specifications. However, the industry is beginning to formally recognize the value of AI in WLANs. In 2024, the IEEE 802.11 Working Group established the Artificial Intelligence / Machine Learning Standing Committee (AIML SC) to explore relevant use cases and assess the technical feasibility of integrating AI/ML into future 802.11 systems.

2.1.1.1. Channel Estimation

Researchers have leveraged deep learning to enhance channel estimation and signal detection in WiFi OFDM receivers. One notable example is the DeepWiPHY project, which replaced traditional components—such as the channel estimator, phase correction, and equalizer—in an IEEE 802.11ax receiver with a deep neural network (DNN). Trained on over 110 million synthetic and 14 million real WiFi 6 OFDM symbols (captured using a USRP testbed), DeepWiPHY achieved comparable or superior BER/PER performance relative to conventional receivers across diverse channel conditions and SNRs.

In parallel, other work has focused on improving pilot-based channel estimation. For instance, lightweight Convolutional Neural Networks (CNNs) -enhanced least squares estimator (LSDNN) was implemented on a Xilinx Zynq SoC for OFDM PHY. This hybrid model refined traditional LS estimates using a small convolutional neural network, delivering equivalent MSE and BER to prior deep learning approaches but with significantly reduced computational complexity.

2.1.1.2. Modulation and Signal Classification

Another key physical-layer task improved by AI is Automatic Modulation Classification (AMC) and signal recognition. Traditional approaches relied on hand-engineered features—such as cyclostationary patterns or higher-order statistical moments—but often struggled in low SNR environments or with varied signal types. Deep learning, however, sidesteps this by learning directly from raw IQ data, achieving significantly better results.

Recurrent Neural Networks (RNNs) and CNNs are particularly effective for identifying WiFi signals or modulation schemes in the spectrum—supporting applications like cognitive radio and interference detection. RNNs, especially LSTMs, are suited for sequential signal analysis by modeling IQ samples as time-series data. Still, CNNs typically outperform RNNs when paired with appropriate preprocessing, such as transforming IQ samples into amplitude-phase images, and currently represent the state-of-the-art in AMC performance.

2.1.2. 5G

The PHY layer in 5G NR handles core radio functions like modulation, coding, beamforming, and channel estimation. These processes are mathematically complex and must adapt quickly to changing radio environments. AI offers the ability to learn, generalize, and optimize PHY tasks with greater flexibility and accuracy than traditional rule-based methods.

2.1.2.1. Channel State Information (CSI) Feedback

CSI (Channel State Information) refers to feedback sent from the UE (User Equipment) to the gNB (Next Generation NodeB) that describes the condition of the radio channel. This feedback is crucial for the gNB to make intelligent decisions about scheduling, beamforming, modulation, and other physical layer optimizations.

To enable this, the gNB transmits CSI-RS (Channel State Information Reference Signals)—special reference signals that allow the UE to measure the radio channel accurately.

Based on these measurements, the UE reports key CSI metrics back to the gNB, including:

- Channel Quality Indicator (CQI): Reports overall channel quality to guide modulation and coding choices.
- Precoding Matrix Indicator (PMI): Suggests the optimal beamforming direction or precoding strategy.
- Rank Indicator (RI): Indicates the number of independent data streams (MIMO layers) the channel can support.

- Layer Indicator (LI): Recommends how many data layers should be transmitted.
- Interference Measurements (IM): Provides information on the interference environment, useful for interference-aware scheduling.

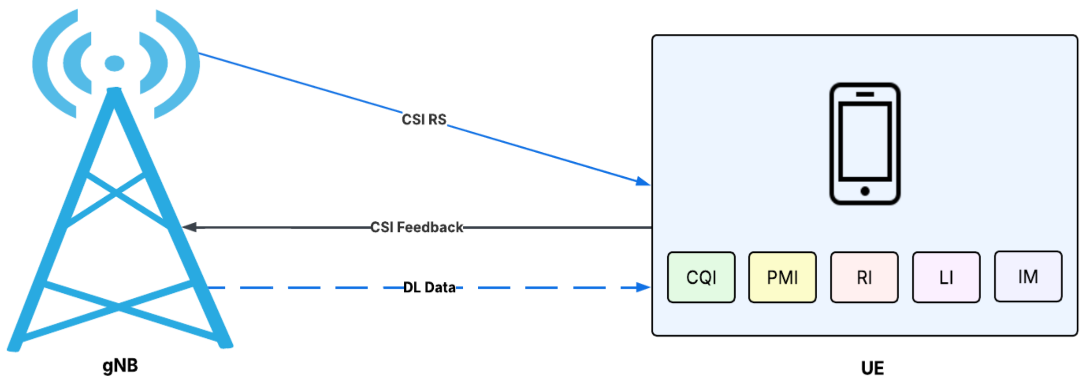

Figure 1: CSI Feedback

The use of artificial intelligence is gaining significant traction for enhancing CSI feedback in 5G-Advanced. In recognition of its potential, 3GPP Release 18 includes a dedicated study item titled "AI/ML for CSI feedback enhancement," which investigates applications such as CSI compression, prediction, and feedback optimization to improve system efficiency.

One prominent technique is DeepCMC, an AI-based autoencoder model that incorporates learnable quantization and entropy coding to significantly compress CSI feedback. DeepCMC achieves comparable reconstruction quality to earlier models like CsiNet while using only ~20% of the feedback bits, reducing overhead by a factor of five and achieving up to 6 dB lower NMSE.

Additionally, reinforcement learning (RL) has been employed to dynamically adjust the feedback periodicity. In one approach, a deep neural network predicts the current channel condition, while an RL agent determines whether new feedback is necessary. If the channel remains stable or predictable, the feedback is skipped; otherwise, it is triggered—reducing unnecessary signaling.

To further minimize the need for frequent full CSI reports, time- and frequency-domain prediction has been explored. Models such as LSTM and, more recently, Transformers have demonstrated the ability to learn and predict temporal correlations in wireless channels, enabling more efficient and proactive CSI feedback mechanisms.

2.1.2.2. Beam Management

Beam management is a vital component of 5G networks, playing a crucial role in enhancing the efficiency, reliability, and performance of wireless communication. By enabling the targeted direction of signals toward specific users, beam management improves spectral efficiency and signal quality, reducing interference and enhancing the signal-to-noise ratio. It supports advanced technologies like massive MIMO, facilitating simultaneous transmissions and improving overall network throughput. Furthermore, effective beam management is essential for handling user mobility, minimizing latency, and ensuring consistent connectivity. As 5G networks cater to diverse applications such as the Internet of Things (IoT) and smart cities, efficient resource allocation and enhanced coverage become increasingly important.

Using AI for beam management in 5G networks offers numerous advantages that enhance performance and efficiency. AI enables predictive capabilities, allowing for proactive adjustments based on historical data and current conditions, while also facilitating dynamic adaptation to user mobility and environmental changes. By minimizing measurement overhead, AI optimizes the selection process, leading to improved resource allocation and faster decision-making. It effectively manages complex scenarios with high user density, supports advanced use cases that require low latency and high reliability, and continuously learns from performance feedback to refine strategies. Ultimately, AI-driven beam management not only improves service quality but also leads to cost savings for network operators by optimizing existing resources and infrastructure.

Below are some of the use cases for how AI can be utilized for beam management:

- Spatial-Domain Downlink Beam Prediction (BM-Case 1): Utilizes AI to predict optimal downlink beams from candidate beams, enhancing signal quality and reducing interference through methods like Support Vector Machines (SVM) for classification and Random Forest (RF) for improved prediction accuracy.
- Temporal Downlink Beam Prediction (BM-Case 2): Applies AI to use historical measurement data for future beam predictions, adapting to channel characteristics with Recurrent Neural Networks (RNN), specifically Long Short-Term Memory (LSTM) networks, and refining predictions with Gradient Boosting Machines (GBM).
- High-Speed Applications: AI-based beam management is crucial for high-speed environments, employing Deep Q-Networks (DQN) to optimize selection policies and Convolutional Neural Networks (CNN) to analyze spatial patterns in beam measurements.
- Intra-Cell Beam Handovers: AI facilitates smoother handovers between beams within the same cell, using Decision Trees (DT) to make handover decisions and K-Nearest Neighbors (KNN) to select target beams based on historical data.
- Interference Coordination: AI optimizes beam selection to reduce interference, leveraging Reinforcement Learning (RL) for adaptive strategy learning and Genetic Algorithms (GA) for evolving beam management configurations.
- Data Collection Optimization: AI enhances the data collection process by determining optimal time window sizes, utilizing Principal Component Analysis (PCA) for dimensionality reduction and Recursive Feature Elimination with Cross-Validation (RFECV) to select the most relevant features.

2.2. Data Link Layer (Layer 2)

2.2.1. WiFi

Artificial Intelligence (AI) is being increasingly applied to optimize WiFi MAC (Medium Access Control) functions, replacing static algorithms with adaptive learning-based solutions. The main applications include contention management, rate control and scheduling for QoS.

2.2.1.1. AI-Driven Backoff and Contention Window (CW) Adaptation

AI-driven backoff and contention window (CW) adaptation has emerged as a robust alternative to the traditional Binary Exponential Backoff (BEB) mechanism in IEEE 802.11 networks. By leveraging machine learning techniques, these approaches enable nodes to dynamically adjust their CW parameters in response to real-time network conditions, rather than relying on fixed heuristics. One method uses online learning strategies that incorporate historical channel observations to optimize CW values, resulting in improved throughput, reduced latency, and enhanced fairness in both infrastructure and ad hoc networks. Another approach applies supervised learning, where classifiers detect and mitigate selfish behavior from nodes using overly aggressive CW_min settings, leading to substantial gains in fairness and performance for compliant devices. Additionally, deep reinforcement learning (DRL) has been applied to fully replace contention-based access, allowing distributed nodes to coordinate channel access through learned, collision-free scheduling. These AI-enhanced MAC techniques demonstrate significant potential to improve efficiency and adaptability in dense or dynamic wireless environments.

2.2.1.2. AI for Link Adaptation (Rate/MCS Selection)

AI-based link adaptation has shown significant promise in optimizing modulation and coding scheme (MCS) selection to maximize throughput and maintain robust connectivity under dynamic wireless conditions. Traditional rate control mechanisms, such as Minstrel HT, rely on periodic probing and threshold-based heuristics, which often react slowly to channel variations. In contrast, AI-driven techniques—particularly deep reinforcement learning (DRL) and contextual bandit frameworks—enable faster, data-driven decision-making. DRL approaches, such as those based on Deep Q-Networks (DQN), learn to select the optimal MCS by observing link quality metrics like SNR, leading to substantial improvements in throughput and responsiveness. Contextual bandit models, including latent Thompson Sampling, frame MCS selection as a multi-armed bandit problem, effectively accelerating convergence by exploiting correlations between rates. Additionally, lightweight neural network models have been proposed for resource-constrained devices, delivering rapid, low-latency decisions while maintaining high-quality performance in real-time applications such as VR and gaming. These adaptive learning-based solutions eliminate the need for manual tuning and can seamlessly adjust to environmental changes, offering a more resilient and efficient approach to rate control in modern WLANs.

2.2.1.3. AI-Based Traffic Scheduling and QoS Enforcement

AI-based traffic scheduling and Quality of Service (QoS) enforcement in WiFi networks leverage intelligent decision-making to manage diverse application demands under variable network conditions. Traditional MAC scheduling mechanisms like EDCA employ static contention window parameters, which are suboptimal for handling mixed traffic profiles such as latency-sensitive VR streams and throughput-intensive downloads. Reinforcement learning (RL) agents have been introduced to dynamically adjust MAC parameters, including EDCA contention windows and token bucket rate limits, in response to real-time QoS metrics like throughput and latency. These AI agents learn cross-layer policies that balance multiple objectives simultaneously, outperforming fixed policies in dynamic environments. Furthermore, deep reinforcement learning has been applied to airtime slicing across virtual network slices, enabling real-time resource allocation tailored to varying QoS requirements such as delay, reliability, and bandwidth. AI-driven schedulers have also been explored for OFDMA resource allocation and mesh network time-slot management, allowing more efficient prioritization of critical traffic flows. These approaches highlight AI's capability to adaptively optimize traffic handling in dense, heterogeneous networks, ensuring application-level performance without manual configuration or static tuning.

2.2.2. 5G

In the 5G MAC layer, AI-driven traffic scheduling and QoS enforcement aim to meet stringent service requirements across diverse network slices and user profiles. Unlike static scheduling policies, AI techniques—particularly deep reinforcement learning (DRL)—enable real-time prioritization and dynamic resource allocation in response to varying latency, reliability, and throughput demands.

2.2.2.1. Dynamic Scheduling and Resource Allocation

Dynamic scheduling and resource allocation in the 5G MAC layer are essential for meeting the diverse and stringent requirements of services like eMBB, URLLC, and mMTC. Traditional schedulers, which rely on static rules or heuristics, struggle to adapt to rapidly changing traffic patterns, user mobility, and variable channel conditions. To overcome these limitations, AI—particularly Deep Reinforcement Learning (DRL)—has been increasingly adopted to enable intelligent, context-aware scheduling decisions. These learning-based models can dynamically allocate time-frequency resources per Transmission Time Interval (TTI) by continuously optimizing long-term objectives such as throughput, latency, fairness, and QoS compliance.

Several AI methods have been explored in this domain. Deep Q-Networks (DQN) are commonly used for discrete scheduling actions, leveraging features like channel state, buffer levels, and service type. Policy-gradient methods such as Proximal Policy Optimization (PPO) and Actor-Critic frameworks are well-suited for continuous or fine-grained resource allocation and provide training stability in complex scenarios. In distributed settings, Multi-Agent Reinforcement Learning (MARL) enables coordination between multiple schedulers or base stations. Hybrid models combining supervised learning for traffic prediction with RL for resource decisions further enhance adaptability. These techniques collectively allow the MAC layer to shift from reactive, rule-based scheduling to a proactive, self-optimizing framework that better supports the dynamic nature of 5G networks.

2.2.2.2. HARQ Optimization and Retransmission Control

Hybrid Automatic Repeat Request (HARQ) mechanisms are critical for ensuring reliable data transmission in 5G networks, particularly under fluctuating channel conditions and tight latency constraints. Conventional HARQ strategies operate using fixed timers, redundancy versions (RVs), and retransmission limits, which often fail to adapt to dynamic traffic profiles or service-level requirements. AI-driven HARQ optimization introduces intelligence into retransmission control by learning when and how to retransmit, select RVs, or adjust HARQ timing to meet varying Quality of Service (QoS) demands. This is especially relevant in Ultra-Reliable Low-Latency Communication (URLLC) scenarios, where inefficient retransmissions can violate delay budgets.

Deep reinforcement learning approaches, such as Deep Q-Networks (DQN) and Actor-Critic models, have been applied to learn optimal HARQ actions based on features like channel state information, ACK/NACK history, and latency targets. These models can dynamically adjust retransmission intervals or preemptively decide on early termination or proactive repetitions to minimize delay and packet loss. Some architectures integrate cross-layer feedback—e.g., PHY-layer reliability metrics—into the HARQ decision loop, allowing more informed and QoS-aware retransmission control. AI-based HARQ frameworks significantly outperform static baselines in both spectral efficiency and reliability, offering a flexible and adaptive solution for next-generation MAC layer retransmission strategies.

2.2.2.3. QoS Management and 5G Network Slicing Enforcement

AI-powered QoS management and network slicing enforcement in the 5G MAC layer are central to delivering differentiated service levels across diverse applications, from low-latency URLLC to high-throughput eMBB. Traditional scheduling and resource allocation methods are inadequate for enforcing strict service-level agreements (SLAs) across slices, particularly in dynamic and congested environments. AI techniques, especially deep reinforcement learning (DRL), enable real-time, policy-aware decision-making that adjusts MAC parameters and resource allocation strategies based on evolving network conditions and slice-specific QoS requirements. By learning optimal policies from traffic patterns, channel states, and SLA feedback, AI agents can enforce latency, throughput, and reliability guarantees without manual tuning.

Advanced DRL models such as Proximal Policy Optimization (PPO) and multi-agent systems are used to manage inter-slice fairness and resource partitioning. These models dynamically allocate spectrum, time slots, or transmission opportunities to each slice, considering factors like slice priority, congestion level, and application demand. AI agents also support cross-layer optimization, aligning MAC-level resource decisions with RAN and transport-layer goals. This intelligent orchestration ensures that high-priority slices consistently meet their performance targets while maximizing overall system efficiency. As network slicing becomes integral to 5G and beyond, AI-based QoS enforcement frameworks will be critical for scalable, autonomous slice management in heterogeneous, service-rich environments.

2.2.2.4. Load Balancing Across gNBs and Network Slices

Load balancing across gNBs and network slices in 5G is critical for maximizing resource utilization, minimizing latency, and ensuring service continuity under high mobility and traffic variability. Conventional load balancing relies on threshold-based handover and static association strategies, which often lead to resource underutilization or congestion in dense deployments. AI-based load balancing introduces adaptive and context-aware decision-making using machine learning models that dynamically steer users or traffic across gNBs and slices. These models consider real-time metrics such as RSRP/RSRQ, buffer occupancy, user mobility patterns, and slice-specific SLAs to distribute load optimally across available radio and core resources.

Deep reinforcement learning (DRL) techniques like Actor-Critic and Proximal Policy Optimization (PPO) have been employed to manage inter-gNB handovers and slice-aware resource allocation jointly. These models learn optimal policies that balance traffic while minimizing handover failures and service disruption. In multi-slice scenarios, AI agents can proactively redistribute traffic among slices based on predicted demand and congestion trends, ensuring SLA compliance for high-priority services while maintaining system-wide efficiency. Overall, AI-enhanced load balancing offers a scalable and autonomous solution for dynamic, multi-dimensional resource orchestration in complex 5G deployments.

2.2.2.5. Latency-Aware Scheduling

Latency-aware scheduling in the 5G MAC layer is crucial for supporting real-time applications such as URLLC, autonomous driving, and AR/VR. Traditional schedulers often prioritize throughput or fairness, neglecting the strict latency constraints these applications demand. AI-based scheduling mechanisms, particularly those employing deep reinforcement learning (DRL), are capable of learning latency-sensitive policies that dynamically allocate resources to meet delay budgets. These models monitor real-time metrics—such as buffer occupancy, transmission delay, and deadline violations—and make scheduling decisions that minimize end-to-end latency while balancing resource efficiency.

Techniques such as Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and hybrid DRL-supervised models have been explored for latency-aware optimization. These agents adapt Transmission Time Interval (TTI) selection, user prioritization, and HARQ timing in response to evolving delay profiles. Some architectures integrate latency prediction models that proactively identify packets at risk of deadline violation and preemptively boost their priority. This proactive, data-driven approach allows for finer control over delay distribution, significantly improving the reliability of latency-critical services. Overall, AI-enhanced latency-aware scheduling provides a scalable and adaptive solution for meeting the ultra-low-latency requirements of next-generation 5G applications.

2.3. Network Layer (Layer 3)

As wireless networks evolve to support increasingly diverse applications—ranging from ultra-reliable low-latency communications (URLLC) and massive IoT to high-throughput media streaming—the role of the network layer has expanded beyond simple packet forwarding. In both 5G and WiFi ecosystems, the network layer must now dynamically manage routing, mobility, traffic flows, resource allocation, and service-level differentiation across a highly variable and dense environment. Traditional rule-based mechanisms and static policies are insufficient to meet the agility, scalability, and performance demands of modern wireless systems.

To address these challenges, Artificial Intelligence (AI) has emerged as a transformative enabler for network-layer intelligence. By leveraging machine learning (ML), deep learning, and reinforcement learning techniques, AI allows networks to observe, learn, and adapt to real-time conditions—optimizing decisions that span routing, load balancing, anomaly detection, QoS enforcement, and virtual network slicing.

2.3.1. AI for Traffic Routing and Path Optimization

AI-driven routing at the network layer enhances path selection in both 5G and WiFi by leveraging real-time traffic metrics and environmental context. In 5G, AI optimizes data plane path selection through SDN-controlled routing, dynamically steering traffic between User Plane Functions (UPFs) or across data centers based on congestion forecasts and SLA adherence. In WiFi mesh networks, particularly in multi-hop environments, reinforcement learning (RL) agents learn to choose next-hop links that minimize delay and maximize reliability using SNR, RSSI, and queue metrics. Advanced approaches like Graph Neural Networks (GNNs) model the network as a dynamic graph, enabling intelligent path reconfiguration in response to topology changes. These AI-based systems outperform static routing protocols by adapting to varying link quality, interference, and user demand.

2.3.2. AI-Based Mobility Management

AI enhances mobility management by predicting user movement and proactively initiating handovers, reducing latency and session drops in both WiFi and 5G. In WiFi, supervised learning models analyze client mobility and RSSI patterns to anticipate when devices should reassociate to a new access point, minimizing disruptions in dense deployments. Similarly, in 5G networks, AI is applied at the control plane (e.g., in the Access and Mobility Function) to optimize gNB reselection, anchor point switching, and route reconfiguration. Recurrent neural networks and LSTM-based models are particularly effective at forecasting user trajectories and dwell times, enabling seamless handovers and improved QoE in mobile scenarios.

2.3.3. Load Balancing Across gNBs, APs, and Network Slices

AI enables real-time load balancing by dynamically redistributing users and traffic across access points, base stations, and network slices based on observed traffic load, congestion, and service requirements. In 5G, deep reinforcement learning and multi-agent models are used to shift user sessions across gNBs or slices to maintain SLA compliance and balance resource utilization. Similarly, in WiFi networks, AI agents steer clients to less congested APs or optimal frequency bands, using bandit models or contextual decision-making frameworks. Federated learning is increasingly employed to coordinate load-aware decisions across distributed nodes without centralizing user data. These adaptive mechanisms ensure system-wide efficiency and fairness in dense or high-demand environments.

2.3.4. AI-Enabled Anomaly Detection and Fault Management

Anomaly detection using AI allows proactive fault identification and performance degradation alerts across both WiFi and 5G networks. Unsupervised models such as autoencoders, one-class SVMs, and isolation forests are deployed to detect deviations in network behavior based on traffic patterns, latency, or control-plane events. In WiFi, these techniques are applied to identify rogue APs, link failures, or client performance drops. In 5G, anomaly detection is used to uncover slice violations, signaling issues, and backhaul bottlenecks. AI-based diagnostic tools also assist with root-cause analysis, enabling faster recovery through automated remediation or alerting systems.

2.4. Transport Layer (Layer 4)

The transport layer is fundamental in ensuring reliable, ordered delivery of data across networks. However, the performance of traditional transport protocols—especially TCP—often degrades in dynamic wireless environments like 5G and WiFi due to factors such as variable latency, interference, and packet loss not related to congestion. These challenges necessitate adaptive transport-layer mechanisms capable of real-time responsiveness to network variability. Artificial Intelligence (AI) is increasingly being integrated into the transport layer to address these limitations, offering learning-based techniques for congestion control, packet loss recovery, flow control, and end-to-end performance prediction. By incorporating AI, both 5G and WiFi systems can significantly improve throughput, reduce latency, and maintain QoS across a wide range of traffic profiles and conditions.

2.4.1. AI-Based Congestion Control

AI techniques are used to predict and adapt to network congestion far more efficiently than traditional TCP variants. In 5G and WiFi, Deep Reinforcement Learning (DRL) and Supervised Learning models observe features like RTT, jitter, and queue length to dynamically adjust sending rates. For example, DRL agents can outperform loss-based and delay-based congestion controllers by learning when to throttle or accelerate transmission, even under rapidly changing wireless conditions. AI-enhanced congestion control is particularly effective in multipath environments (e.g., 5G with bonded connections or WiFi with mesh paths), where traffic must be load-balanced across fluctuating links.

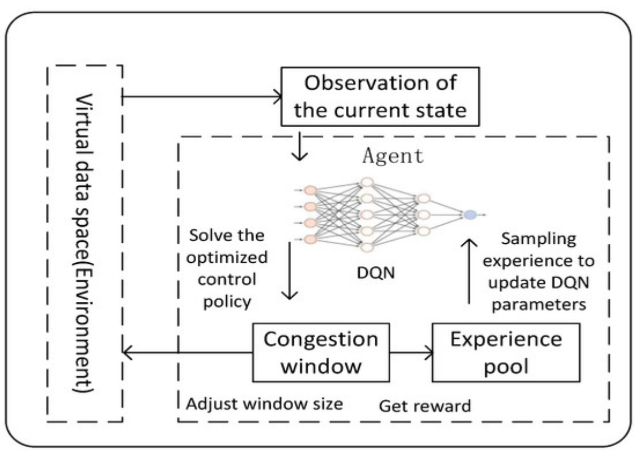

Figure 2: AI based congestion control TCP-DQN framework [Courtesy: https://www.mdpi.com/1999-5903/13/10/261]

2.4.2. AI for Packet Loss Recovery and Flow Control

Packet loss in wireless networks can result from channel fading or interference, not just congestion. AI models help differentiate these loss types and apply appropriate recovery strategies. For instance, Neural Predictors can estimate retransmission probabilities and proactively adjust retransmission intervals. In both 5G and WiFi, AI-driven flow control can tune receive window sizes and pacing rates to match end-to-end path characteristics, avoiding bufferbloat or underutilization. Such mechanisms are highly effective in ultra-low-latency scenarios and when using unreliable transport protocols like QUIC.

2.4.3. AI for Transport Layer QoS and Performance Prediction

AI models are also used to forecast application-level QoS metrics such as throughput, delay, and reliability. Time-series forecasting models (e.g., LSTM, ARIMA) or graph-based learning techniques can predict transport performance under current and future network states. These predictions can then inform adaptive transport-layer configurations—such as congestion window scaling, retransmission thresholds, or prioritization of critical packets—especially in slice-aware 5G systems or latency-sensitive WiFi enterprise deployments. These predictive capabilities allow the transport layer to proactively adjust its behavior, improving end-to-end reliability and QoE.

3. AI Driven Security WiFi and 5G Networks

Security in modern wireless networks—particularly in 5G and WiFi—faces growing complexity due to increased device density, virtualization, and exposure to dynamic threats such as spoofing, denial-of-service (DoS), rogue access, and signaling abuse. Traditional rule-based or signature-driven security approaches could be inadequate for detecting sophisticated or zero-day attacks in real time. AI offers a transformative capability at the intersection of network intelligence and cybersecurity by enabling anomaly detection, intrusion classification, threat prediction, and automated response. Leveraging techniques such as deep learning, unsupervised clustering, and reinforcement learning, AI-driven security frameworks can detect subtle behavioral deviations, adapt to evolving threats, and provide scalable protection across both WiFi and 5G infrastructures. This fusion of AI and cybersecurity enhances network resilience and responsiveness while reducing manual overhead.

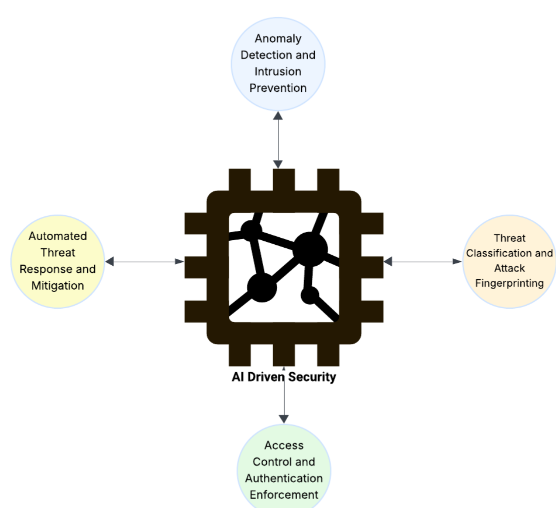

Figure 3: AI Driven Security

3.1. AI for Anomaly Detection and Intrusion Prevention

AI enhances network-layer security by detecting anomalous behavior that may indicate intrusions, malware propagation, or policy violations. In both WiFi and 5G, unsupervised learning methods such as autoencoders, Isolation Forests, and clustering algorithms—are used to model normal traffic behavior and identify outliers without requiring labeled attack data. These models monitor features like packet inter-arrival times, signal anomalies, traffic bursts, and abnormal authentication patterns. In WiFi, this enables early detection of rogue APs, MAC spoofing, or DoS attacks. In 5G, anomaly detection is applied to both RAN and core network traffic to identify signaling floods, slice misuse, or botnet activity.

3.2. AI for Threat Classification and Attack Fingerprinting

Supervised learning algorithms are employed to classify known and evolving threats based on traffic patterns, payload features, and device behavior. Random Forests, SVMs, and CNNs have been applied to accurately identify attack types such as port scanning, ARP spoofing, or protocol-specific exploits. In WiFi, these models are integrated into access controllers or network monitors to flag and label malicious activity in real time. In 5G, AI-driven classification aids in identifying slice-specific threats, DDoS vectors targeting UPFs, and signaling-layer abuse. Additionally, deep packet inspection (DPI) combined with AI enhances detection accuracy in encrypted traffic environments.

3.3. AI-Driven Access Control and Authentication Enforcement

AI enhances access control mechanisms by learning behavioral fingerprints of legitimate users and devices. Recurrent neural networks (RNNs) and statistical models can identify behavioral drift—e.g., sudden changes in location, session patterns, or usage metrics—that may indicate account compromise or credential theft. In WiFi, AI aids in enforcing zero-trust policies and dynamic access control based on device behavior rather than static credentials. In 5G, AI enables context-aware access enforcement, helping detect and prevent SIM cloning, fake base station association, or anomalous slice access. These AI-driven methods can integrate with AAA systems and policy engines to enable fine-grained, adaptive security.

3.4. AI for Automated Threat Response and Mitigation

Reinforcement learning and AI rule engines are increasingly used for automating real-time threat mitigation. AI agents can isolate devices, redirect flows, or reconfigure access policies without human intervention. In 5G, AI-enabled policy controllers interact with network functions to dynamically throttle suspicious traffic or trigger slice-level isolation. In WiFi, mitigation includes automatic client deauthentication, channel switching, or flow diversion to honeypots. These intelligent mitigation systems reduce mean time to detect (MTTD) and mean time to respond (MTTR), improving overall network resilience and minimizing damage from active threats.

4. Enhanced Customer Experience in 5G and WiFi Networks

In modern 5G cellular and WiFi networks, artificial intelligence (AI) plays a pivotal role in optimizing customer experience (CX) at scale. 5G networks are highly complex and data-rich, while WiFi deployments (from home routers to enterprise WLANs) face dynamic RF conditions. By 2025, telecom providers and network vendors have increasingly integrated AI-driven solutions to automate customer support, monitor and predict Quality of Experience (QoE), personalize network services to user behavior, and proactively maintain network health.

4.1. Customer Support Automation

AI-powered customer support automation in 5G and WiFi networks relies heavily on natural language processing (NLP) and transformer-based large language models (LLMs) to handle user inquiries in real time. These models, trained on domain-specific telecom data, power virtual assistants capable of interpreting and resolving complex customer queries via chat or voice channels. Techniques such as Retrieval-Augmented Generation (RAG) improve answer accuracy by integrating external knowledge bases. Sentiment analysis and intent recognition further enhance user interactions by enabling dynamic routing and prioritization. On the backend, AI assists human agents by summarizing interactions, suggesting resolutions, and retrieving internal documentation. Hybrid deployment strategies using cloud platforms ensure scalability and reliability, while models are continuously fine-tuned with human feedback to enhance precision and maintain trustworthiness in support systems.

4.2. QoE Monitoring and Prediction

AI models are integral to measuring and predicting Quality of Experience (QoE) in wireless environments. Supervised learning models, such as random forests and neural networks, are trained on large datasets mapping network KPIs (latency, jitter, signal strength) to user satisfaction metrics like Mean Opinion Score (MOS). Deep learning architectures (e.g., CNNs and LSTMs) capture non-linear dependencies in multimedia QoE, enabling dynamic quality prediction for video, voice, and interactive services. Reinforcement learning agents adaptively adjust network parameters—like channel assignment and resource allocation—to optimize real-time QoE. These AI models are typically deployed in analytics platforms integrated with 5G NWDAF functions or WiFi cloud controllers, facilitating continuous assessment and proactive intervention. Industry platforms like Juniper Mist and Quvia's QoE engine demonstrate real-time traffic steering and RF optimization based on predicted user experience.

4.3. Network Personalization Based on User Behavior

Personalized networking employs AI to dynamically adapt service delivery based on individual user behavior. Clustering algorithms segment users into behavioral profiles, while predictive models forecast demand and optimize network configurations accordingly. In 5G, reinforcement learning and policy learning are used to manage network slices per user intent, while in WiFi, AI controllers can adjust parameters such as SSID access, airtime allocation, or band steering based on a user's location and historical patterns. Recommendation systems analyze usage history to offer personalized plans or optimize edge caching strategies. AI-driven personalization engines are typically embedded within BSS/OSS platforms or real-time controllers, enabling closed-loop decisions that tailor the wireless experience. These solutions reduce churn, increase service uptake, and enable intent-based service provisioning with minimal manual intervention.

4.4. Fault Prediction and Proactive Maintenance

AI enhances network resilience by enabling predictive maintenance and fault prevention in both WiFi and 5G infrastructure. Time-series forecasting using LSTMs and anomaly detection via autoencoders or clustering models allows early identification of degrading components based on telemetry such as signal degradation, power usage, or thermal anomalies. Supervised learning models trained on historical failure data can predict the probability of device or link failures, facilitating just-in-time maintenance. Deep learning-based image or audio analysis adds value in physical inspections via drones or sensors. AI systems are typically deployed in centralized NOCs or edge analytics platforms that integrate with operational workflows, triggering automated tickets or reconfiguration. Industry solutions like Nokia PredictX and

AT&T's AIOps platform exemplify how AI-driven diagnostics reduce downtime, optimize technician dispatch, and shift maintenance from reactive to preventive mode.

5. Beyond the Network

5.1. Intelligent Urban Living

AI-driven smart cities leverage wireless networks—such as 5G, WiFi 6/7, NB-IoT, and LPWAN—to enable real-time data exchange and intelligent decision-making across critical urban systems. AI techniques including deep learning, reinforcement learning, computer vision, and natural language processing are deployed over these wireless infrastructures to manage services like traffic flow optimization, energy distribution, public safety, and infrastructure maintenance. For instance, wireless-connected sensors and edge AI allow traffic lights to adapt dynamically to congestion, while smart grids use predictive models over 5G or LPWAN telemetry to manage renewable energy supply and detect faults. Public safety systems integrate AI-enabled video analytics and sensor data to automate threat detection and accelerate emergency responses. Similarly, predictive maintenance is enabled through AI models analyzing data from wirelessly connected infrastructure sensors and drones.

Beyond operational efficiencies, AI over wireless networks is transforming citizen-facing services and laying the foundation for future urban autonomy. NLP-powered chatbots and mobile apps running over public WiFi or cellular networks support 24/7 civic interaction and automated service request handling. Smart waste management systems use AI to interpret fill-level data from connected bins, optimizing collection routes. Looking ahead, trends such as federated learning and edge computing will support privacy-preserving AI training and ultra-low-latency processing directly on distributed city devices. Autonomous systems—like AI-guided drones and self-driving public transport—will increasingly rely on high-throughput, low-latency wireless connectivity for coordination. Together, these innovations drive cities toward scalable, adaptive ecosystems where AI and wireless infrastructure jointly enable responsive, intelligent urban living.

5.2. Autonomous Driving

AI-driven autonomous driving is a cornerstone of intelligent transportation in smart cities, relying heavily on wireless communication and distributed intelligence. Autonomous vehicles (AVs) utilize a combination of computer vision, LiDAR, radar, and AI-based sensor fusion to perceive their environment. These systems run deep learning models—such as convolutional neural networks (CNNs) for object detection and recurrent neural networks (RNNs) for trajectory prediction—on embedded edge processors. To augment local perception, vehicles are connected via 5G-V2X (Vehicle-to-Everything) links, enabling low-latency communication with other vehicles (V2V), infrastructure (V2I), pedestrians (V2P), and cloud services (V2N). This wireless integration allows AI agents in AVs to share hazard warnings, traffic updates, and route optimizations in real time, improving both safety and coordination across the road network.

6. Conclusion

The convergence of artificial intelligence and wireless technologies like 5G and WiFi marks a pivotal evolution in how networks are built, managed, and experienced. As network demands grow in complexity and scale, AI enables unprecedented levels of automation, adaptability, and insight across all layers—from physical transmission and MAC scheduling to network routing, transport control, and real-time threat mitigation.

By embedding AI into these core functions, networks become more than just conduits for data—they transform into intelligent systems capable of predicting issues, optimizing resources, and enhancing user satisfaction autonomously. The applications of this synergy stretch beyond connectivity, fueling innovations in smart cities, autonomous vehicles, and hyper-personalized digital experiences.

In essence, AI is no longer a support tool but a foundational component of next-generation wireless ecosystems. Its role will continue to expand, redefining not only how networks operate but also how society interacts with the digital world.

Abbreviations

5G	fifth generation mobile network
802.11	ieee standard for wlan
802.11ax	wifi 6
AAA	authentication, authorization, and accounting
AI	artificial intelligence
AIML SC	artificial intelligence / machine learning standing committee
AIOps	ai for it operations
ARIMA	autoregressive integrated moving average
ARP	address resolution protocol
BEB	binary exponential backoff
BER	bit error rate
BSS/OSS	business support systems / operations support systems
CNN	convolutional neural network
CQI	channel quality indicator
CSI	channel state information
CSI-RS	channel state information reference signal
CW	contention window
DDoS	distributed denial of service
DNN	deep neural network
DoS	denial of service
DPI	deep packet inspection
DQN	deep q-network
DRL	deep reinforcement learning
DT	decision tree
eMBB	enhanced mobile broadband
GA	genetic algorithm
gNB	next generation node b
GNN	graph neural network
HARQ	hybrid automatic repeat request
IEEE	institute of electrical and electronics engineers
IM	interference measurement
KNN	k-nearest neighbors
LI	layer indicator
LLM	large language model
LS	least squares
LSDNN	least squares + deep neural network
LSTM	long short-term memory
MAC	medium access control
MAC spoofing	media access control address spoofing
MARL	multi-agent reinforcement learning
MCS	modulation and coding scheme
ML	machine learning
mMTC	massive machine-type communications
NWDAF	network data analytics function
OFDM	orthogonal frequency-division multiplexing

OFDMA	orthogonal frequency-division multiple access
PCA	principal component analysis
PER	packet error rate
PHY	physical layer
PMI	precoding matrix indicator
PPO	proximal policy optimization
QoE	quality of experience
QoS	quality of service
RAG	retrieval-augmented generation
RAN	radio access network
RF	random forest
RFECV	recursive feature elimination with cross-validation
RI	rank indicator
RL	reinforcement learning
RNN	recurrent neural network
RSSI	received signal strength indicator
SDN	software defined networking
SIM	subscriber identity module
SLA	service level agreement
SNR	signal-to-noise ratio
SoC	system on chip
SSID	service set identifier
SVM	support vector machine
TTI	transmission time interval
UE	user equipment
UPF	user plane function
URLLC	ultra-reliable low-latency communications
USRP	universal software radio peripheral
V2I	vehicle-to-infrastructure
V2N	vehicle-to-network
V2P	vehicle-to-pedestrian
V2V	vehicle-to-vehicle
V2X	vehicle-to-everything
WiFi	wireless fidelity

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