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A Review of Using Artificial Intelligence to Improve Signal Reception in 5G and Future Mobile Networks

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Abstract
Wireless communication systems are constantly evolving from 5th generation (5G) networks to beyond-5G (B5G) and 6th generation (6G) networks, presenting unprecedented requirements for highly reliable and efficient reception of signals. Advanced applications like autonomous vehicles, industrial automation, remote healthcare, extended reality and integrated sensing demand ultra-reliable communications with low latency (URLLC), massively connected devices and quality of service. The multipath fading and co-channel interference, dynamic user mobility, blockage and penetration losses of millimeter-wave and terahertz frequencies, and rapidly changing propagation environments, however, severely affect the reception of signals in modern wireless systems. These impairments affect signal to noise ratio (SNR), signal to interference-plus-noise ratio (SINR), bit error rate (BER), throughput, and overall communication reliability. Artificial Intelligence (AI) has become a game-changer that can tackle such challenges with data-driven and adaptive optimization. In this review, the authors comprehensively examine the roles that Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), Federated Learning (FL), and Explainable Artificial Intelligence (XAI) play in improving the reception of signals in 5G and future mobile networks. It is used in key applications such as channel estimation, equalization, beamforming, blockage prediction, interference mitigation, predictive handover, power control, and intelligent resource allocation. The literature provides ample evidence of the significant improvements of AI-based techniques over traditional methods in terms of SINR, BER, throughput and reliability in highly dynamic environments.

Keyword: Artificial Intelligence, 5G, 6G, Signal Reception, Machine Learning, Deep Learning

1. Introduction
1.1 Background
1.1.1 Evolution from 1G to 5G and Future 6G

The evolution of cellular communications started with the 1G cellular systems that were introduced in the early 1980s, such as Advanced Mobile Phone System (AMPS) [1]. In the past, these analog systems were only used for voice communications and were limited in capacity [2], in security and in spectral efficiency [3]. The second generation (2G) of wireless networks, led by Global System for Mobile Communications (GSM), brought in digital modulation and coding techniques which provided superior voice quality, higher network capacity, and short message services (SMS) [4]. Third generation (3G) systems under the 3rd Generation Partnership Project (3GPP) brought WCDMA and packet-switched services to allow access to the Internet and multimedia applications from mobile devices [5]. The fourth generation (4G) Long-Term Evolution (LTE) took a giant leap forward for cellular technology with the introduction of orthogonal frequency division multiplexing (OFDM), all-IP architecture and complex scheduling algorithms which enabled broadband data rates and low-latency communications which were ideal for video streaming and cloud-based services [6]. The 5G generation (3GPP Releases 15-18) is a tremendous paradigm shift in the wireless communications world [7]. To achieve these data rates, 5G will combine technologies such as Massive MIMO [6] and Millimeter Wave (mmWave) communications, beamforming, network slicing and edge computing [8] to enable connection densities of up to one million devices per square kilometer [9] and user experienced data rates of at least 100 Mbit/s. The services are divided into three categories: enhanced Mobile Broadband (eMBB), massive Machine-Type Communications (mMTC) and Ultra-Reliable and Low-Latency Communications (URLLC) [10].

In addition to 5G, 6G networks are expected to be AI-driven and comprehensive communication systems [11]. 6G will utilize: Terahertz Communication [12], Reconfigurable Intelligent Surface (RIS) [13], integrated sensing and communications (ISAC) [14] as well as quantum communication and non-terrestrial networks, such as satellites, unmanned aerial vehicles, and high-altitude platforms [15]. The features of 6G are set to include terabit per second data rate, microsecond-level latency, centimeter-scale localization accuracy and pervasive intelligence [16] which will enable holographic communications, digital twins, and autonomous cyber-physical systems [17] as shown in Fig. 1.

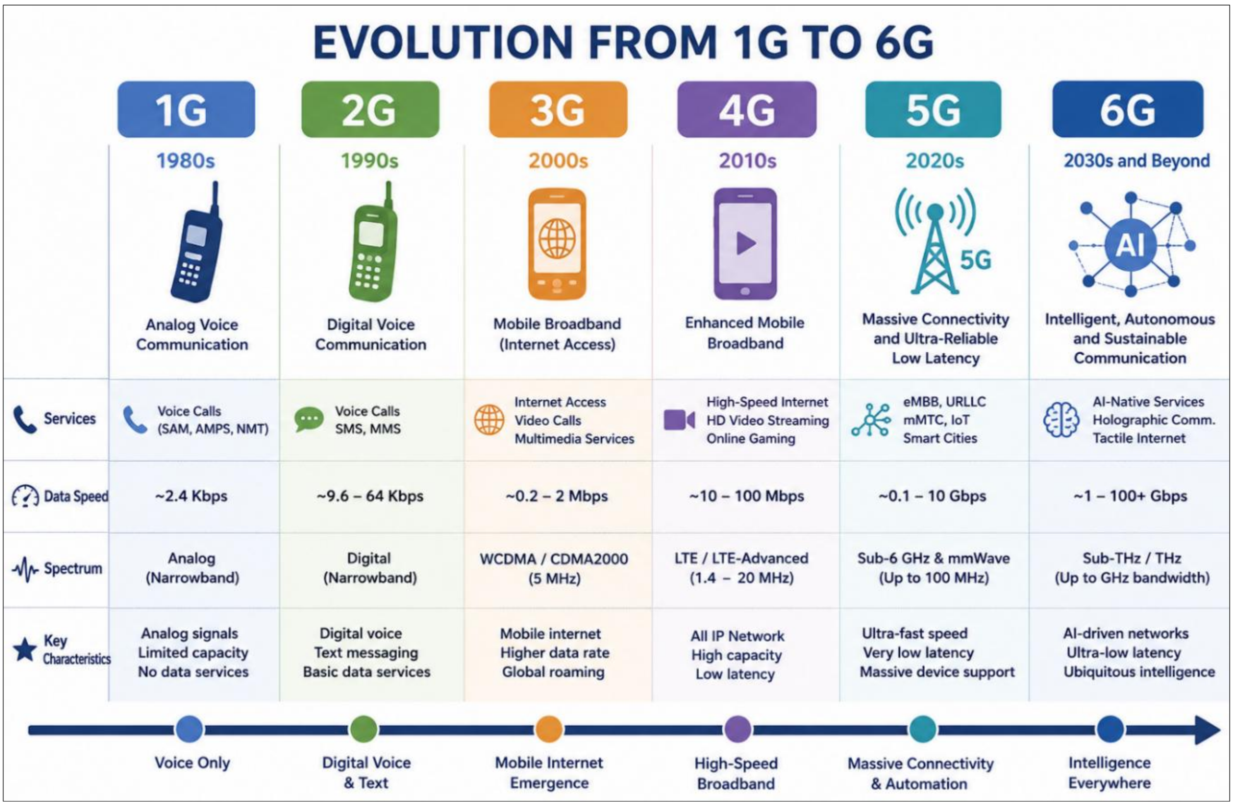

Fig 1: Historical Evolution of Cellular Networks from 1G to 6G, Highlighting Services, Data Rates, Spectrum, and Key Technological Characteristics

1.1.2 Increasing Demand for Ultra-Reliable and Low-Latency Communications (URLLC)

Ultra-Reliable and Low-Latency Communications (URLLC) is one of the biggest innovations proposed by 5G, which is required for applications where failure to communicate or delay could have catastrophic consequences. URLLC aims to provide an end-to-end latency of less than 1ms and a reliability of higher than 99.999%, offering highly reliable connectivity for mission critical services [18].

URLLC is a key enabler for a multitude of industries. In industrial automation, the robotic control systems must be deterministic and exchange data in close time frame. Telesurgery and remote patient monitoring applications in health care require continuous communication with minimal time delay [19]. Real-time V2X communication is essential for autonomous vehicles' navigation and collision avoidance [20]. The need for highly reliable wireless links is also prevalent in smart grids, public safety systems and critical infrastructure monitoring [19, 20].

The need to meet URLLC requirements is challenging because reliability and latency are not necessarily competing requirements. To achieve ultra-low latency, one has to employ short transmission intervals, and to ensure ultra-high reliability, one has to use strong coding and redundancy, and intelligent scheduling [21]. This trade-off has encouraged plenty of research on adaptive signal reception methods, predictive resource allocation and optimization using AI [22, 23].

1.1.3 Importance of High-Quality Signal Reception for Enhanced Network Performance

Signal reception quality is essential in wireless communication and plays a key role in the strength and reliability of the systems. The receiver is required to correctly estimate the channel, manage interference, compensate for distortion and reconstruct the transmitted information despite the impairments of the environment. Low reception results in low SINR, high BER, packet retransmission, high latency, low throughput and high energy consumption [24].

The reception of these signals becomes difficult in the context of 5G and 6G networks, due to the fact that high frequency propagation, narrow beam radiation, massive antenna arrays and dense deployment of devices make it difficult to receive these signals [25]. For mmWave systems, the signal is easily obstructed by walls, vehicles and even people [26]. When operating in Massive MIMO, high-dimensional channel matrices need to be processed in real-time at the receiver [27]. In an IoT application, millions of the devices will be fighting for radio resources, thus generating substantial radio interference and radio congestion [28].

Therefore, good signal quality is crucial in order to keep connections stable, maximize spectral efficiency, lower transmission power and meet strict quality-of-service requirements. It supports key applications like channel estimation, synchronization, beam alignment, interference suppression and handover management [29]. With the development of smart and autonomous wireless systems, more and more sophisticated Artificial Intelligence techniques are used to improve the wireless system reception at complex and dynamic operating conditions and to optimize the wireless system performance [30].

1.2 Contributions of This Review

In this review, a detailed and systematic study is provided on the techniques used in Artificial Intelligence (AI) to improve signal reception in 5G and future 6G wireless networks. This paper makes the following key contributions:

1. A comprehensive and structured classification of the AI techniques, such as Machine Learning, Deep learning, Explainable AI, Federated learning or Reinforcement Learning, specifically for signal reception enhancement.
2. Comparative study of the performance limitations and advantages of traditional signal processing techniques and AI based techniques in terms of accuracy, complexity, adaptability and real-time applicability.
3. A comprehensive study on applications of AI in various communication tasks such as channel estimation, beamforming, interference management, mobility management and resource allocation.
4. Critical research gaps were identified, such as challenges in deploying the model in real time, generalizing it across a wide range of situations, handling the large amount of computation involved, and ensuring data availability.
5. A forward-looking research agenda detailing future research directions for AI native 6G networks, with a focus on autonomous communication systems, edge intelligence and integration with emerging technologies like RIS and THz communication.

2. Fundamentals of Signal Reception in 5G and Future Networks

The signal reception is a fundamental step in the operation of a wireless receiver, in which the receiver receives, processes and reconstructs the information carried by the radio channel. For modern mobile systems this process includes synchronization, channel estimation, equalization, interference suppression, beam alignment, demodulation, and decoding [31]. The quality of the signal received affects the reliability and efficiency of wireless communication systems and is directly related to important measures such as signal-to-interference-plus-noise ratio (SINR), bit error rate (BER), packet error rate (PER), throughput, latency and spectral efficiency [32]. The new signal reception has been made much more complex in 5G and future 6G networks, as they are built using high-frequency bands, large-scale antenna arrays, ultra-dense deployments, and highly dynamic network architectures [33].

5G systems are based on disruptive technologies that satisfy the tight requirements of enhanced Mobile Broadband (eMBB), Ultra-Reliable and Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC) [34]. These technologies include Massive MIMO, Millimeter Wave (mmWave) communications, dense Small Cell deployments, and Network Slicing [34]. These innovations combine to change the nature of radio and significantly affect the way radio is transmitted and received [35]. The knowledge of these architectural aspects plays a crucial role in comprehending the challenges and opportunities of using AI for enhancing signal reception [36].

2.1 Architecture of 5G Networks

The 5G architecture is a service-oriented and highly flexible design that can be used to accommodate a variety of applications that have different performance requirements [37]. 5G has been standardized by the 3rd Generation Partnership Project (3GPP) and will include the New Radio (NR) air interface and a cloud-based core network with software-defined and virtualized functions [38]. The radio access network uses advanced antenna systems, high-frequency spectrum and distributed edge intelligence to maximize capacity and responsiveness [39]. Massive MIMO, mmWave communications, small cells, and network slicing are four fundamental technologies that are pivotal to delivering better signal reception and network performance [40].

2.1.1 Massive MIMO

One of the most important technology advancements of 5G is massive MIMO. It is an extension of multiple-input multiple-output (MIMO) systems with multiple antenna elements at the base station, allowing to support simultaneous communication with multiple users via spatial multiplexing and highly directional beamforming [41, 42]. The spatial dimension, when exploited by Massive MIMO, can lead to a tremendous improvement of spectral efficiency, coverage and energy efficiency and of inter-user interference [41, 43]. In a signal reception point of view, Massive MIMO improves the quality of the received signal by concentrating the energy of the transmission towards the user of interest and mitigating the unwanted signal [42, 43].

2.1.2 Millimeter Wave (mmWave)

Millimeter-wave communication is a technology that makes use of frequencies in the range of approximately 24 GHz to 100 GHz, which has large and unused blocks of spectrum that can support multi-gigabit-per-second data rates [44]. A key application for mmWave bands is for 5G dense urban deployments, fixed wireless access, and high-capacity hotspots [44, 45].

The biggest benefit of mmWave communication is the ability to use a wide channel bandwidth that provides a very large number of channels and vastly improves system capacity. However, mmWave signal reception is always difficult. Propagation loss rises as the frequency increases, buildings and obstacles block signals, signals can be blocked by vehicles, walls, foliage, and even human bodies [46]. Therefore, proper reception requires accurate beamforming, beam tracking and quick adaptation to changing channel conditions [47].

Predict blockage event, optimize beam alignment, and carry out fast channel estimation in mmWave environments [44, 48] is increasingly performed by AI techniques. These are essential features to ensure strong service coverage and reduce service interruptions [47].

2.1.3 Small Cells

Small cells are small base stations that deliver local, low-power coverage and boost network capacity in areas of high population density [49]. These consist of microcells, picocells, femtocells and access points inside buildings. Small cells increase received signal strength, improve SINR and increase spectral reuse [50] by decreasing the distance between transmitters and receivers.

5G networks are particularly dependent on small cells to help compensate for the short range of mmWave propagation [51]. The high-density deployment also poses new challenges in terms of inter-cell interference, mobility management and backhaul coordination [49, 51]. Chunky handovers and fast varying interference patterns make signal reception challenging, especially for handheld devices [52].

AI-driven solutions have demonstrated promising results in areas such as Small-Cell deployment optimization, Small-Cell load balancing, Small-Cell interference coordination, and Small-Cell predictive handover management [51, 53]. These techniques help to ensure a more stable reception or better quality of service in UDsNs [51].

2.1.4 Network Slicing

Network slicing is a virtualization technology which allows the separation of a single physical infrastructure into several logical networks that are customized to meet the needs of the applications that will be hosted on them [54]. For instance, one slice can be designed for high-bandwidth multimedia services, another one for mission-critical URLLC applications and another one for low-power IoT connectivity [55]. The radio resource management, security policies, and quality-of-service parameters can be customized for each network slice. This is because signal reception strategies can be optimized based on the requirements of the service [54].

Slice orchestration, prediction of resource demand, and dynamic adjustment of parameters to achieve target performance levels are key use cases of AI in automating slice orchestration [54, 56]. AI-based network slicing will be fully autonomous in the future 6G networks, adapting the networks to traffic conditions and user requirements in real-time [56].

2.2 Propagation Characteristics and Challenges

Signal propagation is one of the most important signal reception performance factors in today's wireless communications systems. End route from transmitter to receiver, the electromagnetic waves undergo many physical processes, such as attenuation, reflection, diffraction, scattering, absorption, and interference [1]. These effects affect the quality, strength and reliability of the received signal and thus directly influence the important communication performance metrics like Signal-to-Noise Ratio (SNR), Signal-to-Interference-plus-Noise Ratio (SINR), Bit Error Rate (BER), throughput and network reliability [57].

In ideal free space environment, radio waves travel in straight line-of-sight and the signal loss is mainly due to distance and frequency. In such cases, the received power can be accurately calculated with existing theoretical models and free-space propagation can be used as a reference for comparing the performance of wireless systems. But the real world where it is used is significantly more complex and does not always meet the ideal assumptions [58].

In urban wireless environments, buildings, vehicles, trees, and other objects can cause many problems as they affect propagation characteristics [59]. They create various propagation paths whose delays, amplitudes and phases are different, causing multipath fading, shadowing effects, delay spread, and fast signal variations [46]. Such phenomena generate very dynamic radio channels which makes solving the problem of channel estimation, beam alignment, synchronization and reliable signal detection difficult. In this context, 5G and future 6G systems need to be equipped with advanced signal processing and adaptive communication methods to ensure high-quality connectivity in densely populated metropolitan areas [59].

The propagation challenges grow even further in the deployment of Millimeter Wave (mmWave) and future Terahertz (THz) communication systems [60]. High frequency signals suffer from much larger path loss, and have much less diffraction range, than conventional sub-6 GHz signals [61]. This makes communication links particularly susceptible to blocking due to buildings, vehicles, trees, walls and even to human interference [46]. Results of temporary obstructions are sudden and severe signal attenuation, which causes reduced power, poor SINR, significant packets loss and communication interruption [46, 60].

One of the other big problems is the loss of penetration while passing through construction materials like brick, concrete, glass, metal-coated windows, and interior walls [59]. The penetration loss rises significantly with carrier frequency and can significantly restrict the indoor coverage for high frequency wireless systems [6]. For this reason, dense small-cell deployments, intelligent reflecting surfaces (IRS), relay-assisted communications and adaptive beamforming techniques will play a crucial role in future networks to guarantee reliable coverage in the future [60, 61].

In addition to path loss, multipath propagation, blockage and penetration loss, the overall communication space is highly dynamic and may be unpredictable [46, 57]. Such obstacles are even more severe for mobile users, ultra-dense deployments, and mission-critical applications with ultra-reliable and low latency requirements [59]. So, the ability to accurately describe and predict the propagation characteristics has become an integral part of modern wireless system design [46, 58].

In response to such propagation problems, AI has proven to be a promising solution [62]. By analyzing a large-scale measurement dataset, Machine Learning and Deep Learning algorithms can learn complex propagation patterns, predict blockage events, estimate channel conditions, optimize beam selection, and help to adapt the network proactively [57, 62]. AI can help alleviate the challenges posed by wireless signals being easily lost and restricted in certain environments, as well as help to implement effective communication strategies in advance and when required [62].

2.3 Performance Metrics

In wireless communication systems, signal reception can be assessed by a range of quantitative measures that quantify the quality, efficiency and reliability of the signal received [63]. Such performance indices are used as a basis for comparing the effectiveness of the communication and are commonly employed to compare various transmission schemes, signal processing algorithms, antenna configurations and Artificial Intelligence (AI) optimized schemes. Performance metrics are now taking increasing importance in 5G and future 6G networks as the network is required to meet stringent requirements for ultra-reliable low-latency communications, massive connectivity, high data rates and intelligent network operation [64].

One of the most basic indicators is the Signal to Noise Ratio (SNR), defined as the ratio of the power of the received signal to the power of the background noise. A higher SNR usually leads to higher quality detection accuracy, and higher signal quality. But in practical cell environments, the interference from neighboring transmitters frequently becomes the predominant constraint. Therefore, the Signal-to-Interference-plus-Noise Ratio (SINR) is more realistic to consider as a metric for communication performance as it also accounts for the noise and interference effects [65]. Enhanced SNR and SINR improves the quality of signal reception, improves the reliability of communications and improves the use of radio resources directly.

The other important means is the Bit Error Rate (BER), that indicates the likelihood of a bit being received incorrectly [63]. BER is a direct measure of the accuracy of the receiver and the reliability of communication. Improved performance (reception of the signal and decoding success) equates to lower BER values, especially when propagation conditions are difficult (fading, interference, and mobility).

Throughput is the amount of actual user data delivered to the communication channel during a period of time [64]. Throughput is the actual performance of the network which involves network protocol overhead, packet re-transmissions, scheduling, and channel impairments, unlike theoretical channel capacity. Better signal reception tends to lead to higher data rate—due to the ability to use more sophisticated modulation techniques and lower error rates in the transmission [63].

Another important parameter of performance, which measures the utilization of the frequency spectrum is called Spectral Efficiency [65]. When spectrum resources are scarce and valuable as they are in many modern wireless communications systems, spectral efficiency is now a primary design goal (expressed in bits per second per Hz (bit/s/Hz)). Massive MIMO, beamforming, and other technologies like AI-based resource allocation are designed to achieve maximum spectral efficiency while ensuring reasonable reliability and QoS.

Reliability is the probability that information is transmitted accurately to the required time [63, 64]. It is typically measured by the packet success rate, outage probability, and block error rate (BLER) [65]. For mission-critical applications, such as autonomous vehicles, industrial automation, long-distance medical care and smart traffic systems, reliability is of paramount importance, as a failure in the system can have serious consequences. The future wireless networks are anticipated to offer very high reliability as well as low latency and massive connectivity [64].

In addition, SNR, SINR, BER, throughput, spectral efficiency, and reliability enable a complete perspective of the performance of signal reception in modern wireless communication systems. They are also widely used in the evaluation of communication quality, the utilization of the resources, and robust operation in highly dynamic network scenarios in Artificial Intelligence based optimization techniques, where machine learning algorithms are used to optimize these metrics [63, 65]. They are therefore at the heart of the testing of effectiveness of both traditional and AI based methods for improving signal reception in 5G and future 6G networks.

2.4 Limitations of Conventional Signal Reception Techniques

Wireless communication systems have been based on conventional signal reception techniques for several decades. In the previous cellular generations, a variety of methods including Least Squares (LS), Minimum Mean Square Error (MMSE), Linear Minimum Mean Square Error (LMMSE), Kalman Filtering, adaptive equalization and optimization-based beamforming techniques have been successful. But, the transition to 5G and future 6G networks has shown a number of drawbacks to these traditional methods.

Most conventional methods depend on simplified mathematical assumptions such as channel linearity, mathematical assumptions of Gaussian noise distribution, stationarity, and statistical knowledge of the channels. In reality, wireless environments are known to suffer from highly dynamic propagation characteristics, the often-large scale movement of users, nonlinear hardware effects, changing interference patterns, and many periods of blocking. Hence, the estimation accuracy and the performance of the receiver are compromised due to model mismatch [66].

Computational complexity is also a significant challenge. For technologies like Massive MIMO, ultra-dense networks and high-frequency communication systems, processing large channel matrices and complex optimization problems in real time is required. For some of the traditional algorithms, the dimensionality of the system is a challenge for efficient realization. Also, they tend to be sensitive to the correctness of their Channel State Information (CSI) which is often contaminated by the pilot's noise or delayed. Besides, the performance of there is susceptible to the correctness of their Channel State Information (CSI) which is usually contaminated by the noise of the pilot and is often delayed.

Conventional techniques are also reactive, reacting when channel conditions have evolved. They cannot learn from past experiences, forecast channel reactions and proactively adapt to various network conditions. In addition, these methods are frequently applied to just one protocol layer, leaving insufficient opportunities to utilize the information from different layers over the whole network for global network optimization [67].

The restrictions have encouraged the use of Artificial Intelligence (AI) methods in the modern wireless communication system [66, 67]. AI-based solution ensures data-driven learning, adaptive decision-making, predictive optimization, and modeling of very nonlinear relationship, which makes it ideally suited for solving complex challenges of 5G or future 6G signal reception.

3. Overview of Artificial Intelligence Techniques

Artificial Intelligence (AI) refers to a wide range of algorithms and techniques used to make the technology learn from data, identify patterns, make decisions, and adapt to changing conditions in an environment using very little human input [68]. AI has proved to be a game-changer in wireless communications, overcoming the constraints of traditional model-based approaches.AI has become a revolutionary paradigm that can overcome the limitations of traditional model-based methods in wireless communications. AI algorithms can take advantage of the massive amount of network measurement data, channel observations, mobility traces, and traffic information to model highly nonlinear interactions and optimize signal reception in a dynamic and uncertain environment. Some applications are channel estimation, beamforming, interference mitigation, mobility management, resource allocation, anomaly detection and autonomous network orchestration [68, 69].

Advancements in 5G and future 6G networks will rely on extensive applications of AI because wireless environments are becoming more complex. High-dimensional data, such as those created by massive antenna arrays, dense small-cell deployments, millimeter-wave and terahertz frequencies, network slicing and ultra-low-latency applications, are hard to analyze using traditional analytical methods. AI methods offer adaptive and scalable solutions that can adapt on the fly and continually improve results. This section introduces the main artificial intelligence techniques that have shown great promise in improving signal reception and the intelligence of the network.

Artificial Intelligence (AI) is defined by a variety of learning paradigms, algorithms, and optimization techniques, which have become more crucial in today's wireless communication systems [68]. While each approach has its own learning mechanisms, computational needs, and the types of applications it can be used for, they all work towards enhancing signal reception, network efficiency, and intelligent decision-making. Figure 2 shows an exhaustive taxonomy of the most important AI paradigms used in wireless communications along with the corresponding methods, representative algorithms, application domains, and performance goals [69].

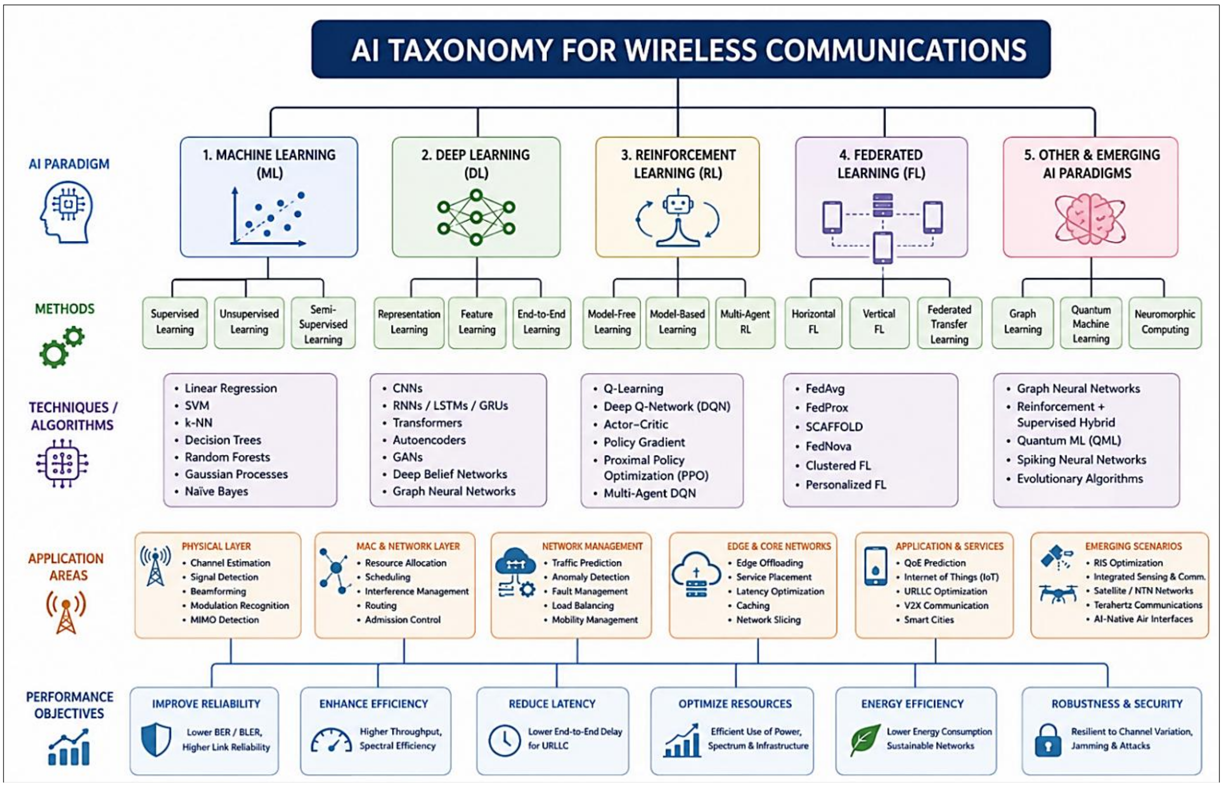

Fig 2: Comprehensive Taxonomy of Artificial Intelligence Paradigms, Algorithms, Application Areas, and Performance Objectives in 5G and Future Wireless Networks

3.1 Machine Learning Approaches

The Machine Learning (ML) field, which is one of the oldest and most widely used areas of Artificial Intelligence (AI), is already a part of wireless communications. Machine Learning (ML) is one of the earliest and most widespread fields of Artificial Intelligence (AI) that is already an integral part of wireless communications. ML algorithms learn patterns from past and current data to help with prediction, classification, clustering and optimization problems without explicit programming [70]. In the current wireless networks, ML has been widely used in channel quality prediction, interference classification, modulation recognition, traffic forecasting, spectrum sensing, anomaly detection and predictive mobility management [14, 70].

Usually, machine learning techniques are divided into three types: supervised, unsupervised and semi-supervised. Supervised learning uses labeled data sets to build relationships between features in the input and output, and is well suited for channel prediction and classification problems [71]. Unsupervised learning can be used to find hidden structures in unlabeled data, and is widely used for clustering of users, anomaly detection, and interference pattern analysis [71, 72]. Semi-supervised learning uses both labeled training and unlabeled test data, to enhance performance when it is costly or impractical to obtain labeled wireless datasets [71].

With the increasing of network measurements, user mobility trace, channel statistics, etc., the applicability of machine learning techniques in wireless communications has drastically increased [14]. In the field of wireless communications, ML algorithms can be used to extract meaningful data from huge amounts of data, thereby making the network more adaptive, intelligent and efficient, and improving the quality of the received signals in conditions of dynamic wireless networks [14, 70].

3.2 Deep Learning Approaches

The concept of Deep Learning (DL) arises from the application of multi-layer neural networks with the ability to learn very complex and nonlinear relationships directly from data [52] and thus surpassing traditional machine learning. Deep learning has emerged as one of the most promising technologies to be leveraged for improving the reception of signals in 5G and future 6G networks, thanks to its outstanding feature extraction abilities.

There are a number of deep learning architectures which have shown outstanding performance on wireless communication applications. Convolutional Neural Networks (CNNs) have been shown to be powerful tools for modeling the spatial structure in channel matrices and radio maps which is suitable for channel estimation, beam prediction, and spectrum sensing applications [52]. The key temporal dependency learning characteristic of RNNs and its variants, such as the well-known Long Short-Term Memory (LSTM) networks, has been successfully exploited in channel prediction, mobility prediction, blockage prediction, and adaptive beam tracking [73]. More recently, Transformer based architectures have gained a lot of attention due to their self-attention mechanism that can be used efficiently to model long-range dependencies and communication datasets of large size [74].

In highly dynamic and complex wireless environments, deep learning techniques have been consistently outperforming the traditional analytical methods [52, 73]. They are also useful for future wireless networks with an AI paradigm due to their capacity to process high dimensional data and capture nonlinear propagation effects [74].

3.3 Reinforcement Learning Approaches

In Reinforcement Learning (RL), an intelligent agent is a problem-solving agent that operates in an environment and adapts its behavior to maximize the rewards it receives over time. In contrast to supervised learning, RL does not need any labeled dataset, and it is well suited for problems of sequential optimization, where actions affect the future state of the system [75].

For wireless communications, reinforcement learning has proven to be a very powerful method for managing resources dynamically and for optimizing wireless networks [76]. Recent works have shown the successful use of algorithms such as Q-Learning, Deep Q-Networks (DQN), and Proximal Policy Optimization (PPO) in the optimization of beamforming, spectrum allocation, power control, interference mitigation, mobility management, and network slicing for wireless networks [75, 77]. These methods allow wireless systems to adjust themselves to dynamic network features and provide the system with suitable operational policies by continually engaging with the surrounding environment [75].

Reinforcement learning's self-learning and adaptive properties are particularly promising for future 6G networks, where communication networks are envisioned to be more autonomous, intelligent, and self-optimizing [77].

3.4 Federated Learning and Explainable AI

In the future, distributed learning paradigm will be an interesting new approach to wireless communication that has gained a lot of attention, called Federated Learning (FL). Unlike conventional centralized machine learning approaches, Federated Learning enables multiple devices to collaboratively train a global model without sharing raw data. Rather, only model parameters or updates are communicated among the devices involved and a central coordinator. This method can greatly improve user privacy, decrease communication overhead and enable compliance with data protection laws. To date, FL has been effectively used in wireless networks for channel prediction [78] and traffic estimation [79] as well as intrusion detection, in edge intelligence and user-centric resource optimization. Federated Learning is anticipated to be a key technology for achieving privacy-preserving AI-driven communication networks in the era of distributed intelligence and edge computing [78].

Alongside, Explainable Artificial Intelligence (XAI) has become a growing focus as AI systems are becoming increasingly embedded in wireless networks, decisions and procedures. While advanced machine learning and deep learning models may yield high prediction accuracy, they are often hard to interpret when it comes to their decisions making. To overcome this, XAI offers transparency and understanding of how the model acts by means of methods like saliency maps, attention visualization, SHAP, and LIME. In wireless communications, explain ability creates trust in AI assisted beamforming, mobility management, interference mitigation and resource allocation decisions. Moreover, XAI can be used for model validation, anomaly detection, regulatory compliance, and operator trust, which makes it a crucial part of the future AI-native wireless networks [80].

The Artificial Intelligence techniques mentioned in this section have varying learning mechanisms, computational needs, application areas and operating capacities. Machine Learning can efficiently solve prediction and classification problems, and Deep Learning can model complex nonlinear wireless environments better. Reinforcement Learning facilitates adaptive decision-making in dynamic network environments, Federated Learning tackles distributed intelligence while prioritizing privacy concerns and Explainable AI strives to foster transparency and trust in autonomous network operations. The characteristics, strengths, and limitations of these AI paradigms are summarized comparatively in Table1, along with typical wireless communication applications.

Table 1: Artificial Intelligence Techniques for Enhancing Signal Reception in 5G and future wireless networks: Comparative Analysis

AI Technique	Learning Type	Typical Applications	Main Advantages	Limitations	Computational Complexity
Machine Learning	Supervised / Unsupervised	Channel quality prediction, traffic forecasting, interference classification	Interpretable, low computational requirements, fast training	Requires feature engineering and labeled data	Low–Moderate
AI Technique	**Learning Type**	**Typical Applications**	**Main Advantages**	**Limitations**	**Computational Complexity**
Deep Learning	Representation Learning	Channel estimation, beam prediction, signal detection, CSI reconstruction	High accuracy, strong nonlinear modeling capability	Large datasets and computational resources required	High
Reinforcement Learning	Sequential Decision Making	Beamforming, power control, spectrum allocation, mobility management	Adaptive and self-learning in dynamic environments	Slow convergence and training instability	High
Federated Learning	Distributed Learning	Edge intelligence, channel prediction, intrusion detection	Preserves privacy and reduces raw data exchange	Communication overhead and non-IID data issues	Moderate–High
Explainable AI	Model Interpretation	Decision validation, network automation, anomaly analysis	Transparency, trustworthiness, regulatory compliance	May reduce model simplicity and increase processing requirements	Moderate

4. AI-Based Channel Estimation and Equalization

Two of the simplest signal processing applications in wireless communication systems are channel estimation and equalization. The purpose of channel estimation is to infer the temporal characteristics of the channel connecting the transmitter and the receiver, and the purpose of equalization is to remove the distortions caused by multipath propagation, Doppler frequency shifts, interference and hardware distortions. These processes allow information to be transmitted reliably and accurately, and are directly related to important performance metrics like Signal-to-Interference-plus-Noise Ratio (SINR), Bit Error Rate (BER), throughput, and reliability [81].

Channel estimation and channel equalization are becoming more and more difficult in 5G and future 6G wireless systems due to Massive MIMO, Millimeter Wave (mmWave), Terahertz (THz) communications, highly directional beamforming and highly varying propagation environments. While these conventional model-based algorithms are still in broad use, the performance can suffer when the channel statistics are not known, when there are significant nonlinearities, or when the dimensionality of the system becomes very large [82]. Artificial Intelligence (AI), with its subfields of Machine Learning (ML) and Deep Learning (DL), has proved to be a potent alternative with the capability of learning complex channel behavior directly from the data and adapting to the changing network conditions [82, 83].

This section summarizes the traditional channel estimation techniques, analyzes channel prediction techniques based on AI, and explores the behavior of deep learning equalizers and compares their results with traditional methods [81].

The overall flow of the receiving process is shown in figure 3, which shows that the signal receiving process includes signal acquisition, signal feature extraction, intelligent reception and processing, decision making and performance feedback mechanisms. This framework will be used as the basis for channel estimation and equalization methods that will be discussed in this section, but which are based on artificial intelligence [83].

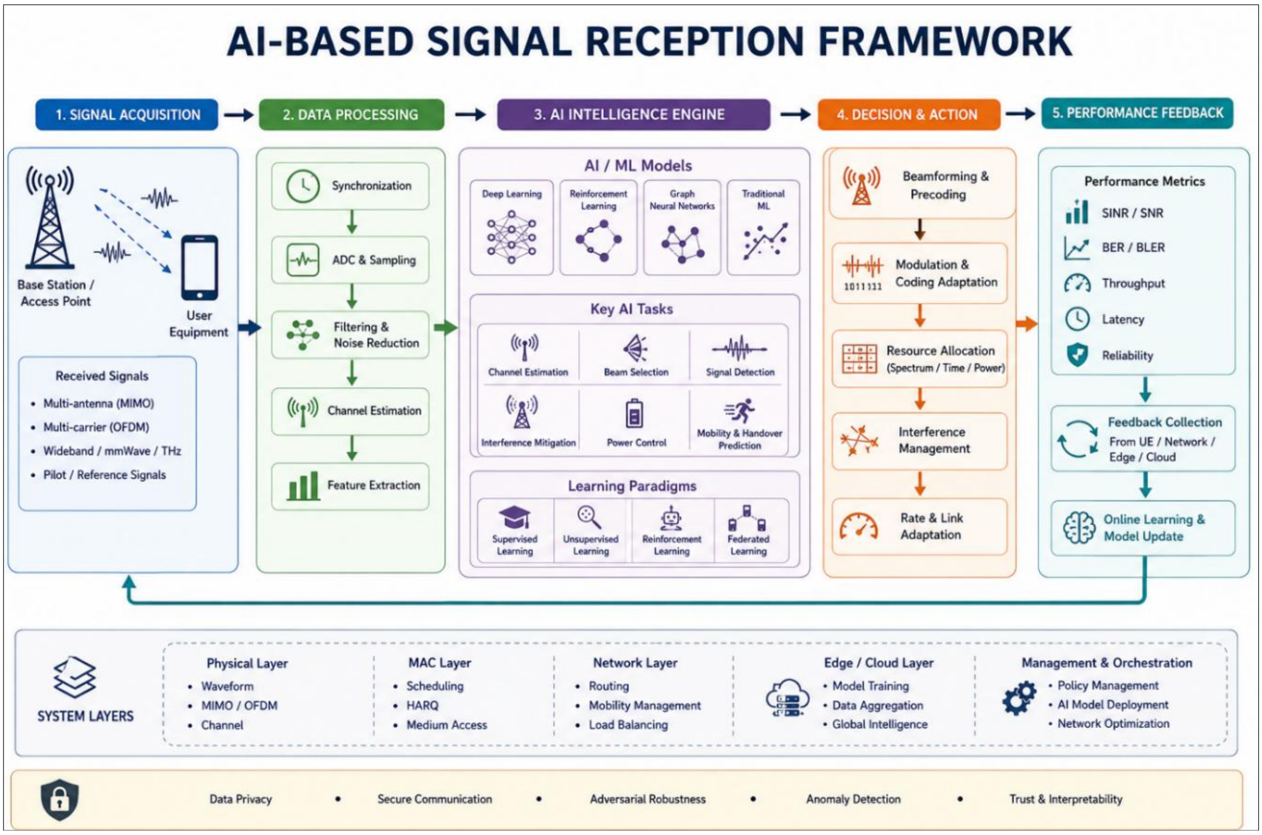

Fig 3: End-to-End AI-Based Signal Reception Framework Including Signal Acquisition, Data Processing, Intelligent Decision-Making, and Performance Feedback.

4.1 Conventional Channel Estimation Methods

Most common channel estimation techniques rely on pilot signals, statistical signal processing and mathematical optimization [84]. Some of the most common methods are Least Squares (LS), Minimum Mean Square Error (MMSE), Linear Minimum Mean Square Error (LMMSE), Kalman Filtering and Sparse Channel Estimation. LS estimation is easy to implement and fast to compute but is very sensitive to noise, especially in low Signal-to-Noise (SNR) situations [84]. The accuracy of the estimate can be improved with MMSE and LMMSE, which use the channel statistics and noise information; however, this requires good prior knowledge and, in general, increasing the computational complexity, especially if matrix operations are needed [84, 85].

Recursive algorithm which takes advantage of previous states and current observations is generally employed for time varying channels, known as Kalman Filtering [84]. This feature allows it to be used in mobility scenarios, but only if an accurate empirical model of the channel evolution is assumed [84, 85]. For Millimeter Wave (mmWave) and Terahertz (THz) systems, the channels typically have sparse angular-domain characteristics, and Sparse Channel Estimation, such as compressed sensing, is especially beneficial in these scenarios. These techniques can decrease the pilot overhead, but they can be limited in certain cases where the sparsity assumption is not met [84].

While the conventional approaches are still relevant because of their theoretical simplicity and practical maturity, there are still several drawbacks to them in the modern 5G and future 6G networks [84, 86]. They may fail when the propagation is nonlinear, Channel State Information (CSI) is not ideal, mobility is high, pilot contamination, hardware impairments and large-scale Massive MIMO configurations are present [84, 86]. These restrictions have spurred the creation of channel estimation methods based on artificial intelligence (AI) that can learn the complex channel behavior directly from data and adjust to dynamic wireless conditions [84, 86].

4.2 AI-Driven Channel Prediction

The AI-driven channel prediction provides a prediction of future channel states or the channel coefficients, without using explicit analytical models solely based on data-driven models. These methods can provide the pilot with less excess effort and greater estimation accuracy in complex scenarios by learning the spatial, temporal and frequency domain correlation between different elements [87].

Machine Learning-Based Prediction

The traditional machine learning algorithms like Support Vector Regression (SVR), Random Forests and Gradient Boosting can predict the channel quality indicators like SNR, SINR and the Channel State Information (CSI). Both methods work well when the data is moderately dimensional and there are labeled datasets [88].

Deep Learning-Based Prediction

The high-dimensional channel data is well suited for deep neural networks [87, 88].

- Channel matrices are captured with spatial correlations by using a Convolutional Neural Network (CNN) [88].
- Long Short-Term Memory (LSTM) is a temporal dependency learning mechanism that is capable of capturing changing channels [87, 88].
- Transformer Neural Network uses self-attention to learn complex CSI relationships [87].

Applications

Based on AI channel prediction methodologies, the following are some channels that have been successfully used:

- The massive MIMO CSI reconstruction is addressed in [87, 88]
- mmWave beam prediction [87]
- High-speed vehicular channels [88]
- Blockage forecasting [87]
- Pilot reduction [87]

These methods can yield better performance than LMMSE and Kalman filtering in nonlinear and non-stationary environments [88].

4.3 Deep Learning-Based Equalizers

Inter-symbol interference, multipath distortion, nonlinear channel response and hardware defects can be corrected by learning complex nonlinear mappings between received and transmitted signals using deep learning-based equalizers. This has been approached using several different neural architectures, such as fully connected neural networks for approximating inverse channel functions, convolutional neural networks (CNNs) for taking advantage of local signal correlations, and recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) for modeling temporal channel dependencies [89]. The more advanced approaches, such as neural receivers or an autoencoder-based communication system, are capable of optimizing transmission and reception processes in a unified learning framework [90]. The proposed AI-based equalization methods have shown excellent performance in terms of Bit Error Rate (BER), robustness, and adaptability in complex wireless channels, making them promising approaches for emerging 5G and 6G communication systems [89, 90].

In recent wireless communication systems, deep learning has proven to be one of the most promising solutions to channel estimation. Deep learning models can be used to estimate the channel characteristics of channels with complex spatial and temporal characteristics directly from pilot signals received using multi-layer neural network architectures, which lead to more accurate estimation of the channel under challenging propagation conditions. Figure 4 shows a typical framework for deep learning channel estimation, which includes the data structure, deep learning networks, training method, optimization method, and evaluation method used for deep learning-based wireless communication systems [91].

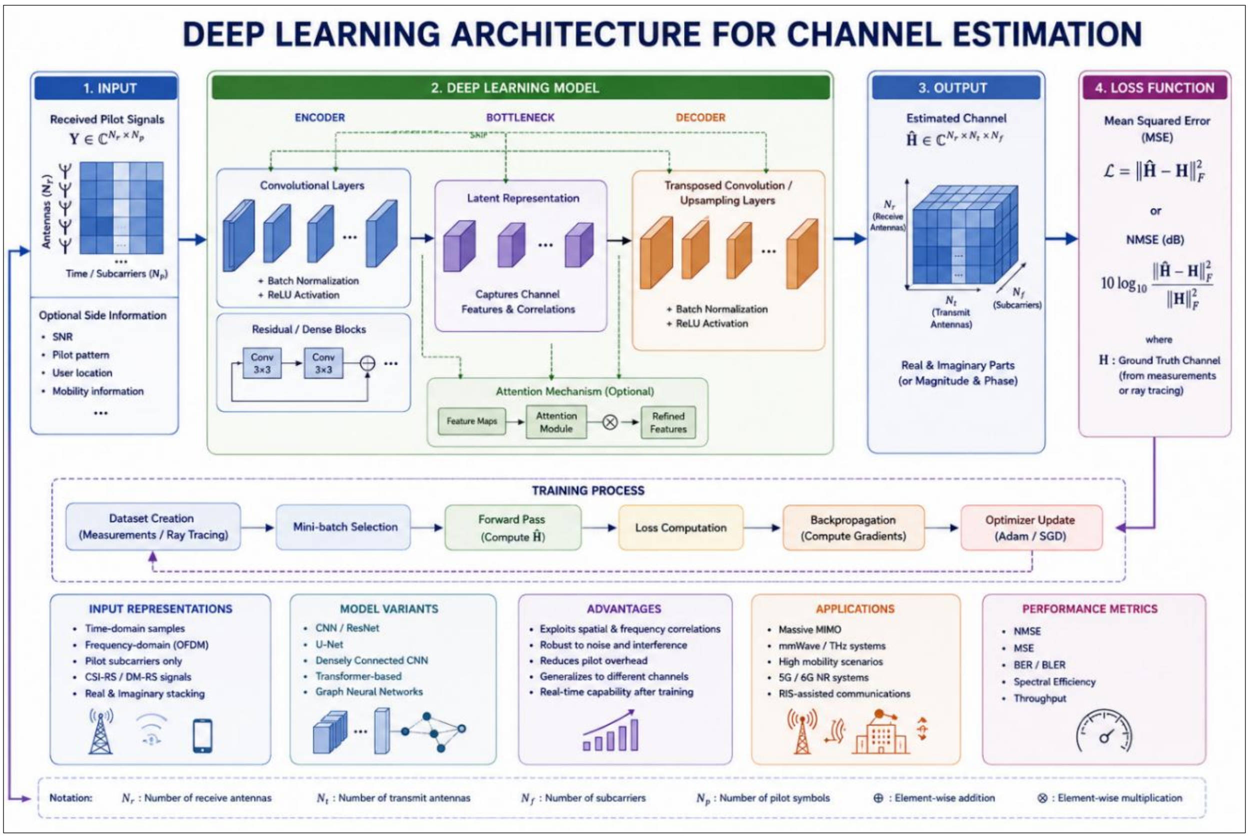

Fig 4: Encoder–Decoder Deep Neural Network Architecture with Attention Mechanism for AI-Based Channel Estimation

4.4 Comparative Performance Analysis

The use of channel estimation and equalization based on Artificial Intelligence (AI) has been shown to outperform traditional methods in complex and dynamic wireless environments in recent studies. Although these traditional methods are mathematically well grounded, predictable, and relatively simple to implement, they are still popular [92]. But in large-scale, nonlinear and time-varying communication systems, especially those, where accurate channel modeling is challenging, they show degraded performance in many cases [92, 93].

Machine Learning and Deep Learning methods, on the other hand, can learn complex channel characteristics directly from data based on the data and do not make strong analytical assumptions [92]. These have been found to work best in terms of accurate channel estimation, Bit Error Rate (BER) reduction, interference immunity and adaptability to rapidly varying propagation conditions [93, 94]. Moreover, Reinforcement Learning-based techniques offer intelligent decision-making capabilities for dynamic optimization problems like beam selection, power allocation, and interference mitigation [94].

The key features and performance of typical conventional and AI channel estimation and equalization methods studied in recent 5G and future 6G communication systems are summarized in Table 2.

Table 2: This section presents the comparative performance analysis of the conventional channel estimation techniques with the AI based techniques. In this section, Comparative Performance Analysis of Conventional and AI Based Channel Estimation techniques are presented

Method	Estimation Accuracy	BER Performance	Computational Complexity	Adaptability	Main Advantages	Main Limitations
LS	Moderate	Moderate	Low	Low	Simple implementation, low complexity	Sensitive to noise and channel variations
MMSE	High	Good	High	Moderate	Improved estimation accuracy	Requires channel statistics and matrix inversion
LMMSE	High	Good	Moderate–High	Moderate	Good balance between accuracy and complexity	Depends on accurate statistical information
Kalman Filter	High	Good	Moderate	High	Effective for time-varying channels	Performance depends on channel model accuracy
CNN-Based Estimation	Very High	Very Low BER	Moderate–High	High	Captures spatial channel features effectively	Requires large training datasets
LSTM-Based Estimation	Very High	Very Low BER	High	Very High	Excellent temporal channel prediction	High training complexity
Transformer-Based Estimation	Excellent	Very Low BER	High	Very High	Captures long-range dependencies and complex channel relationships	Large computational requirements
Reinforcement Learning-Based Methods	High	Low BER	Moderate–High	Excellent	Adaptive optimization and autonomous learning	Training convergence may be slow

Table 2 demonstrates that overall, the performance in terms of estimation accuracy, bit error rate (BER) and adaptability is generally better for AI-based approaches compared with conventional approaches, especially in noisy and rapidly varying wireless environments. However, the benefits of these improvements often come at the expense of high computational complexity, high training requirements, and high overheads for implementing the algorithms. Therefore, the hybrid strategy involving model-based signal processing and AI-based learning mechanisms is gaining traction as the most promising solution for future 6G communication systems and practical 5G applications. To form a visual picture of these comparative differences, the relative performance of the conventional, machine learning, deep learning and reinforcement learning methods of signal reception enhancement are shown in Figure 5.

5. AI-Assisted Beamforming and Massive MIMO Optimization

One of the most significant and viable technologies in modern wireless communications is the beamforming technology that allows the transmitter and receiver to focus their electromagnetic energy in selected spatial directions instead of broadcasting them in every direction. Beamforming can adjust the amplitude and phase of the signals received by several antenna elements, which can help amplify the desired signal, diminish interference, and greatly improve the signal-to-interference-plus-noise ratio (SINR), spectral efficiency, and energy efficiency. For 5th generation (5G) and future 6th generation (6G) networks, beamforming is tightly coupled with Massive MIMO, which is based on a base station with tens or hundreds of antennas simultaneously supporting multiple users through the highly directed beam of transmission [95].

Given the increased propagation loss with carrier frequency, beamforming is crucial for the use of Millimeter Wave (mmWave) and terahertz. These losses are offset by highly directional beams by focusing the radiated energy into narrow angular sectors. The problem, however, is that it is the optimal beam that must be identified, maintained while moving, and controlled for performance, without adding too much complexity to the hardware [95, 96]. Spatial and temporal patterns obtained by learning from channel measurements, user locations and historical network data have proven to be very effective in solving these problems with the help of Artificial Intelligence (AI) [96, 97].

This section introduces the basic concepts of beamforming, and explores intelligent beam selection and adaptive beam tracking, as well as hybrid analog-digital beamforming architectures which are becoming increasingly optimized with artificial intelligence [95, 97].

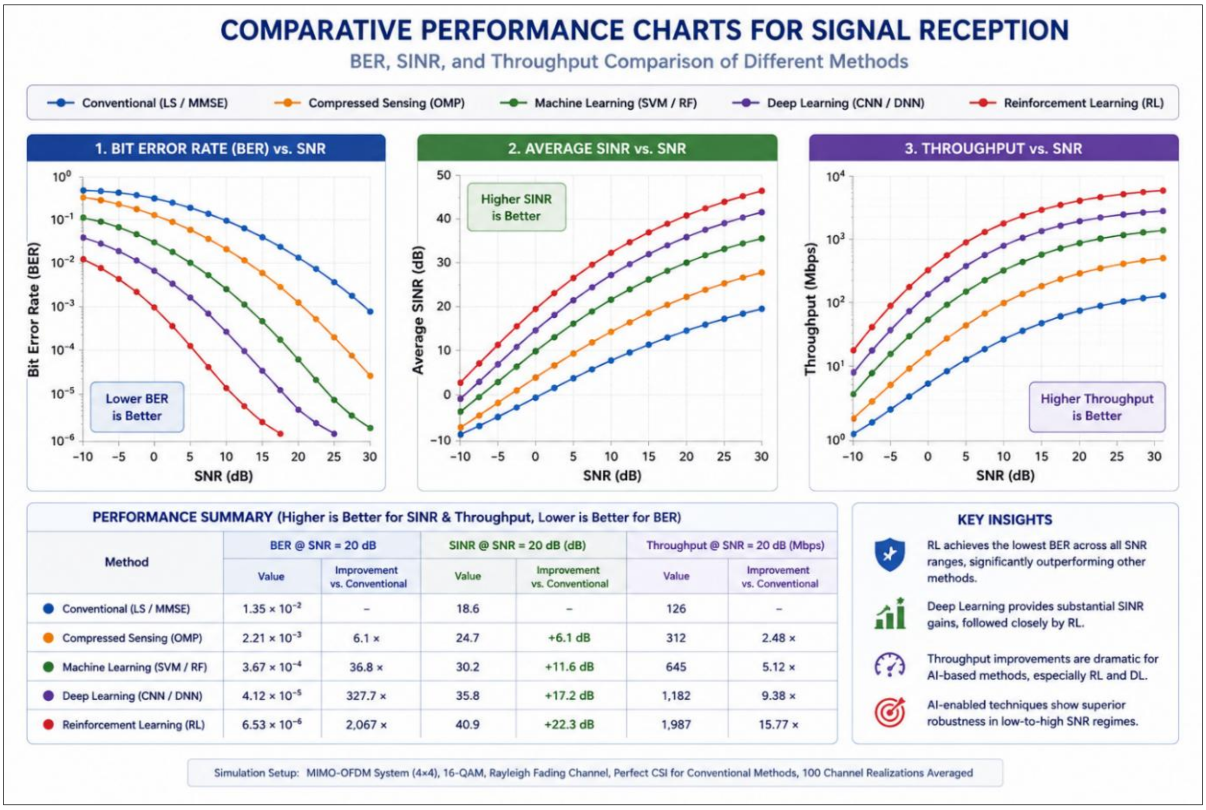

Fig 5: Performance Comparison of Conventional, Machine Learning, Deep Learning, and Reinforcement Learning Techniques for Signal Reception Enhancement

Table 3 shows the most important features of the different beamforming architectures that are widely used in wireless communication systems. AI-assisted beamforming offers benefits of adaptive and predictive beamforming, which enhance the selection, tracking, and overall quality of the received beam, whereas conventional analog and digital beamforming approaches offer valuable performance benefits. The operational part of intelligent beamforming optimization is shown in Figure 6.

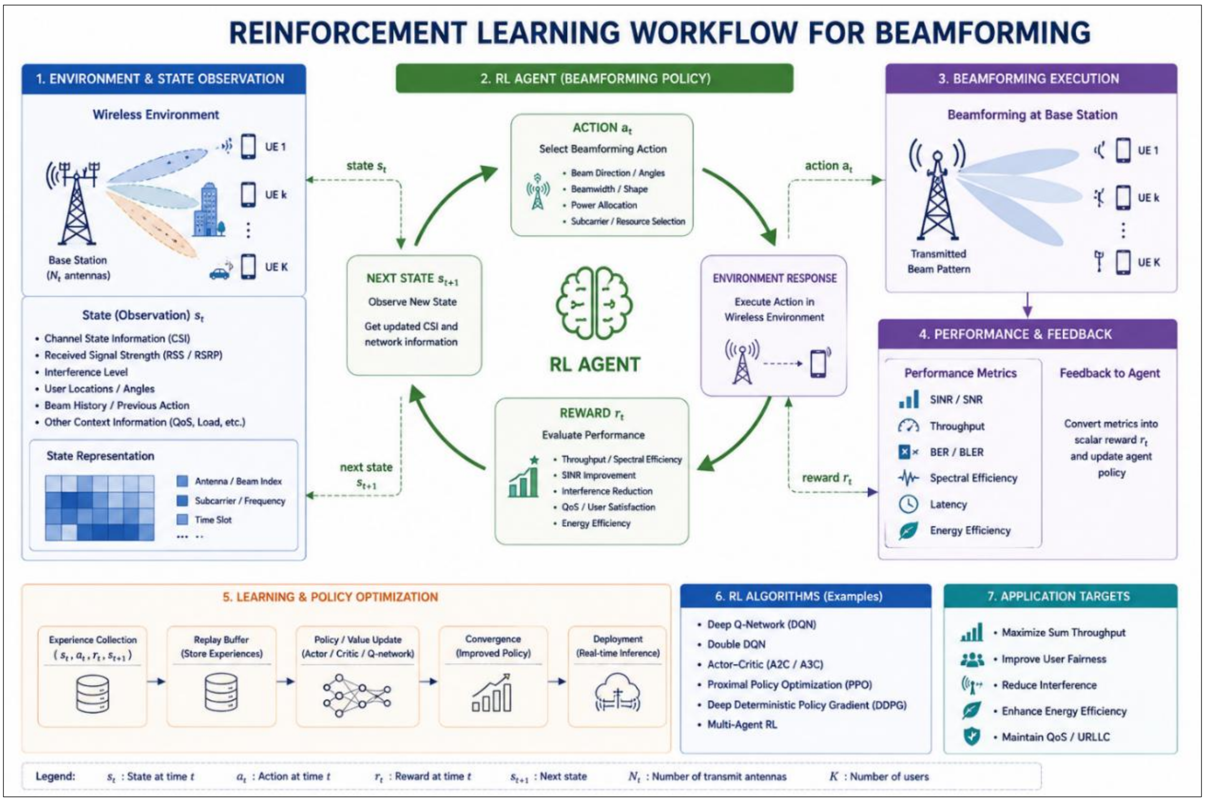

Fig 6: Reinforcement Learning-Based Beamforming Framework Including State Observation, Action Selection, Reward Evaluation, and Policy Optimization.

Table 3: Comparison of Beamforming Architectures in 5G and Future Wireless Networks

Architecture	Hardware Complexity	Energy Efficiency	Flexibility	Typical Application
Analog Beamforming	Low	High	Limited	mmWave Access Networks
Digital Beamforming	High	Moderate	Very High	Massive MIMO Systems
Hybrid Beamforming	Moderate	High	High	Practical 5G and 6G Deployments
AI-Assisted Beamforming	Moderate–High	High	Very High	Intelligent Adaptive Networks

5.1 Beamforming Fundamentals

Beamforming is a signal processing method that focuses electromagnetic energy on desired users using the amplitude and phase control of the signals emitted by multiple antenna elements [98]. Beamforming is a crucial technique in 5G and future 6G networks for mitigating propagation loss in Millimeter Wave (mmWave) and Terahertz (TeraHZ) communications, as well as to enhance Signal-to-Noise Ratio (SNR), Signal-to-Interference-plus-Noise Ratio (SINR), coverage and spectral efficiency [76]. Beamforming can be achieved with a digital, analog or hybrid architecture [98]. The most flexible is the digital beamforming but needs a radio-frequency chain for each antenna element [99]. Analog beamforming has less hardware complexity and power consumption, and less flexibility [98]. A hybrid beamforming approach has been adopted and it is the preferred solution for actual Massive MIMO deployments, as the combination of both approaches has more benefits [99]. All these beamforming methods together improve the quality of the received signal and make wireless communication more reliable and high quality with a higher capacity [76].

6. AI for Interference Management

One of the most important factors that affect the performance of wireless communication systems is interference. In cellular networks, several transmitters may transmit at the same time using the same frequency resources, resulting in unwanted signal components to interfere with the reception of the desired users. This results in a decrease in Signal to Interference plus Noise Ratio (SINR), increase in Bit Error Rate (BER), and decrease in throughput and reliability [66]. IOT applications require an efficient use of radio resources, while in 5G and future 6G networks the volume of deployed small cells, Massive MIMO, D2D communications, Massive MIMO, non-terrestrial networks and the coexistence of heterogeneous services with very different QoS requirements have created a greater complexity of interference management [66, 100].

Previous wireless system designs have achieved significant improvements using traditional interference mitigation methods like static power control and fractional frequency reuse (FFR) and optimization-based scheduling. Such strategies, however, typically assume simple models and a fixed control policy that is not sufficiently adaptive to highly dynamic environments [101]. AI, such as Machine Learning (ML) and Reinforcement Learning (RL), provides a data-driven and predictive approach to interference identification, predicting network congestion and allowing self-regulation of transmission parameters in real-time [66, 100, 101]. AI techniques can optimize radio resources more effectively than traditional techniques, while preserving good signal quality in the face of rapidly changing conditions, using historical measurements and contextual information [100].

In this section, the main sources of interference in dense networks are analyzed, the concept of machine learning based interference classification is discussed, reinforcement learning strategies for avoiding the interference in such networks are reviewed and finally the concept of Coordinated Multi-Point (CoMP) optimization is reviewed and discussed for the future intelligent wireless network [101, 102].

6.1 Interference Sources and Challenges

In today's wireless communications, one of the major impairments of the received signal is interference. The use of ultra-dense 5G and future 6G networks has led to a dramatic surge in the number of devices that are able to transmit simultaneously, and hence to very dynamic interference scenarios [103]. Neighboring cells using the same frequency resources, leakage from adjacent channels, overlapping transmissions in dense small-cell deployments, device-to-device communication, Internet of Things (IoT) networks and future integrated terrestrial–non-terrestrial communication systems [104] are all potential sources of interference. These interference sources are all responsible for reducing Signal-to-Interference-plus-Noise Ratio (SINR), increasing Bit Error Rate (BER), decreasing throughput, and decreasing the reliability of communication [103, 104]. As the wireless environment is becoming increasingly complex, intelligent and adaptive interference management techniques that can adapt to the changing environment of the networks are required [100].

A number of Artificial Intelligence (AI) techniques have been suggested to overcome interference related problems of the modern wireless system [100]. These methods vary in their learning mechanisms, operational goals and implementation needs. Table 4 shows a comparative summary of the most commonly used techniques for interference management using AI.

Table 4: Techniques to manage interference in wireless networks using AI. Interference Management techniques in Wireless networks using AI

AI Technique	Primary Objective	Typical Application	Advantages	Limitations
Machine Learning	Interference Classification	Network Monitoring and Detection	Fast classification and prediction	Requires labeled datasets
Deep Learning	Interference Pattern Recognition	Dense Cellular Networks	High accuracy in complex environments	Computationally intensive
Reinforcement Learning	Dynamic Interference Mitigation	Spectrum Sharing and Power Control	Adaptive and self-learning	Convergence may require training time
Federated Learning	Distributed Interference Prediction	Edge Networks	Privacy-preserving learning	Communication overhead

As indicated in Table 4, there are significant improvements in interference awareness, adaptive resource allocation and transmission optimization provided by AI based approaches. Among these techniques, reinforcement learning has been shown to have great potential because it can learn optimal interference mitigation policies automatically and continually interact with the wireless environment.

7. AI-Driven Handover and Mobility Management

Mobility management is an important service function in cellular communication systems that maintains connectivity when users traverse different coverage areas of base stations, sectors or radio access technologies [105]. The handover process is the core of mobility management as it involves the movement of an ongoing communications session from one serving cell to another due to radio conditions, traffic load, or service requirements. To ensure high quality signal reception, minimize service interruptions, and maintain strict quality of service requirements in fifth-generation (5G) and future sixth-generation (6G) networks [105, 106], effective handover decisions are crucial.

Today's wireless systems are becoming more complex, making handover management much more complex. 5G networks will use ultra-dense small cells, Massive MIMO, Millimeter Wave (mmWave) communication and highly directional beamforming [107]. These technologies offer an unprecedented level of capacity and low latency, but also decrease cell size and cause signal issues when blocked and when mobile. [105] The channel conditions could also vary in a split of few milliseconds in high-speed environments like highways, railways, and unmanned aerial vehicle corridors, leading to higher risk of radio link failures, frequent handovers, and service degradation [108, 109].

Threshold-based rules are generally used for traditional handover algorithms, for example based on Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), and hysteresis margins [105]. In relatively stable environments, these are good methods, but they are essentially reactive in nature and can't predict sudden variations in the signal quality or user location [107]. Artificial Intelligence (AI) solutions, such as Machine Learning (ML), Deep Learning (DL) and Reinforcement Learning (RL), provide a predictive and adaptive solution which can learn mobility patterns, predict channel evolution and optimize the handover timing and target selection in real-time [51, 109].

This section covers the main handover challenges in high-speed mobility, overview of predictive handover algorithms, advanced wireless network user trajectory forecasting methods, and how AI can minimize ping-pong effect and call drop in advanced wireless networks.

7.1 Handover Challenges in High-Speed Mobility

With dense small-cell deployments, highly directional beamforming and the use of Millimeter Wave (mmWave) and Terahertz (THz) communication technologies, mobility management in 5G and future 6G networks has become more complex [108],[109]. Radio conditions can fluctuate significantly as users traverse the network, due to fading, interference, blockage events, Doppler effects, and radio propagation geometry variations [105]. These interactions can lead to cell transitions, misalignment of beams, uncertainty about the handover decision and overhead in signaling [107]. In addition to that, mission critical applications with Ultra-Reliable and Low-Latency Communications (URLLC) requirements have high requirements in terms of latency and reliability for handover [109]. This makes it difficult to maintain seamless connectivity in highly dynamic scenarios with conventional threshold-based handover mechanisms, prompting the need for AI-based predictive mobility management solutions [51, 106].

The efficiency of handover and mobility management in next-generation wireless networks has been studied using different Artificial Intelligence techniques [51]. They vary in terms of their learning styles, predictive power and deployment needs. The most popular AI-driven mobility management methods are summarized in Table 5.

Table 5: AI Based Techniques for handover and mobility management

AI Technique	Application	Main Benefits	Limitations
Machine Learning	Handover Prediction	Improved decision accuracy	Requires historical data
Deep Learning	Mobility and Trajectory Prediction	Captures complex movement patterns	High computational requirements
Reinforcement Learning	Autonomous Handover Optimization	Adaptive decision-making	Training convergence challenges
Federated Learning	Distributed Mobility Prediction	Privacy-preserving operation	Communication overhead

As depicted in Table 5, the mobility management techniques based on AI offer significant gains in terms of handover prediction accuracy, connectivity continuity, and service reliability. These techniques can help minimize unnecessary handovers, minimize call dropouts and enhance the overall user experience in highly dynamic wireless networks by learning the mobility patterns of users and predicting network conditions.

8. AI for Resource Allocation and Power Control

Optimization functions in wireless communication systems are among the most important functions as they govern the distribution of limited radio resources including spectrum, transmission power, time slots and spatial beams among users and services. The quality of the signal as received, the capacity of the system, the energy efficiency, fairness and quality of service are directly affected by the management of the resources [110]. These tasks have grown more complex in fifth-generation (5G) and future sixth-generation (6G) networks, as networks are ultra-dense, service needs are diverse, Massive MIMO, Millimeter Wave (mmWave) communications, network slicing, and billions of connected devices have all become part of the deployment picture [110, 111].

Existing methods that are motivated from traditional optimization approaches including water filling, convex programming, heuristic scheduling, and fixed power-control rules have been able to offer successful approach under simplified assumptions. But these techniques are not always suitable for the complex and dynamic nature of contemporary wireless scenarios [112] that are high-dimensional, nonlinear, and uncertain. Artificial Intelligence (AI), specifically Machine Learning (ML), Deep Learning (DL) and Reinforcement Learning (RL), provide an alternative that is data-driven, adaptive and predictive [110, 111]. Through a method of learning the complex relationships between channel conditions, user behavior, traffic demands, and interference patterns, the resource allocation and transmission power can be optimized in real-time [112].

The role of AI in improving the reception of signals and the overall network performance is highlighted, and a review of its use in spectrum allocation, dynamic power control, scheduling and load balancing, and multi-objective optimization is presented.

8.1 AI-Driven Resource Allocation and Power Control

Optimizing resource allocation and power control are crucial for maximizing network capacity and enhancing the quality of signal reception, while ensuring reliable communication in 5G and future 6G networks [111]. The modern wireless systems need to allocate the spectrum resources, transmission power, time slots and beamforming configurations dynamically and at the same time having to consider interference, mobility, energy efficiency and quality-of-service requirements [112]. Traditional optimization techniques bequeathed from wired networks are increasingly hard to apply in wireless networks because of the growing complexity of the wireless environment [110].

Under the highly dynamic network condition, the techniques of Artificial Intelligence can offer a data-driven solution for optimizing resource utilization [11]. Machine Learning algorithms can predict traffic demand and the variation of channel quality, and Deep Learning model can be used to find complex relationships between network parameters and user behavior [112]. Reinforcement Learning is a way to make autonomous decision-making with continuous adaptation of resource allocation/power control strategies based on the varying environmental conditions and network goals [110, 111].

The use of AI to manage resources has shown great potential to increase spectral efficiency, throughput, energy efficiency, and communication reliability [112]. These techniques can also be used to implement intelligent scheduling, load balancing, interference mitigation and network slicing features, which are essential for future AI-native wireless communication systems [111].

The optimization of resource allocation and transmission power in the next generation wireless networks has been widely studied using Artificial Intelligence techniques [110, 112]. These strategies vary in terms of optimization, computation, and goals. Finally, a comparative summary of the most frequently used resource management techniques based on artificial intelligence is shown in Table 6.

Table 6: AI Applications in Resource Allocation and Power Control

AI Technique	Application Area	Main Objective	Benefits	Limitations
Machine Learning	Traffic Prediction	Resource Planning	Fast prediction and low complexity	Requires historical data
AI Technique	Application Area	Main Objective	Benefits	Limitations
Deep Learning	Resource Allocation	Performance Optimization	High accuracy in complex environments	Computationally intensive
Reinforcement Learning	Power Control	Dynamic Decision-Making	Adaptive and self-learning	Training complexity
Federated Learning	Distributed Optimization	Privacy Preservation	Decentralized learning	Communication overhead

9. AI in Millimeter-Wave and Terahertz Communications

One of the key technological trends for the upcoming fifth generation (5G) and sixth generation (6G) wireless systems is the shift from lower frequency bands to higher ones. Conventional cellular networks have been operating below 6 GHz, but new and future architectures are increasingly taking advantage of the very large chunks of spectrum defined by Millimeter Wave (mmWave) and Terahertz Communication (THz) bands [113]. These bands offer the highest bandwidth resources ever available that can support multi-gigabit and even terabit-per-second data rates, ultra-low latency and high-resolution sensing [114]. It is, therefore, obvious that they can be seen as essential enablers for new applications like holographic tele-presence, immersive XR applications, digital twins, autonomous transportation, and integrated sensing and communications [113, 114].

Although the potential of mmWave/THz is great, it is also challenging to receive signals at these frequencies. The number of propagation losses is much greater with the increase in frequency, diffraction is limited, atmospheric absorption is significant, and buildings, vehicles, vegetation and human bodies cause strong blockage of signals [115]. In addition, the dynamics of the channels are significantly affected by the beam alignment, impairment of the hardware and molecular absorption effects [113]. The characteristics of these environments produce extremely nonlinear and dynamic spaces which are challenging to model using traditional analytical means [115].

Artificial Intelligence (AI) has proven to be a promising solution to these challenges [114]. With the study of large amounts of channel measurements, beam patterns, user trajectories, and environmental context, AI algorithms can predict the blockages, optimize programmable propagation surfaces, build accurate THz channel models, and control extremely large antenna arrays [115]. These are some of the capabilities that will be central to making the HF communication paradigm a viable reality that is both viable and scalable [114].

This section will cover the major applications of AI in mmWave and THz systems, such as blockage prediction, intelligent reflecting surfaces, THz channel modeling, and ultra-massive MIMO optimization.

9.1 Blockage Prediction and Intelligent Propagation Control

One of the most important issues regarding Millimeter Wave (mmWave) and Terahertz (THz) communication systems is the blockage problem [115]. These high-frequency signals are very sensitive to obstacles like buildings, vehicles, vegetation and humans, because they are very directional and have low diffraction. Severe attenuation and communication interruptions can be caused even by temporary obstructions [115]. Artificial Intelligence techniques have proven to be very promising in forecasting blockage events, based on previous channel measurements, user mobility patterns, beam information and environment data [114, 115]. Furthermore, AI-driven Reconfigurable Intelligent Surfaces (RIS) could dynamically control the propagation of electromagnetic waves to create alternative communication channels, to optimize coverage and to enhance the reliability of the reception of the signals [113]. In sum, blockage prediction and intelligent propagation control are important components of robustness and resilience in the future high-frequency wireless network environment [113, 115].

Overcoming the propagation and optimization issues in Millimeter Wave and Terahertz communication systems is crucial and involves the use of Artificial Intelligence [114]. Several methods for blockage prediction, beam management, intelligent surface optimization, and channel modeling have been recommended by various AI-based techniques [113, 115]. Table 7 provides an overview of the key applications of AI in the field of high-frequency wireless communications.

Table 7: The use of AI in Millimeter-Wave and Terahertz Communication Systems. Applications of Artificial Intelligence in Millimeter-Wave and Terahertz Communication Systems

Application Area	AI Technique	Objective	Benefits
Blockage Prediction	Deep Learning, LSTM	Predict signal blockage	Improved link reliability
Beam Management	Reinforcement Learning	Optimize beam selection and tracking	Reduced beam misalignment
RIS Optimization	Machine Learning, RL	Intelligent propagation control	Enhanced coverage and SINR
THz Channel Modeling	Deep Learning	Accurate channel characterization	Improved estimation accuracy
Ultra-Massive MIMO	Deep Learning, RL	Antenna and beam optimization	Higher spectral efficiency

10. Comparative Review of Published Studies

Comparative studies of published work are crucial for the identification of the different ways in which artificial intelligence techniques have been applied to enhance the signal reception, channel estimation, beam management, interference mitigation, and resource allocation in 5G and future wireless networks [116]. Preliminary work reveals that deep learning has been applied extensively for physical-layer applications like channel estimation and beam prediction [117], and reinforcement learning is favored in resource allocation and power-control challenges [118]. Recently, federated learning has attracted a significant amount of interest due to its ability to train distributed models without centralized access to raw user data, thus crucial for privacy-sensitive 5G/6G systems [119].

There have been many studies focused on the use of Artificial Intelligence techniques to enhance the wireless communication and signal reception performance [116, 117]. The methodologies used for AI, the communication situation, the datasets used, the evaluation metrics, and the reported results vary considerably across these studies [120]. Table 8 is presented to present a summary of the representative published works and the main objectives, methods (AI techniques) used, main findings and identified limitations.

10.1 Critical Comparative Analysis of AI Techniques

From an in-depth comparative study of the available research papers, it is found that there is no one Artificial Intelligence technique which can be superior over all wireless communication scenarios. Rather, the efficiency of each method varies significantly with the type of system model, channel conditions, computation limitations and application requirements [66, 68].

In high dimensional and highly nonlinear environments, such as channel estimation and beam prediction tasks, the Deep Learning approaches consistently outperform other approaches [52, 73, 91]. For instance, CNN-based and LSTM-based models have been proven to be very accurate in capturing spatial and temporal channel correlations [87, 88]. But these improvements sometimes come with the cost of complexity of the computation, large training datasets and higher latency of inference, which could impede their use in real-time and resource-constrained settings [82, 116, 127].

In contrast, traditional Machine Learning methods have a lower computational requirement, which makes them applicable to light-weight applications like interference classification and traffic prediction [70, 71]. However, they are very limited in their ability to model complex nonlinear relationships and their dependence on handcrafted features limits their performance in advanced 5G and 6G scenarios [66, 72].

The methodology of Reinforcement Learning techniques has a unique advantage in dynamic and sequential decision-making problems such as power control, resource allocation and mobility management [75, 77]. They can learn optimal policies for network operation by interacting with the environment, allowing them to operate the network adaptively and autonomously [94, 100]. There are still many problems with implementation in practice, with slow convergence, training instability, and reward design sensitivity being among them [75, 101, 118].

To enable a collaborative model training process without sharing raw data, Federated Learning offers a promising paradigm for distributed intelligence [78, 79]. This enables achieving a better level of privacy and reduces the communication overhead, especially in edge-based 6G system scenarios [48, 119]. The aforementioned benefits come with significant non-independent and identically distributed (non-IID) data, communication efficiency, and model synchronization challenges that need to be overcome [78], [128, 129].

Another complementary line of research is Explanatory Artificial Intelligence, ensuring transparency and interpretability of the decisions made in the context of beamforming, handover and resource allocation for AI assistance [56, 80]. While XAI might lower model complexity or raise computational demands, it has been recognized as crucial for operator trust and regulatory compliance, as well as for fault diagnosis in autonomous 6G networks [80].

In conclusion, the comparative analysis suggests that a hybrid system combining the most recent developments in model-based signal processing with AI-enabled learning is the most promising future development to ensure high-performance and practical solutions in wireless communication systems [67, 86, 92]. In Massive MIMO, mmWave, and THz deployments, the combination of both methods can take advantage of the benefits of AI but retain the certainty and simplicity of traditional techniques [35, 97].

Table 8: This table presents a comparative summary of representative published studies on signal reception enhancement using AI

Reference	AI Technique	Communication Scenario	Target Problem	Evaluation Metrics	Key Contributions	Main Limitations
O'Shea and Hoydis (2017) [121]	Deep Learning	Physical-Layer Wireless Communications	End-to-End Communication Learning	BER, BLER, Detection Accuracy	Demonstrated the feasibility of learning transmitter and receiver functions using neural networks	Primarily simulation-based with limited practical validation
Wang *et al*. (2017) [122]	Deep Learning	OFDM Systems	Channel Estimation and Signal Detection	BER, Estimation Error	Improved signal detection under nonlinear and imperfect channel conditions	Requires large training datasets and robust generalization
Alkhateeb (2019) [123]	Deep Learning	mmWave and Massive MIMO	Beam Prediction and Channel Learning	Beam Prediction Accuracy,	Introduced the DeepMIMO dataset for reproducible AI-	Ray-tracing environments may not

				Achievable Rate	based wireless research	fully capture real deployments
Ma *et al.* (2023) [124]	Deep Learning	mmWave Communications	Beam Management and Beam Prediction	Beam Accuracy, Training Overhead	Reduced beam-search complexity and enhanced beam-management efficiency	Sensitive to environmental changes and domain mismatch
Khan *et al.* (2023) [125]	ML/DL Survey	mmWave and THz Networks	Beam Management and Tracking	Alignment Accuracy, Latency, Outage Probability	Identified AI as a promising solution for highly dynamic channels	Challenges remain in mobility support and real-time deployment
Tefera *et al.* (2023) [126]	Deep Q-Learning	Multi-Cell Networks	Power Control and Interference Management	Sum Rate, Power Efficiency	Improved power allocation decisions in complex interference environments	Scalability and training stability issues
Reference	AI Technique	Communication Scenario	Target Problem	Evaluation Metrics	Key Contributions	Main Limitations
Lv *et al.* (2023) [127]	Deep Learning Review	Wireless Physical Layer	Channel Estimation	NMSE, BER, Estimation Accuracy	Comprehensive review of DL-based channel estimation techniques	Open issues remain in complexity, robustness, and interpretability
Bartsiokas *et al.* (2024) [128]	Federated Learning	Beyond-5G Networks	Relay Selection and Resource Allocation	Resource Allocation Efficiency, Power Consumption	Enabled privacy-preserving distributed optimization	Communication overhead and non-IID data challenges

10.2 Analytical Discussion

The studies summarized in Table 8 highlight how Artificial Intelligence is making an impact in wireless communication systems in several application areas. Because of its capability of modelling complex nonlinear channel behavior and extracting meaningful features from raw communication data, Deep Learning has become the overwhelming solution to overcome challenges such as channel estimation, channel detection, or beam management [116, 117]. A few studies have indicated high accuracy of estimation, beam prediction and communication reliability in comparison to the traditional signal processing methods [117].

Dynamic network optimization problems such as power control, interference management, and resource allocation have proven to be very promising for Reinforcement Learning [76, 118]. Unlike the supervised learning methods, reinforcement learning allows communication systems to adjust themselves with time by interacting continuously with the environment, while network conditions evolve. Federated Learning has been a rising star of privacy-preserving distributed intelligence in Beyond-5G and future 6G networks, too [119, 129].

Regardless of these advances, the reviewed studies indicate that there are common limitations. However, simulated environments and benchmark datasets are still largely relied on in most AI-based solutions, which limits the ability of the models to generalize to real-world deployment scenarios and raises concerns about potential failures in such situations [76, 120]. Other challenges are computational complexity, communication overhead, lack of interpretability, and robustness to dynamic channel changes [116, 119]. The results suggest that future studies not only need to increase the accuracy of predictions, but also to create systems that are both practical and easy to scale, as well as trustworthy, for use in future wireless communication systems, which will be the subject of study [120, 129].

10.3 Performance Trade-Offs and Practical Considerations

An interesting finding of the reviewed literature is that there are basic trade-offs between accuracy of the performance, the computational complexity, and the applicability to real time. Deep learning techniques offer significant gains in Bit Error Rate (BER), Signal-to-Interference-plus-Noise Ratio (SINR) and throughput, but their practical application in real-world systems can be limited by factors such as latency, hardware constraints and energy efficiency. In Ultra-Reliable Low-Latency Communication (URLLC) applications, such as those in eHealth, where even a few microseconds of delay can cause performance issues, this is especially crucial.

Moreover, many of the AI solutions are based on simulated channels, and the characteristics of these channels and hardware impairments may not reflect the actual characteristics of real-world channels. Also, the environmental variability may be different than in the real world. Consequently, there is an increasing demand for real-world measurement-based validation and model generalization is still a major challenge.

Another challenge is the integration of AI models into the current communication system architecture. Support for legacy protocols, scalability in ultra-dense networks, and resistance to adversarial conditions must be considered. In this context, lightweight AI models, model compression techniques, and edge computing frameworks are becoming key enablers for actual deployment.

The above factors show that future studies need not only to consider improving the algorithmic performance, but also the system level issues in terms of deployment scale and robustness in practical wireless environments.

10.4 Summary of Comparative Insights

To summaries, the comparative analysis of the published works shows that the Artificial Intelligence has made significant developments in the field of signal reception and wireless communication optimization. The utility of AI methodologies, however, is dependent on context, and there are factors specific to a system that must be considered when implementing AI in practice, including availability of data, computational resources, and constraints. Efficient, scalable and interpretable AI frameworks, capable of functioning consistently in varying and changing environments, will likely play a key role in the transition to 6G AI-native networks. Therefore, it is crucial for future research to investigate the combination of several AI paradigms, validation in the real world and the co-design of communication systems and intelligent algorithms.

11. Public Datasets and Simulation Platforms

Artificial Intelligence (AI) is making a huge impact on wireless communications, and there is a great demand for high-quality public datasets and reproducible simulation platforms. Analytical models used in conventional signal processing methods are more effective while machine learning and deep learning algorithms need a vast and representative dataset to learn the statistical relationship between propagation conditions, channel state information (CSI), beam indices, user location and network performance indicators [123]. This role is strongly emphasized for public datasets and standard simulation environments, which facilitate objective performance comparisons, reproducibility and unbiased comparison of different algorithms [12].

In fifth generation or future 6th generation systems, datasets play a crucial role, as the radio environment in this context is extremely complex and variability, including Massive MIMO, Millimeter Wave (mmWave) propagation, user mobility, blockage and beamforming, are all critical. Several publicly available datasets and frameworks have been developed to meet this need, including DeepMIMO and NYU WIRELESS [123] to date, which are the most popular and influential. The resources contain detailed channel information and realistic propagation scenarios for developing AI algorithms for channel estimation, beam prediction, blockage detection and resource optimization [12].

11.1 Datasets: DeepMIMO

DeepMIMO is one of the most popular benchmark datasets utilized in the field of AI-based wireless communication research. It has been developed by Alkhateeb, which is a configurable framework for realistic ray-tracing-based datasets containing the channel coefficients, propagation parameters, beamforming information and user location data [123]. The dataset has been widely used for beam prediction, channel estimation, blockage prediction, localization, intelligent reflecting surface optimization, reinforcement learning-based beam management, etc. [130]. It has several major advantages: it is reproducible; it is flexible; it is suitable for Massive MIMO and mmWave scenarios; and it is widely used in the research community. But it is mostly a simulated ray-tracing based channel environment and thus, may not be fully representative of real-world channel characteristics and hardware impairments [12]. However, DeepMIMO is still one of the most significant benchmark platforms for the research and testing of AI-based wireless communication system solutions [123].

11.2 Simulation Tools

AI-driven signal reception methods for 5G and future 6G systems depend critically on sophisticated simulation platforms and software frameworks, which are frequently expensive and hard to replicate, before they can be developed and evaluated. MATLAB and Python are among the most popular ones, offering full development environments for signal processing, machine learning, deep learning, channel modeling, beamforming and performance analysis [12]. MATLAB has dedicated communication and 5G toolboxes equipped with advanced visualization capabilities, and Python has an open-source, flexible environment that is backed by libraries like NumPy, Scikit-learn, TensorFlow, and PyTorch [20]. In combination, these platforms provide the basis for modern wireless communication research with AI, which allows for efficient algorithm development, simulation, training, and performance evaluation [12, 131].

For the purpose of supporting wireless communications research in the field of Artificial Intelligence, a number of public datasets, simulation environments and software frameworks have been created [123, 130]. These resources can be used to create realistic communication scenarios, train and validate AI models, and test system performance in various network conditions [20]. Table 3 presents a comparison of the most commonly used datasets and simulations tools used in wireless communication research with AI.

Table 9: A collection of public datasets and simulation tools for research in AI-powered wireless communication. A repository of publicly available datasets and simulation tools for wireless communication research with AI

Dataset / Tool	Category	Primary Application	Key Advantage	Main Limitation
DeepMIMO	Dataset Framework	mmWave and Massive MIMO Research	Reproducible and configurable	Simulation-based environment
NYU WIRELESS	Measurement Dataset	mmWave Channel Modeling	Real-world measurements	Limited deployment scenarios
MATLAB	Simulation Platform	Signal Processing and 5G System Modeling	Comprehensive engineering toolboxes	Commercial licensing cost
Python	Programming Platform	AI Development and Data Analysis	Open-source and highly flexible	Requires multiple package integrations
NS-3	Network Simulator	Protocol and Network-Level Evaluation	Realistic network modeling	Relatively steep learning curve
TensorFlow	Deep Learning Framework	Neural Network Training and Deployment	Scalable and production-oriented	Higher implementation complexity
PyTorch	Deep Learning Framework	AI Research and Prototyping	Flexible and user-friendly	Additional optimization for deployment

Table 9 shows the most frequently used datasets, simulation environments, and software frameworks for wireless communication research using AI. These platforms offer researchers reproducible testbeds for designing, training and testing intelligent communication algorithms in various 5G and future 6G scenarios.

12. Conclusion

In this review, the authors provide a thorough and systematic analysis of the impact of Artificial Intelligence (AI) on the enhancement of signal reception of 5G and upcoming 6G wireless communication systems. The study has classified and highlighted the various AI paradigms such as Machine Learning, Deep Learning, Federated Learning, Reinforcement Learning, and Explainable Artificial Intelligence, showing the impact of data-driven methods on the evolution of the traditional signal processing framework into intelligent, adaptive, and predictive communication systems.

The results show that the capability of the AI techniques to outperform traditional model-based approaches in complex and dynamic wireless environments is consistently demonstrated across various scenarios, including channel estimation, beamforming, interference mitigation, mobility management, and resource allocation. These improvements are witnessed as an improvement in Signal-to-Interference-plus-Noise Ratio (SINR), Bit Error Rate (BER), Throughput and system reliability. The benefits of these performance improvements can come at a cost of higher data dependency, complexity, and implementation challenges.

This review revealed that the AI-powered models will not supplant conventional methods of communication, but rather will complement them to create hybrid intelligent communication systems. These strategies merge the strength and understandability of analytical techniques and the flexibility and learning potential of AI, allowing for efficient operations across varying and uncertain network situations.

AI algorithms will be crucial in the integration of the communication stack as wireless networks become AI-driven 6G networks. This paradigm shift will allow autonomous network operation and real time network optimization and context-aware decision making, thus facilitating the development of the next generation of communication systems that will be ultra-reliable, low latency and massively scalable. Thus, Artificial Intelligence is not just an enhancement tool, but a real enabler of next-generation wireless communication.

13. Research Gaps and Open Challenges

Even though the signal reception technology for 5G and future 6G networks is advancing rapidly with the help of artificial intelligence, there are still a few challenges that cannot be solved:

- Generalization and Real-World Deployment: AI models are often trained on simulated data sets and might not generalize well to real-world conditions with unknown propagation conditions.
- High computational requirements and latencies are significant issues for deep learning and reinforcement learning models, which may not be easily implementable for real-time applications like URLLC.
- Data Availability and Quality: There are few high-quality datasets with labels for wireless communication, and it is expensive and time-consuming to gather real world data.
- Model Interpretability: Lack of transparency in many AI models hinders trust and adoption in critical communication systems.
- One of the key challenges for the future is scalability in Ultra-Dense Networks, where networks will include billions of connected devices that necessitate scalable and distributed AI solutions.
- Further, integration with emerging technologies, like Reconfigurable Intelligent Surfaces (RIS), Terahertz communication, and edge computing, is still an open research topic.

Solving these problems is critical to the realization of the AI-native wireless communication system.

14. Future Perspectives and Research Directions

While substantial advances have been made in the field of signal reception using AI and the optimization of wireless communication, there are still several key areas of research that need to be explored and developed to realize the vision of AI-native 6G networks.

A key challenge is the creation of real-time and low-power efficient AI models that can function within strict latency and energy limits. Future research should focus on lightweight architectures, model compression techniques, and hardware-aware AI design to enable deployment in edge devices and resource-constrained environments.

Improvements of model generalization and robustness are another important direction. The majority of AI-based solutions are based on simulated or limited data sets that do not fully capture the propagation conditions that may be encountered in the field. Thus, the incorporation of real-world measurements, transfer learning, and domain adaptation methods will be crucial for improving the reliability of the model in various settings.

Distributed and privacy-preserving learning frameworks, especially Federated Learning, are also important enablers for the future wireless systems. But, issues such as data distribution that is not IID, communication overload, and synchronization need to be addressed to achieve scalable and efficient collaborative learning.

Additionally, the use of Explainable Artificial Intelligence (XAI) will play a key role in bolstering trust, transparency, and interpretability in AI-based communication systems, particularly in critical sectors like autonomous vehicles, healthcare, and industrial automation.

New technologies, like Reconfigurable Intelligent Surfaces (RIS), Terahertz (THz) communication, integrated sensing and communication (ISAC), and digital twin networks provide new prospects for AI optimization. The future should see further research into the interaction between the design of these technologies and AI, to allow for intelligent and adaptive wireless environments.

Last, the full autonomy and self-optimization of networks is the ultimate vision of 6G systems. To realize this goal, a combination of various AI paradigms, cross-layer optimization, edge intelligence and timely decision-making capabilities will have to be integrated in a single framework.

Finally, future investigations should transition from optimizing individual algorithms to a more comprehensive design of the system level, where AI is an integral part of the wireless system's architecture. Such a transformation will be vital for the capabilities of next-generation communication systems — which are performance, scalable, and intelligent.

15. References

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