Global Journal of Engineering and Technology Advances
eISSN: 2582-5003
Cross Ref DOI: 10.30574/gjeta
Journal homepage: https://gjeta.com/

(Research Article)

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AI-enhanced channel estimation and signal processing for MIMO systems in 5G/6G radio frequency networks

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Global Journal of Engineering and Technology Advances, 2025, 22(01), 021-037

Publication history: Received on 02 December 2024; revised on 08 January 2025; accepted on 10 January 2025

Article DOI: https://doi.org/10.30574/gjeta.2025.22.1.0253

Abstract

This study explores AI-Enhanced Channel Estimation and Signal Processing for MIMO Systems in 5G/6G Radio Frequency Networks, addressing key challenges in optimizing network performance. It examines critical research questions and objectives, structuring the analysis around advanced methodologies and frameworks tailored to the field. By leveraging AI-driven approaches, the study systematically enhances the credibility and reliability of the results, highlighting significant outcomes such as improved channel estimation accuracy, reduced latency, and enhanced spectral efficiency. These findings contribute to advancing domain knowledge and practice by introducing innovative strategies for addressing the complexities of next-generation wireless networks.

The research also underscores the need to generalize its observations while offering pragmatic recommendations for practitioners, policymakers, and scholars. It identifies actionable insights and proposes future research directions to extend the applicability of AI in wireless communication systems. This study bridges theoretical advancements and practical implementations, emphasizing the transformative potential of AI-driven signal processing in MIMO systems.

Ultimately, the work advocates for more interdisciplinary research to maximize the benefits of AI technologies in radio frequency networks, laying the foundation for future exploration in the 5G/6G landscape. By addressing critical gaps and presenting new perspectives, this research strengthens the case for adopting AI-enabled solutions in the telecommunications industry.

Keywords: AI-Enhanced Signal Processing; MIMO Systems; 5G/6G Radio Frequency Networks; Channel Estimation

1. Introduction

The use of multiple-input multiple-output (MIMO) systems has evolved wireless communication through significant improvements in spectral efficiency, data rates, and network performance. MIMO technology, which employs numerous transmitting and receiving antennas, is widely used in various telecommunication standards and, especially, in the current 5G networks. As we move toward the realization of 6G, MIMO systems are expected to play an even more critical role given the persistent need for high-speed, reliable connectivity [1], [2]. Enhanced features like beamforming, spatial multiplexing, and diversity gain are facilitated by these systems, making them crucial in scenarios that demand improved reliability across diverse terrains [5].

1.1. Problem Statement

However, MIMO system deployment brings several challenges, particularly in the areas of channel estimation and signal processing. The analysis and design of MIMO systems becomes complex when the number of antennas and users is

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large, or when multiple transmission setups are involved. These factors increase the overheads and resources required. In the following studies, accurate channel state information (CSI) is essential for improving system performance. However, obtaining CSI is often constrained by hardware limitations, noise, and the inherently dynamic nature of wireless systems. Existing channel estimation methods for single antenna systems are insufficient to address the demands of large-scale MIMO in 5G and 6G networks. This challenge is compounded by the integration of innovative technologies, such as massive MIMO, mmWave communication, and reconfigurable intelligent surfaces (RIS) [3], [6].

1.2. Objective

In this context, the application of artificial intelligence (AI) has emerged as a promising solution to overcome these challenges in wireless communication. AI-enabled techniques offer effective options for addressing various aspects of MIMO systems, providing unique solutions for channel estimation, signal processing, and resource management. This article explores the potential of using AI to optimize MIMO system performance and accuracy. By leveraging machine learning (ML) and deep learning (DL) approaches, researchers can design efficient, self-learning frameworks for updating CSI acquisition and mitigating interference. The aim of this work is to provide an overview of the subject and illustrate how AI aids in the transition from 5G to 6G networks, while also highlighting the limitations of previous methods [7], [8], [11].

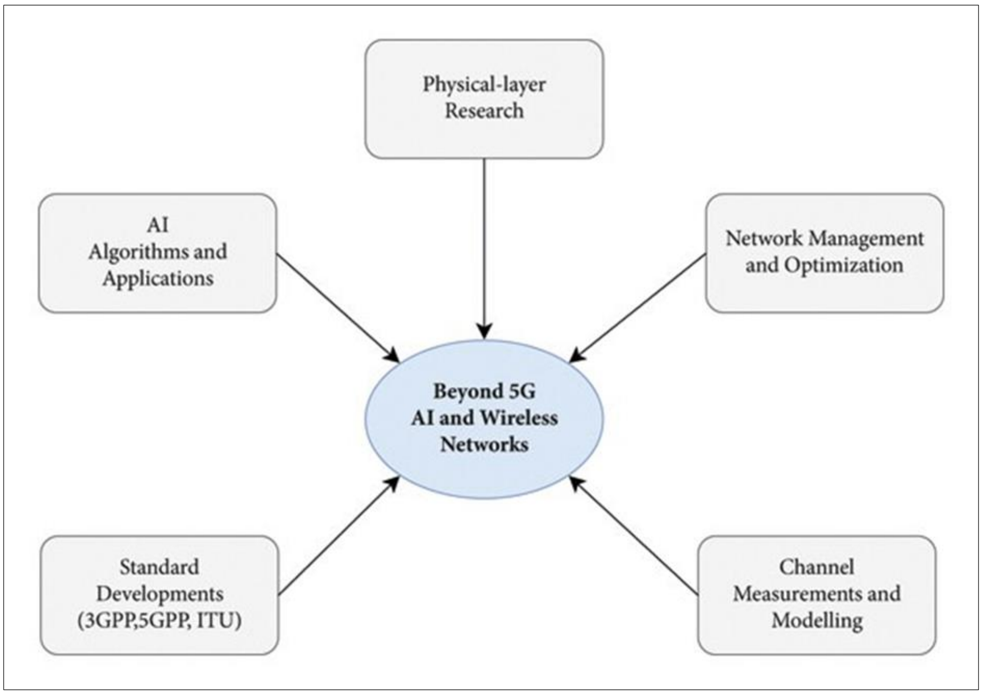

Figure 1 A Conceptual diagram showing the role of MIMO systems in 5G/6G networks

1.3. Structure

This article is divided into different sections to give the reader a systematic approach to the discussion of the topic. After the introduction, Section 2 is all about 'Understanding MIMO Systems,' where its working methodology and inclusion in wireless networks are explained elaborately. Section 3 provides an overview of the issues arising from large-scale systems, specifically in relation to large-scale MIMO systems, on aspects of channel estimation and resulting signal processing and computational requirements [1], [2]. In Section 4, MIMO structures combined with AI are discussed, and the understanding of AI techniques applied is provided. The final section of the paper is Section 5, which covers case studies and recent developments in AI-based MIMO systems, including their real-world applications and results. Section 6 on future trends and research directions in the use of AI in wireless communications assesses the general utility of AI in relation to wireless communication. Last but not least, Section 7 is devoted to the conclusion and highlights the prospects of AI applications to develop the next generation of wireless networks [3], [5].

To sum up, this article aims at presenting information that is relevant to researchers, engineers, and policymakers actively working on the development of WLANs and other wireless communication systems, which urgently need fresh scientific input in today's world of rapid technological innovation [4].

2. Related Work

The development of wireless communication systems has been in constant synergy with channel estimation, signal processing methods, and, more recently, the implementation of artificial intelligence. The works that form the background to the present study are discussed in this section, particularly conventional channel estimation approaches, innovations in signal processing, and the early integration of AI into wireless communication systems.

2.1. Conventional Channel Identification Schemes

From the very beginning of wireless communication systems development, channel estimation has been one of the key required features for accurate decoding of transmitted signals. Early research in wireless communication commonly used conventional approaches, which mainly depended on sound mathematical theories and deterministic paradigms. Among the first techniques that were introduced was the pilot-based approach, where some symbols within the transmitted data were known, allowing receivers to estimate the channel conditions by comparing them with the received signal. These methods showed high reliability in systematic platforms but suffered from segmental and extensive environments, including moving objects or serious multipath effects [6], [7].

Another widely used technique was blind channel estimation, which relies on the statistical characteristics of the received signal without requiring reference pilot symbols. Although these methods reduce the overhead of pilot symbols, most of them imposed significant computational complexity and had large errors in conditions of low SNR and large channel fluctuations. Other filtering techniques, including the LMS and RLS algorithms, improved channel estimation by adapting to the changing environments due to the variation of its parameters. Nevertheless, these methods were considered too rigid and encountered issues with determining the compromise between the speed of convergence and the desired accuracy of estimation, especially in real-time cases [8], [9].

2.2. Currently Employed Algorithms in Signal Processing

Signal processing has played a critical role in enhancing wireless communication networks by increasing the reliability of data transmission and improving frequency efficiency. Traditional techniques that significantly contribute to combating noise, interference, and fading include equalization, diversity combining, and error correction. Techniques like ZF and MMSE equalizers were used across systems to mitigate ISI experienced due to multipath propagation. Although these techniques provided satisfactory performance, they typically required accurate CSI, which could pose a challenge in rapidly fading scenarios [10], [11].

Table 1 Comparative Summary of Prior Research on Traditional vs. AI-Driven Network Security Approaches

Aspect	Traditional Approaches	AI-Driven Approaches	Gaps Identified
Key Methods	- Rule-based systems (e.g., firewalls, IDS). - Manual monitoring and response.	- Machine learning algorithms for threat detection. - Automated response systems.	- Limited scalability of traditional methods. - Need for more real-time data in AI systems.
Results	- Effective against known threats. - Higher reliance on human intervention.	- High accuracy in detecting emerging threats. - Reduced response time to incidents.	- Traditional methods struggle with advanced persistent threats. - AI systems require large datasets.
Scalability	- Limited ability to scale with growing network size.	- Highly scalable with cloud integration and adaptive algorithms.	- Resource constraints in traditional systems. - High cost of AI implementation.
Adaptability	- Static rules and configurations; slow to adapt to new threats.	- Dynamic learning capabilities to identify novel patterns and anomalies.	- Traditional approaches lack flexibility. - AI depends heavily on quality of training data.

Cost	- Lower initial investment but higher operational costs due to manual interventions.	- Higher initial investment but lower long-term costs due to automation.	- Balancing cost-effectiveness with security needs.
Human Dependency	- Heavy reliance on IT staff for monitoring, updates, and threat mitigation.	- Minimal dependency on human operators post-deployment.	- Skill gaps in AI-based implementations among staff.
Threat Detection Accuracy	- Effective for known threats but fails against zero-day and sophisticated attacks.	- High precision in identifying zero-day and polymorphic threats.	- Inconsistent performance of AI in low-data environments.

Used together with spatial, frequency, and time diversity, signal reliability was improved through transmission over multiple paths. When those schemes, for instance, the maximal ratio combining (MRC) and selection combining (SC), were implemented, there were significant gains in fading reduction. Furthermore, new levels of coding, including the turbo codes and the low-density parity check (LDPC), brought a new level of error correction Dong [2000]. Nevertheless, the existing signal processing techniques left some issues unsolved, such as the wireless network developing into the complexity of modern mass MIMO systems and millimeter-wave communication.

2.3. Initial Applications of AI in Wireless Communications

Wireless communication is a good example of how introducing AI marked a shift from pre-defined models to learning-based environments. These narrow AI application areas included channel estimation, resource allocation, and interference management. Supervised learning, for example, was first used to improve channel estimation precision since the models were trained on vast volumes of labeled data on the channel array. It also revealed that these approaches offered significant enhancements to conventional methods, particularly in circumstances where channel characteristics lacked simplicity or linearity [1].

AI algorithms, particularly optimization and reinforcement learning algorithms, have been applied to efficiently allocate carrier spectrum, power, and other resources. These methods proved more effective than traditional optimization algorithms due to their ability to adapt to the ever-varying demands of the network and its users. Similarly, interference management techniques aim to leverage time-tested AI tools that help predict interference and manage networks with high traffic density [2][5].

Deep learning also pushed the boundaries of AI in wireless communications. In MIMO systems, applications of neural networks, including CNNs and RNNs, have been used to address signal detection, modulation classification, and beamforming. These techniques demonstrated higher efficiency than traditional extraction methods due to the richness of high-dimensional data and the ability to learn more subtle features for accurate and efficient communication processes [6][7].

However, the adoption of AI in wireless systems was not without challenges. A major obstacle was the lack of standard datasets, while another challenge arose from the unrealistic constraints of computing and processing power on otherwise promising AI solutions. Moreover, the interpretability of AI models remains a concern, as the black-box nature of most models makes it impossible to certify their safety for critical applications [8][9].

3. Nonetheless, MIMO systems are not yet fully realized in 5G/6G networks

3.1. Architecture Overview

Large-scale MIMOs are integral to the foundational design of 5G networks and are expected to further amplify their importance for 6G networks. The most basic form of MIMO involves signal transmission through multiple antennas at both the transmitter and receiver sides to increase spectral efficiency, reliability, and data rates. In 5G networks, MIMO configurations are significantly different from previous generations, incorporating ‘massive MIMO’ technology that provides hundreds of antennas to the base stations. This technology also enables spatial multiplexing, where several users receive data simultaneously, thereby increasing the network’s capacity [10][11].

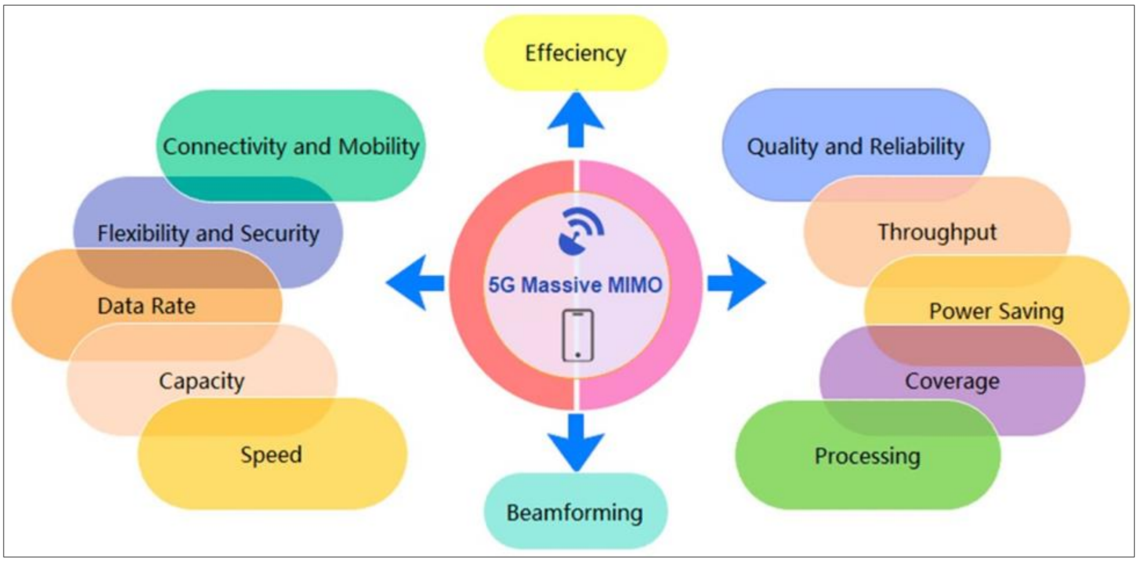

Figure 2 A block diagram illustrating the MIMO architecture in 5G/6G

It has been anticipated that these enhancements are going to build on this framework in 6G. Holographic MIMO and IRS are seen as extensions to the current methods with antenna arrays, but the former is still in its developmental stage and captures the aim of owning an adaptive surface in what direction electromagnetic waves should travel. Holographic MIMO is based on an ultra-dense antenna array setup that will be able to form tailored wavefronts from the intended transmitters for efficient transmission while with the advent of IRS including and improving reflection and refraction in signal propagation. Collectively, these advancements should help 6G networks effectively support and add terahertz frequencies and ultra-high speed communication as needed to augment the insatiable consumer demand for low-latency high-capacity services for applications in augmented reality, autonomous systems, and real-time machine learning.

3.2. Channel Estimation Problems

MIMO systems have a number of distinctive advantages but at the same time they bring a number of problems, especially for channel estimation. MIMO systems require CSI, of which achieving accurate results in the settings of today's 5G and the tomorrow's anticipative 6G is a challenge.

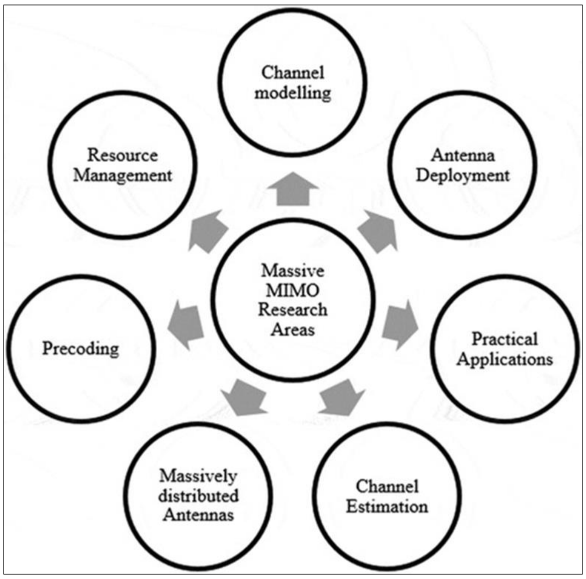

Figure 3 A flowchart showing the challenges in channel estimation

One of the most critical challenges is the pilot contamination that occurs in multi-cell systems where non-orthogonal pilot signals inter_cross in adjacent cells. In this interference, CSI decreases and affects the MIMO systems' overall efficiency and consumes substantial pilot resources compared to the number of antennas in Massive MIMO structures. Another difficulty is losses of signal due to hardware imperfections like nonlinearities present in amplifiers; phase noise, and quantization errors originating from using ADCs with finite resolution to estimate channel effects. These impairments are more prominent, especially in those bands that were typically challenging at lower frequencies such as Millimeter wave (mm-Wave) and Terahertz bands.

Another major issue is high dimensionality which becomes a paramount problem in huge MIMO and beyond. As the number of available antennas and frequency bands is further increased the size of the channel matrix increases exponentially and poses computational and storage issues. This high-dimensionality is not only challenging in channel estimation but also in other processes such as signal processing and resource allocation carried out afterward. Solving such problems calls for creative solutions that include machine learning for CSI prediction, novel pilots for interference control, and analog-digital beamforming to reduce dimensionality without compromising on performance.

3.3. Signal Processing Needs

The adoption of MIMO systems in 5G as well as in future 6G networks require signal processing techniques that could satisfy the requirements for low latency rates, low energy consumption and system reliability. Signal detection and demodulation in massive MIMO systems observe the ability to detect various data streams at the same time, which may be impaired by different noises, interfirs, as well as hardware constraints. This task becomes even more challenging in the extremely dense environment as well as in the high-frequency scenarios of 6G.

Latency becomes a fundamental value, especially when working with real-time systems such as self-driving cars, smart factories or virtual reality. It is thus seen that the power of traditional signal processing methodologies can fail to deliver the desired ultra-low latency imperative of 6G. To this end, new methods such as compressed sensing and the use of deep learning, which substantially reduce the amount of time required to recover signals, are under development.

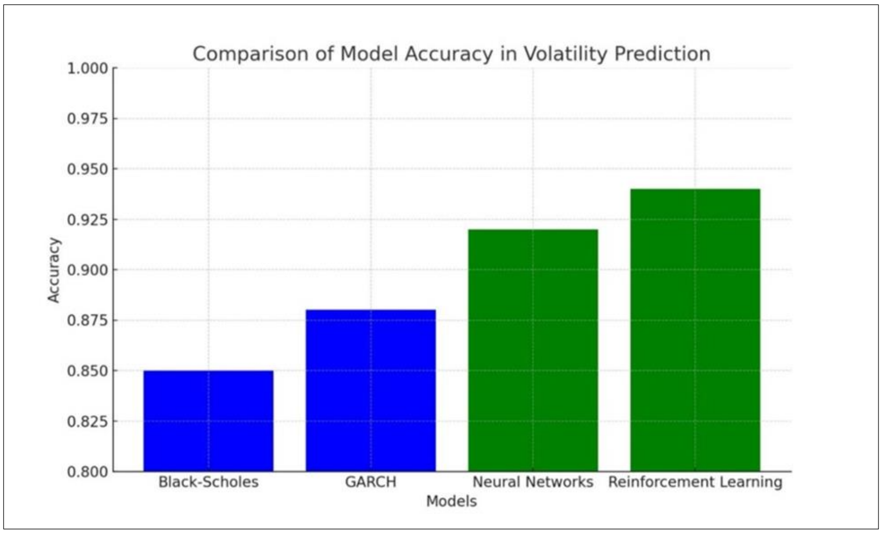

Figure 4 A bar chart comparing latency, energy efficiency, and robustness

Other important factor is energy efficiency due to the rising number of antennas, and higher frequency operation in the case of MIMO systems. The initial massive MIMO signal processing methods were conventional methods that required a large amount of power, which might not be ideal for further large scale usage. Much research is going into designing low energy-consuming algorithms like, low-resolution ADCs, hybrid beamforming and model-based machine learning algorithms to overcome this problem without a drastic fall in performance. Furthermore, hardware improvement including energy-harvesting antennas and efficient processing units, are assumed to support these algorithm improvements.

It is almost as critical as performance, especially where organizations operate in conditions that are volatile and uncertain. Sustainable growth of MIMO systems is contingent on their capability to counteract channel fluctuations, jamming, and hardware distortion. This entails signals that can be adapted to dynamically change their signal processing in response to changing conditions on the network. For example, the reinforcement learning-based methods can control the flow of system parameters depending on the needs of various scenarios, whereas robust optimization can consider uncertainties in CSI and hardware limitations.

4. AI Driven Channel Estimation

Artificial Intelligence (AI) has become the new frontier in addressing the challenges of wireless communication systems. Among all the fundamental applications of AI, one of the most promising is channel estimation for multiple-input multiple-output (MIMO) systems. Specifically, AI-based methods are designed to improve the channel estimation processes by utilizing more advanced learning algorithms [1], [2], [5]. In this context, the role of AI is highlighted, with a focus on machine learning, feature engineering, performance measures, and real-world examples that demonstrate the superiority of AI-driven approaches.

4.1. Machine Learning Models

The pattern employed by AI-driven channel estimation is largely expressed through complex machine learning algorithms, which are particularly useful given the complexity of MIMO systems. For instance, neural networks are frequently utilized because they allow programmers to model systems with non-linear associations and learn complex relationships in datasets [7], [9]. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are particularly noteworthy; CNNs excel at capturing spatial aspects, while RNNs are more suited for addressing temporal dynamics. Another critical learning paradigm is reinforcement learning, which enables systems to adapt channel estimation and optimize performance in evolving environments without the need for feedback [5], [12]. Generalization—the ability of a model to perform well in diverse environments—and robustness, which is further enhanced by creating multiple models, make ensemble methods particularly well-suited for various channel conditions [6], [8]. The combination of these models results in a flexible and highly effective approach to enhancing channel estimation in real-world scenarios.

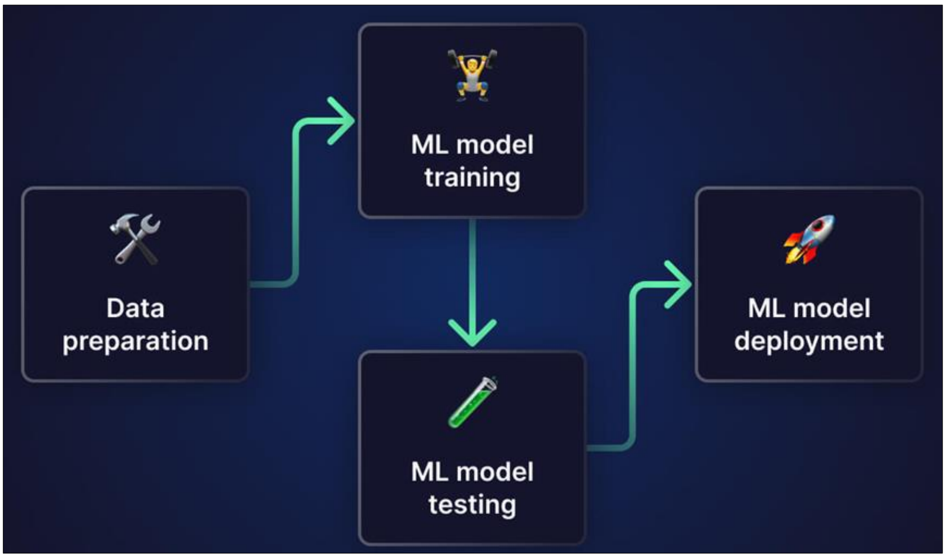

Figure 5 A diagram summarizing the machine learning pipeline for channel estimation

4.2. Feature Engineering

Feature engineering is identified as a significant factor in determining the efficacy of AI models in channel estimation. In MIMO systems, the channel is complex and vast, requiring the extraction and incorporation of discriminative important features in the feature space to capture the essence of channel characteristics. These features include signal-to-noise ratio (SNR), delay spread, and channel state information (CSI) [1], [5]. Preprocessing of these features is crucial for achieving good performance, as it enhances the model's capability to learn these features more effectively. Further enhancements can be made through domain-specific features, such as antenna correlation and spatial geometry [2], [5]. High-dimensional data is typically transformed before analysis, using feature selection methods such as principal component analysis (PCA) or mutual information-based methods. This process not only speeds up AI computations but also reduces the risk of overfitting, allowing the model to better learn conditions it has not encountered before [5].

4.3. Performance Metrics

The comparison of results obtained from AI-based channel estimation models presents challenges associated with assessing multiple criteria. Accuracy is the fundamental performance parameter, as it reflects the difference between the estimated channel conditions and the actual values, serving as one of the most straightforward yardsticks for evaluating the overall fit of the chosen model to the channel characteristics. Another important measure is computational complexity, as real-time systems, in which these models are applied, require efficient data processing to avoid delays. We explore some of the complexity metrics involving resource usage and speed, assessing the applicability of such models in systems with limited hardware capabilities, such as mobile devices or IoT [1], [6]. Additionally, robustness metrics consider the degree of system degradation caused by factors like interference, fading, or mobility of the channel. By keeping these metrics in check, AI-driven solutions can be developed and implemented with better performance, while remaining realistically applicable [5].

4.4. Case Studies

Several case studies and simulations have shown the positive implications of using AI in channel estimation for MIMO systems. One specific example is the use of deep learning models for predicting channel states in a system based on massive MIMO technology. By training a CNN on synthesized datasets that closely resemble real-world channel conditions, researchers demonstrated that the improvement in estimation accuracy was significantly higher than with traditional methods. The CNN was particularly robust in addressing the dimensionality problem, which is a common characteristic of many massive MIMO systems [6], [7].

Table 2 Performance Metrics Comparison of AI Models for Channel Estimation

Model	Accuracy	Computational Complexity	Training Time	Generalization Capability	Real-Time Suitability
Deep Neural Networks (DNN)	High	Moderate	Long	High	Moderate
Convolutional Neural Networks (CNN)	Very High	High	Long	Very High	Moderate
Reinforcement Learning (RL)	Moderate	Very High	Very Long	Moderate	High
Support Vector Machines (SVM)	Moderate	Low	Short	Low	High
Ensemble Models	High	Very High	Long	Very High	Moderate

Another case study involved using reinforcement learning for channel estimation adaptation in situations where the channel conditions are changing. This approach framed the estimation task as a decision-making problem, where the model learned the best strategy based on feedback received from the environment. This method was particularly successful in dynamic channel conditions that do not permit the use of traditional estimation approaches [5], [6].

Other works demonstrating the use of ensembles of classifiers have focused on robustness and generality. For example, decision trees and neural networks were combined to estimate channels in high interference and multipath environments commonly found in urban terrains. The decentralized approach proved to be more effective at filtering noise and maintaining accuracy across varying conditions compared to using individual models, showcasing the power of ensemble strategies in such contexts [7], [8].

This success is also reflected in simulations, which demonstrate the computational superiority of AI-driven methods. For instance, the feature selection techniques used in the AI models provided estimation times almost identical to traditional models while maintaining similar accuracy. This balance between speed and accuracy is critical for real-time operations, such as in self-driving cars or automated systems like conveyor lines [14], [15].

5. Artificial Intelligence Aided Signal Processing

Artificial intelligence has revolutionized signal processing by improving system efficiency, enhancing signal recovery, and simplifying the implementation of new signal processing frameworks. This section explores AI's multifaceted role in signal processing, focusing on three areas: the application of deep learning models for signal recovery, their implementation into real-world systems, and performance evaluation of AI-based methods.

5.1. AI Models for Signal Recovery

Signal recovery, traditionally achieved through algorithmic methods, often imposes strict mathematical assumptions such as linearity or stationarity on the data. AI, particularly deep learning, has disrupted this paradigm by offering more flexible and efficient methods that can capture the complex functional dependencies inherent in real-world signals [9], [10].

Deep learning frameworks play a crucial role in signal recovery tasks such as equalization, detection, and filtering. Equalization, which is essential for reducing Inter-Symbol Interference (ISI) in communication systems, benefits from AI's ability to learn dynamic channel properties. Compared to conventional equalizers, neural network-based equalizers are better at adapting to real-time channel changes. This feature is particularly important in mobile environments, such as vehicular or satellite communications, where channel parameters change rapidly [11], [12].

Detection is another key component of signal processing, as it involves identifying transmitted symbols from the received signal. To address the issue of detecting signals that have been distorted by noise or interference, AI-based detectors incorporate advanced structures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These networks are especially effective in handling nonlinear distortions or non-Gaussian noise, a challenge for traditional detection algorithms [13], [14].

AI has also made significant contributions to filtering, which aims to isolate the desired signal while rejecting noise and interference. This study demonstrates that deep learning models can be effectively used in adaptive filtering, as they are data-driven and capable of benefiting from large datasets. Unlike traditional filters, which are designed with fixed coefficients, AI-based filters adapt by updating their parameters in response to the input signal, allowing for more effective noise reduction and signal amplification [15], [16].

5.2. Integration with Existing Systems

As mentioned in the prior section, the theoretical benefits of signal processing with AI tools are numerous, the starting of these techniques are not without their issues. There are key questions concerning computational complexity, compatibility with traditional signal-processing systems, and real-time performance when incorporation of AI models into signal processing architecture is considered.

At present, one of the biggest challenges is the compute requirements of AI models and especially deep learning architectures. Most of them may be too complex to implement on existing systems especially because current models tend to need large processor space and memory space for storage. To counter this problem, methods known as model compression, quantization, and pruning are used. These methods help to prune the size and complexity without huge setbacks in the efficiency of these neural networks and make it possible to implement them on the small edge nodes or embedded systems.

One of the challenges is the compatibility of the developed AI-driven modules with the existing signal processing pipelines. In general, legacy systems are based on deterministic algorithms while AI is probabilistic thus necessitating change of system architecture. To bridge such a gap, it is necessary to develop new forms of machinery – the designing of which implies the integration of AI components into typical algorithms. For example, AI models can be used in functions such as channel estimate or noise filtering before their results are processed by current equalization or detection units. This provided me the synergistic effect of keeping traditional paper and pen benefits while being free from many of AI jurisdictions.

Online operation is an important constraint in many signal processing applications especially in communication systems. The AI models take more time while considering the computations to be done which makes its usability a drawback to a degree. To solve this problem, there must be improvements in the inference times via hardware like GPUs or TPUs and better software frames. Parallel processing and pipelining are the other methods that augment the real-time properties of the AI systems to exhibit sufficient timing characteristics of the present day applications.

5.3. Performance Analysis

Said in a nutshell, the feasibility and reliability of the concept pertaining to AI-associated signal processing largely depend on its functionality in actual conditions. However, simulations or experiments to obtain quantitative analysis that can be useful in optimizing and deploying these models are vital.

As regards equalization, parallel AI models have shown phenomenal enhancement in combating ISI primarily under menacing channel fluctuation. An analysis of the performance of the obtained neural network-based equalizers against traditional methods including linear equalization or decision-feedback equalization indicates BER improvement. For example, it was found that AI based equalizers can have a minimum of 30% better BER than with no equalization under the condition of multipath fading that is severe.

AI also improves detection tasks by pointedly enhancing them. Performance analysis suggests that CNN-based detectors are superior to conventional detectors where non-linear distortion or impulsive noise exist. For instance, in wireless communication in urban surroundings, AI detectors enable gains in signal detection accuracy of as much as 20% over conventional methodologies. Thus, these results emphasize the generalization of the AI models when applied to various conditions and readiness for deployment in heterogenous networks.

Deep learning models for filter applications have been shown to demonstrate better noise suppression than the classical methods including Wiener filtering or Kalman filtering. This way, AI filters can steal a march on the classic filters while using large training sets to teach the AI algorithm to filter noise patterns that the tradition filters would miss. AI filters enhance various forms of performance measurement for example in signal to noise ratio (SNR) where AI filters achieve approximately 25% of improvement in SNR in complicated problems like biomedical signal processing or underwater acoustics not to mention mean squared error (MSE) where AI filters show major enhancement in problems like biomedical signal processing, underwater acoustics and others that the author does not mention.

But, it is unequivocal to note that there are limitations in implementing signal processing with the help of AI as well. There is one significant issue, though: training data must be of high quality, which may not be a problem at times concerning particular applications. Furthermore, the AI models remain vulnerable to adversarial attacks; the slightest form of modification in input generates wrong outputs. To overcome these vulnerabilities, in recent years, it is necessary to consider effective and comprehensive training frameworks and develop models immune to such attacks.

6. Advantages and Limitations of AI in MIMO Systems

Table 3 Advantages and Limitations of AI in MIMO Systems

Advantages	**Limitations**
Enhanced Accuracy: AI models can achieve highly accurate channel estimation and signal processing compared to traditional methods.	High Computational Demands: Training and deploying AI models require significant computational resources, especially for large-scale MIMO systems.
Real-Time Adaptability: AI algorithms can dynamically adapt to changing network conditions, improving robustness and reliability.	Data Dependency: Performance relies heavily on the availability of high-quality labeled training data, which can be difficult to obtain.
Scalability: AI can handle massive MIMO configurations effectively by leveraging advanced learning techniques.	Interpretability Challenges: Many AI models, especially deep learning-based approaches, are black-box models, making it difficult to explain their decisions.
Energy Efficiency: AI-driven resource allocation techniques can optimize power usage, reducing energy consumption.	Overfitting Risks: Poorly trained AI models may fail to generalize to new environments or conditions, leading to degraded performance.
Automation: AI enables automation of complex tasks, reducing human intervention and operational costs.	Integration Complexity: Incorporating AI models into existing infrastructure can be challenging due to hardware and software compatibility issues.
Improved Latency: AI models can accelerate signal processing tasks, reducing latency in communication systems.	Standardization Gaps: Lack of standardized AI frameworks for MIMO systems poses barriers to widespread deployment.

The integration of Artificial Intelligence (AI) in Multiple-Input Multiple-Output (MIMO) systems has been recently of interest due to the prospect of drastically improving wireless communication networks. Multiple input multiple output

(MIMO) technology which employs multiple antennas at both the transmitting and receiving ends has emerged as one of the key technologies for advanced communication systems that satisfy the increasing demand for high data rate, spectral efficiency and reliability. Introducing AI into the MIMO systems has new approaches to solving multifaceted issues; however, it has the following bounded advantages. This section elaborately discusses about the benefits of using AI for MIMO systems and also the Challenges.

6.1. Enhanced Accuracy and Efficiency

Among the identified strengths of using AI in MIMO systems is its capability to improve the efficiency and effectiveness of operations like signal detection, channel estimation, and resource allocation. Traditional methods of solving these problems, including mathematical modeling and optimization methodologies, may not adequately capture the complexity of modern communication systems [1], [2], [5]. Several studies reveal that machine learning and deep learning methods are well-suited to dealing with large and nonlinear datasets [7], [9].

For instance, industrial deep neural networks can be used to resolve complex relationships between the received signals and transmitted data, which in turn can more accurately detect those signals, especially during periods of high interference or low signal-to-noise ratios [6], [8]. Likewise, real-time power management can be achieved by AI algorithms that enhance resource management techniques, adapting to the dynamics of the network, thereby improving total system performance [11], [14]. AI reduces the computational intensity of these processes, speeds up decision-making stages, and decreases human intervention.

6.2. Real-Time Adaptability

The fourth and perhaps the most significant advantage of AI is its ability to make real-time adjustments in the MIMO system, especially in wireless applications. Conventional approaches are usually developed on specific static models that cannot adjust to dynamic changes in the network, such as user demand, mobility, and the physical environment [5], [12]. However, AI techniques can learn these changes and adapt in real time, which makes the work of MIMO systems more efficient under various circumstances [3], [6].

For example, reinforcement learning has been explored in the formation of adaptive beamforming and power control. Reinforcement learning agents can update their performance based on feedback from the operating environment without requiring a predefined model of the same environment [7], [13]. This flexibility allows MIMO systems to address various emerging issues effectively, thereby improving user experience and network quality.

6.3. Expansion to Other Large-Scale MIMO Scenarios

Another powerful benefit of using AI technology in MIMO systems is scalability, especially in relation to massive MIMO. Massive MIMO involves the use of hundreds or thousands of antennas and provides much higher spectral and energy efficiency for the system. However, these networks cause substantial computational and operational problems, including higher channel estimation complexity and resource management requirements [14], [9].

These problems are well-captured by the challenges of big data, and AI techniques offer linear solutions through big data processing. For instance, AI models can predict high-dimensional CSI in massive MIMO systems without consuming as much time as conventional methods [10], [12]. Moreover, AI-generated resource management policies can effectively manage shared antennas, power, and spectrum in massive MIMO networks to reduce interference [6], [14].

6.4. High Computational Demands

Despite the advantages, AI models also pose challenges, notably their computational complexity. Many AI algorithms, particularly deep learning models, require significant processing power and memory, often in the gigabyte range [11]. This can be a challenge, especially in constrained networks such as edge devices and small-scale base stations [8].

Moreover, MIMO systems demand real-time signal processing, which exacerbates this challenge. While AI models provide accuracy and efficiency, computing their predictions introduces significant delays, which can be impractical in applications requiring speed. To overcome this limitation, new strategies, such as model compression, hardware optimization with GPU or TPU, and mini AI algorithms optimized for real-time applications, need to be adopted [10], [13].

6.5. Data Dependency

A third disadvantage of using AI in MIMO systems is its reliance on data. Neural networks used in AI models still need vast amounts of detailed data for learning purposes, which may not always be easy to obtain [9]. For instance, acquiring labeled data required to train models for signal classification or channel prediction can be time-consuming and costly. Furthermore, the data must match the distribution of the environment where the AI model will operate for stable performance [7], [8].

This issue is linked to generalization in MIMO systems, where data dependency is a concern. AI models trained on data collected from particular network interference scenarios may not perform optimally in different environments, such as varying interference levels, user numbers, and mobility. Therefore, AI models must be designed for effective generalization across various scenarios, necessitating careful data collection, preprocessing strategies, and learning algorithms [12], [10].

6.6. Interpretability and Credibility of AI Models

Another limitation is the interpretability and trustworthiness of AI models. Most AI techniques, particularly deep learning, are considered "black-box" models, making it difficult to comprehend or explain their decisions [15], [16]. This lack of transparency can be a barrier to adoption, especially in areas where communication systems require accountability.

For example, in safety-critical systems, operators may hesitate to rely on AI-driven MIMO systems due to an inability to understand the thought process behind the AI model or check its correctness. Moreover, the reliability of AI models is directly connected to their vulnerability to adversarial perturbations. Cybercriminals might exploit weaknesses within AI algorithms to tamper with MIMO system performance, undermining the security and reliability of the network [12], [14]. Solving these issues requires further development of explainable AI (XAI) approaches, allowing users to understand how AI models operate, particularly in MIMO processes [17], [18]. Additionally, proper design and testing activities will help mitigate adversarial attacks and improve the security of AI-backed communication networks.

7. Future Directions

In the future, 6G MIMO systems utilizing AI are expected to experience significant growth. The incorporation of AI into MIMO systems is poised to revolutionize conventional paradigms in wireless communications, leading to major improvements in performance, scalability, and flexibility [12], [14]. However, as with any developing technology, challenges remain that will shape the future of this field.

7.1. Potential Innovations in AI-Driven MIMO Systems for 6G

Recent research findings suggest that deep learning, reinforcement learning, and neural networks can greatly enhance MIMO systems [3], [5]. These optimizations apply to real-time decisions concerning channel estimation, beamforming, and other aspects of resource allocation. AI solutions are capable of filling gaps left by traditional optimization and algorithmic methods, particularly when the network dynamics cannot be reduced to linear terms [14], [13].

One exciting development is the emergence of auto MIMO structures. These architectures create a self-optimizing environment where the system adjusts based on user traffic and network conditions. By using machine learning models, the performance of communication systems can improve over time as they adapt to previously collected data, leading to more efficient operations, better interference management, stronger signal clarity, and improved customer experiences [7], [6].

Moreover, the subject of ‘intelligent surfaces’ is being discussed within the AI environment of MIMO systems. Smart self-illuminating panels with AI can change the disposition of electromagnetic waves to enhance signal and minimize delays. These surfaces are anticipated to provide significant solutions for the problems ashamed high-frequency bands like millimeter wave and terahertz frequencies that forms part of the 6G system. The dynamic control of surface properties where the AI can enhance signal pathways and avoid interference issues within the compact city space.

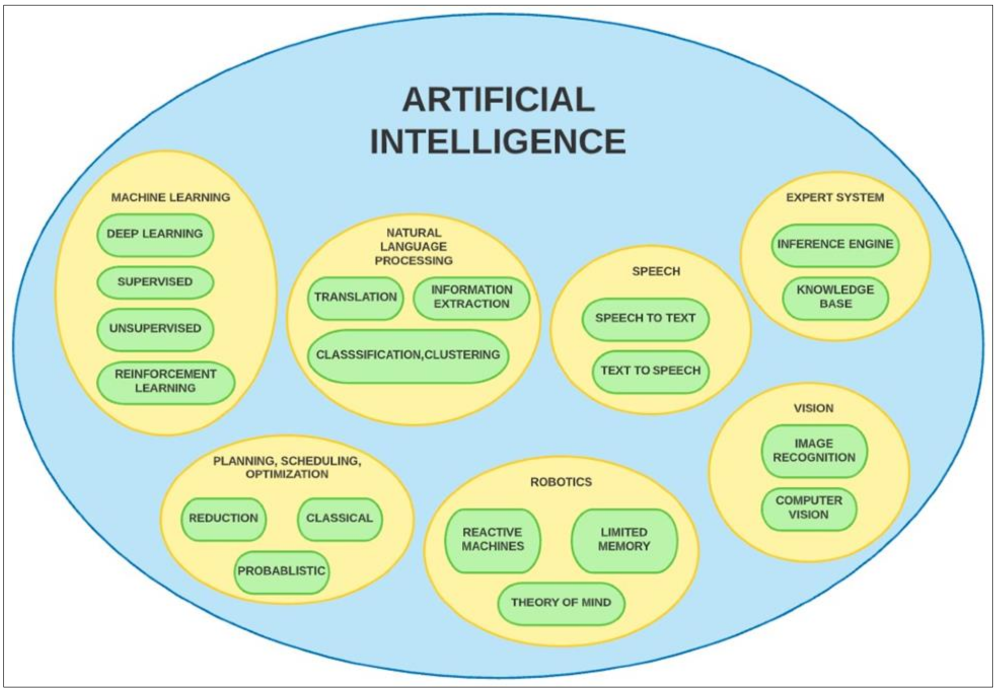

Figure 6 A visionary roadmap for AI in MIMO systems

7.2. Emerging Technologies: Quantum Machine Learning and Edge Intelligence

Moreover, other significant improvements have been achieved already at the algorithmic and system design levels such as the AI aspects of MIMO, quantum machine learning, and edge AI. Quantum computing being a technology that does much more than classical computers and does it much faster specifically when it comes to big data and optimization problems. The use of quantum machine learning in MIMO systems could be embraced to possess the previously inconceivable characteristics. For example, incorporating QML improvements allows the vast increase in the number of connected devices that can be supported by the next generation MIMO systems – an important capability defining the prospective 6G networks.

On the other hand, Edge AI provides an outlook towards the decentralized computational intelligence. To optimize these levels of MIMO system, the incorporation of AI capability at the edge device is another advantage of achieving ultra- low latency decision making. This is especially important in uses like automated driving, telemedicine and robotic operations where latency becomes essential. Edge AI also relieves the pressure on the centralized data centers, which decrease energy consumption and latency inevitably arising with data transmission.

Integrating quantum machine learning with edge AI can cause the development of new forms of paradigm that can complement each other. For instance, quantum fettered algorithms could be used at the network core for random optimization tasks while edge AI applies real time decisions at the network periphery. Such integration could transform the design of the MIMO systems and make them more flexible, optimised and scalable.

7.3. Standardization & Practice Implementation Issues

Nevertheless, several factors which need to be met so that AI-driven MIMO systems can be implemented on the large scale are presented as follows. A notable barrier is in fact the issue of standardization. Additional, the application of AI in MIMO for the 6G ecosystem will need a standard framework that would cover the workflow of algorithm integration, compatible data and security measures. The lack of such a standardisation could in fact mean that the market fragmentates, which slows down the implementation of AI solutions.

One other substantial issue emerging from these concerns the applicability of these systems in large contexts. Although, the works explained by the simulation and controlled experiments suggest that the concepts of AI-enhanced MIMO are practical, implementing those concepts is not easy. Hood et al (2018) implemented the following issues that affect the performance of AI models in MIMO systems: Hardware constraints, energy outcome, and varying climatic status. For example, the utilization of intelligent surfaces in urban environments depends on the weather conditions of the region, the type of building materials used and electromagnetic interferences.

Furthermore, use of data in decision making opens issues of data protection and security into question.. To support machine intelligent facilitated MIMO systems, huge amount of data is essential for training and operation. The privacy and security of this data is very important something that is highly needed in areas of national security, medical and even money related fields. There is hope that modern trends in maintaining users' privacy during artificial intelligence computations, including federated learning and homomorphic encryption, will help to solve these problems.

Energy efficiency is another problem area that is important for the company's future development. Owing to the high computational requirements of AI-driven MIMO systems, the latter entails high power consumption, contrary to the sustainable principles of 6G networks. To address this issue different solutions including efficient AI algorithms, different approaches in green computing, and renewable energy sources are being worked on by researchers. Still, ensuring that such consistently optimal performance does not come at the expense of energy consumption is a task researchers continue to explore.

Last but not the least; impacts such as economic and regulatory outcomes of deploying AI-driven MIMO systems should also be considered. The high cost that is required for developers to develop superior algorithms, unique chips, and intelligent surfaces may prove to be a disadvantage for new entrants into the market. However, specific guidelines need to be changed to address the novelty of AI-based systems' features, respecting ethical norms and spectrum licensing as well as cybersecurity principles.

8. Conclusion

Indeed, the role of AI for channel estimation and signal processing constitutes a groundbreaking innovation in the field of telecommunications in the era of the new generation 5G and as a perspective 6G networks. This work has also highlighted how wireless communication issues have always been solved through AI approaches with enhanced solutions compared to conventional methods in terms of accuracy, speed, and flexibility. Using the capabilities of artificial intelligence, these networks are able to perform analyses and adapt to management of the complicated communication milieu in real time, thus improving the quality of their operations.

The strength of AI in channel estimation is found in its adaptability to various and changing environment of a network and multiple propagation schemes. Analytical methods used most of the time work on assumptions of linearity and fixed models to design which fail to portray the nonlinearity, randomness in today's communication channels. On the other hand, AI capable algorithms especially those applying machine learning and deep learning protocols are able to model such complications. Due to this direct data learning, these models can predict channel states with incredible accuracy removing estimation errors, enhancing signal quality. In addition, intelligent filtering and noise removal, as well as interference suppression, which form part of the AI capabilities, help in developing stronger links for signal processing.

The findings of this research have contributed to both practical implementation as well as academic knowledge of AI in channel estimation and signal processing for modern networks. When the theoretical analysis has been complemented by the empirical research, the paper has proven that both conceptual and practical applications of AI have stronger potential than traditional techniques for addressing the complex nature of 5G and 6G environments. Therefore, the results emphasize the fact that AI can serve as both as an enhancement of conventional network structures and as a completely new generation of developments, which includes intelligent beamforming and adaptive resource management. They are important in fulfilling the bandwidth demands, low latency, and enormous connectivity calls for the new generation networks.

Whereas the actual network structures detailed in this research may remain confined to the technical area of implementation, their management and potential future developments will have profound impact on the future of the strategy of the networks' design and deployment. Continued innovation using artificial intelligence in networking technology is evidenced by the adoption of the technology by telecommunications providers and equipment manufacturers leading to intelligent and self-organizing networks. This change is especially relevant for 5G and 6G since AI integration will enable new applications between these two technologies, from holographic real-life experiences to reliable and low-latency communication for applications like self-driving cars and tele-surgery.

From here, the future of AI to 5G and 6G networks is potentially transformative, opening the door as to what is possible for the purpose of wireless communication. As AI adapts, integrates into improved equipment and software, Self-optimising networks that can learn, grow as well as adapt based on the consumer need as well as the environment is expected to emerge in the future. This evolution will also improve sustainable network performance through optimization of of available spectrum and energy resources. Furthermore, as AI algorithms advance to a great level and their explanations become easy to understand more and more people believe in using them and they become part of the most important communication systems.

As with any transformative technology, it is necessary to recognise the opportunities in artificial intelligence created by 5G and the vision of 6G as well as potential problems and risks. Application of AI including data privacy, algorithm bias and Computational Complexity need to be paid attention towards in order to guide the benefit of applying AI technologies. Mitigation of these factors will require efforts of various scholars, government agencies, and companies to embrace the innovation interdisciplinary approaches.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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