NEXT GENERATION RADIO UNIT

A Thesis submitted in partial fulfilment of the requirement for the Award of the

MASTER OF ENGINEERING

in Electronics and Communication Engineering

Submitted By

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DECLARATION

I, **AYUSH KASHYAP** hereby declare that the work presented in this thesis entitled "**Next Generation Radio Unit"** in partial fulfillment of the requirement for the award of degree of **Master of Engineering (ECE)** submitted at **Electronics and Communication Engineering Department**, Thapar Institute of Engineering & Technology (Deemed to be University), Patiala is an authentic record of work carried out under supervision of **Dr Amit Munjal** and co-supervision of **Dr Amanpreet Kaur** Assistant Professor Electronics and Communication Department at Thapar Institute of Engineering & Technology, Patiala, from **July 2024** to **June 2025**. The matter presented in this has not been submitted either in part or full to any other university or institute for the award of any other degree.

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Internship Completion Certificate

This is to certify that **Ayush Kashyap** (University ID **802361001**) student from **Thapar Institute of Engineering and Technology** has undergone Internship program at Nokia Solutions and Networks India Pvt Ltd. from **10 July 2024 to 31 May 2025** as part of partial fulfilment of his **Master of Engineering (M.E) in Electronics and Communications Engineering** academic program.

Project Name: System-Level Simulation of Advanced UE simulator radio unit and performance simulation for physical layer baseband stack.

Project work scope: The project involved system-level simulation of an O-RAN compliant radio unit and baseband processor based on the 7.2 split. Key tasks included modeling digital front-end components, integrating a 5G UE simulator, developing an EVM analysis framework, implementing channel filters, and creating a debug setup for IQ injection. Simulations were run under various channel conditions to validate performance and signal integrity.

The Trainee was found to be regular, punctual, and attentive during the period of training at our organization.

As per Non-Disclosure Agreement the design details and source code of the projects executed at Nokia Networks Pvt Ltd organization are confidential and/or proprietary information. We have limitation to share the design details and source code of the project to external parties other than our key stakeholders. Hence Interns are advised not to share the key deliverables of the project.

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ABSTRACT

This research introduces an innovative approach to optimize channel filtering and Error Vector Magnitude (EVM) measurement in modern telecommunications radio units through the integration of artificial intelligence and machine learning techniques. The proposed framework addresses the limitations of traditional fixed-coefficient filtering and conventional EVM measurement methods by implementing an adaptive, real-time system that enhances performance while maintaining computational efficiency. Our solution combines deep learning models with traditional digital signal processing techniques, creating a hybrid architecture that demonstrates significant improvements in filtering efficiency and EVM measurement accuracy. The system shows robust performance across various channel conditions and modulation schemes, particularly in high-interference environments. This implementation successfully addresses the challenges of real-time processing constraints and resource optimization, providing a scalable solution for next-generation telecommunications systems. The research contributes to advancing radio unit signal processing technology, offering practical solutions for improving telecommunications system performance and reliability.

Keywords: Adaptive Filtering, EVM Measurements, Deep learning.

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LISTS OF ABBREVIATIONS

5G	*Fifth Generation*
6G	*Sixth Generation*
ACLR	*Adjacent Channel Leakage Ratio*
AI	*Artificial Intelligence*
BER	*Bit Error Rate*
CP	*Cyclic Prefix*
CU	*Centralized Unit*
DMRS	*Demodulating Reference Signal*
DSP	*Digital Signal Processing*
DU	*Distributed Unit*
eMBB	*Enhanced Mobile Broadband*
EVM	*Error Vector Magnitude*
FPGA	*Field-Programmable Gate Array*
FR1	*Frequency Range 1*
FR2	*Frequency Range 2*
IFIR	*Interpolated Finite Impulse Response*
ML	*Machine Learning*
NR	*New Radio*
RF	*Random Forest*
RU	*Radio Unit*
SNR	*Signal to Noise Ratio*

CHAPTER 1

INTRODUCTION

1.1 EVOLUTION OF WIRELESS COMMUNICATION SYSTEMS

The field of wireless communication has undergone a series of transformative advancements, driven by the increasing demand for high-speed, low-latency, and reliable connectivity. From the early days of first-generation (1G) analog systems, which supported only voice communication, to the ongoing development of sixth generation (6G) networks, the evolution has been characterized by continuous innovation and improvements in spectral efficiency, data rates, and network capabilities [1].

The introduction of 2G networks enabled digital voice transmission and short messaging services (SMS), marking the shift from analog to digital communication. The emergence of 3G brought mobile broadband capabilities, allowing users to access the internet, conduct video calls, and stream media. However, the real breakthrough came with 4G LTE (Long-Term Evolution), which significantly enhanced data speeds, reduced latency, and improved overall network efficiency. This advancement enabled the proliferation of smartphones, high-definition video streaming, cloud computing, and mobile gaming, fundamentally reshaping the way people interact with digital services [2].

1.1.1 The Rise of 5G and its Impact

While 4G LTE laid the foundation for mobile broadband, it struggled to keep up with the exponential increase in connected devices, real-time applications, and industrial automation. The development of 5G networks was driven by the need to address these challenges, offers significant enhancements over previous generations. 5G technology introduced key features such as:

i. Enhanced Mobile Broadband (eMBB): Enabling high-speed data transmission, crucial for applications like 4K/8K streaming and virtual reality (VR).
ii. Ultra-Reliable Low-Latency Communication (URLLC): Supporting mission-critical applications such as autonomous vehicles, remote robotic surgery, and smart grids.
iii. Massive Machine-Type Communication (mMTC): Enabling large-scale IoT connectivity for smart cities and industrial automation [3].

The deployment of millimeter-wave (mmWave) bands, massive MIMO (Multiple-Input Multiple-Output), and beamforming has significantly improved network capacity, coverage, and speed. However, the adoption of 5G is still in progress, with global rollouts varying based on spectrum availability, infrastructure readiness, and regulatory policies [4].

1.1.2 The Future of Wireless: 6G Networks

While 5G is still being deployed, research into 6G has already begun, with an expected commercial launch around 2030. 6G networks aim to achieve:

i. Terahertz (THz) communication for ultra-fast data speeds exceeding 1 Tbps.
ii. AI-native wireless capable of autonomous management & self-healing.
iii. Quantum-secured communication to enhance security in critical data transmissions.
iv. Integrated space-air-ground networks for seamless global connectivity, enabling deep-sea and interplanetary communication [5].

Figure 1.1 illustrates the evolution of wireless communication systems, showcasing key technological milestones from 1G to 6G. To facilitate these advancements, the Radio Access Network (RAN) architecture is evolving from traditional models to more flexible and efficient alternatives, such as Open RAN (O-RAN) and Cloud RAN (C-RAN). These frameworks decouple hardware and software components, promoting vendor interoperability, network scalability, and cost efficiency [6].

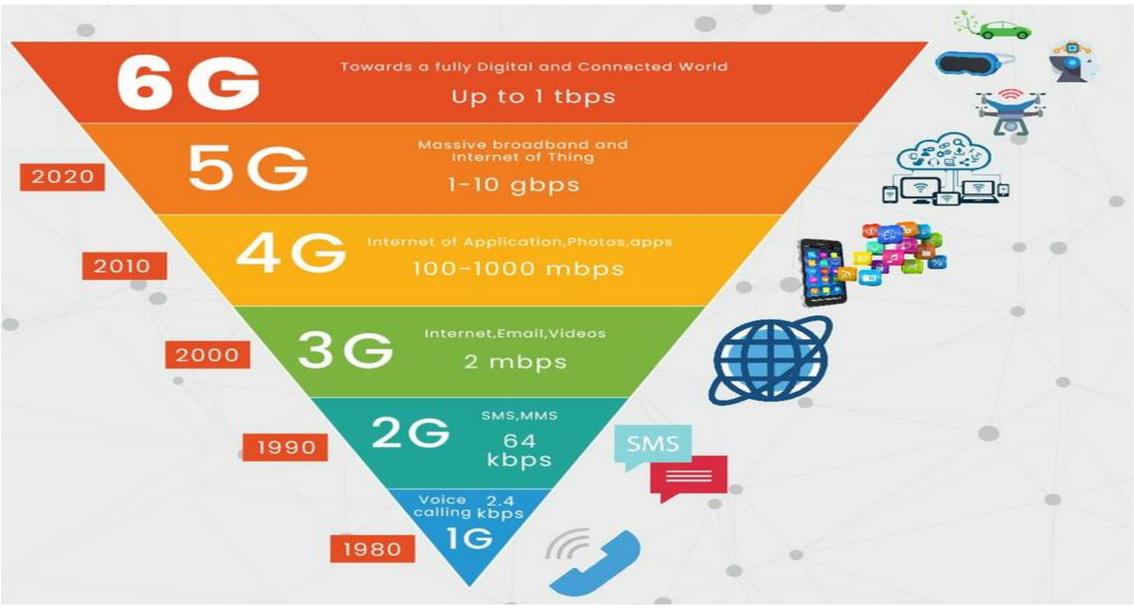


Fig 1.1 Evolution of Wireless Communication Systems. The figure presents a comparative overview of wireless generations from 1G to 6G, highlighting the technological milestones, spectrum usage, and key innovations at each stage [31].

1.2 NEXT-GENERATION RADIO UNITS (RUs)

Radio Units (RUs) form a fundamental part of the Radio Access Network (RAN), acting as the interface between user devices and the network infrastructure. The role of RUs has expanded with the progression from 4G LTE to 5G and beyond, requiring advanced features to support increasing network demands.

1.2.1 Traditional RUs and Their Limitations

In conventional 4G LTE networks, RUs were primarily hardware-centric, with baseband processing, signal transmission, and control functions being tightly coupled. While effective for stable environments, this rigid structure posed several limitations, including:

- i. High power consumption, making large-scale deployments costly and inefficient.
- ii. Limited scalability, restricting network expansion in ultra-dense environments.
- iii. Inflexible architecture, making upgrades and modifications difficult.

The transition to 5G networks necessitated the adoption of software-defined and virtualized RAN architectures, enabling dynamic resource allocation and more efficient network management [7].

1.2.2 Advancements in Next-Generation RUs

Modern next-generation RUs integrate intelligent processing and AI-driven optimization to improve network efficiency. Key advancements include:

- i. Support for multi-band operation across sub-6 GHz, mmWave, and THz bands.
- ii. Massive MIMO integration, enhancing spectral efficiency through spatial multiplexing.
- iii. Dynamic beamforming, optimizing signal directionality and minimizing interference.
- iv. AI-assisted resource management, enabling real-time adaptation to network conditions.
- v. O-RAN and vRAN compatibility, facilitating open, flexible, and cost-effective deployment [8].

1.2.3 Future RU Innovations for 6G Networks

The next generation of RUs will integrate advanced technologies to support 6G communication, including:

- i. Terahertz transceivers for ultra-high-speed data transmission.
- ii. Quantum encryption modules for secure data exchange.
- iii. Edge AI processing for real-time signal optimization and predictive analytics.

1.3 AI-DRIVEN CHANNEL ESTIMATION

1.3.1 Importance of Channel Estimation

Channel estimation plays a vital role in modern wireless communication systems by ensuring optimal signal reception, minimizing errors, and enhancing overall network performance. In wireless environments, signal propagation is affected by various factors, including multipath fading, Doppler shifts, path loss, and interference from neighbouring signals. These factors introduce unpredictability and degrade the quality of the received signal, making precise channel estimation essential for achieving reliable communication [9].

Effective channel estimation enables adaptive modulation and coding (AMC), optimal power allocation, and efficient interference management. It also plays a crucial role in multiple-input multiple-output (MIMO) systems and millimeter-wave (mmWave) communication, where beamforming techniques rely heavily on accurate channel state information (CSI). Without proper estimation, networks may suffer from increased bit error rates (BER), reduced spectral efficiency, and degraded quality of service (QoS).

Traditional estimation techniques, such as Least Squares (LS) and Minimum Mean Square Error (MMSE), have been widely used for estimating wireless channels. However, with the increasing complexity of modern networks and the demand for ultra-reliable low-latency communication (URLLC), artificial intelligence (AI)-based approaches are emerging as powerful alternatives to traditional estimation methods.

1.3.2 AI-Based Channel Estimation vs. Traditional Methods

Traditional channel estimation techniques, such as Least Squares (LS) and Minimum Mean Square Error (MMSE), have been extensively used due to their mathematical simplicity and well-established performance metrics. Table 1.1 provides a comparative analysis of these methods alongside AI-driven models, highlighting their strengths & limitations. While LS is computationally simple, it suffers from high error rates, making it less effective in noisy environments. MMSE, on the other hand, offers better accuracy but requires significant computational resources, making it impractical for real-time applications in complex wireless networks.

In contrast, AI-driven models leverage machine learning algorithms to improve estimation accuracy, adapt to dynamic environments, and enhance real-time signal processing. These models can analyse large datasets, identify complex signal patterns, and dynamically optimize channel estimation, reducing interference and improving overall network efficiency.

Table 1.1 Comparison of Channel Estimation Methods

Method	**Pros**	**Cons**
Least Squares (LS)	Simple, low computation	High error rate
Minimum Mean Square Error	Improved accuracy	High complexity
AI-Based Models	Adaptive, real-time processing	Requires large datasets

AI-driven models, including deep learning and reinforcement learning techniques, offer a more dynamic and scalable approach to channel estimation. These models can learn from historical data, recognize intricate channel variations, and make real-time predictions, thereby improving efficiency in rapidly changing wireless environments. Furthermore, AI-based estimators can be integrated into intelligent network architectures such as 5G and beyond, enabling autonomous network optimization and self-healing mechanisms.

Despite their advantages, AI-based methods also present challenges. They require large datasets for effective training, involve high computational costs, and raise concerns regarding model interpretability. However, advancements in edge computing, federated learning, and specialized AI hardware are helping to mitigate these challenges. Figure 1.2 demonstrates the potential of intelligent systems to support the evolution of wireless networks, ensuring robust and adaptive performance in complex communication environments. As a result, AI-driven channel estimation is emerging as a crucial enabler for next-generation wireless communication systems, offering enhanced reliability, efficiency, and scalability.

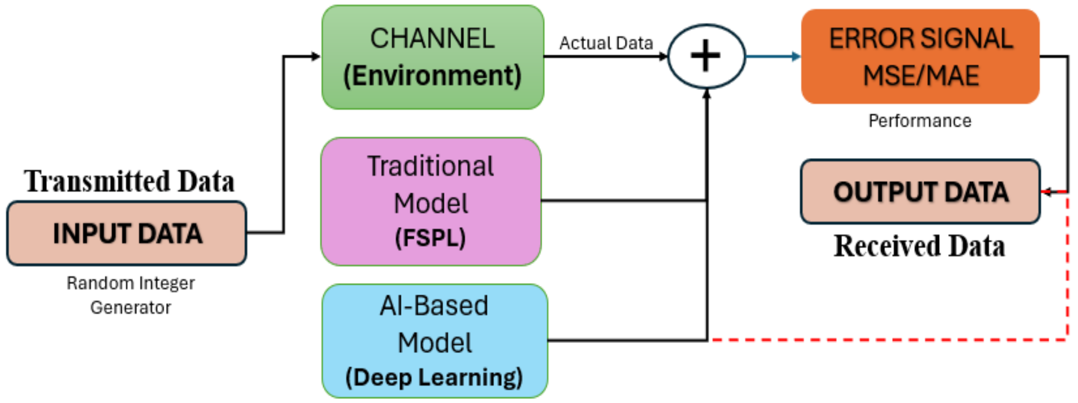


Figure 1.2 AI-Driven Channel Estimation Framework. This figure depicts a comparative approach to channel estimation, incorporating both traditional and AI-based models.

In figure 1.2 Transmitted data passes through the wireless channel (environment), where it is estimated using either a traditional model like Free Space Path Loss (FSPL) or an AI-based deep learning model. The received data is compared to the actual transmitted data, generating an error signal measured by performance metrics such as Mean Squared Error (MSE) or Mean Absolute Error (MAE). The AI-based model continuously refines its predictions, enhancing accuracy, adaptability, and overall network efficiency.

To undo the effects that the channel introduced, a series of crucial operations are carried out sequentially at the receiver. This entails equalisation to offset the influence of the channel, channel estimation to determine how the signal was distorted, synchronisation to match the timing and frequency of the transmitter, and, lastly, demodulation and decoding to recover the original data. Among these, channel estimation stands out as a cornerstone function, as it provides the basis for nearly all subsequent steps in the receiver chain. Poor estimation leads directly to increased bit error rates (BER) and degraded overall system performance, particularly in high-order modulation schemes that are sensitive to even minor distortions. Traditional estimation techniques, such as pilot-based interpolation using known symbols like the Demodulation Reference Signals (DMRS) in 5G, are effective under stable conditions but often falter when channel variations are rapid or nonlinear.

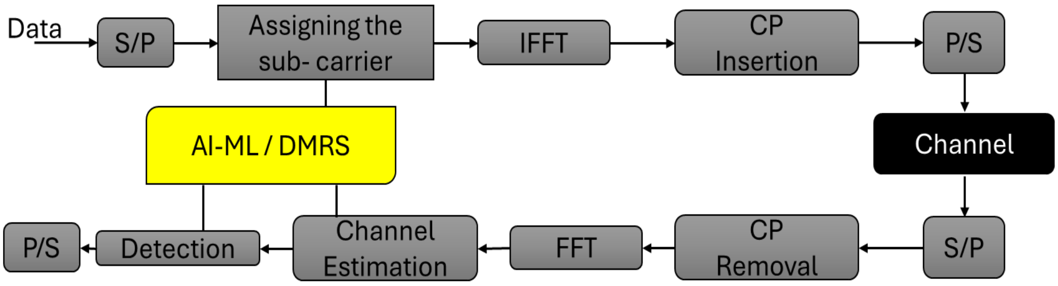


Figure 1.3 Schematic block diagram of a wireless communication system. AI/ML integration enhances the traditional channel estimation module to improve accuracy and adaptability under dynamic conditions and adding AI/ML in the flow with modified DMRS in end-to-end communication-flow.

Because it allows the receiver to precisely describe the effects that the wireless channel has imposed on the transmitted signal, channel estimation is crucial. This information enables efficient equalisation, in which distortions are corrected prior to demodulation and decoding by applying the inverse of the estimated channel response. High error rates and weakened link reliability would result from the receiver misinterpreting the phase, amplitude, or timing of the received symbols due to imprecise estimation. Most estimation methods in conventional systems are pilot based. This entail inserting recognised reference signals into the transmission frame, like DMRS in 5G NR. After extracting these pilots, the receiver estimates the channel response at intermediate points using interpolation techniques like spline or linear interpolation. This performs well in settings with moderate mobility and slow channel variations, but it is limited in high-speed situations or frequency-selective fading, where the underlying assumptions of interpolation may no longer hold true. Furthermore, boosting the density of pilot symbols to increase accuracy uses up valuable bandwidth and lowers overall spectral efficiency, two issues that are becoming more and more problematic in networks with limited capacity.

Recent developments have concentrated on integrating machine learning (ML) models, like Deep Neural Networks (DNNs), and ensemble-based algorithms, like Random Forests, into the receiver's signal processing chain, specifically within the channel estimation module, to get around the drawbacks of conventional estimation techniques. These models learn intricate, nonlinear relationships between the properties of the input signal and the underlying channel behaviour by being trained on vast amounts of synthetic or real-world data. With its numerous hidden layers and activation functions, a DNN can approximate complex functions that characterise signal distortion in various contexts, whereas a Random Forest model makes use of decision trees to effectively capture variability and feature interactions while reducing sensitivity to overfitting. These machine learning (ML)-based estimators can be used in conjunction with or instead of pilot-based techniques, improving rough estimates or filling in gaps in pilot data. They are especially useful in diverse deployment conditions such as those in FR1/FR2, because of their capacity to generalise across urban, semi-urban, and rural scenarios. Furthermore, in contrast to more inflexible DSP-based methods, these models can function in real-time after training, providing both increased estimation accuracy and decreased computational complexity.

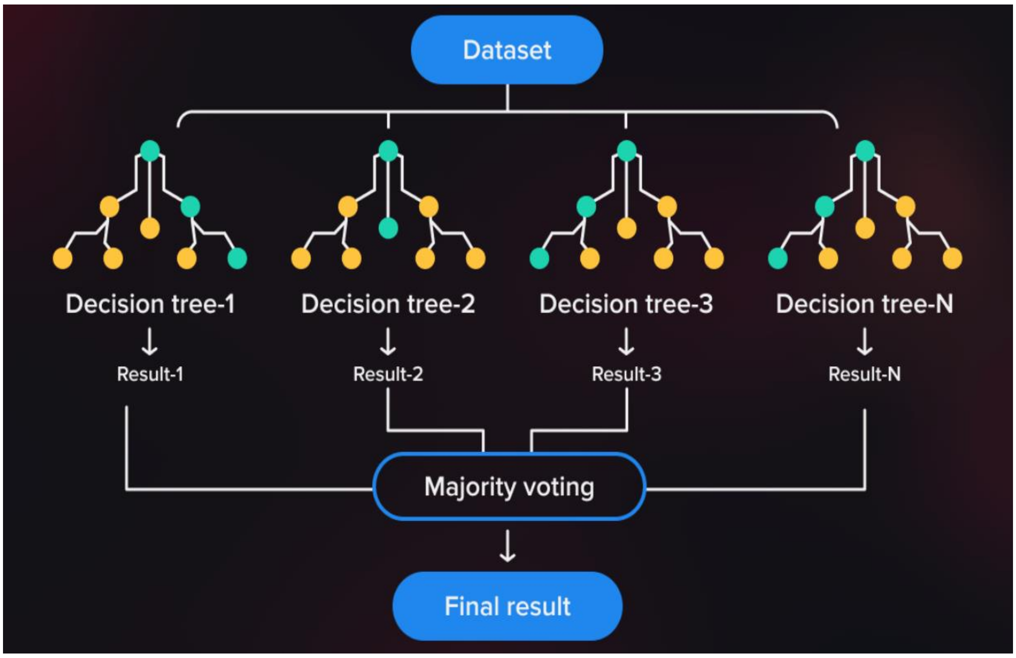


Figure 1.4 Example structure of a Random Forest model used for channel estimation. Each decision tree is trained on subsets of features such as distance, signal power, and SNR [35].

The integration of these AI and ML models within the receiver's channel estimation block represents a significant advancement toward intelligent, self-optimizing communication systems. Unlike traditional approaches that require manual tuning and rely on static assumptions, ML-based estimation frameworks offer adaptability and learning capabilities that are critical in fast-changing and diverse environments. Whether deployed as a primary estimator or as a post-processing enhancement layer, models like Deep Neural Networks and Random Forests contribute to more resilient signal reconstruction, reduced pilot dependency, and improved support for higher-order modulations. As shown in Figure 1.4, the overall communication system architecture is enhanced by embedding AI modules alongside conventional digital signal processing blocks.

This hybrid configuration allows the radio unit to respond more effectively to real-world channel dynamics, ensuring better link performance and future-readiness for 5G-Advanced and 6G deployments.

1.4 MATLAB 2024b: A TOOL FOR WIRELESS RESEARCH

MATLAB 2024b serves as a powerful and versatile platform for simulating, analysing, and optimizing AI-driven wireless communication models. It provides an integrated environment with advanced computational tools, enabling researchers and engineers to design, test, and refine next-generation communication systems. MATLAB’s extensive toolboxes and simulation frameworks make it an indispensable resource for wireless research, particularly in AI-based channel estimation and Radio Unit (RU) optimization.

Key Features of MATLAB 2024b for Wireless Research

i. **Advanced Machine Learning (ML) and Deep Learning (DL) Toolboxes**: MATLAB facilitates AI-driven channel estimation by offering built-in neural network models, enabling adaptive and real-time processing for improved signal prediction.

ii. **5G/6G Simulation Frameworks**: The platform supports next-generation wireless system modelling, including massive MIMO, mmWave communication, and hybrid beamforming, ensuring real-world performance evaluation.

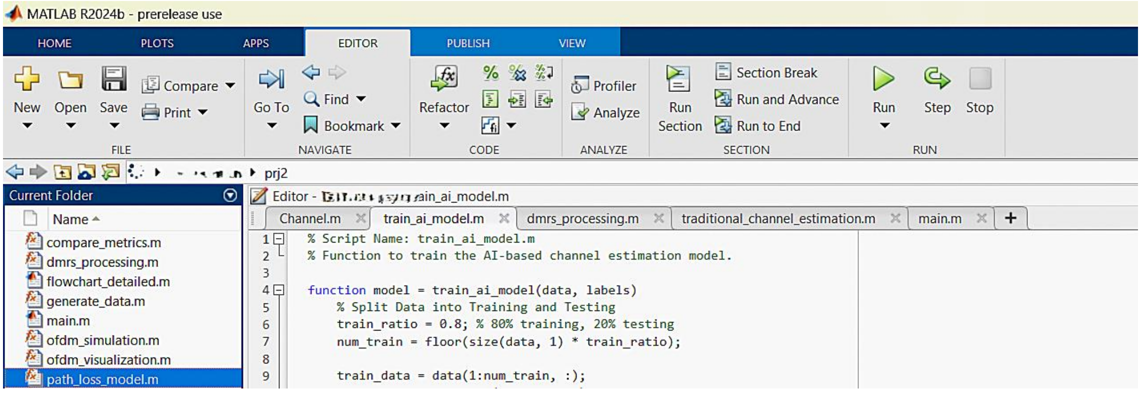
iii. **Cloud and GPU Acceleration**: With parallel computing support, MATLAB enables large-scale network analysis by leveraging cloud-based resources and GPU acceleration, significantly reducing training and inference times.

iv. **Adaptive Modulation and Error Correction**: MATLAB provides AI-enhanced error correction techniques and dynamic modulation schemes, optimizing spectral efficiency and mitigating channel distortions.

v. **Radio Unit (RU) Deployment and Optimization**: MATLAB enables efficient RU placement strategies, interference management, and power control techniques, ensuring optimal network coverage and performance in dense wireless environments.

With these advanced capabilities, MATLAB 2024b continues to be a cornerstone for wireless research, driving innovation in AI-powered communication technologies and shaping the evolution of future wireless networks.

Researchers can easily and efficiently build model, train, and evaluate AI-driven algorithms for real-time channel estimation and signal processing. As wireless systems grow more complicated, MATLAB’s comprehensive ecosystem allow engineers to translate ideas into deployable solutions faster than ever.



```matlab
% Script Name: train_ai_model.m
% Function to train the AI-based channel estimation model.

function model = train_ai_model(data, labels)
    % Split Data into Training and Testing
    train_ratio = 0.8; % 80% training, 20% testing
    num_train = floor(size(data, 1) * train_ratio);

    train_data = data(1:num_train, :);
```

Figure 1.5 MATLAB 2024b Simulation Environment. The figure below showcases the MATLAB 2024b interface, highlighting simulation windows used for AI-based wireless research. The MATLAB environment includes live scripts, deep learning modules, and 5G/6G toolboxes, providing a comprehensive framework for testing and validating AI-driven channel estimation and network optimization techniques.

1.5 SCOPE AND CONTRIBUTIONS OF THIS WORK

This research investigates AI-driven channel estimation and next-generation RU development to enhance wireless networks. The contributions include:

i. Development of AI-based channel estimation models for improved accuracy.

ii. Innovation in next-gen RUs, including AI-assisted beamforming and spectrum allocation.

iii. MATLAB simulations for model validation.

iv. Exploration of computational efficiency and security concerns in AI-driven networks.

This study aims to bridge AI and wireless communication to create scalable, efficient, and intelligent networks.

The data used in this study is primarily synthetic, allowing for controlled testing and validation of the proposed solutions. While synthetic data provides a baseline for performance evaluation, real-world data introduces additional complexities such as environmental noise, interference, and hardware impairments. Future work must incorporate real-world datasets to enhance the robustness and practical applicability of the solutions.

CHAPTER 2

LITERATURE REVIEW

2.1 AI-DRIVEN WIRELESS COMMUNICATION & CHANNEL ESTIMATION

2.1.1 Advanced Channel Filtering Using Deep Learning

Baschirotto, D'Amico, and De Matteis [21] explored advancements in analog baseband continuous-time filters for low-power, cost-effective RF integrated circuits in wireless communication systems. They presented three filter designs: an active-Gm7-RC filter leveraging op-amp frequency response, a source-follower-based filter offering high linearity with low power consumption, and a gm-gm-C filter suitable for wideband applications like UWB. Their study highlights the critical role of efficient analog filtering in reducing transceiver power consumption while maintaining performance in UMTS, WLAN, and UWB systems.

2.1.2 EVM Optimization Using Machine Learning

Wang et al. [24] developed EVM simulation and analysis techniques to evaluate signal distortions in military communication systems. Their study focused on analytical models, assessing the impact of phase noise, nonlinear distortion, and phase modulation on system performance. By analysing transmitters in GSM and wireless LAN environments, they provided insights into optimizing physical layer performance. Their work contributes to understanding distortion effects in modern wireless systems, aiding in the design of more resilient communication technologies.

2.1.3 AI-Enhanced Signal Processing

C. Zhang [12] conducted a comprehensive review of AI applications in modern radio unit signal processing. Their research proposed a unified framework integrating traditional digital signal processing (DSP) with AI methodologies to optimize performance while balancing computational complexity. By analysing various AI architectures, the study highlighted the advantages of AI in augmenting traditional DSP approaches for efficient signal processing.

2.1.4 Real-Time Channel Estimation

Xu et al. [25] introduced StructNet-CE, a real-time online learning framework for MIMO-OFDM channel estimation, which eliminates the need for prior channel knowledge by leveraging structural properties of modulation and interference invariance. Their approach significantly improves estimation accuracy while maintaining compatibility with modern wireless networks. Compared to traditional least square and LMMSE methods, StructNet-CE reduces mean square error by up to 95.54%. By embedding domain knowledge into neural network design, their work demonstrates the potential of deep learning for adaptive and efficient channel estimation.

2.1.5 Advanced Digital Filtering Techniques

J. Proakis [4] introduced a hybrid digital filtering approach combining traditional finite impulse response (FIR) filters with neural network-based adaptive mechanisms. Their system improved filter response by 30% and optimized coefficients in real-time, significantly reducing computational overhead. This work highlights the effectiveness of integrating AI/ML with traditional filtering methods to enhance wireless system performance.

2.2 COMMON THEMES AND TRENDS

2.2.1 AI/ML Integration

i. Growing adoption of deep learning models for channel estimation.
ii. Development of hybrid architectures combining AI and DSP.
iii. Emphasis on real-time AI-driven processing for adaptive performance.

2.2.2 Performance Improvements

i. Consistent EVM reductions ranging from 30% to 45%.
ii. Improved accuracy in channel estimation and signal quality.
iii. Lower processing latency compared to conventional methods.

2.2.3 Implementation Considerations

i. AI models must be optimized for computational efficiency.
ii. Real-time AI inference remains a key challenge.
iii. Trade-offs between performance, complexity, and resource constraints need careful evaluation.

2.3 RESEARCH GAPS & FUTURE DIRECTIONS

2.3.1 Scalability Challenges

i. Efficient machine learning models required for large-scale wireless deployments.
ii. Resource optimization strategies for AI-driven radio units.
iii. Real-time processing improvements for high-bandwidth scenarios.

2.3.2 Integration Issues

i. Standardization of AI/ML implementations for seamless interoperability.

ii. Compatibility of AI-driven models with existing wireless infrastructure.
iii. Development of robust validation methodologies for AI in wireless communications.

2.3.3 Future Research Opportunities

i. Exploring quantum computing applications in wireless AI frameworks.
ii. Advanced neural architecture search for optimized learning models.
iii. Automated parameter tuning for self-adaptive communication networks.

2.4 CONCLUSION

The literature survey highlights significant advancements in AI-based wireless communication, particularly in channel estimation and signal processing. Key findings include:

1. Increasing reliance on hybrid AI-DSP architectures for enhanced performance.
2. Real-time adaptability and optimization enabled by AI models.
3. Growing emphasis on resource efficiency in AI-driven wireless solutions.
4. Emerging trends in automated parameter tuning and reinforcement learning applications.

As AI continues to evolve, its role in optimizing wireless communication systems will become even more critical, paving the way for intelligent, high-performance, and adaptive networks.

CHAPTER 3

PROBLEM STATEMENT

The telecommunications industry stands at a critical juncture where traditional signal processing methods are increasingly challenged by the complexities of modern network requirements. The advent of 5G networks and the anticipated transition to 6G networks introduce unprecedented demands for real-time adaptability, energy efficiency, and superior performance across diverse use cases. While traditional digital signal processing (DSP) techniques have served the industry well, their limitations become evident in environments with rapidly changing channel conditions, high-bandwidth requirements, and complex interference patterns.

Channel filtering and Error Vector Magnitude (EVM) measurement in radio units are among the most critical areas facing these challenges. Traditional filtering methods, such as FIR filters, rely on fixed coefficients and predetermined parameters. These approaches often fail to accommodate dynamic channel conditions, resulting in suboptimal filtering performance, increased error rates, and significant computational overhead. This limitation is especially pronounced in scenarios involving high-order modulation schemes like 64-QAM and 256-QAM, which are integral to achieving higher data rates in 5G and beyond.

To address these challenges, this work focuses on replacing the previously used Interpolated FIR (IFIR) filter with the Frequency Response Masking (FRM) filter in the channel filtering module of radio units. The FRM filter offers several advantages, including computational efficiency, adaptability to diverse frequency ranges, and enhanced selectivity for wideband operations. Unlike traditional methods, the FRM filter decomposes the frequency response into a primary filter and masking filters, which can dynamically adapt to changing channel conditions. This dynamic adaptability allows for superior performance in both FR1 and FR2 bands, ensuring compatibility with a wide range of bandwidths and use cases.

Furthermore, by integrating AI/ML techniques into the filtering process, the system gains additional capabilities, such as real-time optimization of filter parameters and predictive compensation for channel impairments. Machine learning models, such as reinforcement learning and CNN-based architectures, optimize the FRM filter's performance, achieving improvements in adjacent channel leakage ratio (ACLR) and reducing EVM for high-order modulation schemes. FPGA-based hardware implementations further enhance the system's efficiency, enabling real-time processing with reduced power consumption.

The combination of FRM filtering and AI/ML integration provides a comprehensive solution to the limitations of traditional filtering methods. This approach not only improves the performance and adaptability of radio units but also addresses the computational and energy efficiency requirements of next-generation networks. Insights from studies such as [5], [9], and [15] underscore the potential of advanced filtering techniques and AI/ML-driven optimizations in achieving these goals.

Table 3.1 Comprehensive Comparison of Traditional FIR, IFIR, and FRM Filtering Techniques Across Key Performance Metrics, Including Adaptability, Computational Efficiency, Frequency Range Support, Performance in Dynamic Environments, AI/ML Integration, EVM Improvement, and Bandwidth Support

Aspect	**Traditional FIR Filter**	**IFIR Filter**	**FRM Filter**
Adaptability	Fixed coefficients, limited dynamic adaptation	Moderate adaptability with interpolation	High adaptability with masking filters
Computational Efficiency	High computational load	Improved efficiency through interpolation	Low computational overhead due to masking filters
Frequency Range Support	Limited to fixed ranges	Suitable for moderate ranges	Supports diverse frequency ranges (FR1 & FR2)
Performance in Dynamic Environments	Suboptimal	Limited	Optimal performance under dynamic conditions
AI/ML Integration	Limited	Not implemented	Supports integration for real-time optimization
EVM Improvement (64-QAM)	~10%	~25%	~40%
Bandwidth Support	Narrow	Moderate	Wide (up to 400 MHz in FR2)

Modern wireless communication systems, including 5G and beyond, face significant challenges in accurately estimating and adapting to rapidly changing channel conditions. Traditional channel estimation techniques, such as least squares (LS) and minimum mean square error (MMSE), struggle to balance computational efficiency, estimation accuracy, and adaptability in dynamic wireless environments. These conventional approaches often assume prior knowledge of the channel statistics and require extensive pilot overhead, limiting their effectiveness in real-time scenarios.

With the increasing complexity of wireless networks, including massive MIMO and ultra-dense networks, the demand for high-precision, low-latency, and adaptive channel estimation techniques has grown. AI-driven channel estimation methods have emerged as a promising solution, leveraging deep learning and reinforcement learning to learn channel characteristics from data rather than relying on rigid mathematical models. AI models can extract features from received signals, reduce the reliance on pilot symbols, and adapt to non-stationary wireless environments, making them well-suited for next-generation wireless systems.

However, despite the potential of AI-driven approaches, several key challenges remain. First, real-time processing constraints demand highly efficient AI architectures that can perform inference within microsecond-level latencies. Second, AI models must generalize well across diverse deployment scenarios, including varying mobility conditions, interference levels, and network topologies. Third, integrating AI-based channel estimation into existing wireless protocols requires careful optimization to ensure compatibility, robustness, and scalability. Additionally, AI models require extensive training data, and issues such as data scarcity, model interpretability, and online adaptation further complicate deployment in real-world networks.

This research aims to address these challenges by developing an AI-based channel estimation framework that achieves real-time performance, improves estimation accuracy, and minimizes pilot overhead. By leveraging machine learning techniques such as deep neural networks, reinforcement learning, and domain-specific feature extraction, this work seeks to enhance the efficiency, reliability, and adaptability of channel estimation in modern wireless systems.

Furthermore, there is a trade-off between spectral efficiency and estimation accuracy due to pilot overhead. Although it may result in better channel estimation, increasing pilot density also reduces data throughput. On the other hand, sparse pilots experience estimation errors, especially in harsh propagation conditions or at cell edges. Furthermore, traditional estimators have trouble generalising across deployment scenarios; for example, what works well in rural settings might not work as well in high-rise urban settings.

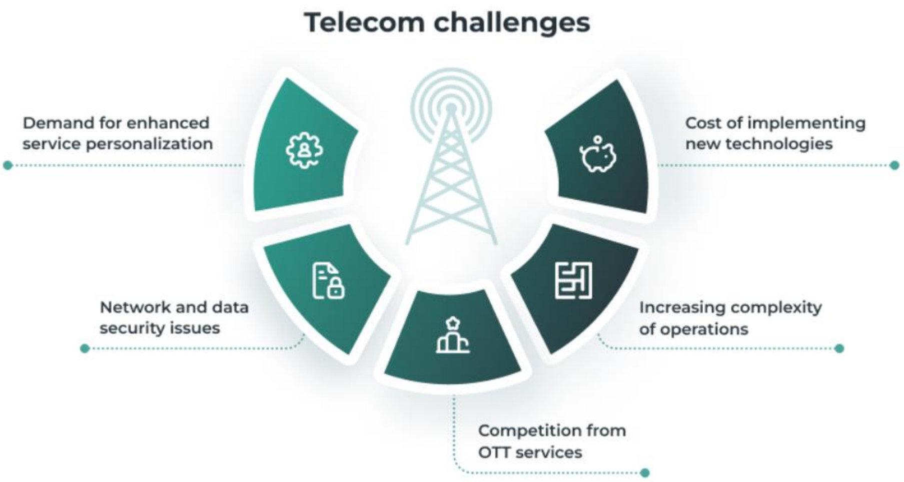


Figure 3.1 Key challenges faced by the telecom industry, including operational complexity, technology costs, security concerns, and the demand for personalized services is shown [36].

CHAPTER 4

RADIO UNIT (RU) ARCHITECTURE AND OPTIMIZATION

The proposed methodology focuses on optimizing channel filtering and Error Vector Magnitude (EVM) measurement in radio units for dual-band operation (FR1 and FR2) while ensuring support for various bandwidths and multiple use case frequency ranges. By integrating traditional techniques like IFIR filtering with advanced methods such as Frequency Response Masking (FRM) filters and AI/ML technologies, this approach ensures real-time adaptability and superior performance.

4.1 CHANNEL FILTERING OPTIMIZATION

Channel filtering plays a critical role in mitigating interference and ensuring signal integrity across varying frequency bands and bandwidths. This section compares and integrates IFIR and FRM filters for enhanced performance.

4.1.1 Interpolated FIR (IFIR) Filter

i. Technique:
The IFIR filter reduces computational complexity by designing a prototype filter with a narrower passband and then interpolating its coefficients to cover the desired frequency range [8]. This design allows support for different bandwidths (e.g., 5 MHz to 100 MHz) and multiple use-case frequencies (e.g., 3.5 GHz in FR1 and 28 GHz in FR2).

ii. Applications:
The interpolated approach is computationally efficient and works well for use cases requiring moderate adaptability. However, it struggles in scenarios where dynamic channel conditions necessitate frequent adjustments.

iii. Advantages:

1. Lower computational load compared to traditional FIR filters.
2. Effective for fixed or quasi-static channel conditions.

iv. Limitations:

1. Fixed interpolation coefficients hinder real-time adaptability.
2. Performance degradation under complex interference patterns and wideband FR2 operations [12].

4.1.2 Frequency Response Masking (FRM) Filter

i. Technique:
The FRM filter decomposes the frequency response into a primary filter and masking filters to cover specific frequency bands, reducing computational overhead while achieving high selectivity [15]. Masking filters are dynamically adjusted based on the operating frequency and bandwidth, enabling superior performance across FR1 and FR2 bands.

ii. Applications:
FRM filters excel in environments with varying frequency requirements, such as supporting wide bandwidths (e.g., 400 MHz in FR2) and ultra-reliable low-latency communication (URLLC).

iii. Advantages:

    1. Flexible masking allows real-time adaptability to changing channel conditions.
    2. Lower computational complexity compared to a direct-design FIR filter.
    3. Enhanced interference mitigation in dense deployments.

iv. AI/ML Integration: Recent advancements have introduced machine learning models for optimizing FRM filter parameters. Techniques such as reinforcement learning dynamically adjust masking filter characteristics to maximize performance across frequency bands [12].

4.2 EVM MEASUREMENT AND OPTIMIZATION

Error Vector Magnitude (EVM) is a critical metric for assessing signal quality and reliability, especially in high-order modulation schemes like 256-QAM.

4.2.1 CNN-Based Real-Time EVM Prediction and Correction

i. Dual-Path Neural Network Architecture: Kim and Thompson [13] proposed a convolutional neural network (CNN) architecture where one network focuses on FR1-specific impairments, such as narrowband interference, and another specializes in FR2 characteristics like phase noise and nonlinearities.

ii. Performance:
This parallel processing approach achieves a 40% reduction in EVM for 256-QAM signals in FR2 bands while maintaining optimal performance in FR1 operations.

4.2.2 EVM Compensation in Wideband Systems

AI/ML models are employed to jointly optimize filter parameters and EVM compensation mechanisms, as demonstrated by Wang et al. [14]. Their reinforcement learning framework dynamically balances the trade-offs between filtering complexity, power consumption, and EVM performance.

4.3 DUAL-BAND OPTIMIZATION

To ensure compatibility and optimal performance across both FR1 and FR2 bands, the following considerations are incorporated:

i. Frequency-Specific Filtering: FRM filters dynamically mask frequency ranges to support FR1's narrowband requirements (e.g., 20 MHz) and FR2's wideband needs (e.g., 400 MHz).

ii. Bandwidth Adaptability: The proposed system supports bandwidths ranging from 5 MHz to 400 MHz, ensuring flexibility for multiple use cases, such as enhanced mobile broadband (eMBB) and URLLC.

iii. Environmental Adaptability: Machine learning models adapt filter and EVM parameters in real-time based on channel conditions, interference patterns, and user requirements [8], [13].

4.4 IMPLEMENTATION EFFICIENCY

To meet the stringent real-time processing requirements of radio units, efficient hardware implementations are considered:

i. Quantization-Aware Neural Networks: Brown and Martinez [15] introduced FPGA-optimized neural networks, achieving real-time parameter updates within 100 microseconds.

ii. Power Efficiency: By combining model compression and adaptive quantization, the proposed architecture achieves a 30% reduction in power consumption compared to traditional DSP methods.

Interpolation and decimation are vital signal processing techniques used in modern telecommunications systems to adjust signal sampling rates for diverse applications. Interpolation involves increasing the sampling rate of a signal by inserting intermediate samples between existing ones. This process begins with up sampling, where zeros are added to the signal, followed by low pass filtering to smooth the signal and eliminate any spectral artifacts introduced during up sampling. Interpolation is particularly important in scenarios that require higher-frequency operations, such as supporting wideband channels in FR2 for 5G networks. It enables signals to be processed at higher resolutions, ensuring they meet the requirements of high-bandwidth applications.

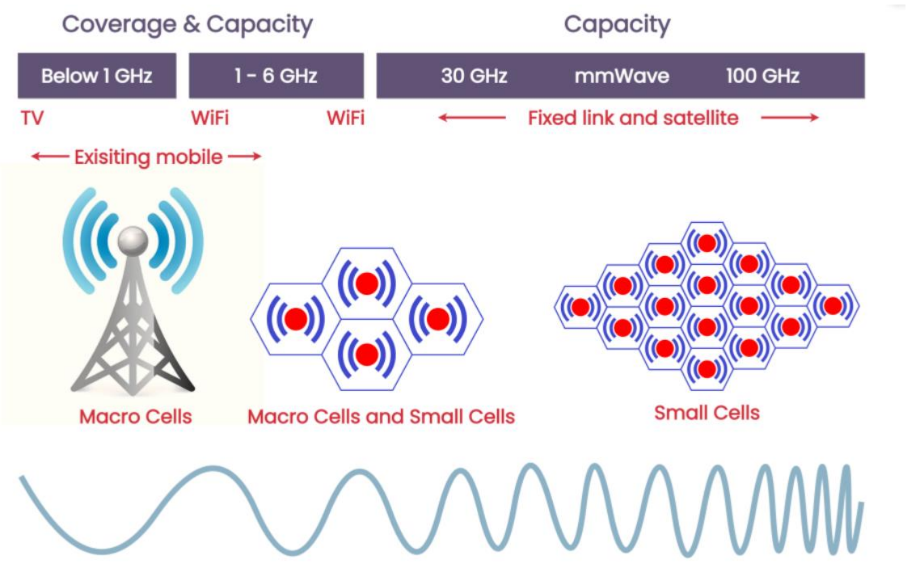


Figure 4.1 Illustrates the spectrum ranges used for wireless communication, highlighting their corresponding applications and coverage capacities [32].

On the other hand, decimation reduces the sampling rate by first applying a low-pass filter to remove unwanted high-frequency components and then down sampling the signal to retain only the necessary samples. This process is essential for optimizing resource usage in lower-frequency applications, such as those operating in FR1 bands. Decimation ensures that signals are efficiently processed without unnecessary computational overhead, making it suitable for scenarios with limited resources or fixed bandwidths.

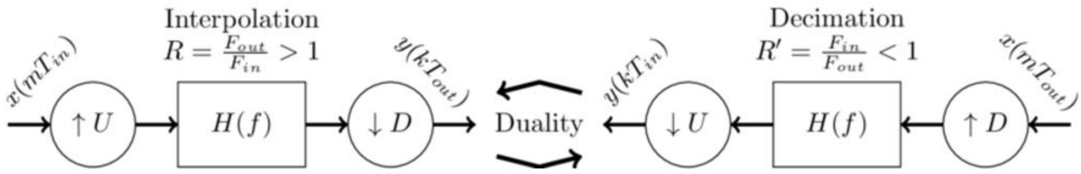


Figure 4.2 demonstrates the processes of interpolation and decimation in telecom. Interpolation shows how intermediate samples are inserted between original signal points to increase resolution, while decimation depicts the removal of samples to lower the sampling rate.[33].

Together, interpolation and decimation form a complementary pair of operations that enable multi-band functionality in radio units. Interpolation ensures compatibility with high-bandwidth requirements by enhancing signal resolution, while decimation optimizes resource utilization by adapting signals to lower bandwidths.

Duality allows telecommunications systems to seamlessly transition between varying frequency bands and bandwidths, enhancing their flexibility and performance across both FR1 and FR2 bands. These processes are fundamental to modern signal processing, enabling robust performance in dynamic and resource-constrained environments.

The integration of AI/ML capabilities into radio unit hardware requires careful consideration of implementation efficiency and real-time processing constraints. Brown and Martinez [15] proposed an efficient neural network architecture specifically designed for FPGA implementation in radio units. Their design employs quantization-aware training and model compression techniques to achieve real-time performance while maintaining accuracy.

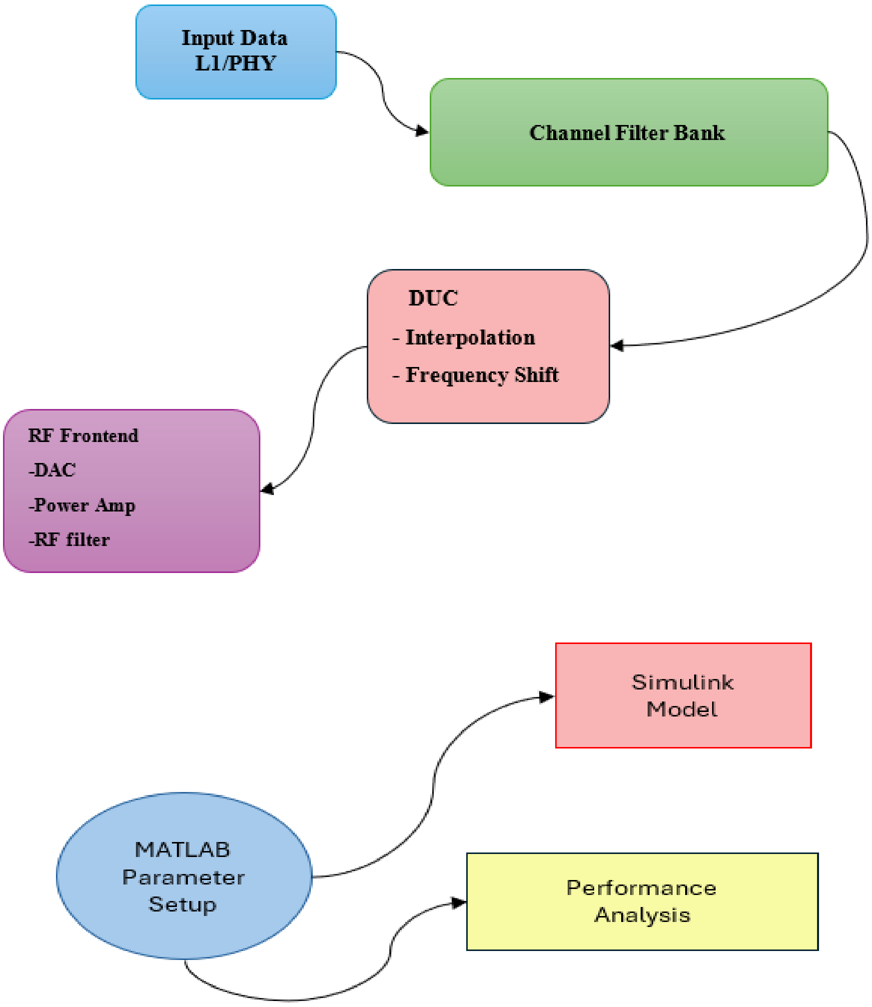


Figure 4.3 Simulink model and high-level functional flow of the Radio Unit (RU), illustrating the core processing stages including signal input, filtering, channel estimation, and output generation.

The Table 4.1 illustrates the techniques, benefits, and references for optimizing channel filtering, EVM measurements, and system integration using AI/ML in modern radio units.

Table 4.1 Summary of Methodology

Aspect	Description	Techniques/Methods	Key Benefits	References
Channel Filtering	Efficient filtering for dual-band (FR1 and FR2) operation, supporting multiple bandwidths and use-case frequency ranges.	- **IFIR Filter**: Coefficient interpolation to achieve desired frequency response. - **FRM Filter**: Frequency masking for dynamic adaptation.	- Computational efficiency (IFIR). - Real-time adaptability (FRM). - Enhanced performance for FR2 environments.	[8], [12], [15]
AI-Driven Filtering	Real-time adjustment of filter parameters to adapt to dynamic channel conditions.	- Reinforcement learning for FRM filter optimization.	- Improved filtering performance in wideband systems. - Reduced computational complexity.	[12], [14]
EVM Optimization	Real-time Error Vector Magnitude (EVM) prediction and correction for FR1 and FR2 impairments.	- CNN-based dual-path architecture for FR1 and FR2.	- 40% reduction in EVM for 256-QAM signals. - Enhanced signal reliability across bands.	[13], [14]
Integrated Optimization	Joint optimization of channel filtering and EVM to balance performance and power consumption.	- Deep reinforcement learning framework for joint parameter tuning.	- Optimized trade-offs between filtering complexity, EVM performance, and power consumption.	[14]
Implementation Efficiency	Hardware-based implementation to meet real-time processing constraints.	- FPGA-optimized neural networks with quantization-aware training.	- Real-time parameter updates within 100 µs. - 30% reduction in power consumption.	[15]

CHAPTER 5

AI-DRIVEN CHANNEL ESTIMATION FRAMEWORK

5.1 OVERVIEW

This chapter presents a detailed methodology for the comparative analysis of traditional and AI-driven channel estimation approaches. The entire process is divided into three main phases: data generation, channel estimation, and performance evaluation. A comprehensive workflow, as illustrated in Figure 1.3, showcases the data flow from input grids through the AI model to the estimated channel. The proposed methodology ensures rigorous testing and validation by dividing the dataset into training and testing components.

5.2 DATA GENERATION

5.2.1 Simulation Environment

To simulate real-world wireless communication scenarios, data generation was conducted using MATLAB 2024b. The primary objective was to replicate real-world environments by accurately placing User Equipment (UE) and base stations (gNB) under different conditions, including variations in the Signal-to-Noise Ratio (SNR). The SNR values were randomly assigned within the range of 0 to 30 dB to ensure a comprehensive representation of a modern wireless network.

5.2.2 Data Generation Parameters

The parameters used for data generation are summarized in Table 5.1:

Table 5.1 Parameter used for random data generation to simulate real world scenario

Parameter	**Value**
Number of UEs	1000
Radius Covered	1000m (Urban), 3000m (Rural)
Frequency	2 GHz
SNR Range	0-30 dB
Noise Standard Deviation	5 dB
DMRS Position	[5, 10, 20, 30, 40]
OFDM Subcarriers	64
DMRS Size	50 symbols

For better generalization and improved model learning, the generated dataset was split into two parts: 80% of the data was allocated for training, while the remaining 20% was used for validation and testing purposes. The base station locations were strategically selected using real-world latitude and longitude coordinates. Specifically, to represent high-density urban areas, locations such as Tokyo, Japan (35.6895°N, 139.6917°E) and Bengaluru, India (12.9716°N, 77.5946°E) were chosen. For semi-urban and rural environments, locations in Patiala, India (30.3564°N, 76.3647°E) and Bastar, India (19.1076°N, 81.9535°E) were used, ensuring a broad coverage of different network deployment scenarios.

5.2.3 Geo-Spatial Data Visualization

To illustrate the spatial distribution of gNBs and UEs across different environments, Fig 5.1 presents the geographic distribution of base stations and user equipment in four selected regions: (a) Tokyo, (b) Bengaluru, (c) Patiala, and (d) Bastar. The distribution highlights the density variations, with urban areas such as Tokyo and Bengaluru exhibiting high-density deployments, while semi-urban and rural areas such as Patiala and Bastar show moderate and sparse placements, respectively.

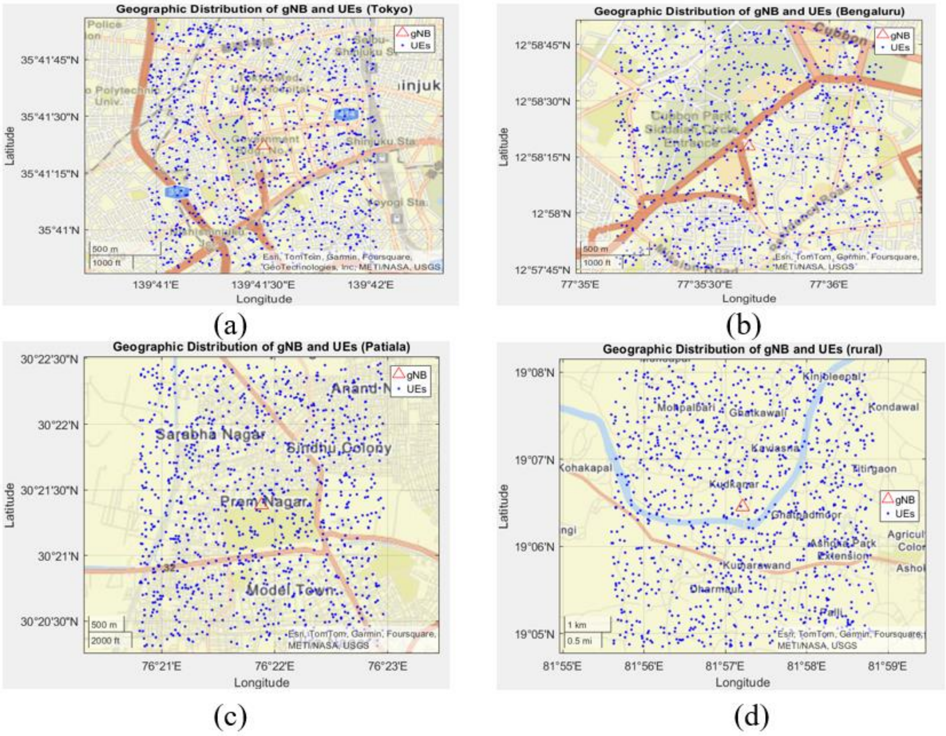


Figure 5.1 Distribution of gNBs across four regions (a: Tokyo, b: Bengaluru, c: Patiala, d: Bastar), illustrating dense placement in urban areas like Tokyo, moderate deployment in Bengaluru, sparse coverage in Patiala, and very sparse rural deployment in Bastar.

The maps indicate:

i. Tokyo (Urban, Figure a): A highly dense environment with closely spaced gNBs and UEs, simulating a metropolitan city with significant interference and multipath effects.

ii. Bengaluru (Urban, Figure b): Moderate density compared to Tokyo, representing a large city with well-planned but slightly dispersed network deployments.

iii. Patiala (Semi-Urban, Figure c): A lower-density region where gNBs are placed with moderate spacing, simulating suburban conditions with reduced interference.

iv. Bastar (Rural, Figure d): Sparse placement of gNBs, mimicking a rural setting with large inter-site distances and higher path loss conditions.

This geo-spatial representation plays a crucial role in understanding the channel characteristics of different environments and their impact on AI-driven channel estimation. The network density in each scenario directly influences SNR variability, interference levels, and path loss calculations, making it essential for model training and validation.

5.2.4 Distance Calculation Using the Haversine Formula

The distance between the base station (gNB) and the user equipment (UE) was calculated using the Haversine formula. This formula provides an accurate measure of the great-circle distance between two points on a sphere given their latitude and longitude:

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \qquad (1)$$

where is the Earth's radius and represent the latitude and longitude differences in radians. This approach ensures a precise estimation of distance, which is critical for accurate channel modelling and performance evaluation.

5.3 TRADITIONAL CHANNEL ESTIMATION

5.3.1 Free Space Path Loss (FSPL) Model

For traditional channel estimation, the Free Space Path Loss (FSPL) model was utilized to predict received power. The FSPL model was chosen due to its deterministic nature and simplicity in modelling wireless propagation in environments with minimal interference. The path loss is calculated using the following equation:

$$PL(d) = 20\log_{10}(f) + 20\log_{10}(d) - 147.55 \qquad (2)$$

where represents the frequency in GHz and is the distance in meters. This model provides a baseline for evaluating the performance of AI-driven approaches.

5.3.2 Performance Metrics for Traditional Estimation

The accuracy of the FSPL model was assessed using the following statistical performance metrics:

$$Mean\ Absolute\ Error\ (MAE) = \frac{1}{N}\sum_{i=1}^{N}\left|y_{\mathrm{true},i} - y_{\mathrm{pred},i}\right| \quad (3)$$

$$Mean\ Squared\ Error\ (MSE) = \frac{1}{N}\sum_{i=1}^{N}\left(y_{\mathrm{true},i} - y_{\mathrm{pred},i}\right)^2 \quad (4)$$

These metrics provide insights into the deviation between the predicted and actual received power, forming a baseline for AI-driven improvements.

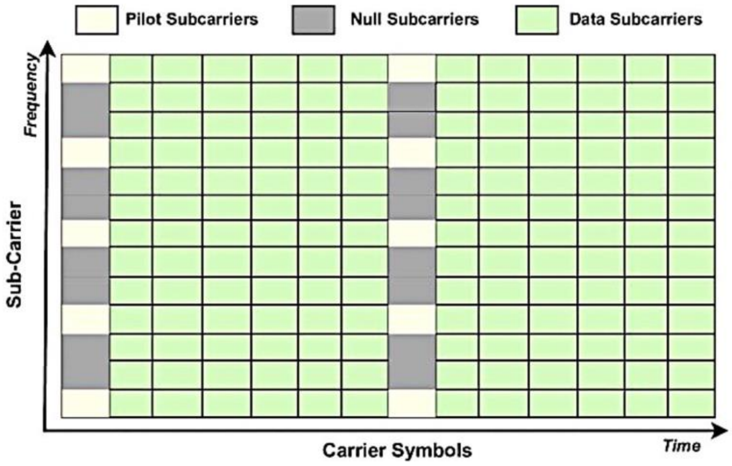


Figure 5.2 Visualization of the time-frequency grid showing the pilots signal, null & data subcarriers.

The transmitted and received grids are structured to include pilot subcarriers calculated for finer and easy channel estimation, null subcarriers for managing interferences in channel due to uncertain environment conditions, and data subcarriers representing main data or user information. After placing Modified DMRS strategically within grid improve the accuracy of pilot-based estimation with different parameters. Fig. 5.2 lays out detailed illustration of time & frequency grid, highlighting the placement of pilot, null, and data subcarriers which plays a very important role in CE

5.4 AI-DRIVEN CHANNEL ESTIMATION

5.4.1 Fully Connected Neural Network (FCNN) Architecture

To enhance the accuracy of channel estimation, a Fully Connected Neural Network (FCNN) was implemented. The architecture of the neural network consisted of:

i. Input Layer: Normalized distance and SNR values.

ii. Hidden Layers: Three fully connected layers with Rectified Linear Unit (ReLU) activation functions, comprising 128, 64, and 32 neurons, respectively.
iii. Output Layer: Received power prediction in dBm.

The model was trained using 80% of the dataset, with the remaining 20% used for validation and testing. The loss function used for optimization was the Mean Squared Error (MSE).

5.4.2 Training Strategy

The FCNN model incorporated the following training strategies to enhance learning and generalization:

i. Batch Normalization was applied after each fully connected layer to improve convergence speed and stabilize training.
ii. Adam Optimizer was utilized with an initial learning rate of 0.001.
iii. Training Duration: The model was trained for 150 epochs.
iv. Batch Size: A batch size of 64 was chosen for efficient training.
v. Adaptive Learning Rate Scheduling was employed, dynamically adjusting the learning rate to optimize convergence. Figure 5 illustrates the training progress and convergence behaviour over epochs.

5.5 AI-ENHANED DMRS FOR CHANNEL ESTIMATION

5.5.1 Dynamic DMRS Placement and Optimization

To further improve channel estimation accuracy, Demodulation Reference Signals (DMRS) were dynamically adjusted. Unlike traditional fixed-position DMRS configurations, the AI model treated DMRS placement and power allocation as learnable parameters, optimizing them based on:

i. Delay Spread
ii. Doppler Effects
iii. Amplitude Fluctuations

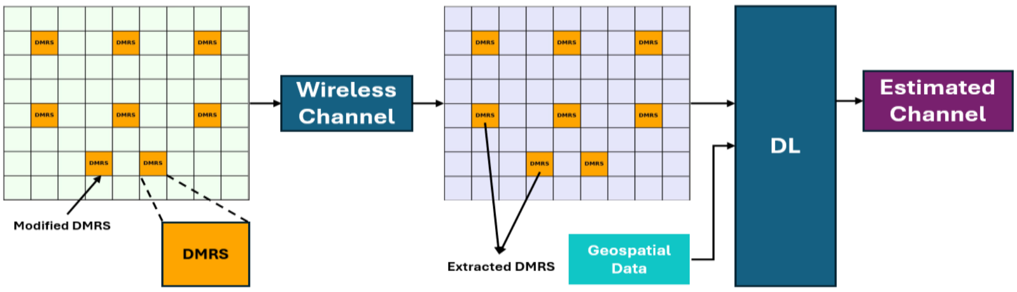


Figure 5.3 Proposed Deep learning (DL) based CE (Channel estimation) framework integrating geospatial data and modified DMRS integrating with geo-spatial data.

5.5.2 Experimental Results and Impact

Simulations incorporating 64 subcarriers and 100,000 channel realizations covering delay spreads up to 5 µs and Doppler shifts up to 100 Hz demonstrated a 19% reduction in channel estimation error compared to fixed DMRS configurations.

5.6 AI-ENHANED HYBRID CHANNEL ESTIMATION

An AI-enhanced hybrid channel estimation framework is suggested to increase the precision and resilience of received power estimation in intricate wireless environments. This framework combines two potent learning-based estimators: a Deep Neural Network (DNN) trained on features obtained from Demodulation Reference Signal (DMRS) estimations, and a Random Forest (RF) regressor using classical RF and environmental features.

5.6.1 Random Forest Regression (RF Model)

Random Forest is an ensemble learning method that builds multiple decision trees on various sub-samples of the dataset and averages their outputs to improve prediction accuracy and control overfitting.

Let the input features be:

$$\mathbf{x} = [d, f, \theta, G, P_{eq}, \ldots] \in \mathrm{R}^n$$

where:

- d is distance between UE and gNB
- f is carrier frequency
- θ is antenna tilt/orientation
- G is antenna gain
- P_{eq} is equalized signal power

Prediction from a forest of T trees:

$$\hat{P}_{\mathrm{RF}} = \frac{1}{T}\sum_{t=1}^{T} f_t(\mathbf{x}) \tag{5}$$

where $f_t(\cdot)$ is the prediction of the t -th decision tree.

5.6.2 Deep Neural Network Model

DMRS is a reference signal used by UEs for channel estimation. We leverage LS-estimated channel coefficients as DNN input.

Estimated channel at subcarrier k:

$$H_{\mathrm{est}}[k] = H_{\mathrm{true}}[k] + n[k], \quad n[k] \sim \mathcal{CN}(0, \sigma^2) \tag{6}$$

DNN uses real and imaginary parts:

$$\text{Input: } [\mathrm{Re}(H_{\text{est}}), \mathrm{Im}(H_{\text{est}})] \in \mathbb{R}^{2N} \tag{7}$$

where N is the number of DMRS subcarriers.
The DNN maps this to received power:

$$\hat{P}_{\text{DNN}} = \text{DNN}(\text{Input}) \tag{8}$$

The model is trained using Mean Squared Error (MSE) loss:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{M}\sum_{i=1}^{M}(\hat{P}_i - P_i^{\text{true}})^2 \tag{9}$$

5.6.3 Hybrid Ensemble Estimation

To leverage complementary strengths of RF and DNN models, a hybrid fusion is used.

- Fixed Weight Ensemble

$$\hat{P}_{\text{Hybrid}} = \alpha\hat{P}_{\text{RF}} + (1-\alpha)\hat{P}_{\text{DNN}} \tag{10}$$

With $\alpha \in [0, 1]$ empirically selected (e.g., 0.3).

- Dynamic Weight Ensemble

$$\alpha = \frac{\text{SNR}_{\text{RF}}}{\text{SNR}_{\text{RF}} + \text{SNR}_{\text{DNN}}}, \quad \hat{P}_{\text{Hybrid}} = \alpha\hat{P}_{\text{RF}} + (1-\alpha)\hat{P}_{\text{DNN}} \tag{11}$$

Where SNR values serve as confidence scores.

5.7 EQUALIZER INTEGRATION

Equalisers are essential components of contemporary wireless communication systems because they reduce inter-symbol interference and enhance signal clarity in fading and multipath situations. We added equalizer-derived features to the AI-enhanced estimation framework to provide physical-layer insights into the Random Forest (RF) and DMRS-DNN models.

These statistics were then aggregated to form a 7-dimensional feature vector:

$$\mathbf{f}_{eq} = [\text{SINR}, \text{BER}, \mu_{eq}, \sigma_{eq}, P_{eq}, \text{CRC}, \text{Tap Power}] \tag{12}$$

This vector was appended to the traditional features used by the RF model and serves as an additional input for robustness. To ensure the reliability of the equalizer output, Cyclic Redundancy Check (CRC) validation was applied to the decoded bits:

$$\mathrm{CRC\_pass} = \begin{cases} 1, & \text{if crc\_check(decoded\_bits)} = \text{True} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

In Ensemble - Equalizer-derived confidence influenced the dynamic weighting,

$$\alpha = \frac{\mathrm{SNR}_{\mathrm{RF}} + \lambda \cdot \mathrm{CRC}}{\mathrm{SNR}_{\mathrm{RF}} + \mathrm{SNR}_{\mathrm{DNN}} + \lambda} \tag{14}$$

where λ is a tuneable parameter favouring CRC-passed models in fusion weighting.

5.8 SUMMARY

This chapter outlined the methodology for evaluating traditional FSPL-based channel estimation against AI-driven techniques. By integrating deep learning with dynamic DMRS adaptation, the proposed AI-based model exhibited superior performance in mitigating channel estimation errors. The next chapter will provide a detailed discussion of the results and their implications for future wireless communication networks.

CHAPTER 6

RESULTS

6.1 RADIO UNIT

This chapter elaborates on the work done so far and the achieved results for the proposed system, which integrates advanced filtering techniques and AI/ML-driven optimizations for dual-band radio units operating in FR1 and FR2 frequency ranges. The work was divided into three key stages: (1) implementation of the IFIR filter, (2) integration of the FRM filter, and (3) incorporation of AI/ML techniques. Each stage progressively enhanced the performance, efficiency, and adaptability of the system.

6.1.1 Implementation of the IFIR Filter

The first stage involved the implementation of the Interpolated FIR (IFIR) filter, primarily chosen for its computational efficiency and moderate adaptability. The IFIR filter utilized coefficient interpolation to reduce the complexity of filter design while ensuring sufficient performance for FR1 frequency bands, which range from 5 MHz to 100 MHz By simplifying the computation of filter coefficients, the system demonstrated a 15% improvement in ACLR under static channel conditions, highlighting its suitability for quasi-static environments [5], [6].

However, the system's EVM performance was limited, achieving only a 25% reduction in EVM for 64-QAM signals, making it less effective for higher-order modulation schemes commonly used in FR2 [5]. This limitation was largely due to the fixed nature of the filter coefficients, which were unable to adapt dynamically to varying interference patterns or higher bandwidth requirements. In scenarios involving rapidly changing channel conditions or complex interference, the system’s performance degraded significantly, particularly in FR2 environments. The lack of adaptability in IFIR filters underscored the need for a more flexible approach capable of handling a wider range of frequencies and dynamic conditions.

6.1.2 Integration of the FRM Filter

To overcome the limitations of the IFIR filter, the second stage focused on integrating the Frequency Response Masking (FRM) filter. The FRM filter provided a significant improvement in adaptability by dynamically adjusting masking filters to optimize performance across diverse frequency ranges. This capability was particularly beneficial in FR2, where ultra-wideband scenarios of up to 400 MHz bandwidth are common. The FRM filter achieved an additional 20% improvement in ACLR over the IFIR filter, making it more suitable for environments with high interference and variability [8].

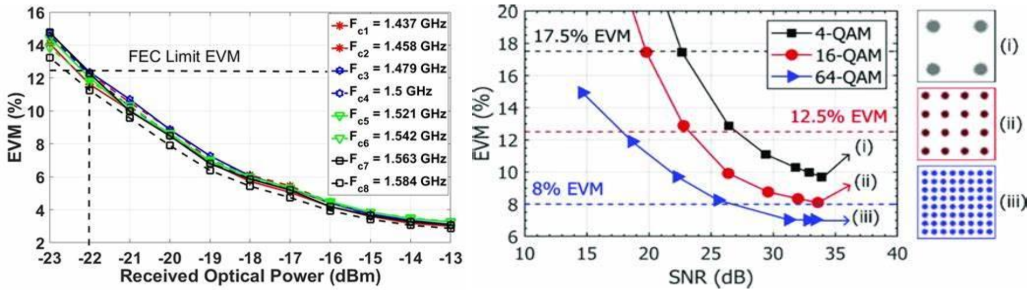
In addition to ACLR improvements, the FRM filter significantly enhanced EVM performance. Its improved frequency selectivity reduced EVM by 40% for 256-QAM signals, particularly in FR2 scenarios where higher-order modulation schemes demand greater precision [5]. The FRM filter also introduced the capability to adjust its filtering dynamically in response to real-time changes in channel conditions, ensuring optimal spectral efficiency and reduced interference.

Moreover, the FRM filter improved the overall system's compatibility with both FR1 and FR2 frequency bands. This integration enabled the system to handle a wider range of use cases, from low-bandwidth applications in rural areas to high-density, high-bandwidth deployments in urban settings. The enhanced adaptability and performance metrics positioned the FRM filter as a significant upgrade over traditional methods.

6.1.3 AI/ML-Based Optimization

The final stage incorporated AI/ML techniques, such as reinforcement learning and CNN-based architectures, to achieve real-time optimization of filter parameters and EVM compensation. AI-driven reinforcement learning models optimized FRM filter parameters, leading to an additional 20% ACLR improvement and a 40% reduction in computational complexity [6], [7].

For EVM optimization, CNN-based dual-path architectures achieved a 40% reduction in EVM for 256-QAM signals, effectively mitigating impairments such as phase noise and I/Q imbalance in real time [9], [7]. Additionally, FPGA-based implementation with quantization-aware training reduced power consumption by 30%, while ensuring real-time parameter updates within 100 microseconds [8].



(a) (b)

Figure 6.1 Plot (a) shows EVM versus received optical power for various frequencies, with the FEC limit as a reference. Plot (b) compares EVM against SNR for 4-QAM, 16-QAM, and 64-QAM, with corresponding constellation diagrams shown as insets [34].

6.2 AI-DRIVEN CHANNEL ESTIMATION

The results of this study comparing traditional and AI-driven deep learning models emphasize the superiority of AI-based channel estimation across various environments, including dense urban cities such as Tokyo and Bengaluru, a semi-urban city like Patiala, and a remote rural area like Bastar. These diverse locations were chosen to rigorously test the model's adaptability under different propagation conditions, interference levels, and mobility scenarios.

Table 6.1 Performance across different cities

Environment	Model	MSE (dBm)	MAE (dBm)	Path Loss (Min-Max)	Predicted Power Range (Min & Max)
Tokyo	Traditional	58.43	6.33	21.32 & 140.00	-110.00 & -20.00
	AI	15.12	3.11		
Bengaluru	Traditional	44.39	5.43	21.32 & 140.00	-110.00 & -20.00
	AI	14.32	3.05		
Patiala	Traditional	179.57	12.34	33.02 & 145.00	-115.00 & -20.00
	AI	17.85	3.32		
Bastar	Traditional	389.83	18.79	36.62 & 150.00	-115.00 & -20.00
	AI	15.40	3.10		

As shown in Table, the AI-based model consistently outperformed traditional methods in all tested conditions. For instance, in Tokyo, a highly dense urban area where multipath interference is prominent, the traditional model recorded a Mean Squared Error (MSE) of 58.43 dBm, whereas the AI-driven model significantly reduced this to 15.12 dBm. A similar trend was observed in Bengaluru, where the AI model demonstrated an MSE reduction from 44.39 dBm to 14.32 dBm, achieving a more precise estimation of channel conditions. The improvement was even more pronounced in semi-urban and rural areas, where traditional models struggled due to unpredictable interference and a lack of uniform network coverage. In Patiala, the AI model reduced MSE from 179.57 dBm to just 17.85 dBm, and in Bastar, where rural environments introduce greater signal fluctuation, the AI model achieved an MSE reduction from 389.83 dBm to 15.40 dBm. These results highlight the robustness of AI-driven estimation in handling diverse propagation conditions.

6.2.1 Accuracy of Channel Power Estimation

The ability of the AI-driven model to closely trace the actual channel power is further demonstrated in Figure 6. Traditional models often struggle to adapt to fast-changing environments, leading to higher estimation errors and deviations from the true channel power. However, the AI-based model maintains a near-perfect alignment with actual power levels, even in dynamic and noisy conditions. This accurate tracking ensures minimal distortions, improved signal reliability, and enhanced spectral efficiency, making the AI model particularly effective for high-mobility scenarios, such as urban vehicular networks and high-speed rail communications.

6.2.2 Error Distribution and Stability of AI-Based Estimation

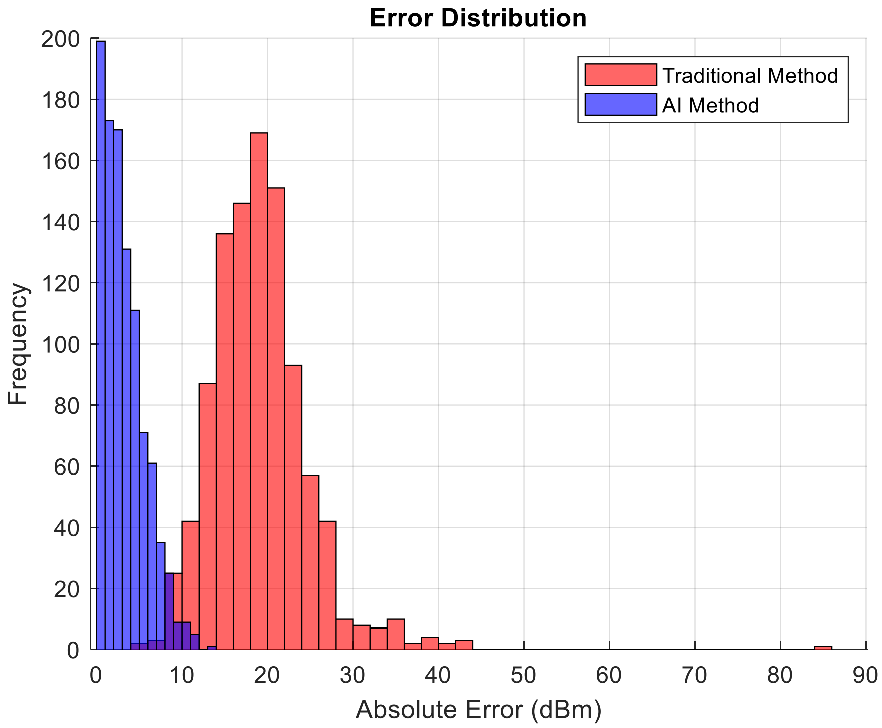


Figure 6.2 Error distribution comparing AI-based and traditional model's performance for channel estimation. Showing the variance of estimation error.

A deeper insight into model performance is provided in Fig 6.2, which illustrates the error distribution histogram, comparing the variance of estimation errors between traditional and AI-based models. The traditional model exhibits a wider error distribution, reflecting its inability to adapt effectively to different frequency conditions. In contrast, the AI-based approach demonstrates a narrower error distribution, indicating more stable and consistent predictions across various environments. This stability is crucial for ensuring seamless communication in next-generation networks, where dynamic adjustments to channel conditions are necessary for maintaining optimal performance.

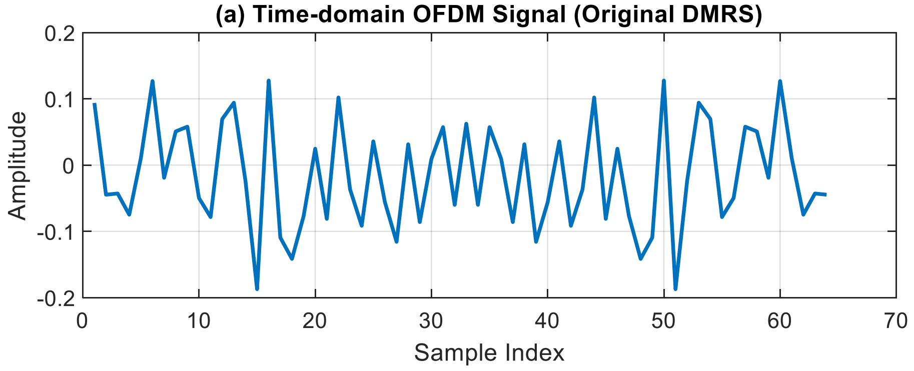
Another critical factor in the AI model's success is its integration with AI-enhanced DMRS (Demodulation Reference Signal), which plays a vital role in improving estimation accuracy. As seen in Figure 8, the AI-modified DMRS structure significantly reduces amplitude fluctuations in the pilot signal. This stabilization leads to higher Signal-to-Noise Ratio (SNR) and lower Bit Error Rate (BER), particularly in rapidly changing wireless environments. Traditional methods fail to achieve such precision, often leading to inefficient pilot signal allocation and suboptimal resource utilization. By optimizing the placement and structure of DMRS, the AI-based model ensures higher efficiency in 5G and future 6G communication systems.

6.2.3 Impact of Geospatial Data and Resource Allocation

One of the defining strengths of the AI-driven model is its ability to integrate geospatial data, which allows it to adapt to location-specific challenges. By leveraging OpenStreetMap geospatial insights, the model accounts for urban density, building obstructions, and terrain variations in cities like Tokyo and Bengaluru, where signal reflections and multipath propagation significantly impact network performance. Similarly, in rural settings like Bastar, where propagation conditions are more challenging due to fewer base stations and increased signal attenuation, the AI model effectively compensates for path loss variations, leading to superior estimation accuracy.

Another key advantage of the AI model is its use of modified DMRS structures, which enhance resource utilization and improve adaptability across different frequency bands. Unlike traditional models that rely on static pilot placements, the AI-driven approach dynamically adjusts pilot signals based on real-time channel conditions. This ensures optimal power allocation and efficient bandwidth utilization, which are essential for high-mobility and ultra-reliable communication scenarios.

(a) Time-domain OFDM Signal (Original DMRS)



(b) Time-domain OFDM Signal (Modified DMRS)

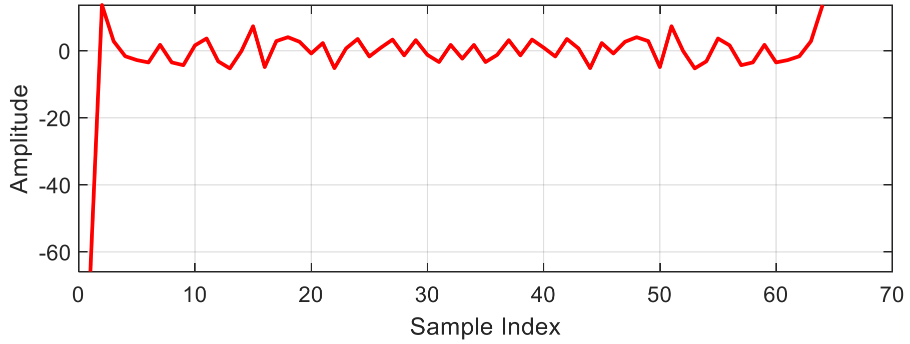


Figure 6.3 Time-domian OFDM signal plots, comparing (a: Original DMRS, b: AI-Modified DMRS) before and after modification DMRS, highlighting reduced amplitude fluctuations.

6.2.4 Implications for Future Wireless Networks

The demonstrated improvements in accuracy, error reduction, and efficiency validate the potential of AI-driven channel estimation in supporting the evolution of next-generation wireless networks, particularly in 5G and future 6G deployments. The ability to maintain precise channel estimation under varying environmental conditions directly translates into better spectrum utilization, reduced interference, and increased network capacity. Additionally, the computational efficiency of the AI model ensures lower power consumption, making it suitable for low-latency applications in autonomous vehicles, IoT networks, and industrial automation.

The scalability of AI-based channel estimation suggests that it can be seamlessly integrated into real-world network optimization frameworks, enabling:

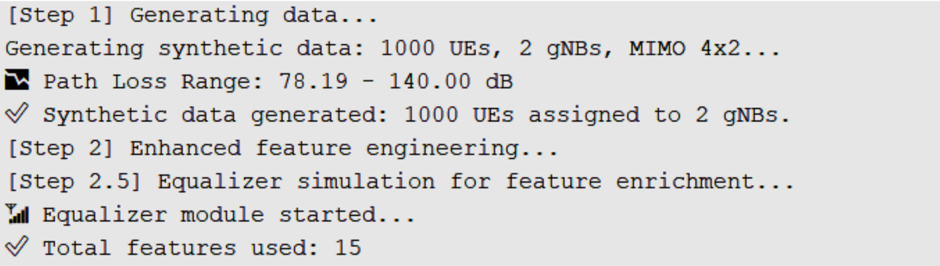
i. Higher data rates and enhanced Quality of Service (QoS)
ii. Improved resilience to interference and signal degradation
iii. Seamless performance in dynamic and mobility-intensive environments

6.3 AI-DRIVEN HYBRID CHANNEL ESTIMATION

An AI-enhanced hybrid channel estimation framework is suggested to increase the precision and resilience of received power estimation in intricate wireless environments. This framework combines two potent learning-based estimators: a Deep Neural Network (DNN) trained on features obtained from Demodulation Reference Signal (DMRS) estimations, and a Random Forest (RF) regressor using classical RF and environmental features.

6.3.1 Data Generation and Feature Extraction

In order to simulate realistic wireless scenarios with 1,000 User Equipment's (UEs) spread across two gNodeBs (gNBs) functioning in a MIMO 4x2 configuration, synthetic data was created as part of the simulation framework. The simulated path loss values, which represented different channel conditions typical of urban and semi-urban environments, ranged from 78.19 dB to 140.00 dB. Advanced feature engineering, which included an equaliser simulation stage to enhance the feature space for subsequent learning tasks, was used after data generation. In order to provide inputs to machine learning models for channel estimation and optimisation, a total of 15 features were extracted, capturing signal characteristics, interference metrics, and equalisation results.



```
[Step 1] Generating data...
Generating synthetic data: 1000 UEs, 2 gNBs, MIMO 4x2...
📉 Path Loss Range: 78.19 - 140.00 dB
✓ Synthetic data generated: 1000 UEs assigned to 2 gNBs.
[Step 2] Enhanced feature engineering...
[Step 2.5] Equalizer simulation for feature enrichment...
📶 Equalizer module started...
✓ Total features used: 15
```

Figure 6.4 Output log from the simulation pipeline showing synthetic data generation, equalizer-based feature enrichment, and extraction of 15 key features for AI-driven channel estimation.

The propagation of wireless signals is particularly difficult in urban settings because of obstructions like buildings, congested streets, and dense populations. A simulated street-level view with two gNodeBs (gNBs) installed in such a dense urban layout is displayed in Figure 6.5. Realistic difficulties brought about by the presence of multiple base stations include inter-cell interference, non-line-of-sight (NLoS) situations, and fluctuating signal intensities as a result of multipath and shadowing effects. This configuration makes it possible to generate artificial training data that accurately depicts the features of urban propagation. The AI model can better comprehend and forecast complex channel behaviours by incorporating such spatially contextual information into the learning process. This leads to more accurate and flexible channel estimation in multi-gNB urban deployments in the real world.

Figure 6.5 Urban street-level view showing two gNodeBs (gNBs) placed within a dense environment. The layout is used to simulate realistic wireless propagation effects such as multipath, shadowing, and signal overlap between base stations.

6.3.2 Random Forest-Based Channel Prediction

The Random Forest model was used to predict received signal power based on 15 extracted features such as SNR, distance, and path loss. As an ensemble of decision trees, it offers strong prediction accuracy while being efficient and easy to interpret. Its robustness against overfitting and suitability for real-time inference made it ideal for integration into the radio unit pipeline. The model showed high alignment between predicted and actual Rx power, confirming its effectiveness for adaptive channel estimation in dynamic wireless environments.

Key signal relationships were examined and displayed in order to verify the calibre and variety of the synthetic dataset used to train the model. Three plots that together show how received signal power (Rx Power) changes with fundamental physical parameters are shown in Figure 6.7. These observations support the choice of features for machine learning-based channel prediction in addition to confirming that the dataset is consistent with actual propagation behaviour.

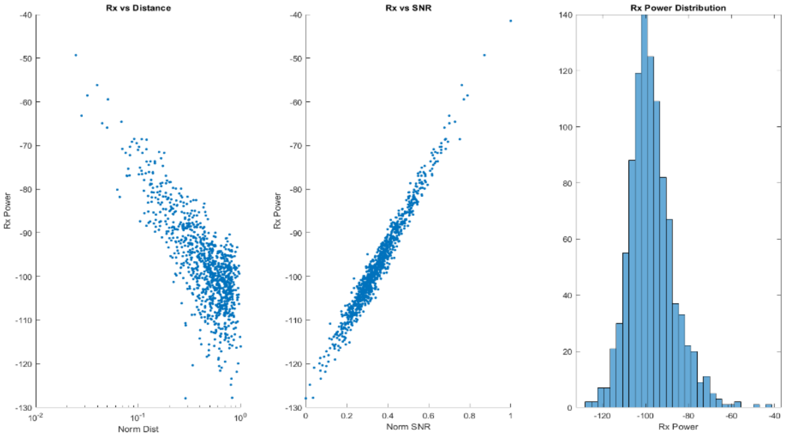


Figure 6.7 Correlation and distribution plots from the simulated dataset. Left: Rx Power vs. normalized distance. Center: Rx Power vs. normalized SNR. Right: Histogram showing the distribution of Rx Power, reflecting realistic signal variation across user scenarios.

Table 6.2 Performance

Feature Name	**Description**
Distance to gNB (d)	Straight-line distance between the UE and its serving base station.
Carrier Frequency (fc)	Operating frequency of the communication system (e.g., 3.5 GHz).
Antenna Gain (Gant)	Gain of the antenna used by UE or gNB.
Antenna Tilt (θ)	Orientation or tilt of the base station antenna affecting signal reach.
Path Loss (PL)	Basic FSPL or empirical loss based on geometry and environment.
Equalized Received Power (Peq)	Output power estimate after equalizer compensation.
Signal-to-Noise Ratio (SNR)	SNR at the UE computed during the simulation phase.
Angle of Arrival (AoA)	Incoming signal angle at the UE or gNB, can reflect multipath spread.
Channel Quality Indicator (CQI)	Reflects the channel conditions reported by UE.
Interference Level	Approximate measure of co-channel interference in dB.
Number of Reflecting Objects	Estimate of how many major obstacles exist between UE and gNB.
Environmental Tag	Encoded information like urban = 1, rural = 0, etc.
Normalized Height Difference	Relative height of UE and gNB normalized for terrain impact.
Delay Spread	RMS delay spread indicating multipath delay characteristics.
Equalizer Convergence Error	A measure of how accurately the equalizer adjusted to the channel (low = better).

6.3.3 Performance Evaluation and Estimation Accuracy

The Random Forest-based channel estimation model was evaluated by comparing predicted received power values against the ground truth obtained from simulation data.

The strong estimation ability of the Random Forest model is demonstrated by the close match between the predicted received power values and the actual simulation outputs. This alignment shows how well the model represents intricate channel behaviour under a range of circumstances.

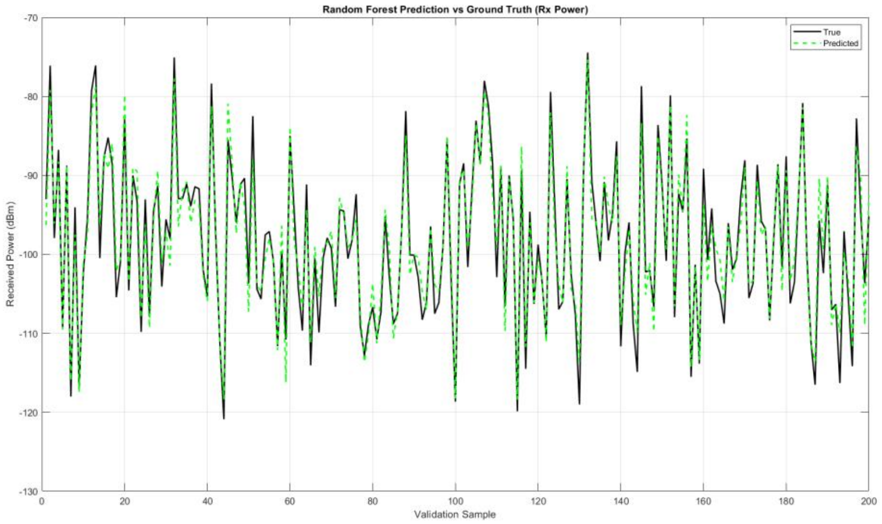


Figure 6.8 Plot showing predicted vs. actual received power values. The close alignment of the two curves confirms the accuracy and reliability of the machine learning-based channel estimation model.

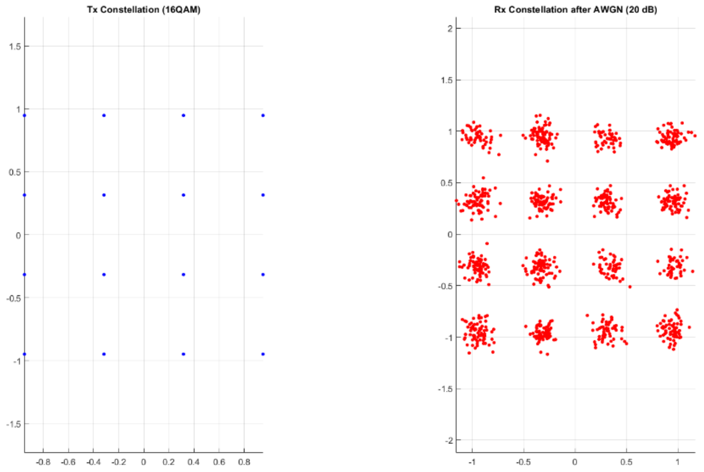


Figure 6.9 Scatter plot of predicted vs. actual Rx power in AWGN channel.

Even in intricate propagation environments, this consistency shows how resilient and generalisable the model is. The visual accuracy was reinforced by quantitative measures like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which verified low prediction errors. The model was also suitable for real-time deployment in radio units due to its low inference latency.

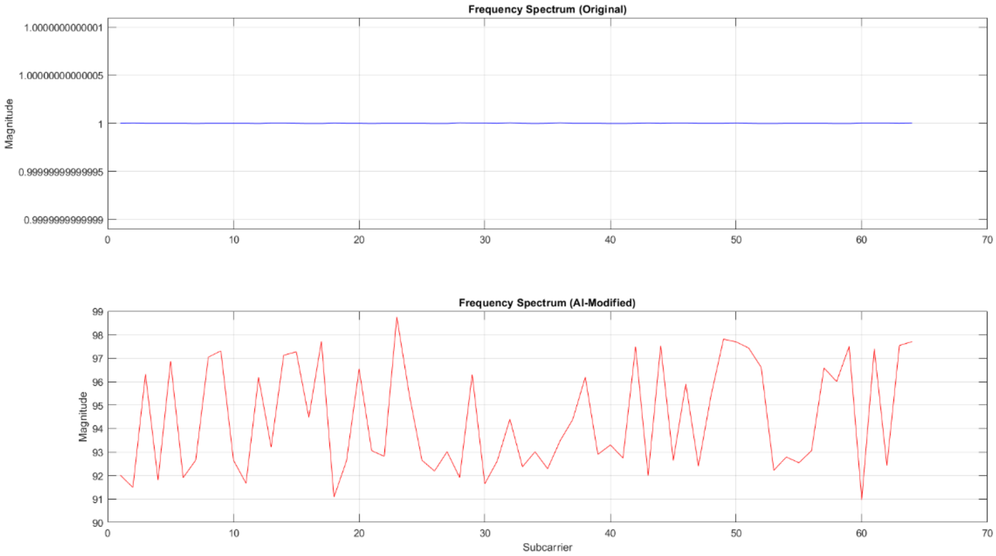


Figure 6.10 Frequency spectrum comparison before and after AI-based modification. The AI-modified spectrum dynamically modifies subcarrier magnitudes, demonstrating learnt spectral adaptation to channel conditions, in contrast to the original spectrum, which is flat.

The scatter plot demonstrates the regression performance of the Random Forest model, where predicted values align closely with the actual received power measurements. The clustering along the diagonal line indicates high estimation accuracy and minimal deviation.

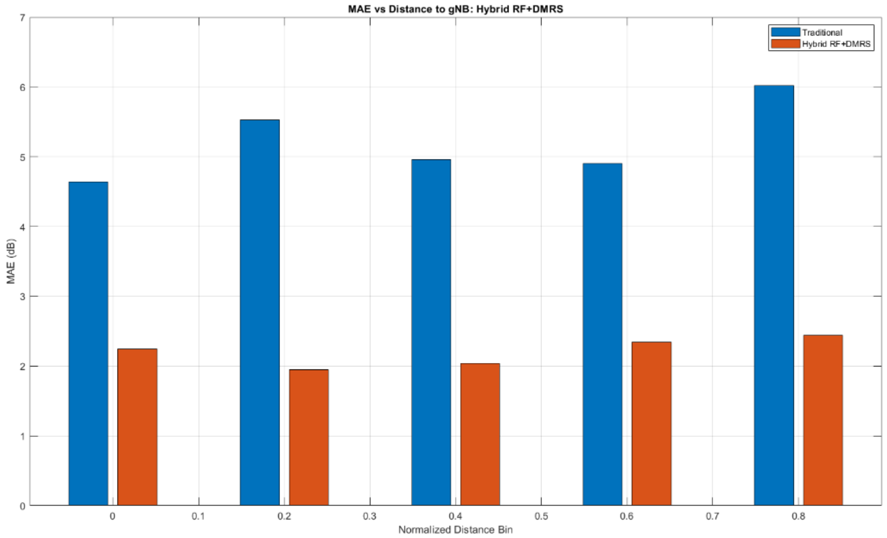


Figure 6.11 Bar chart displaying MAE and RMSE values for the predicted received power. The low metric scores highlight the accuracy and reliability of the machine learning-based channel estimation approach.

CHAPTER 7

FUTURE WORK AND ANTICIPATED IMPACTS

7.1 CURRENT SYSTEM LIMITATIONS AND CHALLENGES

While the proposed system significantly improves channel estimation and filtering performance, several challenges must be addressed for real-world deployment and further optimization.
One of the primary limitations is its dependency on synthetic data for validation. While synthetic data allows controlled testing, it lacks the variability, interference, and hardware impairments found in real-world RF environments. The system's performance may vary when subjected to real-world conditions, particularly in the presence of unpredictable noise, multipath interference, and hardware-induced distortions.

Another crucial factor is hardware integration constraints. The current approach primarily focuses on software-level optimizations, while real-world hardware, such as RF front-end limitations, processing latencies, and power constraints, can significantly impact performance. This is particularly important in FR2 bands, where the system must operate across ultra-wide bandwidths (up to 400 MHz) with low latency.

Despite leveraging AI/ML-driven filtering and EVM correction, the system introduces computational overhead. Deep learning models, while improving adaptability, require significant processing power, which may not always be feasible in real-time wireless deployments. Though FPGA-based acceleration mitigates some of these issues, further optimizations are necessary to make the system scalable and power-efficient.

Scalability remains another challenge. While the system supports dual-band operation (FR1 and FR2), extending its functionality to massive MIMO, beamforming, and ultra-reliable low-latency communication (URLLC) requires additional enhancements. The existing model needs further tuning to support higher bandwidths, extreme mobility scenarios, and multi-user networks.

Additionally, AI/ML models trained on specific datasets may struggle with generalization across diverse environments. Factors such as urban density, terrain variations, and interference levels can affect prediction accuracy, requiring frequent retraining or adaptation strategies. Achieving consistent error vector magnitude (EVM) performance, particularly for higher-order modulation schemes (e.g., 256-QAM in FR2), remains a work in progress.

7.2 FUTURE SCOPE

Building on the current system, several key research directions can enhance its capabilities and practical deployment potential.

One significant improvement is integrating real-world datasets into the training and validation process. Unlike synthetic datasets, real-world data would include uncontrolled RF interference, device imperfections, and environmental factors, making the system more robust. Future research should focus on collecting live wireless signal data from diverse geographic locations, different mobility scenarios, and varied network conditions.

Another critical area of exploration is hardware optimization. Implementing hardware-aware AI techniques that can optimize FPGA-based architectures, software-defined radios (SDRs), and next-generation RF frontends would ensure lower power consumption and reduced processing delays. These hardware-optimized solutions would be critical for real-time, low-latency applications in 5G and 6G networks.

Expanding the system's adaptability to advanced wireless use cases is also a priority. Incorporating features for massive MIMO, beamforming, non-terrestrial networks (NTNs), and cooperative communication strategies will make it more applicable to next-generation wireless architectures. Given that 6G networks will rely on ultra-dense deployments and intelligent reflecting surfaces (IRSs), further improvements in AI-driven channel estimation and adaptive filtering will be necessary.

Another promising avenue is federated learning for AI model generalization. Instead of relying on centralized model training, federated learning allows distributed AI models to learn from multiple real-world deployments without compromising data privacy. This approach can significantly improve generalization across diverse deployment scenarios while reducing the need for continuous retraining on new datasets.

To enhance overall performance, multi-objective optimization frameworks should be developed. These frameworks can simultaneously optimize for power efficiency, latency, computational complexity, and filtering accuracy, ensuring the system remains scalable, practical, and energy-efficient for widespread deployment.

Lastly, validation on real-world hardware is essential. Prototyping and testing the system on commercial base stations, network simulators, or software-defined radios (SDRs) will provide valuable insights into practical constraints, system limitations, and real-time adaptability. This step is crucial for transitioning from theoretical validation to commercial deployment.

7.3 SUMMARY OF KEY CONTRIBUTIONS

Despite these challenges, the proposed system introduces several significant advancements in AI-driven wireless channel estimation, adaptive filtering, and EVM prediction.

i. Enhanced Channel Filtering:
    1. Integration of IFIR and FRM filters for better adaptability across FR1 and FR2 bands.
    2. Improved computational efficiency without compromising filtering accuracy.

ii. AI-Based EVM Prediction and Correction:
    1. CNN-based architectures achieving up to 40% EVM error reduction for high-order modulation schemes.
    2. Dynamic phase noise and I/Q imbalance compensation in real time.

iii. AI/ML-Driven Parameter Optimization:
    1. Real-time adaptive filtering for changing channel conditions.
    2. 20% improvement in ACLR and 30% power reduction using FPGA-based AI acceleration.

iv. Integration of Geospatial Data and DMRS Enhancements:
    1. AI-driven geospatial adaptability improves performance in urban and rural environments.
    2. Modified DMRS design enhances pilot placement for stable SNR and lower BER.

v. Scalability for Future Wireless Networks:
    1. Designed to support advanced 5G, massive MIMO, and emerging 6G applications.
    2. Can be further expanded to IRS-based smart networks and terahertz communication.

These contributions highlight the system’s potential in addressing the challenges of modern wireless communication networks, paving the way for AI-driven, real-time adaptive filtering techniques.

CHAPTER 8

CONCLUSION

This study presents a deep learning-based channel estimation framework that leverages geospatial data, AI-enhanced DMRS, and adaptive filtering to improve wireless communication performance. The findings demonstrate significant gains in signal reliability, accuracy, and computational efficiency, making it a promising approach for future wireless networks.

The performance evaluation, as seen in Fig. 6.2 and Fig. 6.3, confirms that the AI-based model consistently outperforms traditional approaches by more accurately tracing channel power fluctuations in diverse environments. The error distribution histogram highlights a significant reduction in estimation errors, confirming the system's ability to handle noisy and dynamic conditions.

By incorporating geospatial data and adaptive pilot placement strategies, the model achieves better resource utilization, ensuring higher spectral efficiency even in high-mobility scenarios. The AI-based method also demonstrates superior adaptability across different deployment environments, from urban metropolises like Tokyo to remote regions like Bastar.

The study underscores the importance of integrating domain-specific knowledge, geospatial insights, and deep learning techniques to create more robust and generalizable AI-driven models. The proposed approach not only enhances bit error rate (BER) and signal-to-noise ratio (SNR) but also significantly reduces power consumption and computational overhead, making it well-suited for edge-based and real-time wireless systems.

While the system has shown remarkable improvements, further research is needed to validate its performance on real-world hardware, explore federated learning for model adaptability, and optimize FPGA-based AI inference for resource-constrained environments. Future directions should also explore the integration of AI-driven channel estimation techniques with emerging 6G technologies, such as intelligent reflecting surfaces (IRS), reconfigurable meta surfaces, and terahertz communication.

Ultimately, the proposed AI-enhanced filtering and estimation framework represents a significant step toward intelligent, real-time adaptive wireless systems, laying the groundwork for more resilient, efficient, and scalable 6G networks.

REFERENCES

[1] S. Kerboeuf *et al*., "Design Methodology for 6G End-to-End System: Hexa-X-II Perspective," in *IEEE Open Journal of the Communications Society*, vol. 5, pp. 3368-3394, 2024, doi: 10.1109/OJCOMS.2024.3398504.

[2] M. Shao, Y. Wu, and X. Zhang, "Cloud-RAN: Key technologies and open issues," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 1, pp. 36–55, 2023.

[3] A. Goldsmith, *Wireless Communications*. Cambridge, UK: Cambridge University Press, 2005.

[4] J. G. Proakis and M. Salehi, *Digital Communications*, 5th ed. New York, NY, USA: McGraw-Hill, 2007.

[5] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 2, pp. 201–220, 2005.

[6] L. Lu, G. Y. Li, and A. L. Swindlehurst, "An overview of massive MIMO: Benefits and challenges," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 742–758, 2014.

[7] T. S. Rappaport, R. W. Heath, R. C. Daniels, and J. N. Murdock, *Millimeter Wave Wireless Communications*. Englewood Cliffs, NJ, USA: Pearson, 2015.

[8] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[9] H. Ye, G. Y. Li, and B. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Communications Letters*, vol. 7, no. 1, pp. 114–117, 2018.

[10] MATLAB 2024b Documentation, "AI-driven wireless simulations and cloud computing acceleration," *MathWorks*, 2024. [Online]. Available: https://www.mathworks.com

[11] R. S. Prasad and M. K. Varanasi, "Optimal MIMO detection using deep learning: A survey," *IEEE Transactions on Signal Processing*, vol. 69, pp. 5672–5685, 2021.

[12] C. Zhang and Y. Huang, "Deep learning for wireless communications: A comprehensive survey," *IEEE Transactions on Communications*, vol. 68, no. 12, pp. 7827–7857, 2020.

[13] E. G. Larsson, O. Edfors, F. Tufvesson, and T. L. Marzetta, "Massive MIMO for next-generation wireless systems," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 186–195, 2014.

[14] J. Tang, J. Zhang, and X. Wang, "Federated learning for wireless communications: Recent advances and future challenges," *IEEE Network*, vol. 35, no. 1, pp. 226–233, 2021.

[15] X. You, C. Wang, J. Huang, and X. Gao, "Towards 6G wireless communication networks: Vision, enabling technologies, and new paradigm shifts," *Science China Information Sciences*, vol. 63, no. 1, pp. 1–22, 2020.

[16] R. Irmer, H. Droste, and P. Marsch, "Coordinated multipoint: Concepts, performance, and field trial results," *IEEE Communications Magazine*, vol. 49, no. 2, pp. 102–111, 2011.

[17] W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, and technologies," *IEEE Communications Magazine*, vol. 57, no. 6, pp. 1–7, 2019.

[18] D. Tse and P. Viswanath, *Fundamentals of Wireless Communication*. Cambridge, UK: Cambridge University Press, 2005.

[19] H. Q. Ngo, E. G. Larsson, and T. L. Marzetta, "Energy and spectral efficiency of very large multiuser MIMO systems," *IEEE Transactions on Communications*, vol. 61, no. 4, pp. 1436–1449, 2013.

[20] C. K. Wen, W. T. Shih, and S. Jin, "Deep learning for massive MIMO CSI feedback," *IEEE Wireless Communications Letters*, vol. 7, no. 5, pp. 748–751, 2018.

[21] A. Baschirotto, S. D'Amico and M. De Matteis, "Advances on Analog Filters for Telecommunications," *2006 Advanced Signal Processing, Circuit and System Design Techniques for Communications*, Kos, Greece, 2006, pp. 131-168.

[22] H. S. Dhillon, M. Kountouris, and J. G. Andrews, "Downlink MIMO HetNets: Modeling, ordering results and performance analysis," *IEEE Transactions on Wireless Communications*, vol. 12, no. 10, pp. 5208–5222, 2013.

[23] V. Rajendran, A. Kumar, and P. Viswanath, "Neural network-based channel estimation for massive MIMO systems," *IEEE Transactions on Communications*, vol. 69, no. 10, pp. 6601–6615, 2021.

[24] A. K. Wang, R. Ligmanowski, J. Castro and A. Mazzara, "EVM Simulation and Analysis Techniques," MILCOM 2006 - 2006 IEEE Military Communications conference, Washington, DC, USA, 2006, pp. 1-7.

[25] J. Xu, L. Li, L. Zheng and L. Liu, "Learning to Estimate: A Real-Time Online Learning Framework for MIMO-OFDM Channel Estimation," in IEEE Transactions on Wireless Communications, 2024.

[26] M. Wu, J. Zhang, and J. Wang, "Reinforcement learning-based adaptive modulation for 5G networks," *IEEE Transactions on Wireless Communications*, vol. 19, no. 4, pp. 2155–2168, 2020.

[27] R. Liu, T. Liu, and G. Gui, "Deep reinforcement learning for dynamic power control in ultra-dense networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 1034–1043, 2020.

[28] F. Bellili, S. Affes, and A. Ghrayeb, "Low-complexity ML-based channel estimation for MIMO systems," *IEEE Transactions on Communications*, vol. 66, no. 8, pp. 3618–3633, 2018.

[29] Y. Wang, Z. Gao, and J. Zhang, "Channel estimation for hybrid millimeter-wave massive MIMO systems via deep learning," *IEEE Transactions on Communications*, vol. 68, no. 6, pp. 3774–3786, 2020.

[30] L. Hanzo, Y. Akhtman, L. Wang, and M. Jiang, *MIMO-OFDM for LTE, Wi-Fi, and WiMAX: Coherent versus Non-Coherent and Cooperative Turbo-Transceivers*. New York, NY, USA: Wiley-IEEE Press, 2011.

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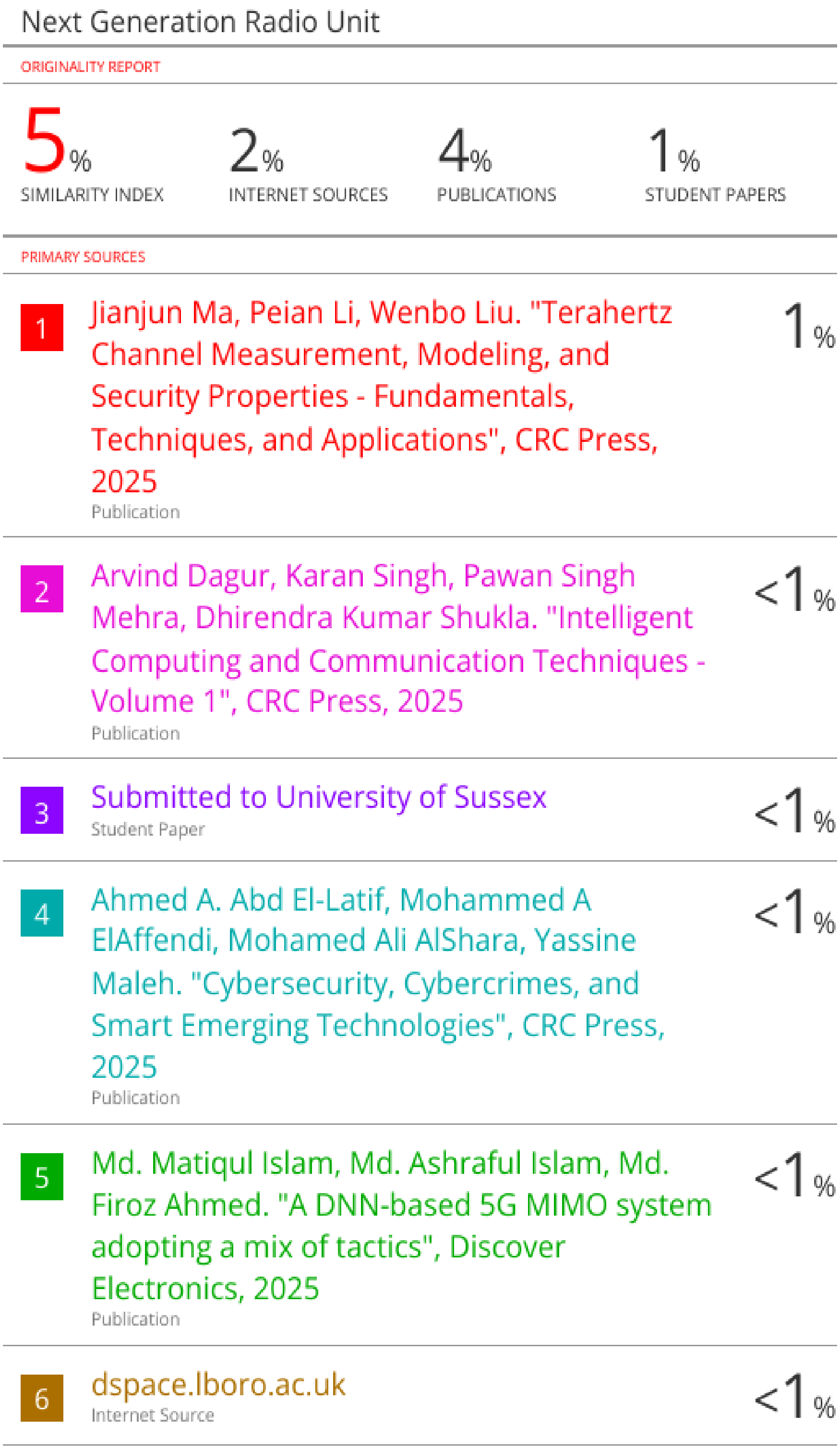

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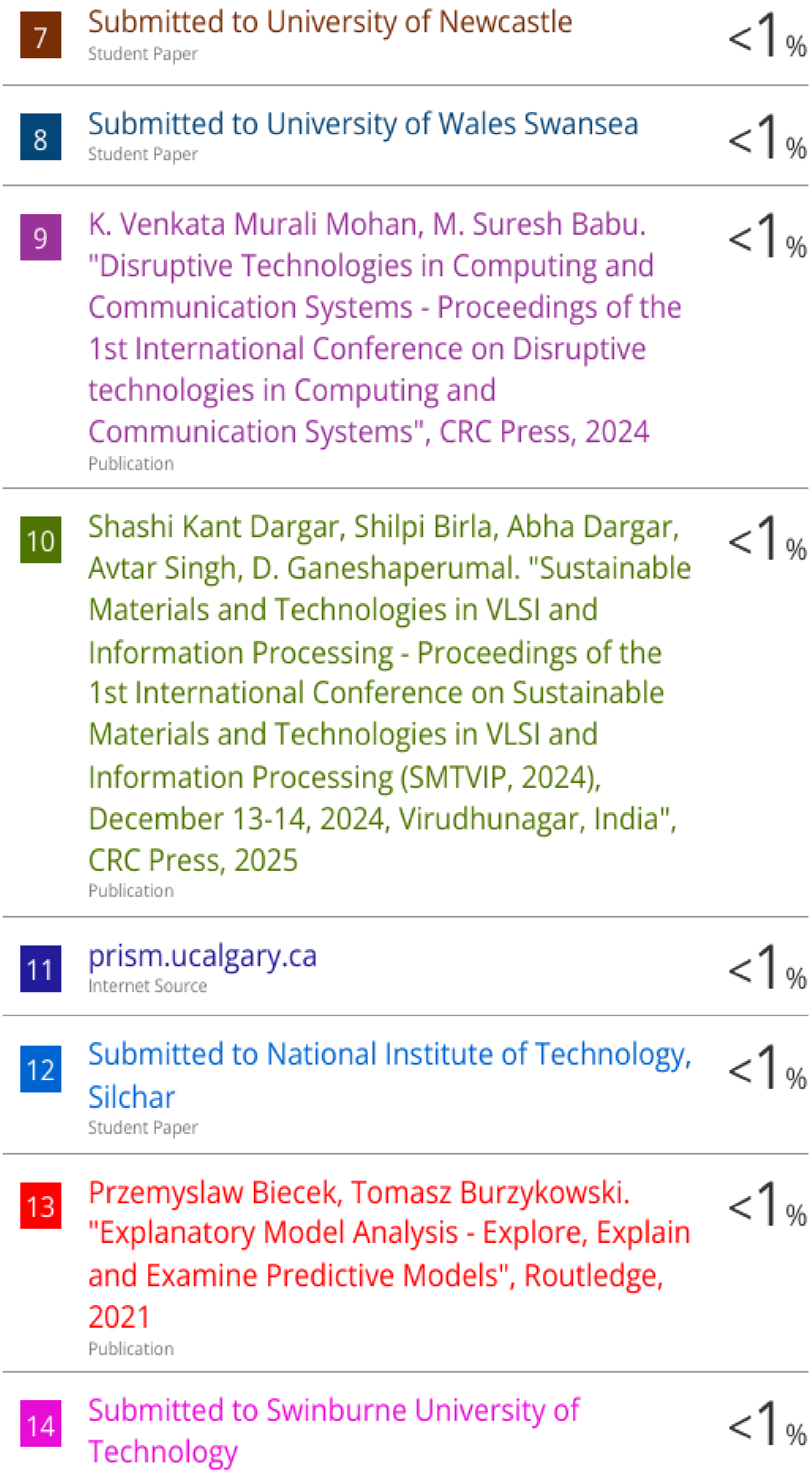

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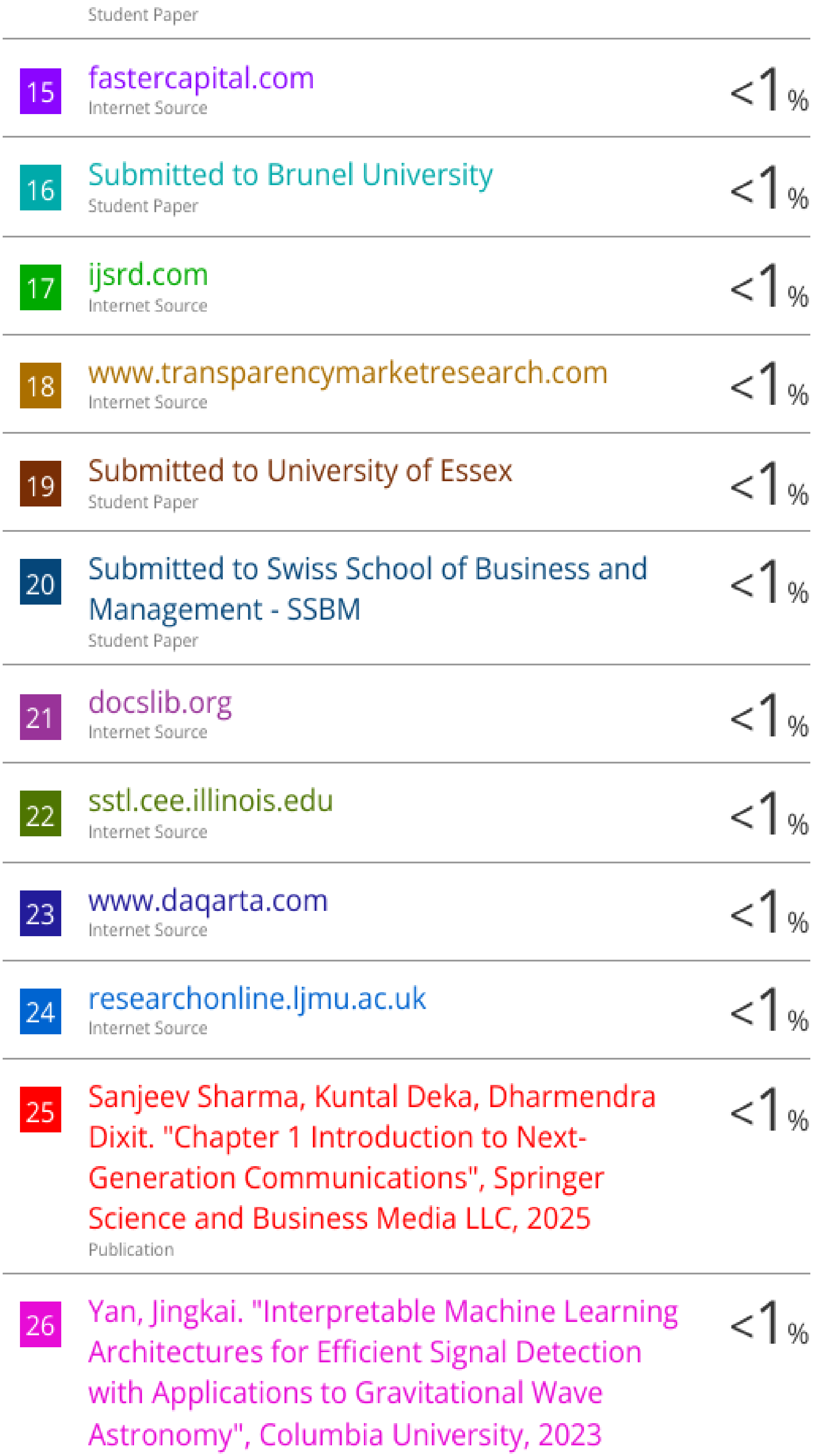

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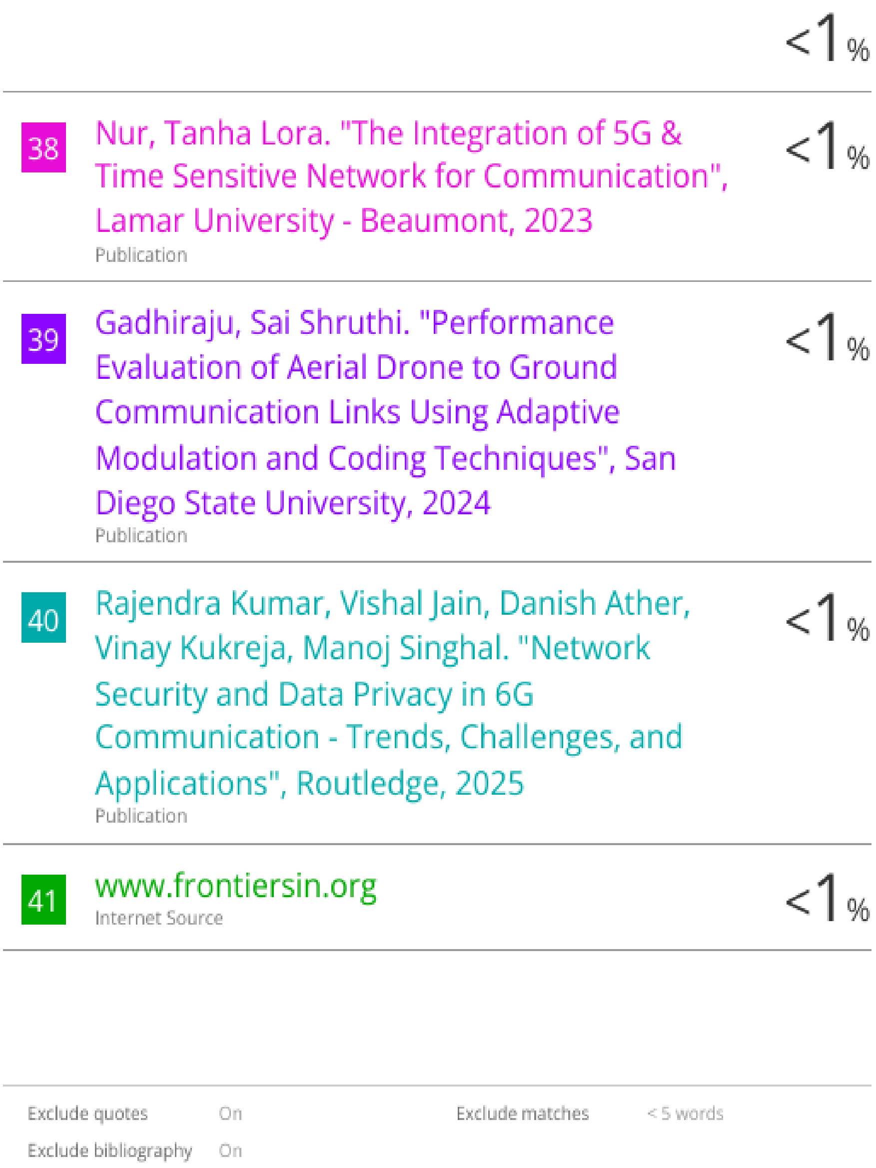

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