

5G to 6G: Inclusion of Edge Computing and AI-Native Computing

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Dedication

I want to sincerely thank my family and supervisor for their unfailing encouragement and support during this journey. My supervisor's advice, tolerance, and perceptive criticism were crucial in moulding my work and encouraging me to advance academically. My family also supported me at every turn, providing unwavering encouragement, empathy, and emotional fortitude in times of uncertainty and stress. Their encouragement transformed obstacles into teaching moments, and their faith in me became my greatest source of bravery. Without their love, commitment, and unwavering support, this achievement would not have been achieved.

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I am also deeply thankful for my family, whose intellectual curiosity and spirited motivational debates at home sparked my interest in engineering from a young age. Their continuous support and belief in my academic pursuits have been instrumental in my success.

This dissertation reflects not only my work but also the collective support of everyone who has touched my life academically and personally. The journey has taught me the value of questioning and the importance of diverse perspectives in enriching our understanding of complex engineering problems.

Abstract

This work intends to leverage simulation techniques to get knowledge regarding the designing and analysis of wireless communication networks. The parameters, for instance, throughput, Signal-to-Noise Ratio, and latency among others are used to compare the efficiency of 5G networks against that of 6G. The main aim of this work is to evaluate the advantages of next generation communication networks over the present one.

As such, this work starts with the theoretical framework of wireless communication systems, specifically the development from 5G towards 6G technology and the need for complex network optimization techniques in this process. This wireless communication system has been designed in a hierarchical form that consists of five layers namely; user equipment, base station, wireless channel, edge computing, and 6G AI. In essence, this is a powerful design concept since it allows the simulation of real-life communication behavior. Given its ability to perform computations and visualization, the MATLAB software becomes the preferred simulation tool here. The modules include initialization, channel modeling, computation of performance parameters, and output visualization. Path loss computation, received signal power calculation, calculation of SNR, throughput computation. In order to ensure uniformity of comparative analysis, these steps are performed in various practiced environments.

AI-based optimization in 6G network is illustrated apart from modeling communication normally done in practice. Some of these include improved SNR performance, throughput adaptability, reduced latencies, and efficient use of resources. It also incorporates theoretical measures such as security and data handling practices.

The process of testing and evaluation reveals the differences between the 5G system and 6G system under identical conditions. When comparing these two technologies based on the throughput, SNR, and latency, one can observe that 6G outperforms 5G in all aspects. Additionally, the use of edge computing and AI optimization enhances their performance.

The work successfully demonstrates how theoretical models can be

transformed into simulations. It has been analyzed that the sixth generation of wireless communication technology is far superior to its predecessor, especially with regard to providing faster, intelligent, and low latency networks for future applications.

Contents

| | | |
|----------|--|----------|
| 1 | Introduction | 1 |
| 1.1 | Project Background | 2 |
| 1.2 | Problem Statement | 3 |
| 1.2.1 | Lack of Unified AI-Native Architecture | 3 |
| 1.2.2 | Inefficient Computation Offloading Under Mobility | 3 |
| 1.2.3 | Limitations of 5G for Future Demands | 3 |
| 1.2.4 | Security Vulnerabilities in Distributed Edge Networks | 4 |
| 1.2.5 | Underexplored Combination of RIS, Semantic Communication, and IEC | 4 |
| 1.3 | Aim of the Study | 4 |
| 1.4 | Research Objectives | 4 |
| 1.5 | Research Questions: This study aims to answer the following key questions: | 5 |
| 1.6 | Significance of Studies | 5 |
| 1.7 | Scope of Study | 6 |
| 1.8 | Limitations | 7 |
| 1.9 | Research Motivation | 7 |
| 1.10 | Research Contribution | 8 |
| 1.10.1 | Theoretical Contribution | 8 |
| 1.10.2 | Analytical Contribution | 8 |
| 1.10.3 | Simulation Contribution | 8 |
| 1.10.4 | Architectural Contribution | 9 |

| | | |
|----------|--|-----------|
| 1.11 | Ethical considerations | 9 |
| 1.12 | Summary | 9 |
| 2 | Literature Review | 10 |
| 2.1 | Introduction | 11 |
| 2.2 | Evolution of Edge Computing | 12 |
| 2.2.1 | Background and Motivation | 12 |
| 2.2.2 | Historical Evolution of Distributed Computing Paradigms | 12 |
| 2.2.3 | Capabilities and Application Domains | 13 |
| 2.2.4 | Limitations and Open Challenges | 14 |
| 2.3 | Mobile Edge Computing (MEC) | 15 |
| 2.3.1 | MEC Architecture and Functional Principles | 15 |
| 2.3.2 | MEC as a Component of 5G Systems | 15 |
| 2.3.3 | MEC Research Challenges | 16 |
| 2.4 | Intelligent Edge Computing (IEC) | 16 |
| 2.4.1 | Conceptual Foundations of IEC | 16 |
| 2.4.2 | Evolution from MEC to IEC | 17 |
| 2.4.3 | Use Cases of IEC in Next-Generation Networks | 18 |
| 2.4.4 | Challenges and Future Research Directions | 18 |
| 2.5 | Fifth-Generation (5G) Wireless Networks | 19 |
| 2.5.1 | Architecture and Key Components | 19 |
| 2.5.2 | Capabilities of 5G | 20 |
| 2.5.3 | Limitations of 5G | 20 |
| 2.6 | Sixth-Generation (6G) Wireless Networks: Vision, Architecture, and Enabling Technologies | 21 |
| 2.6.1 | Introduction to 6G | 21 |
| 2.6.2 | AI-Native 6G Architecture | 22 |
| 2.6.3 | Semantic Communication | 23 |
| 2.6.4 | Reconfigurable Intelligent Surfaces (RIS) | 24 |
| 2.6.5 | Integrated Space–Air–Ground–Sea (SAGS) Networks | 25 |
| 2.6.6 | THz Communication and Optical Wireless Technologies | 26 |

| | | |
|--------|---|----|
| 2.6.7 | Quantum-Aware Semantic Channels | 26 |
| 2.6.8 | Bio-Inspired Networks and Sensing | 26 |
| 2.7 | Security in 6G Networks | 27 |
| 2.7.1 | Threat Landscape Expansion | 27 |
| 2.7.2 | Zero Trust Architecture (ZTA) for 6G | 28 |
| 2.7.3 | Blockchain for Distributed Trust Management | 28 |
| 2.7.4 | Post-Quantum Cryptography (PQC) | 29 |
| 2.7.5 | AI-Driven Threat Detection | 29 |
| 2.8 | Synthesis and Identified Research Gaps | 30 |
| 2.8.1 | Lack of Unified AI-Native Architecture | 30 |
| 2.8.2 | Edge Intelligence Coordination Challenges | 30 |
| 2.8.3 | RIS and Semantic Communication Co-Design is Underexplored | 30 |
| 2.8.4 | Security Gaps in Multi-Layer 6G Ecosystems | 31 |
| 2.8.5 | Scalability in SAGS and Ultra-Dense Networks | 31 |
| 2.8.6 | Lack of Standardized Benchmarks for AI-Native 6G | 31 |
| 2.9 | Computation Offloading in Edge and Mobile Networks | 31 |
| 2.9.1 | Definition and Motivation | 31 |
| 2.9.2 | Offloading Models | 32 |
| 2.9.3 | Fundamental Challenges | 33 |
| 2.9.4 | Improved Offloading with AI and 6G | 33 |
| 2.10 | Comparative Analysis | 34 |
| 2.10.1 | Thematic Mapping | 34 |
| 2.10.2 | Methodological Trends Observed | 34 |
| 2.10.3 | Strengths and Limitations | 35 |
| 2.11 | Conceptual Framework | 35 |
| 2.11.1 | Edge-MEC-IEC Continuum | 35 |
| 2.11.2 | MEC-in-NFV and Orchestration | 35 |
| 2.11.3 | Security and Privacy Plane | 36 |
| 2.12 | Research Roadmap | 36 |
| 2.12.1 | Standardized MEC-IEC APIs and Interoperability | 36 |
| 2.12.2 | Robust Trust Mechanisms for Edge | 36 |

| | | |
|----------|--|-----------|
| 2.12.3 | Edge Placement and UPF Optimization | 37 |
| 2.12.4 | Privacy-Preserving Distributed Learning | 37 |
| 2.12.5 | Performance-Security Tradeoffs | 37 |
| 2.13 | Practical Recommendations for Implementers | 37 |
| 2.14 | Summary | 37 |
| 3 | Requirement Specifications | 39 |
| 3.1 | Introduction | 40 |
| 3.2 | Research Design | 40 |
| 3.3 | Research Approach | 41 |
| 3.4 | System Model | 41 |
| 3.4.1 | Network Structure | 42 |
| 3.4.2 | 5G System Configuration | 42 |
| 3.4.3 | 6G System Configuration | 42 |
| 3.5 | Tools and Software Used | 43 |
| 3.5.1 | MATLAB | 43 |
| 3.5.2 | Literature Resources | 43 |
| 3.6 | Wireless Communication Model | 43 |
| 3.6.1 | Path Loss Model | 44 |
| 3.6.2 | SNR | 44 |
| 3.6.3 | Throughput (Shannon Capacity) | 44 |
| 3.6.4 | Latency | 44 |
| 3.7 | Parameter Selection | 44 |
| 3.8 | Scenario Development | 44 |
| 3.9 | Simulation Procedure | 45 |
| 3.10 | AI-Native and Edge Computing Modeling | 45 |
| 3.11 | Data Analysis Method | 45 |
| 3.12 | Validation of Model | 46 |
| 3.13 | Ethical Considerations | 46 |
| 3.14 | Limitations of Methodology | 46 |
| 3.15 | Chapter Summary | 46 |
| 4 | System Design | 47 |

| | | |
|----------|--|-----------|
| 4.1 | Introduction | 48 |
| 4.2 | Objectives of Testing | 48 |
| 4.3 | Testing Methodology | 48 |
| 4.4 | Test Environment Setup | 49 |
| 4.5 | Test Cases and Scenarios | 49 |
| 4.6 | Performance Metrics Used | 50 |
| 4.7 | Throughput Evaluation | 50 |
| 4.8 | SNR Evaluation | 50 |
| 4.9 | Latency Evaluation | 51 |
| 4.10 | Comparative Analysis of 5G and 6G | 51 |
| 4.11 | Validation of Simulation Results | 52 |
| 4.12 | Discussion of Results | 52 |
| 4.13 | Limitations of Testing | 52 |
| 4.14 | Summary | 53 |
| 5 | System Implementation | 54 |
| 5.1 | Introduction | 55 |
| 5.2 | System Architecture | 55 |
| 5.2.1 | User Layer (User Equipment - UE) | 56 |
| 5.2.2 | Base Layer (BS) | 56 |
| 5.2.3 | Wireless Channel Layer | 57 |
| 5.2.4 | Edge Computing Layer | 57 |
| 5.2.5 | AI Optimization Layer (6G Only) | 57 |
| 5.3 | Tools and Technology Used | 58 |
| 5.3.1 | MATLAB Environment | 58 |
| 5.3.2 | Simulation Parameters | 59 |
| 5.4 | Development Environment and Programming Approach | 60 |
| 5.5 | Processing Logic and Algorithm Designs | 61 |
| 5.6 | Implementation of Scenario | 62 |
| 5.6.1 | Throughput Scenarios | 62 |
| 5.6.2 | SNR Scenarios | 62 |
| 5.6.3 | Latency Scenarios | 63 |

| | | |
|----------|---|-----------|
| 5.7 | AI-Native Implementation for 6G | 63 |
| 5.8 | Application Access Security | 64 |
| 5.9 | Database and Data Handling Security | 64 |
| 5.10 | Performance Optimization Techniques | 64 |
| 5.11 | Implementation Challenges | 65 |
| 5.12 | Summary | 65 |
| 6 | System Testing and Evaluation | 67 |
| 6.1 | Throughput | 68 |
| 6.1.1 | Case 1: Throughput of HD Streaming Vs. Throughput of URLLC | 68 |
| 6.1.2 | Case 2: Throughput of Dense Offices vs Throughput of XR Holograms | 72 |
| 6.1.3 | Case 3: Throughput Under Congestion vs Effective Throughput with IRS Beaming | 76 |
| 6.1.4 | Case 4: Effective Throughput of Balanced Load vs Effective Throughput of Digital Twin | 81 |
| 6.1.5 | Case 5: Throughput of Rural Long Distance vs Throughput of AI Automation | 84 |
| 6.2 | Signal-to-Noise Ratio (SNR) | 89 |
| 6.2.1 | Case 1: SNR of Indoor Baseline vs SNR of AI Surgery | 89 |
| 6.2.2 | Case 2: SNR of High Device Density vs SNR of XR Holograms | 93 |
| 6.2.3 | Case 3: SNR of Urban Dense vs SNR of IRS Indoor | 96 |
| 6.2.4 | Case 4: SNR of Semi-Urban vs SNR of Digital Twin Factory | 99 |
| 6.2.5 | Case 5: SNR of Rural Long Distance vs SNR of Smart Grid | 103 |
| 6.3 | Latency Analysis | 108 |
| 6.3.1 | Case 1: Latency of HD Streaming and Ultra Reliable Low Latency Communication | 108 |
| 6.3.2 | Case 2: Latency of Dense Office and XR Holograms | 114 |

| | | |
|----------|---|------------|
| 6.3.3 | Case 3: Analysis of Latency under Congestion and IRS Beaming | 117 |
| 6.3.4 | Case 4: Latency Analysis of Balanced Load and Digital Twin | 123 |
| 6.3.5 | Case 5: Latency Analysis of the rural long distance and the AI Automation | 128 |
| 7 | Conclusion | 131 |
| 7.1 | Conclusion | 132 |
| 7.2 | Future Works | 132 |
| | References | 134 |

List of Figures

| | | |
|------|---|----|
| 6.1 | Throughput of HD Streaming | 68 |
| 6.2 | Throughput of Ultra Reliable Low Latency Communication | 69 |
| 6.3 | Throughput of Dense Offices | 72 |
| 6.4 | Throughput of XR Holograms | 73 |
| 6.5 | Throughput Under Congestion | 77 |
| 6.6 | Throughput of IRS Beaming | 78 |
| 6.7 | Throughput of Balanced Load | 82 |
| 6.8 | Throughput of Digital Twin | 83 |
| 6.9 | Throughput of Rural Long Distance | 85 |
| 6.10 | Throughput of AI Automation | 86 |
| 6.11 | SNR of HD Streaming | 89 |
| 6.12 | SNR of Ultra Reliable Low Latency Communication | 90 |
| 6.13 | SNR of High Devices Density | 94 |
| 6.14 | SNR of AI Automation | 95 |
| 6.15 | SNR of Urban Dense | 97 |

| | |
|--|-----|
| 6.16 SNR of IRS Beaming | 98 |
| 6.17 SNR of Semi Urban Dense | 100 |
| 6.18 SNR of Digital Twin | 101 |
| 6.19 SNR of Rural Long Distance | 104 |
| 6.20 SNR of the Smart Grid | 105 |
| 6.21 Latency of HD Streaming | 108 |
| 6.22 Latency of Ultra Reliable Low Latency Communication | 109 |
| 6.23 Latency of Dense Offices | 114 |
| 6.24 Latency of XR Holograms | 115 |
| 6.25 Latency Under Congestion | 118 |
| 6.26 Latency of IRS Beaming | 119 |
| 6.27 Latency of Balanced Load | 123 |
| 6.28 Latency of Digital Twin | 124 |
| 6.29 Latency of Rural Long Distance | 128 |
| 6.30 Latency of AI Automation | 129 |

Chapter 1

Introduction

1.1 Project Background

The fast-paced advancement in wireless communication technology, artificial intelligence, and distributed computing is revolutionizing the way today's network processes, distributes, and analyzes information [1], [2]. The networks of today are not merely passive conduits for transferring raw data; they have evolved to become intelligent entities that can analyze information locally, be aware of their surroundings, make predictions, and even make decisions autonomously [3], [4]. All of this has been made possible mainly by the exponential rise in mobile phones, IoT nodes, high-definition content, smart environments, and low-latency applications [1], [5].

It is increasingly difficult for conventional cloud computing systems to cope with this challenge. Centralized computation inevitably leads to delays, exacerbates congestion in the backhaul link, and gives rise to issues pertaining to energy efficiency, scalability, privacy, and real-time capability [6], [7]. In order to tackle this problem, two promising frameworks, namely, edge computing (EC) and mobile/multi-access edge computing (MEC), can be employed to move the computation closer to the user [5], [6]. MEC, which leverages the local storage and computation capacity of base stations, proves to be very useful for a wide variety of applications, including video analytics, industrial automation, VR/AR, autonomous vehicles, and telemedicine [8], [9].

Nonetheless, as network architecture becomes increasingly complex due to the shift from 5G to 6G worldwide, the weaknesses of conventional MEC systems begin to show [10], [11]. The existing MEC systems are mainly responsible for computation offloading functions and lack built-in intelligence, adaptability, and awareness of the situation. For this reason, the concept of IEC has been developed as an enhancement of MEC with

the integration of AI at the network edge, allowing for real-time analysis, semantic understanding, forecasting, and decision making [3], [4].

Future 6G systems will be designed to be AI-driven systems incorporating advanced techniques like semantic communication, RIS, THz frequency bands, digital twins, holographic telepresence, and terrestrial-aerial-satellite communication [11], [9], [2]. Such technologies pose new challenges in terms of intelligent resource management, offloading, security, and energy-efficient computing [1], [10]. It is, therefore, important to gain insight into how MEC, IEC, and emerging 5G/6G technologies will interoperate. [5]

1.2 Problem Statement

While MEC and IEC are rapidly growing technologies, there are various issues and gaps associated with next generation networks, including:

1.2.1 Lack of Unified AI-Native Architecture

Most current networks use AI as an add-on system rather than integrating AI within their design. There is currently no single MEC-IEC-semantics-RIS platform.

1.2.2 Inefficient Computation Offloading Under Mobility

Variability in the wireless channel, mobility of devices, and fluctuating workloads cause poor offloading decisions and lead to latency problems and inefficiencies.

1.2.3 Limitations of 5G for Future Demands

Holographic communication, XR, massive digital twins, and autonomous systems need extremely low latencies, very high throughput, and semantically-

aware services that exceed those supported by 5G. [11]

1.2.4 Security Vulnerabilities in Distributed Edge Networks

Edge nodes introduce risks like adversarial ML attacks, model poisoning, data leakage, fake base stations, slice-based intrusions, and untrusted third-party applications. [12]

1.2.5 Underexplored Combination of RIS, Semantic Communication, and IEC

While each of these fields of technology are mature studied individually, how to merge them together especially for AI-native 6G remains understudied. [13], [14]

1.3 Aim of the Study

This project intends to understand, model, simulate, and assess future wireless communication scenarios with an integrated framework consisting of Mobile Edge Computing (MEC), Intelligent Edge Computing (IEC), and future 5G/6G technologies under latency, throughput, path loss, and computation efficiency.

1.4 Research Objectives

1. To perform an in-depth literature review of MEC, IEC, semantic communication, RIS, 5G and 6G technologies [15].
2. To analyze and evaluate the important performance metrics (latency, throughput, frequency, bandwidth, path loss) of 5G vs 6G wireless networks [15].

3. To construct and evaluate MATLAB scenarios for computation offloading and wireless channel analysis [16].
4. To design an initial prototype recommendation of how edge intelligence, semantic communication and RIS can merge into AI-native 6G networks of the future [16].

1.5 Research Questions: This study aims to answer the following key questions:

1. **How do MEC and IEC improve the performance and capabilities of 5G and 6G networks?**
2. **What are the major performance differences between 5G and 6G in terms of latency, throughput, and frequency bands?**
3. **How do computation offloading strategies perform under different wireless scenarios?**
4. **How can semantic communication and RIS be incorporated into next-generation network design?**
5. **What architectural elements are essential for enabling AI-native 6G systems?**

1.6 Significance of Studies

The present investigation is highly valuable both in academia, industry, and technology. In terms of academic significance, the work contributes to a comprehensive examination of MEC, IEC, semantic communications, RIS, and novel advancements in 6G technology while filling some voids

in current literature and adding knowledge about native AI systems [2]. In addition, the investigation presents a comparative analysis of 5G and 6G networks' performance. Industrial-wise, the study helps telecom service providers plan the migration to 6G networks. The work will be helpful to companies that adopt automation, digital twin models, predictive maintenance, and real-time analytics by enabling effective computation offloading and edge computing [5]. Technologically, the research makes use of simulations using the MATLAB environment on realistic wireless networks where offloading affects latency, throughput, and reliability, among other parameters [10], [11].

1.7 Scope of Study

The scope of the research includes:

- The comparison of 5G and 6G wireless communication technologies using simulation is the main topic of this work.
- Throughput, SNR, latency, and outage probability are among the important performance indicators it assesses. The study examines many scenarios, including XR apps, URLLC, and HD streaming.
- Various settings, including rural, dense urban, and interior settings, are taken into account.
- The impact of route loss and signal attenuation is investigated using distance-based performance. Conceptual 6G aspects like edge computing and AI-based optimisation are included in the paper.
- It compares 5G and 6G's dependability and efficiency under the same circumstances.

- The implementation is restricted to MATLAB-based simulation.
- This study does not cover actual experimental validation or real-world implementation.
- Theoretical presumptions and anticipated future capabilities form the basis of the 6G parameters.

The study does not include hardware prototyping or real-world deployments due to resource limitations.

1.8 Limitations

While having a lot of advantages, the study does possess some weaknesses. To start with, the underlying assumptions of the simulation models used in the work might not completely coincide with reality [15], [16]. Another issue to mention here is that the problems of energy consumption and mobility are discussed on an intuitive level only since the authors did not conduct any experiments to verify their claims. Furthermore, the fact that only two simulations were used to demonstrate the performance of the technology might indicate that some network aspects have not been considered [17], [18], [19].

1.9 Research Motivation

The rationale behind carrying out this study is the constant changing nature of modern wireless networks as well as the shortcomings of current architecture. In view of the increased need for intelligent and real-time applications, existing broadband systems have become inefficient when it comes to network performance. The move to intelligent networks, edge

computing, and low-latency requires that new approaches be considered as far as computing, networking, and resources management are concerned.

Furthermore, critical tasks in a variety of areas such as healthcare, transport, manufacturing, and even the military require real-time processing of vast amounts of data. Existing architectures for multi-access-edge computing and cloud computing do not offer efficient solutions to these needs. This is what provides impetus for coming up with new approaches concerning future 6G network architectures.

1.10 Research Contribution

This study contributes the following:

1.10.1 Theoretical Contribution

- Synthesizes MEC, IEC, semantic communication, RIS, and 6G technologies.
- Identifies critical research gaps in distributed intelligence and semantic processing.

1.10.2 Analytical Contribution

- Compares 5G vs. 6G performance across latency, throughput, and path loss.
- Evaluates computation offloading behavior in multiple scenarios.

1.10.3 Simulation Contribution

- Provides MATLAB-based simulations modeling wireless behavior and offloading.

1.10.4 Architectural Contribution

- Proposes a conceptual framework integrating MEC, IEC, RIS, and semantic communication.

1.11 Ethical considerations

The study does not involve human subjects but recognizes the following considerations:

- Privacy considerations in edge computing.
- Risks of bias and adversarial attacks in AI systems.
- Importance of honest reporting and transparency in simulation results.
- Environmental concerns related to energy consumption in large-scale networks.

1.12 Summary

The background, rationale, research problem, aims, importance, and limitations of this study have been discussed in this chapter. These factors combined serve as the basis for other chapters, which focus on the literature review, methods, simulations, and performance analysis.

Chapter 2

Literature Review

2.1 Introduction

The fast development of wireless communication technology, computing models, and intelligent network architecture is behind the revolutionary change that is happening to make systems more distributed, autonomous, and responsive. The recent years have seen the impact of edge computing, MEC, IEC, and novel 5G/6G communication paradigms on the theoretical borders of network and computing offloading design. Such advancements were triggered by an unprecedented rise in mobile traffic volume, IoT growth, and the need for ultra-reliable low-latency communication (URLLC). Meanwhile, the rising use of artificial intelligence (AI) in communication infrastructure, especially 6G communication infrastructure, has brought forward such innovative concepts as AI-native networks, semantic communication, and reconfigurable intelligent surfaces (RIS), signaling the end of the Shannon-centric world of data transmission [2], [20], [21].

In this chapter, we provide an extensive review of what has been done regarding ten major research topics discussed in the uploaded papers. The first topic deals with the fundamentals of edge computing, while the second is focused on the architecture of MEC and IEC [22]. Computation migration and resource management are considered as the third and fourth topics, respectively, followed by the design of 5G and 6G architectures and their respective visionaries [23]. Communication semantics and the use of RIS in wireless communication networks are also highlighted in two different topics. Then, the seventh and eighth topics address the design of native 6G architecture and its security issues, respectively. Lastly, the ninth and tenth topics focus on the design of 5G and 6G secure network architectures using Zero Trust, blockchain, and post-quantum cryptography

concepts [24], [25]. Through the systematic review of relevant literature, it is evident how each research area has evolved over time, the challenges that persist, and the limitations of the existing practices [26].

2.2 Evolution of Edge Computing

2.2.1 Background and Motivation

The introduction of edge computing was made possible due to the problems facing cloud infrastructure [27], [19]. In the light of the increased number of users of the cloud infrastructure, devices, and applications, the cloud infrastructure seems to be having difficulty dealing with all of that. Based on the report by Ergen et al., in 2025, the number of connected devices will exceed 75 billion and be around 500 billion by 2030. This poses an unbearable load to the cloud backhaul infrastructure, not to mention the user privacy problem [2], [22].

By moving networking, data, and processing capabilities closer to the customers' homes, edge computing can solve this problem and significantly lower latency while relieving strain on the backbone infrastructure. For applications that need minimal latency, such self-driving vehicles, industrial robotics, surgical robots, and extended reality (XR), this technological revolution is tremendously important. Edge computing becomes crucial since current cloud computing systems cannot provide contextual awareness and latency of less than one millisecond.

2.2.2 Historical Evolution of Distributed Computing Paradigms

The concept of distributing computation near the user has evolved through several generations of paradigms:

Content Delivery Networks (CDNs)

Designed originally to counteract the impact of flash crowds, CDN used geographically distributed caching servers to enhance responsiveness. While mainly geared towards content delivery and not computations, the CDN system established the groundwork for service locality concepts [28].

Cloudlets and Fog Computing

Cloudlets enhanced the CDN model with computational features close to the end user devices that allowed applications with stringent latency requirements like real-time analytics and offloading of VR. Fog computing brought about a hierarchy of computing layers in between cloud and IoT devices [2], [22].

Mobile Edge Computing (MEC)

Formalization of MEC (Multi-access Edge Computing) came through the initiative of ETSI, which made computation possible in base stations, access points, and aggregation nodes. MEC provides support for radio aware optimization, intelligence, and low latency service delivery. [23], [24]

Edge computing incorporates the benefits of all three models mentioned above. It correlates very well with the architecture of future generation networks, including 5G and 6G. [23]

2.2.3 Capabilities and Application Domains

Edge computing empowers advanced applications that cannot tolerate cloud-based latency or round-trip delays. Major use cases include:

- Autonomous vehicle perception and inter-vehicle coordination

- Real-time video analytics, including drone surveillance
- Smart factories and Industry 4.0 systems
- Telemedicine, remote diagnostics, and robotic surgery
- Smart city analytics, traffic monitoring, and environmental sensing
- Holographic communications and XR environments

With MEC, local computing and storage enable better privacy protection, increased resilience, and real-time response capabilities. As mentioned by Ergen et al., mission-critical systems require latency of less than 5 milliseconds, and cloud-computing does not meet this requirement. [23], [25]

2.2.4 Limitations and Open Challenges

Even with considerable advancements, edge computing encounters various issues, which include:

- Resource allocation is complicated because of the discrepancies in devices.
- Accessibility is affected negatively by the lack of balance in edge nodes across various geographic locations.
- Decentralized systems bring about security threats.
- Resource allocation is difficult because of the fluctuations in the workload.
- The scalability aspect is affected by temperature and energy sustainability.

In turn, it becomes apparent through these principles how vital it is to apply approaches that combine artificial intelligence with collaboration [29].

2.3 Mobile Edge Computing (MEC)

2.3.1 MEC Architecture and Functional Principles

The addition of computing within 5G base stations, access points, and aggregation routers through MEC extends cloud services at the mobile network edge. MEC architecture typically includes:

- Edge servers capable of executing latency-critical tasks
- Virtualization infrastructure enabling flexible service deployment
- Service orchestration coordinating resource allocation
- Radio Network Information Service (RNIS) for radio-aware optimization

MEC reduces the cost of backhaul because it processes the computations locally, thereby reducing latency and improving QoE. [23], [24]

2.3.2 MEC as a Component of 5G Systems

MEC is a vital technology within 5G networks for providing radio-aware services and context-aware services. As per the literature, the features of 5G enabled through MEC include:

- Ultra-Reliable Low-Latency Communication (URLLC)
- Massive Machine-Type Communication (mMTC)

- Enhanced Mobile Broadband (eMBB)

As stated by the results of the survey carried out for 5G security [26], the MEC framework is vital in maintaining agility and efficiency in the network, notwithstanding the challenges inherent in the decentralized aspect of the framework [30].

2.3.3 MEC Research Challenges

The primary research challenges of MEC include:

- Joint computation and communication optimization
- Offloading decision-making under uncertainty
- Handling user mobility in dynamic environments
- Scalability in dense IoT and V2X networks
- Security and privacy in multi-tenant edge environments [6]

The development of intelligent and autonomous MEC systems is required as mobile applications become more intolerant of latency, opening the door for intelligent edge computing (IEC).

2.4 Intelligent Edge Computing (IEC)

2.4.1 Conceptual Foundations of IEC

A technical framework that combines edge computing and artificial intelligence (AI) is known as intelligent edge computing (IEC). Intelligent edge computing uses machine learning capabilities at edge nodes to optimise and analyse data quickly, whereas standard MEC frameworks focus on

lowering latencies through proximity. The next generation of 5G and 6G network infrastructure need these kinds of technology.

IEC’s conceptual architecture includes:

- Edge AI engines that perform inference or lightweight training
- Distributed learning frameworks such as federated learning
- Context-aware decision controllers for resource allocation
- Dynamic orchestration mechanisms enabling self-optimizing networks

As per [4], embedding artificial intelligence within the network edge facilitates higher level semantic processing that empowers the network not just to communicate data but also to understand what the communicated data means—an important consideration for 6G networks [4], [30]

2.4.2 Evolution from MEC to IEC

The following three MEC system constraints are responsible for the switch from MEC to IEC:

1. **Restricted Intelligence:** MEC servers historically acted as passive compute units, lacking autonomous reasoning and relying on centralized cloud decision-making.
2. **Latency Bottlenecks in Offloading to Cloud AI:** Round-trip delays make real-time inference unsuitable for safety-critical applications.
3. **Growing Complexity of IoT Ecosystems:** Modern IoT systems require adaptive understanding of environment, device behavior, and context-aware coordination.

By incorporating intelligence at the edge nodes to create an artificial intelligence-based intelligence fabric, these drawbacks can be addressed. As a result, a cognitive network that guarantees self-optimization and real-time inference capabilities is formed. [25]

2.4.3 Use Cases of IEC in Next-Generation Networks

IEC enables a wide range of advanced applications:

- Autonomous vehicles and V2X communication
- AR/VR and metaverse environments requiring sub-5 ms latency
- Real-time inferencing for drone and defense surveillance
- Smart healthcare diagnostics and robotic surgery
- Smart grid prediction and fault detection
- Distributed industrial robotics for Industry 5.0 [25], [27]

These use-cases demand low latency, decentralization, and robustness – all intrinsic qualities of IEC.

2.4.4 Challenges and Future Research Directions

However, IEC has to overcome a number of obstacles:

- Heterogeneous device capability limits standardization
- Communication overhead in distributed AI training
- Privacy-preserving learning in multi-party environments
- High energy consumption of AI models at the edge

- Lack of unified orchestration frameworks across edge-cloud layers

[26] point out that combining IEC with semantic communication and RIS is a new and challenging approach which needs to be explored.

2.5 Fifth-Generation (5G) Wireless Networks

2.5.1 Architecture and Key Components

5G networks incorporate a new network architecture called a service-based architecture (SBA).

- Next Generation Radio Access Network (NG-RAN)
- gNodeB (gNB) base stations
- 5G Core Network (5GC)
- User Equipment (UE)
- Network Slicing planes

This architecture comprises of the separation into three tiers as per 3GPP TS 33.501:

1. Application Stratum
2. Home/Serving Stratum
3. Transport Stratum

They consist of six security domains with their own distinct mechanisms, as mentioned in [4]'s comprehensive security review.

2.5.2 Capabilities of 5G

5G's performance improvements include:

- Up to 100× faster data rates (eMBB)
- Sub-1 ms Ultra-Reliable Low-Latency Communication (URLLC)
- 1 million devices per km² (mMTC)
- Network slicing for isolated logical networks
- Integration with MEC for local computing

Such features allow the development of intelligent manufacturing systems, IoT sensor networks, and telemedicine applications.

2.5.3 Limitations of 5G

Despite significant improvements over LTE, 5G faces several limitations:

Shannon-Centric Paradigm

While 5G excels in ensuring the optimal transfer of bits, it has no concept of semantics. As [5] point out, what is needed now more than ever is meaning rather than mere quantity of data.

Latency Constraints of Cloud-Dependent AI

Even with MEC, many applications still depend on cloud-based AI models, which introduce unavoidable latency.

Security Vulnerabilities

[25] identify vulnerabilities in:

- RAN
- Device authentication procedures
- Radio interface protocols
- Vendor-specific configurations

Attack vectors for 5G include spoofed base station, handover, protocol downgrade, and slicing cross-contamination.

Insufficient Support for Emerging Applications

For use cases like holographic communication, tactile internet, and digital twins:

- Terabit-per-second links
- Nano-level synchronization
- Native AI reasoning

These needs surpass what 5G technology can handle, hence the push towards 6G networks.

2.6 Sixth-Generation (6G) Wireless Networks: Vision, Architecture, and Enabling Technologies

2.6.1 Introduction to 6G

In order to deliver an intelligent, contextual, and autonomous communication system, 6G aims to overcome the shortcomings of 5G technology.

In contrast to 5G networks, which prioritise throughput and latency optimisation, 6G networks envision intelligent networks that can continually see, reason, learn, and adapt. 6G networks are able to prioritise meaning and intent over mere data transport because to a fundamental paradigm change from bit-based to semantic-based communication. [1]

According to [?], 6G aims to integrate three foundational pillars:

1. Semantic communication
2. Reconfigurable Intelligent Surfaces (RIS)
3. Edge intelligence

working synergistically to deliver ultra-reliable and intelligent connectivity.

Transformative applications, according to the concept of 6G, will include holographic telepresence, massive digital twins, XR metaverse, autonomous mobility ecosystem, and bio-sensing solutions.

2.6.2 AI-Native 6G Architecture

AI-native networking is another characteristic feature of 6G. AI is incorporated into the architecture of 6G as a fully-fledged technology and not an afterthought like AI in 5G. As noted by [1], [12]., whereas AI in 5G is application-specific, 6G networks make use of AI across all layers of the communication architecture, from the physical layer to the service layers.

Core Intelligence

Through federated, multi-agent, and reinforcement learning techniques, the system's intelligence is transferred to the edge nodes, base stations, and linked devices.

Distributed Intelligence

The artificial intelligence would be available at all these locations through federated learning, multi-agent learning, and reinforcement learning techniques.

Self-Evolving Protocol Stack

The sixth generation technology can provide a protocol stack that can have the ability to reconfigure itself, optimize itself, and even heal itself for continuous adaptation as per application requirements.

AI in the Control Loop

AI becomes central to link adaptation, scheduling, beamforming, channel state prediction, and resource allocation—leading to real-time, goal-driven orchestration.

This architecture allows logical intelligence, enabling networks to reason autonomously and respond on time to differing ecological and application conditions.

2.6.3 Semantic Communication

In semantic communication, there is considerable development in communication theory, transcending the fidelity of Shannon’s bit-level theory. It stresses on:

- Task-specific meaning
- Context relevance
- Intent interpretation
- Minimization of redundant data [25]

[27] stresses that 6G will change not just information but also knowledge, reducing superfluous communication loads and executing intelligent tasks even when bandwidth is constrained [28].

Semantic communication is necessary for applications such as:

- Autonomous driving
- Robot coordination
- Industrial automation
- XR and holographic communications

It is able to cut down bandwidth usage by 10 to 1000 times in some applications and hence facilitate highly efficient communication.

2.6.4 Reconfigurable Intelligent Surfaces (RIS)

RIS technology reconfigures wireless environments using the manipulation of electromagnetic waves. Programmable surfaces that can reflect, scatter, and steer radio waves constitute RIS. Motivations for RIS technology in 6G include:

- Greater energy efficiency
- Better coverage in complicated terrains
- Decreased dependence on powerful base stations
- Silent communication during stealth missions
- Improvements in physical layer security

Reconfigurable intelligent surfaces convert passive terrains into active participants in the network infrastructure. [15] believe that RIS is indispensable for optimizing channel conditions in semantic-aware and URLLC-driven 6G systems [16].

2.6.5 Integrated Space–Air–Ground–Sea (SAGS) Networks

Future generation 6G networks will be developed to offer ubiquitous coverage via integration with SAGS architecture:

- Terrestrial base stations
- High/Low Altitude Platforms (HAPS/LAPS)
- Unmanned Aerial Vehicles (UAVs)
- Low Earth Orbit (LEO) satellites
- Maritime communication systems

A multilayer network will guarantee universal connectivity by:

- Maritime operations
- Remote communities
- Disaster recovery
- Autonomous logistics

The SAGS network will emphasize continuous sensing and environment monitoring [9], [12].

2.6.6 THz Communication and Optical Wireless Technologies

The 6G technology will use THz and VLC technologies to deliver terabit-per-second transmission rates. THz communication provides:

- Ultra-high data rates
- High-resolution environmental sensing
- Ultra-dense network deployments

Some of the major issues include atmospheric attenuation, obstructions, and hardware constraints.

2.6.7 Quantum-Aware Semantic Channels

Recent studies focus on quantum communications' incorporation within 6G semantic frameworks, which facilitate [2], [9]:

- Ultra-secure communication channels
- Increased accuracy of semantic reasoning
- Better entanglement-based communication

According to Ogenyi et al., quantum semantic channels can be considered future research avenues to reinforce communication intelligence. [26]

2.6.8 Bio-Inspired Networks and Sensing

Bio-inspired 6G architectures model:

- Human cognition
- Neural structures

- Swarm intelligence
- Adaptive learning behaviors

These techniques improve resilience, context awareness, and environmental adaptation of autonomous IoT systems. [26]

2.7 Security in 6G Networks

The increased attack surface in 6G networks is due to pervasive use of AI, distributed network architecture, and multiple layers of connectivity. The survey article by Scalise et al. gives fundamental understanding regarding security aspects of 5G networks that seamlessly extend to 6G networks.

2.7.1 Threat Landscape Expansion

6G introduces vulnerabilities in:

- Distributed AI inference models
- Federated learning exchanges
- Reconfigurable Intelligent Surface (RIS) manipulation attacks
- Semantic spoofing and intent poisoning
- Ultra-dense device ecosystems
- Satellite and aerial platform security
- Security of satellites and aerial platforms

Security must thus be intrinsic in the design. [3], [4]

2.7.2 Zero Trust Architecture (ZTA) for 6G

Zero Trust Architecture (ZTA) operates on the premise of no automatic trust but continuous validation. It will likely form the basis of 6G owing to diversity and mobility of devices [10], [12].

Principles of ZTA:

- “Never trust, always verify”
- Continuous authentication
- Strict least-privilege access
- Micro-segmentation of services

ZTA is very important in MEC/IEC contexts since edge devices tend to operate beyond centrally protected zones.

2.7.3 Blockchain for Distributed Trust Management

Blockchain provides:

- Decentralized authentication
- Tamper-proof ledger maintenance
- Smart-contract-enabled access control
- Safe data exchange for federated learning

Blockchain technology along with MEC increases multi-party trust, particularly in multi-tenant scenarios.

2.7.4 Post-Quantum Cryptography (PQC)

PQC is necessary owing to the expected quantum attacks that can undermine conventional asymmetric cryptographic schemes. [29] notes PQC as a key factor in the development of 5G/6G cybersecurity architecture, stressing its importance for securing network and application layer protocols in future communication systems.

Popular PQC methods are:

- Lattice-based cryptography
- Hash-based signatures
- Multivariate polynomial cryptosystems

2.7.5 AI-Driven Threat Detection

6G networks benefit from AI-enabled detection of:

- Malware anomalies
- Identity spoofing
- Radio interface attacks
- Slice-crossing intrusions
- RIS manipulation attempts

However, AI models themselves introduce risks:

- Adversarial inputs
- Machine learning poisoning
- Data contamination

- Inference attacks

Ensuring model robustness becomes an essential research direction [2], [4].

2.8 Synthesis and Identified Research Gaps

Across the ten research papers, multiple converging research gaps become evident.

2.8.1 Lack of Unified AI-Native Architecture

While AI-native 6G visions exist, practical frameworks for integrating semantic communication, RIS, IEC, and distributed learning remain underdeveloped.

2.8.2 Edge Intelligence Coordination Challenges

Distributed learning across thousands or millions of edge nodes poses challenges in:

- Communication overhead
- Energy consumption
- Privacy protection
- Model synchronization

2.8.3 RIS and Semantic Communication Co-Design is Underexplored

Current literature discusses RIS and semantic communication independently. Their joint optimization is essential for URLLC and intent-driven

services but remains insufficiently studied.

2.8.4 Security Gaps in Multi-Layer 6G Ecosystems

Emerging attack surfaces, particularly in semantic systems, federated learning, and RIS, lack mature defense frameworks.

2.8.5 Scalability in SAGS and Ultra-Dense Networks

Integrating terrestrial, aerial, maritime, and satellite systems requires new techniques for:

- Routing
- Synchronization
- Dynamic resource sharing

2.8.6 Lack of Standardized Benchmarks for AI-Native 6G

Research is fragmented, and no common benchmark datasets or testbeds exist for evaluating 6G intelligence components.

2.9 Computation Offloading in Edge and Mobile Networks

2.9.1 Definition and Motivation

Computation offloading refers to the delegation of processing tasks from user devices—often energy- or computation-constrained—to more powerful remote nodes such as edge servers, cloud servers, or nearby devices. Offloading seeks to:

- Reduce latency
- Enhance computational efficiency
- Conserve device energy
- Improve Quality of Experience (QoE)
- Support complex AI/ML workloads

This becomes necessary due to the proliferation of user-centric applications (XR, gaming, AI vision tasks) that exceed mobile device capabilities [1], [5].

2.9.2 Offloading Models

The literature identifies multiple offloading models:

Binary Offloading

A task is either executed entirely locally or entirely offloaded.

Partial Offloading

Complex tasks are partitioned so that separable components can execute in different locations.

Cooperative Offloading

Multiple nearby devices collaborate, utilizing idle resources.

Vertical and Horizontal Offloading

- Vertical: device \rightarrow edge \rightarrow cloud
- Horizontal: device \leftrightarrow device (peer-assisted computing)

Partial and cooperative offloading are essential in highly mobile environments such as vehicular networks.

2.9.3 Fundamental Challenges

Key issues in computation offloading include:

- Task splitting in an uncertain channel environment
- Balancing latency and energy consumption
- Link unreliability due to mobility
- Dynamic workload scheduling
- Service continuity during mobility

[1], [27] emphasize that offloading grows more complicated due to the existence of diverse geographical regions in which edge servers can be heterogeneous.

2.9.4 Improved Offloading with AI and 6G

The use of AI will improve offloading by:

- Wireless channel state prediction
- Mobility anticipation
- Dynamic resource optimization
- Anomaly detection for enhanced security.

Offloading will also be made to be semantic-aware in the 6G context, placing emphasis on meaning, relevance, and intent. [12], [26]

2.10 Comparative Analysis

Herein, a comparative analysis of the aforementioned five research studies will be made, bringing together the relevant themes, methodology, strengths, weaknesses, and contribution to the field.

2.10.1 Thematic Mapping

- **MEC foundations and architecture:** [23] presents an exhaustive review of MEC, covering the ETSI MEC reference architectures, orchestration, and offloading taxonomy.
- **Edge security and performance:** [4], [23], [27] deal with trust and authentication aspects in MEC/IEC systems.
- **IEC and 6G convergence:** [5] presents IEC as a backbone for AI-driven 6G systems enabling autonomous vehicles and AR/VR.
- **Survey methodologies:** [2] conducts systematic classifications of 5G/6G research using structured review techniques.
- **6G enabling technologies:** [6] examines non-terrestrial networks, placement of user-plane functions, and edge network integration.

2.10.2 Methodological Trends Observed

- **Systematic reviews:** [5], [23], [24] perform literature review using taxonomy approach.
- **Analytical modeling:** [6], [23] present approaches to model edge placement and resource management.

- **Use-case driven design:** [4], [29] illustrate applications such as AR/VR, self-driving vehicles, and telemedicine through their use cases.

2.10.3 Strengths and Limitations

Strengths:

- Standards-aware MEC analysis aligned with ETSI/NFV frameworks.
- Broad coverage of MEC, IEC, 5G, and 6G ecosystems.

Limitations:

- Variation in scope across studies limits direct comparison.
- Most works are conceptual or simulation-based with limited real-world validation.

2.11 Conceptual Framework

2.11.1 Edge–MEC–IEC Continuum

- Device/End: lightweight sensing and local inference
- Edge/MEC: latency-critical processing and orchestration
- Regional/Core: global optimization and long-term analytics

MEC serves as the primary layer for latency-sensitive services, while IEC introduces distributed intelligence across nodes [15].

2.11.2 MEC-in-NFV and Orchestration

MEC integrates with NFV MANO including:

- MEC Host (MEH)
- MEC Platform (MEP)
- MEC Orchestrator (MEO)
- MEC Platform Manager (MEPM)
- Virtualized Infrastructure Manager (VIM)

Orchestration considers radio context, energy constraints, and security policies.

2.11.3 Security and Privacy Plane

Security mechanisms include:

- Lightweight authentication
- Federated identity management
- Secure enclaves
- Privacy-preserving computation

2.12 Research Roadmap

2.12.1 Standardized MEC–IEC APIs and Interoperability

Focus on defining APIs, telemetry models, and NFV-compatible descriptors.

2.12.2 Robust Trust Mechanisms for Edge

Develop lightweight authentication, attestation, and provenance tracking systems.

2.12.3 Edge Placement and UPF Optimization

Optimize joint placement of user-plane functions and edge servers using MILP and heuristic models [18].

2.12.4 Privacy-Preserving Distributed Learning

Enable federated learning with secure aggregation and poisoning attack mitigation.

2.12.5 Performance-Security Tradeoffs

Develop benchmarks combining latency, reliability, and security overhead analysis.

2.13 Practical Recommendations for Implementers

- Utilize MEC and NFV MANO based on ETSI standards
- Utilize federated learning along with secure logging
- Containerization of MEC microservices
- Edge placement optimization for URLLC applications
- Implementation of Zero Trust security incrementally

2.14 Summary

The focus of this chapter has been on MEC, IEC, 5G and 6G. Some key areas that required further work in the fields of MEC, IEC, 5G and 6G include ensuring that intelligence is distributed, the communication is coherent, and the edge infrastructure is secure. An innovative strategic plan has been

formulated for guiding the development process of 6G networks specifically designed for artificial intelligence applications, and such a plan is based on an appropriate framework of 6G and MEC, IEC, 5G and 6G [2], [5], [20].

Chapter 3

Requirement Specifications

3.1 Introduction

The proposed approach for this chapter indicates the comparative analysis of 5G and 6G networks considering various aspects of performance, network architecture, and computation of artificial intelligence in both the networks. For analysis of performance factors like latency, throughput, bandwidth utilization, and route loss, this research study will be conducted based on simulations performed in MATLAB. Analysis of this study methodology, system model, tools used, selected parameters, scenario construction, simulation procedure, and techniques employed in analysis form the objective of this chapter.

3.2 Research Design

This research follows a quantitative and simulation-based design. A comparative analysis technique is used to evaluate differences between 5G and 6G technologies under controlled wireless conditions.

The study does not involve human participants; instead, it uses mathematical modeling and simulation.

The research design includes:

- Development of wireless communication models
- Implementation in MATLAB
- Creation of multiple performance scenarios
- Measurement of key wireless metrics
- Comparative evaluation

Simulation-based design is preferred because real 6G deployment is not yet available.

3.3 Research Approach

The comparative analytical approach follows these steps:

- Study theoretical foundations of 5G and 6G
- Develop mathematical models
- Implement models in MATLAB
- Simulate multiple scenarios
- Compare performance metrics
- Analyze performance improvement

This integrates:

- Wireless channel modeling
- Shannon capacity analysis
- Path loss modeling
- Latency estimation
- Throughput calculation

3.4 System Model

The system model represents a simplified cellular communication environment.

3.4.1 Network Structure

- One Base Station (BS)
- Multiple User Equipment (UE)
- Wireless channel
- Edge computing layer
- AI-based optimization layer (6G conceptual)

3.4.2 5G System Configuration

- Carrier frequency: 3.5 GHz
- Bandwidth: 100 MHz
- Moderate SNR
- Sub-6 GHz propagation
- Traditional edge computing

3.4.3 6G System Configuration

- Carrier frequency: 100 GHz (THz concept)
- Bandwidth: 1 GHz
- Higher SNR
- AI-native optimization
- Intelligent edge computing

3.5 Tools and Software Used

3.5.1 MATLAB

MATLAB was used to:

- Define wireless parameters
- Implement path loss models
- Calculate SNR
- Compute throughput
- Estimate latency
- Generate comparison graphs

3.5.2 Literature Resources

IEEE research papers were used to validate parameter selection and performance metrics such as latency, throughput, reliability, and outage probability. The wireless channel includes path loss, fading, shadowing, and noise. Key parameters include:

3.6 Wireless Communication Model

The wireless channel includes path loss, fading, shadowing, and noise. Key parameters include:

- Carrier frequency
- Transmission power
- Bandwidth

- Antenna gains
- Distance

3.6.1 Path Loss Model

$$PL(dB) = 20 \log_{10}(d) + 20 \log_{10}(f) + 32.44 \quad (3.1)$$

3.6.2 SNR

$$SNR = \frac{P_{signal}}{P_{noise}} \quad (3.2)$$

3.6.3 Throughput (Shannon Capacity)

$$C = B \log_2(1 + SNR) \quad (3.3)$$

3.6.4 Latency

$$Latency = \frac{\text{Packet Size}}{\text{Throughput}} \quad (3.4)$$

3.7 Parameter Selection

The frequency used in 5G is 3.5 GHz with 100 MHz bandwidth and in 6G is 100 GHz with 1 GHz bandwidth. The distance varies between 50-500 m and SNR for 5G is 10 dB and for 6G is 20 dB.

3.8 Scenario Development

Three scenarios are defined:

- Short range: 50–150 m
- Medium range: 200–350 m
- Long range: 400–500 m

3.9 Simulation Procedure

Steps include:

- Initialize parameters
- Compute path loss
- Calculate received power
- Compute SNR
- Calculate throughput
- Estimate latency
- Plot results

3.10 AI-Native and Edge Computing Modeling

6G integrates AI for:

- Adaptive bandwidth allocation
- Beamforming optimization
- Resource scheduling

Edge computing reduces latency by processing data closer to users.

3.11 Data Analysis Method

Performance improvement is calculated as:

$$Improvement = \frac{6G - 5G}{5G} \times 100 \quad (3.5)$$

Metrics include throughput, latency, and path loss.

3.12 Validation of Model

Validation is done using:

- Shannon capacity verification
- Free space path loss consistency
- Trend analysis across scenarios

Results confirm realistic wireless behavior.

3.13 Ethical Considerations

This study is simulation-based and involves no human data. All models are derived from literature with proper citation and academic integrity [2], [11], [30].

3.14 Limitations of Methodology

Limitations include:

- 6G parameters are theoretical
- Simplified channel modeling
- No real-world hardware testing
- AI effects modeled conceptually

3.15 Chapter Summary

This chapter presented a MATLAB-based simulation methodology for comparing 5G and 6G networks using standardized wireless models and performance metrics.

Chapter 4

System Design

4.1 Introduction

This chapter provides information about the testing and analysis of the developed system in order to assess the performance of the 5G and 6G wireless communication systems [9], [10]. The verification of the correctness of the simulation model and analysis of the system's behavior under different operational conditions are the primary objectives of this process. The key performance metrics such as throughput, SNR, latency, and outage probability are mainly focused upon during the evaluation process [17]. These performance metrics are verified through different predefined scenarios to ensure the correctness and consistency of the results obtained from the system [27].

4.2 Objectives of Testing

Testing is mainly carried out with the purpose of ensuring that the system put into use is efficient and accurate. Testing makes it possible for there to be a direct comparison between the behaviors of the 5G and 6G networks [9, 10]. Additionally, testing can help to verify that the results obtained from the system implemented using MATLAB are correct [17]. Testing also aims at verifying the reliability and consistency of the system [27].

4.3 Testing Methodology

In order to identify the system in a precise and replicable manner, an approach that involves testing via simulations is employed. In this approach, the system is tested through simulations on MATLAB for pre-defined cases, and the output parameters are noted in a systematic manner. Such parameters include latency, SNR, and throughput [17]. Graphs are used to plot

this information, enabling comparisons to be made easily. The purpose of this evaluation is to illustrate the strengths and weaknesses of both 5G and 6G networks [9], [10].

4.4 Test Environment Setup

In order to ensure uniformity and objectivity in evaluation, the testing conditions are strictly prepared beforehand. These testing conditions consist of the simulation platform of the MATLAB which comprises the system with pre-defined parameters, for example frequency, bandwidth, and SNR levels [17]. To minimize external variation, the noise levels will be adjusted while the distance will range from 50 to 500 meters. Testing the two systems under identical environmental conditions assures that any performance differences can be attributed solely to the system attributes [9], [10].

4.5 Test Cases and Scenarios

In order to evaluate the system's performance under different scenarios, several test cases have been considered. Some examples of throughput scenarios include XR hologram, high-definition streaming, and URLLC [21], [27]. On the other hand, latency scenarios analyze the system's performance under normal, congested, and AI optimized scenarios, whereas SNR scenarios consider different scenarios [15], for example indoor, dense urban, and rural areas. Each scenario provides a detailed analysis of the system's performance and tries to reflect actual scenarios [17], [21].

4.6 Performance Metrics Used

A collection of important performance measures that offer a thorough grasp of system behaviour are the foundation of the evaluation. Throughput describes the speed at which data is sent and shows how effective the network is [17]. The SNR determines how well a signal is received and how well it resists noise [25]. Since the outage probability represents the likelihood of communication failure, the latency refers to the delay in data transmission, which is essential in time-sensitive applications [27]. Overall, the assessments make an accurate and unbiased evaluation of the performance of both 5G and 6G technologies [9], [10], [21].

4.7 Throughput Evaluation

Throughput will be tested over varying distances to gauge the capability of the system to transmit information. Through exploration, it is evident that even with 5G network, there is sustained throughput, although it begins to diminish due to loss through distance when the conditions are relatively mild. In comparison to 5G, throughput capacity in 6G is significantly higher owing to increased capability and better ways of communication. In demanding applications such as XR, data rates are exceedingly high in 6G network.

4.8 SNR Evaluation

Evaluating the strength of signals at different distances and under different environmental conditions is the core purpose of the SNR analysis. It can be observed from the results that the attenuation in the signal leads to a decrease in SNR with an increase in distance in both the 5G and 6G net-

works. However, due to advanced technology and improvements in signal processing, the SNR is constantly higher in the 6G network. Moreover, due to lower signal attenuation indoors, the SNR is generally higher [24], [30].

4.9 Latency Evaluation

For instances where real-time communication is required, latency is considered an essential performance metric. According to the study results, although the 5G network provides low latency performance within normal working conditions, latency performance is considerably higher in cases of network congestion. However, since the 6G network employs edge computing and artificial intelligence algorithms, it provides lower latency performance. In addition, 6G technology can support future technological innovations such as remote surgery, autonomous vehicles, and real-time experiences due to its ability to reduce latency performance.

4.10 Comparative Analysis of 5G and 6G

Comparing the 5G network with the 6G one shows significant differences between the two in all considered aspects. The results show that the 6G network is better suited for future uses due to its superior performance compared to the 5G network when considering factors such as throughput, latency, and reliability [13],[14][20]. While the 5G network can be used for current communication requirements, the 6G network was designed specifically for future purposes. Increased bandwidth availability, artificial intelligence implementation, and advanced communication technologies play a critical role in this process [12], [14].

4.11 Validation of Simulation Results

By contrasting the simulation findings with accepted theoretical models and anticipated system behavior, the results are verified. While route loss behavior is consistent with established wireless communication models, the observed throughput patterns are consistent with Shannon capacity principles. Furthermore, performance variances in many contexts show consistent and logical trends. The correctness and validity of the implemented model are confirmed by the agreement between simulation results and theoretical predictions.

4.12 Discussion of Results

There are many valuable observations which can be made from these results regarding the behavior and progress of wireless systems. It has been observed that distance is a critical determinant of all parameters related to performance, whereby increased distance leads to poorer quality signals and throughput. Increased data speed is possible due to high frequencies, particularly in the 6G system, although there are certain limitations to this, like less range. Also, it has been found that further progress in artificial intelligence in conjunction with edge computing leads to increased efficiency and optimized resource usage. [1], [2], [5]

4.13 Limitations of Testing

However, there are certain issues with the tests for 6G. In particular, the simulations are developed based on very basic models which fail to demonstrate the full complexity of the reality. Such factors as interference and obstacles are not taken into account. The system lacks realism in its con-

sideration of the user behavior. Moreover, 6G technology is currently under development, while the artificial intelligence component is only theoretical in nature. As a result, the parameters related to it are hypothetical as well. Consequently, further studies need to be conducted and applied to develop future projects using 6G technology. Thus, we need to consider certain aspects of 6G technology [2], [3], [4], [10].

4.14 Summary

The system developed was rigorously evaluated in this chapter, demonstrating its capability to effectively model the characteristics of wireless communications and compare the efficiency of 5G and 6G networks. The findings demonstrate that the system is capable of generating valid solutions under different conditions. Considering everything, the 6G network outperforms the 5G network concerning throughput, latency, SNR, and outage probability. Hence, it can be deemed a credible choice for future wireless communications.

Chapter 5

System Implementation

5.1 Introduction

The suggested approach designed to evaluate and contrast 5G and 6G wireless communication networks is put into practice in this chapter. This chapter uses MATLAB to convert the system designs and theoretical modeling of throughput, latency, and SNR that were covered in the previous chapter.

The implementation's main goal is to replicate, under controlled circumstances, the behavior of wireless communication in the actual world. Path loss modeling, SNR computation, Shannon capacity-based throughput prediction, and delay computation are all integrated. In order to represent the features of next-generation networks, conceptual integration of edge computing and AI-based optimization for 6G systems is also included.

This chapter's goal is to show how the planned scenarios are carried out, data is processed, and outcomes are produced for performance assessment.

5.2 System Architecture

A layered architecture that simulates a straightforward yet realistic wireless communication environment is used in the implementation of the system [13], [14]. This method makes it possible to represent various system functional components separately while maintaining coherent interactions between them. From user devices to sophisticated optimization methods, each layer represents a crucial component of contemporary communication systems [19]. The architecture is designed to show how 5G and 6G have evolved, especially in terms of intelligence, efficiency, and latency reduction. The model is simpler to examine, adjust, and expand for further study when the system is arranged into discrete layers [12], [14].

5.2.1 User Layer (User Equipment - UE)

The user layer is responsible for the user equipment or mobile devices, which become the source and destination for data transmission within the system. The user equipment includes smartphones and Internet of Things devices among others, which are capable of transmitting signals wirelessly. One of the key factors here is the signal strength or quality, since the distance between a user and the base station is critical for it. In addition, the ability of users to catch the signal depends greatly on their technological limitations and conditions surrounding them. The third important point is the usage of data by users who might differ in terms of bandwidth requirements [11], [19], [27].

5.2.2 Base Layer (BS)

Base station layer acts as a major point of contact for communication between user terminals and the network. It takes care of the functions of transmitting signals, managing channels, and proper allocation of resources to users. This layer functions as a conventional gNodeB in a 5G environment, carrying out these functions in accordance with predetermined algorithms and network circumstances [19], [30]. On the other hand, by including AI-assisted decision-making skills, the 6G implementation improves this layer. This enables the base station to better adapt to shifting network needs, enhance signal quality, and dynamically modify resource distribution. In next-generation systems, this makes the base station more intelligent and adaptable [7], [8], [27].

5.2.3 Wireless Channel Layer

The physical medium by which signals go from the base station to user devices is modeled by the wireless channel layer. The most significant real-world elements that affect signal transmission, for instance path loss, noise, and distance-based attenuation, are incorporated into this layer. However, noise takes into consideration interference from electrical and environmental sources, path loss indicates the decrease in signal strength as it moves over space. As users become farther away from the base station, it becomes increasingly difficult for them to communicate because of attenuation based on the distance. The model assists in evaluating how the system functions in different scenarios and provides a realistic representation of the wireless communication environment [11], [23], [19].

5.2.4 Edge Computing Layer

Through the provision of a way through which the data can be processed closer to the end user instead of relying only on the central server, the edge computing layer contributes to better performance. Multi-access Edge Computing (MEC), a technology that decreases latency and provides quick reaction for important services, is applied in 5G networks in order to attain this effect. The edge computing layer evolves into a more advanced and intelligent platform within the framework of 6G, which will be able to conduct complex computation and real-time decision making [11], [23], [19].

5.2.5 AI Optimization Layer (6G Only)

This AI optimization layer, which is an abstract concept designed specifically for 6G systems, aims at improving the intelligence and overall performance of the entire network [12], [14]. The allocation of bandwidth is done

dynamically depending on the demand and state of the network through sophisticated algorithms. There is a need to constantly monitor and optimize SNR conditions in order to ensure quality communication [11]. Resource management is improved through prediction and adaptive methods, which allow the network to predict requirements of the user and make adjustments accordingly [17]. There is a marked difference between this layer and rule-based systems, with this layer adopting intelligent optimization strategies [12], [14].

5.3 Tools and Technology Used

The correct modeling and simulation techniques, as well as technologies that make it possible, have to be used in order to implement the proposed system. They were selected based on the ability to handle complex mathematical operations, generate reliable results, and provide comprehensible visuals. To ensure versatility and easy experimentation, simulation technology was selected from all the other options available. It made it possible to conduct a proper testing and evaluation of different scenarios for 5G and 6G wireless communication networks [24], [25], [30].

5.3.1 MATLAB Environment

Due to the fact that it has great abilities in terms of numerical computing as well as wireless systems modeling, the MATLAB platform will be used as the simulation environment. This provides an adaptable framework which allows the easy implementation of complex mathematical formulae and communication models. Moreover, MATLAB is a reliable choice for modeling next generation wireless networks because it is usually employed in scientific studies [24], [25].

The ability of the MATLAB platform to perform mathematical modeling is one of its key advantages. This makes it possible to apply calculations dealing with signal propagation, route loss, SNR and outage probability systematically and precisely [11], [23], [30].

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5.3.2 Simulation Parameters

| Parameter | 5G Value | 6G Value |
|-----------|----------|----------|
| Frequency | 3.5 GHz | 100 GHz |
| Bandwidth | 100 MHz | 1 GHz |
| SNR | 10 dB | 20 dB |
| Distance | 50–500 m | 50–500 m |

Table 5.1: Comparison of 5G and 6G Parameters

These values are aligned with the methodology defined earlier.

5.4 Development Environment and Programming Approach

MATLAB scripts are utilized to create the system, and a modular programming technique is employed to preserve the code's organization, flexibility, and ease of maintenance. Because of this structure, various system components may be independently built and tested while still making a contribution to the simulation as a whole. The system becomes more scalable and flexible for further improvements by breaking the implementation up into clearly defined modules, especially when expanding from 5G to 6G situations.

Setting up all simulation settings before to execution is the responsibility of the Initialisation Module. This entails specifying the number of users, bandwidth, noise levels, transmission power, and distance ranges. The technology guarantees consistency across all computations and enables rapid modifications when testing various situations by centralising these parameters.

Wireless channel behavior can be modeled via the Channel Modelling Module. This takes into account such significant aspects as signal attenuation, noise, and route loss. Due to its ability to manage the degradation process, this module becomes necessary in order to provide an authentic environment in regard to the functioning of the system [1], [25].

It becomes possible to determine such key performance indicators as throughput, delay, outage probability, and SNR through the use of the Performance Calculation Module that employs data generated by the modelling module. Such calculations based on mathematical models become critical for comparing 5G and 6G performance.

These should then be conveyed in a clear and easy-to-understand way

through the use of the Output Visualisation Module. This produces graphical representations of things like latency comparisons or the probability of an outage against distance, which make it simpler for analysis of the system's behavior and conclusions to be drawn from the simulation outputs.

Each component of the system is designed to have its own unique task to ensure the system's efficiency, reusability, and scalability. Aside from simplifying testing and debugging, this allows for other features to be added easily, including artificial intelligence-powered optimisation for 6G networks [7], [8], [27].

5.5 Processing Logic and Algorithm Designs

For the purpose of ensuring an accurate performance evaluation, the process follows a systematic order through which each simulation is conducted. In Step 1, the critical constants such as the speed of light and noise power together with critical parameters such as frequency, bandwidth, SNR, and distance range have to be determined. In Step 2, route loss is calculated for each individual distance in order to know the extent to which the signal degrades when traveling through the wireless link. Step 3 uses the obtained results from Step 2 in conjunction with transmission power in calculating the signal power received. This shows the actual strength of the received signal at the receiving end of the user. SNR, which is the measure of quality of the signal, can be determined in Step 4 by dividing the received signal power by the noise power. Using the Shannon capacity function, $C = B \log_2(1 + \text{SNR})$, the throughput can be calculated in Step 5, where this function gives the maximum attainable throughput. Step 6 shows the latency that results in data transfer through packet size and calculated throughput. For the sake of maintaining consistency when making

comparisons, all the scenarios that have been mentioned in Chapter 6 will be executed in Step 7 through the use of identical procedures. Finally, in Step 8, graphs will be generated to provide a representation of system performance in terms of throughput against distance, SNR against distance, and latency against distance.

5.6 Implementation of Scenario

The system implements multiple scenarios defined in Chapter 6:

5.6.1 Throughput Scenarios

- HD Streaming vs URLLC
- Dense Office vs XR Holograms
- Congestion vs Intelligent Beamforming

Each scenario modifies parameters such as:

- Bandwidth efficiency
- Interference level
- Distance Variation

5.6.2 SNR Scenarios

Different environments are simulated:

- Indoor Baseline
- Urban Dense
- Rural Long Distance

5.6.3 Latency Scenarios

Latency is evaluated under:

- High traffic conditions
- Edge-assisted processing
- AI-optimized communication

5.7 AI-Native Implementation for 6G

The simulated behaviour of AI is supposed to represent theoretical modelling of the expected future development of next-generation communication networks regardless of whether AI training in the actual scenario is present. Improved SNR value, reduced latency, and adaptive throughput scaling are thus built into the model to achieve this objective. These changes are meant to simulate how an intelligent system can achieve maximum utilization of the network in the most dynamic situation possible without relying on actual learning algorithms in real-time operation. As such, the model does not add unnecessary computational load while still representing performance benefits commonly attributed to artificial intelligence applications.

A number of intelligent networking capabilities, including effective scheduling which ensures better distribution of resources according to need, are represented in the model concept. Moreover, predictive allocation of resources, based on the capability of predicting user needs and taking appropriate action, is considered [5], [18]. Finally, the intelligent optimization of network is achieved through dynamic enhancement of system efficiency and improved use of resources. All of these factors, when taken together,

provide a fair approximation of the potential impact of AI in 6G network optimization.

5.8 Application Access Security

For instance, within the framework of 6G technology, these features become more advanced by assuming intelligent anomaly detection through artificial intelligence, as well as the use of dynamic security policies that ensure intelligent reactions to any possible threat to achieve high levels of network security. In terms of security, there are mechanisms like authentication of access, encryption of channels, and prevention of access from other sources.

5.9 Database and Data Handling Security

The system employs principles that make data management safe and reliable despite the absence of any physical database as follows: simulation data remains very accurate by maintaining its integrity during execution, all data resulting from the simulations remain accurate by keeping them in their actual forms without alteration [27], and there is no way for any form of interference with the data externally. Moreover, while this design works independently currently, some of the areas for future enhancements include cloud data storage and even blockchain technology [6], [12], [14].

5.10 Performance Optimization Techniques

To increase the system's effectiveness and execution speed, a number of optimization techniques are used, especially in MATLAB. These include vectorized calculations, which greatly increase processing performance by working on whole data arrays rather than individual items, and the use of

effective loop structures to reduce needless repeats. In order to maintain the simulation's speed and scalability even while handling several situations, efforts are also undertaken to lower the total computing complexity. In the context of 6G, edge computing is used to decrease processing delays by putting computation closer to the user, while further conceptual optimization is added using AI-based approaches that assist reduce latency and increase responsiveness [7], [8], [27].

5.11 Implementation Challenges

Several problems that required proper consideration and solving emerged during the installation stage. Given that reality contains complicated and dynamic aspects, which cannot always be replicated properly within the simulated environment, the first challenge involved the replication of realistic behavior of wireless communication [11], [23]. Another difficulty consisted in dealing with the high frequency features of 6G, which contributed to increased complexity in propagation and attenuation [3], [14]. Moreover, an important point to take into account was the need to find an appropriate compromise between computational accuracy and model complexity, as overly simplistic models could have been misleading, while overly complex models would not work properly [3], [14]. Another drawback associated with the development of 6G technology was the lack of validation data due to the ongoing development process. To address these difficulties, theoretical assumptions were introduced [5], [15].

5.12 Summary

In this chapter, it has been shown how theoretical concepts discussed in previous chapters are transformed into a realistic simulation through a

complete MATLAB-based implementation of the proposed system. It allows an extensive evaluation of the 5G and 6G performances based on metrics such as data throughput, delay, and other factors that can be accurately modeled due to the accurate representation of wireless communication characteristics in the proposed model [24], [25]. Moreover, it also provides conceptual understanding and integration of state-of-the-art concepts such as edge computing and AI-based optimization, giving an idea about the future potential of next-generation networks [6], [9], [27]. Overall, the implementation provides a good foundation for performance evaluation, and in the next chapter, the focus will be on testing and evaluation [9], [18].

Chapter 6

System Testing and Evaluation

6.1 Throughput

6.1.1 Case 1: Throughput of HD Streaming Vs. Throughput of URLLC

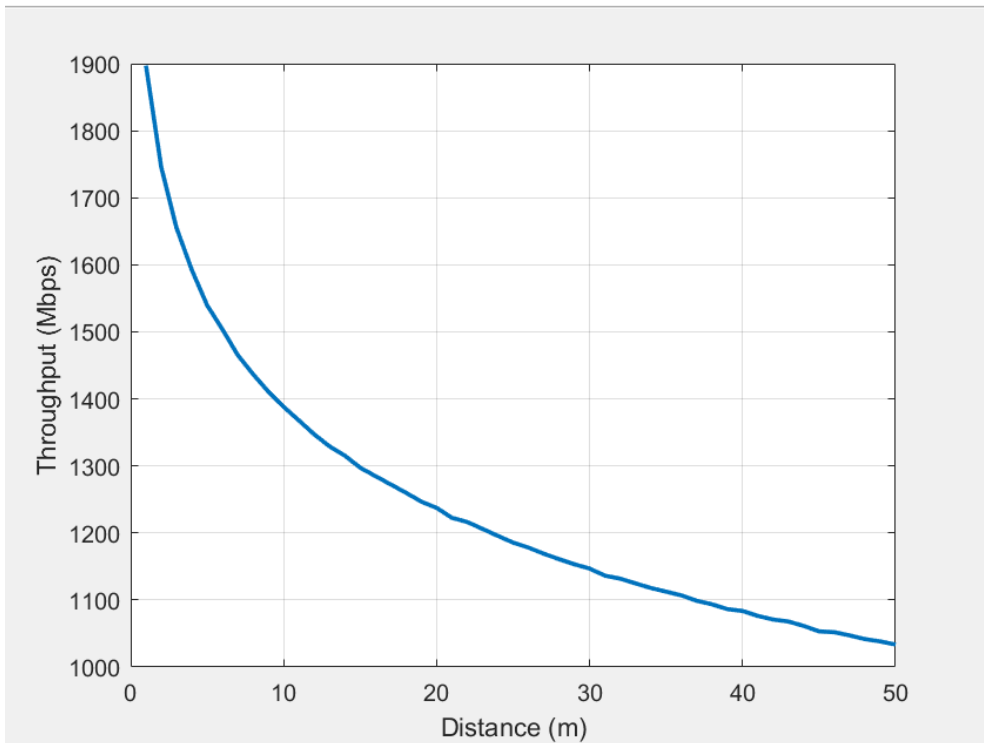


Figure 6.1: Throughput of HD Streaming

It is particularly important for the purposes of cloud computing, virtual environments, and high-definition video streaming. The need for testing the performance of the networks in varied scenarios and for varied applications becomes very important as technology in the field of wireless communication evolves into highly complex networks. Comparison is necessary because each application, such as HD streaming and URLLC, requires something different from its counterparts.

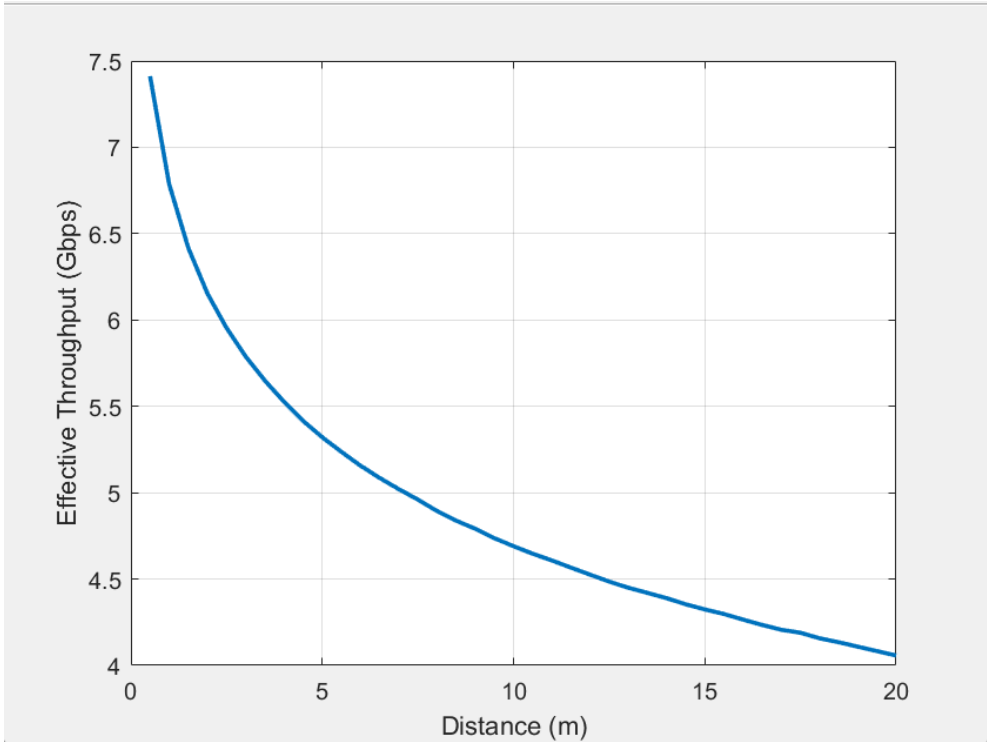


Figure 6.2: Throughput of Ultra Reliable Low Latency Communication

As wireless communication technologies continue to evolve toward advanced systems, it becomes essential to assess network performance under various scenarios and application requirements. Different use cases, such as HD streaming and Ultra-Reliable Low-Latency Communication (URLLC), impose distinct demands on throughput, reliability, and latency, making comparative analysis necessary.

The comparative analysis, as shown in Figure 6.1, highlights the fundamental differences in frameworks and performance objectives between 5G and 6G communication systems. In both scenarios, the theoretical foundation is based on Shannon’s ergodic capacity formula:

$$C = BW \log_2(1 + SNR) \quad (6.1)$$

This equation represents the maximum achievable transmission rate under ideal conditions. In simulations, capacity is computed by averaging over multiple SNR samples to account for variations in indoor channel conditions. However, Shannon capacity assumes perfect coding, absence of protocol overhead, infinitely long code blocks, and complete bandwidth utilization. Therefore, it serves as an upper bound rather than a direct indicator of practical user-experienced throughput.

In the 5G indoor HD streaming scenario, an efficiency factor of 0.85 is considered. This implies that approximately 85% of the theoretical capacity is achieved as usable throughput, while the remaining 15% is lost due to practical system constraints such as channel coding redundancy, pilot signaling, framing structures, and Hybrid Automatic Repeat Request (HARQ) mechanisms. Since HD streaming applications can tolerate moderate latency and limited packet loss, they do not require excessive redundancy or ultra-short packet structures. This flexibility allows the use of larger transport blocks and relaxed reliability constraints, leading to efficient spectrum utilization. Consequently, 5G maintains high throughput over indoor distances, making it well-suited for applications such as high definition video streaming, smart classrooms, enterprise networking, and enhanced mobile broadband (eMBB) services, where stable data rates are prioritized over absolute reliability.

On the other hand, the URLLC application area of the 6G network uses an efficiency factor of 0.75. The reason for this decrease is the need for ultra-reliable and ultra-low-latency communications. Certain applications like artificial intelligence-supported remote surgery need to have highly ef-

efficient communication links, with absolutely no room for errors or any type of delay. To achieve this level of perfection in communication performance, the URLLC application area of 6G utilizes sophisticated error-correction procedures, frequent retransmissions, multiple data transmissions, and additional control signaling. Although all of these features are required for ensuring reliability, they come at the cost of reducing spectral efficiency. Furthermore, 6G supports larger bandwidths and higher frequency spectrums, including the sub-THz range, which allows high speeds but sacrifices some of that capacity.

The primary difference between 5G and 6G technologies can be seen in their design philosophies. In the case of 5G technology, the emphasis is on higher throughput and spectrum efficiency, while 6G technology focuses on reliability and low latency, although at the cost of efficiency. Thus, 5G is suited for applications that require robust and high-speed connectivity, while 6G is suited for critical missions.

Finally, it is important to highlight that while both 5G and 6G have been developed based on Shannon's theory, their performance levels are different because of efficiency restrictions in practice. While 6G operates less efficiently than 5G, it still performs better as a whole because of higher frequencies, greater bandwidth, and advanced physical layer technology. Although 5G can be successfully used for HD video streaming and mobile connectivity, 6G allows for more innovative applications like artificial intelligence-based remote surgeries, self-driving technologies, and holography. In other words, 6G is an important improvement in the field of wireless communications, which emphasizes both speed and smart performance.

6.1.2 Case 2: Throughput of Dense Offices vs Throughput of XR Holograms

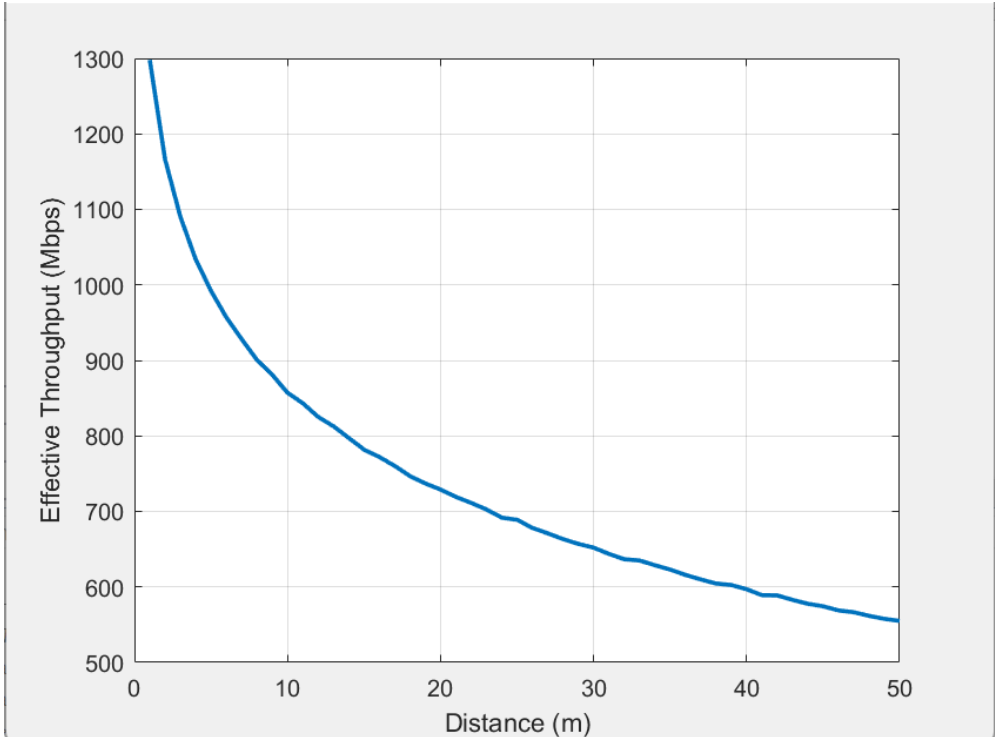


Figure 6.3: Throughput of Dense Offices

This analysis will cover two distinct instances where data is transferred under certain circumstances and examine how effectively this can be achieved in each case. The first instance pertains to a congested workspace where a number of users are linked to the network at the same time. While all devices are within a reasonable proximity of the access point, there are certain obstacles that interfere with the signals and affect the speed of transmission.

However, the latter technology is dedicated to XR holographic communication, which involves the use of extended reality holograms. Such

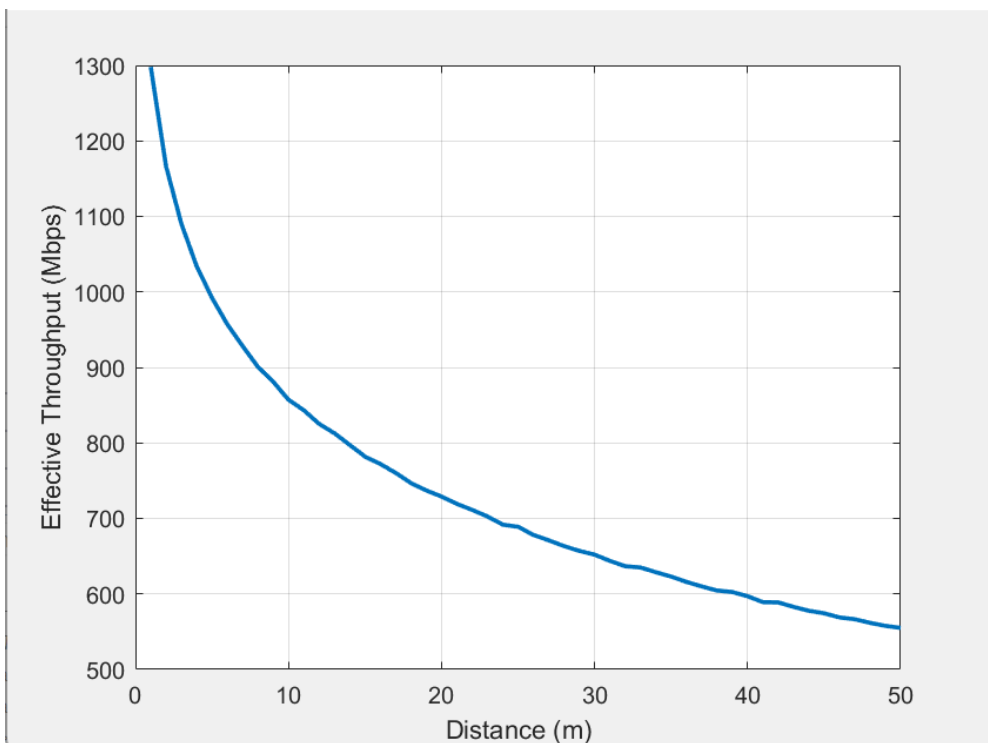


Figure 6.4: Throughput of XR Holograms

holograms need to be transmitted at extremely high data speeds and low latency levels to function properly. Due to these stringent requirements, it is essential to evaluate how effectively modern wireless systems can support such high-demand applications.

As shown in Figure 6.3, the findings of Scenario 2 (dense office setup) indicate that the throughput is inversely proportional to the distance between the transmitting and receiving ends. At a small distance of about 1 meter, the throughput attains a value of 1300 Mbps, which shows the high intensity of the signal as well as high SNR. In this case, higher order modulations may be used for speedy data transfer.

With the increase in distance up to 10 meters, the throughput drops

to about 870-900 Mbps. Path loss, which causes attenuation of the transmitted signals, is the main factor contributing to this phenomenon. Indoor multipath is also another cause for the decrease in throughput; it refers to a scenario whereby the signals travel through several paths by bouncing from the walls before reaching the destination.

In the range from 20 m to 30 m, the throughput keeps decreasing, reaching the level of 650–720 Mbps. While this number is much lower compared to 1 GHz, there is no disruption in the connection due to appropriate adjustment of transmission parameters like modulation and coding.

At 50 meters away, however, the throughput will be reduced to around 550 Mbps, which is a marked decrease in comparison to its close-range speed. But still, this is an acceptable amount for most tasks, including the streaming of videos, collaboration software, and cloud computing services. In conclusion, from this experiment, Scenario 2 proves that office buildings that have a thick concentration of equipment can attain high throughputs at certain distances provided that proper planning is done.

Scenario number two, depicted in Figure 6.4, involves XR holographic communications. This system is intended to provide an extremely high bit rate to transmit and render highly complex three-dimensional data. Such applications include immersive telepresence, virtual collaboration, and the metaverse.

It has been observed that the throughput values have been quite high compared to that in the case of a densely packed office setup. Even at an extremely close distance of about 1 m, the throughput value goes up to around 950 Gbps, which is much higher than traditional wireless technology by many orders of magnitude. Such outstanding performance is possible due to state-of-the-art technologies like high frequency spectrum use, etc.

However, the throughput in an XR system starts decreasing quickly when the distance is increased. At about 5 meters, the throughput drops drastically to around 63 Gbps. This is the typical nature of high frequency communications, which undergo greater attenuation and have a greater tendency to be blocked.

The throughput is also greatly diminished to about 50 Gbps when the distance becomes 10 meters. Even though this has seen a huge fall, the data speed is still enough to support the needs of applications like hologram and immersive XR.

The throughput reduces to about 34 Gbps at roughly 20 meters. Such findings suggest that XR holography systems operate efficiently within short ranges including smart rooms, specific meeting rooms, and other confined environments where ultrahigh-speed data transfers can be supported.

The comparison between Figure 6.3 and Figure 6.4 reveals the critical distinctions between the two system designs and their performance goals. The dense office case (Scenario 2) is built for stability and reliability, delivering high bandwidth to a large area within a building, capable of handling several users at once, providing hundreds of Mbps of throughput. On the other hand, the XR hologram scenario is geared towards ultra-high throughput, delivering tens to hundreds of Gbps of throughput but only over a much shorter distance.

A further key difference is related to how the throughput depends on distance. In the second scenario, there is a slow degradation in the throughput with an increase in distance, while in the XR scenario, the drop is very sharp. The reason behind this is the constraints associated with high-frequency transmissions.

These distinctions indicate the different needs of contemporary wire-

less technologies. Dense office spaces need good coverage, reliability, and multidevice capability, thus being ideal for conventional use cases like corporate networking and education. Meanwhile, the holographic communications that are used in the extended reality require high bandwidth and extremely low latency.

In summary, this comparative analysis highlights how wireless communication technology is constantly developing. Whereas conventional wireless communication systems prioritize efficiency and accessibility, new technologies are geared towards providing ultrahigh data rates and digital experience. Future wireless communication technology will combine both perspectives, allowing for effective daily interaction while simultaneously facilitating innovative applications in the digital age.

6.1.3 Case 3: Throughput Under Congestion vs Effective Throughput with IRS Beaming

The findings discussed in this section deal with studying the characteristics of the functioning of wireless communication technologies in the presence of two basic situations: the traditional situation where there is congestion and the enhanced one brought about by the utilization of Intelligent Reflecting Surfaces (IRS).

Throughput under Congestion shows the base case where communication takes place in a congested environment without any enhancement to the environment itself, whereas Throughput of IRS Beamforming shows the enhanced case where communication happens due to the use of IRSs. From the comparison of Figures 6.5 and 6.6, it is clear that we are dealing with future wireless technologies, not just some numbers.

Clearly, the results shown in Figure 6.5 illustrate the shortcomings of traditional wireless communication systems in case of congestion. The

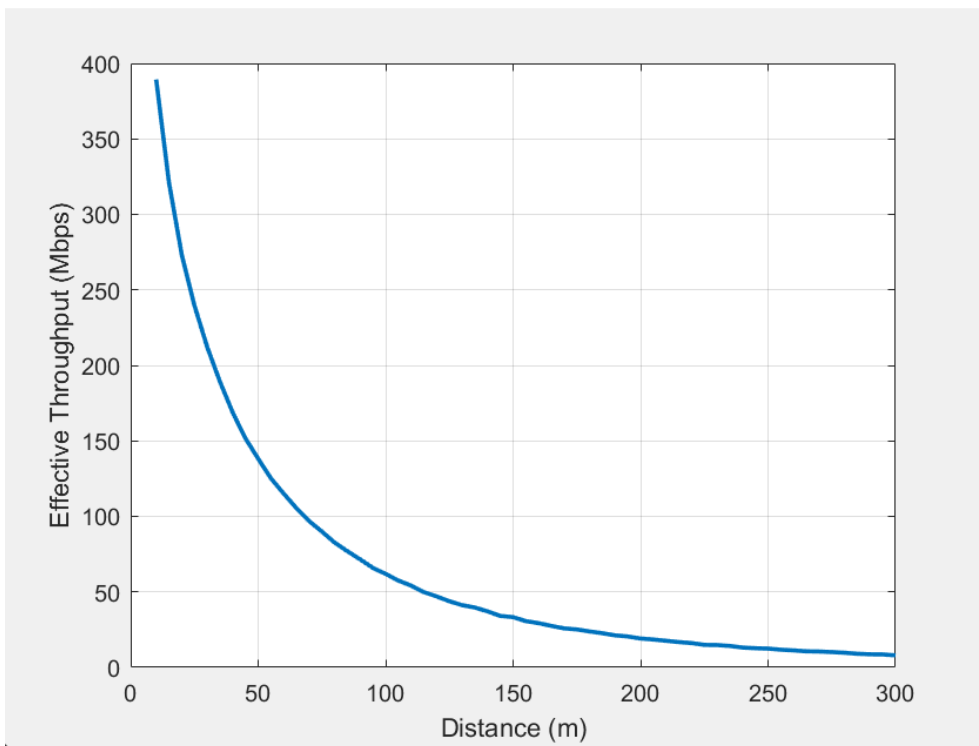


Figure 6.5: Throughput Under Congestion

system works fine when the distances are smaller; the obtained throughputs in this case are close to 380 Mbps. However, the efficiency strongly depends on the distance, and the throughput drops sharply with an increase in this parameter, going down to less than 10 Mbps.

This phenomenon can be explained by the interplay between path losses and network congestion. First of all, the traditional wireless channels are associated with signal power losses due to both spreading losses and attenuation. Secondly, the shared usage of communication resources leads to negative impacts on the throughput of the system.

Mathematically, this relationship can be approximated as:

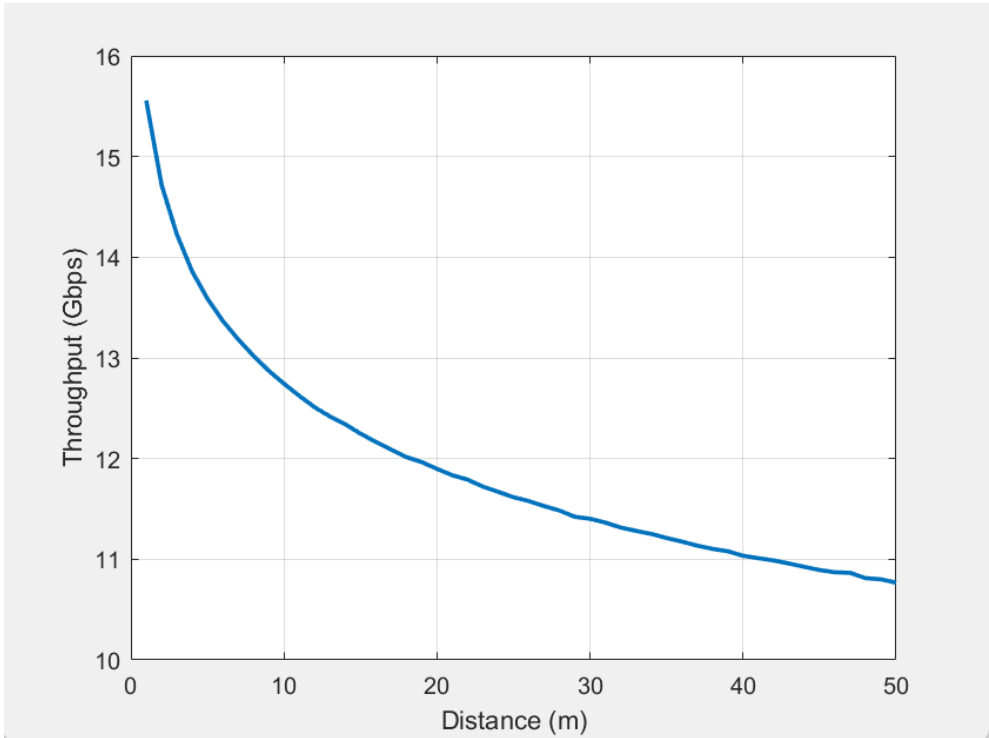


Figure 6.6: Throughput of IRS Beaming

$$T(d) \propto \frac{1}{d^n} \tag{6.2}$$

[17]

where n represents the path loss exponent, which depends on the propagation environment. In congested and obstructed scenarios, n increases, resulting in a faster degradation of throughput compared to ideal free-space conditions.

It is important to note that not only does throughput decrease, but the rate of degradation is also significant. The curve in Figure 6.5 exhibits a steep and nonlinear decline, indicating severe performance loss at larger distances. Such behavior makes the system unreliable for applications re-

quiring consistent data rates.

In contrast, the results shown in Figure 6.5 demonstrate a significantly improved throughput profile with the integration of IRS technology. The IRS enhances communication by enabling controlled reflection of electromagnetic waves, thereby creating additional optimized propagation paths between the transmitter and receiver.

At shorter distances, the throughput reaches values as high as 15.5 Gbps, which is substantially higher than the baseline scenario. More importantly, as the distance increases, the throughput does not degrade as sharply. Even at larger distances, where conventional systems struggle, the IRS-assisted system maintains throughput above 10 Gbps.

This improvement can be explained through the combined channel model:

$$T(d) \propto |h_{\text{direct}} + h_{\text{IRS}}|^2 \quad (6.3)$$

where h_{direct} represents the direct channel component and h_{IRS} represents the IRS-reflected component. By intelligently adjusting the phase shifts of reflected signals, IRS enables constructive interference, thereby enhancing the received signal strength and improving the SNR. This directly contributes to higher achievable throughput.

The difference from the traditional one is that the decrease in Figure 6.6 occurs gradually and resembles linearity. Thus, the system is much more robust to distance-induced degradation, which makes it more useful for real-life implementations that require reliability.

By comparing the graphs directly, it can be seen that the systems have quite different properties. The graph in Figure 6.5 has a sharp decline, which shows the exponential nature of decay caused by unpredictable en-

vironmental factors. In turn, the graph in Figure 6.6 is rather flat, which means that the degradation is controllable.

It is evident that there is a paradigm shift here because the environment is viewed as an obstacle in traditional systems but as a tool in IRS-aided ones. Such a shift allows for effective signal degradation prevention.

One more difference between the two systems is their throughput scale. Thus, while Figure 6.5 provides results in Mbps, Figure 6.6 reaches a gigabit throughput.

Performance degradation due to congestion becomes highly significant in the case of the base scenario. With an increase in the number of users, interference levels also increase and result in an increase in error levels, hence increasing the rate of transmission errors. However, in IRS systems, the level of interference is minimized, resulting in reduced error transmission and thus improving the spectrum efficiency.

In today's communication systems, reliability is one of the important requirements. It is necessary especially in the case of real-time streaming, autonomous systems, and critical infrastructures. Due to instability seen in Fig. 6.5, it cannot be considered useful in this respect. Conversely, the system depicted in Fig. 6.6 shows high stability levels, as evidenced by the gradual change in throughput.

In terms of efficiency, traditional solutions experience losses in energy because of poor propagation characteristics and multiple transmissions. In contrast, IRS-based solutions enhance the energy effectiveness through aiming at the destination, which does not require the transmission of large amounts of energy and thus increases efficiency.

Regarding implementation, while IRS adds an extra layer of complexity to the system by virtue of its hardware components, the dramatic improvements in the performance characteristics that come with such an approach

make it a viable solution for future networks.

An important takeaway here is the switch from adaptation to control. While traditional solutions seek to adapt to the existing environment, IRS-based solutions are focused on controlling the environment in order to achieve the required result.

In summary, the above discussion makes it evident that IRS-based communication systems outperform traditional methods in multiple aspects. Although Figure 6.5 emphasizes the issues arising due to network congestion and loss due to distance, Figure 6.6 depicts how these problems could easily be overcome using intelligent signal processing techniques. It is evident that IRS technology has great capabilities for future communication systems.

6.1.4 Case 4: Effective Throughput of Balanced Load vs Effective Throughput of Digital Twin

Comparison of the system performance in terms of effective throughput with respect to the transmission distance can be done using Figure 6.7 and Figure 6.8. The performance is estimated by calculating the dependence between throughput, expressed in Gbps, and distance, expressed in meters. The effects of throughput variations on system design, optimization, and implementation are considered.

Each of the two systems operates in different environmental and operational conditions; however, there is a general tendency that the same in both cases, that is, throughput is reduced when distance increases. For the shortest distances (between 1 and 5 meters), throughput achieves very high values of more than 30 Gbps. With the increase of the distance, the decrease of throughput occurs in a non-linear way, with the initial sharp reduction leveling off. For the longest distances (50 meters), throughput

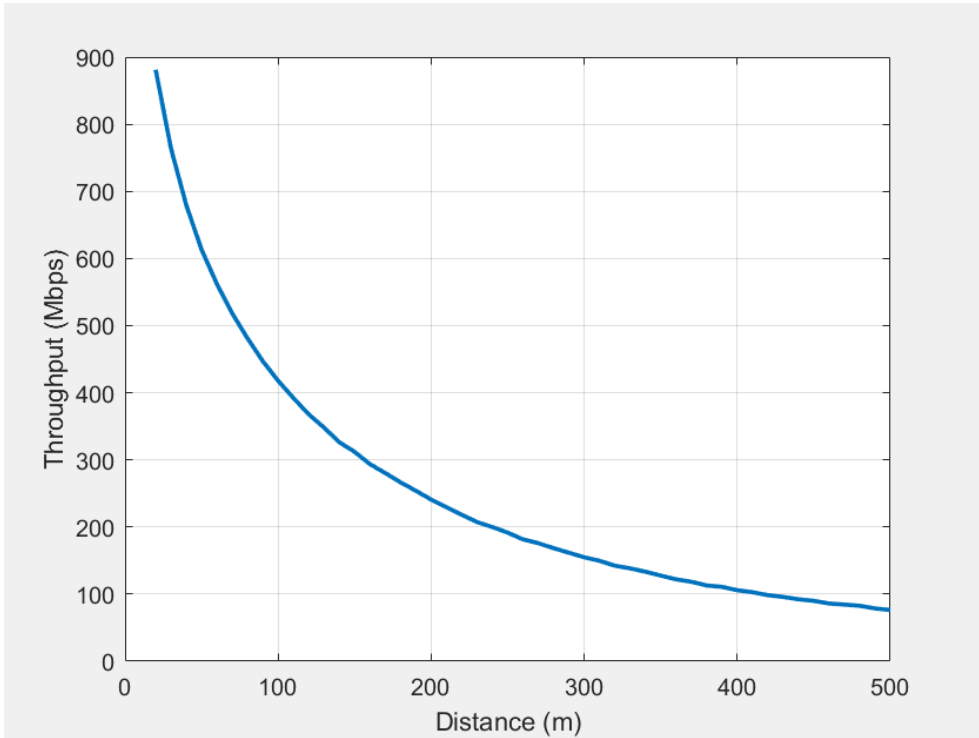


Figure 6.7: Throughput of Balanced Load

reaches the value of about 12-13 Gbps.

The throughput in Figure 6.7 (Balanced Load case) has maximum values of about 33–34 Gbps at small distances, which implies the highest channel efficiency and minimum interference. However, as the distance increases, there is a fast decrease in throughput. At distances of approximately 10 meters, the throughput falls to values of around 21–22 Gbps. Such a significant drop demonstrates that the balanced load case works great at short distances but it is very sensitive to the losses. Therefore, this scenario can be successfully applied to the environments where extremely high throughput is required on a relatively small range of coverage.

At the same time, throughput in Figure 6.7 (Digital Twin case) decreases much slower compared to 6.8. Although the peak throughput in

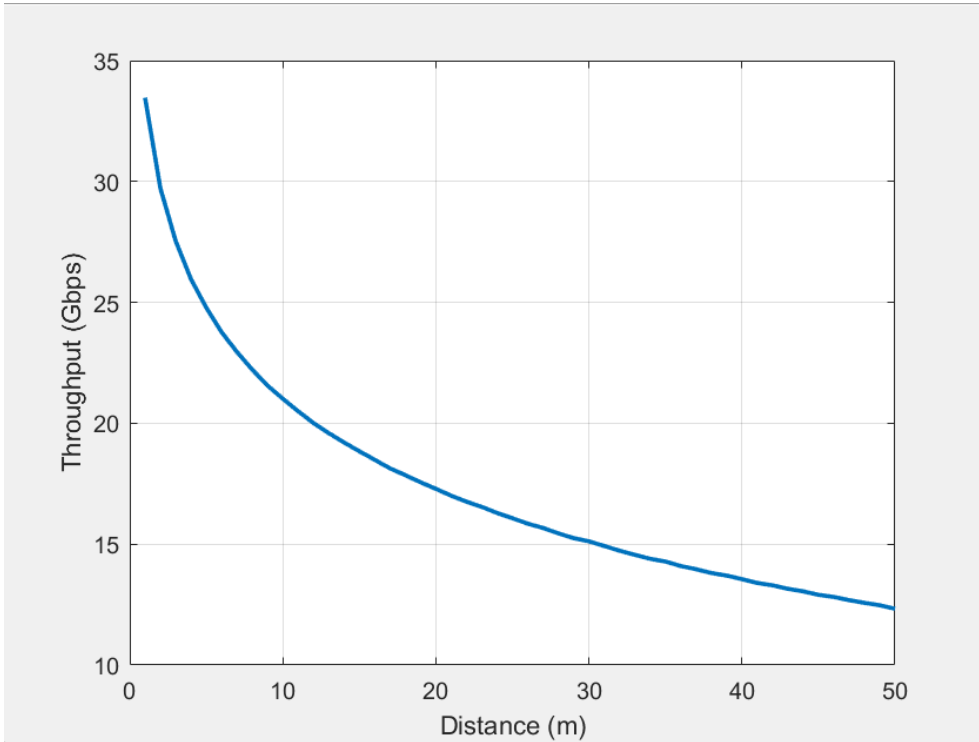


Figure 6.8: Throughput of Digital Twin

Figure 6.8 (Digital Twin case) at small distances is the same as in Figure 6.7 (Balanced Load case), it experiences less degradation. As a result, the Digital Twin scenario has much better stability of performance. It can provide stable operation in a wider range of distances. Specifically, the Digital Twin scenario will work fine in the middle distance range of 10 to 30 meters.

The difference in performance between the two cases becomes evident when they are compared directly. In very close ranges, their performances are fairly equivalent; however, in balanced load case, the maximum throughput is somewhat higher. For mid-range values, the digital twin scenario performs better due to a more gentle decrease in throughput. With

further increase in the distance, both cases approach a nearly equivalent throughput, but the digital twin case still retains a certain margin.

In terms of stability, the digital twin scenario provides a higher level of performance. The more stable decline of throughput implies fewer fluctuations that are important for applications requiring consistent data transmission. In addition, the balanced load case provides a higher peak throughput at the expense of increased fluctuations with growing distance.

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6.1.5 Case 5: Throughput of Rural Long Distance vs Throughput of AI Automation

The correlation between the distance and the throughput is one of the important factors in wireless communications because it depends on both the physical and environmental constraints, as well as the design options that can be utilized for this system. The current section will compare two cases which involve two different types of systems, namely a rural long-distance communication and a high-throughput AI automation. Both

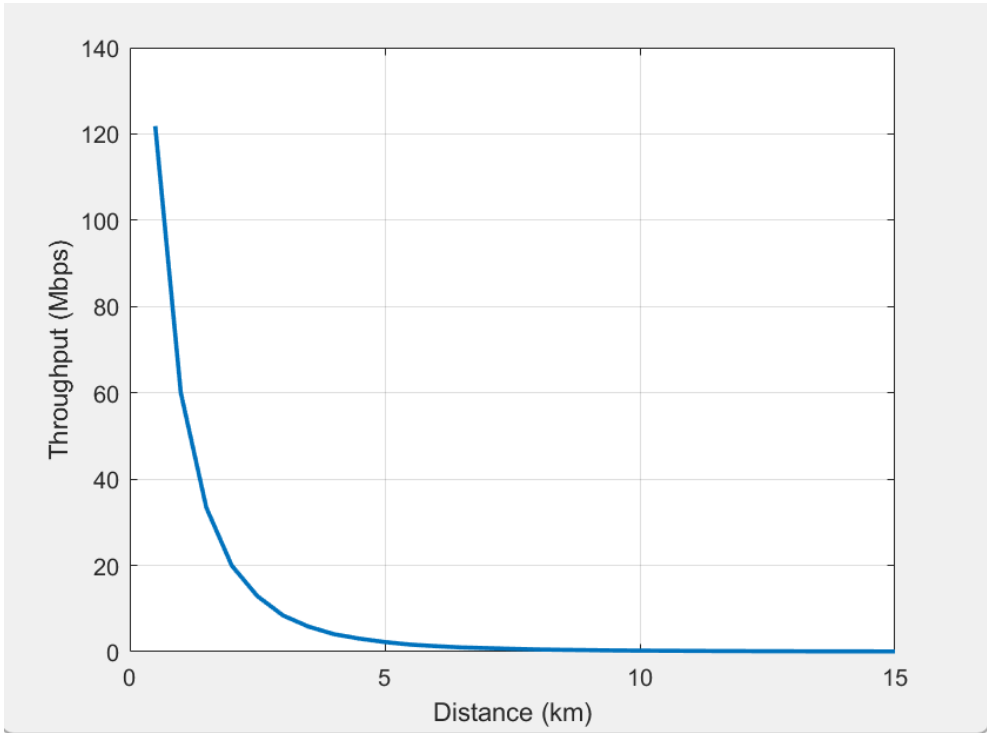


Figure 6.9: Throughput of Rural Long Distance

cases show a negative impact of distance on the throughput, although to different extents.

Throughput is the effective speed of successful data transfer over the communication link, considering real-life losses, including noise, interference, retries, and overhead. Distance influences the power of the signal using the attenuation caused by processes like free space path loss, diffraction, scattering, and absorption. The interaction of both plays a significant role in determining the performance of the system.

In Scenario 1 (Figure 6.9), throughput is expressed in megabits per second (Mbps). Here, the communication process takes place over distances of 15 kilometers. In general, it works on low-frequency bands. Low-frequency bands offer excellent propagation properties, which allows the signals to

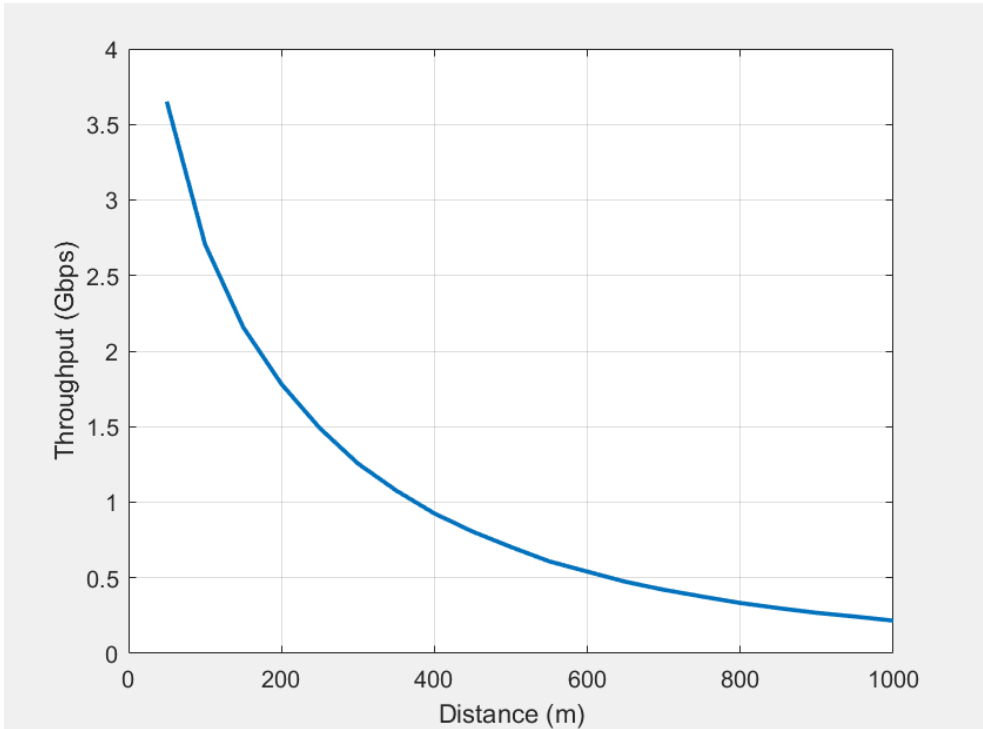


Figure 6.10: Throughput of AI Automation

be transmitted over large distances even without line-of-sight. But low-frequency bands suffer from a small bandwidth constraint.

With increased distances, there is a sharp drop in throughput levels due to path loss and reduced SNR. In order to compensate, the system adopts measures that include the use of reliable modulations and code types instead of high-performing ones. In this regard, lower-order modulation methods are adopted, leading to a drop in throughput levels but maintaining connectivity. For this reason, this example depicts an SNR-limited case.

On the other hand, the second scenario shown in Figure 6.10 depicts an intelligent automation system working in closer proximity at distances up to 1000 meters and achieving throughput rates of gigabits per second

(Gbps). In this case, high-frequency bands such as millimeter waves or sub-THz bands could be adopted in the transmission process. As a result, high initial values of throughput, more than 3 Gbps, have been achieved.

Although there is higher vulnerability to attenuation for high-frequency waves, the rate of decline in throughput in this case is relatively slower compared to the previous scenario. The reason behind this is because of modern communication methods such as beamforming, directional antennas, and power amplification that help ensure adequate SNR. Furthermore, due to the large bandwidth, even with a low SNR, it is possible to achieve high data rates.

The above behavior can be explained using Shannon's formula:

$$C = BW \log_2(1 + SNR) \quad (6.4)$$

In the case of the rural long distance transmission model, the availability of limited bandwidth causes throughput to become very dependent upon the SNR. As a result, the performance of this system will suffer greatly in terms of throughput reduction due to a decline in SNR. However, the model of the AI automated process involves abundance of available bandwidth, thus being able to preserve its high throughput even as SNR is declining.

As one can see, the two different types of scenarios have very distinctive differences. First of all, this is due to the coverage-capacity tradeoff that is involved in the design of each of the systems. While the first is primarily designed to support wide-area coverage and connections, the second system is intended to achieve the highest possible rate of speed with minimum delays.

The two networks also represent a certain type of heterogeneous archi-

ture that consists of macro-cell layer and small-cell layers respectively. Thus, it can be suggested that the rural system works as the former layer, while high-frequency processes provide the latter one. Coordination of the two types of networks is essential.

The performance of systems is also affected by environmental elements. Low frequency systems can cope better with physical obstacles as well as various atmospheric conditions while the high frequency systems are extremely vulnerable to interference caused by obstacles or atmospheric phenomena such as rain attenuation. In such a way, despite the obvious advantage in terms of performance in an ideal environment, the AI automation model might prove to be less efficient in adverse conditions.

Another issue which should be taken into account relates to the consumption of energy and cost-related aspects. First of all, rural area networks would require fewer base stations per mile than high capacity ones. Besides, there would be fewer users per station in the rural networks thus implying greater economy when talking about energy usage.

However, future technologies are aimed at providing the necessary balance between the two discussed dimensions. Massive MIMO, intelligent beam forming, dynamic allocation of frequencies and other technologies based on artificial intelligence are likely to improve the performance of communication systems in terms of both range and capacity.

Although the above-mentioned evaluation was done using relatively simple models, the emerging tendencies are supported by the fundamental principles of wireless communications. In real-world implementations, other aspects like user mobility, network congestion, and interference from the surroundings would affect the system operation as well.

To sum up, a comparative assessment of both throughput-distance cases reveals the complementary nature of these two technologies. Specif-

ically, a rural long-range technology would provide connection across a broad area, whereas an AI-based technology would ensure very high data rate at smaller distances. These technologies do not conflict; on the contrary, they are designed to complement each other within a single wireless communication system.

6.2 Signal-to-Noise Ratio (SNR)

6.2.1 Case 1: SNR of Indoor Baseline vs SNR of AI Surgery

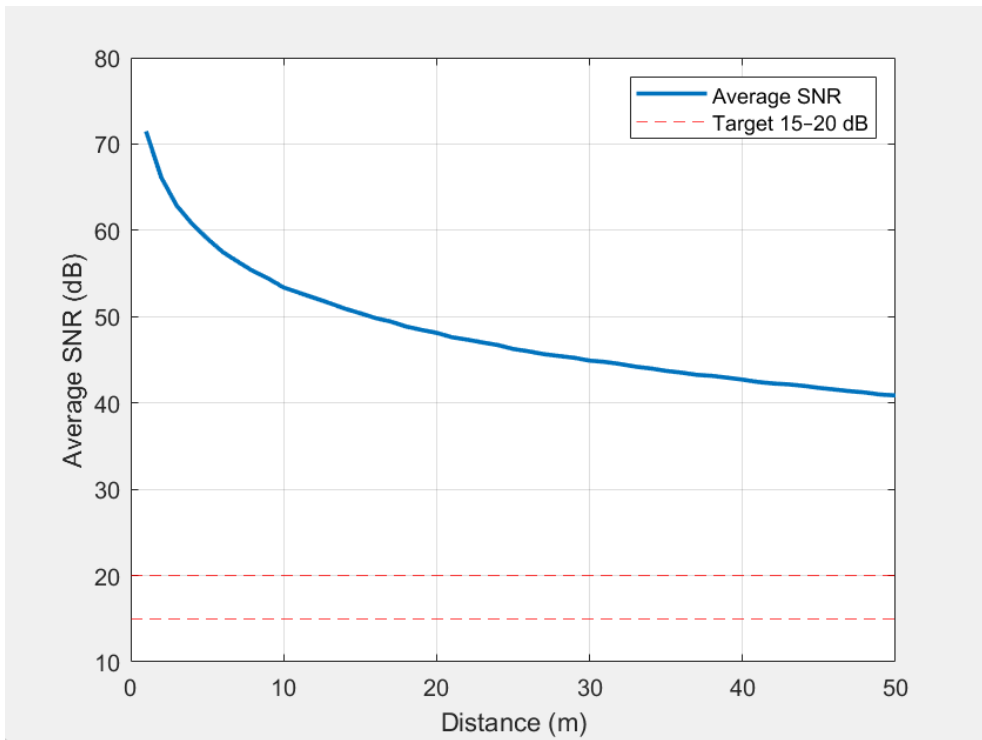


Figure 6.11: SNR of HD Streaming

The signal to noise ratio (SNR) is a key indicator used to gauge the reliability and performance of indoor wireless communication systems. The

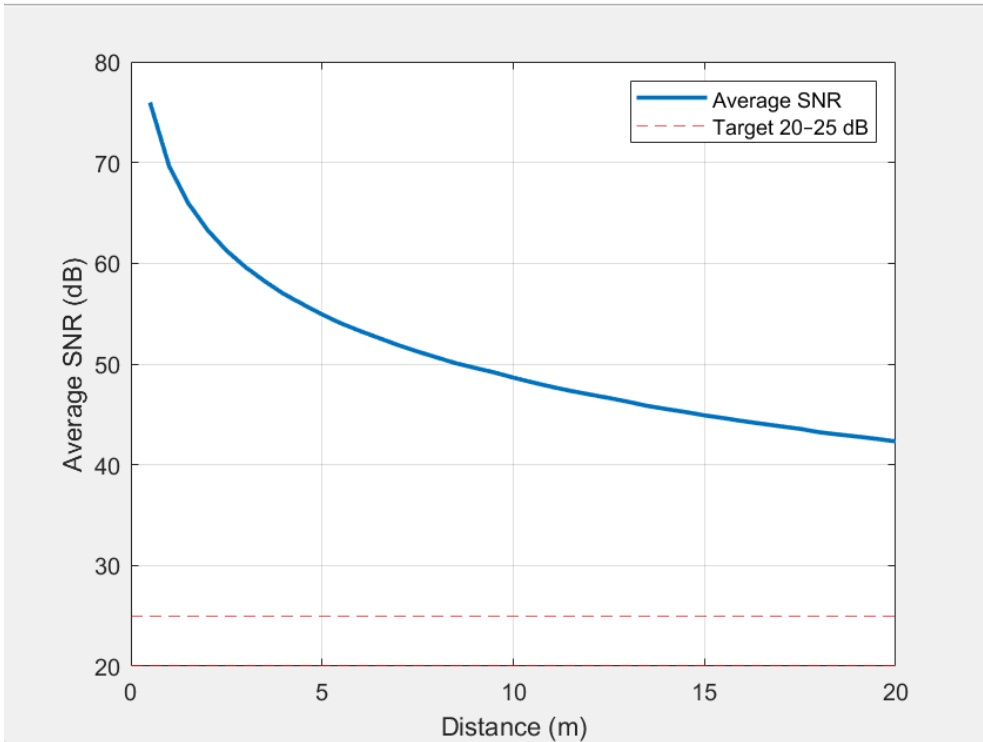


Figure 6.12: SNR of Ultra Reliable Low Latency Communication

importance of such an indicator is related to its significance in estimating the effects of multipath, attenuation, and shadowing on signal quality. In the current section, the evaluation of two different environments will be conducted based on SNR. These include a general environment (Figure 6.11) and an AI-assisted surgery scenario (Figure 6.12). Both of these environments share the same principles of wireless propagation; however, their performance varies based on the restrictions and requirements of each case.

In each scenario, the decreasing trend of SNR is observed when the distance between transmitter and receiver is increased. This trend is expected because of the decrease in signal strength due to path loss in the

environment and the constancy of noise power.

In the case of short distances, both setups have very high SNR values, exceeding 70 dB, which means high-quality signal reception and absence of significant interference. As the distance increases, the SNR gradually starts decreasing, but the decrease in SNR value is not linear since the sensitivity of the system in terms of separation of the devices is higher at smaller distances, while at greater distances, it occurs more slowly following logarithmic path loss pattern that is typical for indoor wireless communication channels.

While the general behavior is quite similar for both cases, there exist some minor deviations that can be traced through the graphs. For instance, as it can be seen in Figure 6.11, the initial value of SNR in the setup of AI-assisted surgery is slightly higher compared to indoor baseline scenario. It is explained by the presence of optimal environmental conditions in the surgical room along with proper positioning of the transmitters.

Thus, the similarity of the decline in SNR shows that the main factors responsible for differences in link performance are related to the configuration of the transmission setup. Moreover, the performance gap between both scenarios is negligible across the mid-range distances (about 5-15 meters).

One important difference between the two scenarios involves the maximum operating distance. The baseline scenario is extended to 50 meters and will be used for a variety of general-purpose locations including offices, homes, and outdoor areas. The second scenario, AI-assisted surgery, however, is restricted to only 20 meters because of its specific use in controlled locations like operating rooms.

Another important distinction relates to the SNR threshold. This describes the lowest possible SNR value at which communication will still be

reliable in the considered scenario. The URLLC demands a higher SNR threshold in the second scenario because it cannot afford any communication failure and hence must provide extremely high levels of reliability. Regardless of having a high SNR threshold requirement, the second scenario is designed to have an SNR margin greater than the required threshold at any distance.

Having a high SNR margin in the second scenario shows that the links are under strong conditions with respect to SNR. This may imply that there is an excess of link provision under normal operation. As a result, it becomes possible to consider further improvements in terms of link utilization.

Dependence on the distance continues to be the primary consideration that dictates the level of SNR in both cases. The variations in the environment play a minor role compared to distance dependence and system configuration. It is clear from this that system design considerations have much more weight when it comes to providing reliable wireless communications under these conditions.

Conclusively, the comparative study shows that despite the similarities in the degradation trends, there are marked differences between the two scenarios in terms of system design objectives. In one scenario, the emphasis is put on coverage and communication capability, while in the other case, it is all about reliability and precision. The study outcomes prove that the respective designs are adequate in terms of meeting their design purposes.

6.2.2 Case 2: SNR of High Device Density vs SNR of XR Holograms

In both scenarios, one observes that the average SNR is decreasing along with the distance; however, these examples have quite a lot of differences in terms of the considered scale, operational circumstances, and performance metrics, which leads to various conclusions.

As seen from the graph with the caption *Average SNR vs Distance (High Device Density)*, at close distances, the SNR starts at a relatively high level (about 70 dB) and continuously decreases up to 35 dB at 50 meters. The graph line has a gentle and steady drop after the first drop-down. It can be concluded that SNR degrades gradually at distances within this case. The highest observed SNR at 50 meters distance is quite high and exceeds the minimum level of acceptable operation (usually 10–15 dB).

It should be noted that under these circumstances, the system works reliably, although usually, at a high density of devices, interference should be much more. Hence, such high SNR values allow us to make a conclusion about the network efficiency, data rate reliability, and good resistance to the negative influence of interferences.

On the other hand, the *THz XR Scenario (SNR vs Distance)* scenario presents a totally different performance pattern. This setup uses a relatively short coverage range, ranging from 1 to 20 meters. Its starting SNR value is fairly high, at around the mid-60 dB mark, and it experiences a significant rate of decline as the distance increases. At 20 meters, the SNR is estimated to be 25 dB.

As for the XR applications, the necessary SNR range is usually between 25 and 35 dB because of the data rates and latencies involved. In the

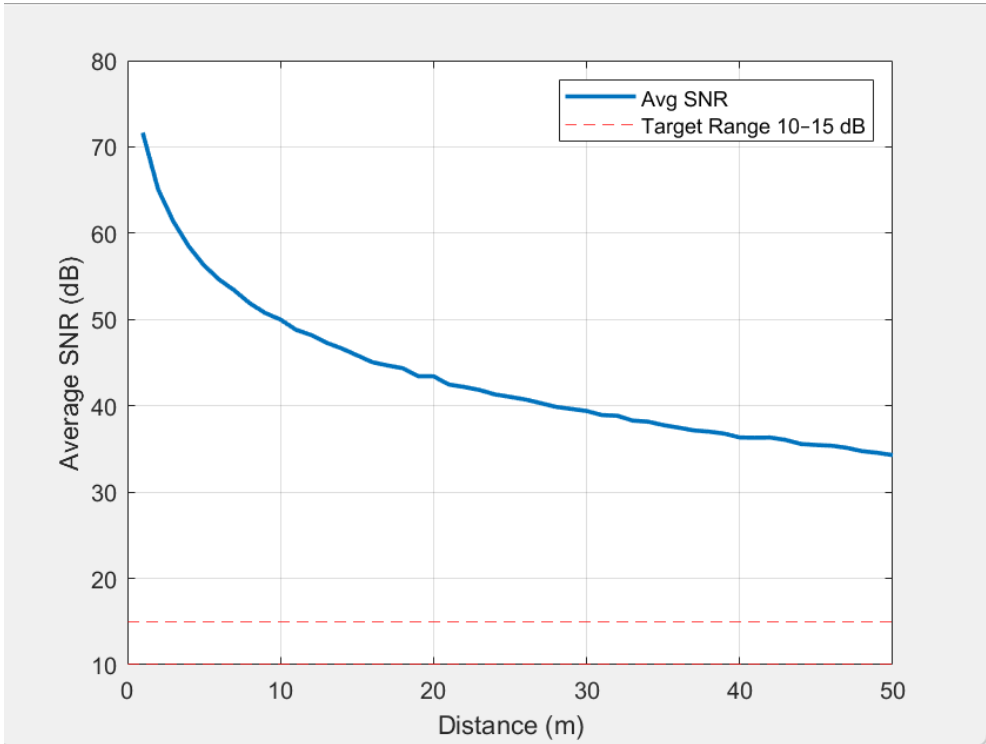


Figure 6.13: SNR of High Devices Density

present case, while the SNR graph stays above the minimum threshold at first, it gradually moves closer to the boundary. This suggests that the coverage range beyond this point will likely be inadequate. Thus, it can be observed that THz communication systems in XR applications are inherently limited by the distance factor.

One major distinction between the two situations arises from the correlation between the two and the SNR region of interest. While in the high device density scenario, the SNR curve stays above the operational limit at any given distance, this implies that there is no critical limitation for the system performance in the tested range. Conversely, in the case of THz XR, the curve cuts through the SNR band, implying that the performance

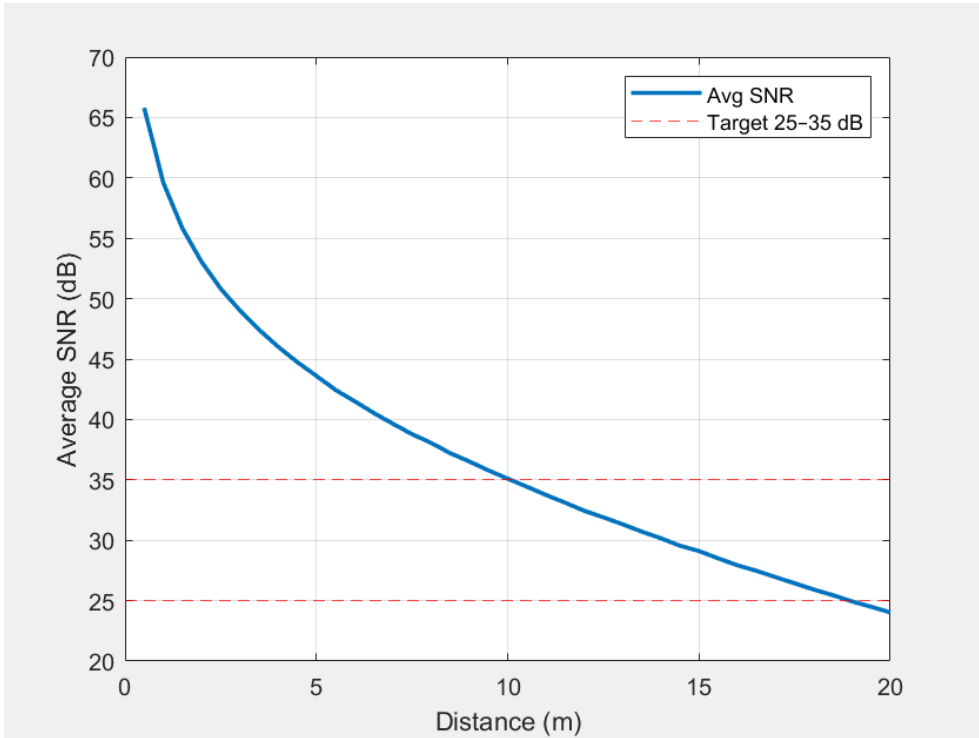


Figure 6.14: SNR of AI Automation

of the system will depend on the distance.

The reason why the two cases differ comes from the differences in the physics of communication at the frequencies. The signals of THz have more path loss, blockages, and absorption due to the atmosphere than in normal frequency ranges. However, they are used where high bandwidth is required.

The other key difference is that of the scale of distance at which these two methods operate. The high device density scenario can operate up to a 50-meter range and yet retain the strong levels of SNR, hence making it useful in scenarios like indoor networks and multi-user environments. Conversely, the THz XR method works best in a short range of about 10-

15 meters and beyond that its effectiveness drops drastically. This shows the importance of dense infrastructure in supporting these networks.

Moreover, the curve slopes show differences in the sensitivities of the two systems. In the high device density scenario, there is a gradual fall in the level of signal reception as a result of efficient handling of interference and stable transmission conditions. In the case of the THz XR system, the sharp fall in the level of SNR indicates that the system is sensitive to any change in distance conditions.

Overall, even though both systems have high SNR when used close to each other, they are not the same when looking at their performance over a large distance. In the case where there is a high number of devices, reliability, stability, and range are important, whereas the second system focuses on high performance but in a limited area.

6.2.3 Case 3: SNR of Urban Dense vs SNR of IRS Indoor

The indoor Intelligent Reflecting Surface (IRS) scenario and the urban dense scenario prove that the propagation medium plays a vital role in shaping the characteristics of wireless signals over distance. In the indoor scenario with an Intelligent Reflecting Surface (IRS), the SNR begins with an extremely high value of over 110 dB, and slowly but steadily decreases to 80 dB at 50 meters distance. It is obvious that the network is working under favorable environmental conditions.

The availability of Intelligent Reflecting Surfaces helps in controlling the signal propagation pattern by reflecting and redirecting the electromagnetic wave energy towards the receiver in an efficient manner. Thus, there is no need for any further scattering of the signal, which means that the rate of degradation is greatly reduced. The SNR graph shows a steady and predictable pattern. Even when the maximum distance limit is reached,

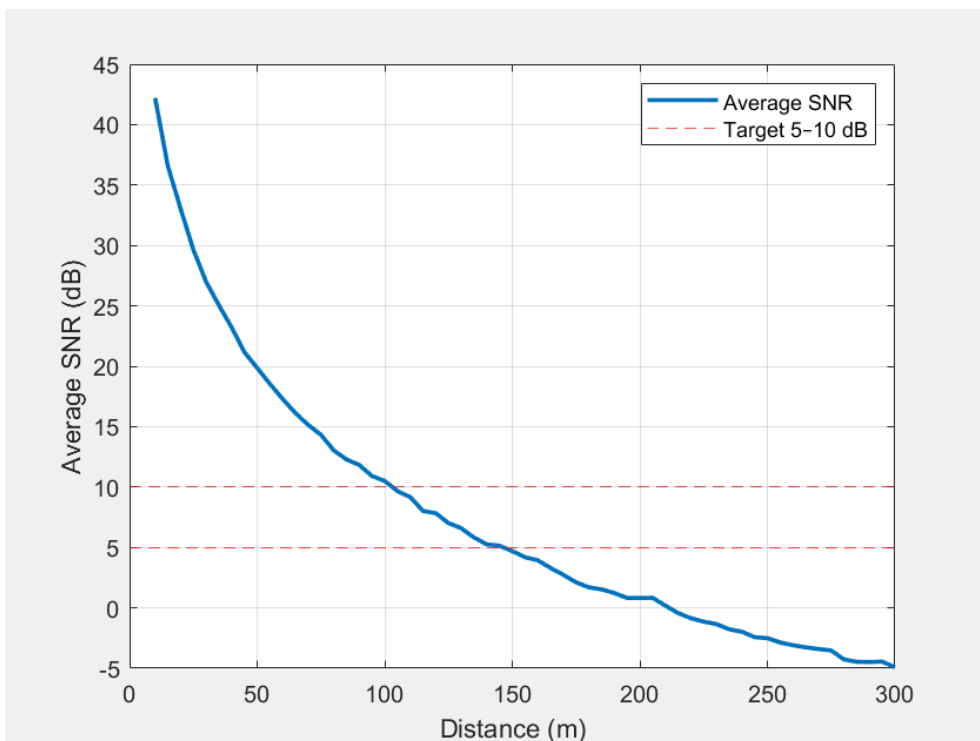


Figure 6.15: SNR of Urban Dense

the SNR value remains well above the threshold requirement of 15-20 dB.

On the contrary, the behavior of SNR under the urban dense condition is entirely different. Here, the initial SNR starts at approximately 40 dB and then falls rapidly. The SNR will fall below 0 dB within 300 meters, signifying the degraded quality of the signal and unreliable communication process due to the high level of environmental interferences. It occurs due to several reasons such as multipath propagation, unpredictable reflections of signals, and the presence of interference.

In the same manner, unlike the IRS assisted indoor scenario, there is no means to manipulate reflections to achieve enhanced SNR. Therefore, the SNR will fall dramatically at shorter distances and gradually fall down at

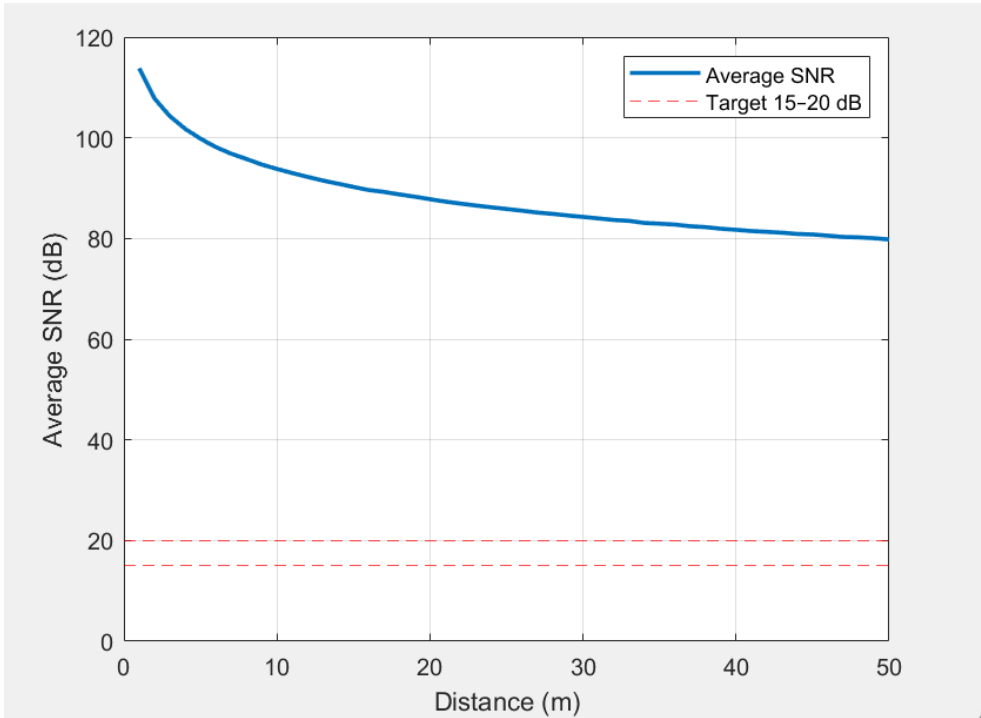


Figure 6.16: SNR of IRS Beaming

longer distances. Furthermore, since the SNR range of the target is rather low (i.e., 5–10 dB), it will also make achieving a good SNR difficult over longer distances.

A comparative analysis between the two scenarios reveals that distance has a greater influence on both situations although the impacts differ considerably. While the distance has been less problematic in the IRS indoor scenario because of the controlled propagation environment and effective reflection, the opposite is true in the latter case where SNR falls drastically because of the complexities of the environment.

The final aspect is system reliability margins, which can be seen from the fact that IRS assisted indoor channel has a consistently high signal to noise ratio that exceeds the threshold value even at larger distances, mean-

ing that there is a sufficient link margin in the system providing immunity to the effects of noise and fading. Urban scenarios show a decrease in SNR below the threshold level at larger distances, which means the system has a higher vulnerability to failures like packet losses and decreased data rate.

Such analysis also reveals the dependency of the system design on application needs and limitations. While IRS assisted indoor system was developed with applications requiring high system performance and reliability in mind, including smart homes, industry automation systems and medical communications, its ability to provide high signal to noise ratio ensures high data rate transmission. Conversely, urban dense deployment describes the standard outdoor wireless communication conditions with significant challenges regarding system performance maintenance. In urban environments, additional engineering techniques are required, including denser base stations deployment and better antenna systems.

To summarize, both cases are guided by the basic rule that the SNR reduces with distance. Nonetheless, the magnitude and pace of reduction are highly dependent on the environment and the technology used. The IRS-supported indoor case has proven more effective in managing the impact of distance by manipulating the signal, thus performing better. On the other hand, the dense urban case shows the difficulties of wireless communication in the real world. While the degradation caused by distance is difficult to avoid, it can be efficiently handled using sophisticated technology like IRS.

6.2.4 Case 4: SNR of Semi-Urban vs SNR of Digital Twin Factory

The comparison of the Semi-Urban wireless communication network with the Digital Twin Factory setting gives important insight into the effects

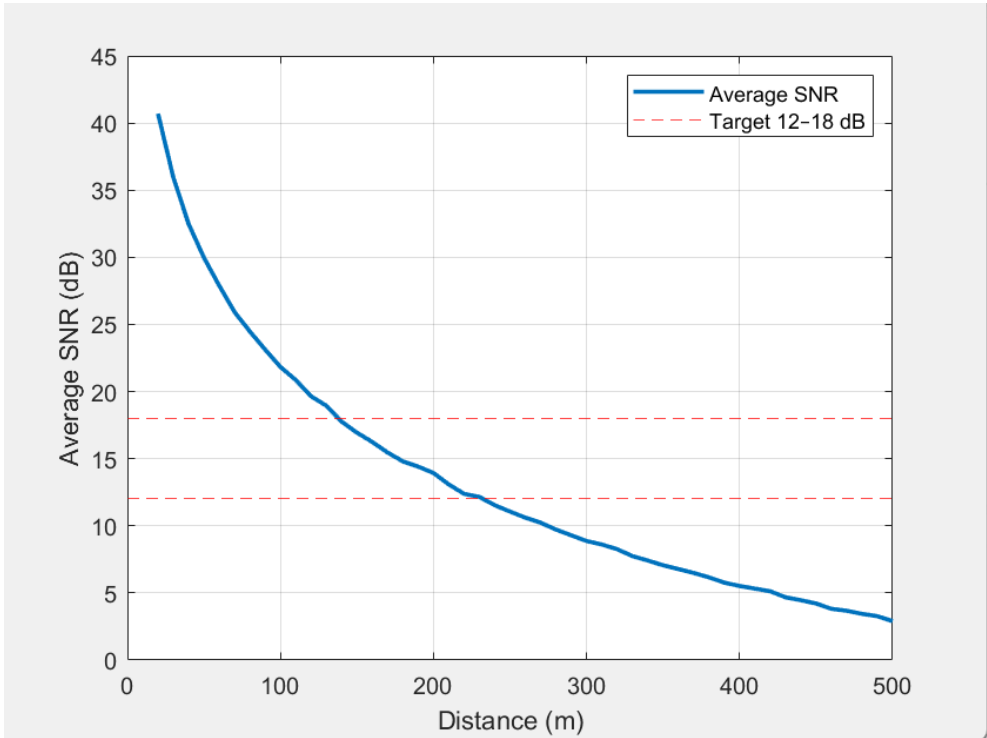


Figure 6.17: SNR of Semi Urban Dense

of signal propagation, environmental factors, and system parameters on the performance of the Signal to Noise Ratio. In both cases, the SNR value decreases with distance increase, but the rate of decrease, operating points, and performance are noticeably different due to dissimilarities in environmental complexity and system design.

In the Semi-Urban environment (Figure 6.17), the SNR value starts from about 40 dB when the distance is small and then slowly drops off as the distance grows up to 500 m. The drop-off pattern is non-linear, with more rapid signal decrease in the beginning (the first 100 m) and slower in further regions. Such a characteristic reflects typical behavior of a wireless transmission, whereby the signal suffers rapid attenuation at the initial distance due to factors like near-field losses, multipath propagation, and

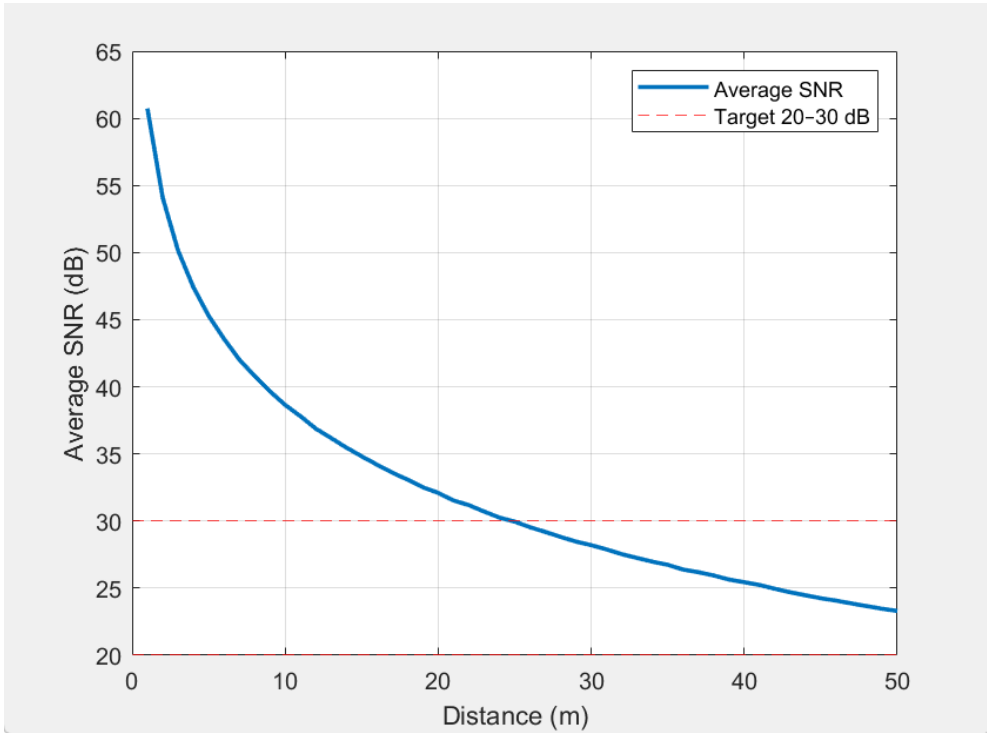


Figure 6.18: SNR of Digital Twin

interference from environmental obstacles (buildings, trees, hills).

One of the most important observations in the Semi-Urban scenario is crossing the threshold of SNR. In the Semi-Urban scenario, the system works with SNR greater than 18 dB up to about 150-180 meters. However, outside this range, the SNR drops to unacceptable values and eventually reaches 3-5 dB. Hence, we can conclude that although the Semi-Urban system is capable of transmitting data over relatively large distances, it does not do so effectively because of the significant noise and distortion in signals.

On the other hand, the Digital Twin Factory scenario presents another set of characteristics. In this scenario, the SNR threshold begins at about 60 dB, which corresponds to good conditions for signal transmission. It

transmits signals within a shorter range, which is around 50 meters. In this range, SNR drops slightly, but nevertheless, it always exceeds 20 dB.

These performance improvements in the Digital Twin Factory use case scenario could be attributed to multiple reasons. First, the environment provides better conditions, where there are no distractions from outside sources and where the location of the transmitter and receiver devices could be optimized. Second, more complex methods of communications, such as the use of beamforming, higher frequencies, and industrial standards for communication, could be implemented. Finally, the reduced distance at which the communication is established leads to a decrease in losses and maintains high SNR levels.

The first key difference between these scenarios is the required SNR value for reliable transmission. In the Semi-Urban setting, the acceptable SNR range is rather low, as the communication network should cover a wide geographical territory, and thus the SNR range is about 12-18 dB. However, in the Digital Twin Factory setting, the minimum SNR range is relatively high and is about 20-30 dB, as the communication needs to be highly reliable and efficient.

The next important distinction is related to the balance between coverage distance and performance. For example, in the case of the Semi-Urban scenario, there is an opportunity to achieve high communication coverage (up to 500 m), but this comes with poor signal strength beyond certain distances. At the same time, in the Digital Twin Factory scenario, the focus is on performance and low coverage distance of around 50 m with SNR remaining high throughout this distance range.

Finally, the speed of SNR reduction varies for both scenarios considered. While in the Semi-Urban scenario, SNR reduces sharply in the beginning due to environmental impact and multipath effects, the decrease

in SNR is smooth and slower for the Digital Twin Factory scenario, which indicates that the channel has better conditions in comparison with the previous scenario.

As a system design concept, Semi-Urban would likely benefit from the use of relay placement, adaptive modulation, and dynamic power control to enhance performance over greater distances. On the other hand, the Digital Twin Factory scenario indicates that maintaining high SNR values is possible without using too much transmission power, provided environmental conditions are optimized and the operating range is limited.

To sum up, both experiments illustrate that the fundamental rule that SNR drops off as a function of distance holds true for any wireless communication system. Nonetheless, their respective performance qualities vary widely due to design considerations. While the Semi-Urban system focuses on coverage and flexibility at the cost of poor performance at long ranges, the Digital Twin Factory system favors reliability and accuracy within a constrained environment.

6.2.5 Case 5: SNR of Rural Long Distance vs SNR of Smart Grid

These two cases illustrate two fundamentally different approaches to wireless communication, which is immediately evident from the SNR variation with distance in these two cases. The first case illustrates a rural long-distance communication network that spans a maximum distance of 15 km, whereas the second case deals with a smart grid communication network that has a relatively small operational span of around 1 km.

For the first part, the rural communication setting starts off with a fairly high initial SNR value of about 25 dB. Meanwhile, the smart grid scenario is characterized by a higher initial SNR value of 35 dB. This

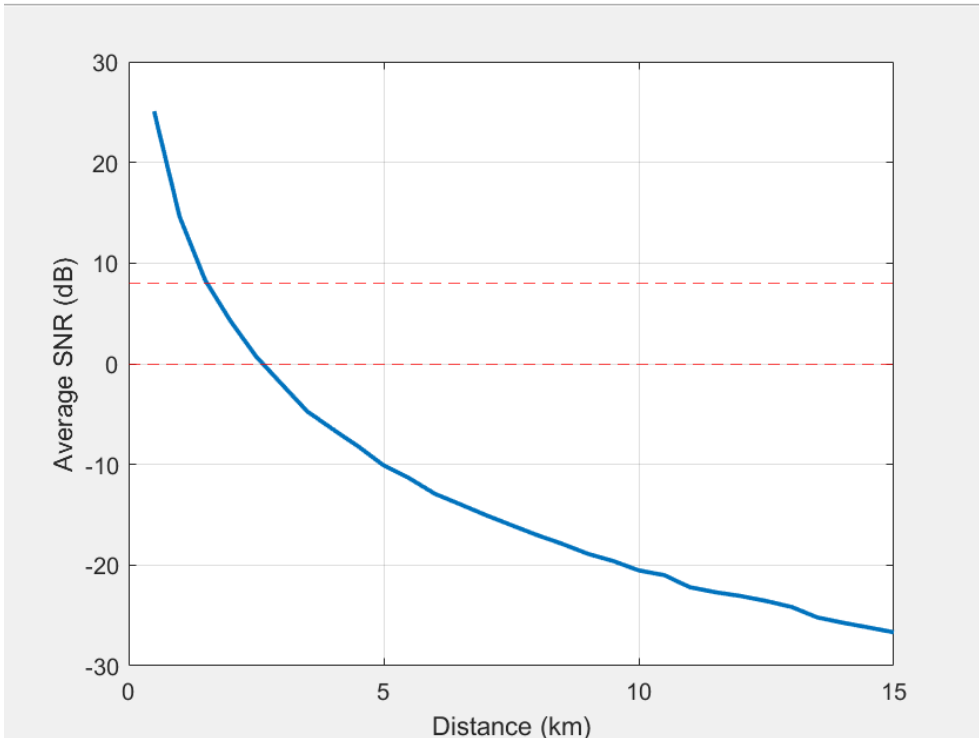


Figure 6.19: SNR of Rural Long Distance

suggests that smart grids are designed with efficient short range communication systems and well-optimized antenna setups, which in turn result in lower environmental effects. Moreover, shorter communication distances automatically mean lower levels of path loss, hence increased reception. On the other hand, rural settings focus on covering larger areas, not on increasing signal strength.

Both examples involve a nonlinear SNR degradation model, although the rates are vastly different. For the long-distance rural case, SNR falls sharply in the beginning before stabilizing to a more gradual rate of fall. At 15 km, SNR drops to about -28 dB, suggesting that there is severe interference in the area. These patterns are indicative of a logarithmic

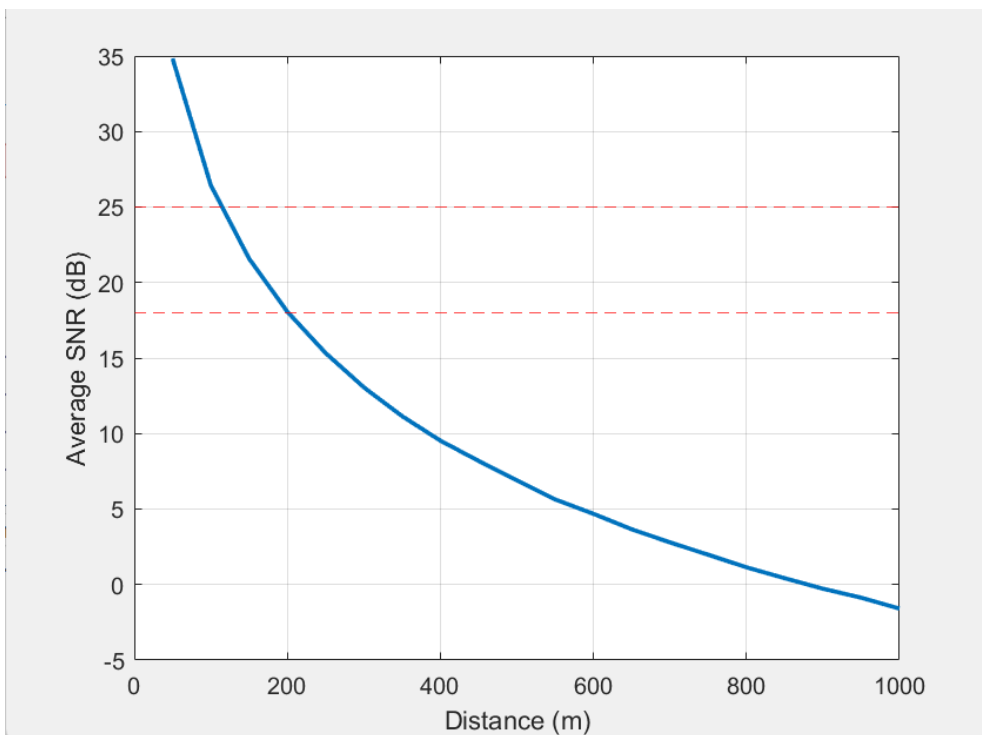


Figure 6.20: SNR of the Smart Grid

path loss phenomenon, where the initial stages of signal fall experience the effect of geometric spreading, whereas the latter stages depend more on the surrounding environment.

The smart grid model, on the other hand, shows a more steady and controlled level of SNR decline. The SNR is fairly steady throughout the range of operation before dropping below 0 dB towards the end of the operational period. This implies that there is more stability in channel conditions due to better infrastructure coverage, optimal placement of nodes, and minimized interference levels in the smart grid. This way, reliable communication is sustained through the whole range.

There are thresholds included in both models which represent the minimum acceptable performance standards needed in order to establish re-

liable communication. In the rural environment, SNR drops off to levels below the threshold within a couple of kilometers. In addition, it stays at levels below the acceptable threshold for much of the transmission distance. This suggests poor reliability in long distance communication and further support systems will be necessary for maintaining quality communication.

On the other hand, the smart grid scenario keeps the SNR level well above the minimum value at most points along its operation range, with only the final stages approaching dangerous limits. Thus, this technology proves extremely reliable and ensures efficient communications, which makes it applicable to mission-critical tasks, such as instant energy monitoring and smart control of infrastructure.

Finally, it is crucial to consider the distance parameter, since the two systems operate on quite different scales. Specifically, the rural scenario operates at a very wide range of distances (0–15 km), whereas the smart grid scenario operates in a relatively short range (0–1 km). While there is a clear degradation of SNR in both cases, a normalized comparison suggests that smart grids maintain better density of SNR per unit distance traveled, with the rural scenario exhibiting even stronger degradation effects.

Environmental aspects also have a considerable impact. First of all, although rural areas feature less physical barriers, they suffer from free-space path loss associated with increased distances traveled. Smart grid scenarios, in contrast, feature structured deployments and shorter link distances, resulting in an increased efficiency of radio signal propagation through a network.

From a system design point of view, these two examples indicate very distinct goals and compromises. First, the rural communication system focuses on extensive geographic coverage and makes use of techniques like energy-efficient transmission, good error detection/correction, as well as

supplementary infrastructure, such as tower and relay station. But at the same time, it comes with the drawback of lower signal to noise ratio and poor reliability for distant locations.

On the other hand, the smart grid communication system stresses more on high reliability and short latency and thus has better signal to noise ratios owing to a carefully designed deployment, shorter distances, and network architecture.

| Feature | Rural Scenario | Smart Grid Scenario |
|-------------------|--------------------------|----------------------------|
| Distance Range | Very long (up to 15 km) | Short (up to 1 km) |
| Initial SNR | Moderate (~ 25 dB) | High (~ 35 dB) |
| SNR Decay Pattern | Rapid then gradual | Smooth and controlled |
| Final SNR | Very low (negative) | Near 0 dB |
| Reliability | Low at long distances | High within range |
| Design Focus | Coverage | Reliability and stability |

Table 6.1: Comparison of Rural Long Distance and Smart Grid SNR Performance

Distance-dependent attenuation is the main determinant of SNR in both cases; however, its effect is much more pronounced in the rural case because of the increased distance involved. The rural communication system compromises on signal strength to ensure wide area coverage, which leads to degraded performance as the distance increases. On the other hand, the smart grid communication system is designed for controlled use and therefore ensures relatively high SNR levels.

In summary, the comparison between the two cases underscores an important engineering consideration in wireless communication systems. In the case of long-distance communication in rural areas, there is an inherent compromise between coverage and signal strength. This is contrary to the smart grid communication system where stability and performance are prioritized.

6.3 Latency Analysis

6.3.1 Case 1: Latency of HD Streaming and Ultra Reliable Low Latency Communication

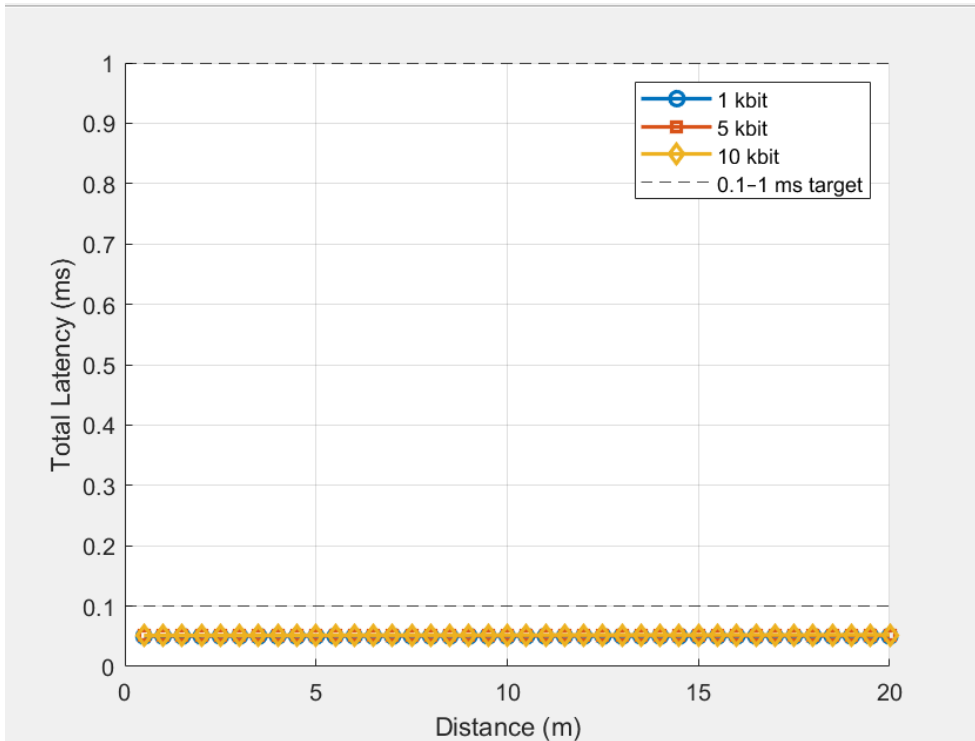


Figure 6.21: Latency of HD Streaming

Latency refers to the entire period that takes place while sending data packets from the origin point to the destination point. Latency is a significant parameter in wireless communication networks because it affects the efficiency and response time of the system.

The two cases—**AI Surgery** and **HD Streaming**—clearly exhibit different latency characteristics. Despite being in the same wireless environment, their latency specifications and behaviors are quite distinct due

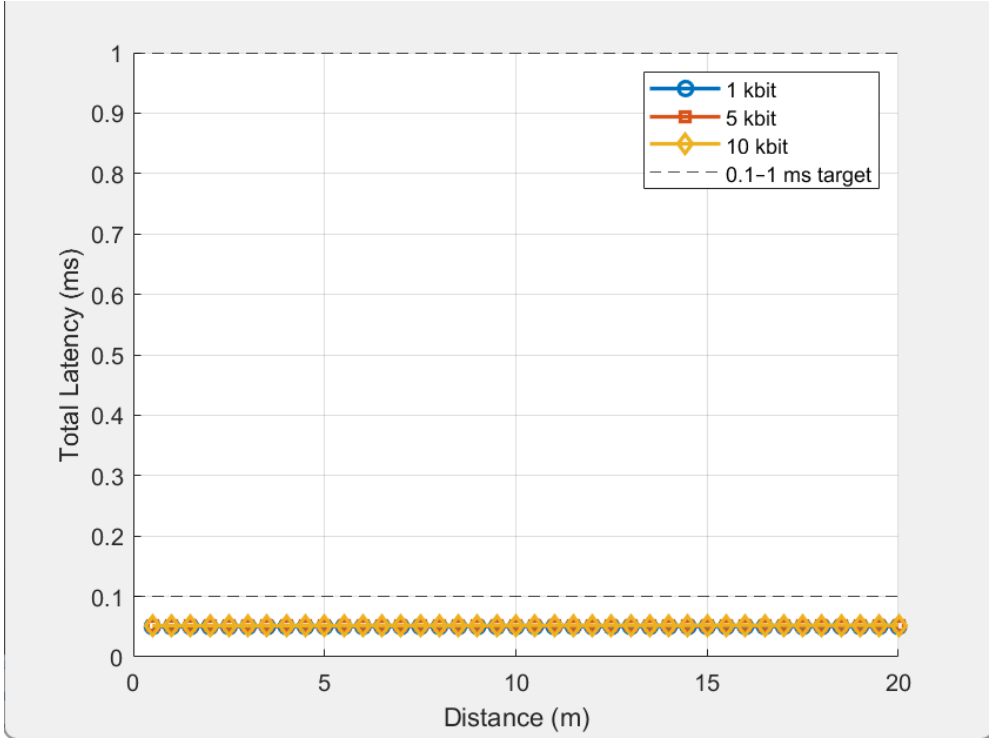


Figure 6.22: Latency of Ultra Reliable Low Latency Communication

to differing degrees of application sensitivity, packet sizes, and operating conditions.

Transmission latency is a function of packet size and transmission rate, and is calculated as:

$$D_{\text{transmission}} = \frac{\text{Packet Size}}{\text{Data Rate}} \quad (6.5)$$

However, in the case of HD Streaming, where packet size is relatively large (10 kBytes – 500 kBytes), latency becomes high because of longer transmission time [10][19][30]. Conversely, in the AI Surgery system, latency is low owing to very small packet size (1–10 kbits).

Latency varies with respect to the distance in both cases; however, the

nature of variation varies significantly.

In the case of HD Streaming, latency varies from about 1 ms to 1.5 ms with respect to distance varying from 1 m to 50 m. The latency increases smoothly and almost linearly, largely owing to propagation delay, along with some processing delays. Latency still remains low, below the acceptable threshold limit of 5 to 10 ms.

AI Surgery scenario, in comparison, shows latency values from 0.05 ms to 0.06 ms for a much shorter range of distances from 1 m to 20 m. It is a very small range, which almost does not vary and can be described as constant. Here, we observe a system where latency is strictly controlled and does not depend on distance too much. The system works below the necessary limitation of 0.1–1 ms. This analysis shows the obvious superiority of the AI Surgery system in comparison with HD Streaming, in spite of acceptable latency in the former.

The size of packet matters in terms of latency because it affects transmission delay and processing time. As the comparison shows, there is a significant difference in the approach:

- HD Streaming is characterized by high priorities to larger packets for greater throughput efficiency.
- AI Surgery is characterized by high priorities to very small packets to reduce latency.

The major factor influencing latency by distance is propagation delay and signal attenuation. The greater the distance, the greater the time needed for signal transmission, resulting in latency in both cases. Nevertheless, latency sensitivity is better controlled in the case of AI Surgery.

For the HD Streaming scenario, it is clear that latency depends on distance. In the full range of 50 m, there is an increasing trend, albeit

a slight one, but nevertheless noticeable. This means that the system is somewhat dependent on distance due to the accumulation of transmission and processing times.

On the other hand, the latency for the AI Surgery system is almost unaffected by distance. It does not change even when the distance varies between 1 and 20 meters. This implies that the system uses:

- High-speed communication links
- Efficient encoding and decoding mechanisms
- Minimal buffering
- Edge computing or localized processing

For surgical applications, where even slight delays can impact precision and safety, this low sensitivity to distance is critical.

AI-assisted surgery operates under an extremely strict latency requirement of 0.1–1 ms, whereas HD Streaming functions within an acceptable range of 5–10 ms. Each system is evaluated against its respective threshold.

In HD Streaming, even under worst-case conditions such as maximum transmission distance and larger packet sizes, latency does not exceed 1.5 ms. This remains well below the acceptable limit, indicating a highly efficient system capable of ensuring continuous playback, minimal buffering, and a smooth user experience.

In the AI Surgery scenario, latency values are typically around 0.05 ms, which is significantly lower than the required threshold. This demonstrates exceptional system performance. For surgical applications, ultra-low latency is essential for real-time responsiveness, accurate control, and operational safety, as even minimal delays can lead to critical consequences.

The differences between the two systems are evident in terms of their intended purposes.

The AI Surgery system is built for accuracy, safety, and rapid responses, while the HD Streaming system is built for user satisfaction and effective data transfer.

The intended purpose of the HD Streaming system is to attain:

- High-speed data transfer
- Effective use of bandwidth
- Tolerance to delay

While large packets ensure effective data transfer, there is a little delay introduced. This is acceptable since humans have a threshold for tolerating small delays in videos.

The AI Surgery system prioritizes:

- Extremely low latency
- Real-time responsiveness
- High accuracy and reliability

To minimize transmission delay, very small packet sizes are used. Additionally, the system likely incorporates:

- Specialized communication protocols
- Edge computing for instant processing
- High-frequency transmission technologies

In this context, latency is not only a performance metric but also a critical safety requirement.

Each system involves different trade-offs between latency, efficiency, and coverage.

HD Streaming tolerates slightly higher latency while efficiently handling large volumes of data, making it ideal for multimedia applications. In contrast, AI Surgery demands ultra-low latency for real-time accuracy, which limits the amount of data transmitted.

This comparison highlights that no single system is universally optimal. Instead, the design approach depends entirely on application requirements. HD Streaming prioritizes data handling capacity, whereas AI Surgery focuses on minimizing latency. Therefore, the optimal strategy is application-specific.

In real-world scenarios, latency requirements vary depending on application demands.

For HD Streaming systems, maintaining latency within a few milliseconds ensures smooth playback, minimal buffering, and high user satisfaction. These systems leverage buffering and adaptive streaming techniques to manage large data volumes, making small latency variations largely imperceptible to users.

Conversely, AI-assisted surgical systems require extremely low latency to enable precise feedback and real-time control of surgical instruments. Even minor delays can disrupt synchronization and potentially lead to critical errors, directly impacting patient safety.

Therefore, such systems demand highly reliable, near-zero latency communication. This comparison demonstrates that AI Surgery represents the highest level of latency optimization, while HD Streaming adopts a balanced approach focused on performance, efficiency, and consistent quality

of experience.

6.3.2 Case 2: Latency of Dense Office and XR Holograms

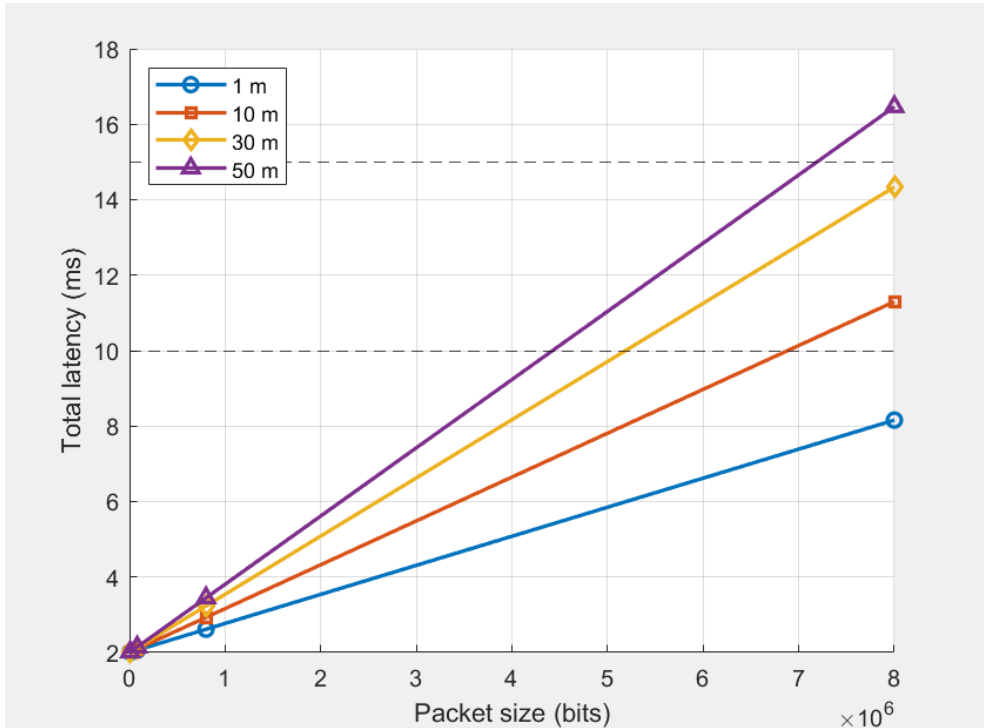


Figure 6.23: Latency of Dense Offices

The transmission delay becomes the most significant part in such conditions, as can be seen from Figure 6.23, which shows a clear linear dependence of latency on the size of packets for any of the considered distances. The latency of packets depends directly on their size and grows linearly when increasing from very small sizes to multi-megabit values. The higher the distance between nodes, the higher the slope of the graphs. This phenomenon can be explained by the growing importance of the propagation delay in combination with possible lower quality of signals. The use of large packets is costly because of the increased number of bits that must

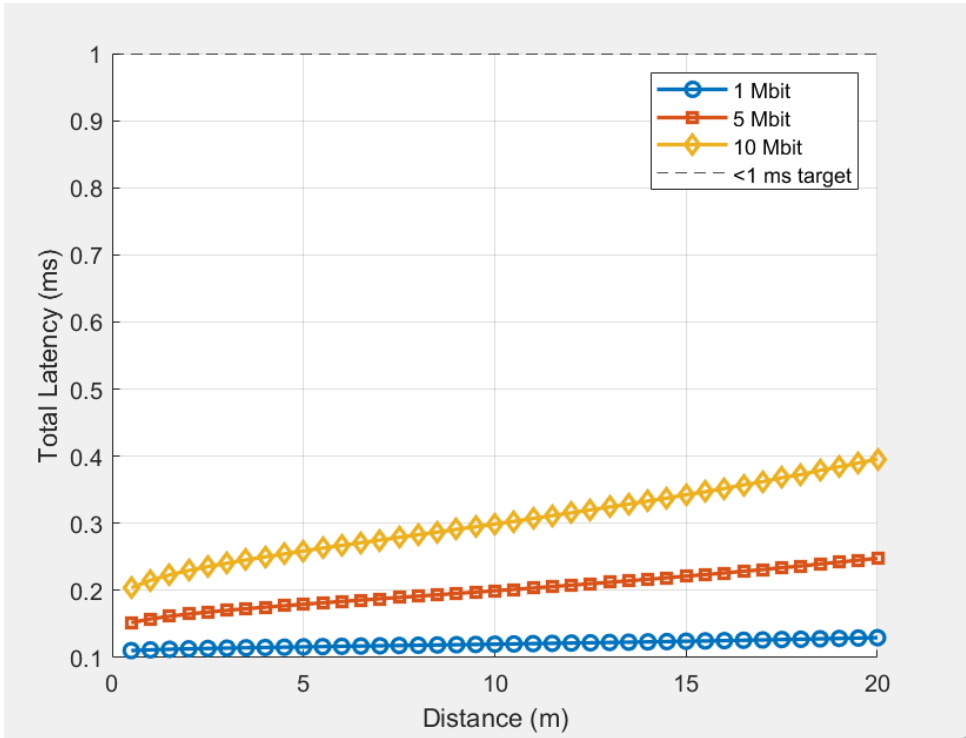


Figure 6.24: Latency of XR Holograms

be sent. Although even with a maximum size of the packet, the latency is significantly less than the maximum value in the range of 1 meter, and high throughput is ensured, the delay will exceed the limit at about 50 meters.

On the contrary, the second graph (Figure 6.24) demonstrates a completely different approach to the problem when latency is extremely low—within sub-milliseconds—for all distances and rates considered. As the result of comparatively low data amounts (1-10 Mbit) or very high data rates, latency grows smoothly with growing distance, but the gradient is rather flat showing that propagation delay becomes the key aspect here, whereas transmission delay gets to its minimum. At the same time, even with the

20-meter distance, latency still stays within the 1 ms range, which allows saying that the proposed configuration is applicable to applications sensitive to latencies, such as immersive or interactive systems. In terms of the impact of data rate on latency, one may observe how the graphs are spaced apart: the larger the bit rate (for instance, 10 Mbit), the higher latency is; however, this latency is negligible in relation to the required performance criteria.

Upon analysis, the above diagrams (Figure 6.23 and 6.24) reveal that there is a shift from one mode of operation to another; in the first mode, latency varies greatly with the packet size, indicating that for delay-sensitive transmissions in long-distance communication, achieving optimized throughput becomes very important. For the second mode, on the other hand, the operation is such that the communication system is operating very efficiently so that distance emerges as the main variable affecting the process within the latency constraint. From this comparison, we conclude that for applications where delays have to be met, the key considerations are control of data packets and efficient transmission rather than distance even in slightly longer ranges. This implies that for smaller payloads and faster transmissions, distance is not an important issue. Analytically, total latency can be defined as:

$$T_{\text{total}} = T_{\text{tx}} + T_{\text{prop}} = \frac{L}{R} + \frac{d}{v} \quad (6.6)$$

where L stands for packet size (bits), R for data rate (bits/s), d for distance (m), and v for signal propagation speed (m/s), which is usually around the medium's speed of light. The transmission term L/R , which becomes dominant as L increases, is directly responsible for the first figure's linear increase in delay with packet size. The additive propagation term

v/d explains the divergence between curves over varying distances by shifting each parameters higher in proportion to distance. This offset becomes more noticeable for bigger d , and when paired with large L , the overall delay exceeds the allowable limit. L/R is insignificant in the second figure because either L is very tiny or R is high enough. Because of this, latency is mostly controlled by v/d , which results in the slow, almost linear rise with distance. The transmission term is still influenced in the differences across the curves (1, 5, and 10 Mbit), but its contribution is still negligible, maintaining overall delay well below the sub-millisecond limit. The transition between the two regimes is explained by this formulation: the system is transmission-limited when $L/R \ll v/d$ (first figure) and becomes propagation-limited when $L/R \gg v/d$ (second figure).

6.3.3 Case 3: Analysis of Latency under Congestion and IRS Beaming

When an intelligent reflecting surface (IRS) is incorporated, the latency performance behaves fundamentally differently compared to traditional urban propagation environments. In the urban congestion scenario, packet size significantly influences the overall delay, which increases nonlinearly with distance. At shorter ranges, the system maintains relatively low latency; however, as distance extends toward several hundred meters, latency rises sharply, reaching values on the order of tens of milliseconds. This effect becomes more pronounced for larger payloads, where transmission delay, queuing effects, and potential retransmissions collectively contribute to increased delay. The curvature observed in the latency–distance relationship indicates degradation in communication efficiency due to channel impairments such as interference, signal attenuation, and reduced link quality at longer distances. Consequently, the system struggles to consistently sat-

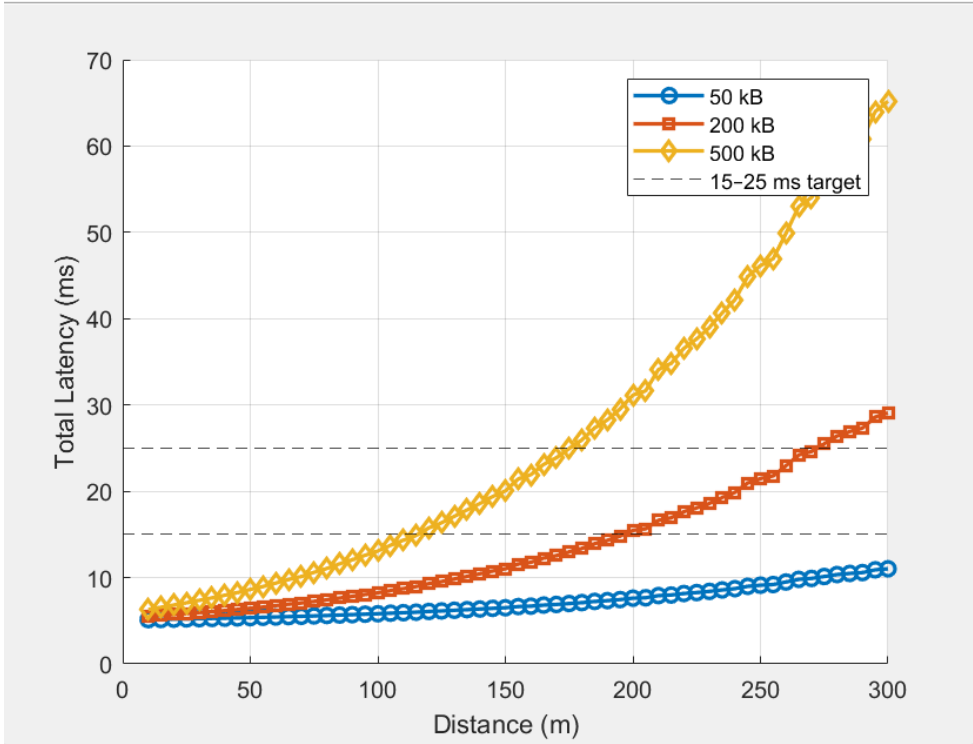


Figure 6.25: Latency Under Congestion

isfy the 15–25 ms latency requirement, particularly under higher data load conditions.

In contrast, the IRS-assisted scenario demonstrates a nearly constant latency profile across the evaluated distance range. As the separation increases from 1 m to 50 m, the total delay exhibits minimal variation, remaining well within the sub-millisecond range. Moreover, the close overlap of curves corresponding to different packet sizes indicates that the impact of payload size becomes negligible in this configuration. This behavior suggests that baseline transmission and processing delays dominate the overall latency, rather than channel-induced impairments. The absence of nonlinear growth highlights the effectiveness of IRS in enhancing the propagation

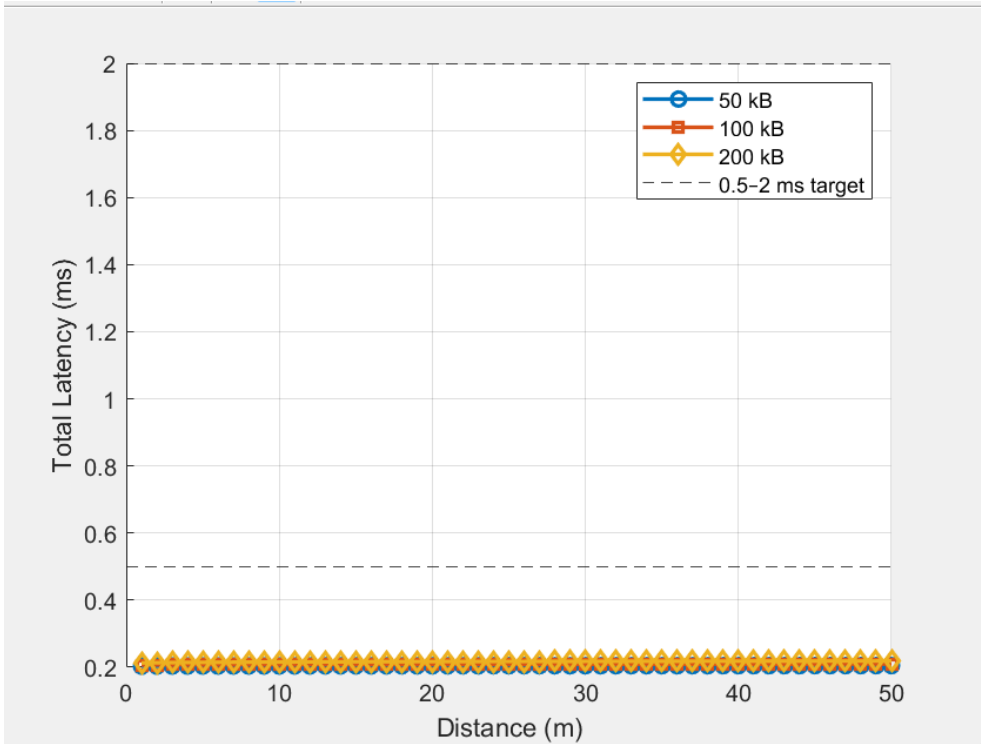


Figure 6.26: Latency of IRS Beaming

environment by maintaining strong and reliable communication links. As a result, retransmission overhead is minimized, error rates are reduced, and path loss effects are significantly mitigated.

Overall, the comparison reveals a clear transition from a congestion- and channel-limited regime in urban environments to a controlled and optimized communication regime enabled by IRS technology. This demonstrates the potential of IRS-assisted systems in meeting stringent latency requirements for next-generation wireless applications, even under varying payload conditions and moderate distance scaling.

The ramifications are substantial from the standpoint of service quality. As operational conditions deteriorate, the urban system becomes increas-

ingly unstable and only intermittently satisfies its latency requirements. In contrast, the IRS-assisted system not only meets but significantly exceeds its target latency constraints under all evaluated scenarios. This performance margin enables latency-critical applications to operate without requiring additional optimization and provides resilience against emerging network disruptions.

Overall, the findings demonstrate that the incorporation of IRS fundamentally transforms latency dynamics within the communication system. By actively shaping the wireless channel, IRS mitigates the primary causes of delay escalation present in conventional environments. The resulting system exhibits ultra-low, distance-invariant latency with minimal sensitivity to traffic load, highlighting the transformative potential of IRS for next-generation low-latency communication networks.

In the urban scenario, packet size has a significant impact on overall delay, which rises nonlinearly with distance. Path loss and interference cause the effective data rate R to decrease with increasing distance, which raises T_{tx} . Furthermore, worse channel conditions increase the packet error rate, which raises T_{retx} . The observed nonlinear delay, especially for greater payloads, is the result of these combined effects. For many operating sites, latency exceeds the required range of 15–25 ms, reaching tens of milliseconds at long distances. This suggests that in an urban setting, system performance is dominated by both transmission inefficiency and reliability problems.

The latency performance exhibits fundamentally different behavior under conventional urban propagation conditions and when an intelligent reflecting surface (IRS) is introduced. The total end-to-end latency can be expressed as:

$$T_{\text{total}} = T_{\text{tx}} + T_{\text{prop}} + T_{\text{proc}} + T_{\text{queue}} + T_{\text{retx}} \quad (6.7)$$

where $T_{\text{tx}} = \frac{L}{R}$ represents the transmission delay for a packet of size L over a data rate R , $T_{\text{prop}} = \frac{d}{c}$ denotes the propagation delay over distance d with signal speed c , T_{proc} is the processing delay, T_{queue} is the queuing delay, and T_{retx} accounts for retransmissions due to packet errors. In the urban scenario, packet size has a significant impact on overall delay, which increases nonlinearly with distance. Path loss and interference reduce the effective data rate R as distance increases, thereby increasing the transmission delay T_{tx} . Furthermore, degraded channel conditions lead to a higher packet error rate, which in turn increases the retransmission delay T_{retx} . The observed nonlinear growth in latency, particularly for larger payloads, results from the combined effect of these factors. In contrast, the IRS-assisted scenario maintains an almost constant latency profile across the evaluated distance range. The inclusion of IRS effectively enhances the channel gain, resulting in an increased achievable data rate R_{IRS} . Consequently, the transmission delay component becomes:

$$T_{\text{tx(IRS)}} = \frac{L}{R_{\text{IRS}}} \quad (6.8)$$

Thus, under comparable conditions, $R_{\text{IRS}} \gg R$. Moreover, the improved signal quality significantly reduces packet error rates, leading to $T_{\text{retx}} \approx 0$. As a result, the overall latency simplifies to a form dominated by minimal and stable components:

$$T_{\text{total(IRS)}} \approx \frac{L}{R_{\text{IRS}}} + T_{\text{proc}} + \frac{d}{c} \quad (6.9)$$

Since both $\frac{L}{R_{\text{IRS}}}$ and $\frac{d}{c}$ are small and only weakly dependent on distance

within the considered range, the results indicate that the total latency remains nearly constant (approximately 0.2 ms). The system operates in a regime where high data rates and reliable links suppress the dominant delay components observed in the urban scenario. This behavior is further supported by the minimal separation between curves corresponding to different packet sizes.

When IRS is used, latency is improved by orders of magnitude, according to a direct comparison. The IRS-assisted system continuously runs at 0.2 ms, whereas the urban scenario shows latency values ranging from around 10 ms to over 60 ms depending on distance and packet size. This translates to a reduction factor between around $50\times$ and over $300\times$. Such a significant increase shows that IRS stabilizes system performance by successfully reducing the main causes of delay, which are lower data rates and retransmissions.

The urban network falls short from the perspective of fulfilling latency requirements as the distance between nodes increases along with payload sizes. On the contrary, the IRS-supported system consistently operates below its required threshold, thus providing significant room for maneuver. In situations when minimal latency is essential, such reliability is extremely important.

All in all, the research demonstrates that through enhancing channel qualities and minimizing variations in delays, IRS plays a pivotal role in transforming the latency behavior. By increasing data transfer speeds and decreasing the need for repeated transmission due to failures, regardless of distance or packet size, IRS ensures that latency is consistently low and practically constant at all distances and payload sizes considered in the experiment.

6.3.4 Case 4: Latency Analysis of Balanced Load and Digital Twin

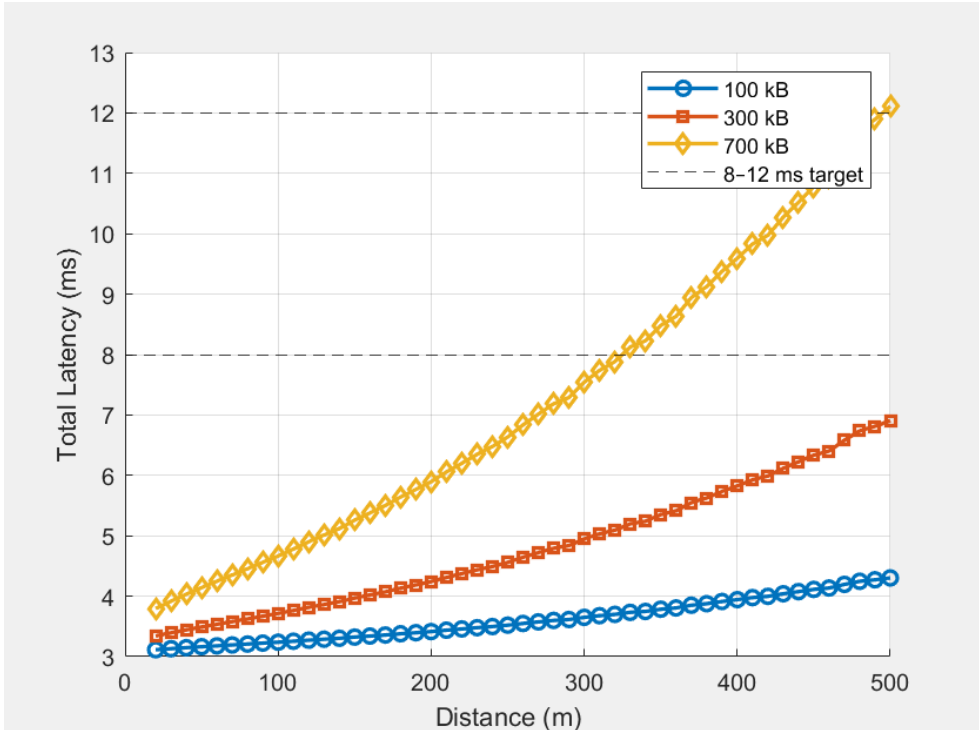


Figure 6.27: Latency of Balanced Load

An analysis of the two latency charts, which represent communication situations that are entirely distinct from each other, helps understand the effect of capacity, message payload, and distance on overall performance. In this regard, it is possible to state that two basic components that influence latency in these two cases, regardless of whether any calculations are done or not, include the distance over which the messages have to travel and the volume of data that should be transmitted. The difference between the semi-industrial and factory scale situation lies in the fact that the impact of these two elements is quite different, which causes performance differences

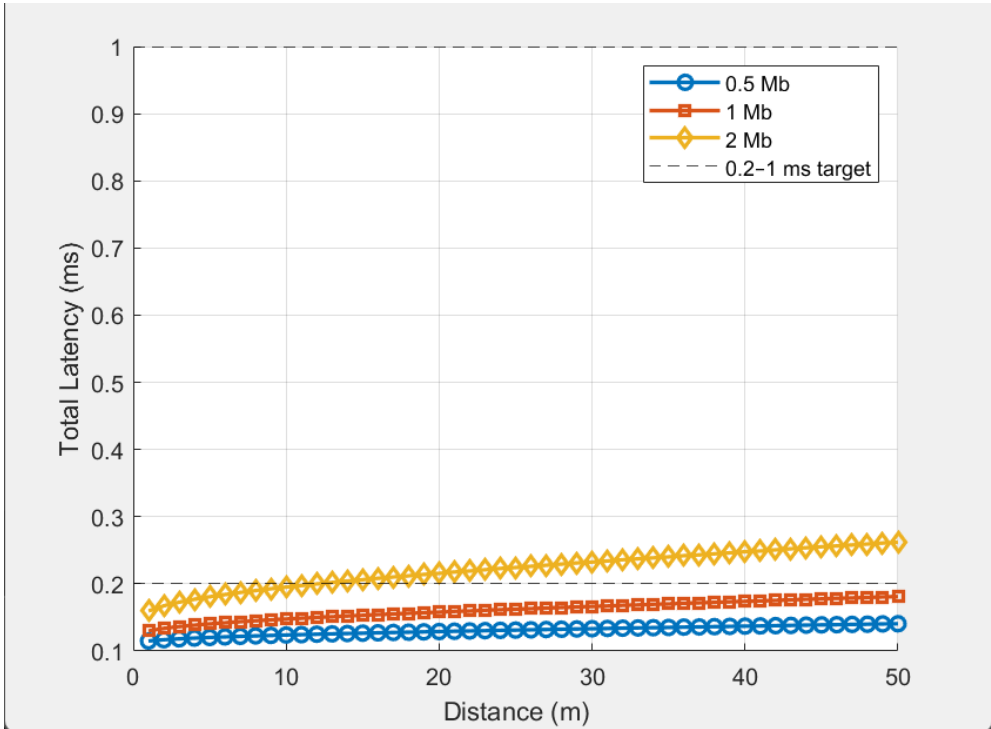


Figure 6.28: Latency of Digital Twin

as well.

Distance increase leads to increased delay in semi-industrial situation. With increasing distance to hundreds of meters, the delay will increase to rather significant levels from negligible values as distance gets shorter. Such a tendency can be attributed to the unavoidable delay caused by the actual transmission of information over longer distances. Even though this increase might not be obvious during the first part of the chart, it is still quite obvious at longer distances, which makes delay somewhat difficult to reduce without a major redesign of the system.

However, in this particular example, there is a considerable influence of the payload size on the result. With increasing distance, the three curves, which symbolize small, average, and large data sizes, become distinctly

divergent. While the delay for the largest payload increases at a much higher rate compared to the smallest one, which remains quite narrow, we can infer that the processing time becomes significantly larger as the amount of transmitted data increases. Moreover, such results show that a long communication link is a factor that contributes greatly to the increase in delay time. In fact, the largest payload causes latency to approach and go beyond the limit range by the time distance achieves its maximum value.

Another peculiar feature of the graph that shows semi-industrial latency development is the fact that the curves do not form perfectly straight lines, especially in cases of the largest amounts of cargo. This means that there could be some other influences that affect latency, rather than distance and payload size only. Such effects might be related to the processing overhead, buffering, and other reasons for delay formation.

When it comes to the factory-level scenario, there appears to be quite a different level of regulation regarding latency. Distance proves to have less influence on delay as it covers only a relatively narrow range. As the distance gets bigger, the curves remain rather flat, which shows that the time required to pass a signal is too insignificant to affect the total delay significantly. Despite all the minor differences that could occur in relation to distance in the particular range, the process creates a stable baseline with continuous low latency levels.

As for payload, it is true that it has some influence on the delay in the factory-level scenario, yet, it is rather insignificant compared to the semi-industrial case. Curves differ from one another by a few values only, having a slightly ascending trend. All figures are within the range that is set as a standard, and even the highest figure does not cause any considerable growth in the value of latency. The system can handle relatively large volumes of data and avoid transmitting delays thanks to its sufficient

capacity.

How close each of them is to their performance constraints is another important factor distinguishing between the two scenarios. For the semi-industrial scenario, the maximum payload over larger distances approaches or exceeds the tolerable constraint in latency. This implies that there is no room left for an increase in workload or diversity in the system. Performance degradation may arise from any increase in demand, data or distance, and the same will be unacceptably low. However, for the factory-level scenario, all testing scenarios produce satisfactory results within the target range of the system. There is ample margin in the system that ensures the absence of any performance issues in ordinary working conditions.

These findings emphasize the importance of scale and environment from a system design perspective. In larger and less constrained settings, both transmission distance and data volume must be carefully managed to control latency. Potential solutions include enhancing communication capacity, improving data processing capabilities, or restructuring the network into shorter and more efficient communication paths. However, such modifications often involve trade-offs in terms of cost, complexity, and scalability. These challenges are clearly illustrated in the semi-industrial scenario, where achieving low latency becomes increasingly difficult as system size and demand grow.

On the other hand, the industrial scale environment brings out the benefits that result from working in an efficient and small environment. With good communications and enough capacity in the system, there will always be low and predictable latency levels despite increased volumes of data. This makes the system ideal for applications that require accurate timing and quick responses, like in real-time systems. In such cases, having predictability of latency is essential in ensuring reliable operation of the

system.

In addition, another fundamental difference is related to the level of predictability and uniformity. In fact, factory-scale curves appear to be quite uniform and close, which indicates a high level of predictability. At the same time, the curves in the case of semi-industrial systems demonstrate higher variability and dispersion, which means that the process is more sensitive to changing conditions. This factor is crucial since latency variability may prove to be equally harmful to applications with strict timing requirements as high latency itself.

On the whole, such comparison allows drawing an important conclusion concerning the issue at hand. Latency performance is highly context-specific and depends on the distance of operation and the volume of data. In this respect, it appears that systems working over long distances with large data loads experience more difficulties, which cannot be avoided entirely. At the same time, short-range systems that have enough bandwidth capabilities are able to demonstrate low latency.

In conclusion, the two scenarios highlight distinct approaches to the development of communication systems. As a result of the joint effect of payload size and distance, the semi-industrial communication system operates near its maximum capacity and suffers from high and variable latency. The factory-scale system, on the other hand, keeps a reserve of capacity and limits the distance between the points of communication to ensure low and stable latency. It is essential to consider such differences when choosing and constructing systems for different types of applications.

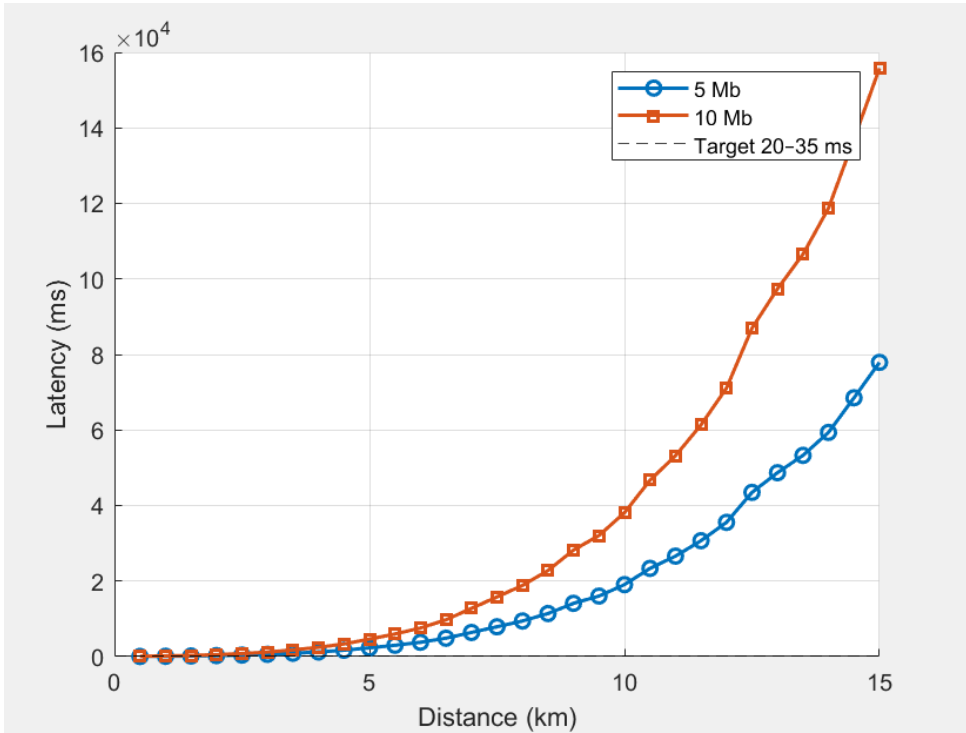


Figure 6.29: Latency of Rural Long Distance

6.3.5 Case 5: Latency Analys of the rural long distance and the AI Automation

The dependency illustrated in both cases reveals itself as clear and distinctive – delay is increasing non-linearly with distance, yet the absolute values and speed of increasing may differ greatly based on system design and data transmission. In the case where distance surpasses a certain midpoint in the first scenario (long-distance, kilometer scale), delay starts increasing rapidly. While at a lower data load level (5 Mb), the increase of delay starts off slowly but then becomes noticeably rapid around 8-10 km, which marks the start of increased losses of propagation. Yet, in the case of larger data loads (10 Mb), the curve has even steeper slope and there is an increasing

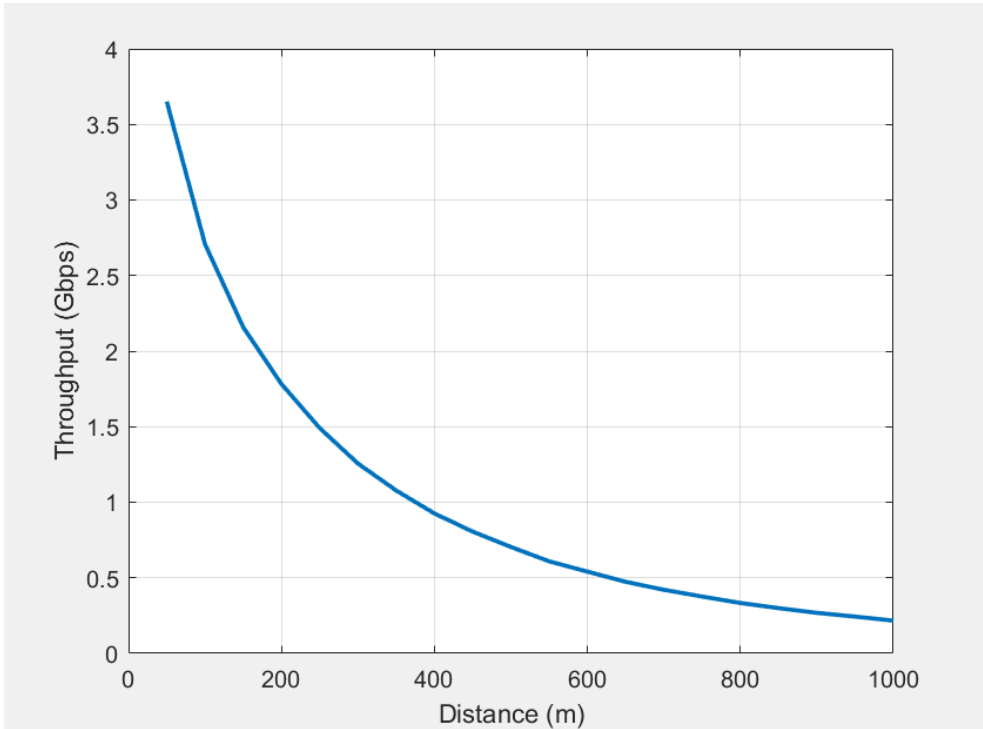


Figure 6.30: Latency of AI Automation

delay with distance. As can be seen, higher throughput demands increase the impact of the detrimental factors on the channel, causing delays, congestion or retransmission problems. This difference is particularly apparent at distances exceeding 10 km. In contrast, the second example portrays a significantly regulated delay distribution (short range, meter scale). The latency remains considerably below 1 ms across all distances in the case of the smallest data rate (0.1 Mb), even as distance increases up to 1000 meters. In this case, there is evidently an effective communication situation where there is no significant distance-dependent sensitivity to delay. However, as data rate increases from 0.5 Mb to 1 Mb, latency also increases, but in an incremental manner. Remarkably, at larger data rates, the delays only exceed the 1 ms point at relatively small distances, showing that

throughput requirement—instead of distance—is the major determinant in setting the limitations in this scenario. Clearly, due to favorable channel conditions, shorter propagation delay, and probably improved network attributes, the increased latency observed here is not as drastic as the one in the previous case.

Difference in Magnitude and Sensitivity is an important point of comparison. The capability of delay in the build-up of the long-distance communication is quite high due to the exponential rise in the latency build-up seen from the analysis of the example of the kilometer range scenario. This reflects the practical performance of long distance wireless communications where there is a lot of influence of factors such as path loss and interference. However, in the case of the meter distance scenario, one can observe that low latency can still be achieved through short distance communication technologies despite increases in data rate with nearly linear/exponential growth.

The importance of target latency thresholds is yet another significant revelation. In the first case, it can be observed that sustaining good latency levels becomes increasingly difficult with an increase in both distance and load because the desirable threshold of 20-35 ms is surpassed very quickly, especially when data is higher. However, despite the use of optimization strategies such as relaying, beamforming, or edge computing, it can be seen that there are limitations to delivering low-latency services over long distances. On the other hand, the second case involves an aggressive 1 ms target level, which can be achieved mostly at smaller distances and with lower loads.

Chapter 7

Conclusion

7.1 Conclusion

Focusing on key metrics such as throughput, SNR, and latency, the current research provides a comprehensive analysis of the evolution from 5G to 6G wireless communication networks using simulations. To replicate practical scenarios for communication, a hierarchical model, which includes user devices, base stations, wireless links, edge computing, and AI-native components of 6G, was developed and implemented using MATLAB. By leveraging edge computing and smart optimisation techniques, next-gen networks provide improved efficiency and agility over the present-day 5G network infrastructure.

It is quite clear from the results obtained that the performance of 6G is superior compared to 5G in all the metrics, thus offering higher throughput, improved signal quality, and less latency under identical conditions. Also, the intelligent edge-computing and native AI enable intelligent decision-making and optimal resource allocation, which make 6G technology more appropriate for emerging technologies such as XR, holography, and automation. The research clearly conveys the revolutionary capabilities of 6G as a faster and smarter communication technology for the future despite some constraints related to the simulated environment assumptions and the absence of practical validation.

7.2 Future Works

Future research could benefit from integrating further dynamic and realistic network conditions into the existing modeling environment. The future modeling process should consider parameters like mobility, intercell interference, fading conditions, and power usage analysis as the assump-

tions made in this work are very simplified. Another step towards more accurate representation of a practical implementation would be achieved through expanding simulation scenarios to cover cases such as ultra-dense networks, multiple architecture types, and varying traffic loads. Increased credibility of findings can be accomplished by adopting advanced channel models and comparing results to standards.

Further research on the integration of AI into network planning is also equally significant. While AI-based optimization falls under the scope of this research, future studies may make use of practical AI-based applications such as machine learning and deep learning algorithms for compute offloading, maintenance prediction, and resource management. Exploring emerging technologies such as federated learning, RISs, and semantic communications will also help build an integrated architecture that utilizes AI for 6G networks. Security features such as post-quantum cryptography, zero-trust architectures, and threat detection systems through AI must also be considered to ensure secure communication networks.

Finally, practical implementation and experimental testing should be prioritised above computer simulations for future studies. The creation of testbeds, hardware implementations, or mini-deployments would provide valuable insight into the feasibility, scalability, and performance of the system.

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