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**Digital Beamforming at the Receiver for
Transmit Power Reduction in Dense IoT
Networks**

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Dedicace

I dedicate this work to my parents and my family, whose unconditional love, support, and sacrifices have always been my greatest source of strength and motivation.

Benamara Roaia

Acknowledgements

I begin by expressing my deepest gratitude to Allah, the Almighty, for His endless blessings and guidance, which have sustained me throughout every stage of this academic journey.

I would like to sincerely thank my parents and family for their unconditional love, continuous encouragement, and profound sacrifices. Their unwavering support has been the cornerstone of all my personal and academic achievements.

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Benamara Roaia

ملخص

يتطلب النمو السريع لأجهزة إنترنت الأشياء وشبكات الجيل الخامس أنظمة اتصالات لاسلكية قادرة على خدمة عدد كبير من الأجهزة منخفضة الاستهلاك في آن واحد. تدرس هذه الأطروحة تشكيل الحزمة الرقمي على مستوى مستقبل المحطة القاعدية بهدف تقليل قدرة الإرسال في شبكات إنترنت الأشياء الكثيفة في اتجاه الرفع، والمبنية على تقنية الهوائيات المتعددة الضخمة (Massive MIMO).

يتم مقارنة ثلاث استراتيجيات لتشكيل الحزمة في الاستقبال: الجمع بنسبة أقصى (MRC) وجمع الحد الأدنى لمتوسط الخطأ التربيعي (MMSE) ونهج ميتاهيورستي مبني على تحسين سرب الجسيمات (PSO). تُجرى محاكاة MATLAB في ظروف قناة تلاشٍ رايلي المترابطة، لتكوينات مختلفة من الهوائيات وأعداد المستخدمين وأخطاء تقدير معلومات حالة القناة.

تُظهر النتائج أن جهاز تشكيل الحزمة المبني على PSO يتفوق باستمرار على الأساليب الكلاسيكية، محافظاً على أداء مستقر حتى في حالة معلومات حالة القناة غير المثالية، مما يجعله حلاً متيناً لشبكات إنترنت الأشياء الكثيفة في ظروف القناة الواقعية.

الكلمات المفتاحية: الهوائيات المتعددة الضخمة، تشكيل الحزمة الرقمي، إنترنت الأشياء، MRC، MMSE، PSO، نسبة الإشارة إلى الضوضاء، معدل خطأ البت، معلومات حالة القناة غير المثالية، تقليل قدرة الإرسال.

Résumé

La croissance rapide des dispositifs IoT et des réseaux 5G exige des systèmes de communication sans fil capables de servir un grand nombre d'appareils à faible puissance simultanément. Cette thèse étudie le beamforming numérique au niveau du récepteur de la station de base afin de réduire la puissance d'émission dans les réseaux IoT uplink denses basés sur la technologie Massive MIMO.

Trois stratégies de beamforming en réception sont comparées : la combinaison à rapport maximum (MRC), le combineur à erreur quadratique moyenne minimale (MMSE), et une approche métaheuristique basée sur l'optimisation par essaim de particules (PSO). Des simulations MATLAB sont effectuées sous des conditions de canal à évanouissement de Rayleigh corrélé, pour différentes configurations d'antennes, nombres d'utilisateurs et erreurs d'estimation du CSI.

Les résultats démontrent que le beamformer basé sur le PSO surpasse systématiquement les méthodes classiques, maintenant des performances stables même en présence d'une information d'état du canal (CSI) imparfaite, ce qui en fait une solution robuste pour les réseaux IoT denses dans des conditions de canal réalistes.

Mots-clés : Massive MIMO, Beamforming Numérique, IoT, MRC, MMSE, PSO, SNR, BER, CSI Imparfait, Réduction de Puissance d'Émission.

Abstract

The rapid growth of IoT devices and 5G networks demands wireless systems capable of serving massive numbers of low-power devices simultaneously. This thesis investigates digital beamforming at the base station receiver to reduce transmit power in dense IoT uplink networks based on Massive MIMO technology.

Three receiver beamforming strategies are compared: Maximum Ratio Combining (MRC), Minimum Mean Square Error (MMSE), and a Particle Swarm Optimization (PSO) based approach. MATLAB simulations are conducted under correlated Rayleigh fading channel conditions for varying antenna counts, user numbers, and CSI estimation errors.

Results demonstrate that the PSO-based beamformer consistently outperforms classical methods, maintaining stable performance even under imperfect channel state information (CSI), establishing it as a robust solution for dense IoT networks under realistic conditions.

Keywords: Massive MIMO, Digital Beamforming, IoT, MRC, MMSE, PSO, SNR, BER, Imperfect CSI, Transmit Power Reduction.

Contents

Dedicace	i
Acknowledgements	ii
ملخص	iii
Résumé	iv
Abstract	v
List of Abbreviations	xii
General Introduction	1
1 Wireless Network Technologies and Architecture: Towards the 5G Era	3
1.1 Definition of a Wireless Network	3
1.2 Advantages of Wireless Networks	4
1.2.1 Mobility and Freedom of Movement	4
1.2.2 Flexibility of Deployment and Installation	5
1.2.3 Scalability and Expansion Capability	5
1.2.4 Reduction of Infrastructure Costs	6
1.2.5 Accessibility in Remote and Isolated Areas	6
1.2.6 Support for Emerging Applications	6
1.2.7 Rapid Deployment and Immediate Activation	7
1.2.8 Diversity of Wireless Technologies	7
1.2.9 Reduction of Physical Constraints	8
1.2.10 Continuous Technological Evolution	8
1.3 Disadvantages of Wireless Networks	8
1.3.1 Security Vulnerabilities	9
1.3.2 Radio Interference	9
1.3.3 Limited Capacity and Network Congestion	10
1.3.4 Sensitivity to Physical Obstacles	10

1.3.5	Limited Coverage Range	10
1.3.6	Infrastructure and Maintenance Costs	11
1.3.7	Dependence on Power Supply	11
1.3.8	Higher Latency Compared with Wired Networks	11
1.4	Evolution of Cellular Networks	12
1.4.1	From 1G to 5G: Historical Overview	13
1.4.2	Limitations of Previous Generations	15
2	System Model and Digital Beamforming	18
	Introduction	18
2.1	IoT Network Model	18
2.1.1	Overview of the Internet of Things	18
2.1.2	System Architecture	20
2.2	Channel Model	20
2.2.1	Channel Matrix Structure	21
2.2.2	Large-Scale Fading	22
2.2.3	Received Signal with Power	22
2.2.4	TDD Reciprocity	22
2.3	Noise Model	22
2.3.1	Noise Variance	23
2.3.2	Noise Figure Extension	23
2.4	Multiple Input Multiple Output (MIMO)	23
2.4.1	MIMO System Types	24
2.4.2	SISO Shannon Capacity	25
2.4.3	MIMO Channel Capacity	25
2.4.4	Massive MIMO Uplink Signal Model	25
2.5	Antenna Array Model (ULA)	26
2.5.1	Steering Vector	27
2.5.2	Array Manifold and Channel Decomposition	27
2.5.3	Array Factor and Beampattern	28
2.6	Digital Beamforming Techniques	29
2.6.1	Maximum Ratio Combining (MRC)	29
2.6.2	Zero-Forcing (ZF)	30
2.6.3	Minimum Mean Square Error (MMSE)	30
3	Particle Swarm Optimization Algorithm	32
3.1	Introduction	32
3.2	Optimization Problem	32
3.3	Elements of Optimization	33
3.4	Approximate Methods	33

3.5	Particle Swarm Optimization (PSO)	34
3.6	Formal Definition and Mathematical Model	35
3.6.1	Biological Inspiration	36
3.7	Swarm Behaviour: Three Local Rules	38
3.8	Key Properties of PSO	38
3.9	Algorithm Parameters	39
3.9.1	Problem Dimensionality	39
3.9.2	Swarm Size	39
3.9.3	Acceleration Coefficients	39
3.9.4	Neighbourhood Topology	39
3.9.5	Maximum Velocity	40
3.9.6	Inertia Weight	40
3.9.7	Constriction Factor	40
3.9.8	Stopping Criterion	40
3.10	Advantages and Limitations	41
4	Simulation Results and Discussion	42
4.1	Introduction	42
4.2	Simulation Setup and Parameters	42
4.3	BER Performance Comparison	43
4.3.1	Impact of Inter-User Interference on MRC and MMSE Algorithms	44
4.4	Beamforming Optimization Using PSO	44
4.4.1	Single-User Scenario ($K = 1, N_t = 2, N_r = 8$)	45
4.4.2	Multi-User Scenario ($K = 4, N_t = 2, N_r = 10$)	46
4.5	Problem Formulation	47
4.5.1	Optimisation Objective	47
4.5.2	Practical Constraints in IoT Scenarios	48
4.6	Impact of the Number of Receive Antennas N_r	48
4.6.1	Effect of the Number of IoT Users K	49
4.6.2	Minimum Transmit Power vs. Number of Antennas	50
4.7	Robustness Analysis under Imperfect CSI	50
4.8	Conclusion	51
	General Conclusion	53

List of Figures

1.1	Basic architecture of a wireless network [7].	4
1.2	Wireless signal interference and propagation obstacles [4].	12
1.3	Comparative evolution of cellular networks from 1G to 5G [6].	12
1.4	5G Network Architecture (UE, RAN, Core Network) [6].	15
1.5	Beamforming and Massive MIMO Concept [10].	16
2.1	Evolution of connected devices [1].	19
2.2	IoT applications [11].	20
2.3	Multipath Propagation in a Rayleigh Fading Channel.	21
2.4	MIMO system [25].	24
2.5	MU-MIMO and SU-MIMO [5].	24
2.6	Uplink and downlink in 5G IoT networks [8].	26
2.7	Geometry of a Uniform Linear Array (ULA) $d = \lambda/2$ [33].	26
2.8	Phased array elements [7].	27
2.9	Radiation pattern for $M = 8, 32$, and 128 antenna elements ($d = \lambda/2$, $\theta_0 = 0$).	28
2.10	Digital beamforming [39].	29
3.1	Principle of Particle Movement in PSO Algorithm [3].	35
3.2	Biological inspiration of PSO [3].	36
3.3	Particle Swarm Optimization flowchart [15].	37
4.1	Effect of the Number of Receive Antennas N_r	43
4.2	BER vs SNR — Impact of inter-user interference on MRC and MMSE algorithms, $N_r = 8$, $\rho = 0.8$	44
4.3	Processes of simulation.	45
4.4	BER vs SNR — Perfect CSI, $K = 1$ user, $M = 8$ receive antennas, MRC vs MMSE vs PSO, correlated Rayleigh fading ($\rho = 0.8$).	46
4.5	BER vs SNR — Perfect CSI, $K = 4$ users, $N_r = 10$ antennas, $\rho = 0.8$, correlated Rayleigh fading, MRC vs MMSE vs PSO.	47

4.6	BER vs SNR for MMSE beamforming with varying number of receive antennas ($N_r = 8, 10, 12$), $K = 4$ IoT users, $\rho = 0.8$, perfect CSI, correlated Rayleigh fading.	48
4.7	BER vs SNR for MMSE beamforming with varying number of IoT users ($K = 2, 4, 6$), $N_r = 12$ antennas, $\rho = 0.8$, perfect CSI, correlated Rayleigh fading.	49
4.8	Minimum transmit power $P_t^{\min}$ as a function of the number of IoT interferers ($K - 1$) for SNR = 10 dB under perfect CSI conditions.	50
4.9	Minimum transmit power $P_t^{\min}$ vs. normalized CSI estimation error ε , for MMSE and PSO blind beamformers. SNR = 10 dB, $M = 8$ antennas, $K - 1 = 5$ interferers, correlated Rayleigh fading ($\rho = 0.8$).	51

List of Tables

1.1	Comparative evolution of cellular networks from 1G to 5G [4, 6].	16
2.1	Summary of multi-antenna system configurations.	24
2.2	Key parameters of the ULA model used in this work.	27
2.3	Comparison of beamforming architectures.	29
2.4	Comparative summary of MRC, ZF, and MMSE receivers.	31
4.1	Simulation Parameters	43

List of Abbreviations

Abbreviation	Meaning
1G, 2G, 3G, 4G, 5G	1st to 5th Generation of Mobile Networks
5GC	5G Core
6G	Sixth Generation
ADC	Analog-to-Digital Converter
AOA	Angle of Arrival
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BS	Base Station
CSI	Channel State Information
DAC	Digital-to-Analog Converter
eMBB	Enhanced Mobile Broadband
FDD	Frequency Division Duplex
GA	Genetic Algorithm
IoT	Internet of Things
LTE	Long-Term Evolution
Massive MIMO	Massive Multiple Input Multiple Output
MIMO	Multiple Input Multiple Output
MISO	Multiple Input Single Output
MMSE	Minimum Mean Square Error
mMTC	Massive Machine-Type Communication
MRC	Maximum Ratio Combining

Abbreviation	Meaning
MSE	Mean Square Error
MU-MIMO	Multi-User MIMO
OFDMA	Orthogonal Frequency Division Multiple Access
PSO	Particle Swarm Optimization
RF	Radio Frequency
SINR	Signal-to-Interference-plus-Noise Ratio
SIMO	Single Input Multiple Output
SISO	Single Input Single Output
SNR	Signal-to-Noise Ratio
SU-MIMO	Single-User MIMO
TDD	Time Division Duplex
UE	User Equipment
UL	Uplink
ULA	Uniform Linear Array
URLLC	Ultra-Reliable Low-Latency Communication
ZF	Zero Forcing

General Introduction

The exponential growth of connected devices has fundamentally reshaped the landscape of wireless communications. By 2025, more than 75 billion IoT devices are projected to be connected worldwide [1, 2], generating over 180 zettabytes of data annually. This massive connectivity, combined with the strict energy constraints of battery-operated IoT sensors, creates a fundamental tension: how to maintain reliable communication for a large number of simultaneously active devices while keeping each device's transmit power as low as possible.

Fifth-generation (5G) networks are specifically designed to address this challenge. Among the enabling technologies identified for 5G and beyond, Massive Multiple Input Multiple Output (Massive MIMO) stands out as one of the most promising. By equipping the base station with a large number of antennas — significantly greater than the number of served devices ($M \gg K$) — Massive MIMO enables simultaneous spatial multiplexing of multiple users within the same time-frequency resources, achieving both high spectral efficiency and strong interference suppression.

However, realising the full potential of Massive MIMO in dense IoT deployments requires effective digital beamforming at the receiver. Classical linear beamforming techniques such as Maximum Ratio Combining (MRC), Zero-Forcing (ZF), and Minimum Mean Square Error (MMSE) are widely used due to their simplicity and analytical tractability. Nevertheless, their performance degrades significantly under practical conditions.

To overcome these limitations, metaheuristic optimization approaches have recently attracted significant attention. Particle Swarm Optimization (PSO), originally proposed by Kennedy and Eberhart in 1995 [3], is a population-based algorithm that iteratively refines a set of candidate beamforming weight vectors without requiring explicit channel knowledge or gradient information. By operating directly on the received signal statistics, a PSO-based blind beamformer is structurally immune to CSI inaccuracies — a property that makes it particularly well-suited to the challenging conditions of dense IoT networks.

Objective and Contributions. The primary objective of this thesis is to investigate and evaluate digital beamforming at the base station receiver for transmit power reduction in dense IoT uplink networks. Specifically, the work proposes a PSO-based beamformer and

demonstrates, through MATLAB simulations under correlated Rayleigh fading channel conditions, that it achieves:

- a minimum transmit power of approximately -12 dB at $M = 16$ antennas, exceeding MMSE by more than 10 dB under perfect CSI;
- stable and robust performance under imperfect CSI over MMSE across the full range of normalized channel estimation errors;
- consistent superiority over MRC and MMSE in all tested scenarios involving multi-user interference.

Thesis Organisation. This thesis is organised into four chapters. Chapter 1 introduces the fundamental concepts of wireless communication networks and their evolution from 1G to 5G, highlighting the technical challenges introduced by dense IoT deployments. Chapter 2 develops the complete mathematical framework for the Massive MIMO IoT uplink, covering the channel model, the antenna array geometry, and the three classical linear beamforming techniques: MRC, ZF, and MMSE. Chapter 3 presents Particle Swarm Optimization in detail, from its biological inspiration to its formal mathematical model and key algorithmic parameters. Chapter 4 presents and discusses the MATLAB simulation results, evaluating the BER performance, the impact of antenna.

Chapter 1

Wireless Network Technologies and Architecture: Towards the 5G Era

Introduction

Wireless communication networks have become a fundamental component of modern telecommunication systems. The exponential growth of mobile data traffic, the widespread deployment of connected devices, and the increasing demand for high-speed and reliable communication services have revealed the limitations of previous cellular generations such as 2G, 3G, and 4G [4]. In this context, fifth-generation mobile networks (5G) represent a major technological advancement capable of providing enhanced performance in terms of data rate, latency, network capacity, reliability, and massive connectivity [5].

This chapter presents a general overview of wireless networks, including their evolution, architecture, and operating principles. It also introduces the fundamental concepts and key characteristics of 5G technology, which is considered one of the most significant innovations in modern telecommunications [6].

1.1 Definition of a Wireless Network

A wireless network is a communication system in which information is transmitted and received without the use of physical transmission media such as cables or optical fibers [7]. Instead, communication is achieved through electromagnetic waves, including radio waves, microwaves, and infrared signals. These waves enable the exchange of information between connected devices over distances ranging from a few centimeters to several kilometers.

Wireless communication systems rely on radio infrastructures composed of transmitters, receivers, antennas, and signal processing equipment capable of handling digital communications [4]. The transmitted signals are modulated in order to carry information between different types of devices, including smartphones, computers, Internet of Things

(IoT) sensors, and base stations.

Unlike wired systems, wireless networks provide flexible and mobile communication capabilities while simplifying network deployment [7]. Consequently, they are widely used in cellular communication systems such as 3G, 4G, and 5G networks, as well as in Wi-Fi, Bluetooth, and wireless sensor networks.

In general, wireless networks are characterized by the following features:

- Absence of physical cabling between communication nodes;
- Use of electromagnetic waves for information transmission;
- Support for user mobility and rapid deployment;
- Capability to connect a large and variable number of devices in different environments.

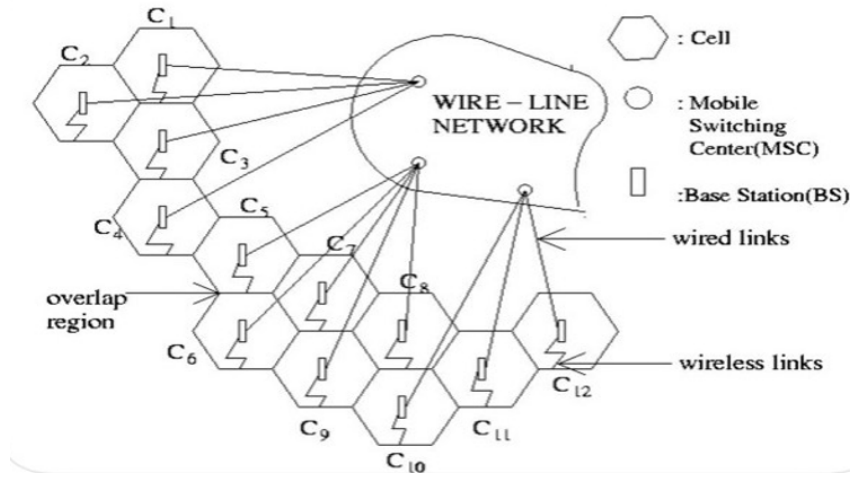


Figure 1.1: Basic architecture of a wireless network [7].

1.2 Advantages of Wireless Networks

Wireless networks offer numerous advantages that explain their extensive adoption in modern communication systems [4]. Compared with traditional wired infrastructures, wireless technologies provide greater flexibility, mobility, scalability, and deployment efficiency. The main advantages are presented below.

1.2.1 Mobility and Freedom of Movement

One of the most important advantages of wireless communication systems is mobility [7]. Users can access communication services, browse the Internet, and use real-time applications while moving freely without relying on fixed physical connections.

The main benefits include:

- Seamless mobility management through automatic handover mechanisms between cells;
- Continuity of communication sessions during movement, such as in vehicles or trains;
- Support for smartphones, tablets, mobile IoT devices, and intelligent transportation systems.

1.2.2 Flexibility of Deployment and Installation

Wireless networks are relatively easy to deploy because they eliminate the need for extensive cabling infrastructure [4]. Their flexibility makes them suitable for several environments and applications.

The main advantages include:

- Reduced installation complexity and deployment time;
- Suitability for industrial sites, rural regions, and temporary installations;
- Rapid deployment in emergency situations or large public events;
- Lower installation and operational costs.

This flexibility enables operators and organizations to rapidly adapt communication infrastructures to evolving requirements.

1.2.3 Scalability and Expansion Capability

Wireless systems can easily accommodate additional users and connected devices without requiring major physical modifications to the infrastructure [6].

Their scalability is ensured through:

- Easy integration of new devices and communication terminals;
- Dynamic resource allocation using advanced technologies such as MIMO and beam-forming;
- Efficient support for large-scale IoT deployments in smart cities and industrial environments [2].

This capability is particularly important in 5G systems, which are designed to support massive machine-type communications.

1.2.4 Reduction of Infrastructure Costs

Compared with wired communication systems, wireless technologies significantly reduce infrastructure-related expenses [4].

The economic advantages include:

- Elimination of extensive cable installations;
- Reduction of civil engineering work;
- Lower maintenance requirements for physical infrastructure;
- Infrastructure sharing between operators, including antennas and transmission towers.

As a result, wireless communication systems contribute to reducing both deployment and long-term operational costs.

1.2.5 Accessibility in Remote and Isolated Areas

Wireless communication technologies provide connectivity in locations where wired installations are impractical or economically unfeasible [4].

Typical examples include:

- Rural and remote regions;
- Mountainous and desert areas;
- Temporary installations and scientific camps;
- Emergency situations following natural disasters.

Modern wireless technologies such as 4G, 5G, and LPWAN enable communication services over large geographical areas [5].

1.2.6 Support for Emerging Applications

Wireless communication systems form the technological foundation of numerous innovative applications [1, 2], including:

- Cloud-based mobile services;
- Internet of Things (IoT) applications;
- Virtual and augmented reality systems;

- Autonomous vehicles and intelligent transportation systems;
- Telemedicine and remote healthcare;
- Smart manufacturing and Industry 4.0 applications.

The capability to provide ubiquitous connectivity without spatial constraints makes wireless networks essential for future technological developments [6].

1.2.7 Rapid Deployment and Immediate Activation

Wireless systems can be deployed more rapidly than wired infrastructures because they do not require extensive physical installations [7].

Their advantages include:

- Fast activation of base stations and access points;
- Automatic connection of communication terminals;
- Software-based configuration and network optimization.

This rapid deployment capability is particularly beneficial in emergency scenarios and temporary communication environments.

1.2.8 Diversity of Wireless Technologies

Wireless communication includes a broad range of technologies adapted to different applications and requirements [4], such as:

- Wi-Fi for local broadband communication;
- Bluetooth and BLE for short-range low-power communication;
- Cellular networks (2G, 3G, 4G, and 5G) for wide-area connectivity;
- LPWAN technologies such as LoRa and NB-IoT for IoT applications [8];
- Zigbee and Thread for home automation and industrial communication.

This diversity makes wireless communication systems highly adaptable to different operational environments.

1.2.9 Reduction of Physical Constraints

The absence of physical cables provides several practical advantages [7], including:

- Reduced infrastructure clutter;
- Lower risk of physical damage to communication links;
- Improved flexibility in equipment installation and organization;
- Better aesthetic integration in residential and professional environments.

1.2.10 Continuous Technological Evolution

Wireless communication technologies continuously evolve from one generation to another [4], resulting in improvements in:

- Data throughput;
- Latency reduction;
- Reliability and quality of service;
- Network capacity;
- Energy efficiency;
- Communication security.

The transition from 3G to 4G and subsequently to 5G demonstrates the continuous development of wireless communication systems toward higher performance and more advanced services [5, 6].

1.3 Disadvantages of Wireless Networks

Despite their numerous advantages, wireless communication systems also present several technical limitations and challenges that may negatively affect network performance, reliability, and security [4]. Unlike wired networks, wireless communications rely on a shared transmission medium that is highly sensitive to interference, environmental conditions, and security threats. The principal disadvantages of wireless networks are discussed in the following subsections.

1.3.1 Security Vulnerabilities

Since wireless communications propagate through the air using electromagnetic waves, they are generally more vulnerable to security attacks than wired networks [7]. Unauthorized users may intercept or manipulate transmitted data if appropriate security mechanisms are not implemented.

The most common security threats include:

- **Eavesdropping:** unauthorized interception of transmitted information;
- **Jamming attacks:** intentional disruption of radio signals in order to block or degrade communications;
- **Spoofing attacks:** impersonation of legitimate users or devices to gain unauthorized network access;
- **Man-in-the-Middle (MITM) attacks:** interception and modification of exchanged data between communicating entities.

To mitigate these threats, modern wireless systems employ advanced security mechanisms such as encryption, authentication protocols, firewalls, and access control techniques [4].

1.3.2 Radio Interference

Wireless networks operate within shared radio frequency spectra, making them susceptible to different forms of interference [4]. Signal degradation may occur due to:

- Other devices operating in the same frequency band, such as Wi-Fi, Bluetooth, or microwave systems;
- Physical obstacles including walls, concrete structures, and metallic objects;
- Atmospheric and environmental conditions such as rain, fog, and humidity;
- Spectrum congestion in densely populated urban environments.

Radio interference can significantly affect communication quality, leading to:

- Reduction of the Signal-to-Noise Ratio (SNR);
- Packet losses during transmission;
- Decreased throughput and reduced coverage area.

1.3.3 Limited Capacity and Network Congestion

Wireless communication systems rely on limited radio resources and shared bandwidth [5]. Consequently, network congestion may occur when a large number of users attempt to access the network simultaneously.

This limitation may result in:

- Saturation of available bandwidth;
- Increased communication latency;
- Reduction in effective data throughput;
- Temporary disconnections or service interruptions.

Network congestion is particularly critical in densely populated areas and during large public events [1].

1.3.4 Sensitivity to Physical Obstacles

Electromagnetic waves are highly affected by physical obstacles encountered during propagation [4]. Materials such as concrete, metal, wood, and glass may attenuate or block wireless signals.

The main obstacles include:

- Thick walls and concrete structures;
- Metallic surfaces and industrial equipment;
- Furniture and indoor obstacles;
- Terrain irregularities and geographical topography.

These propagation losses reduce transmission range and may degrade communication quality.

1.3.5 Limited Coverage Range

Unlike wired networks, wireless coverage strongly depends on several physical and technical parameters [4], including:

- Transmission power;
- Communication technology used (Wi-Fi, 4G, 5G, etc.);
- Operating frequency band;

- Environmental and atmospheric conditions.

Higher frequency bands generally provide higher data rates but shorter transmission ranges. For example, millimeter-wave (mmWave) frequencies used in 5G systems enable extremely high throughput while offering limited propagation distance [6].

1.3.6 Infrastructure and Maintenance Costs

Although wireless networks simplify physical deployment, they still require advanced and often expensive infrastructure components [7], including:

- Antennas and access points;
- Base stations and radio equipment;
- Spectrum management systems;
- Continuous software and security updates.

Furthermore, maintaining optimal network performance requires constant monitoring, optimization, and interference management, which may increase operational costs.

1.3.7 Dependence on Power Supply

Wireless communication devices such as smartphones, routers, sensors, and IoT terminals depend heavily on electrical power sources or batteries [2].

Consequently:

- Battery depletion may interrupt communication services;
- Power outages can affect network availability;
- Energy consumption remains a major challenge for mobile and IoT devices.

Energy efficiency has therefore become a critical research area in modern wireless communication systems [9].

1.3.8 Higher Latency Compared with Wired Networks

Wireless communication systems generally experience higher latency than wired networks due to medium sharing, signal interference, retransmissions, and collision management mechanisms [4].

These factors may introduce:

- Communication delays;

- Jitter (delay variation);
- Reduced performance for real-time applications.

Latency-sensitive services such as online gaming, video conferencing, industrial automation, and remote surgery are particularly affected by these limitations [5].

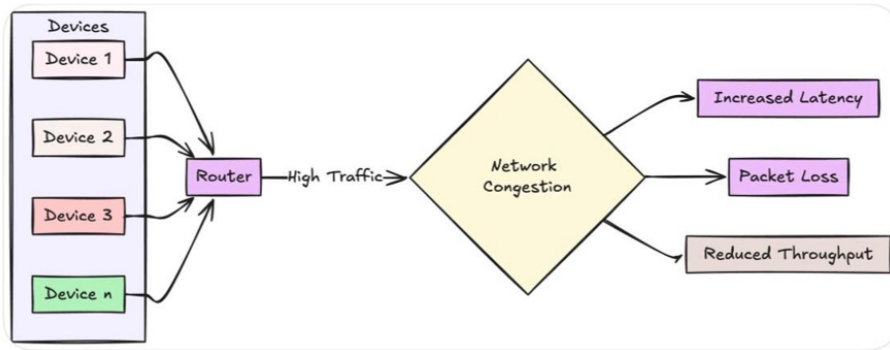


Figure 1.2: Wireless signal interference and propagation obstacles [4].

1.4 Evolution of Cellular Networks

The evolution of cellular communication systems has profoundly transformed modern telecommunications [4]. Each new generation of mobile networks has introduced technological innovations aimed at improving communication quality, increasing transmission speed, reducing latency, and expanding the range of available services.

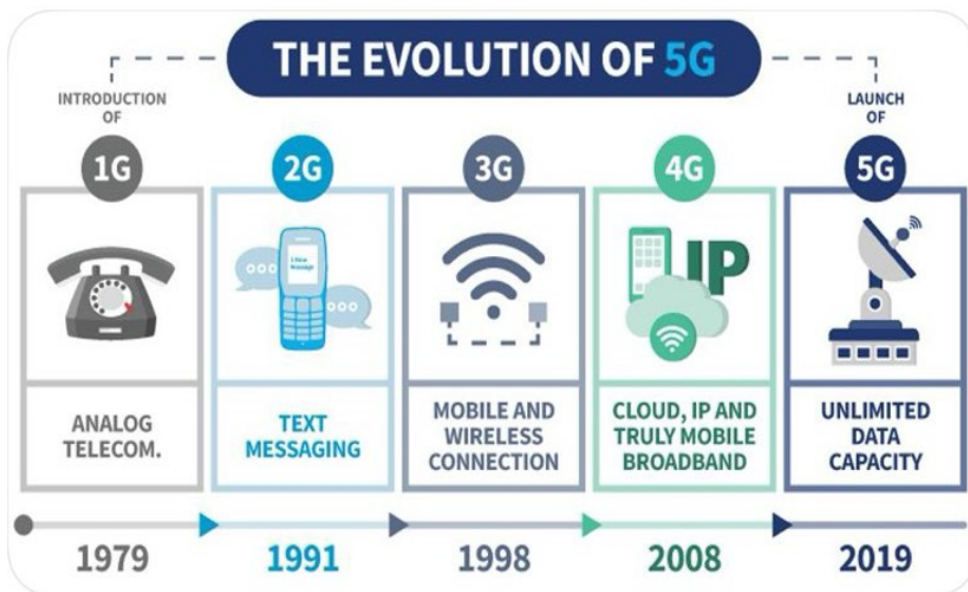


Figure 1.3: Comparative evolution of cellular networks from 1G to 5G [6].

1.4.1 From 1G to 5G: Historical Overview

The development of cellular networks has progressed gradually from analog voice communication toward intelligent and fully connected digital ecosystems [4]. Each generation introduced new capabilities and addressed the limitations of previous systems.

1G: First Generation (1980s)

The first generation (1G) marked the beginning of cellular mobile communications [4]. This generation was entirely based on analog technology.

The main characteristics of 1G systems include:

- Analog voice transmission;
- Operation in the 800–900 MHz frequency band;
- Poor voice quality with high interference levels;
- Lack of communication security due to the absence of encryption;
- Support limited exclusively to voice calls.

Examples of 1G technologies include AMPS, NMT, and TACS. Although limited in performance and security, 1G introduced the concept of mobile communication.

2G: Second Generation (1990s)

The second generation (2G) introduced digital communication technologies, representing a major improvement over analog systems [4].

Its principal innovations include:

- Digital voice transmission with improved quality;
- Introduction of Short Message Service (SMS);
- Enhanced communication security through encryption;
- Reduced energy consumption;
- Initial support for mobile data services.

The most important 2G technologies are GSM, GPRS, and EDGE. 2G systems played a key role in the widespread adoption of mobile phones and mobile messaging services.

3G: Third Generation (2000s)

The third generation (3G) represented the true beginning of mobile Internet services by providing significantly higher data rates [4].

The main features of 3G include:

- Data rates reaching several Mbps;
- Efficient support for web browsing, email, and video calls;
- Improved network coverage and communication quality;
- Emergence of the first smartphone ecosystems.

Major 3G technologies include UMTS, HSPA, and HSPA+. 3G contributed significantly to the growth of multimedia applications and social networking services.

4G: Fourth Generation (2010s)

Fourth-generation networks (4G LTE) introduced an all-IP architecture optimized for high-speed mobile broadband communications [4].

The major improvements include:

- High data rates exceeding 100 Mbps;
- Reduced latency for real-time services;
- Support for HD video streaming and online gaming;
- Efficient integration of smartphones and tablets.

The primary technologies associated with 4G are LTE and LTE-Advanced. 4G enabled the rapid expansion of mobile broadband applications and digital services.

5G: Fifth Generation (Since 2019)

The fifth generation (5G) represents a major transformation in wireless communications, extending connectivity beyond human users to machines, sensors, and intelligent infrastructures [5].

The main characteristics of 5G include:

- Data rates reaching several Gbps;
- Ultra-low latency approaching 1 ms;
- Massive connectivity for IoT devices [1];

- Use of millimeter-wave frequency bands;
- Integration of advanced technologies such as massive MIMO, beamforming, and network slicing [6, 10].

5G networks are mainly designed around three service categories [5]:

1. Enhanced Mobile Broadband (eMBB);
2. Ultra-Reliable Low-Latency Communications (URLLC);
3. Massive Machine-Type Communications (mMTC).

5G technology is expected to support emerging applications such as autonomous vehicles, Industry 4.0, smart cities, and advanced healthcare systems [6, 11].

1.4.2 Limitations of Previous Generations

Despite their technological progress, earlier generations of mobile networks still present several limitations [4], including:

- Saturation of available frequency bands;
- Limited support for massive simultaneous connections [2];
- Relatively high latency;
- Insufficient bandwidth for emerging applications such as virtual reality, telemedicine, and autonomous transportation systems [5].

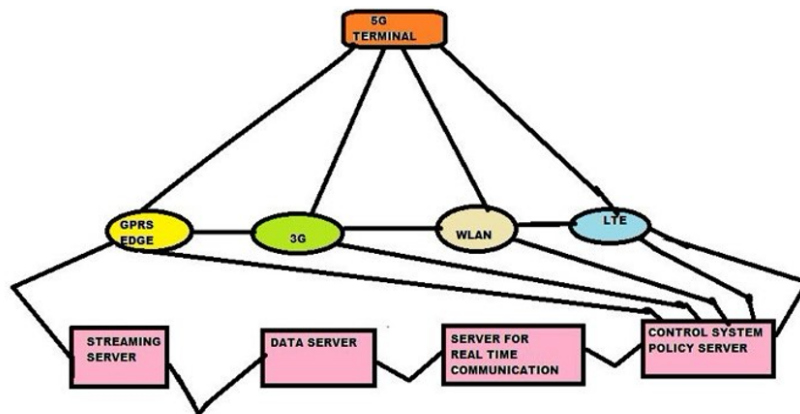


Figure 1.4: 5G Network Architecture (UE, RAN, Core Network) [6].

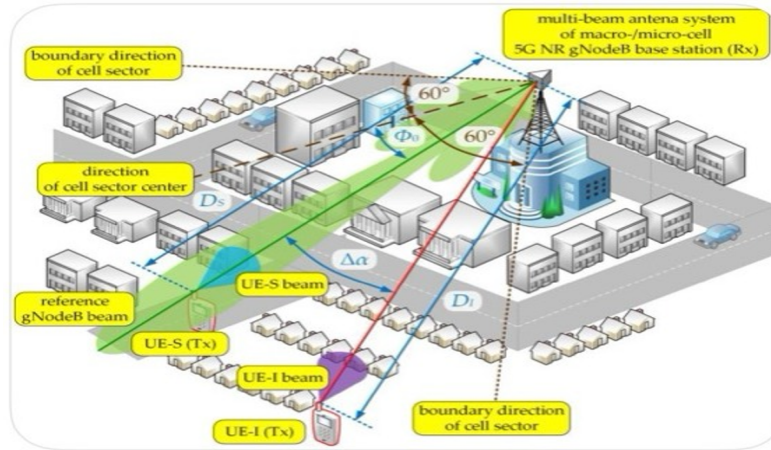


Figure 1.5: Beamforming and Massive MIMO Concept [10].

Table 1.1: Comparative evolution of cellular networks from 1G to 5G [4, 6].

Generation	1G	2G	3G	4G	5G
Technology type	Analog	Digital	Digital broadband	All-IP broadband	Intelligent virtualized network
Main service	Voice only	Voice + SMS	Voice + Internet	High-speed mobile Internet	Massive IoT + ultra-reliable services
Data rate	N/A	~10–200 kbps	up to 2 Mbps	100 Mbps – 1 Gbps	1–10 Gbps
Latency	Very high	High	Moderate	~30–50 ms	~1 ms
Switching type	Circuit switching	Circuit + packet	Packet switching	Fully packet (IP)	Virtualized (SDN/NFV)
Frequency bands	800–900 MHz	900/1800 MHz	2 GHz	2–8 GHz	Sub-6 GHz + mmWave
Mobility support	Basic	Good	High	Very high	Ultra-high
Key innovation	First mobile calls	SMS + digital security	Mobile Internet	Broadband multimedia	Massive connectivity + network slicing

Conclusion

This chapter has presented a comprehensive overview of wireless network technologies and their evolution from the first analog generation to the current 5G era. The fundamental concepts, advantages, and limitations of wireless communication systems have been discussed, highlighting the key role of 5G in addressing the growing demands of modern applications, particularly in the context of massive IoT deployments [1, 2, 5]. The following chapter will develop the complete mathematical framework for the Massive MIMO IoT uplink system considered in this work.

Chapter 2

System Model and Digital Beamforming

Introduction

This chapter develops the mathematical framework underlying the uplink of a massive MIMO IoT network studied in this thesis. The network topology, channel propagation model, noise characterisation, antenna array geometry, and three standard linear digital beamforming receivers — MRC, ZF, and MMSE — are presented in a self-contained manner. All analytical expressions derived here are used directly in the MATLAB simulations reported in Chapter 4, and serve as the performance reference against which the PSO-based optimisation of Chapter 3 is evaluated.

2.1 IoT Network Model

2.1.1 Overview of the Internet of Things

The Internet of Things (IoT) represents a technological paradigm in which everyday physical objects are endowed with sensing, processing, and wireless communication capabilities, enabling them to exchange data autonomously without direct human intervention [1, 2]. The scale of IoT deployment has grown remarkably over the past decade. The worldwide number of connected devices surpassed 27 billion in 2017, and recent projections estimate that this figure will approach 75 billion by 2025 [1, 2]. Alongside this growth, the volume of data generated by IoT systems is expected to exceed 180 zettabytes, underscoring both the technical challenges and the strategic importance of IoT as a major research domain.

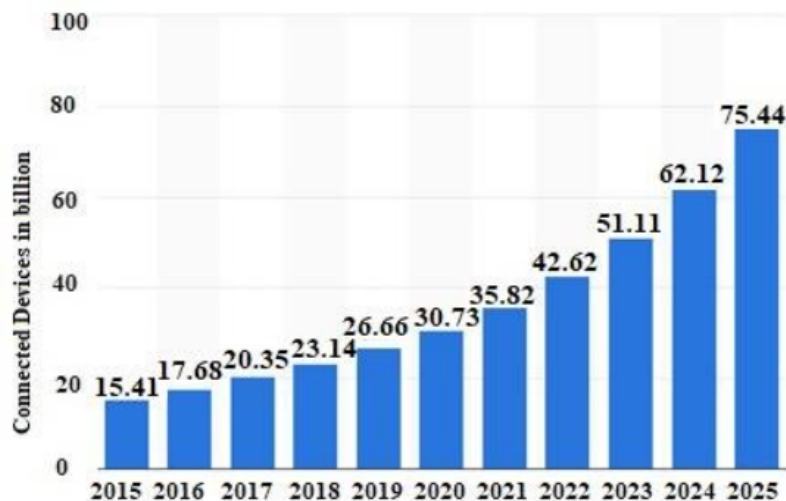


Figure 2.1: Evolution of connected devices [1].

IoT applications span a wide range of sectors. In smart environments, technologies such as RFID tags, intelligent energy meters, and automated control systems are combined to improve security and energy efficiency. In healthcare, wearable sensors collect physiological data continuously and transmit it to cloud-based platforms for remote monitoring. In industrial deployments, machines communicate via Machine-to-Machine (M2M) protocols, forming cyber-physical systems where processes are monitored and controlled in real time [11].

Despite the diversity of these applications, a common requirement emerges: next-generation wireless systems must support massive device connectivity, low latency, and high energy efficiency simultaneously [5]. This motivates the use of massive MIMO technology as the primary access layer for dense IoT scenarios, as detailed in the following sections.

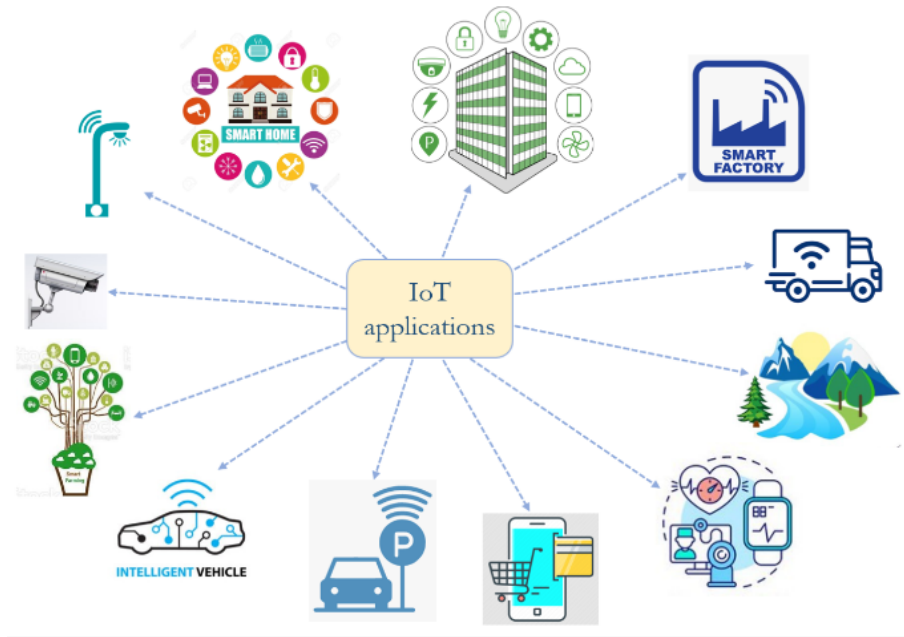


Figure 2.2: IoT applications [11].

2.1.2 System Architecture

The uplink network considered in this work consists of K single-antenna IoT devices randomly distributed within a circular cell of radius R , all transmitting simultaneously to a base station (BS) equipped with M antennas. The system operates in the massive MIMO regime, characterised by the condition:

$$M \gg K, \quad (2.1)$$

which enables efficient spatial multiplexing and interference suppression [12]. This condition guarantees two fundamental asymptotic properties that justify the use of simple linear receivers in this context.

Both properties are rigorously established in [13] and directly justify why low-complexity linear receivers — such as MRC, ZF, and MMSE — approach the theoretical optimum in the massive MIMO regime.

2.2 Channel Model

In mobile wireless systems, the propagation channel between transmitter and receiver introduces attenuation, fading, and phase shifts that depend on the environment [14]. For the dense IoT uplink considered here, a flat Rayleigh fading model is adopted, which is appropriate for rich-scattering environments where no dominant line-of-sight component exists [15].

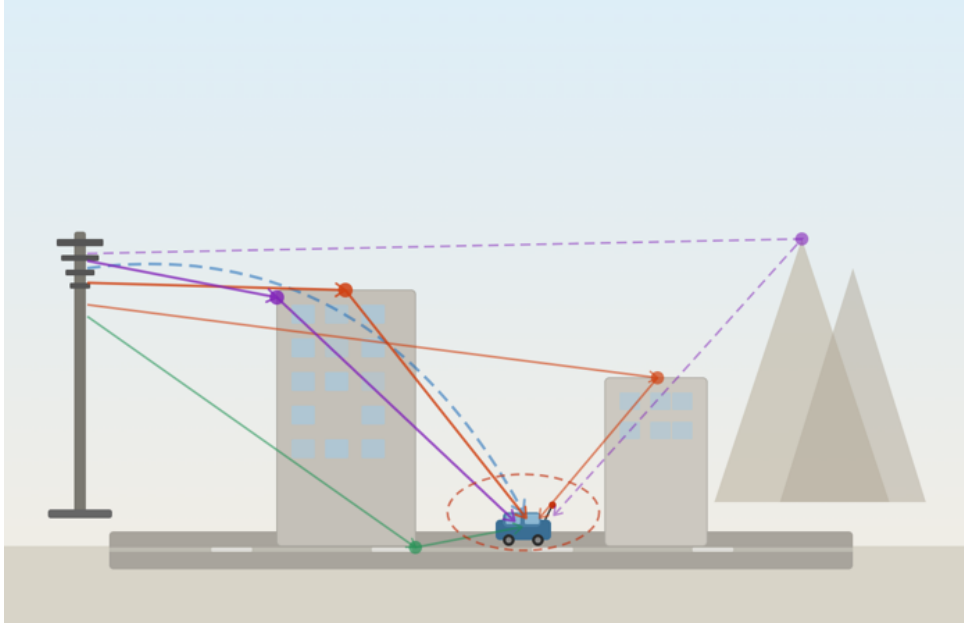


Figure 2.3: Multipath Propagation in a Rayleigh Fading Channel.

2.2.1 Channel Matrix Structure

The channel matrix $H \in M \times K$ collects the channel vectors of all K devices. The channel vector of device k is decomposed as:

$$h_k = \sqrt{\beta_k} g_k, \quad (2.2)$$

where $\beta_k \in^+$ is the large-scale fading coefficient and $g_k \sim \mathcal{CN}(0, I_M)$ is the small-scale fading vector.

Signal Model

The BS applies a digital combining matrix to the uplink transmissions received from all K devices. The received signal vector is:

$$y = Hx + n, \quad (2.3)$$

where $y \in C^M$ is the received signal vector, $H \in C^{M \times K}$ is the channel matrix, $x \in C^K$ is the transmitted symbol vector with $E[xx^H] = P I_K$, and $n \sim \mathcal{CN}(0, \sigma^2 I_M)$ is the additive noise vector.

2.2.2 Large-Scale Fading

The large-scale fading coefficient captures both geometric path loss and log-normal shadowing:

$$\beta_k = \frac{\zeta_k}{(d_k/d_0)^\alpha}, \quad (2.4)$$

where d_k is the device-to-BS distance, d_0 a reference distance, $\alpha \in [2, 4]$ the path-loss exponent, and ζ_k a log-normal shadowing variable with standard deviation $\sigma_{\text{sh}} = 8$ dB [16].

2.2.3 Received Signal with Power

Incorporating the transmit power P explicitly, the received signal at the BS is:

$$y = \sqrt{P} Hs + n, \quad (2.5)$$

where $s \in^K$ is the normalised symbol vector satisfying $ss^H = I_K$.

As $M \rightarrow \infty$, the Gram matrix $(1/M)H^H H$ converges to $\text{diag}(\beta_1, \dots, \beta_K)$, which is the mathematical expression of favorable propagation [17] [18] [19].

2.2.4 TDD Reciprocity

Under the Time Division Duplex (TDD) protocol, uplink and downlink transmissions share the same frequency band within non-overlapping time slots [8]. TDD reciprocity allows the BS to estimate the uplink channel from pilot sequences and use the same estimate to design the downlink precoder [20], greatly simplifying the beamforming design in practical deployments.

2.3 Noise Model

Each receive antenna at the BS is affected by Additive White Gaussian Noise (AWGN), which models the thermal noise generated by the electronic components of the RF front end [21]. The noise vector $n \in^M$ has independent entries:

$$n \sim \mathcal{CN}(0, \sigma_n^2 I_M), \quad (2.6)$$

where σ_n^2 is the noise variance, identical across all antenna elements.

2.3.1 Noise Variance

In physical terms, $\sigma_n^2 = kTBF$ [22]. In the simulations of this work, the noise variance is normalised to unity and the average receive SNR is defined as:

$$= \frac{P}{\sigma_n^2}. \quad (2.7)$$

2.3.2 Noise Figure Extension

The effective noise figure F of a practical receiver chain typically ranges from 3 to 7 dB in massive MIMO systems [23]. For low-resolution ADCs (1–3 bits), quantisation noise adds a supplementary term σ_q^2 to the effective noise variance [24].

2.4 Multiple Input Multiple Output (MIMO)

Multiple Input Multiple Output (MIMO) systems employ multiple antennas at both the transmitter and receiver sides in order to improve wireless communication performance [25]. By exploiting spatial diversity and spatial multiplexing, MIMO systems can significantly enhance data throughput, link reliability, and spectral efficiency.

Consider a MIMO system where the i^{th} user is equipped with M_i antennas, while the base station employs N antennas. The channel matrix associated with user i is expressed as:

The channel matrix associated with user i is expressed as:

$$\mathbf{H}_i = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1K} \\ h_{21} & h_{22} & \cdots & h_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ h_{M1} & h_{M2} & \cdots & h_{MK} \end{bmatrix} \in C^{M_i \times N} \quad (2.8)$$

The received signal vector for user i at time instant n :

$$\mathbf{y}_i(n) = \mathbf{H}_i \sum_{k=1}^K \mathbf{w}_k s_k(n) + \mathbf{v}_i(n) \quad (2.9)$$

MIMO systems exploit multiple antennas to increase data throughput, improve reliability, or suppress interference, all without requiring additional spectrum [25]. The diversity gain increases with the product $N_t \times N_r$.

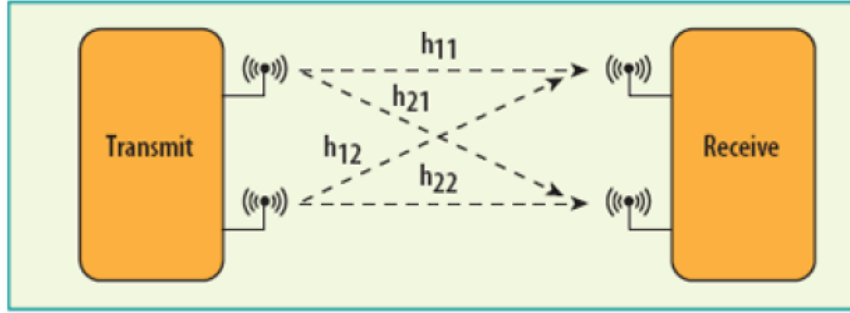


Figure 2.4: MIMO system [25].

2.4.1 MIMO System Types

Table 2.1 summarises the four fundamental multi-antenna configurations. The configuration of interest here is MU-MIMO with $M \gg K$, referred to as massive MIMO [26].

Table 2.1: Summary of multi-antenna system configurations.

Type	Tx	Rx	Key Feature	Application
SISO	1	1	Baseline	Legacy systems
MISO	M	1	Transmit diversity	Downlink cellular
SIMO	1	M	Receive combining	IoT uplink
MIMO	M	M	Spatial multiplexing	Wi-Fi, 4G/5G
SU-MIMO	M	M	Single-user streams	Point-to-point
MU-MIMO	M	K	Multi-user multiplexing	5G BS, Massive MIMO

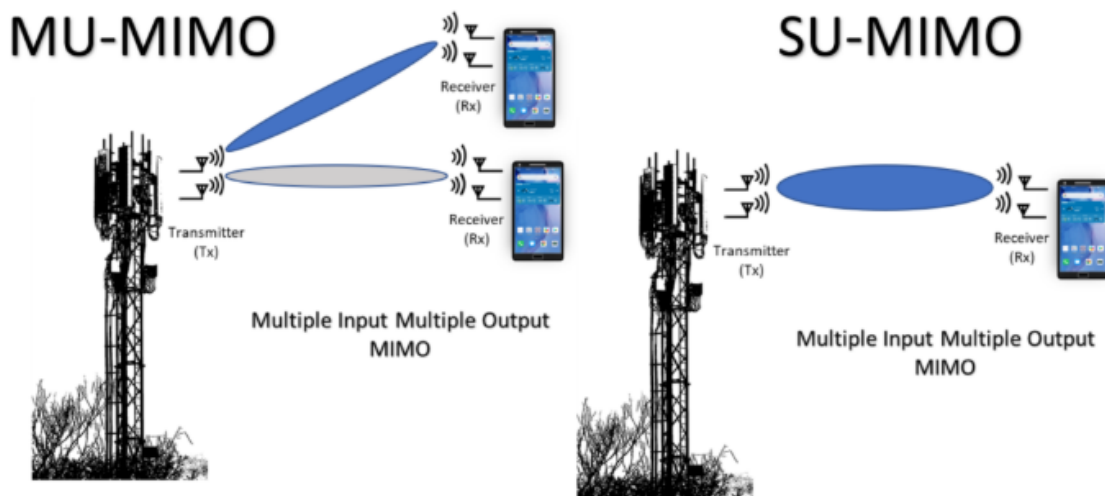


Figure 2.5: MU-MIMO and SU-MIMO [5].

2.4.2 SISO Shannon Capacity

The single-antenna Shannon capacity provides the baseline reference [27]:

$$C = B \log_2(1 + \text{SNR}) \quad [\text{bits/s}], \quad (2.10)$$

Since this expression grows only logarithmically with SNR, deploying multiple antennas is essential to achieve the high spectral efficiencies required by dense IoT networks [28].

2.4.3 MIMO Channel Capacity

A MIMO system with N_t transmit and N_r receive antennas achieves a Shannon capacity of [29]:

$$C = B \log_2 \det \left(I_{N_r} + \frac{1}{N_t} H H^H \right). \quad (2.11)$$

The achievable sum-rate for the MU-MIMO uplink with K devices is [30]:

$$C_{\text{sum}} = \sum_{k=1}^K B \log_2 \left(1 + \frac{P_k}{N_t} H_k^H H_k \right). \quad (2.12)$$

2.4.4 Massive MIMO Uplink Signal Model

With all K devices transmitting simultaneously, the BS applies a linear combining matrix $W \in \mathbb{C}^{M \times K}$ to the received vector:

$$\hat{s} = W^H y = W^H H s + W^H n. \quad (2.13)$$

The per-device SINR at the combiner output is [31]:

$$\text{SINR}_k = \frac{P_u |w_k^H h_k|^2}{P_u \sum_{j \neq k} |w_k^H h_j|^2 + \sigma_n^2 |w_k|^2}. \quad (2.14)$$

As $M \rightarrow \infty$, the interference terms vanish by favorable propagation [32].

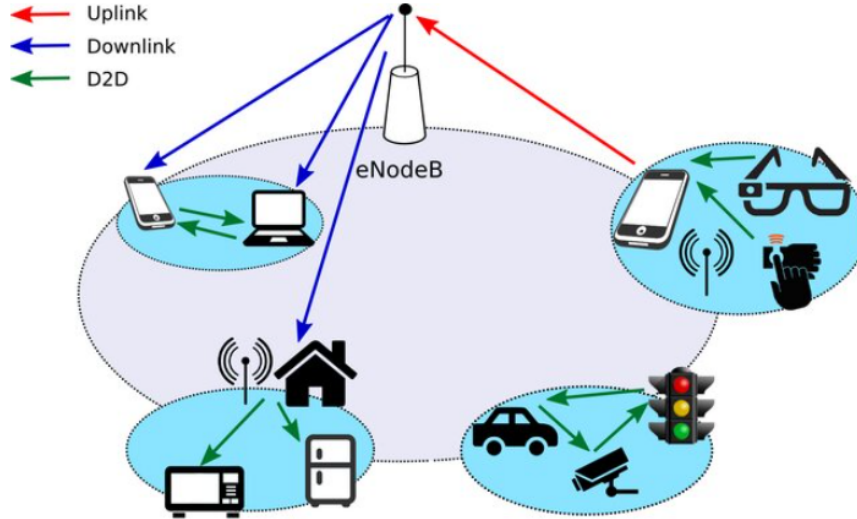
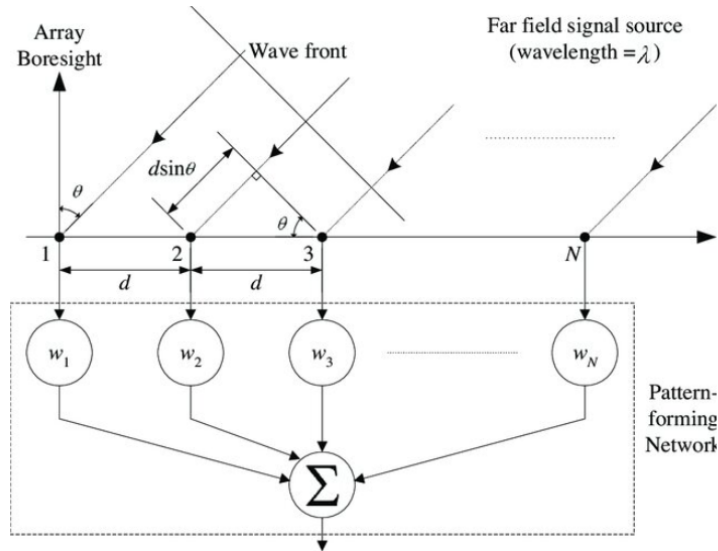


Figure 2.6: Uplink and downlink in 5G IoT networks [8].

2.5 Antenna Array Model (ULA)

The BS antenna array is modelled as a Uniform Linear Array (ULA), consisting of M isotropic elements equally spaced along a straight axis with inter-element separation d [33]. The ULA is the standard reference array in massive MIMO research due to its straightforward implementation and analytical tractability [34].

Figure 2.7: Geometry of a Uniform Linear Array (ULA) $d = \lambda/2$ [33].

2.5.1 Steering Vector

For a narrowband signal arriving from direction θ , the steering vector $a(\theta) \in^M$ encodes the phase progression across the array elements:

$$a(\theta) = [1, e^{-j\pi \sin \theta}, e^{-j2\pi \sin \theta}, \dots, e^{-j(M-1)\pi \sin \theta}]^T, \quad (2.15)$$

where half-wavelength spacing $d = \lambda/2$ has been applied to avoid grating lobes [35, 36].

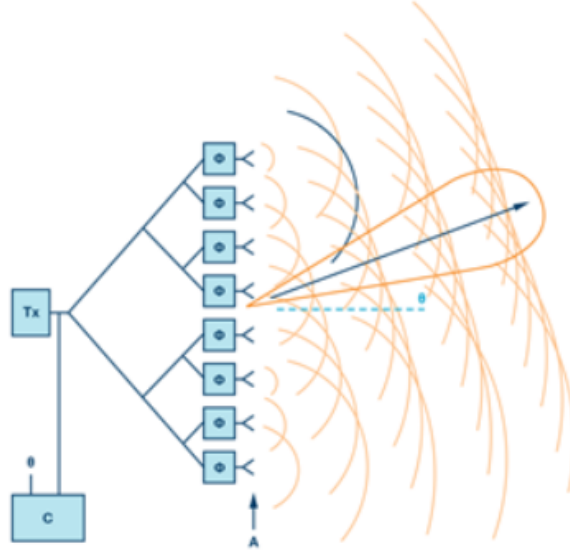


Figure 2.8: Phased array elements [7].

Table 2.2: Key parameters of the ULA model used in this work.

Parameter	Symbol / Value	Description
Number of elements	$M = 8 \dots 128$	Determines array gain
Element spacing	$d = \lambda/2$	Avoids grating lobes
Array aperture	$L = (M - 1)d$	Controls angular resolution
Steering vector	$a(\theta) \in^M$	Phase progression across elements
3 dB beamwidth	$\Delta\theta \approx 0.886\lambda/(Md \cos \theta)$	Narrows with M

2.5.2 Array Manifold and Channel Decomposition

The array manifold matrix is defined as $A = [a(\theta_1), \dots, a(\theta_K)] \in^{M \times K}$. Under the far-field assumption and in a LoS channel, the channel vector of device k simplifies to $h_k = \sqrt{\beta_k} a(\theta_k)$. In rich-scattering non-LoS environments, the i.i.d. Rayleigh model is recovered [38].

2.5.3 Array Factor and Beampattern

The radiation pattern of a ULA is determined by the constructive and destructive combination of the signals radiated by all antenna elements. Assuming M isotropic elements separated by $d = \lambda/2$, steered toward θ_0 , the array factor is:

$$AF(\theta) = \sum_{m=0}^{M-1} e^{jm\pi(\sin\theta - \sin\theta_0)}, \quad (2.16)$$

The normalized beampattern is:

$$F(\theta) = \frac{1}{M} \left| \frac{\sin\left(\frac{M\pi}{2}(\sin\theta - \sin\theta_0)\right)}{\sin\left(\frac{\pi}{2}(\sin\theta - \sin\theta_0)\right)} \right|^2. \quad (2.17)$$

The beampattern consists of three regions [33] :

- **Main lobe:** the central peak centered at θ_0 ;
- **Side lobes:** secondary peaks surrounding the main lobe;
- **Nulls:** angular positions where the array response becomes zero.

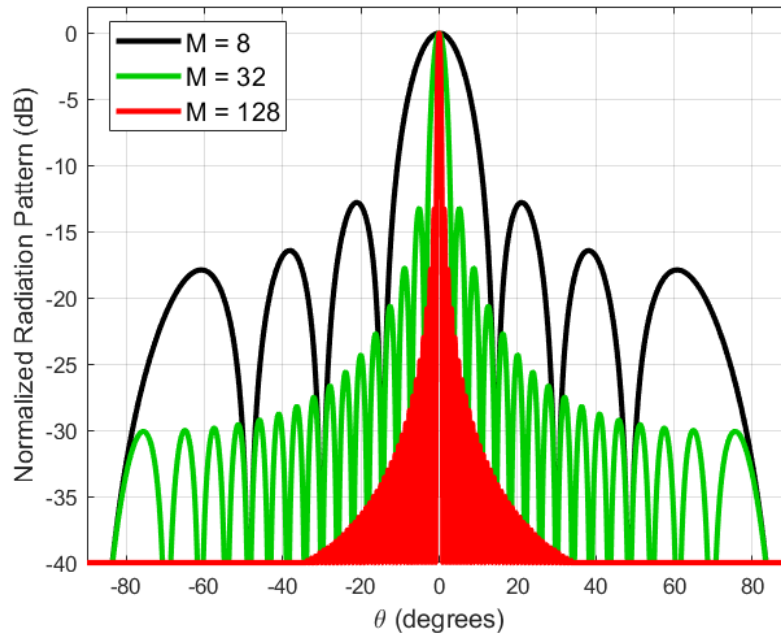


Figure 2.9: Radiation pattern for $M = 8, 32$, and 128 antenna elements ($d = \lambda/2$, $\theta_0 = 0$).

The beamwidth decreases as the number of antennas increases [37, 33]. The array gain increases approximately linearly with M , yielding an SNR improvement proportional to M [26].

2.6 Digital Beamforming Techniques

Digital beamforming (DBF) performs all signal processing in the baseband domain, with one dedicated RF chain per antenna element [39].

Table 2.3: Comparison of beamforming architectures.

Criterion	Analog	Digital	Hybrid
RF chains	1	M	$N_{\text{RF}} \ll M$
Simultaneous beams	1	Up to K	Up to N_{RF}
Phase + amplitude	Phase only	Full complex	Partial
Hardware cost	Low	High	Moderate

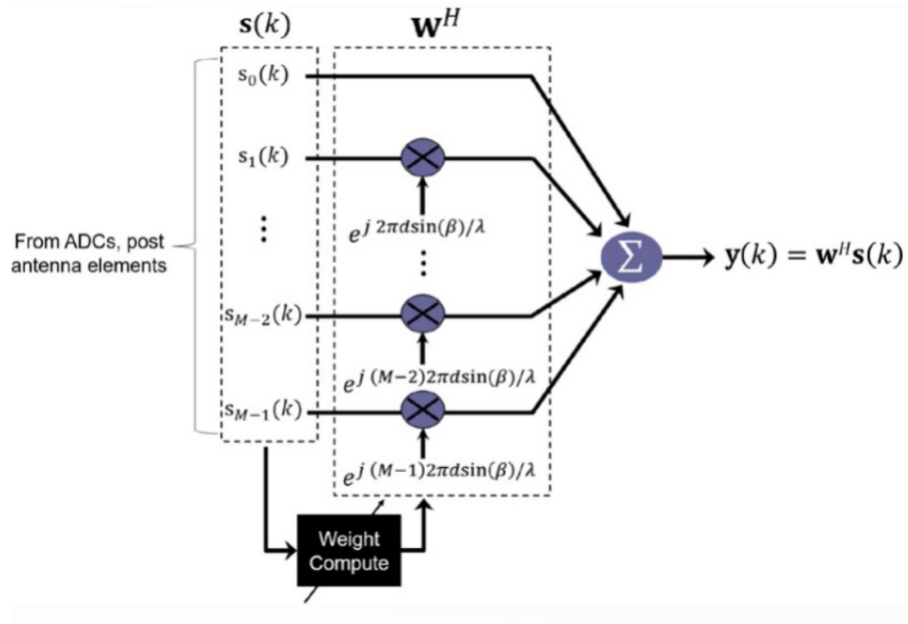


Figure 2.10: Digital beamforming [39].

2.6.1 Maximum Ratio Combining (MRC)

MRC is the simplest linear receiver. It maximises the received SNR for each device by aligning the combining vector with the device's channel response, without accounting for inter-device interference [40]. The combining matrix is:

$$W = H^H. \quad (2.18)$$

The k -th stream estimate after MRC combining is:

$$\hat{s}_k = h_k^H h_k s_k + \sum_{j \neq k} h_k^H h_j s_j + h_k^H n, \quad (2.19)$$

where the array gain $h_k^2 \approx M\beta_k$ grows linearly with M [41]. The per-device SINR under MRC is:

$$\gamma_k = \frac{P_u M^2 \beta_k^2}{P_u \sum_{j \neq k} |h_k^H h_j|^2 + \sigma_n^2 M \beta_k}. \quad (2.20)$$

MRC is best suited to noise-limited or single-device scenarios but degrades in dense multi-device networks [42].

2.6.2 Zero-Forcing (ZF)

ZF completely eliminates inter-device interference by projecting each combining vector onto the null space of all other devices' channels [43]. The combining matrix is:

$$W = H^H (H H^H)^{-1}. \quad (2.21)$$

The per-device SINR under ZF is:

$$\gamma_k = \frac{P_u}{\sigma_n^2 \cdot [(H^H H)^{-1}]_{kk}}. \quad (2.22)$$

ZF requires $M > K$ and is sensitive to imperfect CSI and ill-conditioned channels [44].

[Geometric Interpretation of ZF] ZF projects the signal of device k onto the subspace orthogonal to the channels of all other devices. The dimension of this subspace is $M - (K - 1)$, which explains the requirement $M > K$.

2.6.3 Minimum Mean Square Error (MMSE)

MMSE is the optimal linear receiver: it minimises the mean square error between the estimated and true symbol vectors, simultaneously balancing inter-device interference and noise amplification [45]. The combining matrix is:

$$W = H^H (H H^H + \sigma_n^2 I_M)^{-1}, \quad (2.23)$$

or equivalently:

$$W = (H^H H + \sigma_n^2 I_K)^{-1} H^H. \quad (2.24)$$

MMSE subsumes both ZF and MRC as limiting cases [46]:

- **High SNR** ($\sigma_n^2 \rightarrow 0$): $\text{MMSE} \rightarrow \text{ZF}$.
- **Low SNR** ($\sigma_n^2 \rightarrow \infty$): $\text{MMSE} \rightarrow \text{MRC}$.

The per-device SINR at the MMSE combiner output is:

$$\gamma_k = P_u h_k^H \left(\sum_{j \neq k} P_u h_j h_j^H + \sigma_n^2 I_M \right)^{-1} h_k, \quad (2.25)$$

which is the maximum SINR achievable by any linear receiver [46].

Table 2.4: Comparative summary of MRC, ZF, and MMSE receivers.

Criterion	MRC	ZF	MMSE
Combining matrix	H^H	$H^H(HH^H)^{-1}$	$H^H(HH^H + \sigma^2 I)^{-1}$
Interference suppression	None	Full	Optimal balance
Noise amplification	Low	High	Minimal
CSI sensitivity	Low	High	Moderate
Optimal regime	Low SNR	High SNR	All conditions

Conclusion

This chapter presented the system model used in this study and introduced three classical receive beamforming techniques: MRC, ZF, and MMSE. The main principles and mathematical expressions of each method were described to provide a clear understanding of their operation in massive MIMO systems. This theoretical background serves as a foundation for the next chapter, where the proposed PSO-based beamforming approach will be presented.

Chapter 3

Particle Swarm Optimization Algorithm

3.1 Introduction

Optimization plays an essential role in wireless communications and engineering by searching for the most efficient solution under given constraints. In dense IoT networks, optimization techniques are used to reduce transmit power, limit interference, and enhance overall system performance.

Conventional optimization methods often become less effective when dealing with complex and non-linear problems, such as those encountered in beamforming design. For this reason, metaheuristic techniques such as Particle Swarm Optimization (PSO) have attracted significant attention due to their simplicity and ability to explore large solution spaces without requiring gradient information.

In this thesis, PSO is employed to optimize beamforming parameters for transmit power reduction in dense IoT networks. This chapter presents the basic concepts of optimization and the main operating principles of the PSO algorithm.

3.2 Optimization Problem

An optimization problem consists of identifying the best solution from a defined set of candidates according to a specific performance criterion. The goal is to determine the values of certain decision variables that either maximize a desired quantity, such as efficiency or throughput, or minimize an undesirable one, such as cost or error, while satisfying a set of imposed constraints that restrict the solution space to feasible outcomes only.

What makes such problems challenging is the nature of the search space itself. In many practical cases, the number of candidate solutions is too large for exhaustive enumeration, and the landscape of the objective function may contain multiple local optima

that can mislead conventional solvers [47]. Additionally, real-world problems often involve incomplete information, dynamic conditions, or conflicting objectives, all of which reduce the reliability of classical deterministic methods. These inherent difficulties justify the growing interest in metaheuristic approaches as robust and flexible tools for modern optimization [47].

3.3 Elements of Optimization

Every optimization problem is built around a set of fundamental components that together provide a rigorous mathematical formulation of the decision-making task.

Decision Variables represent the unknowns of the problem — the quantities that the optimizer is free to adjust in order to improve the objective.

Objective Function translates the goal of the optimization into a scalar measure that is either minimized or maximized, formally expressed as:

$$\min_{\mathbf{x} \in \mathcal{F}} f(\mathbf{x}) \quad \text{or} \quad \max_{\mathbf{x} \in \mathcal{F}} f(\mathbf{x}), \quad (3.1)$$

where $\mathbf{x}$ is the vector of decision variables and $\mathcal{F}$ denotes the feasible region.

Constraints impose restrictions on the admissible values of the decision variables:

$$g_i(\mathbf{x}) \leq 0, \quad i = 1, \dots, m, \quad h_j(\mathbf{x}) = 0, \quad j = 1, \dots, p. \quad (3.2)$$

Feasible Region $\mathcal{F}$ is the subset of the search space in which all constraints are simultaneously satisfied.

Optimality Conditions provide mathematical criteria to verify whether a candidate solution $\mathbf{x}^*$ is locally or globally optimal.

Approximation Techniques offer a practical alternative when exact methods become computationally intractable, trading a marginal loss in solution quality for a significant reduction in computation time.

A clear understanding of these components is essential for properly formulating an optimization problem and selecting an appropriate solving strategy [47].

3.4 Approximate Methods

Approximate methods aim to find an admissible solution within a reasonable computation time, without guaranteeing the global optimality of that solution [47]. Their primary

advantage lies in their generality: they can be applied to virtually any problem class, whether simple or highly complex. Moreover, they have demonstrated robustness and efficiency across a wide range of combinatorial optimization problems [19].

Two major families of approximate methods exist:

Heuristics Simple, experience-based rules that guide the search toward good solutions without necessarily reaching the optimum. They are problem-specific and typically fast.

Metaheuristics High-level algorithmic frameworks capable of steering a search process through a large solution space toward regions that are rich in near-optimal solutions. Unlike heuristics, metaheuristics are problem-independent and include strategies such as simulated annealing, genetic algorithms, tabu search, and swarm intelligence methods [47]. They do not guarantee global optimality but consistently deliver solutions that are very close to the optimum within a reasonable time.

3.5 Particle Swarm Optimization (PSO)

Particle Swarm Optimization is a population-based metaheuristic originally proposed by Kennedy and Eberhart in 1995 [3]. It draws inspiration from the collective behaviour of biological swarms — such as flocks of birds and schools of fish — where individuals coordinate their movements through simple local interactions to achieve a globally coherent result.

In PSO, a set of candidate solutions, called *particles*, simultaneously explore the search space. Each particle adjusts its trajectory by combining three influences:

1. its own current velocity (inertia),
2. attraction toward the best position it has personally visited (*cognitive* component),
3. attraction toward the best position found so far by any particle in the swarm (*social* component).

PSO shares conceptual similarities with evolutionary algorithms such as Genetic Algorithms (GA): both maintain a population of solutions that evolve iteratively. However, PSO requires no selection or crossover operators, making it simpler to implement and tune [3].

A particle i moving in a D -dimensional search space $[a, b]^D \subset \mathbb{R}^D$ is defined by its position X_i and velocity V_i , both initialised randomly. Each particle tracks two memory quantities:

- $P_{\text{best},i}$: the best position the particle itself has visited so far (personal best),

- G_{best} : the best position found by any particle in the entire swarm (global best).

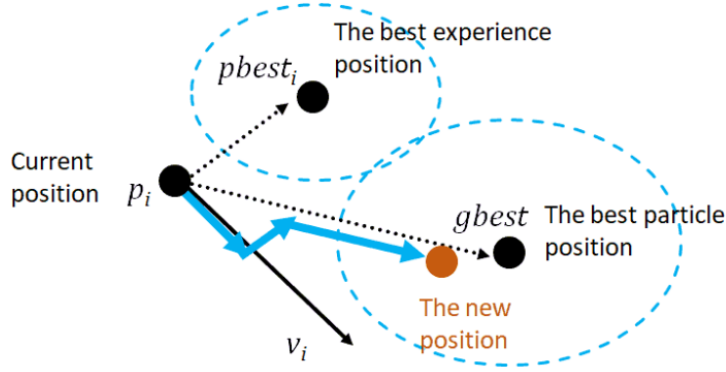


Figure 3.1: Principle of Particle Movement in PSO Algorithm [3].

3.6 Formal Definition and Mathematical Model

At each iteration t , the velocity and position of particle i are updated according to the following two equations [13, 3]:

$$V_i(t+1) = w V_i(t) + C_1 r_1 (P_{\text{best},i} - X_i(t)) + C_2 r_2 (G_{\text{best}} - X_i(t)), \quad (3.3)$$

$$X_i(t+1) = X_i(t) + V_i(t+1), \quad (3.4)$$

where:

- $w \in [0, 1]$ is the *inertia weight*, balancing global exploration and local exploitation;
- $C_1, C_2 > 0$ are *acceleration coefficients* weighting the cognitive and social components, respectively;
- $r_1, r_2 \sim \mathcal{U}(0, 1)$ are independent random numbers drawn at each iteration.

The three terms in Equation (3.3) correspond physically to:

1. **Inertia component** ($w V_i(t)$): the particle tends to continue along its current trajectory.
2. **Cognitive component** ($C_1 r_1 (P_{\text{best},i} - X_i)$): the particle is attracted back toward the best position it has individually experienced.
3. **Social component** ($C_2 r_2 (G_{\text{best}} - X_i)$): the particle is pulled toward the collective best position known to the swarm.

3.6.1 Biological Inspiration

The Particle Swarm Optimization algorithm draws its inspiration from the collective behaviour observed in biological populations [3].

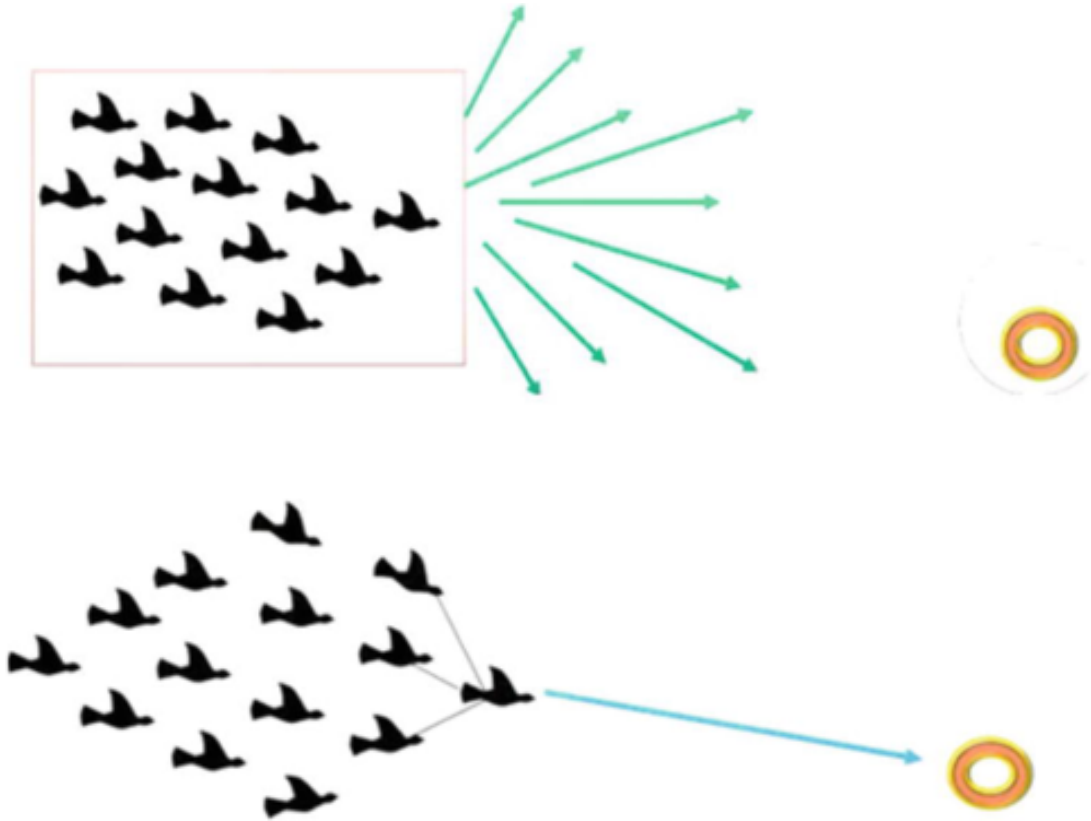


Figure 3.2: Biological inspiration of PSO [3].

Birds collectively moving toward and finding the optimal path to a food source, analogous to PSO particle navigation in a search space [3]. Kennedy and Eberhart [3] translated these biological observations into a mathematical optimization framework.

The process repeats until a stopping criterion is met.

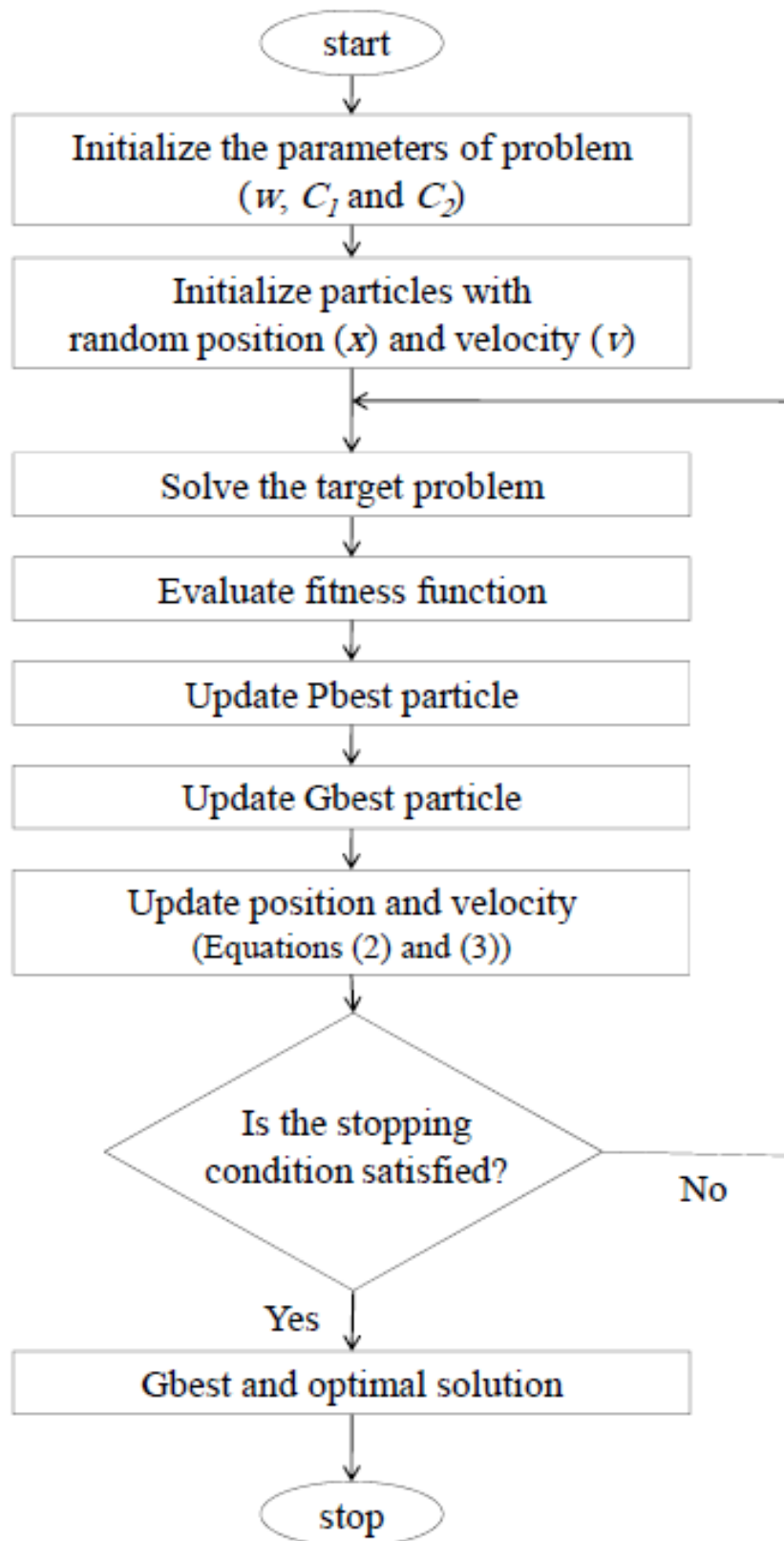


Figure 3.3: Particle Swarm Optimization flowchart [15].

The PSO procedure is summarised in the flowchart above. The swarm is initialised with random positions and velocities; then, at every iteration, fitness values are evalu-

ated, personal and global bests are updated, and velocities and positions are recomputed according to Equations (3.3)–(3.4).

3.7 Swarm Behaviour: Three Local Rules

The emergent collective motion of swarm-based algorithms can be understood through three elementary local rules, inspired by Reynolds’ *Boids* model [48]:

Separation Each individual avoids crowding its immediate neighbours by steering away when they come too close. This prevents collisions and maintains diversity in the swarm.

Alignment Each individual adapts its heading to match the average direction and speed of its local neighbours, promoting coherent group motion.

Cohesion Each individual moves toward the perceived centre of mass of its neighbourhood, keeping the swarm together as a unified group.

Together, these three rules generate the attraction–repulsion dynamics that give PSO its ability to balance exploration of the search space with convergence toward promising regions [48].

3.8 Key Properties of PSO

PSO exhibits several characteristics that make it well-suited for non-linear, continuous, or mixed-variable optimization problems [?]:

- **Simplicity:** the algorithm can be implemented in a few dozen lines of code in any modern programming language.
- **Robustness:** poor parameter choices degrade performance but rarely prevent the algorithm from returning a usable solution [?].
- **No gradient information required:** PSO is a derivative-free method and can therefore be applied directly to non-smooth, non-convex, or black-box objective functions.
- **Parallelism:** since particles update independently, the fitness evaluations can be parallelised straightforwardly.
- **Few hyperparameters:** the essential settings are the swarm size, the inertia weight, and the two acceleration coefficients.

3.9 Algorithm Parameters

The performance of PSO is governed by several hyperparameters, each of which influences the balance between exploration and exploitation.

3.9.1 Problem Dimensionality

The dimensionality D represents the number of variables to be optimized in the search space. The complexity of the optimization problem generally increases with the dimensionality [?].

3.9.2 Swarm Size

The swarm size N corresponds to the number of particles used during the optimization process. A larger swarm improves the exploration capability of the algorithm but increases computational complexity. Typical swarm sizes range from 20 to 100 particles depending on the problem complexity [48].

3.9.3 Acceleration Coefficients

The acceleration coefficients C_1 and C_2 control the influence of the cognitive and social components, respectively. Commonly used values are:

$$C_1 = C_2 = 2.$$

These parameters play an important role in balancing exploration and exploitation during the optimization process [48].

3.9.4 Neighbourhood Topology

The neighbourhood topology defines how particles exchange information within the swarm [49]. Common topologies include:

- **Star topology:** all particles communicate with each other, resulting in fast convergence.
- **Ring topology:** particles communicate only with neighbouring particles, improving diversity and exploration.
- **Wheel topology:** a central particle exchanges information with all other particles.

3.9.5 Maximum Velocity

The maximum velocity $V_{\max}$ limits particle movement inside the search space and prevents unstable trajectories or excessive movements during the optimization process [48].

3.9.6 Inertia Weight

The inertia weight w controls the influence of the previous velocity on the particle movement [50]. A large inertia weight promotes global exploration, while a smaller value favours local exploitation.

A linearly decreasing inertia weight is commonly used:

$$w_{\max} = 0.9, \quad w_{\min} = 0.4.$$

This strategy improves the balance between exploration and convergence throughout the iterations [51].

3.9.7 Constriction Factor

To improve convergence stability, Clerc and Kennedy [52] introduced the constriction factor χ :

$$V_i(t+1) = \chi[V_i(t) + C_1 r_1 (P_{\text{best},i} - X_i) + C_2 r_2 (G_{\text{best}} - X_i)], \quad (3.5)$$

where

$$\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \quad \varphi = C_1 + C_2 \geq 4. \quad (3.6)$$

The constriction factor helps prevent divergence and improves the stability of the swarm during optimization [53].

3.9.8 Stopping Criterion

The algorithm stops when one or more of the following conditions are satisfied:

- the maximum number of iterations has been reached;
- the desired fitness value has been achieved;
- the improvement between consecutive iterations becomes negligible.

Since global convergence cannot always be guaranteed, defining a maximum iteration limit is generally recommended [52].

3.10 Advantages and Limitations

Advantages. PSO is straightforward to implement, requires minimal problem-specific knowledge, and performs well on a broad spectrum of continuous non-linear optimization problems [?]. Its population-based nature makes it naturally resilient to local optima compared to purely gradient-based methods.

Limitations. The main drawback of PSO is *premature convergence*: the swarm may collapse around a local optimum, especially in high-dimensional or multi-modal landscapes. Several remedies have been proposed, including adaptive inertia schedules [51], topological diversity strategies [49], and hybrid algorithms that combine PSO with local search or genetic operators. In this work, careful tuning of N , w , and the stopping criterion is used to mitigate this issue.

Conclusion

This chapter introduced the theoretical foundations of Particle Swarm Optimization. Starting from the biological analogy of collective animal motion, we derived the mathematical update rules that govern particle dynamics and discussed the role of each hyperparameter in shaping the algorithm’s convergence behaviour. Key extensions — the inertia weight and the constriction factor — were also presented, along with their theoretical justifications.

The simplicity and robustness of PSO make it a compelling choice for our work.

Chapter 4

Simulation Results and Discussion

4.1 Introduction

Dense IoT deployments present a unique set of challenges that go beyond what classical wireless system design typically accounts for. When a large number of low-power devices share the same frequency band and transmit simultaneously, the resulting interference cannot simply be treated as background noise — it becomes the dominant performance-limiting factor [1, 2]. Managing this interference while keeping the transmit power of each device as low as possible is therefore not a secondary concern; it sits at the very core of making large-scale IoT networks practically viable.

Digital beamforming at the base station receiver offers a direct handle on this problem. Rather than asking each device to increase its power to overcome interference, beamforming shapes the spatial response of the antenna array so that signals of interest are reinforced and interfering contributions are attenuated [10]. If done effectively, the same quality of reception can be maintained at a fraction of the transmit power that would otherwise be required.

This chapter evaluates how well three receiver beamforming strategies achieve this objective. The techniques considered are Maximum Ratio Combining (MRC), Minimum Mean Square Error (MMSE), and a Particle Swarm Optimization (PSO) based beamformer that operates without explicit channel knowledge. The evaluation is conducted through MATLAB simulations across a range of system configurations, and performance is measured in terms of Bit Error Rate (BER), and the minimum transmit power $P_t^{\min}$ required to meet a given quality of service target.

4.2 Simulation Setup and Parameters

All simulations were carried out in MATLAB under a massive MIMO uplink configuration where K single-antenna IoT devices transmit simultaneously to a base station equipped

with N_r receive antennas. Each IoT device uses $N_t = 2$ transmit antennas and BPSK modulation. The channel between each device and the base station is modeled as a flat Rayleigh fading channel with independent and identically distributed (i.i.d.) complex Gaussian coefficients, which is a standard assumption for evaluating spatial processing in rich-scattering environments [8, 15].

Table 4.1 summarizes the full set of simulation parameters.

Table 4.1: Simulation Parameters

Parameter	Value
Number of receive antennas (N_r)	8, 10, 12
Number of transmit antennas (N_t)	2
Number of active IoT devices (K)	1, 2, 4, 6
Antenna array size (M)	2–16
Modulation scheme	BPSK
Channel model	Rayleigh fading
SNR range	0–25 dB
Beamforming techniques	MRC, MMSE, PSO
CSI error (ε)	0–1

4.3 BER Performance Comparison

Figure 4.1 shows that increasing the number of receive antennas significantly improves the BER performance [17]. Going from $N_r = 8$ to $N_r = 12$, the curves shift left by about 6 to 7 dB, meaning the same link quality is achieved at a much lower SNR.

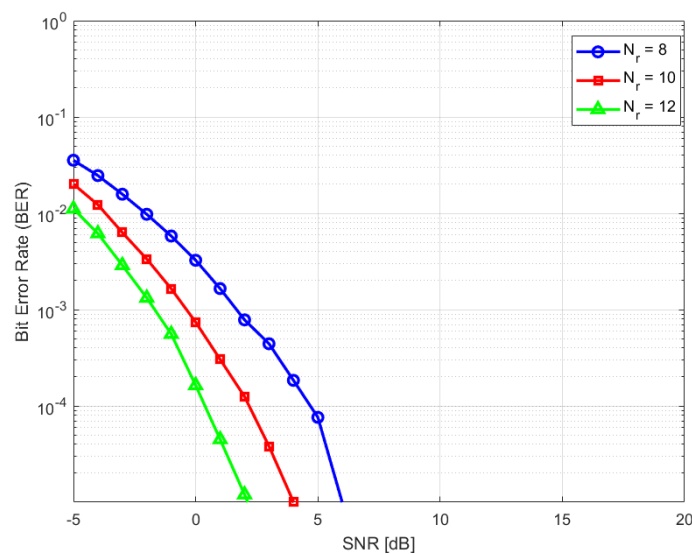


Figure 4.1: Effect of the Number of Receive Antennas N_r .

This confirms that more antennas at the base station allow the MMSE combiner to better separate the desired user from the interfering ones.

4.3.1 Impact of Inter-User Interference on MRC and MMSE Algorithms

Figure 4.2 shows the BER versus SNR performance of MRC and MMSE algorithms with and without inter-user interference [45].

Without interference ($K = 1$), both algorithms achieve similar performance, with the BER decreasing as SNR increases. With interference ($K = 4$), MMSE continues to improve with SNR, while MRC reaches an error floor around 10^{-1} , confirming its inability to suppress inter-user interference [42].

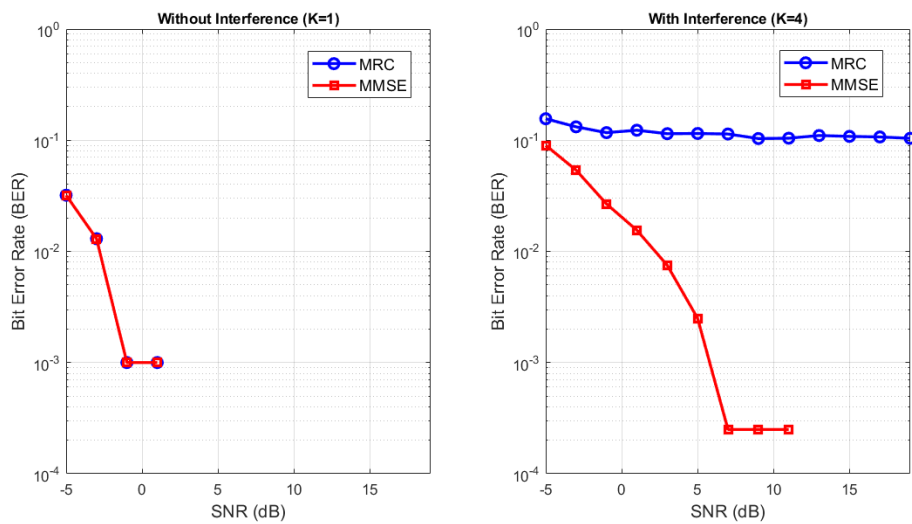


Figure 4.2: BER vs SNR — Impact of inter-user interference on MRC and MMSE algorithms, $N_r = 8$, $\rho = 0.8$.

4.4 Beamforming Optimization Using PSO

Figure 4.3 shows the main steps of the PSO-based beamforming algorithm. First, the signals are collected from the antenna array and an initial beamforming vector $\mathbf{w}_i$ is selected. Then, the PSO particles are initialized with random positions and velocities [3].

At each iteration, the fitness function is evaluated to minimize the transmitted power. If the result is not satisfactory, the particles update their velocity and position, and the process repeats. Once the maximum number of iterations is reached, the best solution found by the algorithm is used as the final beamforming vector $\mathbf{w}_i$ [52].

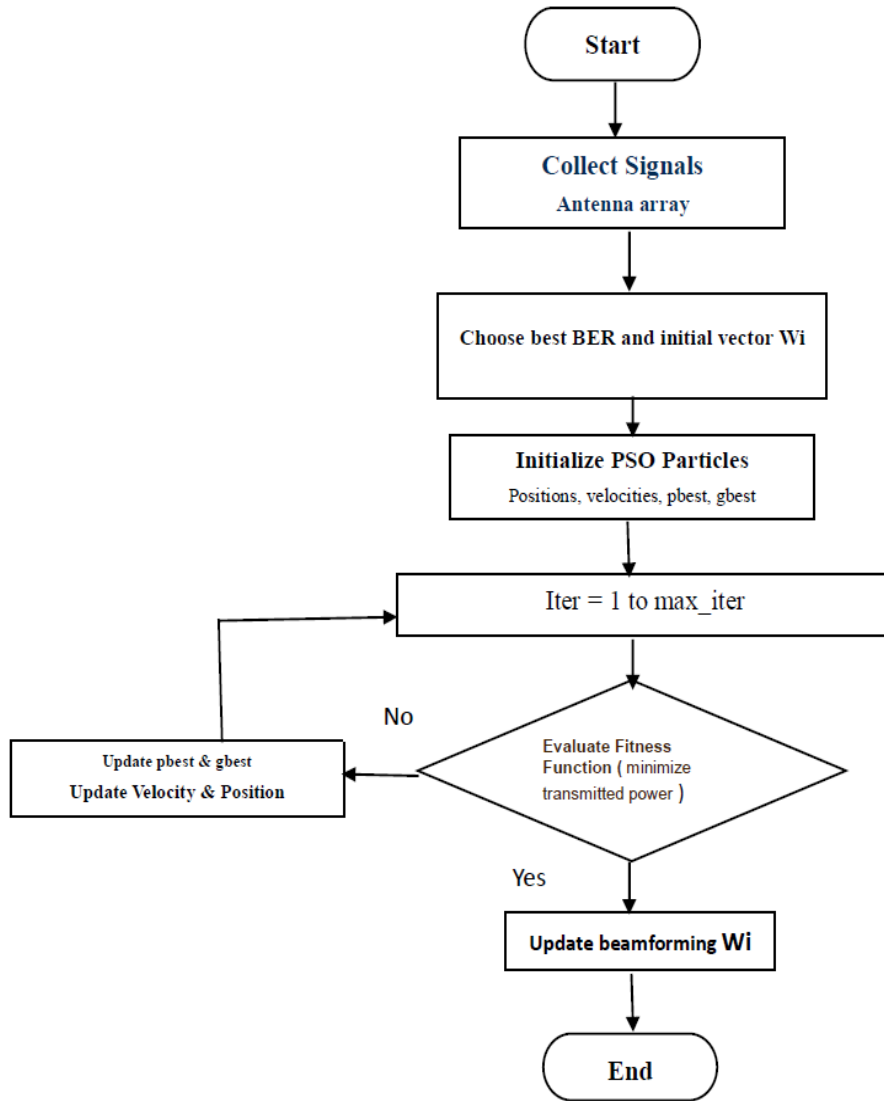


Figure 4.3: Processes of simulation.

4.4.1 Single-User Scenario ($K = 1$, $N_t = 2$, $N_r = 8$)

We first consider the simplest possible case: a single IoT device ($K = 1$) transmitting with $N_t = 2$ antennas to a base station equipped with $N_r = 8$ receive antennas. With no inter-user interference, the only impairment is additive noise, which makes this configuration well-suited for comparing how efficiently each technique exploits the available spatial diversity [8].

Figure 4.4 shows the BER versus SNR performance for a single-user scenario ($K = 1$, $N_t = 2$, $N_r = 8$) under perfect CSI conditions.

As expected, the MMSE algorithm achieves the best performance, reaching a BER below 10^{-4} at around 6 dB SNR, which confirms its ability to fully exploit the spatial diversity offered by the eight-antenna array [46].

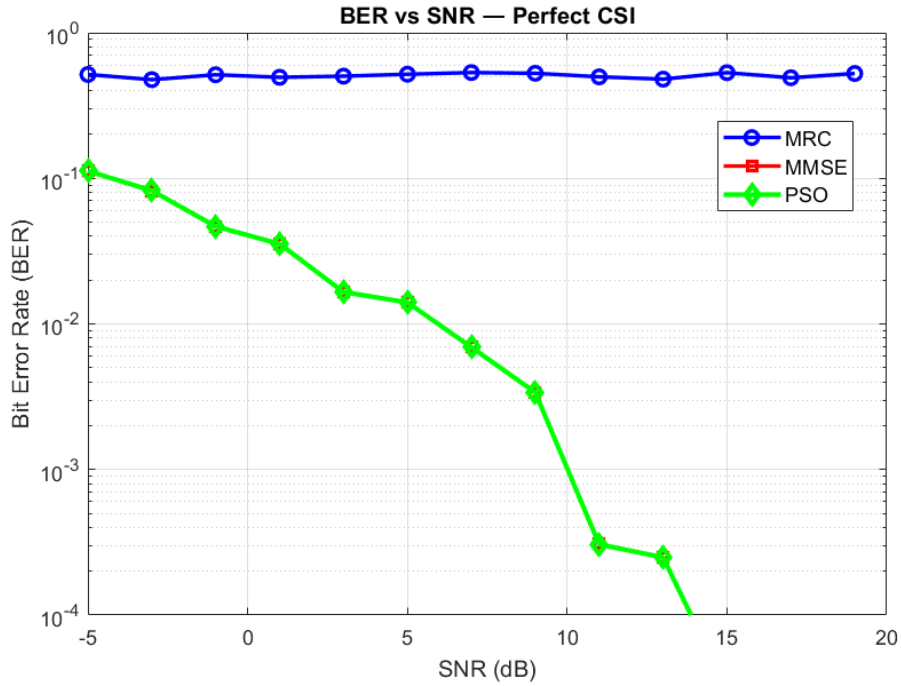


Figure 4.4: BER vs SNR — Perfect CSI, $K = 1$ user, $M = 8$ receive antennas, MRC vs MMSE vs PSO, correlated Rayleigh fading ($\rho = 0.8$).

The PSO algorithm shows a similar decreasing trend, although it converges slightly later than MMSE, demonstrating its ability to find near-optimal beamforming weights without any channel knowledge.

The MRC algorithm, on the other hand, stabilizes around 10^{-3} and does not improve significantly with increasing SNR, due to its inability to suppress residual self-interference.

This result confirms that the simulation framework is behaving as expected. It also establishes that MMSE, even in its simplest form, can support reliable communication for a single IoT device at quite modest SNR levels, which is encouraging from an energy standpoint.

4.4.2 Multi-User Scenario ($K = 4$, $N_t = 2$, $N_r = 10$)

A more realistic picture emerges when multiple devices transmit simultaneously.

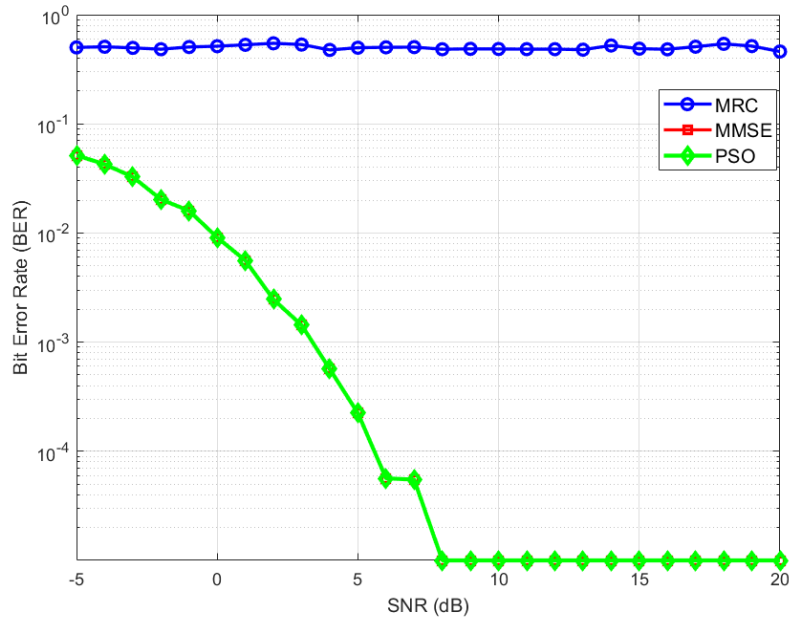


Figure 4.5: BER vs SNR — Perfect CSI, $K = 4$ users, $N_r = 10$ antennas, $\rho = 0.8$, correlated Rayleigh fading, MRC vs MMSE vs PSO.

Figure 4.5 presents the BER for $K = 4$ users and $N_r = 10$ receive antennas. The interference from three co-channel users now changes the landscape considerably.

MRC, which has no mechanism for suppressing interference, stagnates around 5×10^{-2} regardless of SNR. Increasing signal power at this point would not help because the interfering users scale with it equally.

MMSE continues to offer the best performance: by jointly accounting for noise and interference in its weight computation.

The contrast between the single-user and multi-user results underlines an important point: in dense IoT networks where K is not small, MRC alone is insufficient for maintaining acceptable link quality. A technique that can actively manage interference, such as MMSE or the PSO beamformer, becomes necessary.

4.5 Problem Formulation

Having established the system model in full, this section formally states the optimisation problem that motivates the PSO-based beamforming approach of Chapter 3.

4.5.1 Optimisation Objective

The primary objective is to minimise the total transmit power at the BS while guaranteeing a minimum quality-of-service (QoS) level for each IoT device, expressed as a minimum

SINR threshold [10, 11]:

$$\min_{\mathbf{W}} P_t = \|\mathbf{W}\|_F^2 \quad (4.1)$$

Equivalently, the problem can be cast as a sum-rate maximisation:

$$\max_W \sum_{k=1}^K \log_2(1 + \gamma_k(W, H)), \quad (4.2)$$

subject to a per-antenna power constraint $w_k^2 \leq P_{\max}$. Both formulations are non-convex in the general case, motivating the metaheuristic PSO approach of Chapter 3 [47].

4.5.2 Practical Constraints in IoT Scenarios

Three additional constraints characterise dense IoT deployments and distinguish the problem from classical MIMO design [2, 4].

4.6 Impact of the Number of Receive Antennas N_r

In massive MIMO theory, adding receive antennas increases both the diversity order and the degrees of freedom available for interference suppression [26, 32]. Figure 4.6 quantifies this effect for MMSE with $K = 4$ users and $N_t = 2$, varying N_r across 8, 10, and 12.

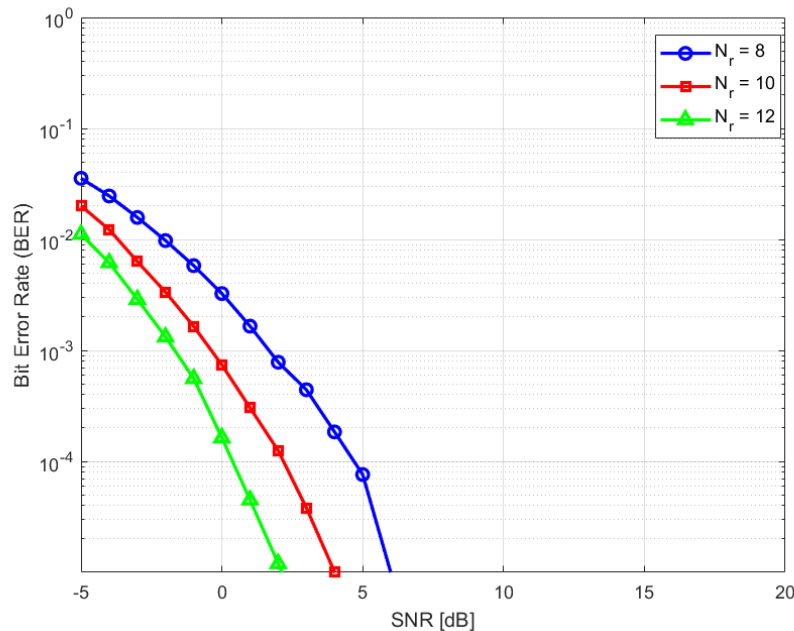


Figure 4.6: BER vs SNR for MMSE beamforming with varying number of receive antennas ($N_r = 8, 10, 12$), $K = 4$ IoT users, $\rho = 0.8$, perfect CSI, correlated Rayleigh fading.

The improvement is consistent and substantial. Going from $N_r = 8$ to $N_r = 12$ shifts the BER curve to the left by several decibels, meaning that a device can reach the same

link quality while transmitting at lower power. At a target BER of 10^{-3} , for example, the required SNR drops by roughly 5 to 7 dB when moving from 8 to 12 antennas. Translated directly into device power consumption, this is a meaningful gain for battery-operated IoT sensors.

With more antennas, the base station has more spatial measurements of the received signal. The MMSE combiner can therefore form a sharper beam toward the user of interest while placing deeper nulls in the directions of interferers. The excess degrees of freedom — the gap between N_r and $K \cdot N_t$ — are what make this possible.

4.6.1 Effect of the Number of IoT Users K

The number of simultaneously active users is the defining characteristic of a dense IoT network [1, 2]. Figure 4.7 shows how MMSE performance degrades as K increases from 2 to 6, with the array fixed at $N_r = 12$ and $N_t = 2$.

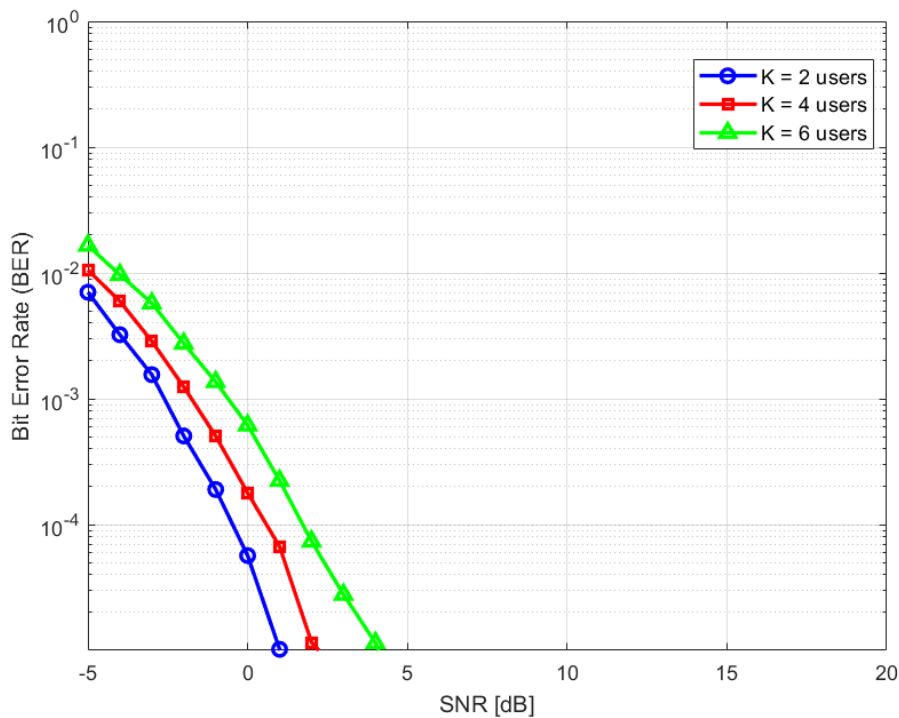


Figure 4.7: BER vs SNR for MMSE beamforming with varying number of IoT users ($K = 2, 4, 6$), $N_r = 12$ antennas, $\rho = 0.8$, perfect CSI, correlated Rayleigh fading.

The curves shift progressively to the right as K increases, reflecting the growing interference load [12]. For $K = 2$, the array operates with a large margin of excess spatial degrees of freedom, and MMSE achieves near-zero BER below 5 dB. As K reaches 6, the same target BER requires nearly 15 dB of SNR, a difference that, in practice, would require a device to transmit at substantially higher power.

4.6.2 Minimum Transmit Power vs. Number of Antennas

Figure 4.8 shows the minimum transmit power $P_t^{\min}$ as a function of the number of IoT interferers $K - 1$ for three beamforming schemes: MRC, MMSE, and PSO.

From the figure, it can be seen that MRC and MMSE behave in a similar way, both requiring a transmit power of around 15 to 20 dB over the entire range of interferers. MRC shows some variation, with a noticeable peak around $K - 1 = 3$, but remains globally stable. MMSE follows almost the same trend, with no clear separation between the two curves.

In contrast, the PSO beamformer requires a much lower transmit power across all values of $K - 1$. At $K - 1 = 1$, PSO starts at approximately -10 dB, and although its power increases slightly as more interferers are added, it only reaches around -2 dB at $K - 1 = 7$. This means that PSO consistently operates 15 to 20 dB below MRC and MMSE throughout the simulation.

These results suggest that the PSO beamformer is more power-efficient and handles interference more effectively than the classical methods. Even as the number of interferers increases, PSO maintains a clear advantage, which indicates that it is better at suppressing unwanted signals while keeping the required transmit power low.

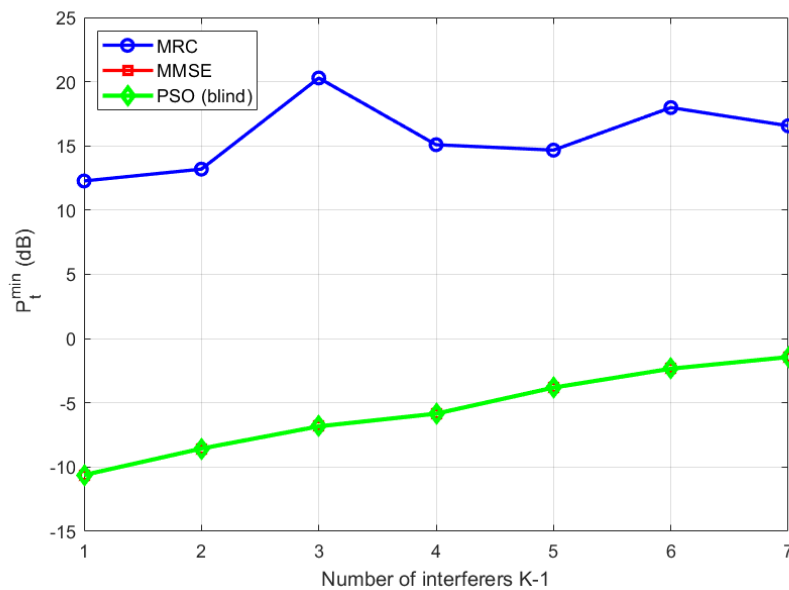


Figure 4.8: Minimum transmit power $P_t^{\min}$ as a function of the number of IoT interferers ($K - 1$) for SNR = 10 dB under perfect CSI conditions.

4.7 Robustness Analysis under Imperfect CSI

In all previous simulations, perfect CSI was assumed at the base station. In practice, channel estimation is done using pilot sequences and always introduces some error, de-

pending on the pilot length, the SNR, and the channel coherence time. In dense IoT networks, where devices transmit short infrequent bursts, these errors can be significant.

Figure 4.9 shows $P_t^{\min}$ as a function of the normalized CSI error ε , for MMSE and PSO, at SNR = 10 dB, $M = 8$ antennas, and $K - 1 = 5$ interferers.

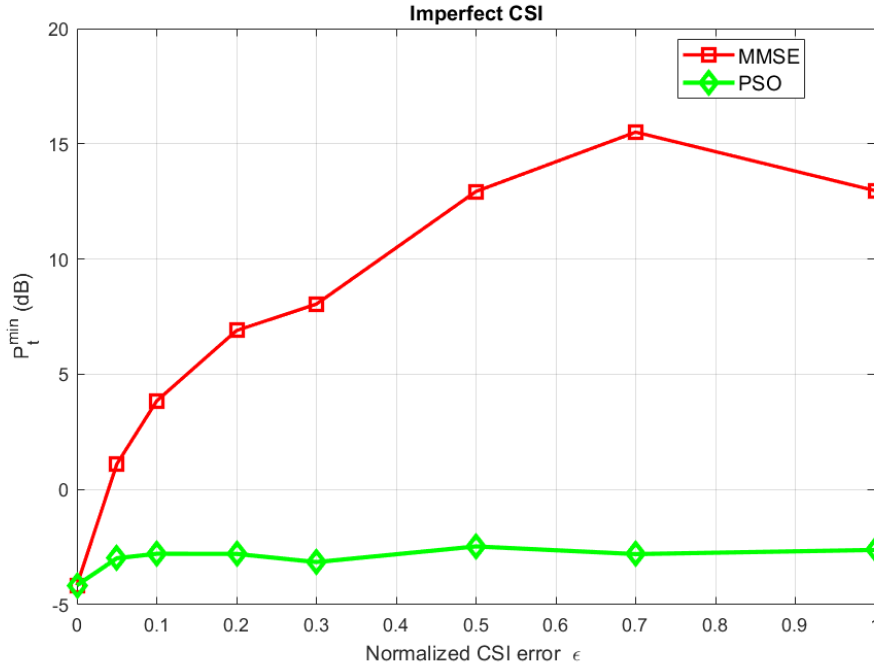


Figure 4.9: Minimum transmit power $P_t^{\min}$ vs. normalized CSI estimation error ε , for MMSE and PSO blind beamformers. SNR = 10 dB, $M = 8$ antennas, $K - 1 = 5$ interferers, correlated Rayleigh fading ($\rho = 0.8$).

As shown in the figure, MMSE is highly sensitive to estimation errors. Its required transmit power varies irregularly with ε , reaching peaks above 20 dB at $\varepsilon = 0.3$ and $\varepsilon = 0.7$, which makes it unreliable in real conditions.

In contrast, PSO remains nearly flat across the entire range of ε , staying just below -3 dB. Since it does not rely on any channel estimate, it is naturally robust to CSI inaccuracies. The average gain over MMSE is approximately $\Delta = 13.9$ dB.

This robustness confirms that the power savings of PSO are not theoretical results — they hold even when channel knowledge is significantly degraded.

4.8 Conclusion

This chapter evaluated three digital beamforming techniques for the massive MIMO IoT uplink, starting from a single-user baseline and gradually increasing the scenario complexity.

Among the classical methods, MMSE consistently achieves better BER than MRC, especially in multi-user scenarios. Increasing the number of antennas improves performance, while adding more IoT users degrades it in a predictable way, reflecting the interference cost of network densification.

The PSO beamformer outperforms all classical methods in terms of SINR, since it directly optimizes the SINR criterion. When the number of antennas increases, PSO reaches approximately -12 dB at $M = 16$, which is significantly lower than MMSE.

Most importantly, PSO maintains this advantage under imperfect CSI, where MMSE degrades significantly, with an average gain of $\Delta = 13.9$ dB. This confirms that the blind PSO approach is a robust and power-efficient solution for dense IoT networks.

General Conclusion

This thesis investigated digital beamforming at the base station receiver as a means of reducing transmit power in dense IoT uplink networks based on Massive MIMO. Three techniques were studied: MRC, MMSE, and a blind PSO-based beamformer. All methods were evaluated through MATLAB simulations under correlated Rayleigh fading ($\rho = 0.8$), for configurations ranging from single-user to six-user scenarios and array sizes from $N_r = 8$ to $N_r = 12$.

Among the classical methods, MMSE consistently outperforms MRC across all tested scenarios. In the single-user case, MMSE achieves a BER below 10^{-4} at around 6 dB SNR. In the multi-user case, MRC saturates around 5×10^{-2} regardless of SNR, confirming its inability to suppress inter-user interference. Increasing the array size from $N_r = 8$ to $N_r = 12$ shifts the MMSE BER curve by 6 to 7 dB, directly reducing the required transmit power.

The PSO beamformer outperforms all classical methods under perfect CSI. Unlike linear methods, which rely on closed-form solutions derived from simplified assumptions, metaheuristic algorithms such as PSO explore the solution space more freely and are not constrained by the linearity of the optimization. This allows PSO to find weight vectors that classical methods cannot reach. Its required transmit power decreases steadily with the number of antennas, reaching -12 dB at $M = 16$, which represents a reduction of more than 25 dB over the no-beamforming reference and more than 10 dB over MMSE.

The most significant result concerns robustness under imperfect CSI. While MMSE degrades severely with estimation errors, PSO remains nearly flat across the entire range $\varepsilon \in [0, 1]$, staying just below -3 dB. This robustness is a direct consequence of the blind nature of the metaheuristic approach: since PSO optimizes its weights based on received signal statistics rather than an explicit channel estimate, it is structurally immune to CSI inaccuracies. The average gain over MMSE is $\Delta = 13.9$ dB, confirming that the blind PSO approach is a robust and energy-efficient solution for dense IoT networks where accurate channel knowledge cannot be guaranteed.

Several directions remain open for further investigation.

1. **Downlink extension.** This work focused on the uplink only. Extending the PSO beamformer to downlink precoding, possibly using TDD reciprocity, is a natural next step.

2. **Adaptive PSO parameters.** The inertia weight w was linearly decreased in this work. Adaptive schemes that dynamically adjust w , C_1 , and C_2 based on swarm diversity could improve convergence speed and solution quality.
3. **Hybrid PSO-MMSE beamformer.** Using MMSE as a warm-start for PSO initialization could reduce the number of iterations needed while keeping the robustness of the blind approach under imperfect CSI.
4. **Exploration of other metaheuristic algorithms.** Other population-based optimization methods such as Genetic Algorithms or Differential Evolution could be tested and compared to PSO in terms of convergence speed, beamforming quality, and robustness under imperfect CSI.

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