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CONTRIBUTIONS	
Participant	Name
Instituto de Telecomunicações(IT)	Prof. Rui Dinis
Instituto de Telecomunicações(IT)	Prof. Marco Gomes
Instituto de Telecomunicações(IT)	Prof. Adao Silva
Instituto de Telecomunicações(IT)	Mohd Adnan
Universidad Carlos III de Madrid (UC3M)	Rubén de Miguel Gil
Ericsson AB (ERS)	Josep R. Fernández Rull
Universidad Carlos III de Madrid (UC3M)	Masoumeh Jamshidi
Universidad Carlos III de Madrid (UC3M)	Andrés Reyes

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Executive Summary

This deliverable presents the research and technical developments carried out under deliverable 2.4, focusing on advanced transmission and reception (Tx/Rx) techniques for future wireless communication systems. The work targets beyond 5G and 6G networks, where high data rates, low latency, reliability, and accurate positioning are critical requirements. The report addresses these challenges by investigating new waveforms, non-coherent communication techniques, positioning-aided transmission strategies, artificial intelligence-based methods, and integrated sensing and communication frameworks.

The deliverable begins by introducing the motivation for exploring new waveform designs capable of operating efficiently under high mobility and severe multipath conditions. In this context, OTFS modulation is analyzed as an alternative to conventional OFDM, with emphasis on its representation of channels in the delay-Doppler domain. The report explains that the delay-Doppler domain representation improves robustness against Doppler dispersion and time variation in high-mobility scenarios. Space-time techniques are further examined to enhance diversity and link reliability. Performance evaluations are presented to quantify the gains achieved by these waveform designs, and current research efforts aimed at further optimization are discussed.

The report then examines non-coherent communication techniques, which aim to reduce receiver complexity and relax synchronization requirements. These techniques are especially relevant for distributed and cell-free architectures operating at high carrier frequencies, where phase coherence across nodes is difficult to maintain. The report analyzes the trade-offs between complexity, robustness, and performance, highlighting scenarios in which non-coherent approaches provide practical advantages.

Then this deliverable investigates positioning-aided techniques. The report demonstrates that location information can be exploited to improve beamforming accuracy, link selection, and spectral efficiency. Positioning-aided beamforming is evaluated through signal-to-noise ratio analysis, TDoA estimation, and positioning error metrics. The results show that incorporating positioning information into the Tx/Rx chain significantly enhances system performance.

The deliverable further explores AI-native techniques for adaptive Tx/Rx design. Machine learning-based methods are discussed for tasks such as beam management, channel estimation, and decision-making in complex propagation environments. These approaches enable data-driven adaptation to dynamic channel conditions and provide a pathway toward intelligent and autonomous wireless systems. Finally, the report examines integrated sensing and communication as a key enabler for future wireless networks. By jointly exploiting communication signals and hardware for sensing and data transmission, ISAC enables simultaneous communication, positioning, and environmental awareness.

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List of Abbreviations

5G	Fifth Generation
5G NR	5G New Radio
6G	Sixth Generation
AR	Augmented Reality
AP	Access Points
AoA	Angle of Arrival
BSR	Buffer Status Report
CPU	Centralized Processing Unit
CP	Cyclic Prefix
CRB	Cramér-Rao Bound
CSI	Channel State Information
D-MIMO	Distributed MIMO
DFRC	Dual-Function Radar-Communication
DL	Downlink
DoF	Degree of Freedom
eMBB	enhanced Mobile BroadBand
EPC	Evolved Packet Core
EKF	Extended Kalman Filter
gNB	gNodeB
GPR	Gaussian Process Regression
GSM	Global System for Mobile Communications
GPS	Global Positioning System
ID	identification
IoT	Internet of Things
IRS	Intelligence Reflecting Surfaces
IT	Instituto de Telecomunicações
JCAS	Joint Communication And Sensing

LCG	Logical Channel Group
LTE	Long-Term Evolution
LoS	Line of Sight
LIDAR	Light Detection and Ranging
ML	Machine Learning
MIMO	Multiple-Input and Multiple-Output
mmW	millimeter Wave
MM	Mobility Management
ms	millisecond
MUSIC	Multiple Signal Classification
MRT	Maximum Ratio Transmission
NSP	Null-Space Projection
OFDM	Orthogonal Frequency Division Multiplexing
OTFS	Orthogonal Time Frequency Space
NOMA	Non-Orthogonal Multiple Access
NLoS	Non Line of Sight
NSP	Null-Space Projection
PA-BF	Positioning-Aided Beamforming
PBCH	Physical Broadcast Channel
PBR	Prioritized Bit Rate
PMI	Precoding Matrix Indicator
PSS	Primary Synchronization Signal
PEB	position Error Bound
QoS	Quality of Service
QoE	Quality of Experience
Rx	Receiver
RAT	Radio Access Technology
RI	Rank Indicator
RLM	Radio Link Monitoring
RRM	Radio Resource Management
RS	Reference Signal
RSRP	Reference Signal Received Power
RSRQ	Reference Signal Received Quality
RSSI	Received Signal Strength Indicator
SBA	Service-Based Architecture

SDR	Semidefinite Relaxation
SI	Self-Interference
SINR	Signal-to-Interference-plus-Noise Ratio
SR	Scheduling Request
SRS	Sounding Reference Signal
SS	Synchronization Signal
SSB	Synchronization Signal Block
SSS	Secondary Synchronization Signal
SNR	Signal-to-Noise Ratio
SE	Spectral Efficiency
SLNR	Signal-to-Leakage & Noise Ratio
SDR	Semidefinite Relaxation
Tx	Transmitter
TA	Timing Advance
Te	Timing error
THz	Terahertz
ToA	Time of Arrival
ToF	Time of Flight
TDoA	Time Difference of Arrival
UE	User Equipment
UL	Uplink
UmMIMO	ultra-massive MIMO
UMTS	Universal Mobile Telecommunications Service
URLLC	Ultra-Reliable Low-Latency Communication
UAV	Unmanned Aerial Vehicle
V2V	Vehicle-to-Vehicle
VR	Virtual Reality
WLS	Weight Least Square
ZF	Zero-Forcing

Chapter 1

Introduction

In a wireless communication system, the transmitter (Tx) and receiver (Rx) form the core entities that enable end-to-end information exchange over the wireless medium. The transmitter prepares and transmits the signal, while the receiver processes the distorted and noisy waveform to recover the transmitted information. The reliability of this process is strongly influenced by channel impairments such as noise, attenuation, delay dispersion, Doppler shifts, and interference. At the physical layer, Tx/Rx operations such as modulation, power control, beamforming, and precoding shape the signal in time, frequency, and space, whereas the receiver performs synchronization, detection, and demodulation to ensure robust data recovery. As wireless systems evolve toward beyond-5G and 6G, ultra-massive multiple-input multiple-output (UmMIMO) and cell-free architectures are emerging as key enablers for meeting the growing demand for higher data rates and improved spectral efficiency. In these architectures, a large number of distributed antennas jointly serve users, often operating at millimeter-wave and higher frequency bands. While such configurations offer substantial performance gains, they also introduce new challenges at the Tx/Rx level. The increased channel dimensionality, highly directional transmissions, user mobility, and stringent scalability requirements place significant pressure on conventional physical-layer processing techniques, which are typically designed for smaller and more centralized MIMO systems.

To cope with these challenges, recent research has explored a range of advanced Tx/Rx techniques that extend beyond traditional approaches. New waveform designs have been proposed to improve robustness under mobility and hardware constraints, while non-coherent transmission schemes aim to reduce the overhead associated with channel estimation in large-antenna systems. In parallel, positioning-aided methods have gained attention by exploiting location information to support beamforming and precoding, particularly in highly directional environments. Data-driven and AI-native approaches further contribute by enabling adaptive Tx/Rx processing in complex and time-varying channels. Moreover, joint communication and sensing techniques open new possibilities by allowing communication signals and transceiver hardware to be reused for environmental awareness. The focus of this deliverable is on Tx/Rx algorithms at the physical layer for ultra-massive MIMO transceivers. In particular, it considers new PHY techniques that make better use of the large number of antennas available in UmMIMO systems. The emphasis is on improving spectral efficiency and enabling higher data rates through efficient transceiver-level signal processing. By refining existing approaches and introducing new ones, these techniques aim to overcome the scalability and performance challenges that arise in future cell-free and distributed MIMO deployments.

1.1 Recent work on Positioning

Accurate localization is essential for reliable communication and beamforming. However, traditional positioning methods continue to face challenges when dealing with wideband and multi-subcarrier signals that are typical of modern wireless networks. In dense urban and outdoor microcell environments, the effects of multipath propagation and shadowing significantly degrade localization performance [1]. To overcome these issues, recent research has focused on applying machine learning (ML) techniques to distributed MIMO (D-MIMO) architectures, enabling data-driven position estimation based on received signal features. The work [2] proposed a gaussian process regression (GPR) framework that maps the uplink received signal strength (RSS) data to user positions while mitigating shadowing effects through probabilistic modeling. This approach has shown notable improvements in localization accuracy compared to conventional deterministic methods. To further enhance computational efficiency, the authors [3] introduced a two-phase clustering and regression strategy, where fingerprint data are first grouped using affinity propagation, and a localized GPR model is trained within each cluster. This method maintains high positioning accuracy while reducing training and inference complexity. Similarly, the authors [4] developed a delay-Doppler domain particle filter that performs direct positioning using the channel state information (CSI) of orthogonal frequency-division multiplexing (OFDM) signals, eliminating the need for strict inter-base-station synchronization. The work [5] applied an extended kalman filter (EKF) to sequentially estimate user position and velocity from combined time-of-arrival (ToA) and angle-of-arrival (AoA) measurements in a D-MIMO environment, demonstrating robust tracking capability and reduced computational complexity compared to particle-filter-based methods. With the evolution toward 6G networks, the demand for ultra-high-precision positioning has become even more critical. 6G aims to support emerging applications such as autonomous driving, drone coordination, and immersive extended reality, all of which require centimeter-level accuracy and ultra-low latency localization [6]. However, achieving this level of precision introduces new challenges due to severe path loss, blockage, and the high sensitivity of mmW and sub-terahertz frequency bands to NLoS propagation [7]. To address these limitations, researchers have started to combine geometric signal processing with data-driven inference to improve positioning robustness and beam alignment. The authors [8] proposed an equivalent fisher information matrix (EFIM) guided hybrid beamforming method that jointly optimizes the beam pattern based on the EFIM, thereby improving both positioning accuracy and communication reliability. As 6G networks push toward higher frequencies and greater localization precision, millimeter-wave (mmW) communication has become a key enabling technology. Operating in the 30-300 GHz range, mmW provides ultra-high data rates, low latency, and fine-grained spatial resolution, which are essential for both high-throughput communication and centimeter-level positioning. Its capability to form narrow, directional beams allows the extraction of rich spatial information, making it highly effective under challenging non-line-of-sight (NLoS) conditions [9]. To further enhance system performance, D-MIMO architectures have been introduced, where spatially separated APs collaborate through a central processing unit (CPU). This distributed design improves spatial diversity and coverage, significantly benefiting localization accuracy and link robustness. Recent studies have demonstrated promising progress in this direction. The integration of these high-precision localization techniques with intelligent beam control has led to the emergence of positioning-aided beamforming (PA-BF), a unified framework that aligns communication and sensing objectives within the same spatial domain. In this paradigm, user location and motion information are not treated as auxiliary data but as core parameters that actively influence beam selection, alignment, and tracking. By leveraging accurate positioning estimates, the network can predict optimal beam direc-

tions and dynamically adjust them to follow user mobility, thereby reducing beam-training overhead and improving reliability under NLoS and high-mobility conditions. This joint design transforms conventional beamforming into a location-aware process that enhances spectral efficiency, minimizes latency, and maintains stable connectivity even in dense urban or fast-changing environments. Within D-MIMO and mmW architectures, PA-BF serves as the key enabler that converts precise localization into actionable beam management intelligence, laying the foundation for adaptive, context-aware, and energy-efficient wireless communication envisioned in 6G systems.

1.2 Recent work on New Waveforms for Integrated Sensing and Communications

Orthogonal Time Frequency Space (OTFS) modulation has recently emerged as a promising waveform for Integrated Sensing and Communications (ISAC), particularly in high-mobility scenarios characterized by large Doppler spreads. Unlike conventional multicarrier schemes, OTFS modulates information symbols in the delay–Doppler (DD) domain, where the signaling dimensions are directly aligned with the physical parameters of sensing, namely range (delay) and velocity (Doppler). As a result, multipath propagation effects manifest as a sparse set of separable impulses in the DD domain, each corresponding to a distinct propagation path or target, with delay encoding range and Doppler encoding relative velocity. This representation enables efficient sparse estimation and robust signal processing, even in the presence of fractional Doppler shifts and rapidly time-varying channels [10; 11; 12].

A key advantage of OTFS is that it converts a highly time-varying frequency-domain channel typical in OFDM into an almost time-invariant channel in the DD domain. Instead of observing severe inter-carrier interference and fast channel fluctuations across subcarriers, the receiver operates on a small number of stable DD-domain channel taps. This property has been shown to significantly improve robustness against Doppler effects compared to OFDM, while preserving the same bandwidth-limited range resolution [12]. Since both OFDM and OTFS occupy the same total bandwidth, the delay resolution for range estimation remains identical. Consequently, OTFS achieves enhanced Doppler resilience without sacrificing range resolution. Recent studies further demonstrate that, when operating at millimeter-wave or terahertz frequencies, OTFS-based sensing systems can achieve sub-centimeter ranging accuracy, making them attractive for high-resolution radar and localization applications.

Alongside OTFS, Affine Frequency Division Multiplexing (AFDM) has also attracted attention as a Doppler-resilient waveform for high-mobility communications and sensing. AFDM is based on chirp-like basis functions generated through affine transformations in the time-frequency plane, enabling robustness to large Doppler shifts while maintaining low-complexity modulation and demodulation [13]. Although AFDM does not explicitly operate in the DD domain like OTFS, it provides an alternative framework for mitigating Doppler-induced interference and has recently been explored for radar sensing and joint communication-radar applications [14]. Nonetheless, OTFS remains particularly appealing for ISAC due to its explicit and sparse DD-domain channel representation, which supports parameter estimation and joint optimization of communication and radar functionalities.

1.3 Recent work on non-coherent MIMO communications

Coherent communication has long formed the basis of most wireless standards. However, it depends on the availability of CSI at the receiver and/or transmitter. CSI is typically obtained by transmitting known reference signals, referred to as pilots, from the transmitter to the receiver for channel estimation, along with feedback of the channel state from the receiver to the transmitter. Due to the time- and frequency-varying nature of wireless propagation channels, accurate channel estimates require frequent pilot transmissions. As a result, acquiring and maintaining CSI becomes challenging or even impractical in many emerging application scenarios, including massive IoT deployments, highly reliable low-latency communications, and high-mobility networks. This limits the effectiveness of traditional coherent communication in such environments.

In light of these challenges, noncoherent communication, in which transmission and reception do not rely on instantaneous CSI, has emerged as an attractive alternative. Such systems can be designed using only statistical CSI, namely the channel distribution, or even without any prior channel knowledge. By removing the requirement for explicit CSI acquisition, noncoherent approaches provide increased robustness and lower system complexity. These benefits make noncoherent communication a promising candidate for future wireless networks. [15] offers a comprehensive overview of recent progress in noncoherent MIMO communications, covering theoretical foundations, system design, practical implementation aspects, and open research challenges.

Chapter 2

New Waveforms developed in MiFuture

The growing demand for spectrum efficiency and intelligent services is driving the integration of communication and sensing functions into unified systems. This shift requires signals to serve not only for transmit data but also for environmental perception, enabling future networks to achieve higher situational awareness and improved resource utilization. Because traditional radar and communication waveforms are specialized for their original functions, they are not directly suitable for joint operation. As a result, ISAC waveform research follows two complementary paths: the development of entirely new multi-purpose ISAC waveforms and the systematic modification of conventional communication waveforms to embed sensing capabilities. Both approaches are essential to enable flexible, high-performance ISAC operation in emerging 6G networks.

2.1 Orthogonal Time Frequency Space (OTFS)

OTFS fits into this context as a promising communication waveform that can be adapted and used for ISAC operation. Its representation of the wireless channel in the delay-Doppler domain provides inherent robustness to mobility, while also estimating the parameters most relevant for sensing tasks, such as range and velocity. This dual sensitivity makes OTFS a strong candidate for extending traditional communication waveforms for joint operation without sacrificing link performance in high-dynamics environments [10; 11]. Therefore, OTFS can serve as a modified communication waveform with integrated sensing capabilities, since delay-Doppler processing enables target detection and parameter estimation using the same signal used for data transmission.

At the same time, its structure aligns well with the broader search for new, unified ISAC waveforms, as the modulation is inherently suited to jointly exploiting time-frequency and delay-Doppler structure. In OTFS systems, channel estimation constitutes a central challenge, particularly the accurate estimation of fractional delay and Doppler components, which has attracted significant research attention. For instance, the authors of [16] evaluated several OTFS channel estimation techniques and introduced a low-complexity method that achieves superior performance compared to the alternatives.

2.1.1 Superimposed Training (ST) with OTFS

In OTFS-based ISAC systems, ST have emerged as an effective strategy to enable simultaneous channel estimation, sensing, and data transmission without dedicating separate resources. By embedding pilot patterns directly onto the delay–Doppler information symbols, the transmitter preserves spectral efficiency while maintaining the coherent processing gain required for range and velocity estimation [17; 18; 19]. This approach also mitigates the overhead associated with guard intervals and facilitates continuous sensing, which is critical for high-mobility scenarios where channel and target parameters change rapidly.

As explained in [17], the transmitter maps the bit streams into a resource grid, which consists of $\mathbf{X}_d M \times N$ information symbols from a Q -ary quadrature amplitude modulation (QAM), where M denotes delay bins (or subcarriers) and N denotes Doppler bins (or symbols) in the dd domain. Each symbol has a normalized energy of one ($\mathbb{E}\{|\mathbf{X}_d[m, n]|^2\} = 1$, for $m = 0, \dots, M-1$ and $n = 0, \dots, N-1$). Then, a pilot sequence $\mathbf{X}_p \in \mathbb{C}^{M \times N}$ is superimposed onto the data symbols as

$$\mathbf{X} = \sqrt{\beta} \mathbf{X}_d + \sqrt{1-\beta} \mathbf{X}_p \in M \times N, \quad 0 \leq \beta \leq 1, \quad (2.1)$$

where β represents the power allocation factor to data. As shown in Figure 2.1, a single Zadoff-Chu sequence of length Z_p is used along a single Doppler bin as follows [17]:

$$\mathbf{X}_p[m, n] = \begin{cases} \sqrt{N} \mathbf{p}[m], & 0 \leq m \leq Z_p, n = n_p, \\ 0, & \text{otherwise.} \end{cases} \quad (2.2)$$

where $n_p = N/2 + 1$ and $\mathbf{p} \in Z_p$ corresponds to the Zadoff-Chu sequence with root μ , following the formula

$$\mathbf{p}[m] = e^{-j \frac{\pi \mu m(m+1)}{M_p}}, \quad m = 0, 1, \dots, Z_p - 1. \quad (2.3)$$

The delay-Doppler symbols are then transformed to the time domain by using the Inverse Discrete Zak Transform (IDZT), and assuming rectangular transmit and receive pulse shapes of duration T .

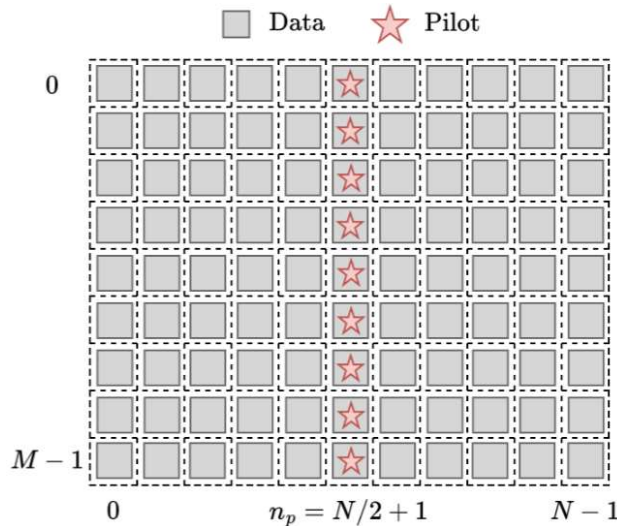


Figure 2.1: Superimposed Training pilot pattern for channel estimation in OTFS.

$$\mathbf{s} = \text{IDZT}(\mathbf{X}) = \text{vec}(\mathbf{X} \mathbf{F}_N^H) = \left[\mathbf{s}_0^T, \dots, \mathbf{s}_{N-1}^T \right]^T MN, \quad (2.4)$$

where $\mathbf{F}_N$ is the N -point dft matrix and $\mathbf{s}_n \in \mathbb{C}^M$ with $n = 0, \dots, N-1$ represents a multicarrier symbol with M time-domain samples, and T have a duration of $\frac{1}{\Delta f}$ seconds, where Δf is the system subcarrier spacing. Finally, zero padding is performed, where L_Z zeroes are appended to each symbol, in order to avoid Interblock Interference within one ZP-OTFS frame [20].

At the receiver, after analog-to-digital (A/D) conversion and zero-padding (ZP) removal, the received time-domain signal $\mathbf{r}_{MN}$ is mapped back to the dd domain using the dzt [20]. Specifically, the received grid in the delay-time (DT) domain, denoted by $\tilde{\mathbf{Y}}_{M \times N}$, is obtained by applying the inverse operation of (2.4) to the time-domain vector $\mathbf{r}$, namely,

$$\tilde{\mathbf{Y}} = \text{vec}_{M,N}^{-1}(\mathbf{r})_{M \times N}. \quad (2.5)$$

The received signal in the dd domain is then obtained by performing an fft along the rows of $\tilde{\mathbf{Y}}$, resulting in

$$\mathbf{Y} = \tilde{\mathbf{Y}} \mathbf{F}_N_{M \times N}, \quad (2.6)$$

where each entry of $\mathbf{Y}$ can be expressed in terms of the time-domain received samples $\mathbf{r}$ as

$$\mathbf{Y}[m, n] = \frac{1}{\sqrt{N}} \sum_{p=0}^{N-1} \mathbf{r}[m + pM] e^{-j2\pi np/N}, \quad (2.7)$$

for $m = 0, \dots, M-1$ and $n = 0, \dots, N-1$. This operation corresponds to the application of the dzt to $\mathbf{r}$.

By vectorizing the received dd-domain grid, the resulting signal $\mathbf{y} = \text{vec}(\mathbf{Y})_{MN}$ can be described through an equivalent dd-domain channel model as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{z}_{MN}, \quad (2.8)$$

where $\mathbf{x} = \text{vec}(\mathbf{X})_{MN}$ denotes the vectorized transmitted dd-domain grid, $\mathbf{z}_{MN}$ represents additive white Gaussian noise (AWGN) with distribution $0\sigma_z^2$, and $\mathbf{H}_{MN \times MN}$ is the equivalent channel matrix in the dd domain. Following [18; 19; 20], this matrix is modeled as

$$\mathbf{H} = (\mathbf{F}_N \otimes \mathbf{I}_M) \left(\sum_{i=1}^{L_p} g_i e^{-j2\pi v_i \tau_i} \mathbf{\Pi}^{l_i} \mathbf{\Delta}^{k_i} \right) (\mathbf{F}_N^H \otimes \mathbf{I}_M). \quad (2.9)$$

Here, $\mathbf{F}_N_{N \times N}$ denotes the normalized discrete Fourier transform (DFT) matrix, $\mathbf{\Pi}_{MN \times MN}$ is the forward cyclic-shift (permutation) matrix, and $\mathbf{\Delta} = [1, e^{j2\pi \frac{1}{MN}}, \dots, e^{j2\pi \frac{MN-1}{MN}}]$.

2.1.2 Results

By superimposing a constant-envelope Zadoff–Chu pilot onto the data symbols, the scheme preserves spectral efficiency and prevents large signal power variations that could degrade transmission performance. Simulation results demonstrate that the proposed approach enables accurate estimation of delay and Doppler shifts, which is critical for sensing, while maintaining bit error rate and channel estimation error performance comparable to that of more sophisticated techniques [17].

Another important observation is about the power trade-off between pilots and data symbols. By tuning this balance, the system can favor either sensing performance or communication throughput, depending on the target application and operating conditions. Notably, even

when a higher percentage of the transmit power is allocated to data, the proposed approach preserves robust sensing capability. Figure 2.2 presents the sensing performance for different values of the power allocation factor assigned to the data symbols (β) [17].

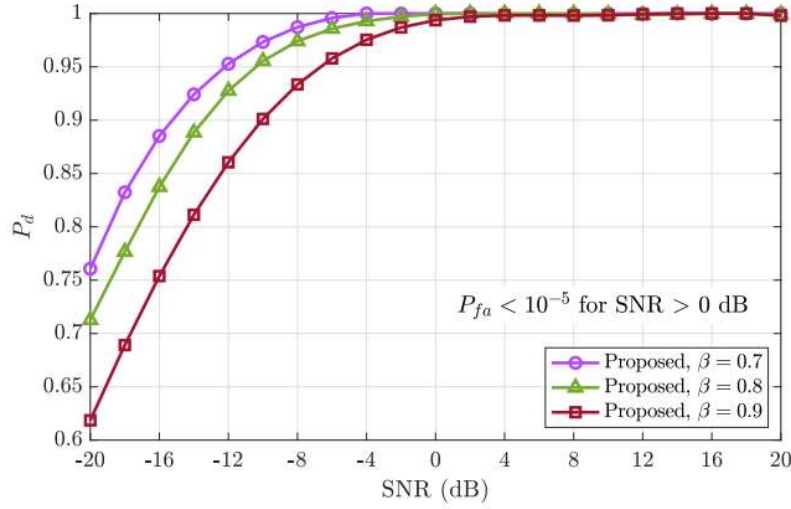


Figure 2.2: Probability of detection, P_d , and probability of false alarm, P_{fa} , vs. SNR for several β values.

In terms of complexity, for the proposed approach, the correlation stage consists of multiplying the received signal by the pilot sequence over M_p samples and for all delay–Doppler hypotheses up to $l_{\max}$ and $k_{\max}$, in order to identify targets via the maximum delay and Doppler shift. Nevertheless, because the ZC pilot sequence p has constant unit magnitude and the Doppler exponential z is also unit-modulus, these complex multiplications can be reformulated as real-valued additions in the phase domain, resulting in a substantial reduction in computational complexity. This reformulation only requires converting the signals from binomial to polar representation, a process that can be efficiently realized using CORDIC-based implementations [21]. Consequently, the overall computational burden of the proposed algorithm is dominated by the detection stage, which entails computing the magnitude of the correlated received signal over the region of interest, yielding $(2k_{\max} + 1)(l_{\max} + 1)$ complex multiplications [17].

2.1.3 Current work

Several ST-based OTFS channel estimation methods introduced in the literature had enhanced channel estimation reliability and accuracy, and mitigate PAPR. However, the majority of these studies rely on the assumption that the channel induces only integer Doppler shifts, an assumption that is generally unrealistic in practical high-mobility scenarios.

If channel estimation relies on integer Doppler estimation, where Doppler shifts are often assumed to align with integer multiples of the Doppler resolution, each path in the delay–Doppler domain is represented by a single tap located exactly at an integer Doppler index, simplifying channel estimation and detection. However, for realistic environments, the actual Doppler shifts are not restricted to the integer Doppler points. As a consequence, the received signal exhibits a considerable path energy spread over the adjacent dd bins along the Doppler axis [22], where Fig. 2.3 illustrates the leakage due to fractional Doppler.

To address this effect, precise and low-complexity signal processing techniques capable of

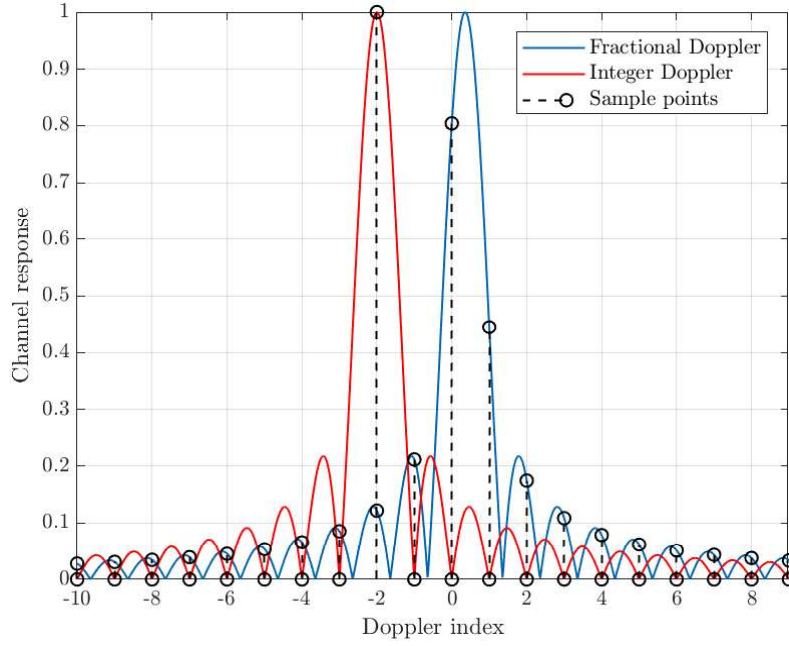


Figure 2.3: Effect of fractional Doppler, $k = -0.3$, compared with the effect of integer Doppler, $k = 2$.

resolving fractional Doppler shifts are required. In this context, high-resolution Doppler estimation methods, such as the algorithm proposed by [23], can be employed to accurately estimate off-grid Doppler components. By enabling precise fractional Doppler recovery, these techniques mitigate Doppler leakage and IDI, thereby improving the fidelity of the estimated delay–Doppler channel representation under realistic high-mobility conditions.

Building upon this and to complete the channel estimation needed for both sensing and communications, the current approach adopts a unified framework composed of three main components: (i) an adaptive thresholding mechanism that dynamically tracks the varying interference floor to identify significant channel paths without requiring prior data decoding; (ii) a Doppler refinement stage that employs a spectral interpolation technique, such as [23], to accurately estimate fractional Doppler components; and (iii) an iterative cancellation loop that progressively reconstructs and subtracts the contribution of the detected paths. This cancellation process systematically reduces the residual interference and noise floor, thereby enabling the reliable detection of weak channel paths without resorting to computationally expensive data equalization procedures.

Chapter 3

Non-coherent techniques developed in MiFuture

Non-coherent wireless communication systems are able to transmit information through the wireless medium without any channel estimation procedure. To achieve this, special modulation schemes are used. MIMO systems, thanks to their channel hardening property brought by the high number of physical channels, bring a prolific environment for non-coherent modulation schemes.

The main problem that non-coherent schemes seek to address is the performance decrease on the uplink of coherent systems under high mobility conditions, where the channel varies rapidly, presenting a choice between incurring more transmission errors or increasing the frequency of the channel estimation procedure, which wastes time-frequency resources. The latter is usually hard to do in practice, due to the rigidness of the standardized pilot schemes, and is also not a viable solution for extreme mobility scenarios. Currently, there are three main kinds of non-coherent modulation schemes for MIMO systems. These are Grassmanian schemes, energy-based schemes, and differential schemes.

3.1 Grassmanian schemes

Grassmanian schemes are closely related to unitary space time modulation (USTM) [24], which is a coherent scheme that proposes composing constellations of symbols which span several transmissions and spatial channels (antennas). USTM is optimal if the coherence time T is bigger than the number of transmitting antennas M [25].

As long as the narrowband assumption is met [26], the effect of the channel $\mathbf{H}$ on an USTM symbol is a linear transformation. If the coherence time is longer than the number of transmissions spanned by the USTM symbol, the linear transformation exerted by the channel will be identical for all the rows (uses of the channel) of the USTM symbol. As a result, the subspace spanned by the columns of the received USTM symbol is identical to the subspace of spanned by the columns of the transmitted USTM symbol. Grassmanian modulation schemes seek to take advantage of this by transmitting information embedded in the subspaces spanned by the columns of the USTM symbol, which are invariant to the effect of the channel $\mathbf{H}$ [15].

These schemes are designed for MIMO systems with low numbers of antennas and tend to suffer from very high computational complexity constellation design as the number of antennas

increases. This makes them a suboptimal choice for ultra-massive MIMO.

3.2 Energy-based schemes

Energy-based schemes for ultra-massive MIMO rely on the same principles as AM systems, i.e., they use only the amplitude of the transmitted signal to transmit information. The way to use AM in multiple antenna systems consists on averaging the received signal energy in each of the antennas of the system according to [27]

$$\frac{1}{N} \|\mathbf{y}\|^2 = \frac{1}{N} \sum_{n=1}^N |y_n|^2, \quad (3.1)$$

where $\mathbf{y}$ is the received signal and N is the number of receive antennas. The averaging exploits the channel hardening property of multi-antenna systems, which makes the average of the channel become more deterministic the higher N is. This helps mitigate the problems AM systems have when dealing with fast fading channels.

While energy-based schemes show attractive capacity scaling with increasing numbers of antennas, they have difficulties multiplexing higher numbers of users, which makes them an unattractive modulation scheme for an ultra-massive MIMO system where a very high number of users is expected to be multiplexed.

3.3 Differential schemes

Differential schemes are an evolution from energy-based schemes that is able to use the information from the phase of the received signal, which enables increased spectral efficiency with respect to energy-based schemes. The assumption underlying these schemes is that the channel coherence time will be higher than twice the symbol time, which allows the channel to be deemed as constant along two consecutive symbols. This channel assumption is met in almost all wireless communication systems and differential schemes exploit it by transmitting information in the difference between consecutive symbols. To do this, the transmitted symbols are precoded with the previously emitted symbol as

$$x[n] = x[n-1] s[n], \quad n > 1, \quad (3.2)$$

where $x[n]$ is the transmitted symbol at time n , and $s[n]$ is the information symbol being differentially encoded. The first emitted symbol will be known and will serve as the starting point of the differentially coded chain. The decoding of the differential symbols can be done by multiplying by the complex conjugate of the previously received symbol as

$$z[n] = y[n-1]^* y[n], \quad (3.3)$$

where $z[n]$ is the decoded symbol and $y[n]$ is the received symbol at time n . It is important to note that there is no error propagation thanks to (3.3) being only dependent on two consecutive received symbols (not decoded symbols). Differential modulation and demodulation can also be done in the frequency domain by doing the coding between contiguous OFDM subcarriers [28].

There have been several differential scheme adaptation proposals for MIMO systems, with the first one being differential unitary space time modulation (DUSTM) [24; 29]. This modulation scheme, like Grassmanian signaling, uses USTM symbols. The difference is that here, instead of coding information into subspaces, the information symbols are transmitted through differential USTM symbols according to

$$\mathbf{X}_\tau = \mathbf{S}_\tau \mathbf{X}_{\tau-1}, \quad (3.4)$$

where $\mathbf{X}_\tau \in \mathbb{C}^{M \times M}$ is the τ^{th} transmitted DUSTM symbol, with M being the number of transmitting antennas; and $\mathbf{S}_\tau \in \mathbb{C}^{M \times M}$ is the τ^{th} USTM information symbol. (3.4) is no more than the USTM expansion of (3.2) and, therefore, also requires the channel coherence time to be twice the symbol time, which in the case of USTM spans $2M$ transmissions. As a result, the higher the number of antennas (and therefore transmissions) used by the USTM symbol, the higher the coherence time of the channel must be in order to maximize the throughput. Because of this, in DUSTM, the condition $T \geq 2M$ must be met [30]. This limitation, together with the user multiplexing problems of USTM, makes this scheme a suboptimal choice for ultra-massive MIMO.

Another adaptation of (3.3) to MIMO systems consists on averaging across the receiving antennas in order to exploit channel hardening [31]

$$z[n] = \frac{1}{N} \sum_{i=1}^N y_i[n-1]^* y_i[n]. \quad (3.5)$$

The effect of channel hardening results in an attractive noise and interference reduction that scales with the number of receiving antennas N . Moreover, the simplicity of (3.5) makes it behave well for high numbers of antennas without employing excessive computational resources.

However, one of the main drawbacks that all differential schemes suffer from is that they must employ a constellation whose different points form a closed group under matrix multiplication, i.e., the product of two constellation points must also be part of the constellation. If this was not true, (3.2) would generate symbols outside of the desired constellation. This limitation of differential schemes forces them to use M-PSK, which significantly reduces their performance at high SNRs compared to coherent schemes, which are able to use the high spectral efficiency QAM constellations. From all the non-coherent schemes, differential non-coherent modulation based on averaging is the the best non-coherent modulation scheme for ultra-massive MIMO. This is because of its low computational complexity, together with its attractive performance scaling with increasing numbers of antennas. Due to this, the next chapter will cover RRM for this kind of schemes.

3.3.1 Multi-user non-coherent schemes

Initial MIMO schemes were designed with the goal of maximizing capacity in a single-user MIMO setup. Non-coherent modulation schemes are no exception and such is the case of Grassmanian schemes, DUSTM, and STBC. Because of this, these schemes do not scale well with increasing numbers of users, and become unfeasible with the expected number of multiplexed users in ultra-massive MIMO. As a result, conceptually simpler schemes, like energy-based and differential schemes based on averaging are desirable. Between these two, differential schemes based on averaging use the information from the phase of the incoming signal, which makes them more robust and leaves open the possibility of doing spatial processing.

The extension of differential schemes based on averaging to a multi-user scenario has been done by multiplexing users in the constellation domain, in a similar manner to multi-user energy based schemes but with the advantage of having the complex plane (a two-dimensional space), instead of just the received energy (a one-dimensional space). The symbols transmitted from several users will sum over the air, forming joint symbols $z[n]$, which stem from the extension of (3.5) to the multi-user case as

$$\begin{aligned} z[n] &= \frac{1}{N} \sum_{k=1}^K \sum_{i=1}^N y_{k,i}[n-1]^* y_{k,i}[n] \\ &= \frac{1}{N} \sum_{k=1}^K \sum_{i=1}^N |h_{ki}|^2 \beta_k s_k[n] + \zeta[n], \end{aligned} \quad (3.6)$$

where K is the total number of users, h_{ki} is the complex channel coefficient from user k to antenna i , β_k is the transmitted power by user k , and ζ represent the interference and noise terms. It can be shown that, if the different users have uncorrelated channels, ζ decreases with increasing N [31].

The joint constellation 3.1 must be known by the receiving base station to assign the correct bits to each user. On top of that, stable power control is required by the user terminals being multiplexed, so that the joint constellation does not degrade excessively.

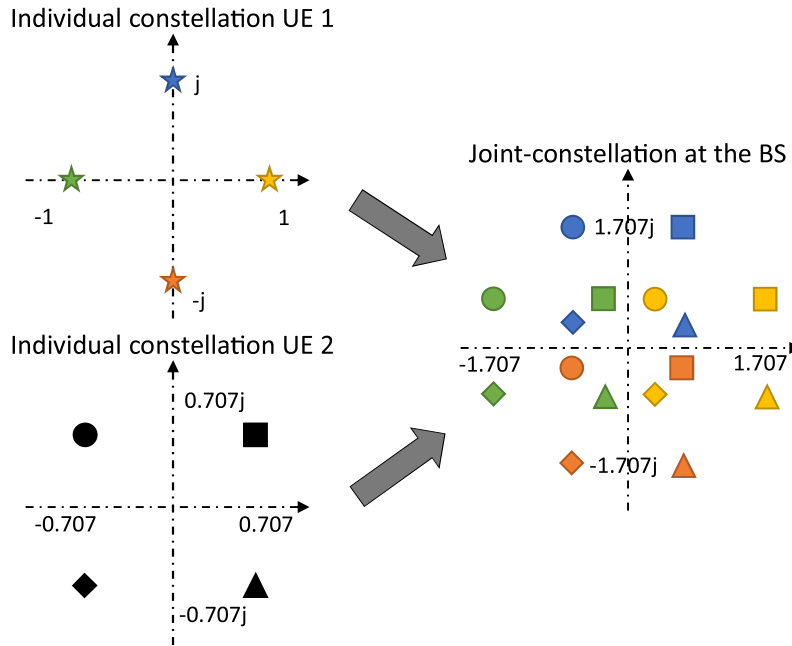


Figure 3.1: Example of a joint constellation for two users.

Multiplexing users using a joint constellation has notable drawbacks. First, the number of constellation points increases exponentially with the number of users to be multiplexed, which considerably limits the maximum number of users that can transmit simultaneously. Second, these technique demands a very strict power control loop to preserve the shape of the joint constellation. And third, the constellation design procedure is a complex process which has to be taken into account when assigning each user its constellation.

3.3.2 Array processing-aided non-coherent communication

The use of array processing techniques becomes more powerful the higher the number of antennas. Therefore, in UmMIMO the potential of array processing-aided communication techniques increases considerably with respect to previous MIMO architectures.

The use of array processing techniques enables for easier user multiplexing in orthogonal spatial resources (beams). Non-coherent architectures can greatly benefit from this, as the use of a joint constellation is no longer required. This solves one of the main drawbacks of differential schemes based on averaging across antennas, which is the limited user multiplexing capabilities. Moreover, the use of array processing to multiplex users in orthogonal spatial resources enables the use of non-constant envelope constellations for each one of the users, greatly increasing the throughput of non-coherent schemes [32].

This is shown in [33], where array processing is used for the spatial filtering of non-coherent communication signals, leading to reduced interference and a consequent decrease in the Symbol Error Rate (SER). This can be seen in Figure 3.2, where the SER of a spatially filtered non-coherent waveform is close to the performance of a pilot-based coherent system. The non-coherent system using AoA information shows a significant performance improvement against a non-coherent MIMO system relying on averaging across the antennas.

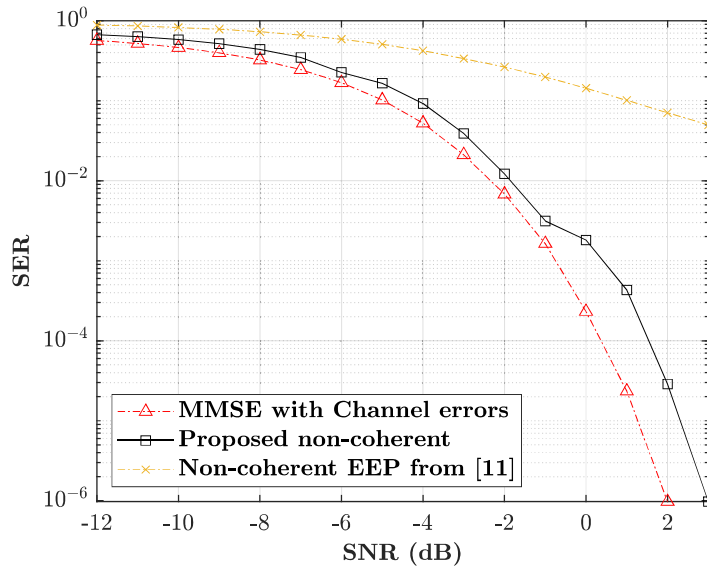


Figure 3.2: SER of a 50 antenna array in a Rician channel with a Rice factor of $K = 10$ for a MMSE coherent scheme (red), an array processing-aided non-coherent scheme (black), and a joint constellation-based non-coherent scheme (yellow).

The performance of array processing-aided non-coherent schemes with ultra-massive numbers of antennas shows a very attractive scaling, thanks to the higher number of spatial resources and the noise reduction capabilities of the array. Figure 3.3 shows a SER comparison between a coherent MMSE scheme and an array processing-aided non-coherent scheme for increasing numbers of antennas.

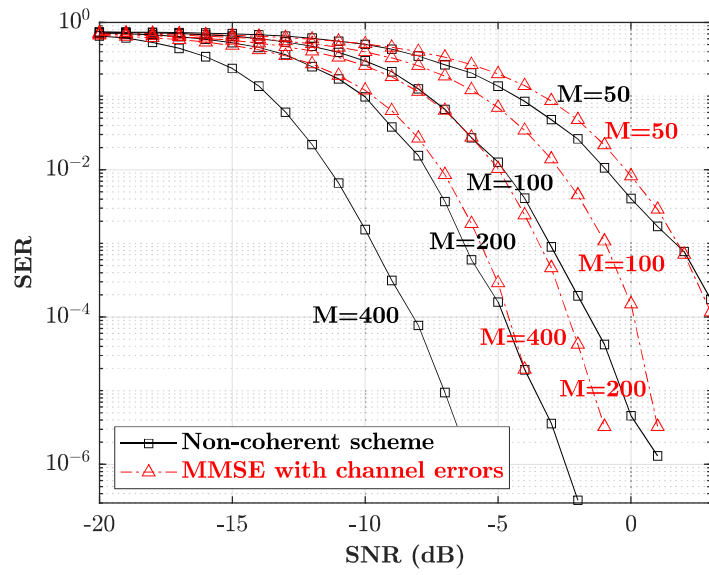


Figure 3.3: SER simulation results for six users and increasing numbers of antennas (M) for an arrayprocessing-aided non-coherent system and a coherent MMSE system.

Finally, the method from [33] has a lower computational cost than advanced coherent methods, e.g. Zero-forcing and MMSE, due to the lack of matrix inversion operations.

Chapter 4

Positioning techniques developed in MiFuture

Positioning-aided beamforming (PA-BF) has emerged as a promising approach to improve the efficiency, reliability, and responsiveness of beam alignment in mmWave communication systems in dynamic, high mobility scenarios. Figure 4.1 elucidates a mmW D-MIMO architecture designed for positioning-aided beamforming, where four multiple access points (APs) are coordinated by a CU. AP1 and AP4 serve users under LoS conditions, while AP2 performs beamforming toward a nearby user group. In contrast, AP3 represents an NLoS scenario, where the presence of urban obstacles introduces uncertainty in user positioning. The CU collects information from all APs to coordinate beamforming, enabling each AP to focus its signal in the right direction toward the user. This coordinated positioning-aware strategy ensures fast alignment, robust connectivity, and low latency even under mobility and dynamic blockage conditions. As mmW and D-MIMO systems aim to provide high accuracy, they still face several challenges in dense urban areas. mmW signals often suffer from high path loss, blockage, and interference in NLoS conditions. These issues can cause errors in user position estimation, leading the AP to send the beam in the wrong direction. In Figure 4.1, AP3 is shown steering the beam in the wrong direction due to inaccurate user positioning, which leads to beam misalignment. Urban obstacles, such as buildings, block the LoS path and force the signal to propagate through reflected NLoS components, leading to reduced reliability and degraded link performance. To overcome these issues, PA-BF has emerged as a promising solution. PA-BF integrates real-time location information into the beamforming process to reduce the beam search space and accelerate beam alignment. This approach not only improves alignment speed but also enhances communication reliability in dynamic environments.

Building on this concept, the authors [34] introduce a probabilistic model that incorporates positioning data to reduce the beam search space. By leveraging this positioning information, the model narrows the beamforming process, significantly improving efficiency and reducing the latency and energy consumption that typically accompany exhaustive beam search. Simulation results showed that over 90 % of the maximum achievable rate can be maintained by testing only the top six beam pairs (out of 256), with consistently lower power-loss probability than neural-network and fingerprinting-based baselines. Although demonstrated for a single-BS scenario, the same position-aided strategy readily generalizes to distributed and CF architectures, where coordinated multi-AP beam selection can further minimize alignment latency and signalling overhead. The paper [35] proposes a method for fast in-band beam selection by leveraging positioning data derived from mmWave signals. By using real-time

positioning information, this technique enables faster connectivity and more efficient beamforming in environments where traditional methods struggle. This method ensures that beamforming is optimized for dynamic conditions, significantly reducing the time needed for beam alignment. In the context of mmW NOMA systems, [36] utilizes positioning data to support beam training. Their approach reduces beam search overhead, improves communication reliability, and increases energy efficiency in high mobility and NLoS environments. The integration of positioning data allows the system to focus beam alignment on the most promising directions, improving efficiency and reducing the time spent searching for optimal beam directions. In [37], the authors propose the use of enhanced convolutional neural networks alongside real-world positioning data to predict the most optimal beam direction. The approach uses real-world global positioning system (GPS) data from datasets like DeepSense 6G to improve beam prediction accuracy. It also reduces beamforming overhead, leading to more reliable and efficient communication. [38] introduced a hierarchical deep Q-network framework to optimize beam alignment for unmanned aerial vehicles (UAVs) in uplink mmW systems. The method exploits positioning information to guide hierarchical beam selection, thereby reducing the beam-search complexity and accelerating convergence. Simulations under 3GPP urban macro-cell NLoS conditions showed that the proposed approach converges approximately 43 % faster than a conventional DQN while achieving comparable data-rate performance. By using location-aware learning, the framework enables UAVs to rapidly adapt to new positions and sustain reliable communication during high-mobility operations. Although evaluated for a single BS configuration, the hierarchical design can be extended to distributed D-MIMO architectures, where coordinated multi-APs beam selection can further improve scalability and responsiveness. Another key contribution is in [39], where the authors track the spatial correlation of the strongest communication paths using positioning data. This method ensures faster beam alignment and reduces beamforming overhead, which is essential for real-time mobile applications. By optimizing beam selection, the system ensures a more reliable link and better communication quality in mobile and dynamic environments.

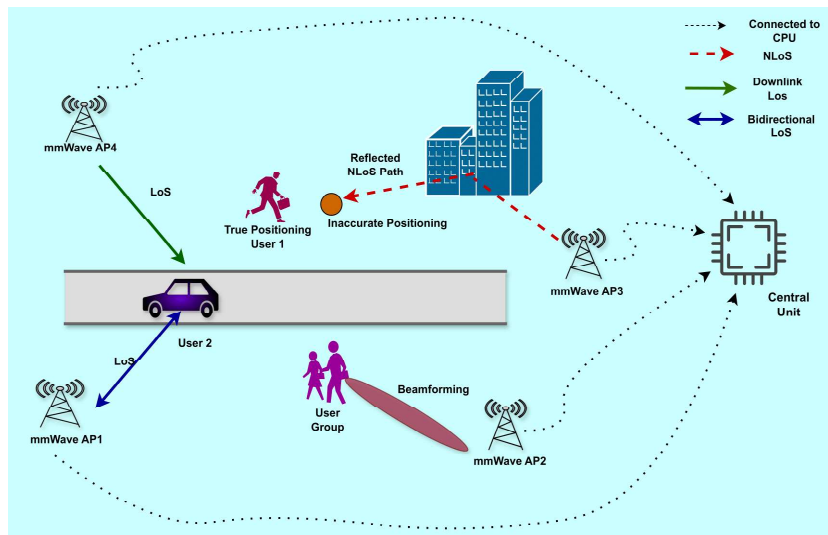


Figure 4.1: PA-BF Architecture

The study [40] proposes an innovative method that combines light detection and ranging data with positioning information to enhance beam prediction accuracy. This NN approach optimizes beam selection. It enables faster and more reliable beam alignment in NLoS en-

vironments. This capability is important for applications such as V2I communication. The integration of light detection and ranging (LIDAR) and positioning data reduces beamforming overhead and improves performance in challenging environments. [41] investigates the use of positioning data such as GPS and LIDAR in autonomous vehicles. This data helps optimize the beam selection process. It improves SNR and enhances communication reliability in high-mobility scenarios. In [42], the authors focus on optimizing beam alignment for backhaul systems with large phased arrays. They incorporate position information into the beamforming process.

This improves accuracy and reduces beam misalignment in large and dynamic environments. The method also enables faster beam alignment and improves overall backhaul performance. It reduces the need for complex control signaling. The work [43] examines the role of real-world GPS data in beam prediction. The authors demonstrate that while GPS data can reduce beam-training overhead, it is constrained by positioning inaccuracies and environmental noise. This study highlights the potential of positioning data to assist in beam selection, while also emphasizing the importance of accounting for real-world factors that affect beam-prediction accuracy. In their experimental evaluation, the authors report that real-world GPS errors result in an average power loss of less than 3 dB between predicted and optimal beams, with beam prediction accuracy ranging from 27% to 55%. Despite this degradation, their approach achieves up to a 95% reduction in beam-training overhead while maintaining 90% reliability. These results provide quantitative evidence that even moderate localization errors lead to measurable beamforming and rate degradation, underscoring the importance of precise positioning in positioning-aided beamforming systems. In [44], the authors propose a 3D beamforming technique for mobile networks. The method integrates positioning data with beamforming strategies to improve downlink communication quality. It uses uplink positioning data to optimize beamforming and reduce initial access latency. The approach also improves throughput in high-speed mobility scenarios. It enables faster beam alignment and supports efficient communication in urban and mobile environments. Their results also quantify the relationship between localization accuracy and beamforming performance. With 1 m positioning accuracy, the proposed 3D positioning-aided beamforming achieves spectral efficiency close to that of exhaustive beamforming. A 3 m error introduces less than 5 % loss, while 10 m and 50 m errors lead to approximately 15 % and over 30 % degradation, respectively. In D-MIMO beamforming, synchronization accuracy among access points is a critical factor for maintaining array gain. Even small timing or phase mismatches can noticeably degrade beamforming performance. For example, a random phase jitter of about 30 degrees typically results in around 1 dB loss in array gain. Because phase jitter corresponds to timing jitter through the carrier frequency, synchronization at the level of a few picoseconds is required at mmWave bands, for example, roughly 3 ps at 28 GHz and 1.5 ps at 60 GHz to keep the loss below 1 dB.

4.1 3D Indoor PA-BF for mmW D-MIMO Systems

We consider a three-dimensional indoor wireless environment in which multiple user equipments and APs are deployed within a common Cartesian coordinate system and operate over mmW carrier frequency. The APs are placed at elevated positions, including locations near the boundaries and the ceiling, while the UEs are positioned at a lower height representative of typical handheld or wearable devices. This deployment enables spatial diversity and supports distributed reception.

The uplink transmission employs a carrier frequency of $f_c = 28$ GHz with a total system bandwidth of 100 MHz. The corresponding wavelength is obtained from the standard relation

$$\lambda = \frac{c}{f_c}, \quad (4.1)$$

where c denotes the speed of light. Thermal noise is modeled using a standard noise power spectral density of -174 dBm/Hz.

An orthogonal frequency-division multiplexing waveform is used for uplink transmission, with a subcarrier spacing of $\Delta f = 120$ kHz and an FFT size of $N_{\text{FFT}} = 1024$. Out of these, N_{sc} subcarriers are actively used for transmission. Pilot tones are inserted at regular intervals of 12 subcarriers to facilitate channel and delay estimation, resulting in a total number of pilot subcarriers given by

$$K_{\text{pilot}} = \frac{N_{\text{sc}}}{12}. \quad (4.2)$$

Based on the number of active subcarriers, the effective bandwidth contributing to delay estimation is expressed as

$$\text{BW}_{\text{used}} = N_{\text{sc}} \Delta f. \quad (4.3)$$

The useful OFDM symbol duration is therefore

$$T_u = \frac{1}{\Delta f}, \quad (4.4)$$

while the cyclic prefix duration is defined as a fraction of the useful symbol time,

$$T_{\text{cp}} = \frac{1}{16} T_u. \quad (4.5)$$

Accordingly, the total OFDM symbol duration is given by

$$T_{\text{sym}} = T_u + T_{\text{cp}}. \quad (4.6)$$

Each UE is equipped with a single transmit antenna, whereas each AP employs a uniform planar array consisting of 64 receive antennas arranged in an 8×8 grid. The inter-element spacing in both horizontal and vertical directions is set to $\lambda/2$, which enables high spatial resolution and effective angular discrimination at mmWave frequencies.

The three-dimensional Euclidean distance between the u -th UE and the m -th AP is defined as

$$D_{u,m} = \sqrt{(x_u - x_m)^2 + (y_u - y_m)^2 + (z_u - z_m)^2}, \quad (4.7)$$

where (x_m, y_m, z_m) and (x_u, y_u, z_u) denote the Cartesian coordinates of the AP and UE, respectively. Based on this distance, the free-space path loss is modeled as

$$\text{FSPL}_{\text{dB}}(u, m) = 20 \log_{10} \left(\frac{4\pi D_{u,m}}{\lambda} \right). \quad (4.8)$$

The directional geometry between each UE–AP pair is derived from their known three-dimensional coordinates. The resulting azimuth and elevation angles provide the necessary directional information for uplink channel modeling, beamforming, and subsequent parameter estimation.

4.1.1 Calculate Power and Signal to Noise Ratio

The received signal power and signal-to-noise ratio are evaluated for each UE–AP link by incorporating path loss, large-scale shadowing, and thermal noise. The uplink pilot transmit power is denoted by P_t^{dBm} and is assumed to be identical for all UEs.

The thermal noise power over the effective OFDM bandwidth BW_{eff} is computed as

$$P_n^{\text{dBm}} = N_0^{\text{dBm/Hz}} + 10 \log_{10}(BW_{\text{eff}}), \quad (4.9)$$

where $N_0^{\text{dBm/Hz}} = -174$ dBm/Hz is the thermal noise power spectral density, and BW_{eff} represents the bandwidth occupied by the active subcarriers.

Large-scale fading is modeled using a log-normal shadowing model. In the dB domain, the shadowing term is expressed as

$$X_{\text{shad}}^{\text{dB}} \sim \mathcal{N}(0, \sigma_{\text{shad}}^2), \quad (4.10)$$

where σ_{shad} (in dB) controls the severity of shadowing and captures slow variations caused by obstacles and indoor propagation effects.

For a given UE u and AP m , the received power is given by

$$P_r^{\text{dBm}}(u, m) = P_t^{\text{dBm}} - \text{FSPL}_{\text{dB}}(u, m) + X_{\text{shad}}^{\text{dB}}(u, m), \quad (4.11)$$

where $\text{FSPL}_{\text{dB}}(u, m)$ denotes the free-space path loss between the UE and the AP, and $X_{\text{shad}}^{\text{dB}}(u, m)$ is the corresponding shadowing realization.

The signal-to-noise ratio of each link is then computed as

$$\text{SNR}_{\text{dB}}(u, m) = P_r^{\text{dBm}}(u, m) - P_n^{\text{dBm}}. \quad (4.12)$$

Since each AP employs a uniform planar array with N_r antenna elements, the effective SNR includes the receive array gain and is given by

$$\text{SNR}_{\text{dB}}^{\text{eff}}(u, m) = \text{SNR}_{\text{dB}}(u, m) + 10 \log_{10}(N_r). \quad (4.13)$$

Only links satisfying predefined minimum received power and SNR thresholds are retained for subsequent processing. This filtering step ensures that weak or unreliable links do not adversely affect delay estimation and localization accuracy.

4.1.2 Calculate Time Difference of Arrival

Based on the retained UE-AP links from the previous step, the propagation delay is estimated using uplink OFDM pilot signals. The true time-of-flight between UE u and AP m is obtained from the geometric distance as

$$\tau_{u,m}^{\text{true}} = \frac{D_{u,m}}{c}, \quad (4.14)$$

where $D_{u,m}$ denotes the Euclidean distance between the UE and AP, and c is the speed of light.

Pilot symbols are transmitted over uniformly spaced OFDM subcarriers. Let k_p denote the set of pilot subcarrier indices, selected across the active subcarriers. The corresponding pilot subcarrier frequencies are given by

$$f_n = \left(k_p - \frac{N_{\text{sc}} + 1}{2} \right) \Delta f, \quad (4.15)$$

where N_{sc} is the number of active subcarriers and Δf is the subcarrier spacing.

Assuming a single-path LoS channel over the pilot subcarriers, the frequency-domain channel response for a given UE–AP link is modeled as

$$H_n(u, m) = \exp(-j2\pi f_k \tau_{u,m}^{\text{true}}), \quad (4.16)$$

which captures the phase rotation induced by the propagation delay.

The direction of arrival of the LoS signal at the AP is determined from the relative geometry between the UE and AP. Let $\mathbf{v}_{u,m}$ denote the vector pointing from the UE to the AP. The azimuth and elevation angles are computed as

$$\phi_{u,m} = \tan^{-1}\left(\frac{v_y}{v_x}\right), \quad (4.17)$$

$$\theta_{u,m} = \tan^{-1}\left(\frac{v_z}{\sqrt{v_x^2 + v_y^2}}\right), \quad (4.18)$$

where (v_x, v_y, v_z) are the components of $\mathbf{v}_{u,m}$. These angles are used to construct the uniform planar array steering vector $\mathbf{a}(\phi_{u,m}, \theta_{u,m})$ at the AP.

The received pilot signal at the antenna array is expressed as

$$\mathbf{Y}_k(u, m) = \mathbf{a}(\phi_{u,m}, \theta_{u,m}) H_k(u, m) + \mathbf{n}_k, \quad (4.19)$$

where $\mathbf{n}_k$ represents complex additive white Gaussian noise with variance determined by the link SNR.

To estimate the propagation delay, the received signals are phase-aligned and averaged across the antenna elements, yielding an effective pilot observation per subcarrier. The unwrapped phase of the averaged signal is then fitted with a linear function over frequency. The estimated ToF is obtained from the slope of the fitted phase response as

$$\hat{\tau}_{u,m} = -\frac{1}{2\pi} \frac{d\phi(f)}{df}. \quad (4.20)$$

The estimation uncertainty of the time of flight (ToF) is modeled as inversely proportional to the effective bandwidth and the square root of the SNR, and is expressed as

$$\sigma_{\tau}(u, m) = \frac{k_{\tau}}{\text{BW}_{\text{eff}} \sqrt{\text{SNR}_{u,m}}}, \quad (4.21)$$

where k_{τ} is a proportionality constant and BW_{eff} denotes the effective occupied bandwidth.

To form time difference of arrival (TDoA) measurements, one AP is selected as a reference for each UE, typically chosen as the AP with the highest SNR. The TDoA between AP m and the reference AP m_0 is given by

$$\text{TDoA}_{u,m} = \hat{\tau}_{u,m} - \hat{\tau}_{u,m_0}. \quad (4.22)$$

The variance of the corresponding TDoA measurement is obtained by combining the ToF uncertainties of the two involved links:

$$\sigma_{\text{TDoA}}^2(u, m) = \sigma_{\tau}^2(u, m) + \sigma_{\tau}^2(u, m_0). \quad (4.23)$$

Using the TDoA measurements obtained in the previous step, the localization accuracy is characterized through the Fisher Information Matrix and the corresponding Position Error Bound. For each UE, a reference AP is first selected, and only the remaining APs contributing valid TDoA measurements are considered.

Let $\mathbf{t}_u \in \mathbb{R}^L$ denote the vector of TDoA measurements for UE u , where L is the number of non-reference APs. The statistical uncertainty of these measurements is captured by the TDoA covariance matrix $\mathbf{R}_{\text{TDoA}} \in \mathbb{R}^{L \times L}$. The diagonal elements of $\mathbf{R}_{\text{TDoA}}$ correspond to the variances of individual TDoA measurements, while the off-diagonal elements account for the correlation introduced by the common reference AP. Specifically, the covariance matrix entries are defined as

$$[\mathbf{R}_{\text{TDoA}}]_{i,j} = \begin{cases} \sigma_r^2(m_i) + \sigma_r^2(m_0), & i = j, \\ \sigma_r^2(m_0), & i \neq j, \end{cases} \quad (4.24)$$

where m_i denotes the i -th non-reference AP, m_0 is the reference AP, and $\sigma_r^2(\cdot)$ represents the ToF variance of the corresponding link.

The relationship between the UE position $\mathbf{p}_u = [x_u, y_u, z_u]^T$ and the TDoA measurements is captured through the Jacobian matrix $\mathbf{J}_u \in \mathbb{R}^{L \times 3}$. Each row of the Jacobian corresponds to the gradient of a single TDoA measurement with respect to the UE position and is given by

$$\mathbf{J}_u(i, :) = \frac{1}{c} \left(\frac{\mathbf{p}_u - \mathbf{b}_{m_i}}{\|\mathbf{p}_u - \mathbf{b}_{m_i}\|} - \frac{\mathbf{p}_u - \mathbf{b}_{m_0}}{\|\mathbf{p}_u - \mathbf{b}_{m_0}\|} \right), \quad (4.25)$$

where $\mathbf{b}_{m_i}$ and $\mathbf{b}_{m_0}$ denote the three-dimensional coordinates of the i -th AP and the reference AP, respectively, and c is the speed of light.

Based on the Jacobian matrix and the TDoA covariance matrix, the Fisher Information Matrix for UE u is computed as

$$\mathbf{F}_u = \mathbf{J}_u^T \mathbf{R}_{\text{TDoA}}^{-1} \mathbf{J}_u. \quad (4.26)$$

The inverse of the fisher information matrix yields the cramér-rao lower bound (CRLB) on the estimation error covariance:

$$\mathbf{C}_u = \mathbf{F}_u^{-1}. \quad (4.27)$$

Finally, the position error bound (PEB), which provides a scalar measure of the achievable localization accuracy, is obtained as

$$\text{PEB}_u = \sqrt{\text{tr}(\mathbf{C}_u)}, \quad (4.28)$$

where $\text{tr}(\cdot)$ denotes the matrix trace. The PEB represents the lower bound on the root-mean-square positioning error for UE u under unbiased estimation.

4.1.3 Calculate Positioning Error

Using the TDoA measurements, the UE position is explicitly estimated via a weighted least-squares (WLS) approach. For a given UE u , let $\mathbf{p} = [x, y, z]^T$ denote the unknown three-dimensional position to be estimated, and let m_0 represent the reference AP selected based on the strongest received SNR.

For each non-reference AP, the predicted TDoA corresponding to a candidate position $\mathbf{p}$ is given by

$$\hat{t}_{u,m}(\mathbf{p}) = \frac{\|\mathbf{p} - \mathbf{b}_m\| - \|\mathbf{p} - \mathbf{b}_{m_0}\|}{c}, \quad (4.29)$$

where $\mathbf{b}_m$ and $\mathbf{b}_{m_0}$ denote the three-dimensional coordinates of AP m and the reference AP, respectively, and c is the speed of light.

Let $\mathbf{t}_u \in \mathbb{R}^L$ denote the vector of measured TDoAs for UE u , obtained by perturbing the estimated TDoAs with zero-mean Gaussian noise consistent with their variances. The statistical reliability of the measurements is captured by the TDoA covariance matrix $\mathbf{R}_{\text{TDoA}}$ derived previously.

The WLS cost function to be minimized is defined as

$$J(\mathbf{p}) = (\mathbf{t}_u - \hat{\mathbf{t}}_u(\mathbf{p}))^T \mathbf{R}_{\text{TDoA}}^{-1} (\mathbf{t}_u - \hat{\mathbf{t}}_u(\mathbf{p})), \quad (4.30)$$

where $\hat{\mathbf{t}}_u(\mathbf{p})$ is the vector of predicted TDoAs evaluated at position $\mathbf{p}$.

The position estimate is obtained by solving the following optimization problem:

$$\hat{\mathbf{p}}_u = \arg \min_{\mathbf{p}} J(\mathbf{p}). \quad (4.31)$$

Since the WLS cost function is nonlinear with respect to $\mathbf{p}$, the optimization is performed iteratively using a numerical search method. The algorithm is initialized with a coarse initial guess $\mathbf{p}_0$, and the cost function is evaluated repeatedly until convergence.

The final estimated position $\hat{\mathbf{p}}_u$ is compared with the true UE position $\mathbf{p}_u^{\text{true}}$ to compute the positioning error,

$$\varepsilon_u = \|\hat{\mathbf{p}}_u - \mathbf{p}_u^{\text{true}}\|, \quad (4.32)$$

which quantifies the localization accuracy achieved by the WLS estimator for UE u .

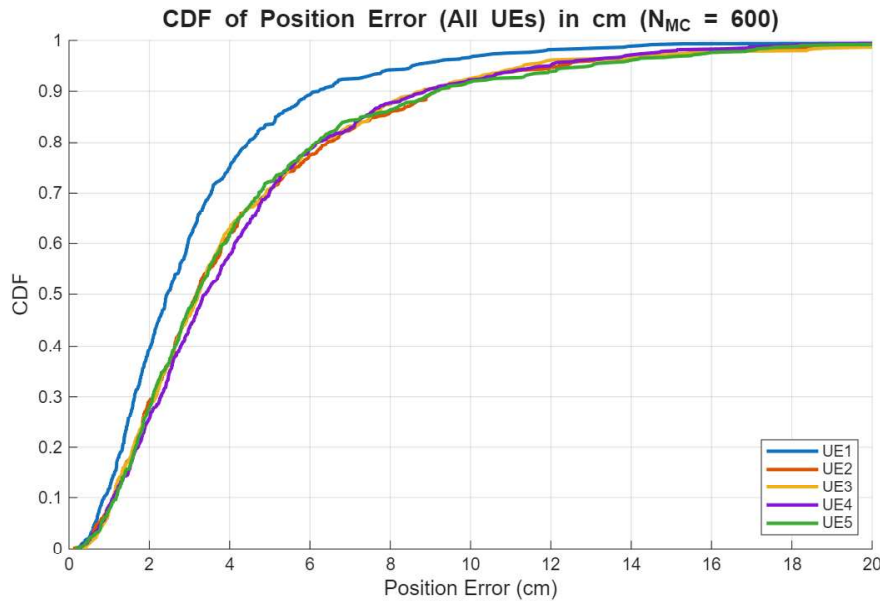


Figure 4.2: CDF vs Positioning Errors

The cumulative distribution function of the positioning error for all UEs, obtained over 600 Monte Carlo trials, is illustrated in Fig. 4.1. The figure shows the empirical distribution of the position estimation error expressed in centimeters for each individual UE. For all UEs, the CDF curves start from zero and monotonically increase toward one, indicating stable and consistent localization performance across trials. It can be observed that a large fraction of

the positioning errors lies within a few centimeters. In particular, for most UEs, approximately 80-90% of the errors are below about 6-8 cm, while the median error occurs around 3-4 cm. UE1 exhibits slightly better performance compared to the other UEs, as reflected by its steeper CDF and lower error values at the same probability levels. The remaining UEs show closely overlapping curves, indicating comparable localization accuracy despite differences in geometry and link conditions.

Chapter 5

AI-native techniques

In UmMIMO transceivers, a significant portion of the physical-layer Tx/Rx performance is determined by the spatial processing of signals through beamforming. Beamforming and beam management constitute fundamental components of the Tx/Rx processing chain and have a direct impact on spectral efficiency, achievable data rates, and link reliability. This becomes particularly critical at millimeter-wave and higher frequency bands, where severe propagation losses make the use of highly directional beams a physical necessity rather than a design choice. In classical frameworks, beamforming and beam management algorithms at the Tx and Rx are primarily based on beam sweeping, sequential signal quality measurements, and reactive codebook-based decision making. Although these approaches are compatible with conventional transceiver architectures, the associated signaling overhead and latency increase substantially as the number of antenna elements grows, beams become narrower, and the propagation environment becomes more dynamic. As a result, beam management emerges as a major performance bottleneck at the PHY layer in UmMIMO systems. Consequently, improving Tx/Rx performance in such systems cannot rely solely on incremental optimizations and instead requires fundamentally new approaches at the level of PHY algorithms [45].

In this context, 5G-Advanced has introduced the concept of an AI-native air interface, enabling artificial intelligence and machine learning to be integrated as intrinsic elements of Tx/Rx algorithm design. Within this paradigm, beamforming and beam management are no longer treated merely as control procedures, but rather as prediction-driven PHY algorithms capable of performing beam selection, tracking, and updating with reduced overhead, lower latency, and improved decision accuracy [46]. Accordingly, this chapter focuses on AI-based Beamforming and Beam Management as a key class of Tx/Rx algorithms at the physical layer. The objective is to examine how AI-native approaches can directly enhance spectral efficiency and achievable data rates in UmMIMO transceivers by reducing exhaustive beam sweeping, improving spatial alignment under mobility and blockage conditions, and accelerating decision making within the Tx/Rx processing chain.

5.1 Limitations of Classical Beam Management Approaches

In conventional beam management architectures, the beam alignment procedure typically consists of four main stages: beam sweeping, signal quality measurement, beam selection, and reporting. During the beam sweeping stage, the transmitter or receiver sequentially transmits or receives a predefined set of beams in order to cover the entire angular space.

While this codebook-based approach guarantees that the optimal beam can eventually be identified, it imposes a substantial cost in both time and frequency resources on the system. A fundamental limitation of this approach is its poor scalability in systems equipped with large antenna arrays. As the number of antenna elements increases and angular resolution improves, the size of the beam codebook grows accordingly, leading to a larger number of beams that must be swept. This directly results in increased initial access latency and a reduction in the resources available for data transmission. In dense deployment scenarios, such overhead can become a limiting factor for overall spectral efficiency.

Beyond signaling overhead, classical beam management methods rely heavily on simplified assumptions regarding channel statistics and environmental stability. In practice, real-world propagation environments are characterized by dynamic blockages, complex multipath reflections, and rapid variations induced by user mobility. As a result, a beam selected based on instantaneous measurements may become suboptimal within a short time interval, necessitating repeated execution of the beam management procedure. User mobility represents one of the most challenging scenarios for classical beam management. At high mobility speeds, the inherent latency between measurement, reporting, and decision execution prevents narrow beams from accurately tracking the user's trajectory. Consequently, the likelihood of link degradation and data rate reduction increases, making it difficult to maintain consistent service quality [47].

5.2 AI-Native Perspective on Beam Management

The AI-native perspective on beam management is based on the principle that channel behavior and the distribution of optimal beams can be viewed as manifestations of environmental knowledge that can be learned directly from observed data. Unlike classical approaches, which design beam selection strategies using simplified analytical models, machine learning algorithms are capable of extracting complex spatial and temporal correlations directly from data. Within this framework, beam decision making transitions from a reactive process driven by instantaneous measurements to a prediction-oriented process. AI/ML models can leverage partial information such as limited reference signal received power (RSRP) measurements, historical beam selection data, or auxiliary network information to predict suitable beams for future transmission intervals. This paradigm shift enables a significant reduction in beam sweeping requirements and, consequently, a reduction in both latency and signaling overhead.

In the context of 5G-Advanced, two primary dimensions for applying AI to beam management have been identified: the spatial dimension and the temporal dimension. The spatial dimension focuses on exploiting spatial correlations between a limited set of measured beams and the target beams, whereas the temporal dimension utilizes channel evolution patterns over time to predict future beam states. Together, these two perspectives form the foundation for the design of beam prediction frameworks in standard-compliant 5G-Advanced systems [48].

5.3 AI-Based Beam Selection without Exhaustive Sweeping

One of the primary objectives of applying AI/ML to beam management is to eliminate, or at least significantly reduce, the need for exhaustive beam sweeping. In classical approaches, identifying the optimal beam requires sequential transmission or reception of reference signals over all beams contained in the predefined codebook. Although this procedure is theoretically

optimal, it incurs a very high cost in terms of time and radio resources in practice, particularly when the number of beams is large. In AI-based approaches, the beam selection problem is formulated as a data-driven prediction task. Instead of directly measuring the quality of all available beams, a machine learning model predicts the most likely beam, or a small set of candidate beams, based on a limited number of observations. These observations may include partial RSRP measurements, outcomes of wide-beam sweeping, or historical information associated with previous beam selections.

A key advantage of this approach is that the relationship between a small subset of measured beams and a much larger set of target beams can be implicitly learned by the model. As a result, the system can identify narrow and near-optimal beams by transmitting only a limited number of reference signals, without requiring exhaustive angular scanning. This concept directly leads to a reduction in signaling overhead and an increase in the resources available for data transmission. From an architectural perspective, AI-based beam selection can be implemented either at the gNB side or at the UE side. In the gNB-side case, the base station performs beam prediction using the measurement data reported by the UE and determines the appropriate beam for subsequent transmissions. In contrast, in the UE-side case, the UE employs a local model to predict suitable gNB beams and reports the corresponding information back to the network. Each of these approaches involves different trade-offs in terms of computational complexity, latency, and energy consumption.

An important aspect of this framework is that AI models are not necessarily restricted to selecting a single beam. In many cases, predicting multiple top-ranked beams provides a favorable balance between prediction accuracy and additional overhead. This strategy allows the system to rapidly switch to alternative beams if the top-ranked beam fails, without reinitiating the full beam management procedure [47].

5.4 AI-Driven Beam Tracking under Mobility

In mobility scenarios, the challenge of beam management extends beyond initial beam selection, and maintaining beam alignment over time becomes a critical issue. User displacement, changes in movement direction, and environmental dynamics cause the optimal beam to vary over short time intervals. Classical approaches that rely on periodic repetition of beam sweeping and measurement procedures suffer from high latency and degraded link quality under such conditions. AI/ML enables beam tracking to be performed in a prediction-oriented manner. By analyzing historical measurement data and past decision outcomes, machine learning models can extract temporal patterns in the evolution of the optimal beam. This capability allows the system to update the beam configuration before link quality degradation occurs.

In standard-compliant 5G-Advanced frameworks, this type of beam tracking is typically based on sequential analysis of measurements collected over multiple beam management cycles. The AI model uses data from several consecutive cycles to predict future beam states. These predictions can be applied over one or multiple upcoming cycles, enabling the gNB or UE to execute adaptive decisions in advance. The primary benefit of AI-based beam tracking in mobility scenarios is the reduced need for frequent measurements and costly reporting procedures. Rather than reacting to changes after they occur, the system can operate proactively. This is particularly important at medium to high mobility speeds, where even small delays can lead to beam misalignment and performance degradation.

Nevertheless, the accuracy of AI-based beam tracking strongly depends on the quality of

historical data and the model's ability to generalize to new conditions. Sudden changes in user trajectory or unexpected blockages may lead to prediction errors. Consequently, many frameworks advocate hybrid solutions that combine AI-based prediction with classical fallback or feedback mechanisms to ensure link robustness [49].

5.5 AI-Driven Blockage-Aware Beam Management

Blockage is one of the most critical factors causing link degradation at millimeter-wave and higher frequency bands. Unlike sub-6 GHz systems, even small obstacles such as the human body or moving objects can result in severe signal attenuation or complete link interruption. In classical approaches, blockages are typically detected only after link quality degradation has already occurred, forcing the system to reactively search for alternative paths or beams with non-negligible delay. AI/ML enables blockage prediction prior to its occurrence. By analyzing temporal patterns in RSRP variations, link quality fluctuations, and beam switching history, machine learning models can estimate the likelihood of an imminent blockage event. This predictive capability allows the system to switch to an alternative beam or path before link interruption takes place.

Integrating blockage awareness into AI-based beam management can significantly enhance link reliability. In such frameworks, beam selection and tracking are performed not only to maximize instantaneous received power, but also to account for the stability and robustness of the communication path. This approach is particularly important in dense urban environments, and high-mobility scenarios [50].

5.6 AI-Driven Codebook-Free Beamforming

One of the fundamental limitations of classical beam management frameworks is their strong reliance on predefined beam sets, commonly referred to as beam codebooks. These codebooks are typically designed in a discrete manner and cover only a limited set of beam directions and beamwidths. As a result, even when the best available beam is selected, precise alignment with the actual propagation path is not always guaranteed, particularly in complex environments with rich multipath reflections. AI-based approaches enable the beamforming process to be liberated from the constraints of predefined codebooks. In this paradigm, machine learning models directly generate beamforming parameters in a continuous domain rather than selecting a beam from a finite set. Such parameters may include antenna weighting coefficients or descriptive beam attributes such as main lobe direction and beamwidth. Compared to discrete codebook-based designs, this approach provides significantly greater flexibility in adapting the beam pattern to the underlying channel conditions [48].

Codebook-free beamforming is particularly relevant for UmMIMO systems, where the very large number of antenna elements enables highly precise beam shaping, while the design of comprehensive and efficient beam codebooks becomes increasingly challenging. By leveraging AI to directly learn the mapping between channel conditions and optimal beam patterns, system performance can be improved and the losses associated with discrete beam approximations can be reduced. Nevertheless, the practical implementation of codebook-free beamforming introduces several challenges. Ensuring beam stability, accommodating hardware constraints, and maintaining compatibility with existing standard frameworks are critical considerations that must be addressed in system design. For this reason, within 5G-Advanced, the primary

focus is placed on approaches that can be introduced in a gradual manner while remaining compatible with current standards [46].

5.7 AI-Driven Low-Latency Beam Management

Rapid decision making at the physical layer is a key requirement of advanced communication systems. In beam management, the latency between observing channel conditions and applying beamforming decisions can have a direct impact on link quality. Classical methods that rely on extensive measurements and sequential reporting often fail to meet stringent latency requirements, particularly in dense deployments or high-mobility scenarios. In AI-based approaches, this limitation is largely mitigated by decoupling the training and inference phases. Machine learning models can be trained offline using large datasets, while in the operational phase, only fast inference is required to support beamforming decisions. This inference typically involves a small number of computational operations and can therefore be executed with very low latency.

Reducing decision latency allows beam management to be more tightly coordinated with other PHY-layer functions, such as modulation and coding adaptation. For instance, if an upcoming change in the optimal beam is predicted, the gNB can proactively update transmission parameters, thereby avoiding sudden link degradation or the need for retransmissions. This coordination plays a critical role in improving user experience and increasing effective data rates. Despite these advantages, AI-based low-latency beam management requires careful architectural design. Factors such as the location of model execution (UE-side or gNB-side), computational power constraints, and energy consumption requirements all influence overall system performance. In practice, achieving an appropriate balance between prediction accuracy and computational complexity remains one of the main challenges in this area.

5.8 Impact of AI-Driven Beam Management on Spectral Efficiency and Data Rate

The application of AI/ML to beam management enables a transition from reactive and resource-intensive approaches to prediction-driven and efficient frameworks. Reducing or eliminating exhaustive beam sweeping, enabling proactive beam tracking under mobility, and incorporating blockage awareness directly reduce signaling overhead and free up additional resources for data transmission. Improved accuracy in beam selection and maintenance directly enhances link quality and increases spectral efficiency. In systems that rely on narrow beams, even modest improvements in beam alignment can lead to significant gains in achievable data rates. From this perspective, AI-based beam management is not merely a performance enhancement but a fundamental enabler for meeting the objectives of 5G-Advanced and Um-MIMO systems.

Overall, AI-based beamforming and beam management techniques, while preserving compatibility with existing 3GPP standard frameworks, provide a clear pathway toward improved scalability, reduced latency, and enhanced performance in advanced cellular networks. These approaches establish a solid foundation for the development of intelligent air interfaces in future generations of wireless communication systems [51].

Chapter 6

Integrated Sensing and Communication

6.1 Introduction

Because of the increasing demand for mobile communication services and the emergence of data-intensive applications, the integration of communication and sensing in wireless networks has become a key enabler for next-generation systems [52]. This paradigm, known as ISAC, leverages the same radio resources to simultaneously transmit data and extract environmental information, thereby improving spectral efficiency and reducing hardware and energy costs [53]. ISAC is particularly relevant for 6G networks, where stringent requirements for low latency and high reliability coexist with advanced sensing capabilities [54]. By exploiting advanced technologies such as massive MIMO, mmW, and terahertz (THz) bands, ISAC enables high-resolution radar-like sensing capabilities while maintaining robust connectivity [55], [56]. This dual-function approach supports a wide range of applications, including Internet of Things ecosystems, smart factories for Industry 4.0, autonomous vehicles and intelligent transportation systems, as well as healthcare monitoring and security surveillance [57], [58]. Furthermore, ISAC facilitates context-aware services, enabling networks to adapt dynamically to user mobility and environmental changes, which is critical for achieving the vision of pervasive and intelligent wireless networks [59].

[55] focuses on how UmMIMO can enable integrated sensing and communication in future 6G networks because it provides spatial diversity for robust links and clutter mitigation; spatial multiplexing for high data rates, and beamforming flexibility for simultaneous communication and sensing beams, as it can be appreciated in figure 6.1. The paper reviews two design paradigms: when communication and sensing share spectrum but operate separately, and when a single platform performs both functions using shared hardware and waveforms.



Figure 6.1: Beamforming illustration on three typical JCAS applications: a) smart home, b) autonomous driving, and c) delivery and environmental monitoring

6.2 Hybrid Beamforming for Multi-Beam ISAC

In [60], the idea is to design a dual-function radar-communication system that uses the same antenna array to perform multi-user MIMO communication and MIMO radar sensing simultaneously. Instead of embedding communication data into a radar waveform, which limits the data rate, the system jointly precodes independent radar waveforms and communication symbols. This approach maximizes the radar degrees of freedom while keeping an acceptable communication quality. The main problems comes from the optimization of the radar beam pattern while ensuring SINR constraints for all users under power constraints per antenna. Two different PHY-layer algorithms are presented as possible solutions: a Joint Transmit Beamforming via semidefinite relaxation (SDR) and via Zero-Forcing.

In [61], the main goal is to jointly optimize transmit and receive beamforming weights in a full-duplex system so that multiple communication beams and a dedicated sensing beam can coexist without causing harmful interference. On the transmitter side, the algorithm combines RF and baseband precoding to form multiple beams for different users, while adding an extra beam for sensing, and it uses null-space projection to suppress inter-user interference. On the receive side, the RF weights are optimized to maximize radar gain in the sensing direction, while implementing multiple frequency nulls to cancel self-interference caused by full-duplex operation. The system employs an OFDM waveform for both communication and sensing, and leverages MIMO processing and the multiple signal classification (MUSIC) algorithm for super-resolution angle estimation, allowing the radar to distinguish targets even when they share the same range.

6.2.1 Joint Transmit Beamforming via SDR

The main objective is to minimize radar loss function under the per-antenna power constraint and SINR constraints for all users.

Considering the transmit signal as: $\mathbf{x}[n] = \mathbf{W}_r \mathbf{s}[n] + \mathbf{W}_c \mathbf{c}[n]$, where $\mathbf{s}[n]$ are the radar waveforms (M elements), $\mathbf{c}[n]$ are the communication symbols (K users), $\mathbf{W}_r$ is the radar precoder ($M \times M$), and $\mathbf{W}_c$ is the communication precoder ($K \times K$), the formulated optimization is the one presented in equation 6.1.

$$\min_{\mathbf{W}} L_r(\mathbf{R}, \alpha) \quad (6.1)$$

Subjected to:

- $\mathbf{R} = \mathbf{W}\mathbf{W}^H$
- Diagonal entries of $\text{diag}(\mathbf{R}) = \frac{P_t}{M}$
- $\text{SINR} \geq \text{threshold}$ for each user

Using SDR, we relax non-convex rank-one constraint to Convex Quadratic SDP, and later solve the convex problem. Upon completion, rank-one precoders using Cholesky decomposition are recovered, and QR decomposition to finally obtain the output precoding matrix $\mathbf{W} = [\mathbf{W}_c, \mathbf{W}_r]$ is done.

6.2.2 Joint Transmit Beamforming via Zero-Forcing (ZF)

The main idea behind this algorithm is the complete cancellation of inter-user interference and radar interference by guaranteeing a high SINR at users.

Considering that $\mathbf{H}\mathbf{W}_c = \text{diag}(\sqrt{p_1}, \dots, \sqrt{p_K})$ and $\mathbf{H}\mathbf{W}_r = 0$, the formulation optimization is:

$$\min_{\mathbf{R}, \alpha} L_r(\mathbf{R}, \alpha) \quad (6.2)$$

Subjected to:

- $\mathbf{R} = \mathbf{W}\mathbf{W}^H$
- $\mathbf{H}\mathbf{R}\mathbf{H}^H = \text{diag}(p)$
- per-antenna power constraint

After the optimization is formulated, the convex QSDP has to be solved for $\mathbf{R}$, and power allocation p_K , later $\mathbf{W}$ has to be recovered using Cholesky and QR decomposition and, finally, output the precoding matrix. The SDR beamforming has a better radar performance, especially when SINR constraints are moderate; however, ZF beamforming -although it has a slight radar performance loss- is much simpler and better for high SINR demands.

6.2.3 TX beamforming optimization and RX beamforming optimization

These are the algorithms presented in [61], which are divided into two main parts: Tx beamforming optimization and Rx beamforming optimization.

Tx Beamforming Optimization

The goal at the transmitter is to form multiple beams for communication users and an additional beam for sensing, while minimizing inter-user interference. First of all, the transmit signal is represented as a combination of RF and baseband precoding, as it is shown in equation 6.3, where $\mathbf{W}_{\text{RF}}^T$ is the RF precoder and $\mathbf{W}_{\text{BB}}^T$ is the baseband precoder.

$$\tilde{\mathbf{x}}_{n,m} = \mathbf{W}_T^{\text{RF}} \mathbf{W}_T^{\text{BB}} \mathbf{x}_{n,m} \quad (6.3)$$

After that, null-space projection (NSP) is applied to the baseband precoders so that each user's precoder lies in the null space of other users' channels, effectively canceling inter-user interference. The optimization objective is to maximize radar power in the sensing direction, while satisfying per-user gain constraints for communication, per-antenna power normalization, and NSP constraints for interference suppression. To obtain it, constrained optimization to jointly optimize RF and BB weights under these conditions is used.

RX Beamforming Optimization

The receiver must sense radar echoes while suppressing self-interference (SI) caused by full-duplex transmission. First of all, the channel between the TX and RX antennas across multiple frequency points is modeled as a SI channel. After that, design RX RF weights for each subarray to lie in the null space of SI channels at N_{freq} frequency samples, ensuring wideband SI suppression. Within the null space, optimized RX RF weights to maximize gain in the sensing direction shown in equation 6.4 are used.

$$\omega_{R,r;l}^{\text{RF}} = \frac{(\mathbf{I} - \mathbf{X}_l \mathbf{X}_l^+) \mathbf{a}_R(\theta_r)}{\|(\mathbf{I} - \mathbf{X}_l \mathbf{X}_l^+) \mathbf{a}_R(\theta_r)\|} \quad (6.4)$$

where $\mathbf{X}_l$ represents the SI channel matrix and $\mathbf{a}_R(\theta_r)$ is the receive steering vector.

6.3 Cooperative and Distributed UmMIMO

The paper [62] introduces a distributed dual-function radar-communications (DFRC) MIMO architecture where multiple radar nodes act as radar and communication transmitters, as shown in figure 6.2. The main idea is to optimize the power allocation across the distributed transmitters in a joint way to achieve radar localization accuracy, expressed through the Cramér-rao bound (CRB), and maximize communication throughput, measured by Shannon capacity. Three optimization problems are presented: one for radar-only operation, another for communication-only using water-filling, and finally a joint DFRC optimization that combines CRB constraints with communication quality-of-service requirements, which demonstrates how multi-objective convex optimization can be applied at the physical layer to balance sensing and communication goals in cooperative networks.

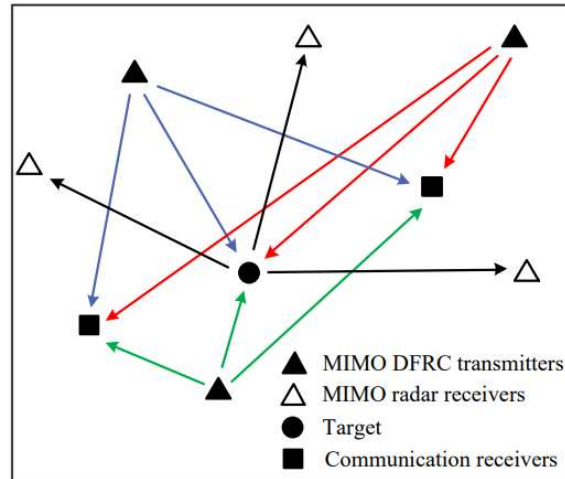


Figure 6.2: Distributed DRFC MIMO system

Meanwhile, [63] focuses on vehicular RadCom networks using MIMO OFDM radar integrated with communication. Instead of relying only on waveform optimization, it introduces an information-fusion approach for multi-target tracking. The method operates in two stages: locally, by combining radar reflections with received communication signals to enhance target estimation; and globally, by merging estimates from neighboring vehicles through vehicle-to-vehicle (V2V) links to form a distributed radar network. At the PHY level, the paper presents several innovations, including joint radar-communication spectrum subtraction to isolate non-communicating targets, covariance differencing for improved direction-of-arrival estimation using MUSIC, and weighted kalman filter fusion that adapts weights based on measurement reliability.

By leveraging OFDM waveforms for dual functionality and exploiting spatial diversity alongside cooperative feedback, this approach significantly improves tracking accuracy in scenarios where radar resolution alone is insufficient. It also demonstrates how distributed processing and cooperative algorithms can complement traditional optimization-based designs, offering robustness in dynamic environments such as intelligent transportation systems. Both works present complementary strategies for enabling ISAC in cooperative MIMO settings. [62] emphasizes optimization-centric PHY algorithms that allocate resources efficiently across distributed nodes, while [63] focuses on fusion-centric algorithms that integrate multiple sources of information for enhanced sensing performance.

6.4 IRS-assisted ISAC

Finally, it is important to talk about the use of intelligence reflecting surfaces (IRSs) for ISAC. In [64], a novel design for a DFRC system that uses an IRS to enhance both radar sensing and communication performance is presented. A NLoS scenario is considered, where the radar uses the IRS-assisted reflection for the detection of the target, while simultaneously serving multiple communication receivers, as it is shown in figure 6.3. The core contribution lies in a joint optimization framework that maximizes a weighted sum of radar and communication SNRs under strict power and constant-modulus constraints on IRS weights. The problem is divided into two issues: Radar waveform design, which is solved via linear programming;

and IRS weight design, which is solved using optimization on a curved constraint surface. This last problem is extremely challenging because the objective function is quartic in the IRS weights, unlike prior work that dealt with quadratic objectives. The solution then consists on an iterative algorithm that ensures convergence while respecting the unit-modulus constraint. Simulation results confirm that IRS deployment significantly boosts radar and communication performance, especially when the number of IRS elements and radar antennas increases. This work introduces a PHY-layer algorithmic approach that combines advanced optimization techniques with IRS-assisted passive beamforming, offering a pathway to overcome NLoS limitations and improve ISAC performance in complex environments.

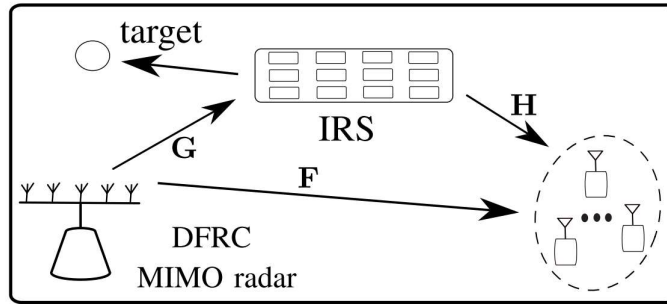


Figure 6.3: Intelligent reflecting surface assisted DFRC system

Meanwhile, [65] addresses the coexistence of radar sensing and communication in mmWave DFRC systems using Reconfigurable Intelligent Surface (RIS) technology. Unlike the previous work that focuses on SNR maximization through alternating optimization, this paper introduces a dynamic RIS partitioning strategy and a hierarchical codebook design for efficient target localization while maintaining strong communication links. The RIS divides into two parts in a dynamic way: one for forming wide or narrow beams for radar localization, and the other for communication beamforming toward the user. The algorithm also works in two modes: surveillance mode, which uses wide beams for coarse detection, and localization mode, which refines beamwidth progressively through multiple stages to find the target. One of the key innovations in the study mentioned above is the method for selecting the number of transmissions per stage in order to achieve a desired localization error probability. It is demonstrated that this approach requires fewer transmissions than exhaustive search methods and achieves spectral efficiency comparable to RIS-assisted MIMO systems without sensing capabilities. This design is a perfect example of a PHY-level solution that integrates adaptive beam management, resource partitioning, and probabilistic performance guarantees, making it highly relevant for real-time ISAC in vehicular or IoT scenarios.

Both papers highlight different strategies for RIS-assisted ISAC. [64] focuses on optimization-centric algorithms that jointly design radar precoders and IRS weights to maximize SNR under manifold constraints, while [65] underlines the importance of an adaptive resource allocation and hierarchical beamforming to balance sensing accuracy and communication throughput. However, both approaches exploit the passive beamforming capabilities of RIS to overcome propagation challenges at high frequencies and demonstrate how intelligent surfaces can fundamentally reshape PHY-layer design for integrated sensing and communication.

Chapter 7

Conclusions

Future cell-free and ultra-massive MIMO wireless systems required transceiver designs that could operate reliably under high mobility, severe propagation conditions, and increasingly tight performance constraints. Conventional physical-layer processing techniques, originally developed for centralized and lower-dimensional MIMO architectures, were not sufficient to meet these requirements. Addressing this gap called for advanced Tx/Rx algorithmic solutions that could jointly enhance robustness, scalability, and efficiency while accommodating the strong coupling between communication, positioning, and sensing functions that characterized beyond-5G and 6G networks.

Building on this need for robust transceiver solutions, the analysis of new waveform designs highlighted the growing importance of delay–Doppler representations in high-mobility environments. The analysis of OTFS-based transmission with superimposed training demonstrated that communication and sensing functionalities could be jointly supported while maintaining spectral efficiency. The results confirmed that accurate delay and Doppler estimation was achievable under dynamic channel conditions. However, practical impairments such as fractional Doppler effects and interference leakage continued to pose challenges, indicating the need for improved estimation, interference mitigation, and low-complexity receiver designs for realistic deployments.

The non-coherent transmission schemes were examined as a scalable alternative to conventional pilot-based coherent methods in ultra-massive MIMO systems. The analysis showed that while Grassmannian and energy-based schemes suffered from complexity and limited multi-user scalability, differential schemes based on antenna averaging achieved a more balanced trade-off between performance and computational cost. When combined with array processing, these approaches exploit spatial selectivity and channel hardening to support reliable multi-user communication with reduced signaling overhead. However, limitations related to constellation design, high-SNR spectral efficiency, and user multiplexing remained, indicating that non-coherent techniques complemented rather than replaced coherent transmission.

Complementing signaling-level robustness, positioning-aided techniques were examined as a key enabler for improving beamforming efficiency in mmW distributed MIMO systems. The proposed 3D indoor positioning framework combined array processing with weighted least-squares estimation and demonstrated the potential to achieve centimeter-level localization accuracy under favorable conditions. The results highlighted the strong sensitivity of positioning accuracy to synchronization errors and measurement noise, particularly in NLoS and multi-path environments. The analysis indicated that accurate timing alignment across distributed APs was critical for reliable localization and formed a necessary foundation for future

positioning-aided transmission and beamforming strategies.

The incorporation of AI-native techniques further extended the transceiver design space by enabling adaptive beam selection, tracking, and blockage awareness without relying on exhaustive beam sweeping or static codebooks. Learning-based approaches demonstrated significant potential in reducing latency and signaling overhead while improving robustness in dynamic and NLoS environments. However, their effectiveness depends strongly on the availability of representative training data, generalization across environments, and resilience to model mismatch, underscoring the need for hybrid solutions that combine data-driven intelligence with model-based signal processing foundations.

Extending these data-driven and context-aware transceiver capabilities, the discussion on integrated sensing and communication positions ISAC as a unifying paradigm for future wireless systems, where communication signals and hardware were jointly exploited for environmental awareness. Hybrid beamforming, cooperative ultra-massive MIMO architectures, and IRS-assisted designs illustrated that sensing accuracy, communication reliability, and resource efficiency could be jointly optimized within a single framework. At the same time, these approaches introduced new trade-offs related to interference management, coordination overhead, and system complexity, particularly in distributed and densely deployed network scenarios.

In summary, Tx/Rx designs for cell-free ultra-massive MIMO systems required tightly integrated physical-layer solutions that jointly support communication, positioning, sensing, and intelligence. While the techniques discussed in this work demonstrated strong potential in improving efficiency and robustness, key challenges related to NLoS operation, synchronization, scalability, and real-time implementation remain. Addressing these issues is essential for enabling practical, reliable, and energy-efficient 6G wireless systems. The MiFuture consortium will keep researching, and this deliverable will be updated with D2.8.

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