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**Millimeter-wave massive MIMO
channel characterization and modelling
for 5G and 6G applications**

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Sciences and Technology

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Dedication

To my mother Mary Chifamba and my beloved family

"Chisingaperi chinoshura, chinobhururuka chinomhara."

Source: Shona idioms and proverbs

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List of acronyms

AOA	Azimuth Angle of Arrival
AOD	Azimuth Angle of Departure
ACF	Auto-Correlation Function
APDP	Average Power Delay Profile
AS	Angular Spread
BS	Base Station
BW	Bandwidth
CDF	Cumulative Distribution Function
CG	Channel Gain
CIR	Channel Impulse Response
COST	Cooperation in Science and Technology
CSI	Channel State Information
CTF	Channel Transfer Function
D2D	Device to Device
DMCs	Dense Multipath Components
DOA	Direction of Arrival
DOD	Direction of Departure
DS	Root Mean Square Delay Spread
EM	Electromagnetic
EVD	Eigenvalue Decomposition
FDD	Frequency Domain Duplexing
FP	Floor Plans
FT	Fourier Transform
GSCM	Geometry based Stochastic Channel Model
I2O	Indoor to Outdoor
i.i.d.	Independent and Identically Distributed
IMT-Advanced	International Mobile Telecommunications Advanced

InF	Indoor Factory
InLab	Indoor Laboratory
InMixOffice	Indoor Mixed Office
InOpOffice	Indoor Open Office
ITU	International Telecommunication Union
LOS	Line of Sight
M2M	Machine to Machine
MCD	Multipath Component Distance
METIS2020	Mobile and wireless communications Enablers for the Twenty-twenty Information Society
MIMO	Multiple Input Multiple Output
MISO	Multiple Input Single Output
mMIMO	Massive MIMO
mmMAGIC	mm-wave based Mobile radio Access network for fifth Generation Integrated Communications
mmWave	millimeter waves
MRC	Maximum Ratio Combining
MRT	Maximum Ratio Transmission
MPCs	Multipath Components
MU-MIMO	Multiple User Multiple Input Multiple Output
MU	Multiple User
NLOS	Non Line of Sight
non-GSCM	Non Geometry based Stochastic Channel Model
O2I	Outdoor to Indoor
O2O	Outdoor to Outdoor
OLOS	Obstructed Line of Sight
PADP	Power Angular Delay Profile
pdf	Probability Density Function
PDP	Power Delay Profile
PL	Path Loss
QUADRIGA	Quasi Deterministic Radio Channel Generator
RMS	Root Mean Square
RX	Receiver
SAGE	Space Alternating Generalized Expectation Maximization
SIMO	Single Input Multiple Output
SISO	Single Input Single Output
SNR	Signal to Noise Ratio
SOTA	State-Of-The-Art

SU-MIMO	Single User Multiple Input Multiple Output
SVD	Singular Value Decomposition
TDD	Time Domain Duplexing
TDL	Tapped Delay Line
TOA	Time of Arrival
T-RIS	Transmitting Reconfigurable Intelligent Surface
TVCFR	Time Varying Channel Frequency Response
TVCIR	Time Varying Channel Impulse Response
TX	Transmitter
2D	Two Dimensional Space
3D	Three Dimensional Space
UE	User Equipment
UC	Unit Cell
US	Uncorrelated Scattering
UWB	Ultra-wideband
V2V	Vehicle to Vehicle
VCA	Virtual Cubic Array
VCR	Virtual Channel Representation
VNA	Vector Network Analyzer
VPA	Virtual Planar Array
WINNER	Wireless World Initiative New Radio
WSS	Wide Sense Stationarity
WSSUS	Wide-Sense Stationary Uncorrelated Scattering
ZFBF	Zero-Forcing Beamforming
3GPP	3rd Generation Partnership Project
3GPP-SCM	3rd Generation Partnership Project Spatial Channel Model
3GPP-SCME	3rd Generation Partnership Project Spatial Channel Model Extension
5G	Fifth Generation
6G	Sixth Generation

Notations

The mathematical notations and variables used in our work are summarized in the following table.

Set Theory

$\mathbb{R}$	Set of real numbers
$\mathbb{R}^{L \times N}$	Matrix of real numbers composed of L lines and N columns
$\in$	Is an element of
$\mathbb{C}$	Set of complex numbers
$\mathbb{C}^{L \times N}$	Matrix of complex numbers composed of L lines and N columns

Mathematical Notations

$\delta(\dots)$	Dirac delta function
$\exp(\dots)$ or e^x	Exponential function
$\sqrt{x}$	Square root of x
$\sum_{n=1}^N$	Summation
$ x $	Absolute value of x
x^n	x raised to the n^{th} power
$\bar{x}$	Average value of x
$\ln$	Natural logarithm
$\mathbf{A}^T$	Transpose of matrix $\mathbf{A}$
$\mathbf{A}^*$	Hermitian transpose of matrix $\mathbf{A}$
$\log_{10}$	Logarithm function base 10
$\mathbb{E}[x]$	Expectation of a random variable x
$tr(\mathbf{A})$	Trace of matrix $\mathbf{A}$
$\odot$	Element-wise Schur-Hadamard multiplication

$\otimes$	Kronecker multiplication
$vec(\mathbf{A})$	Vectorization of matrix $\mathbf{A}$
$\ \cdot\ $	Frobenius norm
$\mathbf{h}_{l,x}^j$	Channel vector of the user equipment x in the cell l and being served with base station j

Variables

B	Bandwidth
c	Speed of light
f_c	Center frequency
$h_c(t, \tau)$	Time varying channel impulse response
τ_{excess}	Maximum excess delay
τ_l	Delay of the l -th discrete path
λ	Wavelength
α_l	Amplitude of the l -th discrete path
ϕ_s	Azimuth steering or scanning angle
θ_s	Elevation steering or scanning angle
ϕ	Azimuth angle
θ	Elevation angle
φ_{RX}	Direction of arrival
φ_{TX}	Direction of departure
L	Number of multipath components (MPCs)
M_j	Number of antennas at the base station j
PDP	Power delay profile
$PL_0 (G_0)$	Path loss (channel gain) intercept in $[dB]$ at the reference distance d_0
d_0	Reference distance equal to 1 m
X_σ	Variation due to long-term fading effects
σ	Standard deviation of the large-scale fading in $[dB]$
σ_τ	Standard deviation of the delay spread in $[ns]$
σ_ϕ	Standard deviation of the azimuth angular spread in $[\circ]$
σ_θ	Standard deviation of the elevation angular spread in $[\circ]$
t	Time
T_c	Coherence time

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Abstract

In recent years and in the scope of Fifth Generation (5G) and Sixth Generation (6G) technologies, the joint deployment of Massive MIMO (mMIMO) and millimeter waves (mmWave) technologies has shown very promising results in the quest to meet the very high consumer data rate demands. To design real mmWave mMIMO wireless systems and predict their performances under certain conditions, it is imperative to have accurate mmWave mMIMO wireless channel models that capture the key characteristics for different scenarios. Very high gain and directive Transmitting Reconfigurable Intelligent Surface (T-RIS)s with electronic beamscanning capabilities are also expected to be ubiquitous in 5G and 6G wireless communication systems and hence the need to investigate the channel and T-RIS joint effect.

This thesis presents different channel characterizations and models for indoor mmWave mMIMO radio propagation channels based on stochastic approaches. Different channel measurement campaigns were carried out in Indoor Laboratory (InLab), Indoor Open Office (InOpOffice), Indoor Mixed Office (InMixOffice), corridors and Indoor Factory (InF) environments. Massive virtual arrays and T-RISs were employed in the channel measurements. Line of Sight (LOS), Obstructed Line of Sight (OLOS) and Non Line of Sight (NLOS) propagation conditions were investigated in these environments.

For the large virtual arrays' measurements, an investigation on the impact of the array size and geometry on the mmWave mMIMO channel characteristics is performed. Spatial channel correlation over the massive array is investigated and Multipath Components (MPCs) are estimated by means of a high resolution detection algorithm. The estimated specular MPCs parameters are then used for further analysis. Dense Multipath Components (DMCs) are quantified. Common MPCs between different sub-arrays of a massive array are identified following a joint temporal, power and angular threshold criterion and their distributions are then analyzed.

For the T-RISs' measurements, an investigation on the T-RISs beamscanning capabilities and the impact of T-RISs beamforming on the indoor mmWave radio channel characteristics is carried out. The T-RISs measurements involve the synthesis of an omnidirectional Power Delay Profile (PDP) in order to extract the critical temporal and spatial characteristics of the MPCs. For the InOpOffice and the InF environments, both the propagation channel and the T-RIS antenna are modelled separately. The T-RIS pattern is then plugged into the propagation channel and the resulting synthesized channel models are compared to the channel models obtained from the actual T-RIS channel measurements.

Path loss and delay spread models for the different indoor environments are modelled and discussed. Statistical spatio-temporal channel models are also derived for the different indoor mmWave mMIMO channel measurements (based on the massive arrays as well as the T-RIS).

Keywords: Massive MIMO, Millimeter waves, Channel Modelling, Channel Sounding, Indoor Channels, Industrial Channels, Propagation, 5G, 6G.

Chapter 1

Introduction

In line with the famous proverb, "Necessity is the mother of all invention", the mankind desire to communicate over distances greater than that feasible with the human voice has led to the invention of numerous and different forms of conveying information. These include postal services and telecommunications. Telecommunications involve the transmission of information over the wire, radio, optical, or other electromagnetic systems. In scenarios where wired communication systems do not exist, are infeasible to deploy or are too costly etc., the wireless radio channel becomes the crucial medium over which information is transmitted. Unlike in wired communications, where signals are transmitted or received via a physical media, in wireless communications, the antenna is a very essential part of the system. The transition of the wireless communication systems from the traditional Single Input Single Output (SISO) systems to Single Input Multiple Output (SIMO), Multiple Input Single Output (MISO) and Multiple Input Multiple Output (MIMO) systems resulted in more robust and reliable communications offering high data rates. The introduction of mMIMO, which in essence is an extension of MIMO, has also led to enhanced system perfor-

mances.

In recent years and in the scope of 5G and 6G technologies, the joint deployment of mMIMO and mmWave technologies has shown promising results in meeting the very high consumer data rates demands. To design real mmWave mMIMO wireless systems and predict their performances under certain conditions, it is imperative to have accurate mmWave mMIMO wireless channel models that capture the key characteristics for different scenarios. Very high gain and directive T-RISs with electronic beamscanning capabilities are also expected to be ubiquitous in 5G and 6G wireless communication systems and hence the need to investigate the channel and T-RIS joint effect. This chapter presents an overview of the State-Of-The-Art (SOTA) on both mMIMO and classical channel measurements and modelling. The chapter commences by introducing the fundamentals of channel modelling. Different channel modelling approaches are discussed and examples of standardized channel models and their characteristics are briefly presented. Extensive references for sub-6 GHz mMIMO and mmWave mMIMO channel characterization and modelling are provided. Finally the thesis contributions and outline are presented.

The remainder of this chapter is outlined as follows: Section 1.1 introduces the double-directional channel concept. The different propagation mechanisms are outlined in Section 1.2. Simplified channel functions are defined in Section 1.3. In Section 1.4, statistical channel metrics are presented while Section 1.5 briefly presents some of the channel parameter estimation techniques. Section 1.6 presents the different channel modelling approaches. Section 1.7 focuses on MIMO channel modelling. Examples of standardized channel models are given in Section 1.8. Section 1.9 introduces mMIMO. mMIMO channel characterization and modelling is discussed in detail in Section 1.10. The T-RIS technology is intro-

duced in Section 1.11. Finally, the last two sections, Section 1.12 and Section 1.13, respectively, present the thesis contributions and gives the thesis outline.

1.1 The Wireless Communication Channel

In wireless communications, an antenna is a very essential part of the system. Understanding the radiation and reception of wireless antennas as well as the propagation of electromagnetic fields between these antennas is very crucial. The wireless communication channel is the medium over which the Electromagnetic (EM) waves from the transmitting antenna reach the receiving antenna. In [3–5], a distinction between the radio channel and the propagation channel is given. Fig 1.1, shows the different channel definitions. The communication system shown comprises a Transmitter (TX) with M antennas and a RX with N antennas.

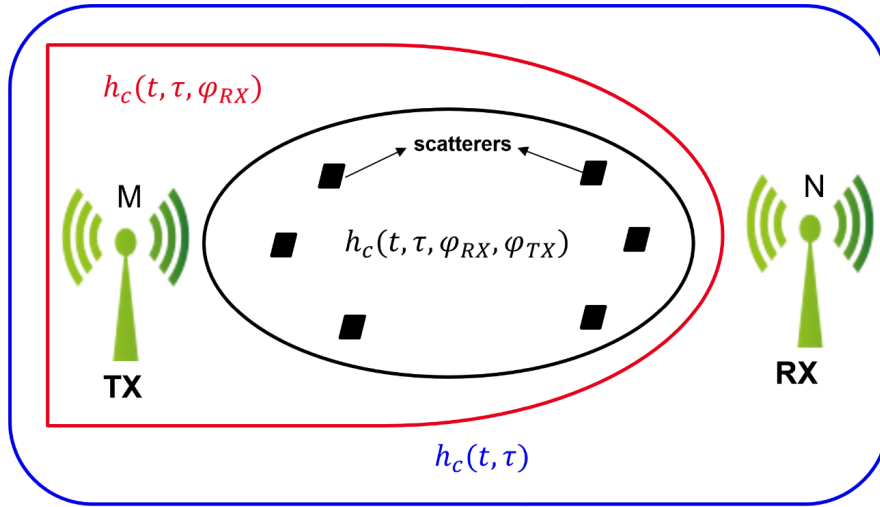


Figure 1.1: Double-directional channel definitions.

1.1.1 Double Directional Radio Propagation Channel

For time-invariant (static) channels, and disregarding the polarization, the propagation channel is described by the double-

directional channel impulse response, $h_c(\mathbf{r}_{RX}, \mathbf{r}_{TX}, \tau, \varphi_{RX}, \varphi_{TX})$. For the sake of compactness, we exclude $\mathbf{r}_{RX}$ and $\mathbf{r}_{TX}$, which are the positions of the RX and TX, respectively, from the double-directional channel and denote it as $h_c(\tau, \varphi_{RX}, \varphi_{TX})$ with the variables defined in (1.1). The propagation channel excludes the antenna influence from the measurement results.

$$h_c(\tau, \varphi_{RX}, \varphi_{TX}) = \sum_{l=1}^L h_{c,l}(\tau, \varphi_{RX}, \varphi_{TX}) \quad (1.1)$$

where τ , φ_{RX} , φ_{TX} , L is the excess delay, the Direction of Arrival (DOA), the Direction of Departure (DOD) and the total number of MPCs, respectively. For planar waves, the contribution of the l -th path can be expressed as a function of Dirac deltas (1.2) while for non-planar waves, appropriately chosen functions are considered.

$$h_{c,l}(\tau, \varphi_{RX}, \varphi_{TX}) = \alpha_l \delta(\tau - \tau_l) \delta(\varphi_{RX} - \varphi_{RX,l}) \delta(\varphi_{TX} - \varphi_{TX,l}) \quad (1.2)$$

where α_l , τ_l , $\varphi_{RX,l}$, $\varphi_{TX,l}$, respectively, denote the complex amplitude, delay, DOA and DOD associated with the l -th MPC.

Regarding time-variant (non-static) channels, the Time Varying Channel Impulse Response (TVCIR) is given by (1.3):

$$h_c(t, \tau, \varphi_{RX}, \varphi_{TX}) = \sum_{l=1}^L h_{c,l}(t, \tau, \varphi_{RX}, \varphi_{TX}) \quad (1.3)$$

1.1.2 MIMO Channel

Considering time-variant (non-static) channels, the radio channel is described by a non-directional TVCIR, $h_c(t, \tau)$. For a MIMO system with M transmit and N receive antennas, the receive signal vector, $\mathbf{y}(t)$ of length N is given by (1.4). The MIMO channel

includes antenna properties and pulse shaping [6].

$$\mathbf{y}(t) = \int_{\tau} \mathbf{H}(t, \tau) \mathbf{s}(t - \tau) d\tau + \mathbf{n}(t) \quad (1.4)$$

where $\mathbf{s}(t)$ is the transmit signal vector of length M , $\mathbf{n}(t)$ models the noise and interference and is of length N . $\mathbf{H}(t, \tau)$ is the $M \times N$ channel matrix (1.5) describing each single realization of the channel.

$$\mathbf{H}(t, \tau) = \begin{bmatrix} h_{c_{11}}(t, \tau) & h_{c_{12}}(t, \tau) & \dots & h_{c_{1n}}(t, \tau) \\ h_{c_{21}}(t, \tau) & h_{c_{22}}(t, \tau) & \dots & h_{c_{2n}}(t, \tau) \\ \vdots & \vdots & \ddots & \vdots \\ h_{c_{m1}}(t, \tau) & h_{c_{m2}}(t, \tau) & \dots & h_{c_{mn}}(t, \tau) \end{bmatrix} \quad (1.5)$$

where $h_{c_{ij}}(t, \tau)$ denotes the time-variant impulse response between the i -th transmit antenna and the j -th receive antenna. In considering polarization, each element of the matrix $\mathbf{H}(t, \tau)$ is replaced by a polarimetric submatrix describing the coupling of vertically and horizontally polarized modes [6].

For time-invariant systems, equation (1.4) is expressed by a delay-only dependent channel matrix $\mathbf{H}(\tau)$ as follows:

$$\mathbf{y}(t) = \int_{\tau} \mathbf{H}(\tau) \mathbf{s}(t - \tau) d\tau + \mathbf{n}(t) = \mathbf{H}(\tau) * \mathbf{s}(t) + \mathbf{n}(t) \quad (1.6)$$

where $*$ denotes the convolution operator. For frequency-flat fading channels, the channel matrix is non-zero only for $\tau = 0$ and therefore equation (1.6) further simplifies to (1.7).

$$\mathbf{y}(t) = \mathbf{H}(t) \mathbf{s}(t) + \mathbf{n}(t) \quad (1.7)$$

For frequency-flat fading channels and for discrete time, equation

(1.6) simplifies to (1.8)

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n} \quad (1.8)$$

1.1.3 Relationship between the double directional radio propagation channel and the MIMO channel

The double-directional impulse response characterizes the physical propagation channel excluding antenna properties and pulse shaping. To the contrary, the MIMO channel includes antenna properties and pulse shaping [6]. In essence, the MIMO channel matrix describes the response between the antennas at both link ends, given a specific antenna configuration and bandwidth [5]. For time-invariant (static) channels and in disregarding polarization, the relationship between the double-directional impulse response and the MIMO channel impulse response is given by equation (1.9):

$$\begin{aligned} h_{c_{ij}}(\tau) = & \int_{\varphi_{RX}} \int_{\varphi_{TX}} \int_{\tau'} h_c(\tau', \varphi_{RX}, \varphi_{TX}) \\ & \times g_{RX}^{(j)}(\varphi_{RX}) g_{TX}^{(i)}(\varphi_{TX}) f(\tau - \tau') d\tau' d\varphi_{TX} d\varphi_{RX} \end{aligned} \quad (1.9)$$

where $h_{c_{ij}}(\tau)$ denotes the time-invariant impulse response between the i -th transmit antenna and the j -th receive antenna. $g_{RX}^{(j)}(\varphi_{RX})$ and $g_{TX}^{(i)}(\varphi_{TX})$, respectively, denote the antenna patterns for the RX and the TX while $f(\tau)$ stands for the overall impulse response of RX and TX antennas and frequency filters.

1.2 Propagation Mechanisms

The emitted EM waves reach the receiving antenna from many directions due to physical propagation mechanisms such as free-space propagation, reflection, refraction, diffraction, and scattering etc. [7, 8]. When there is a direct line of sight (LOS) path from the TX to the receiver, we have free-space propagation. In most cases,

the transmitted wave has no line of sight to the receiver and only the indirect radio wave paths reach the receiver – thanks to the obstacle related phenomena like reflection, refraction, diffraction, and scattering. Reflections occur when electromagnetic signals strike smooth surfaces at an angle and are reflected toward the receiver. For electromagnetic waves striking smooth surfaces (specular reflection), the laws of reflection hold [9]. However for EM waves striking rough surfaces, diffuse reflection or scattering occurs and the laws of reflection may no longer hold. Scattering of the EM signal also happens when the EM signal strikes objects (e.g water droplets or clouds) that are much smaller than a wavelength [10]. Refraction happens when the propagation path of an electromagnetic signal propagating through a structure changes as a result of the difference in the electrical properties of the medium. Boundary conditions help to determine the extent of the refraction [7]. Diffraction occurs when an electromagnetic signal strikes edges or corners of structures that are large in terms of wavelength, such as building rooftops and hilltops [11]. In essence, the aforementioned propagation mechanisms (leading to indirect radiowave paths) are created by obstacles present in the wireless channel. These obstacles include infrastructures, cars, trees, hills, mountains, etc. Due to these physical propagation mechanisms, the receiving antenna receives multiple copies of the transmitted signal from many directions and this is known as multipath propagation. Fig. 1.2 shows the concept of multipath propagation and some of the main propagation phenomena. As a result of multipath in wireless communications, the received signal consists of an infinite sum of attenuated, delayed, and phase-shifted replicas of the transmitted signal. This summation or superposition of the replicas can be constructive or destructive depending on the phase of each individual replica and it is defined for a given time instant t as the Channel Impulse Response (CIR). Phases of the signals arriving at the receiver may

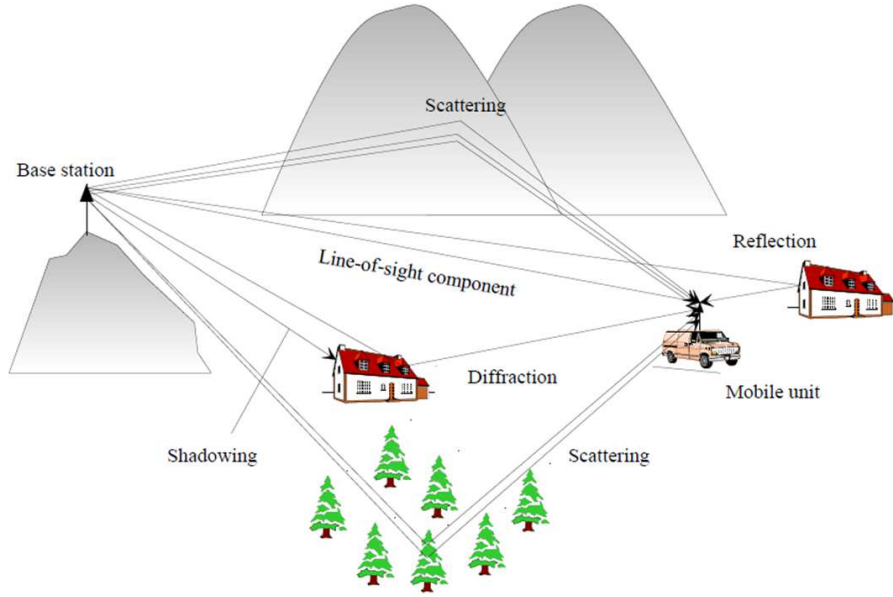


Figure 1.2: Principle of multipath propagation [1].

change due to movement of either the transmitter or the receiver or of any obstacles in the channel. This results in the variation of the received signal strength due to the different ways in which the signals sum together at the RX. This phenomena is called small-scale fading (fast fading or short-term fading) and it will be discussed later. As a result of the aforementioned phenomena, the CIR is time-variant. In practice, characterizing all these processes is not an easy task. Consequently, the widely adopted approach is to describe the channel statistically. Below, we will discuss the channel characterization approaches in detail.

The radio channel can be modelled as a linear filter. This means that the characteristics of the channel can be modelled by finding the impulse response of the channel. The generalized TVCIR is

represented as follows:

$$h_c(t, \tau) = \sum_{l=1}^L \alpha_l(t) \exp(j\psi_l(t)) \delta(\tau - \tau_l(t)) \quad (1.10)$$

where $\alpha_l(t)$ is the time varying amplitude of the l -th path, $\psi_l(t)$ is the time varying phase of the l -th path, which can include effects of Doppler, $\tau_l(t)$ is the time varying delay of the l -th path and t is the absolute time. The Fourier Transform (FT) duality holds for the TVCIR, $h_c(t, \tau)$ and Time Varying Channel Frequency Response (TVCFR), $H_c(t, f)$ as given by (1.11) and (1.12).

$$h_c(t, \tau) = \int_{-\infty}^{\infty} H_c(t, f) \exp(i2\pi f\tau) df \quad (1.11)$$

$$H_c(t, f) = \int_{-\infty}^{\infty} h_c(t, \tau) \exp(-i2\pi f\tau) d\tau \quad (1.12)$$

The delay Doppler function $S(\nu, \tau)$ and the frequency Doppler function $B(\nu, f)$ are two other functions related to the TVCIR and TVCFR, respectively, through the FT operation with respect to the variable t . In particular, $S(\nu, \tau)$ is obtained following (1.13) and $B(\nu, f)$ is obtained following (1.14). $S(\nu, \tau)$ is also known as the spreading function and it describes the spreading effect of the radio channel to the transmitted signal in both the delay and Doppler domains [12].

$$S(\nu, \tau) = \int_{-\infty}^{\infty} h_c(t, \tau) \exp(-i\nu t) dt \quad (1.13)$$

$$B(\nu, f) = \int_{-\infty}^{\infty} H_c(t, f) \exp(-i\nu t) dt \quad (1.14)$$

where ν is a frequency variable and represents the Doppler shift in radians/seconds.

Since the radio channel is a random process, it is therefore interpreted as a random time-variant linear system. To fully describe these radio channels, a joint multidimensional pdf of all the system functions is required. This pdf is in practice, very complicated to get. Consequently, a more realistic approach, yet less accurate, based on second-order statistics of the time variant system functions known as Auto-Correlation Function (ACF)s is often employed. The ACFs of the channel are obtained as follows :

$$R_h(t, t'; \tau, \tau') = \mathbb{E} [h_c(t, \tau) h_c^*(t', \tau')] \quad (1.15)$$

$$R_H(t, t'; f, f') = \mathbb{E} [H_c(t, f) H_c^*(t', f')] \quad (1.16)$$

$$R_S(\nu, \nu'; \tau, \tau') = \mathbb{E} [S(\nu, \tau) S^*(\nu', \tau')] \quad (1.17)$$

$$R_B(\nu, \nu'; f, f') = \mathbb{E} [B(\nu, f) B^*(\nu', f')] \quad (1.18)$$

Fig. 1.3 shows the relationships between the system functions and the correlation functions where $\mathcal{F}_\tau$ or $\mathcal{F}_t$ denote the FT with respect to the subscript variable. Likewise, $\mathcal{F}_\tau \mathcal{F}_{\tau'}$ or $\mathcal{F}_t \mathcal{F}_{t'}$ denote the double FTs with respect to the subscript variables.

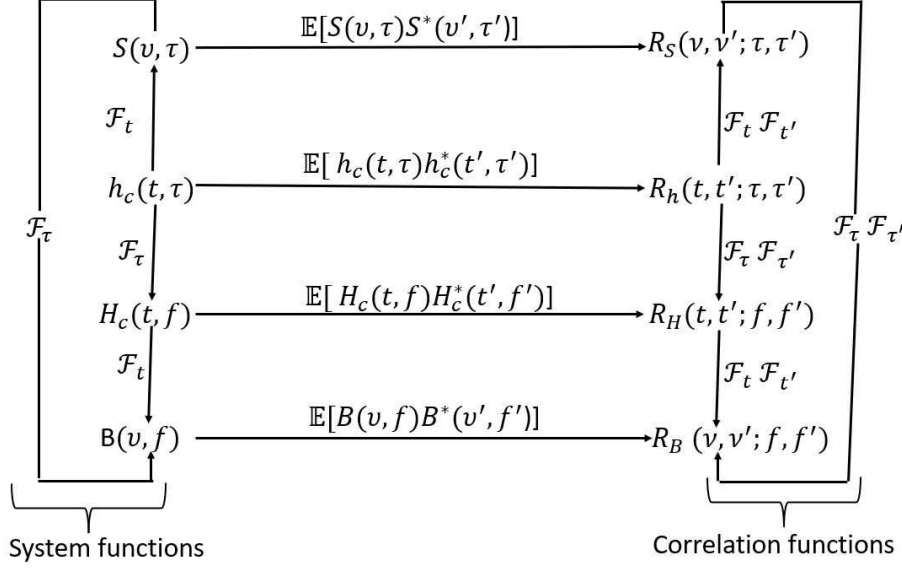


Figure 1.3: Relationships between system functions and correlation functions

1.3 Simplified Channel Functions

1.3.1 Wide-Sense-Stationarity

Wide Sense Stationarity (WSS) implies that the second-order time statistics of the channel are stationary [13]. Over short periods of time or over small spatial distances, mobile radio channels are assumed to be stationary and this stationarity can be wide-sense or weak-sense. Assuming the WSS of the channel over small-scale times and distances, we can further simplify the impulse response (1.10) to be approximated as:

$$h_c(\tau) = \sum_{l=1}^L \alpha_l \exp(j\psi_l) \delta(\tau - \tau_l) \quad (1.19)$$

It is worth noting that the FT duality holds for $h_c(\tau)$ and $H_c(f)$. Wide-Sense-Stationary channels have the property that the channel correlation functions are invariant under a translation in time

or space and this means that the fading statistics do not change over a short time interval and that the ACF is independent of the absolute time. Consequently, the ACF is only a function of the time difference $\Delta t = t - t'$ and not of the absolute time t [12]. Therefore, the ACF of TVCIR (1.15) simplifies to:

$$R_h(t, t'; \tau, \tau') = R_h(\Delta t; \tau, \tau') \quad (1.20)$$

Likewise, in assumming WSS, the other time dependent correlation function (1.16) reduces to:

$$R_H(t, t'; f, f') = R_H(\Delta t; f, f') \quad (1.21)$$

1.3.2 Uncorrelated Scattering

The Uncorrelated Scattering (US) assumption, assumes that the scatterers contributing to the delay spread in the channel have independent fading, that is, the individual scattered components arriving at the RX side (at different propagation delays) are assumed to be uncorrelated. US implies stationarity in the transmission frequency domain, which is the frequency in the passband of the channel [13]. In other words, the second order statistics in frequency depends on the frequency difference $\Delta f = f - f'$ and not on the absolute frequency f . Hence, the ACF of the time variant frequency response TVCFR (1.16) becomes:

$$R_H(t, t'; f, f') = R_H(t, t'; \Delta f) \quad (1.22)$$

Likewise, the ACF of the frequency Doppler function (1.18) becomes:

$$R_B(\nu, \nu'; f, f') = R_B(\nu, \nu'; \Delta f) \quad (1.23)$$

1.3.3 Wide-Sense-Stationary and Uncorrelated Scattering

The combination of WSS and US yield the Wide-Sense Stationary Uncorrelated Scattering (WSSUS) model which is stationary in time and transmission frequency domains and conversely has independent components in the Doppler frequency (ν) and delay (τ) dimensions [13]. US and WSS channels are considered to be time-frequency duals; that is a channel which exhibits US in one domain exhibits WSS in the other domain [12]. Considering WSSUS assumptions, the ACFs reduce to [14]:

$$R_h(t, t + \Delta t; \tau, \tau') = P_h(\Delta t, \tau) \delta(\tau - \tau') \quad (1.24)$$

$$R_H(t, t + \Delta t; f, f + \Delta f) = R_H(\Delta t, \Delta f) \quad (1.25)$$

$$R_S(\nu, \nu'; \tau, \tau') = P_S(\nu, \tau) \delta(\nu - \nu') \delta(\tau - \tau') \quad (1.26)$$

$$R_B(\nu, \nu'; f, f + \Delta f) = P_B(\nu, \Delta f) \delta(\nu - \nu') \quad (1.27)$$

where $P_h(\Delta t, \tau)$ is called the delay cross power spectral density, $R_H(\Delta t, \Delta f)$ is called the time frequency correlation function, $P_S(\nu, \tau)$ is called the delay Doppler function (the scattering function of the channel) and $P_B(\nu, \Delta f)$ is called the Doppler cross power spectral density. These aforementioned functions depend on only two variables and this simplifies the analysis; compared with the autocorrelation functions in equations (1.15, 1.16, 1.17 and 1.18) that depend on four variables. The functions, $P_h(\Delta t, \tau)$, $R_H(\Delta t, \Delta f)$, $P_S(\nu, \tau)$ and $P_B(\nu, \Delta f)$ are related to each other via FTs [12].

1.4 Statistical channel metrics

1.4.1 Power delay profile

The PDP of a channel represents the average power of the received signal in terms of the delay with respect to the first arrival path in multipath transmission. In assuming WSSUS, the $PDP(\tau)$ is computed following (1.28).

$$PDP(\tau) = \mathbb{E} [|h_c(t, \tau)|^2] = \sum_{l=1}^L P_l \delta(\tau - \tau_l) \quad (1.28)$$

where $P_l = \langle |\alpha_l(t)|^2 \rangle = \alpha_l^2$, $\tau_l = \langle \tau_l(t) \rangle$ and $\langle z \rangle$ denote the estimate of the random value z . The $PDP(\tau)$ function can be obtained from $P_h(\Delta t, \tau)$ by setting the time difference to zero or from $P_S(\nu, \tau)$ by summing the power contribution from all the Doppler shifted components [12].

1.4.2 Delay spread

The delay spread is inversely related to the coherence bandwidth of the channel, and it shows an overview of the delay dispersion of the MPCs arriving at the receiver. Coherence bandwidth is the range of frequencies over which the frequency is flat, or has constant gain (no frequency selective fading). The delay spread conveys crucial information with regards to the type of fading (flat or frequency selective) the channel is subjected to. The typical delay spread metrics are root mean square delay spread (τ_{rms}) and the maximum delay spread τ_{max} (also known as the maximum excess delay spread). The former metric is obtained following (1.29) and (1.30). The metric τ_{rms} determines the range of delay over which the PDP is essentially non-zero. τ_{rms} is the second central moment of the PDP. The metric τ_{max} corresponds to the difference between

the longest and the shortest delays of the detected paths.

$$\tau_{rms} = \sqrt{\frac{\sum_{l=1}^L (\tau_l - \tau_m)^2 \alpha_l^2}{\sum_{l=1}^L \alpha_l^2}} \quad (1.29)$$

where τ_m is the mean arrival delay of the multipaths and is computed as follows:

$$\tau_m = \frac{\sum_{l=1}^L \alpha_l^2 \tau_l}{\sum_{l=1}^L \alpha_l^2} \quad (1.30)$$

with L , α_l^2 and τ_l being the number of detected MPCs, the power of the l -th path and the arrival delay of the l -th path, respectively.

1.4.3 Angular spread

The angular spread φ_{rms} , an important parameter in MIMO systems, shows the degree of space selectivity. Typically, large angle spreads support spatial multiplexing and antenna diversity schemes which in turn lead to increased channel capacity. On the other hand, small angle spreads enable efficient beamforming technology [15]. The root mean square angular spread, φ_{rms} , is obtained from (1.31) and (1.32).

$$\varphi_{rms} = \sqrt{\frac{\sum_{l=1}^L (\varphi_l - \varphi_m)^2 \alpha_l^2}{\sum_{l=1}^L \alpha_l^2}} \quad (1.31)$$

where φ_m is the mean arrival or departure angle of the multipath and is calculated as follows:

$$\varphi_m = \frac{\sum_{l=1}^L \alpha_l^2 \varphi_l}{\sum_{l=1}^L \alpha_l^2} \quad (1.32)$$

with L , α_l^2 and φ_l being the number of detected MPCs, the power of the l -th path and the angle of arrival or departure of the l -th path, respectively.

1.4.4 Doppler spectrum and Doppler spread

The Doppler Power Spectral Density, $P_S(\nu)$, is related to the Root Mean Square (RMS) Doppler spread B_d in a similar way the $PDP(\tau)$ is related to τ_{rms} . In essence, the mathematical formulation is the same (replacing the PDP with $P_S(\nu)$ and τ with ν). The $P_S(\nu)$ is obtained from $P_S(\nu, \tau)$ by summing the contribution from all MPCs along the time delay axis [12]. The following equation shows the computation of the Doppler spectrum:

$$P_S(\nu) = \mathbb{E}_\tau [|S(\nu, \tau)|^2] = \int_\tau P_S(\nu, \tau) d\tau \quad (1.33)$$

Doppler spread, B_d , is a measure of spectral broadening caused by the time rate of change of the mobile radio channel. It is defined as the range of frequencies over which the received Doppler spectrum is essentially nonzero. Basically, if the bandwidth of the transmitted signal is much larger than the Doppler spread, the effects of the Doppler spread are considered negligible at the receiver [16]. Coherence time T_c is the time over which the channel remains relatively constant. In other words, it is a statistical measure of the time duration over which the channel impulse response remains unchanged (highly correlated). In static environments, T_c is generally large but in situations involving mobility of either the TX or RX or of obstacles in the channel, the observed channel at the RX will change much quicker with time. T_c is inversely related to the Doppler spread B_d following (1.34).

$$B_d = \frac{1}{T_c} \quad (1.34)$$

During T_c , the channel is considered invariant over time and this is when the normalized time correlation function is $R_H(\Delta t) \simeq 1$. T_c can be approximated as the time it takes to move a substantial

fraction of the wavelength λ , for example $T_c = \frac{\lambda}{4v}$ where v is the velocity of the User Equipment (UE) [17].

1.4.5 Channel components

The channel power can be represented as a combination of three components: Path Loss (PL), large-scale fading and small-scale fading. Fading in propagation channels can either be large-scale or small-scale. Large-scale fading corresponds to path loss of signal as a function of distance and shadowing by large objects such as buildings and hills. As the transmitted EM waves propagate in free space, from the transmitting antenna to the receiving antenna via the wireless communication channel, they experience a reduction in the signals strength (power). This reduction in the signals power is known as the PL. The free space path loss experienced by the EM waves is given by:

$$FSPL(f, d) = \left(\frac{4\pi d}{\lambda} \right)^2 = \left(\frac{4\pi f d}{c} \right)^2 \quad (1.35)$$

where f is the frequency of the radio wave, d is the distance between the TX and the RX and c is the speed of light. The path loss is empirically deduced from measurements. There are different path loss models that are employed to predict the PL and these include the close-in (CI) free-space path loss model and the floating-intercept (FI) path loss model [18, 19].

A typical example of large-scale fading is when a receiver moving at a constant distance from the transmitter suddenly goes behind an infrastructure or a hill, resulting in a drop of the received power. Large-scale fading occurs when the mobile moves through a distance of the order of a cell size, and is typically frequency independent [20]. Extensive channel measurements are used to determine and characterize the large-scale fading. Shadowing in both indoor and outdoor scenarios can be modelled by a log-normal distribution

[21–23]. In essence, large-scale parameters are crucial in predicting the coverage reliability.

Small-scale fading, as previously mentioned, is due to constructive and destructive interference of the multiple signal paths between the transmitter and receiver and it occurs at the spatial scale of the order of the carrier wavelength. Small-scale fading can be frequency dependent. In [24], a detailed mathematical analysis of small-scale fading and some useful models for capturing the effect of small scale fading are presented. The motion of the receiver produces a Doppler shift in the received frequency as compared to the carrier frequency. In a nutshell, small-scale fading is primarily due to random variations in the phases of MPCs and also because of the Doppler frequency [24].

1.5 Channel Parameter Estimation

Many widely adopted spectral-based and parametric algorithms for estimating channel parameters from measurement data can be found in the literature. One of the channel parameters of interest is the direction (arrival or departure). For direction estimations, an array is required to be present at either the TX side or the RX side or at both sides [25]. A lot of different array processing techniques have been introduced to tackle the estimation of the signals direction and we will discuss a few of them below.

1.5.1 Spectral Based Array Processing Techniques

The spectral based techniques can be further grouped into Beamforming techniques or subspace methods.

Beamforming techniques include the Bartlett method [26] and the Capon method [27]. Different beamforming approaches differ by choice of the weighting vector. The two aforementioned methods require a one dimensional search for the estimation of the direction of arrival in the azimuth and are incapable of dealing with coherent

signals (i.e signals that are linearly related or are a linear combination of other signals).

Subspace-based methods depend on the decomposition of the covariance matrix into signal subspace and noise subspace using Eigenvalue Decomposition (EVD). A well known example is the MUSIC (multiple signal classification) algorithm [28].

1.5.2 Parametric Methods

These methods resolves the limitation of the spectral based methods in identifying coherent sources. Compared to spectral based methods, parametric methods have higher computation complexity. In [12, 29], examples of parametric techniques including Maximum Likelihood (ML), Root-MUSIC, ESPRIT and Unitary-ESPRIT are given. In the radio channel characterization, the MPCs are considered coherent signals and not only one parameter (the direction of arrival or departure) is of interest but also the delays, the Doppler and the complex weights of the multipath are important. Therefore, instead of estimating each of these parameters using different algorithms, joint parametric techniques are used to estimate these channel parameters jointly. Examples of these methods are the expectation maximization (EM) algorithm and the Space Alternating Generalized Expectation Maximization (SAGE). With the EM algorithm, all parameters are estimated in parallel and this implies high complexity. The SAGE algorithm is an extension of the EM algorithm in order to reduce the complexity. SAGE algorithms can be time domain based [30–32] or frequency domain based [33–35].

1.5.3 UWB SAGE

In our work, the Ultra-wideband (UWB) SAGE algorithm [35] is used for the MPCs estimation. The measured MIMO Channel

Transfer Function (CTF) (1.36) can also be expressed as (1.37):

$$\begin{aligned}
 H(m, n, f) = & \sum_{l=1}^L \alpha_l \times \exp(-j2\pi f \tau_l) \times \exp(-j2\pi f \frac{\langle \vec{e}_{AOA}, \vec{e}_{RX} \rangle}{c}) \\
 & \times H_{RX}(\phi_{AOA,l}, \theta_{AOA,l}, f) \times \exp(-j2\pi f \frac{\langle \vec{e}_{AOD}, \vec{e}_{TX} \rangle}{c}) \\
 & \times H_{TX}(\phi_{AOD,l}, \theta_{AOD,l}, f) + W(m, n, f)
 \end{aligned} \tag{1.36}$$

where m, n are the TX and RX antenna indices, respectively, f is the frequency point index, l, L are the MPC index and the total number of MPCs, respectively. For the l -th path, α_l is the amplitude, τ_l is the delay, $\phi_{AOA,l}, \theta_{AOA,l}$ are the azimuth and elevation angles of arrival, respectively, $\phi_{AOD,l}, \theta_{AOD,l}$ are respectively, the azimuth and elevation angles of departure. $\vec{e}_{AOA/AOD}$ is a unitary vector whose direction is that of the l -th path and similar to [32], it is uniquely determined by its spherical coordinates. $\vec{e}_{TX/RX}$ are respectively, the coordinates of the m -th and the n -th antenna, $H_{RX}(\phi_{AOA,l}, \theta_{AOA,l}, f)$ and $H_{TX}(\phi_{AOD,l}, \theta_{AOD,l}, f)$ are respectively, the radiation patterns of the RX and TX antenna. $W(m, n, f)$ is an additive white Gaussian noise sample and $\langle . \rangle$ denotes the scalar product.

$$\mathbf{H} = \sum_{l=1}^L \mathbf{S}_l(\psi_l) + \mathbf{W}_l \tag{1.37}$$

where $\mathbf{S}_l(\psi_l)$ denotes the contribution of the l -th MPC, ψ_l is the parameters vector defined as $\psi_l = [\tau_l, \phi_{AOA,l}, \theta_{AOA,l}, \phi_{AOD,l}, \theta_{AOD,l}, \alpha_l]$. The SAGE algorithm comprises two major steps: the Expectation step (E-step) and the Maximization step (M-step). During the E-step, the contribution of the considered MPC (complete data) is estimated from the measured CTF (incomplete data). Similar to [35], the SIC (Successive Interference Cancellation) type procedure is employed in our work. The employment of the SIC procedure for the E-step allows a better estimation of the MPCs parameters, especially in multipath rich envi-

ronments [33]. The SIC is characterized by the following equation (1.38):

$$\hat{\mathbf{S}}_l^{(i)} = \mathbf{H} - \sum_{l'=1}^{l-1} \hat{\mathbf{S}}_{l'}(\hat{\psi}_{l'}^{(i)}) \quad (1.38)$$

where (i) represents the current iteration or cycle.

Maximum likelihood detectors are then used to estimate the parameters of the considered MPC. To this purpose, a correlation function is defined as follows (1.39):

$$\begin{aligned} z(\bar{\psi}_l; \hat{\mathbf{S}}_l) = & \sum_{m=1}^M \sum_{n=1}^N \sum_{f=1}^B \exp(j2\pi f_{n_f} \tau_l) \times \exp(j2\pi f_{n_f} \frac{\langle \vec{e}_{AOA} \cdot \vec{e}_{RX} \rangle}{c}) \\ & \times \exp(j2\pi f_{n_f} \frac{\langle \vec{e}_{AOD} \cdot \vec{e}_{TX} \rangle}{c}) \times \hat{\mathbf{S}}_l(m, n, f) \end{aligned} \quad (1.39)$$

where $\bar{\psi}_l = [\tau_l, \phi_{AOA,l}, \theta_{AOA,l}, \phi_{AOD,l}, \theta_{AOD,l}]$.

In essence, the M-step involves finding the MPC parameters values that maximize the cost function (1.39). Unlike the EM algorithm, the SAGE algorithm estimates the MPC parameters one by one, keeping the other parameters values fixed. After each MPC parameter estimation, the value of the estimated parameter is injected in the correlation function for the estimation of the next MPC parameter [33]. The complex amplitude α_l is the last parameter to be estimated and it is estimated using the updated values of the other five parameters of ψ_l [36]. The successive update procedures are given by equations (1.40)-(1.45) where (i) represents the current iteration or cycle and $(i-1)$ denotes the previous iteration or cycle.

$$\hat{\tau}_l^{(i)} = \arg \max_{\tau_l} \left\{ \left| z(\tau_l, \hat{\phi}_{AOA,l}^{(i-1)}, \hat{\theta}_{AOA,l}^{(i-1)}, \hat{\phi}_{AOD,l}^{(i-1)}, \hat{\theta}_{AOD,l}^{(i-1)}; \hat{\mathbf{S}}_l) \right| \right\} \quad (1.40)$$

$$\hat{\phi}_{AOA,l}^{(i)} = \arg \max_{\phi_{AOA,l}} \left\{ \left| z(\hat{\tau}_l^{(i)}, \phi_{AOA,l}, \hat{\theta}_{AOA,l}^{(i-1)}, \hat{\phi}_{AOD,l}^{(i-1)}, \hat{\theta}_{AOD,l}^{(i-1)}; \hat{\mathbf{S}}_l) \right| \right\} \quad (1.41)$$

$$\hat{\theta}_{AOA,l}^{(i)} = \arg \max_{\theta_{AOA,l}} \left\{ \left| z(\hat{\tau}_l^{(i)}, \hat{\phi}_{AOA,l}^{(i)}, \theta_{AOA,l}, \hat{\phi}_{AOD,l}^{(i-1)}, \hat{\theta}_{AOD,l}^{(i-1)}; \hat{\mathbf{S}}_l) \right| \right\} \quad (1.42)$$

$$\hat{\phi}_{AOD,l}^{(i)} = \arg \max_{\phi_{AOD,l}} \left\{ \left| z(\hat{\tau}_l^{(i)}, \hat{\phi}_{AOA,l}^{(i)}, \hat{\theta}_{AOA,l}^{(i)}, \phi_{AOD,l}, \hat{\theta}_{AOD,l}^{(i-1)}; \hat{\mathbf{S}}_l) \right| \right\} \quad (1.43)$$

$$\hat{\theta}_{AOD,l}^{(i)} = \arg \max_{\theta_{AOD,l}} \left\{ \left| z(\hat{\tau}_l^{(i)}, \hat{\phi}_{AOA,l}^{(i)}, \hat{\theta}_{AOA,l}^{(i)}, \hat{\phi}_{AOD,l}^{(i)}, \theta_{AOD,l}; \hat{\mathbf{S}}_l) \right| \right\} \quad (1.44)$$

$$\hat{\alpha}_l^{(i)} = \frac{1}{MNB} z(\hat{\tau}_l^{(i)}, \hat{\phi}_{AOA,l}^{(i)}, \hat{\theta}_{AOA,l}^{(i)}, \hat{\phi}_{AOD,l}^{(i)}, \hat{\theta}_{AOD,l}^{(i)}; \hat{\mathbf{S}}_l) \quad (1.45)$$

Since the E-step and the M-step require estimated values of the MPCs parameters of the previous iteration, modified correlation functions are considered during the M-step of the initialization cycle. In this work, MPCs of significant powers are considered. The maximum number of resolvable MPCs to be estimated is set to 100. The stopping criteria is when more than 95 percent of the measured channel power has been estimated, or otherwise, when the maximum number of the resolvable MPCs has been reached. The UWB channel can be expressed as a set of subbands [34, 35]. In our case, the 4 GHz bandwidth is split into eight equal subbands. Consequently, the cost function to be maximized is a simple summation of modified loglikelihood of each subband. Time and angular resolutions were respectively set to 1 [ns, °].

1.6 Channel modelling methods

1.6.1 Empirical channel methods

As their name ‘empirical’ suggests, these models are based on experiments and they are directly derived from extensive channel measurement campaigns for a typical scenario. A widely known example of an empirical channel model is the Okumura-Hata model [37]. Empirical channel methods result in channel characteristics that are realistic [38]. However, empirical channel methods are limited in that they do not include any physical interpretations. These models can only characterize a certain specific site, and they tend to require large amount of measurements for time varying channels.

1.6.2 Deterministic channel methods

Deterministic models compute the characteristics of a channel using the physical propagation of EM waves in a certain geographic area. Their accuracy is directly related to the accuracy of the scenario representation. Examples of such models are the ray tracing channel model and stored measurements. Weaknesses of deterministic channel methods include the large computational effort required as well as the approximate nature of numerical computation methods like ray tracing [39, 40].

1.6.3 Stochastic channel models

Stochastic models describe the channel characteristics statistically. These models, unlike empirical methods, are not directly derived from extensive channel measurements. The parameters of stochastic models are derived from typical measurement scenarios. Stochastic models are used to predict the pdf of the channel parameters over a large area (instead of a specific location). The Rayleigh-fading channel model is a typical stochastic channel model. Stochastic models are of two categories: Geometry based Stochastic Channel Model (GSCM) and Non Geometry based Stochastic Channel Model (non-GSCM).

GSCM involves statistically defining the position of scatterers and the scattering properties. This means that for each propagation path, the following channel properties are assigned to it: amplitude, delay and angular information. The capability to adapt to different scenarios by simply changing the shape of the scattering region is what makes GSCMs more attractive (since they implicitly reproduce full channel characteristics). GSCMs can also describe the time evolution of a channel involving mobile receivers or transmitters or scatters and thus they are suitable for modelling non-stationary channels.

In non-GSCM, the paths from the transmitter to the receiver are characterized by statistical parameters, without considering the geometry of the physical environment. The Tapped Delay Line (TDL) model is one example of a non-GSCM model and it is one of the most common time domain channel models.

1.7 MIMO Channel Modelling

In modelling the SISO channel, the following propagation effects are relevant: the large-scale PL, the shadow fading, and the small-scale fading. Multiple studies in the literature have shown that the average received power CG, decreases exponentially with distance. Even for a fixed TX-RX separation distance, the CG can vary substantially from one location to the other. This CG variation is due to shadow fading, which is modelled statistically by a lognormal distribution. Amplitude variations due to small-scale movements (in the order of a wavelength) of the transmitter or the receiver or of the surrounding environment (e.g scatterers) lead to the small-scale fading phenomenon. Distributions that describe the statistics of the real valued amplitude can be found in the literature. These include the Rayleigh distribution, which is used to describe the statistics of the real-valued amplitude for the NLOS scenarios and the Rician distribution, which is employed for the LOS scenarios. For scenarios involving mobility like Vehicle to Vehicle (V2V) communications, large-scale fading is modelled in $[dB]$, by a normal distribution with zero mean, while the small-scale fading is usually modelled with either a Rayleigh or a Rician or a double Rayleigh distribution [41–45]. In mobile scenarios, the Doppler spectrum is also used to measure the movement of the TX and the RX as well as the variation of the local environment. The Nakagami distribution, is another typical distribution that provides even more degrees of flexibility to fit the model to the measured data. A SISO wideband channel can be modelled, either in the time domain or in the frequency domain. The TDL model is one example of the time domain SISO channel modelling approach [46]. In the frequency domain, the SISO channel can be modelled as an autoregressive (AR) process where the poles of this AR process are calculated from the measured channel realizations [47].

In SIMO, MISO, and MIMO systems, the deployment of antenna arrays at one of the two ends or both ends makes the channel modelling problem more sophisticated. The use of antenna arrays is crucial for spatial information i.e. the DOD and DOA of the multiple waves. Some of

the advantages associated with MIMO systems include: enhanced link robustness and reliability due to diversity techniques (sending or receiving multiple copies of the same information via different antennas), increased throughput via sending or receiving different information from different antennas. Multiple antennas support spatial multiplexing and beamforming technologies which are essential for enhanced communication.

Because a MIMO system involves using multiple antennas at both the transmitting and receiving sides, merely modelling each link (i.e., from one transmit antenna element to one receive antenna element) as a SISO channel and assuming that these links or channels are Independent and Identically Distributed (i.i.d.) is a common approach adopted in many theoretical papers for simplifying the MIMO channel. Practical measurements have however shown this assumption or simplification to be untrue [48]. The spatial correlations between different links at both sides of a communication link should therefore be incorporated when modelling wireless channels. Since our work is focused on mMIMO channel modelling, it is therefore necessary to give a brief background of MIMO channel modelling. MIMO channel models can be considered as physical MIMO channel models or analytical MIMO channel models.

1.7.1 Physical MIMO channel models

These models involve constructing a realistic geometric scattering environment and computing the MIMO channel matrix as a sum of the contributions from different rays. These models characterize an environment on the basis of EM propagation by describing the double-directional multipath propagation [5]. The scatterer distributions are related to some important physical parameters, like the DOA, DOD, and the Time of Arrival (TOA). The statistics of these parameters are obtained from the field measurements or from well known postulated distributions with simple geometry. Because the physical parameters are used in these channel models, this makes it possible to separate the MIMO channel and the measurement setup. The major drawback of these models is that finding the correct statistics of the parameters is

not a trivial task (almost impossible in some cases) [49]. Physical models are independent of antenna configurations (antenna pattern, number of antennas, array geometry, polarization, mutual coupling) and system bandwidth [50]. Channel models based on ray tracing, or extension of Saleh-Valenzuela, are examples of physical channel models. We remark that it is easier to convert a physical model to an analytical model but not vice versa [5].

1.7.2 Analytical MIMO channel models

In analytical MIMO channel modelling, the MIMO channel correlation matrix (1.5) is usually obtained from measurements and therefore the measurement setup influences such as antenna heights and antenna element patterns cannot be separated from the channel [48]. Generating a MIMO channel with a specified correlation structure between the single links is not a difficult task [51, 52]. The analytical methods consider the MIMO channel correlation matrix. The correlative models are relevant in scenarios with Rayleigh fading. In most NLOS environments, the wireless channel between the transmitter and the receiver is well modelled as zero mean complex Gaussian [48], that is, the real-valued amplitude is Rayleigh distributed and the phase is uniformly distributed over $[-\pi, \pi]$. The advantage of modelling the wireless channel as a complex Gaussian random vector is that the first- and second-order moments can be used to fully describe the channel [53]. Examples of correlative models include the Kronecker model, the Weichselberger model and structured models.

1.7.2.1 Kronecker Model

This model greatly reduces the complexity of the channel analysis, as it holds the assumption that the correlation between the receive antennas is independent of the correlation between the transmit antennas. The Kronecker model is expressed as (1.46) and it relies on the WSS assumption.

$$\mathbf{H}_{kron} = \frac{1}{\sqrt{\text{tr}\{\mathbf{R}_{\mathbf{R}\mathbf{X}}\}}} \mathbf{R}_{\mathbf{R}\mathbf{X}}^{\frac{1}{2}} \mathbf{G} \left(\mathbf{R}_{\mathbf{T}\mathbf{X}}^{\frac{1}{2}} \right)^T \quad (1.46)$$

where $\mathbf{R}_{TX} = \mathbb{E} \left\{ \mathbf{H}^T \mathbf{H}^* \right\}$ and $\mathbf{R}_{RX} = \mathbb{E} \left\{ \mathbf{H} \mathbf{H}^H \right\}$ denote the transmit and receive correlation matrices, respectively. The variable $\mathbf{G}$ is an i.i.d. random fading matrix with unity-variance and circ. symmetric complex Gaussian entries. The parameters for the Kronecker model are the transmit and receive correlation matrices. The Kronecker model enforces all DODs to be linked to all DOAs. Consequently, the joint DOD-DOA spectrum of a synthesized Kronecker channel is the product of the average DOD and the average DOA spectra. This means that all DODs (DOAs) are linked to all DOAs (DODs) with the same pattern and only the total power of the DOAs (DODs) depends on the chosen DODs (DOAs). Because of the separability assumption of the Kronecker model, it is not able to reproduce MIMO channels with single-bounce interactions [5]. The advantage of the Kronecker model is its simplicity, and it is often used for analytical study of MIMO systems. However, due to the assumption of no coupling between the TX and RX sides, the model may not be accurate enough for some propagation environments. In other words, the main drawback of this model is that it forces both link ends to be separable, irrespective of whether the channel supports this or not [54].

1.7.2.2 Weichselberger model

It is a relatively more complex correlative model and can be more accurate than the Kronecker model since it introduces the coupling effect between the propagation at the transmit and receive sides. The Weichselberger model relaxes the separability restriction of the Kronecker model and allows for any arbitrary coupling between the transmit and receive eigenbase so as to model the correlation properties at the receiver and transmitter jointly [54]. The Weichselberger model can be expressed by (1.49). First we introduce the eigenvalue decomposition of the receive and transmit correlation matrices.

$$\mathbf{R}_{RX} = \mathbf{U}_{RX} \mathbf{\Lambda}_{RX} \mathbf{U}_{RX}^H \quad (1.47)$$

$$\mathbf{R}_{TX} = \mathbf{U}_{TX} \mathbf{\Lambda}_{TX} \mathbf{U}_{TX}^H \quad (1.48)$$

$$\mathbf{H}_{wechsel} = \mathbf{U}_{RX} \left(\tilde{\boldsymbol{\Omega}}_{wechsel} \odot \mathbf{G} \right) \mathbf{U}_{TX}^T \quad (1.49)$$

Where $\mathbf{G}$, is an i.i.d. complex Gaussian random fading matrix, $\tilde{\boldsymbol{\Omega}}_{wechsel}$ is defined as the element-wise square root of the power coupling matrix $\boldsymbol{\Omega}_{wechsel}$. The positive and real-valued elements $\omega_{wechsel,ij}$ of the coupling matrix determine the average power-coupling between the i -th transmit eigenmode and the j -th receive eigenmode. The Weichselberger model suggests the opposite assumption relative to the Kronecker model; scatterers at the two link ends cannot be considered independent and are coupled in some way. The Weichselberger model thus effectively models the average coupling between the spatial subchannels. Because of this reason, the Weichselberger model is more accurate, when compared with the Kronecker model. However, additional complexity is required to define the power coupling matrix. It is worth remarking that the Weichselberger model includes the Kronecker model and the Virtual Channel Representation (VCR) as special cases [55].

1.7.2.3 Virtual Channel Representation

Unlike the Kronecker and the Weichselberger models which model the MIMO channel in the eigenspace, the VCR models the MIMO channel in the beamspace. In VCR, the eigenvectors (in the other models) are replaced by fixed and predefined steering vectors. The VCR is obtained following (1.50).

$$\mathbf{H}_{virtual} = \mathbf{A}_{RX} \left(\tilde{\boldsymbol{\Omega}}_{virtual} \odot \mathbf{G} \right) \mathbf{A}_{TX}^T \quad (1.50)$$

where orthonormal response and steering vectors constitute the columns of the unitary response and steering matrices $\mathbf{A}_{RX}$ and $\mathbf{A}_{TX}$. $\tilde{\boldsymbol{\Omega}}_{virtual}$ is defined as the elementwise square root of the power coupling matrix $\boldsymbol{\Omega}_{virtual}$ whose positive and real-valued elements $\omega_{virtual,ij}$ determine the average power-coupling between the i -th transmit and the j -th receive direction. The accuracy of the VCR model depends on the actual antenna configuration. In fact, VCR's accuracy increases with the number of antennas, as angular bins become smaller. This model is easy to

interpret and it is fully specified by the coupling matrix.

1.8 Standardized Channel Models

For the purpose of testing and optimizing certain wireless standards in a homogeneous way, a number of standardized channel models have been developed. Standardized channel models enable system designers to make critical design decisions pertaining to modulation and coding techniques. The designers can test different algorithms and optimize the system, thanks to the standardized models. Table 1.1 gives examples of standardized channel models (whose different characteristics are presented in detail in the references provided).

Table 1.1: Standardized channel models.

Standardized channel model	References
3GPP-SCM, 3GPP-SCME, 3GPP-3D	[56, 57]
WINNER, WINNER II, WINNER +	[58, 59]
COST 259, COST 273, COST 2100	[60, 61]
IMT-Advanced	[62, 63]
QUADRIGA	[64]
METIS2020	[65]
mmMAGIC	[66, 67]

1.9 Massive MIMO

Since its introduction, MIMO technology has evolved significantly to what we now call mMIMO. First, there was point to point MIMO, also known as Single User Multiple Input Multiple Output (SU-MIMO); a technology which benefits significantly from a rich scattering environment. Then came the Multiple User Multiple Input Multiple Output (MU-MIMO), which unlike SU-MIMO where the base station can only communicate with a single device at a time, the base station can simultaneously communicate with multiple devices. On top of this, MU-MIMO does not necessarily need the environment to be a rich scattering one for enhanced performance. MU-MIMO in its original form is not a scalable technology [68, 69] and it requires that both the trans-

mitter and receiver possess knowledge of the Channel State Information (CSI). The extension of MU-MIMO to using more than 8 base station antennas (hundreds of base station antennas for example) to simultaneously serve K users within the same time-frequency resources, is what we call mMIMO [69, 70]. Fig 1.4 illustrates the mMIMO uplink system.

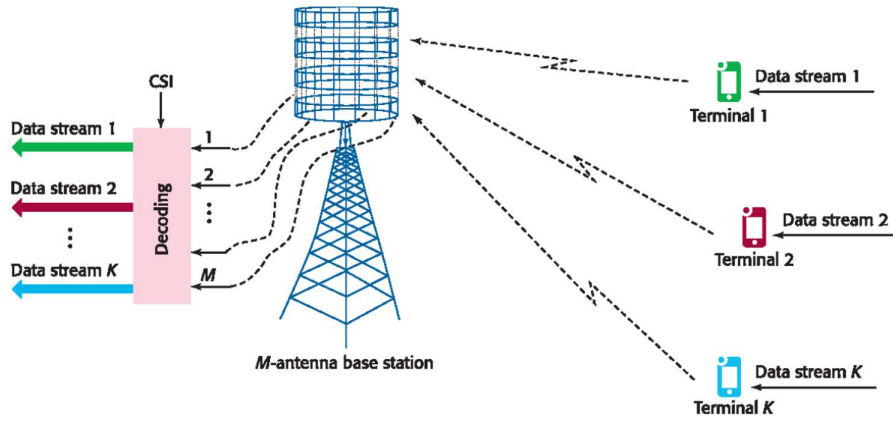


Figure 1.4: mMIMO [69].

It is important to remark that the massiveness of mMIMO is governed by the degree that $M > K$, with M being the number of base station antennas and K as the number of users currently being served by the base station through spatial multiplexing. In the literature, the K users are often considered to be single-antenna terminals, but they can also be considered as multi-antenna terminals. Time Domain Duplexing (TDD) is preferable over Frequency Domain Duplexing (FDD) in mMIMO systems. This is because TDD systems can exploit channel reciprocity while FDD systems cannot. Consequently, FDD systems require considerably more time for training than TDD systems.

The use of very many antennas in mMIMO consequently leads to desirable properties: asymptotic favourable propagation and channel hardening.

Favourable propagation

Considering a base station denoted as j which is in the l -th cell and two users x and y being served by this base station, favourable propagation is when the two channel vectors $\mathbf{h}_{l,x}^j$ and $\mathbf{h}_{l,y}^j$ are pairwise orthogonal. So in general, if any two channel vectors of the K users being served by the base station j are pair-wisely orthogonal then we have favourable propagation as given by (1.51).

$$\mathbf{h}_{l,x}^j (\mathbf{h}_{l,y}^j)^H \rightarrow \begin{cases} \mathbf{h}_{l,x}^j (\mathbf{h}_{l,y}^j)^H \rightarrow 0, & x, y = 1 \dots K, \quad x \neq y \\ \|\mathbf{h}_{l,k}^j\|^2 \neq 0, & k = 1 \dots K \end{cases} \quad (1.51)$$

where $\mathbf{h}_{l,x}^j$ and $\mathbf{h}_{l,y}^j$ are the channel vectors of the users x and y , respectively, being served by the base station j which is in the l -th cell. k and K denote the k -th user and the total number of users served by the base station j .

In reality (1.51), cannot be attained but can be approximated and thus the channels are said to offer approximately favourable propagation [71]. It has also been found that under some assumptions on the propagation environment, as M grows large, it holds that (1.52).

$$\frac{1}{M_j} \mathbf{h}_{l,x}^j (\mathbf{h}_{l,y}^j)^H \rightarrow 0 \quad (1.52)$$

as $M_j \rightarrow \infty$. where M_j is the number of antennas at the base station j and $(\cdot)^H$ is the Hermitian transpose. In this case, the channels are said to offer asymptotic favourable propagation [71]. Asymptotic propagation makes the directions of two UE channels asymptotically orthogonal and thus makes it easier for the base station to mitigate interference between the users, and this in turn improves the spectral efficiency and makes it sufficient to use linear combining and precoding. It is important to remark that in favourable propagation, it is the channel directions of two users that become orthogonal and not the channel responses. A more formal definition of favourable propagation can be found in [17].

Channel Hardening

Channel hardening alleviates the need for combating small-scale fading. A propagation channel $\mathbf{h}_{l,k}^j$ provides asymptotic channel hardening if it satisfies the following equation (1.53):

$$\frac{\|\mathbf{h}_{l,k}^j\|^2}{E\left\{\|\mathbf{h}_{l,k}^j\|^2\right\}} \rightarrow 1 \quad (1.53)$$

almost surely as $M_j \rightarrow \infty$. In other words, in channel hardening, the channel gain is very close to its mean value and this implies that fading has little impact on the communication performance. However, it should be noted that this does not imply that the channel gain becomes deterministic. In essence, channel hardening occurs whenever the randomness of a fading channel is averaged, resulting in a deterministic value for the normalized channel power. A more formal definition of channel hardening can be found in [17].

mMIMO technology has been widely investigated in the last years to increase the channel capacity, the wireless link reliability, and to reduce interference. The capacity is increased through spatial multiplexing [72]. mMIMO technology greatly reduces interference through spatial filtering. Deploying many antennas in mMIMO increases the degrees of freedom and as a result, the wireless propagation channel link reliability is enhanced. Nevertheless, the implementation of mMIMO implies a large number of radio frequency chains, hence larger cost and energy consumption, and an important use of resources to determine the CSI. In essence, the use of the very many M base station antennas facilitates the reduction of transmitted power but also increases the hardware consumed power. In fact, opposed to the common belief (that the transmit power decreases with increasing M), the transmit power should increase with M so as to compensate for the increased circuit power. In [73], it was shown that energy-efficient systems do not operate in the low Signal to Noise Ratio (SNR) regime but operate in a regime where proper interference-suppressing processing like Zero-Forcing Beamform-

ing (ZFBBF) and MMSE (minimum mean squared error) are highly preferred to interference ignoring Maximum Ratio Transmission (MRT) or Maximum Ratio Combining (MRC) processing. Indeed the radiated power per antenna decreases with M and the numerical results in the aforementioned showed that it is in the range of 10–100 mW. Therefore a right balance needs to be found between the number M of base station antennas (related to transmit power reduction) and hardware consumed power. These challenges can be solved through hybrid approaches [74].

Beamforming and Spatial multiplexing

The goal of beamforming is to increase the SNR. MRT and ZFBBF [75] are two typical beamforming approaches that are usually employed to maximize the SNR. The benefits of beamforming include enhanced energy efficiency, improved spectral efficiency as well as increased system security (information relayed only to the intended recipient) [76]. Beamforming can be classified into three types, namely: analog beamforming, digital beamforming and hybrid beamforming. Analog beamforming is the cheapest of the three. Analog beamforming approach is portrayed by phased arrays. It is limited in that only one beam can be present at a time. In digital beamforming, different signals are designed for each antenna in the digital domain. With digital beamforming, it is possible to have multiple beams pointed in different directions at the same time and this makes digital beamforming very suitable for mMIMO scenarios. The downside of digital beamforming is that it is very expensive to implement. Hybrid beamforming is combination of analog beamforming and digital beamforming [77].

In spatial multiplexing, each spatial channel carries independent information, thereby increasing the data rate of the system [78,79]. Spatial multiplexing is different from diversity in that, diversity involves sending multiple copies of the same signal in order to combat multipath fading [80].

1.10 mMIMO Channel Characterization and Modelling

The i.i.d. Rayleigh fading channel model is the canonical mMIMO channel model. In this model, the channel vector is a circularly symmetric complex Gaussian random variable with a scaled identity matrix as the correlation or covariance matrix (1.54) :

$$\mathbf{h} \sim CN(\mathbf{0}, \beta \mathbf{I}_M) \quad (1.54)$$

where β is the variance.

Considering i.i.d. Rayleigh fading, the channel gain $\|\mathbf{h}^2\|$, has an Erlang distribution¹ $(M, \frac{1}{\beta})$. The channel direction, obtained following $\frac{\mathbf{h}}{\|\mathbf{h}\|}$, is uniformly distributed over the unit sphere in $\mathbf{C}^M$. It is important to remark that the channel gain and the channel direction are independent random variables. Because of this, the model is a spatially uncorrelated channel model. The main advantage of the i.i.d. Rayleigh fading channel is that, when using MRC, MRT or ZFBF processing techniques, we can compute closed-form rate expressions. However, in reality practical channels are not spatially uncorrelated. In other words, practical or real channels are spatially correlated, meaning that the channel gain and the channel directions are not independent random variables. The correlation of these two variables is due to the following reasons: Firstly, the propagation environment, where the channel vector is more probable to point in some directions than in others. Secondly, the antennas have spatially dependent antenna patterns. These aforementioned factors explain why in practice, spatial channel correlation always exists [17].

One fundamental property of spatial correlation is that, the base station array receives different average signal power from different spatial directions. This is in contrast with spatial uncorrelation, where the base station receives equal average signal power from different spatial

¹An Erlang distribution is a scaled χ^2 distribution.

directions.

A tractable way to model a spatially correlated channel vector is through Correlated Rayleigh fading (1.55):

$$\mathbf{h} \sim CN(\mathbf{0}, \mathbf{B}) \quad (1.55)$$

where the covariance $\mathbf{B}$ matrix is also the correlation matrix. We have spatially uncorrelated fading only when $\mathbf{B}$ is a scaled identity matrix. The eigenvalue distribution determines how strongly spatially correlated the channel is. If all eigenvalues are identical, then $\mathbf{B}$ is a scaled identity matrix and there is no spatial correlation. If there are a few strong eigenvalues that contain most of the power, then there is very strong spatial correlation and the channel vector is very likely to be (approximately) spanned by the corresponding eigenvectors. A spatially correlated Rayleigh fading channel is experienced for instance, when the correlation matrix has equal diagonal elements and non-zero off-diagonal elements. The off-diagonal elements describe the correlation between the channel coefficients of different antennas. The correlated Rayleigh fading channel, whose correlation matrix properties correspond to the aforementioned correlation matrix, is a reasonable model when deploying a compact base station array on a tower [81]. Another instance of a spatially correlated Rayleigh fading channel is one characterized by a diagonal correlation matrix with different diagonal elements. This model is suitable when deploying distributed antennas, as in the case of cell-free mMIMO [17].

A more general channel model is correlated Rician fading (1.56) :

$$\mathbf{h} \sim CN(\mathbf{b}, \mathbf{B}) \quad (1.56)$$

where $\mathbf{b}$, the mean value, represents the deterministic LOS channel and the covariance matrix $\mathbf{B}$, determines the properties of the fading. The correlation matrix $\mathbf{B} + \mathbf{b}\mathbf{b}^H$ can still be used to determine the spatial correlation of the received signal power. However, from a system perfor-

mance point of view, the k -factor (1.57) which in essence is the fraction between the power of the LOS path and the scattered paths can have a large impact on the performance as well.

$$k = \frac{\|\mathbf{b}^2\|}{tr(\mathbf{B})} \quad (1.57)$$

A channel with a large k -factor provides more reliable communication since it is nearly deterministic. Under correlated fading, it is only the large eigenvalues of the covariance matrix that contribute to the channel hardening. Channel hardening, as has been previously discussed, provides reliability in mMIMO communications [17].

1.10.1 mMIMO Channel Measurements

mMIMO technology can be classified into mmWave and sub-6 GHz mMIMO. The former is deployed for small coverage areas, fewer users and situations involving low user mobility while the latter is deployed for the contrary [17]. The channel capacity [82] is the most investigated metric in sub-6 GHz mMIMO channels. The condition number or the singular value spread (ϖ), is an important performance metric for the mMIMO radio channel analysis. The ϖ is an effective way to study the pairwise orthogonality of the user channel vectors and thus the achievable spatial multiplexing performance for a MIMO system [83]. Considering a mMIMO system involving M base station antennas and K users, the channel matrix $\mathbf{H}$ has the following Singular Value Decomposition (SVD):

$$\mathbf{H} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^H \quad (1.58)$$

where $\mathbf{U} \in C^{K \times K}$ and $\mathbf{V} \in C^{M \times M}$ are unitary matrices. The diagonal matrix $\mathbf{\Sigma} \in C^{K \times M}$ is composed by the singular values $\sigma_1, \sigma_2, \dots, \sigma_k$. The singular value spread ϖ is then computed using (1.59).

$$\varpi = \frac{\sigma_{max}}{\sigma_{min}} \quad (1.59)$$

where σ_{max} and σ_{min} are the maximal and minimal singular values, re-

spectively. The ϖ is the ratio between σ_{max} and σ_{min} and it is bounded within $1 \leq \varpi \leq \infty$. If $\varpi = 1$, this indicates an orthogonal channel matrix. Otherwise, a large ϖ shows that at least two rows of the channel matrix $\mathbf{H}$ are similar, which means that at least one of the K users will not be served. The singular value spread quantifies how different the channel responses to different terminals are. The condition number is a useful metric when the channel is considered to be i.i.d. Rayleigh fading. With i.i.d. Rayleigh fading, the channels are assumed to have equal norms. However, in reality, the norms of the channels are not identical because the terminals are located in different locations. In these circumstances, the condition number is not a good metric to measure whether a channel offers favourable propagation or not. Therefore another metric, *distance from favourable propagation* was introduced in [71].

In order to fully appreciate the theoretical benefits of mMIMO, it is imperative that real channel measurements are performed. These channel measurements are then used to investigate how MIMO systems perform in real propagation environments. Table 1.2 gives some examples of mMIMO channel measurements. We remark that antenna spacings of half the wavelength ($\frac{\lambda}{2}$) were considered in these mMIMO measurement campaigns. In Table 1.2, the acronyms, I2O, APS, UMa and UMi, respectively, stand for Indoor to Outdoor, Angular Power Spectrum, Urban Macro and Urban Micro. We can also notice from Table 1.2 that correlation is one of the widely investigated metrics in sub-6 GHz mMIMO channel measurements. Other detailed sub-6 GHz mMIMO channel measurements in stadiums, halls, Urban Macro, Urban Micro, Rural Macro etc. are given in [84].

Table 1.2: mMIMO channel measurements.

Scenario	Array type, M	BW / Carrier	Metric
Outdoor	Linear, 128	50 MHz / 2.6 GHz	Channel gain, K -factor, APS, eigenvalue distribution, Correlation [85]
I2O	Rectangular, 32 & cylindrical, 128	50 MHz / 2.6 GHz	Correlation [86]
Outdoor	virtual, 112	20 MHz / 2.6 GHz	Correlation, inverse ϖ [87]
Outdoor	Cylindrical & Linear, 128	50 MHz / 2.6 GHz	Large-scale fading & angular resolution [87]
UMa, UMi	Linear, 64	- / 2.6 GHz	SNR [88]
Indoor	Circular, 720	2 GHz / 28-30 GHz	Correlation [89]
Hall	Linear, 128	- / 2,4,6 GHz	PL, PDP [84]

1.10.2 mmWave mMIMO Channel Modelling

Millimeter wave channel modelling involves the modelling of channels that exploit the mmWave spectrum. An extensive study on mmWave channels is presented in [90]. mmWave mMIMO channel modelling can be considered a subcategory of mmWave channel modelling. In mmWave mMIMO channel modelling, one or both of the communicating ends is equipped with an array in the order of hundreds of elements. The mmWave spectrum offers huge bandwidths, which makes it crucial for meeting the 5G and 6G cellular networks high throughputs and data rates. Because of the very high frequencies in the mmWave, this implies that the wavelengths are relatively smaller compared to the sub-6 GHz frequencies wavelengths. This means that the mmWave technology offers advantages in terms of compact dimensions. Other advantages provided by this technology include energy efficiency, flexibility, and adaptivity.

Challenges of the mmWave Technology

However, there are challenges encountered when dealing with this technology. The challenges include high propagation losses in both indoor and outdoor environments. In outdoor environments, losses are due to tropospheric conditions [91, 92]. In indoor environments, most losses are due to shadowing. The shadowing due to the blockage is not independent of other random variables [93]. Therefore the use of mmWaves will involve LOS scenarios and the deployment of very high gain and directive antennas to compensate for the high propagation losses. Another challenge pertains to the acquisition of CSI. The microwave systems usually comprise 1 to 8 antennas in linear arrays, which renders easy obtention of CSI, consequently making spatial multiplexing possible. However, mmWave mMIMO systems comprise Three Dimensional Space (3D) arrays with hundreds of antennas. This makes the CSI very difficult to acquire. Consequently, digital beamforming and spatial multiplexing for mmWave mMIMO systems require considerably higher hardware cost and power consumption [94, 95]. The designing and fabrication of a complete mmWave mMIMO transceiver, covering aspects such as antenna layout, array geometries, RF front-end architectures, local oscillator distribution, optimization of power dissipation, demodulation, baseband processing, sampling, and multichannel data aggregation is of great importance and has not been widely covered in the literature [96]. Mobility in mmWave mMIMO is one of the most important challenges that will need to be addressed. Unlike in microwave networks, where the spatial and temporal correlations of the interferences are introduced due to common receiver or transmitter locations, in mmWave systems, new sources of correlations include physical blockage and high gain beamsteering. These new correlations may significantly degrade the system performance and it is therefore important that they are solved in efficient ways [96]. Despite the mmWave radiation being non-ionizing, the main safety concern is heating of the eyes and skin caused by the absorption of mmWave energy in the human body. It is therefore very important to understand how the propagation

of mmWave affects the human body, as well as the inquiry of potential health effects related to mmWave exposures [97]. The conventional approach from stochastic geometry treats all TXs and RXs as living on a Two Dimensional Space (2D) plane. In rapidly growing urban areas, it is therefore imperative to extend the principles of stochastic geometry from a 2D plane to a 3D plane. This extension is not so trivial due to the nonhomogeneous distribution of users and infrastructure. In the mmWave spectrum, because of the sensitivity to blockages and the use of highly directional 3D beam patterns, this extension is even more sophisticated. As a result, new mathematical tools and models are required to analyze urban geometries and to realize the potential benefits of 3D beamforming in such environments.

Progress on mmWave Channel Modelling

Detailed studies on mmWave channel modelling can be found in [90]. In [98], a modelling framework for sparse high-dimensional MIMO channels encountered in mMIMO and mmWave systems was proposed. The results showed that the proposed approach offers a promising framework for optimizing the performance complexity tradeoffs that are inherent to high-dimensional mMIMO systems. In [99], a survey on salient mmWave propagation characteristics, including the free-space path loss, atmospheric attenuation, rain and foliage attenuation, material penetration and other propagation factors was presented. The survey also highlighted the difficulty of having a single channel model for mimicking the entire mmWave spectrum. The idea of having a single mmWave channel model was also claimed to be impossible by the METIS [65], hence three different channel models were proposed, namely: the map-based, the stochastic and the hybrid mmWave models.

Progress already made in the scope of 3D mmWave channel modelling include the work in [100], where a 3rd Generation Partnership Project (3GPP)-style 3D mmWave channel model was developed with special emphasis on using the ray tracer to determine elevation model parameters. The channel model included distance dependent elevation modelling which is critical for the expected 2D arrays which will be em-

ployed in mmWave mMIMO systems. The work in [101], involved 3D-ray tracing simulations in the downtown areas of Ottawa and Chicago at the 2 GHz band and at the 28 GHz band. Different transmitter heights and different density of buildings were considered. Based on the observations of the ray-tracing experiments, large scale parameters of the radio channel model were obtained, and a preliminary mmWave channel model at 28 GHz was presented. The ray tracing technique was also employed in [102] to characterize the multipath channel associated with highly directional 60 GHz links. The work showed that channel models for highly directional mmWave links are fundamentally different from those for the rich scattering environments corresponding to omnidirectional links at lower carrier frequencies. In [103], a mmWave channel model based on geometry statistics was presented. This channel model is between the ray-tracing based environmental specific channel models and the fully abstracted statistical channel models. The two case studies in [104] demonstrated that the propagation geometry at 60 GHz is very different from those at lower carrier frequencies.

1.10.3 Existing Channel Models Limitations

Since we have already discussed the benefits and challenges associated with mmWave and mMIMO technologies, we now move our attention to the limitations of the existing channel models with regards to mmWave mMIMO. The main limitations of the existing channel models are as a result of the following aspects [99]: Firstly, the lack of measurements. Despite the numerous measurement campaigns done on the 28 GHz, 38 GHz, 60 GHz and 72 GHz bands, the propagation characteristics of a wide mmWave range remains unknown and thus there is still need for extensive measurement campaigns on the other mmWave bands. Secondly, most existing channel models limit the beamforming to the azimuth dimension (2D) but mmWave systems are expected to apply 3D (both azimuth and elevation taken into account) beamforming. Therefore, the extension of the channel models to include the elevation dimension for the sake of achieving both transmit beamforming and receive combining gains is absolutely necessary. Thirdly, existing channel models are

limited in the bandwidth they can support and consequently, cannot be employed for mmWave frequencies, which are characterized by very high bandwidths. On top of that, new scenarios like sport halls and crowded festivals or stadiums, not currently included in the existing models, also need to be included as the mmWave spectrum is expected to be deployed in such scenarios. Fourthly, since the mmWave channel is a sparse multipath channel, users located close to each other would receive the same signal via the same reflected paths, that is these users will have similar Azimuth Angle of Arrival (AOA) and Azimuth Angle of Departure (AOD). This aspect has to be accounted for in the mmWave channel model. Fifthly, the use of directional antennas in mmWave communications mitigates the high signal attenuation experienced at mmWaves as well as reduces the Doppler spread. It is therefore necessary that the effect of directional antennas is considered in the mmWave channel model, in particular in the path loss modelling. Lastly, the mmWave channel model should support the use of very many antennas (mMIMO). The mMIMO mmWave systems may require utilizing spherical wave models, rather than a planar wavefront, for short-range communications and therefore the new channel model should also take into account the spherical wave models, since in most cases the users will be in the near-field region of the base station.

1.11 Transmitting Reconfigurable Intelligent Surfaces

In the development of 5G and beyond networks, mmWave technologies are expected to play a main role to attain unprecedented performance of low-latency and high-data rate. These technologies are often considered in combination with mMIMO transmission and beamforming antennas to counteract the poor link budgets [105]. Reconfigurable Intelligent Surfaces (RIS) are nowadays considered as a new paradigm for wireless communications [106]. The interaction with electric and/or magnetic fields, is typically provided by resonant effects controlled by the geometry of the Unit Cell (UC)s and their distribution, enabling antenna

performance enhancement (beamshaping), flat lens, artificial magnetic conductors, cloaking, absorbers and scattering reduction. Indeed, one of the uses of these surfaces is to realize reflectarrays or transmitarrays as solutions for applications requiring high gain and efficiency, and wide field of view ($>60^\circ$) scanning capabilities. These technologies have recently emerged as a promising alternative to the traditional phased arrays. In the past fixed beam transmitarrays have already been used for channel characterization in the V-band for backscattering measurements [107].

T-RISs Operating Principles

T-RIS also known as transmitarray, is a phase shifting surface that can focus EM waves from a source antenna to produce a high gain beam [108]. Fig. 1.5 shows the general scheme of a T-RIS. The focal source is essentially the feed which illuminates the inner array (receiving layer) operating in the receiving mode. The outer array (transmitting layer) working in transmitting mode is coupled to the inner array (receiving layer) via a matrix of phase shifters. In order to maximize the gain, the focal distance is selected as a trade-off between spillover losses and illumination tapering. In essence, each unit-cell provides the phase shift required to compensate the differential path from the source position and to generate the desired phase distribution. Advantages of T-RISs include the avoidance of feed blockage (a problem encountered in reflectarrays), compactness (through focal distance reduction) and significant loss reduction compared to phased arrays which require a complex feed network [109]. The T-RIS total power efficiency (κ) is obtained as follows:

$$\kappa = \kappa_{FS} \cdot \kappa_{SO} \cdot \kappa_{IL} \quad (1.60)$$

where $\kappa_{FS} = \frac{P_2}{P_1}$ is the ratio between the power radiated from the T-RIS focal source (P_2) and the power fed to the T-RIS focal source (P_1). $\kappa_{SO} = \frac{P_3}{P_2}$ where $P_3 = \sum_{m=1}^M |a_1^m|^2$ is the power collected from the T-RIS receiving layer with a_1^m being the incident wave at the m -th UC and M is the total number of UCs. $\kappa_{IL} = \frac{P_4}{P_3}$ where $P_4 = \sum_{m=1}^M |b_2^m|^2$ is the power transmitted to the transmitting layer with b_2^m being the

transmitted wave at the m -th UC. The relationship between a_1^m and b_2^m is explained further in [109].

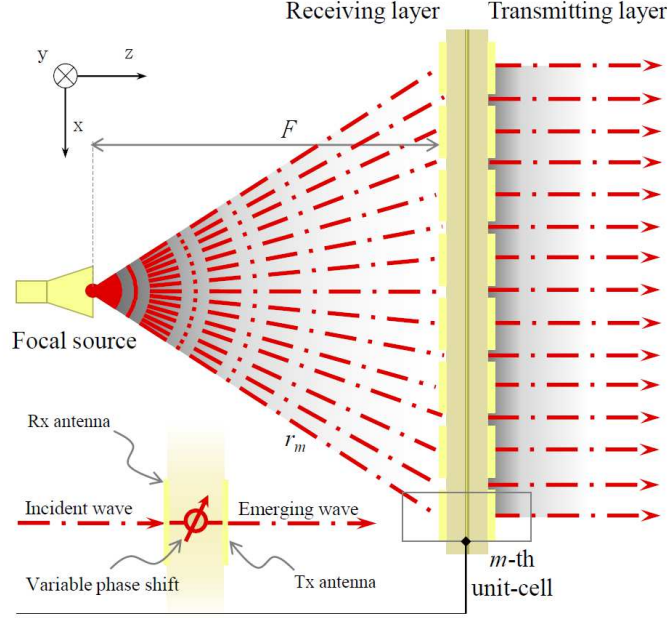


Figure 1.5: T-RIS operating principle [109].

For detailed procedures in the designing of T-RISs, refer to [109–113]. For the purpose of our measurements we considered two types of T-RIS: a linearly polarized and a circularly polarized one.

1.12 Thesis Contributions

Extensive research efforts devoted to sub-6 GHz mMIMO channel measurements and modelling are available in the literature [84,85,87,88]. mmWave channel measurements involving the mechanical steering of directive antennas, followed by the omnidirectional PDP synthesis are also available in the literature. However, there is still need for channel measurements and models involving the electronic steering of very directive antennas in order to investigate the joint channel-antenna interactions. In the scope of 5G and 6G, the emerging technology of reconfigurable intelligent surfaces (RISs) will enable the concept of the wireless environment as a service [114]. Smart antennas such as T-RISs with electronic

beamsteering or beamscanning capabilities, high gain and directivity (thanks to beamforming) are preferred over the mechanically steered horn antennas. Hence, the T-RISs will be ubiquitous in the 5G and 6G wireless communication systems.

On top of this, the properties of the mmWave mMIMO channel for short ranges, typically in indoor environments, demand for specific measurement campaigns and analysis. The impact of different array sizes and geometries on the channel characteristics is essential to better understand the mmWave mMIMO channels.

This thesis aims to address the aforementioned gaps in the literature. In essence, this thesis aims for measurement based characterization and modelling of mmWave mMIMO channels, particularly in InLab, InOpOffice, InMixOffice, corridors and InF environments. The goal is to establish stochastic models. In particular, we investigate the impact of the array size and geometry on the channel characteristics and we analyze how in LOS, OLOS and NLOS conditions, the channel varies along a massive array. In view of hybrid beamforming approaches, where different sub-arrays can be exploited, we analyze the MPCs distributions and similarities between different positions within the massive array. We also investigate the T-RIS beamscanning capabilities and the impact of T-RIS beamforming on the large scale parameters in the InLab, InOpOffice, InMixOffice, corridors and InF environments. We then proceed to evaluate how the geometrical structure of the channel is modified when T-RISs are deployed in mmWave indoor channels.

In summary, the analysis was done in four steps as follows: Firstly, channel measurements and data collection is performed. Secondly, channel characterizations in terms of large scale parameters (path loss, delay and angular spreads) and MPCs extraction is done. Thirdly, MPCs distributions are analyzed and statistical spatio-temporal channel models are derived for some of the indoor environments. Lastly, we investigate how the geometrical structure of the indoor mmWave mMIMO channels is modified when T-RISs are deployed. Synthesized channel models are compared with the actual T-RIS measured channels. Omnidirec-

tional power delay profiles are synthesized for the T-RIS measurements followed by deducing the statistical spatio-temporal channel models.

The contribution of this thesis can be summarized in the following points:

- Indoor mmWave mMIMO channel measurements based on massive arrays as well as T-RISs in InLab, InOpOffice, InMixOffice, corridors and InF environments.
- Investigation on the impact of the array size and geometry on the mmWave mMIMO channel characteristics.
- Investigation on the mmWave mMIMO spatial channel correlation over the massive array.
- Analysis of MPCs distributions over a large array in indoor mmWave mMIMO channels.
- Investigation on the T-RISs beam-scanning capabilities as well as the impact of beamforming on delay spread and path loss.
- Investigation on the impact of T-RISs on the geometrical structure of the indoor mmWave mMIMO channels.
- Statistical spatio-temporal channel models based on both the massive arrays' channel measurements and the T-RISs' channel measurements.

1.13 Thesis Outline

Chapter 2 presents the indoor mmWave mMIMO channel characterization and modelling results based on massive virtual arrays.

Chapter 3 presents the channel characterization and modelling results for channel measurements wherein T-RISs are employed.

Chapter 4 focuses on analyzing the impact of the T-RIS on the geometrical structure of the indoor mmWave channels.

Chapter 5 gives the overall conclusions and future perspectives.

Chapter 2

Indoor mmWave mMIMO Channel Characterization and Modelling with very Large Arrays

In the last years, the scientific community have been proposing different channel models for 5G and 6G communications, including world-wide recognized standards from International Telecommunication Union (ITU) and 3GPP [115] and first approaches to 3D wideband model for 5G mMIMO channels [116–118]. However, mmWave channel modelling is often based on mechanical steering of antennas and reconstruction of the omni-directional power delay profile, while the properties of mmWave mMIMO channel for short ranges, typically in indoor environments, demand for specific measurement campaigns and analysis.

In this chapter, we tackle the problem of mmWave mMIMO channel characterization and modelling in the InLab, InOpOffice, and InF environments. In particular, we investigate the impact of the array size and geometry on the channel characteristics, we analyze how in LOS, OLOS and NLOS conditions, the channel variates along a large array

of 21×21 antennas. In view of hybrid beamforming approaches, where different sub-arrays could be exploited, we analyze the MPCs distributions and similarities between different positions within the large array. The remainder of this chapter is outlined as follows: Section 2.1 presents the channel measurement campaigns in the different environments. The channel characterization and modelling results are presented in Section 2.2. Finally, Section 2.3 concludes the chapter.

2.1 Channel Measurement Campaigns

The channel measurement campaigns were performed in different indoor environments at CEA-Leti. In all environments, two identical, vertically polarized monopole antennas (of measured gain 0 dBi) were employed. The monopole antennas were at the same height above the ground. Table 2.1 shows the measurement parameters. The different environments and floor plans are presented in the following subsections.

Table 2.1: VNA setup and antenna parameters.

Parameter	Value
Frequency band	26-30 GHz
Bandwidth	4 GHz
Number of sweep points	801
IF bandwidth	100 Hz
Transmitted power	10 dBm

The general measurement setup considered in all environments is shown in Fig. 2.1. The measurement setup is based on a VNA and automatic positioners to control antenna movements while scanning virtual spatial grids. The different spatial grids scanned in a particular environment will be specified.

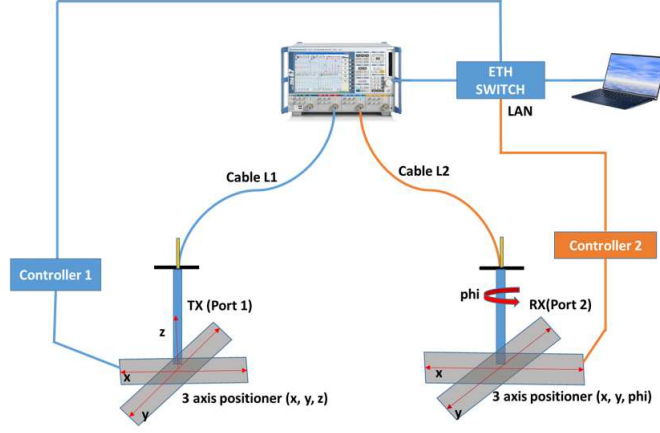


Figure 2.1: Measurement Setup

The vertically polarized monopole antennas measured gain patterns at 28 GHz are shown in Fig. 2.2.

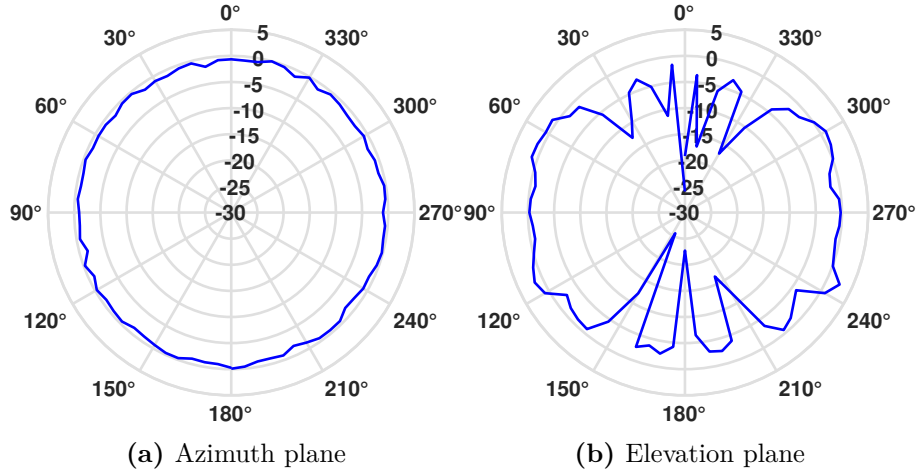


Figure 2.2: Co-polarization: Monopole antenna measured gain patterns.

2.1.1 Indoor Laboratory

The channel measurements were performed in an InLab room with dimensions, 7 m $\times$ 4.3 m $\times$ 2.8 m. The measurement setup is shown

With the center frequency being 28 GHz, a grid step of 5 mm, corresponding to half of the wavelength, was considered on both the TX and the RX grids. Fig. 2.3(b) shows the floor plans.

2.1.2 Indoor Open Office

The dimensions of the InOpOffice room were 12 m $\times$ 6 m. The InOpOffice room is furnished with tables, chairs, desktops, sofas, and a television. The left wall of the room mostly comprises of glass windows and the right side wall also has a portion with a glass window. On the roof, there is also a metallic positioner. The measurement setup follows the general setup shown in Fig. 2.1. On the TX side, spatial grids were scanned in the x, y and z axes, forming a $5 \times 5 \times 5$ Virtual Cubic Array (VCA). On the RX side, no spatial grids were scanned. Fig. 2.4 shows the measurement floorplans.

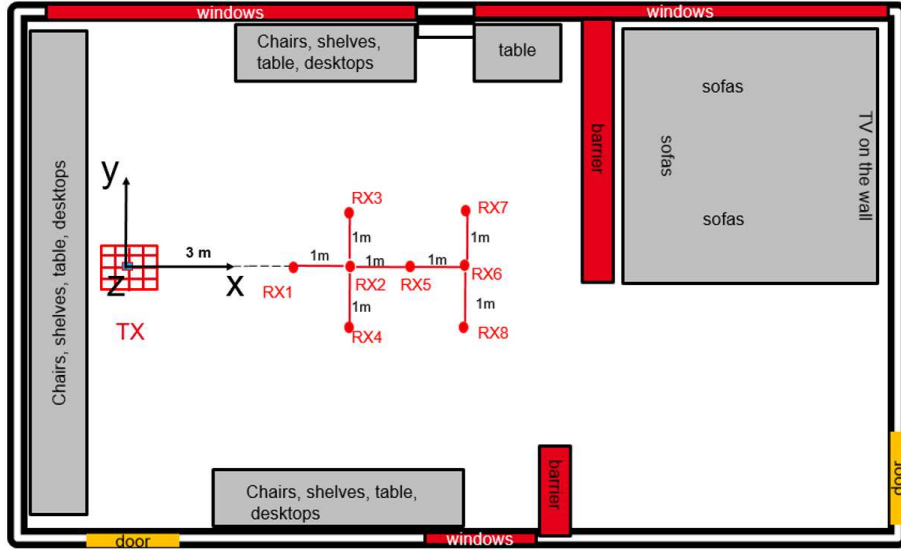


Figure 2.4: InOpOffice floor plans.

The InOpOffice environments are clearly depicted in Fig. 2.5. In this measurement campaign, the monopole antennas were both at a height of 1.52 m above the ground.

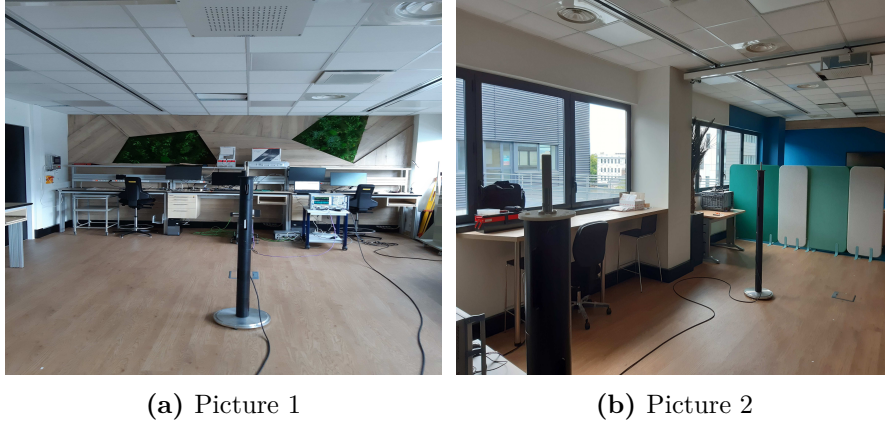


Figure 2.5: Pictures of the InOpOffice room measurement environment.

2.1.3 Indoor Factory

The channel measurements were carried out in an InF environment considering either a VCA or a VPA array at the TX side. For the VCA, $5 \times 5 \times 5$ spatial grids were scanned in the x, y and z axes while for the VPA, spatial grids were scanned in the z and y axes forming a 21×21 VPA in the zoy plane. On the RX side, no spatial grids were scanned. Three propagation conditions were investigated, namely LOS, OLOS and NLOS. The measurement setups follow the general setup shown in Fig. 2.1. To increase the dynamic range for both the OLOS and NLOS conditions, a low noise amplifier of 20 dB was used at the RX side. Hence, attenuators in series are considered during the measurement calibration. Since the attenuators are not used in the actual measurement, their influence is de-embedded during postprocessing. The InF environment floor plans are given in Fig. 2.6 while Fig. 2.7 shows the photos of the three considered propagation conditions.

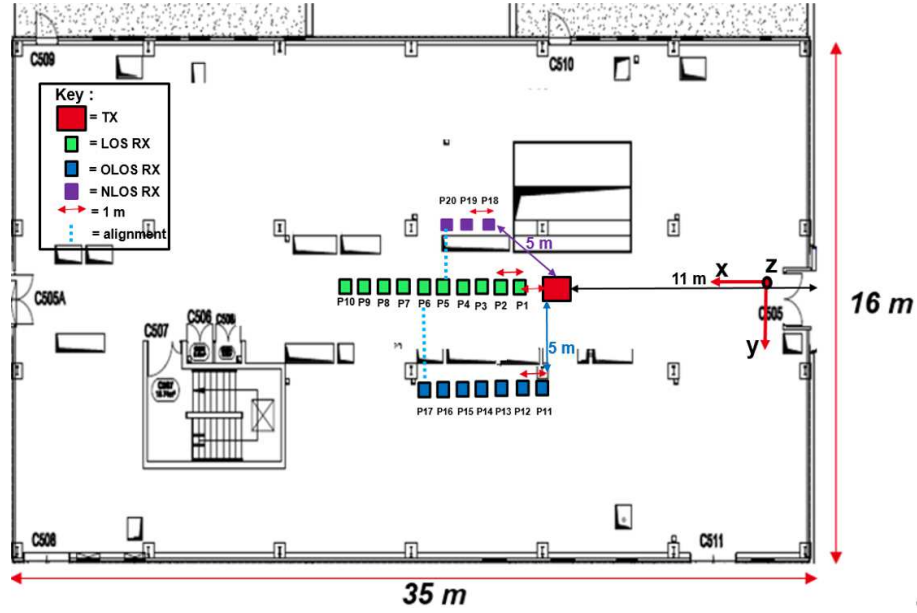


Figure 2.6: InF environment floorplans.



(a) InF LOS



(b) InF OLOS



(c) InF NLOS

Figure 2.7: Pictures of the InF measurement environments.

2.2 Channel Characterization and Modelling Results

In this section we present the channel characterization and modelling results. For simplicity sakes, the $5 \times 5 \times 5$ massive cubic array is referred to as the VCA and the 21×21 massive planar array is called the VPA. Fig. 2.8 shows an example of the InF VCA SAGE estimated MPCs for the RX position P4. In the Power Angular Delay Profile (PADP) shown in Fig. 2.8(a), each circle represents a detected MPC, whose color is the power and the radial distance is the traveled distance in meters. For Fig. 2.8(b), each circle represents a detected MPC, whose color is the power and each circle is represented on the 3D Cartesian coordinate system.

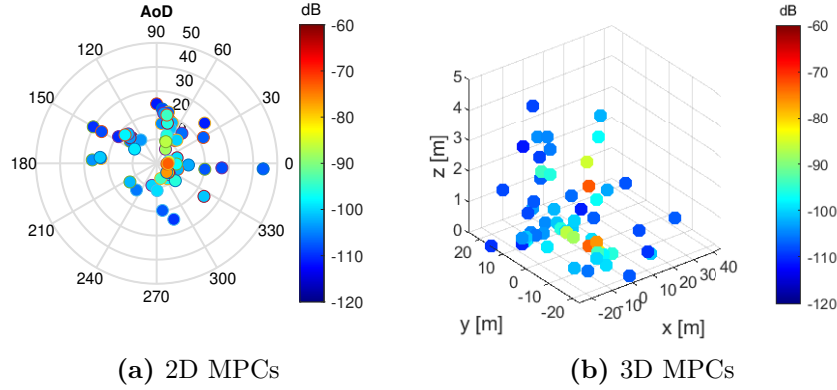


Figure 2.8: InF position P4 MPCs.

Fig. 2.9 shows an example of the InF VCA superposed PDPs for the RX position P4. The measured PDP is the blue one while the red PDP corresponds to the SAGE estimated PDP. The circles represent the detected MPCs.

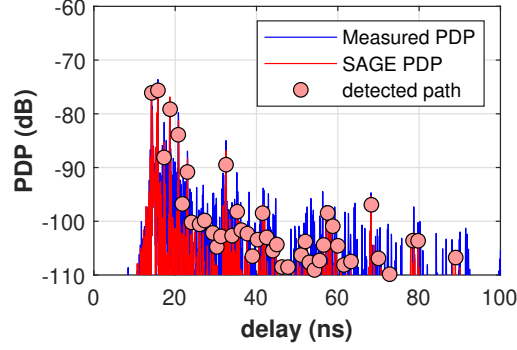


Figure 2.9: InF position P4 PDP example.

For the UWB SAGE estimation, an overall threshold of 3 dB above the noise floor is considered for the InF channel measurements. The estimated MPCs are then used for channel modelling.

2.2.1 Large Scale Parameters

In the InF environments, numerous receiver positions were considered. We therefore proceeded to model the PL and DS, considering the raw measured CTF. From both the VCA and VPA measurements for positions P1-P10 and P11-P17, we derive the CG and DS model. To do so, we combined or merged the VCA and the VPA channel measurements. Here we consider the models derived directly from the raw data, those obtained after denoising the measured CTF and those derived from the SAGE estimated MPCs. We employed the conventional gain power law (2.1) to model the distance dependent CG.

$$G_{dB}(d) = G_0 - n \cdot 10 \cdot \log_{10} \left(\frac{d}{d_0} \right) + X_\sigma \quad (2.1)$$

where G_0 represents the intercept point at reference distance d_0 set to 1 m. The path loss exponent, n indicates the decrease in CG as a function of the distance d between the TX and RX. Both G_0 and n are obtained from the intercept and slope of the best-fit to (2.1) according to the minimum mean square error. X_σ is the variation due to long-term fading effects and is characterized through a normal distribution with

zero mean and a standard deviation σ in dB . We compute the CG from the raw measurements following equation (2.2).

$$CG = \frac{1}{BW} \int_{-BW/2}^{BW/2} |H(f)|^2 df \quad (2.2)$$

where CG is the channel gain, BW is the bandwidth and $H(f)$ is the channel transfer function.

To model the DS, we followed (2.3).

$$\tau_{rms}[ns] = a.d + b + X_\tau \quad (2.3)$$

where a represent the DS exponent, b is the intercept and X_τ denote a zero mean Gaussian random variable with the standard deviation σ_τ which represents the deviation of the DS from the model.

Fig. 2.10 shows the CG and DS models after denoising (in blue) as well as the models obtained from the SAGE estimated MPCs (in magenta). The denoising was performed by considering the same denoising threshold employed in cleaning the measured CTF before running the high detection resolution algorithm. To get the CG curve, at each receiver position, equation (2.2) was followed. The model parameters are given in Table 2.2 and Table 2.3. The negative path loss exponents for positions P11-P17 indicate that for these positions, the CG is generally increasing with TX-RX separation distance. This is because the RX locations are in such a way that P11 is basically in a quasi-NLOS condition, and as we move to P17, the scenario becomes more and more OLOS, with an observable dominant peak.

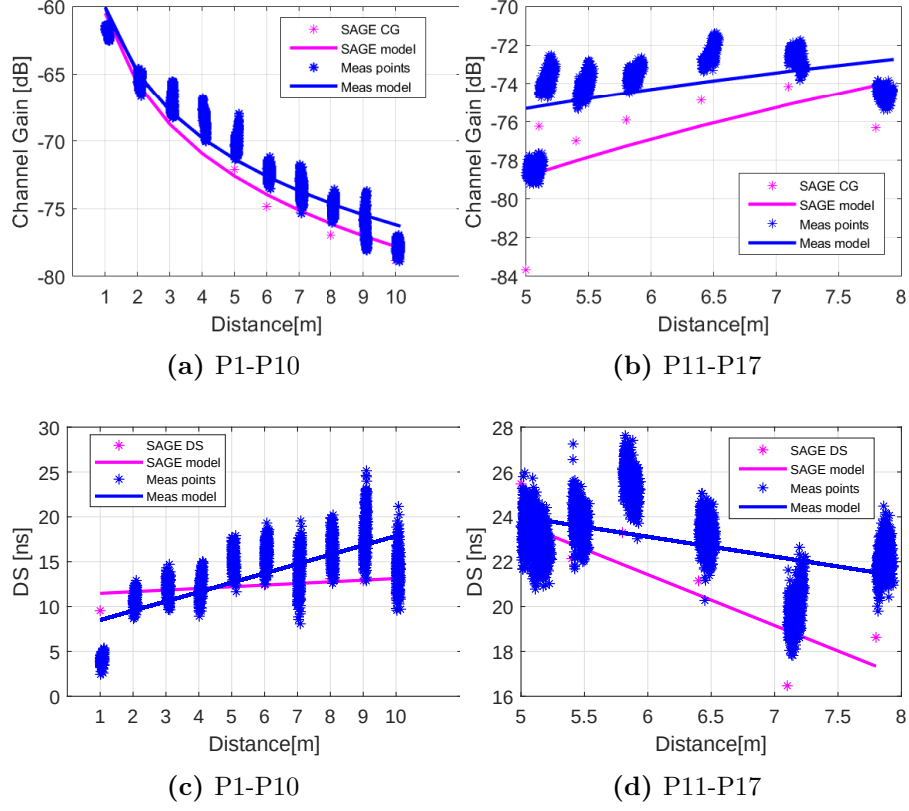


Figure 2.10: InF: Merged models (a), (b) CG and (c), (d) DS.

Table 2.2: InF: Channel Gain Model Parameters.

Scenario	$G_0[dB]$	n	$\sigma[dB]$
P1-P10 (before denoising)	-60.1	1.42	0.8
P1-P10 (after denoising)	-60.1	1.61	1.2
P1-P10 SAGE estimated	-60.5	1.73	1.1
P11-P17 (before denoising)	-83.2	-1.2	1.6
P11-P17 (after denoising)	-84.2	-1.3	1.7
P11-P17 SAGE estimated	-96.1	-2.46	2.6

Table 2.3: InF: Delay spread Model Parameters.

Scenario	$a[ns/m]$	$b[ns]$	$\sigma_\tau[ns]$
P1-P10 (before denoising)	2.81	15.8	8
P1-P10 (after denoising)	1.04	7.5	3
P1-P10 SAGE estimated	0.18	11.3	1.1
P11-P17 (before denoising)	-1.24	34.3	1.2
P11-P17 (after denoising)	-0.89	28.4	0.87
P11-P17 SAGE estimated	-2.27	35	1.7

VCA vs VPA Comparison

In Fig. 2.11, we show the Average Power Delay Profile (APDP)s for both the VCA and the VPA for the LOS positions P1-P10. For a particular position r , the $\mathbf{APDP}(r, \tau)$ vector with dimensions $[1 \times N_\tau]$ is computed as a spatial average over the M measured SISO links as follows:

$$\mathbf{APDP}(r, \tau) = \mathbb{E}_M[\mathbf{PDP}(\tau)] \quad (2.4)$$

where $r=P1, P2, P3, \dots, P10$ is the position, $\mathbf{PDP}(\tau)$ is an $[M \times N_\tau]$ matrix at a particular position, $M = 125$ or 441 , respectively, for the VCA and the VPA and N_τ is the number of delay bins. For both array types, we can clearly see the evolution of the LOS path intensity with distance. The LOS path intensity decreases with increasing TX-RX separation distance. Secondary MPCs due to reflections can also be observed, for instance, the reflection from the door C505A is observed at around 153 ns to around 130 ns . The further from the TX the RX position is, the earlier these reflections from the door are observed (since the RX will be closer to the door).

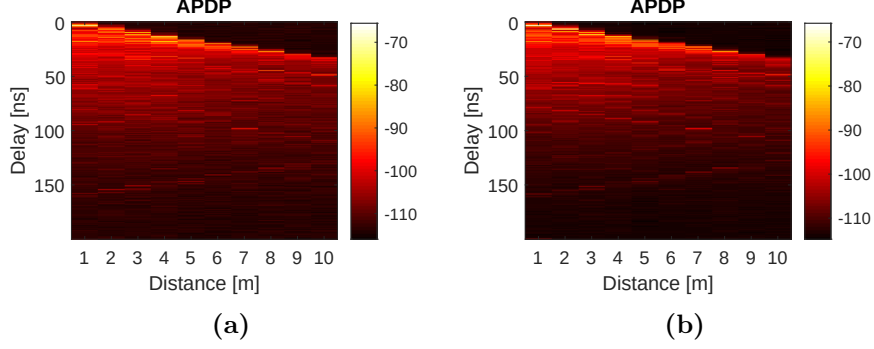


Figure 2.11: APDP (a)VCA and (b)VPA in InF.

We recall that the UWB SAGE algorithm was used for the MPCs estimation. Fig. 2.12(a-c) show the energy contribution of the strongest path in the InF environment for the three different propagation conditions considered. The strongest path energy contribution is computed following equation (2.5).

$$Contribution(\%) = \frac{\alpha_0^2}{\sum_{l=0}^{L-1} \alpha_l^2} \times 100 \quad (2.5)$$

where α_0 is the amplitude of the strongest path, α_l is the amplitude of the l -th path and L is the total number of MPCs. The plots are plotted with respect to the physical distance in the environment. The positions P1-P10 are in LOS condition, the positions P11-P17 are in OLOS condition and finally, the positions P18-P20 are in NLOS condition. In both the VCA and VPA, the highest strongest path energy contribution considering all the 10 LOS positions is obtained at position P1. This is because at this short TX-RX separation distance, the LOS component is the dominant component containing most of the energy. The least strongest path energy contribution obtained at receiver position P4 for the VCA can be explained by Fig. 2.9. We can observe from Fig. 2.9 that the secondary MPCs have very high energy, which in turn will lower the contribution of the strongest MPC. Overall and considering the LOS condition, Fig. 2.12(a) shows that the strongest path energy contribution ranges between (37 to 96.5)% for the VCA and between (46.8 to

90.4)% for the VPA. Fig. 2.12(b) and (c) show the strongest path contribution for the OLOS and NLOS conditions, respectively. For the OLOS condition, the strongest path energy contribution ranges between (11.5 to 64.4)% for the VCA and between (18 to 76.4)% for the VPA. In both massive arrays, the very small contribution of the strongest path at position P11 is due to the fact that this position is in essence quasi-NLOS. For the NLOS condition, the strongest path energy contribution ranges between (26.5 to 33.5)% for the VCA and between (24.8 to 63.5)% for the VPA. With regards to DSs, Fig. 2.12(d-f) show the DSs variation for the three different propagation conditions with respect to the physical distance. We can see in Fig. 2.12(d) that for the LOS condition and at position P1, the VCA has a smaller DS value than the VPA and this is consistent with the first path contributions. At position P1, the first path is the dominant path that contributes most of the energy, that is 90% or more for both massive arrays. Overall and considering the LOS condition, the DSs range between (2.5 to 10.7) *ns* for the VCA and between (2.9 to 12.2) *ns* for the VPA. Fig. 2.12(e) and (f) show the DSs variation for the OLOS and NLOS conditions, respectively. For the OLOS condition, the DSs range between (12.5 to 20.1) *ns* for the VCA and between (12 to 19) *ns* for the VPA while for the NLOS condition, they range between (22 to 23.5) *ns* for the VCA and between (18.7 to 19.9) *ns* for the VPA. The smallest VPA DS value for NLOS position P20 is due to a dominant path that was observed when this relatively large massive array was employed. Concerning the ASs, figures Fig. 2.12(g-i) and Fig. 2.12(j-l) show the ASs variation for the three different conditions with respect to the physical distance. Overall and considering the LOS condition, the azimuth ASs range between (12.6 to 30)° for the VCA and between (28.5 to 105)° for the VPA. Fig. 2.12(h) and (i) show the azimuth ASs variation for the OLOS and NLOS conditions, respectively. For the OLOS condition, the azimuth ASs range between (30 to 60.8)° for the VCA and between (26.4 to 75.8)° for the VPA while for the NLOS condition, they range between (43.6 to 53.6)° for the VCA and between (34.4 to 43.9)° for the VPA. Likewise, considering the LOS condition, the elevation ASs range between (4 to 20.4)°

for the VCA and between $(0.6 \text{ to } 17.7)^\circ$ for the VPA. Fig. 2.12(k) and (l) show the elevation ASs variation for the OLOS and NLOS conditions, respectively. For the OLOS condition, the elevation ASs range between $(3.9 \text{ to } 12)^\circ$ for the VCA and between $(3.2 \text{ to } 10)^\circ$ for the VPA while for the NLOS condition, they range between $(1.5 \text{ to } 4.4)^\circ$ for the VCA and between $(0.9 \text{ to } 1.3)^\circ$ for the VPA.

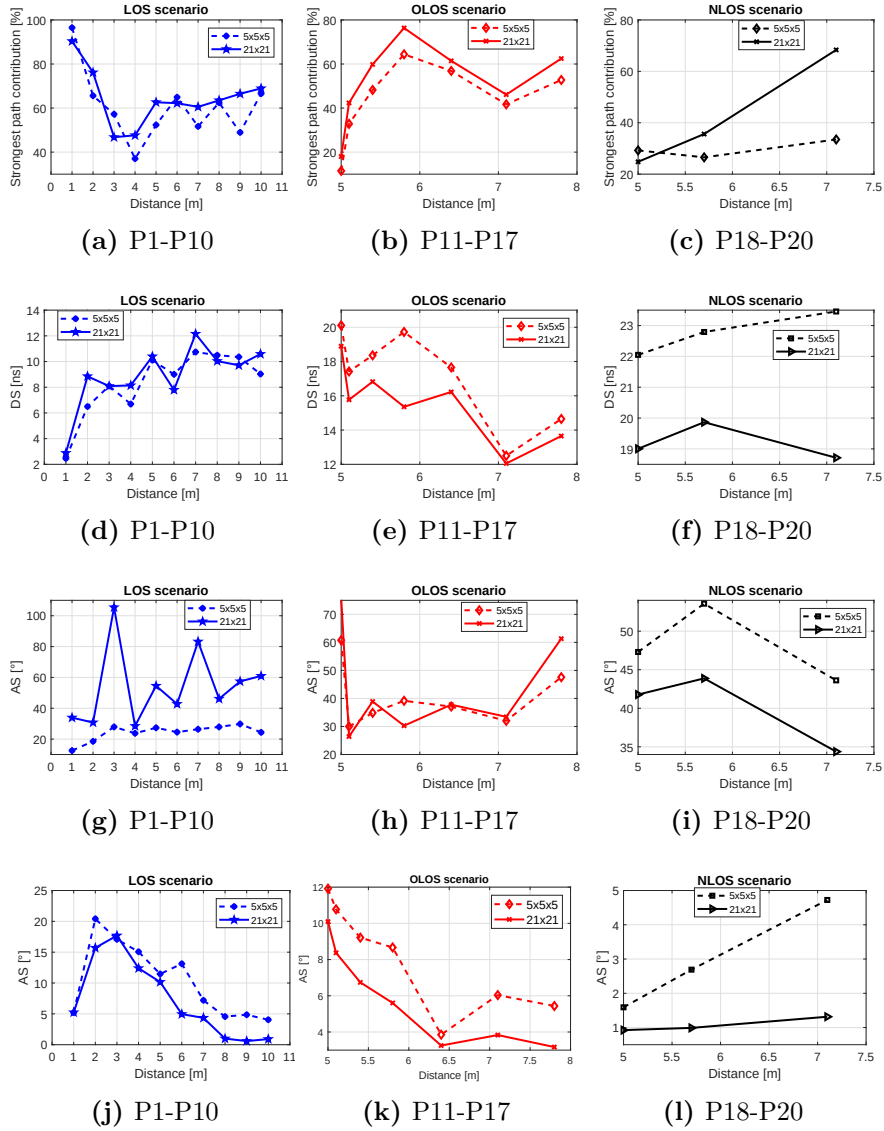


Figure 2.12: P1-P20 VCA vs VPA in the InF environments.

In a nutshell, we can see that the azimuth plane is more spread while the elevation plane is less spread. This behaviour is in line with the monopole antennas radiation patterns.

2.2.2 Statistical Spatio-Temporal Channel Models

In indoor environments, MPCs tend to arrive in clusters which are identified in the delay and angular domains [119–121]. Channel models that do not consider the clustering of MPCs when in fact the MPCs are clustered, result in the overestimation of the channel capacity [122]. A cluster is defined as a set of paths that have similar propagation characteristics in terms of delays and angles of arrival or departure. It is therefore important to consider MPCs clusters and their angular and delay spreads for the efficient design of 5G and beyond communications systems. Here, we investigate the possible clusters by applying the KPowerMeans algorithm [123]. In this analysis, we exploit channel reciprocity and consider the side with an array as the RX. In order to discriminate the clusters, we utilized the Multipath Component Distance (MCD) metric. This metric is computed as follows:

$$MCD^{i,j} = \sqrt{\|MCD_{AOA}^{i,j}\|^2 + MCD_{\tau}^{i,j2}} \quad (2.6)$$

where $MCD_{AOA}^{i,j}$ is the MCD for angles of arrival and is calculated using the following equation:

$$MCD_{AOA}^{i,j} = \frac{1}{2} |\mathbf{a}_i - \mathbf{a}_j| \quad (2.7)$$

where $\mathbf{a}_l = [\sin(\theta_l) \cos(\phi_l), \sin(\theta_l) \sin(\phi_l), \cos(\theta_l)]^T$. The MCD for delays is computed as follows:

$$MCD_{\tau}^{i,j} = \zeta \frac{|\tau_i - \tau_j|}{\Delta\tau_{max}^2} \tau_{std} \quad (2.8)$$

where τ_{std} is the standard deviation of the delays and $\Delta\tau_{max}$ is given by:

$$\Delta\tau_{max} = \max_{i,j} (|\tau_i - \tau_j|) \quad (2.9)$$

and ζ represents a delay scaling factor that sets the importance of the delay domain. In our work, we considered $\zeta = 1$, indicating that the angular domain and delay domain have a comparable weight. To avoid the detection of insignificant clusters, we considered that the power of an identified cluster should be at least 0.1% of the total power.

For the InOpOffice environment, Fig. 2.13 shows the extracted MPCs and the identified clusters for the receiver position RX4.

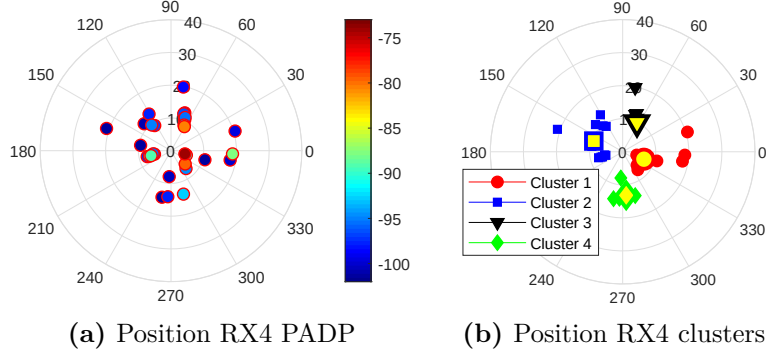


Figure 2.13: InOpOffice Estimated MPCs and clusters at position RX4.

Each cluster is defined by a centroid with a delay:

$$\bar{\tau}_k = \frac{\sum_{l \in C_k} \tau_l \cdot P_l}{\sum_{l \in C_k} P_l} \quad (2.10)$$

and an AOA:

$$\bar{\phi}_k = \frac{\sum_{l \in C_k} \phi_l \cdot P_l}{\sum_{l \in C_k} P_l} \quad (2.11)$$

where L_k is the number of MPCs present in the k -th cluster C_k . τ_l , ϕ_l and P_l , respectively, denote the delay, the AOA and the power of the l -th MPC. The cluster delay spread is computed as follows:

$$\tau_{k,rms} = \sqrt{\frac{\sum_{l \in C_k} (\tau_l - \bar{\tau}_k)^2 \cdot P_l}{\sum_{l \in C_k} P_l}} \quad (2.12)$$

and the AOA spread is given by

$$\phi_{k,rms} = \sqrt{\frac{\sum_{l \in C_k}^{L_k} (\phi_l - \bar{\phi}_k)^2 \cdot P_l}{\sum_{l \in C_k}^{L_k} P_l}} \quad (2.13)$$

Below, we give the identified cluster parameters. Table 2.4 presents the cluster centroids parameters.

Table 2.4: InOpOffice Cluster centroids.

Position	C_k	$\bar{\tau}_k[ns]$	$\bar{\phi}_k[^\circ]$	Centroid power [dB]
RX1	k=1	12.7	0.7	-70.3
	k=2	20.6	160.8	-81.2
	k=3	27.7	67.9	-73.8
	k=4	38.1	300	-88.4
RX2	k=1	16.2	0.8	-72.2
	k=2	25.7	149.9	-80.1
	k=3	23.5	308.6	-92.9
	k=4	32.5	62.1	-79.1
RX3	k=1	21.6	27.3	-70.5
	k=2	20.2	173.4	-88.4
	k=3	35.5	118	-87
	k=4	49.9	309.5	-85.9
RX4	k=1	22.7	340.7	-69.4
	k=2	31	159.6	-82.8
	k=3	32.8	63.8	-77.6
	k=4	44.1	274.6	-88.9
RX5	k=1	21.2	0.7	-73.3
	k=2	24.9	316	-78.9
	k=3	29.6	53.8	-82.6
	k=4	32.9	133.4	-82.5
RX6	k=1	24.9	0.6	-75
	k=2	28.7	316.9	-87.5
	k=3	36.5	145.5	-78.4
	k=4	57.5	54.2	-86.6
RX7	k=1	27.2	10.5	-72.7
	k=2	36	151.8	-91.4
	k=3	30	315.5	-75.9
	k=4	58.8	69.5	-92.1
RX8	k=1	31.4	351.6	-72
	k=2	27.2	188.3	-85.9
	k=3	34.8	54.6	-80
	k=4	35.6	136.1	-89.1

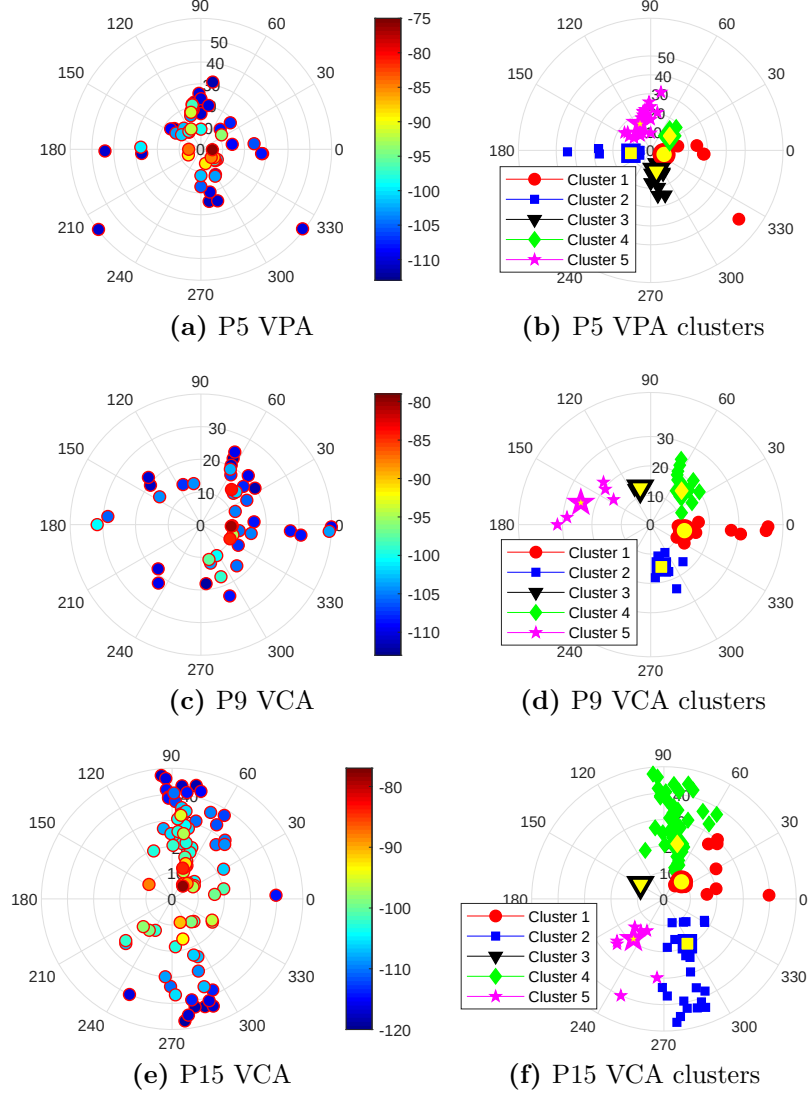
We can observe from Table 2.5 that it is the first cluster which carries most of the energy. This cluster delay line model can be easily used for system performance evaluation.

Table 2.5: InOpOffice cluster energy contributions, delay and angular spreads.

Position	C_k	$\tau_{k,rms}[ns]$	$\phi_{k,rms}[^{\circ}]$	C_k contribution [%]
RX1	k=1	2	0.3	48.3
	k=2	4	37.3	13.7
	k=3	5	2.5	32
	k=4	13	15.1	6
RX2	k=1	2	0.3	51.3
	k=2	5	10.5	20.8
	k=3	2	1.6	4.7
	k=4	5	3.2	23.2
RX3	k=1	6	16.8	69.1
	k=2	1	42.4	8.8
	k=3	9	21.8	10.4
	k=4	12	17.2	11.7
RX4	k=1	9	10.6	58.7
	k=2	8	147	12.4
	k=3	4	2.1	22.7
	k=4	4	10.2	6.2
RX5	k=1	4	0.5	45.1
	k=2	1	0.8	23.8
	k=3	3	1.8	15.5
	k=4	4	6.7	15.6
RX6	k=1	4	0.7	45.9
	k=2	2	2.6	10.9
	k=3	4	50.9	31.1
	k=4	19	5	12.1
RX7	k=1	8	2.7	52.3
	k=2	12	19.1	6
	k=3	1	2	36
	k=4	2	2.3	5.6
RX8	k=1	13	2.9	57.3
	k=2	1	0.8	11.7
	k=3	3	3.5	22.9
	k=4	0.2	1	8.1

In the InF environments, generally 5 clusters were identified per receiver position. Examples of the estimated MPCs and the identified

clusters for the different positions in the InF environments are shown in Fig. 2.14.



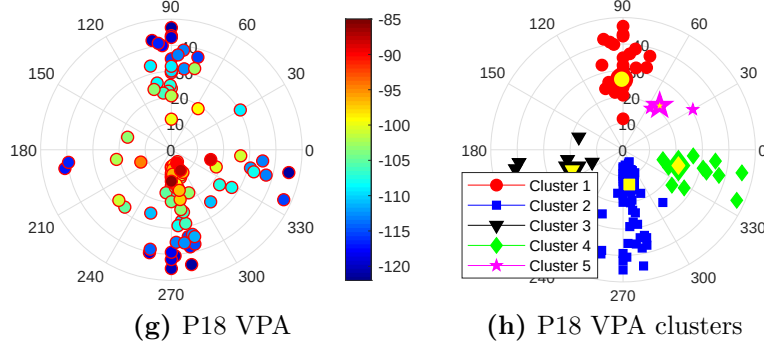


Figure 2.14: InF estimated MPCs and clusters at each receiver position.

Fig. 2.15 shows the percentage cluster power contributions for the $5 \times 5 \times 5$ VCA and the 21×21 VPA arrays for the positions P1-P10.

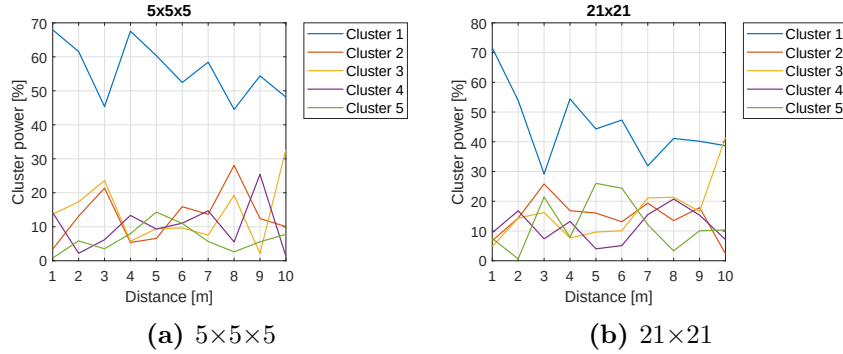


Figure 2.15: InF VCA (a) vs VPA (b): cluster power contributions.

It is clear from the figure that it is the first cluster that carries the most energy. Generally, clusters' contributions in both array types appear to follow a similar trend.

The classical Saleh and Valenzuela (SV) channel model is widely used to model the indoor radio channels [119]. The classical SV model (2.14) does not consider the channel spatial information. The spatial channel information can be incorporated into the classical SV model to give the

extended version of the SV model [124] given by equation (2.15).

$$h(t) = \sum_{k=0}^{K-1} \sum_{l=0}^{L_k-1} \beta_{lk} e^{j\phi_{lk}} \delta(t - T_k - \tau_{lk}) \quad (2.14)$$

where k and l are the cluster and path indices, respectively. K and L_k are respectively, the number of clusters and the the number of MPCs in the k -th cluster. β_{lk} , ϕ_{lk} and τ_{lk} denote the amplitude, phase, arrival delay of the l -th path in the k -th cluster, respectively. T_k is the arrival time of the k -th cluster.

$$h(t, \phi) = \sum_{k=0}^{K-1} \sum_{l=0}^{L_k-1} \beta_{lk} e^{j\phi_{lk}} \delta(t - T_k - \tau_{lk}) \delta(\phi - \Theta_k - \phi_{lk}) \quad (2.15)$$

with the additional terms Θ_k and ϕ_{lk} . Θ_k is the angle of k -th cluster and it is computed as the mean angle of all the MPCs in the k -th cluster. ϕ_{lk} is the AOA of the l -th path(ray) in the k -th cluster.

Similar to [121, 124, 125], we model the path gain as follows :

$$\overline{\beta^2}_{lk} = \overline{\beta^2(T_k, \tau_{lk})} = \overline{\beta^2(0, 0)} e^{\frac{-T_k}{\Gamma}} e^{\frac{-\tau_{lk}}{\gamma}} \quad (2.16)$$

where $\overline{\beta^2(0, 0)}$ is the average power of the first arrival of the first cluster. The average power is a function of the transmitter-receiver separation distance. We recall that in the literature, the fading amplitudes β_{lk} commonly follow Rayleigh or lognormal distributions. In some instances, these amplitudes have also been reported to follow a Nakagami- m distribution [126].

In a similar fashion (as in the aforementioned works), we assume that both the clusters and rays arrival rates follow a Poisson distribution with a fixed rate Λ , λ , respectively. The Poisson distributions are defined as follows:

$$p(T_k | T_{k-1}) = \Lambda e^{-\Lambda(T_k - T_{k-1})}, \quad k > 0 \quad (2.17)$$

$$p(\tau_k | \tau_{(l-1)k}) = \lambda e^{-\lambda(\tau_k - \tau_{(l-1)k})}, \quad l > 0 \quad (2.18)$$

where Λ , λ are respectively, the cluster arrival rate and the ray arrival rate.

With regards to the intracluster and intercluster parameters, Fig. 2.16 and Fig. 2.17 show respectively, the CDFs of rays relative arrival time and clusters relative arrival time.

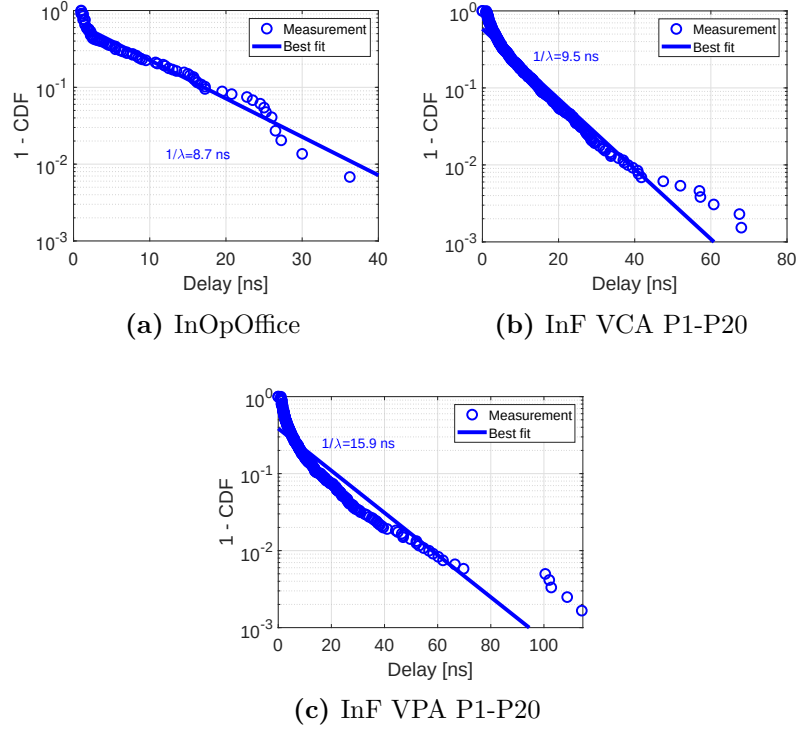


Figure 2.16: CDF of relative arrival times of rays.

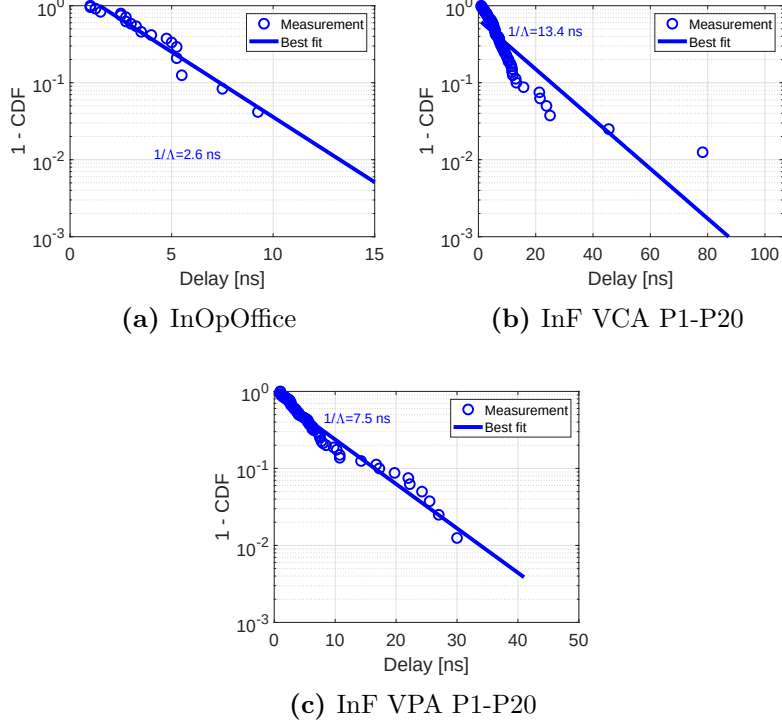


Figure 2.17: CDF of relative arrival times of clusters.

Fig. 2.18 and Fig. 2.19 show the plots of clusters and rays relative powers versus their respective relative delays in the investigated environments. A cluster power is relative to the first cluster's power. In a similar fashion, a ray power is relative to the power of the first arrival in the considered cluster. The same holds true for the delays. The parameters $\frac{1}{\Lambda}$ and $\frac{1}{\lambda}$ are determined by a least-squares fit of the CDF of the conditional probabilities (2.17)-(2.18), respectively. Likewise, parameters Γ and γ are obtained by a least-squares fit of the relative powers of clusters and rays, respectively.

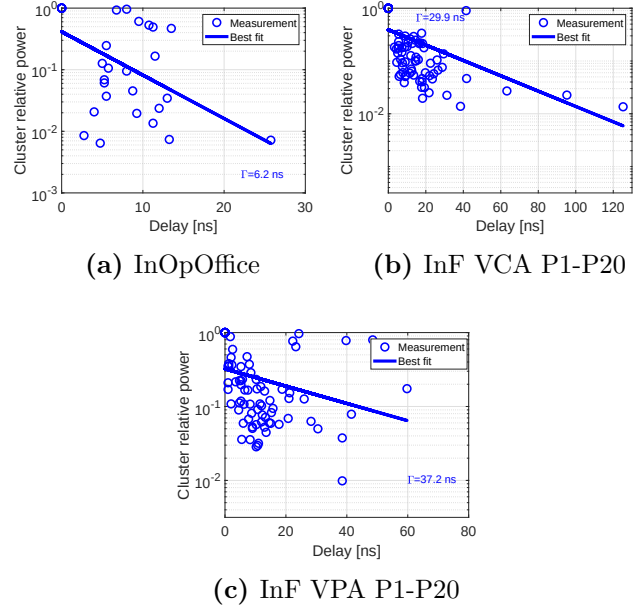


Figure 2.18: Plot of normalized clusters powers versus normalized delays.

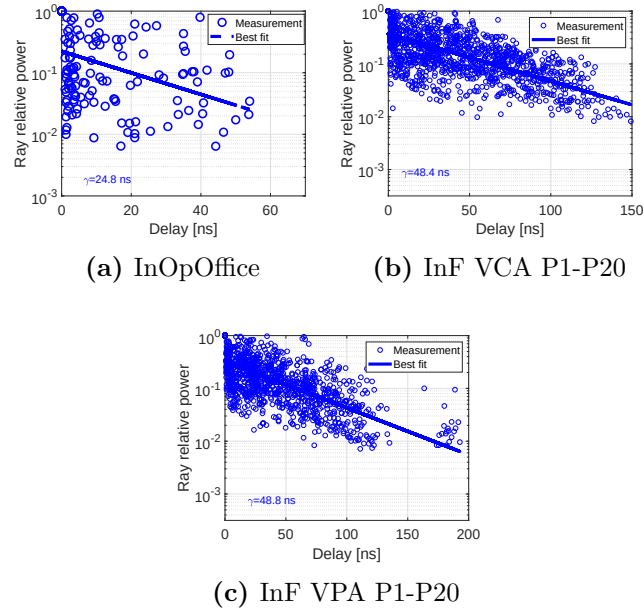


Figure 2.19: Plot of normalized rays powers versus normalized delays.

Table 2.6 summarizes the decay rate and arrival rate of clusters and rays for both the InOpOffice and InF environments (different scenarios and array types).

Table 2.6: Decay rate and arrival rate of clusters and rays.

Scenario	$\Gamma[ns]$	$\gamma[ns]$	$\frac{1}{\Lambda}[ns]$	$\frac{1}{\lambda}[ns]$
InOpOffice VCA	6.2	24.8	2.6	8.7
InF VCA P1-P20	29.9	48.4	9.5	13.4
InF VPA P1-P20	37.2	48.8	7.5	15.9
InF VCA P1-P10	13.9	38.8	6.3	9.9
InF VPA P1-P10	8	53.9	2.6	21.1

The results show that the clusters decay faster in the InOpOffice than in both the InF P1-P10 massive arrays scenarios as well as in both the InF P1-P20 massive arrays scenarios. Considering only the LOS conditions in both environments, the reason why clusters decay faster in the InOpOffice than in both the P1-P10 massive arrays scenarios can be explained in part by the fact that shorter distances were considered in the InOpOffice than in the InF environments. In the InF environments, clusters decay faster in the massive array scenarios P1-P10 than in P1-P20. This is because the P1-P20 scenarios constitute receivers in OLOS and NLOS conditions, whose locations may also favour relatively strong clusters in further distances. We remark that despite the different MPCs estimation thresholds considered in the different environments, the tail of the raw measurements PDP in the InF is longer than that of the InOpOffice, indicating a longer propagation time in the InF environment. This can also explain the faster cluster decaying rate in the InOpOffice. We can see that in all investigated environments, $\Gamma < \gamma$, that is, rays decay slower than clusters. This observation is in line with the findings in [121, 124, 125] and in some environments investigated by the IEEE 802.15.3c channel model subgroup. This phenomenon may be linked to the richness of the channel in multipath arriving in various directions. This richness in multipath could be a result of building construction materials, scatterers, and metallic reflectors present in the en-

vironment, enabling reflections and scattering. Indeed, in the InOpOffice and the InF environments, glass windows, metallic reflectors and scatterers were in abundance, as can be seen in the environment pictures. Since $\Gamma < \gamma$, this implies that clusters overlap in the time-delay domain while they are disjoint in the angular domain [121, 124, 125]. The measured exponential decay of clusters is consistent with those of IEEE 802.15.3c that varied between (4.46-41.9) *ns* and (19.44-109.2) *ns*, respectively, in the residential environment and office scenarios.

In Fig. 2.20, we show a comparison of the cluster delay and angular spreads between the VCA and the VPA.

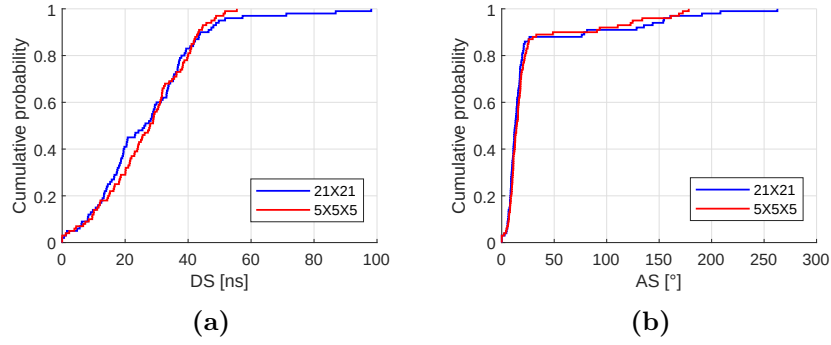


Figure 2.20: InF VCA vs VPA: cluster (a) delay spreads (b) angular spreads.

From a UE perspective, we determine the statistical description of the rays and clusters arrival angles. Ray arrival angles are determined with respect to the mean arrival angle of the considered cluster. Fig. 2.21 shows the pdf of the intra-cluster rays AOA in the InOpOffice and the InF environments (VCA and VPA).

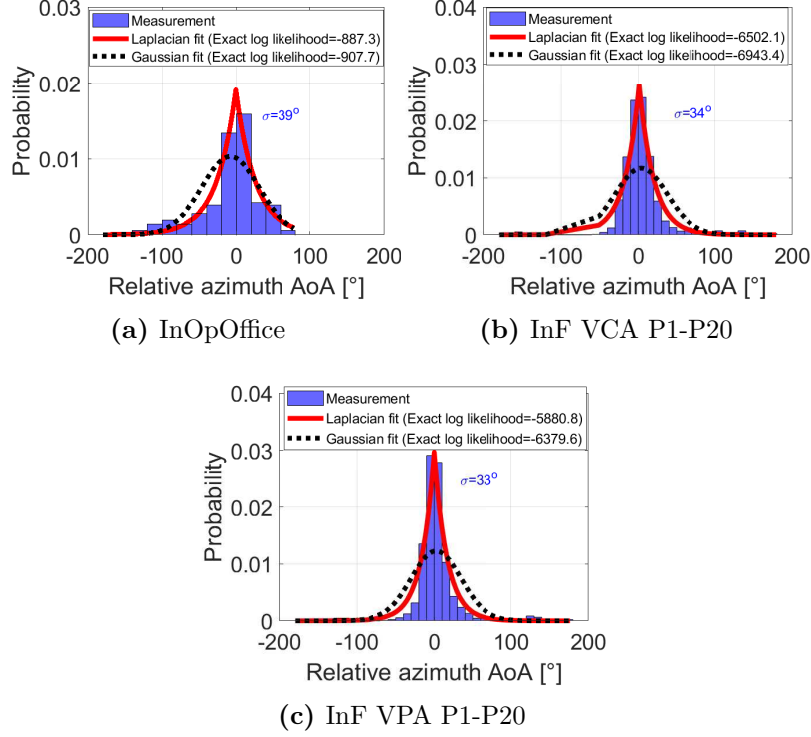


Figure 2.21: pdf of relative arrival angles of the rays.

It is evident that the Laplacian distribution best fits the measurements in the considered environments and scenarios. The standard deviation of the relative arrival angle $\sigma = 39^\circ$ for the InOpOffice, $\sigma = 34^\circ$ and $\sigma = 33^\circ$, respectively, for the VCA and VPA in the InF environments.

$$pdf(\phi_{lk}|\mu, \sigma) = \frac{1}{\sigma\sqrt{2}} e^{\frac{-\sqrt{2}}{\sigma}|\phi_{lk}-\mu|} \quad (2.19)$$

where μ and σ are respectively, the mean and the standard deviation of the relative angles of the rays. In our case, $\mu = 0^\circ$ and the standard deviations have been mentioned above.

In Fig. 2.22, for both environments investigated, we show the CDFs of the clusters relative arrival angles.

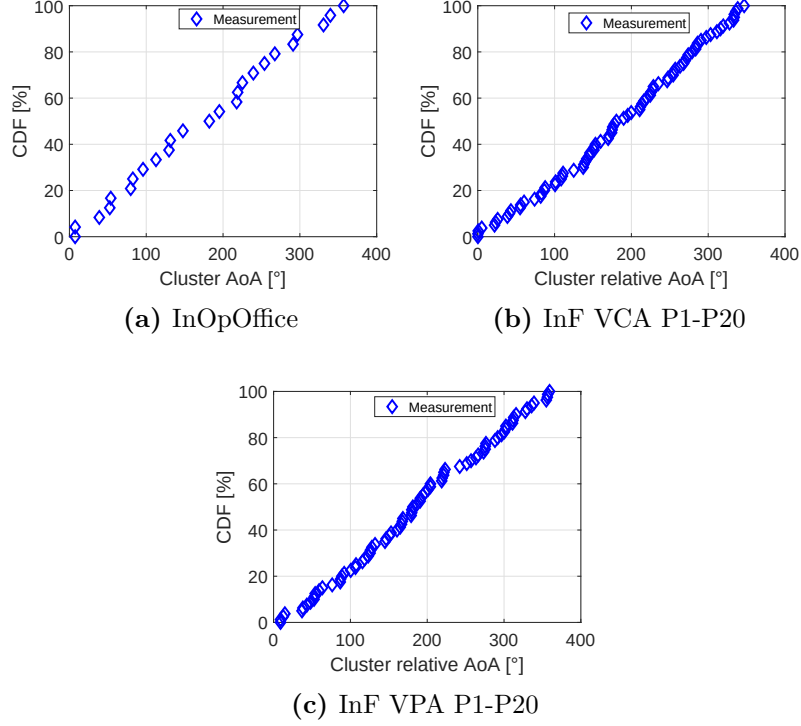


Figure 2.22: CDF of relative arrival angle of the clusters.

Indeed, in all cases, the CDF can be approximated by a straight line. This means that the cluster's relative angle is quasi-uniformly distributed between $[0 - 357]^\circ$ in the InOpOffice and between $[0 - 347]^\circ$ and $[0 - 359]^\circ$, respectively, for the VCA and VPA in the InF environments. It is therefore safe to say that the clusters arrival angles are uniformly distributed over (approximately) all azimuthal angles.

The arrival of clusters and rays are modelled with their pdfs as shown in (2.17)-(2.18) but these distributions can be used only for time-only models (e.g., the original S-V model). In order to extend our model so as to incorporate the spatial component, we introduced the angles of arrival into the model so that the pdfs of clusters and rays arrival become dependent of the corresponding arrival angles. The extended

model is expressed as follows (2.20)-(2.21):

$$p(T_k, \Theta_k | T_{k-1}, \Theta_0) = p(T_k | T_{k-1})p(\Theta_k | \Theta_0) \quad (2.20)$$

$$p(\tau_k, \phi_k | \tau_{(l-1)k}) = p(\tau_k | \tau_{(l-1)k})p(\phi_k) \quad (2.21)$$

The above equations are only valid if the time and angle distributions are independent. Fig. 2.23 and Fig. 2.24, respectively, present the arrival angles of clusters and rays in function of their corresponding arrival times in the investigated environments.

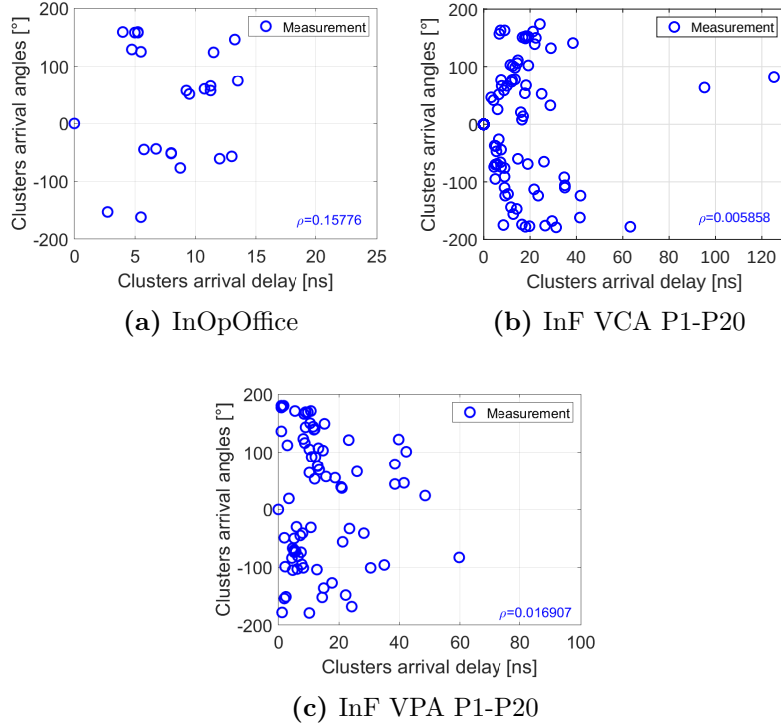


Figure 2.23: Scatter plot of arrival times versus arrival angles of clusters.

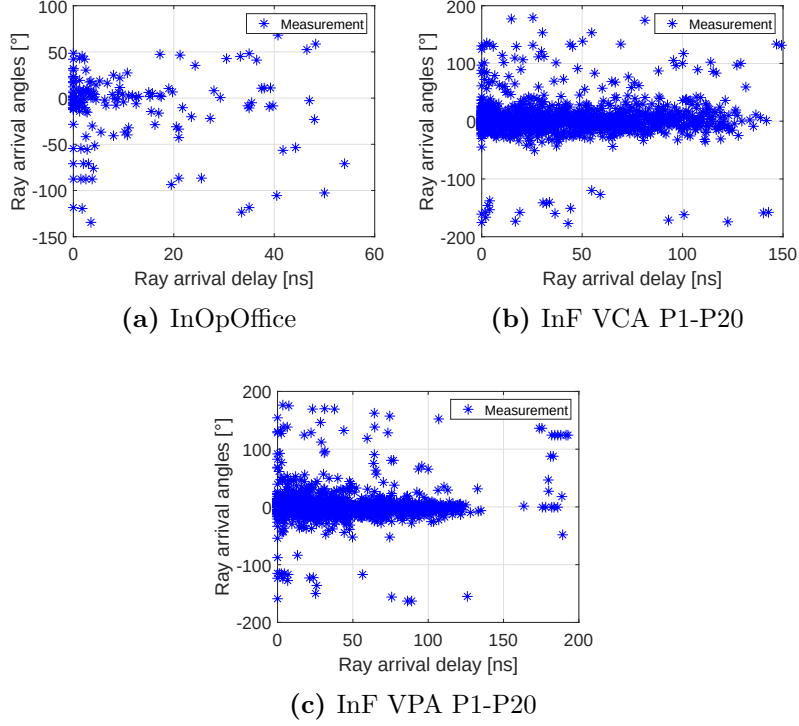


Figure 2.24: Scatter plot of arrival times versus arrival angles of rays.

We can see in Fig. 2.23 that the time of arrival and the AOA of the clusters are not correlated. The correlation values are given by ρ in Fig. 2.23. The same observation applies to the rays as shown in Fig. 2.24. The correlation values for the time of arrival and AOA of the rays shown in Fig. 2.24 were 0.008, 0.006 and 0.016, respectively, for the InOpOffice, InF VCA P1-P20 and InF VPA P1-P20. In essence, higher time of arrival does not imply higher or lower angles of arrival. Similar to the observations made in [121, 124, 125], the decorrelation between the two variables can also be deduced from the fact that a low inter-correlation is obtained between the times and angles of arrival of the clusters. Consequently, their conditional distributions can be expressed as separable functions as shown in (2.20) for the clusters and (2.21) for the rays.

2.2.3 Dense Multipath Components

The DMCs account for the part of the channel that is not described by specular MPCs. In other words, DMCs are the residuals that remain after subtracting the specular MPCs from the measured channel impulse responses that are taken with an angular or spatial variation of transmitter and/or receiver antennas [127]. The DMCs percentage value can be computed following (2.22). The radio specular MPCs are the coherent parts of the radio channel whilst the DMCs are the incoherent parts of the radio channel. The specular MPCs are the deterministic part of the channel and for a specular MPC, both its power and phase information is accessible across the angular and delay domains. However, this is not true for the DMCs, which are the stochastic part of the channel. The DMCs cannot be reliably detected by high resolution algorithms like SAGE because they are too weak and may be too close to other MPCs in the angular and delay domains. Consequently, only the average power of the DMCs across these domains can be modelled, while their phase is inaccessible to the detection algorithm [128]. The DMCs can be within the range of 10% to 95% of the measured channel power in indoor office and industrial environments [128, 129] and for outdoor environments [130] they can range from 10% to 90%. The DMCs power can be modelled as an exponential decay as function of delay [131]. DMCs were initially considered to have an angular-white contribution, but this was found not to be the case in [120]. In [132], it was suggested that determining the DMCs by simply subtracting the specular part (estimated by ESPRIT or SAGE) from the total channel response may be flawed and should be avoided and that high resolution algorithms like the DMC-inclusive RiMAX algorithm [131] are prone to less estimation errors compared to the ESPRIT or SAGE (which do not consider the DMCs). However, in our work we employ the method of subtracting the specular part from the total channel response. In order to understand the propagation characteristics of the DMCs, the dependency of the proportion of DMC in total power of the TX-RX distance is often investigated. In this work, the DMCs percentage values are computed

as follows:

$$DMC \% = \frac{\sum_{f=f_{min}}^{f_{max}} |H_{meas}(f) - H_{SAGE}(f)|^2}{\sum_{f=f_{min}}^{f_{max}} |H_{meas}(f)|^2} \times 100 \quad (2.22)$$

where $H_{meas}(f)$ represents the measured channel transfer function and $H_{SAGE}(f)$ is the SAGE regenerated channel transfer function.

2.2.3.1 Indoor Laboratory

In our work, considering the 49, 3×3 sub-arrays, the DMCs are seen to increase with the TX-RX separation distances for positions ($m1$, $m2$, $m3$, $m4$, and $m5$) with the exception of position $m6$. This behaviour is consistent with the findings in [133, 134]. Fig. 2.25(a) shows the CDF of DMCs percentage values at each RX position. Each CDF curve for a particular RX position comprises 49 DMCs percentage values that are computed using equation (2.22) and considering the SISO link between the TX sub-array and the RX grid centers. Fig. 2.25(b) shows the CDF curves of the overall DMCs percentage values. Each of the 49 overall DMCs percentage values that create the CDF curve for a particular RX position is an average value over the full MIMO links.

When 3×3 sub-arrays were considered, on average, the DMCs account for 18% to 25% of the measured channel power as shown in Fig. 2.25. Considering for instance the position $m1$ and keeping every other SAGE parameters the very same and only varying the size of the transmitter array, it was observed that the DMCs appear to increase with the size of the considered transmitter array. Consequently, fewer specular components are estimated for a massive array compared to the classical 3×3 sub-arrays, see Table 2.7.

Table 2.7: Different DMCs values for different transmitter array size.

Array size	3×3	5×5	7×7	9×9	11×11	13×13	15×15	21×21
DMCs %	17.98	20.9	23.82	24.65	28.84	27.93	32.85	46.9
Number of MPCs	43	38	42	39	34	32	32	31

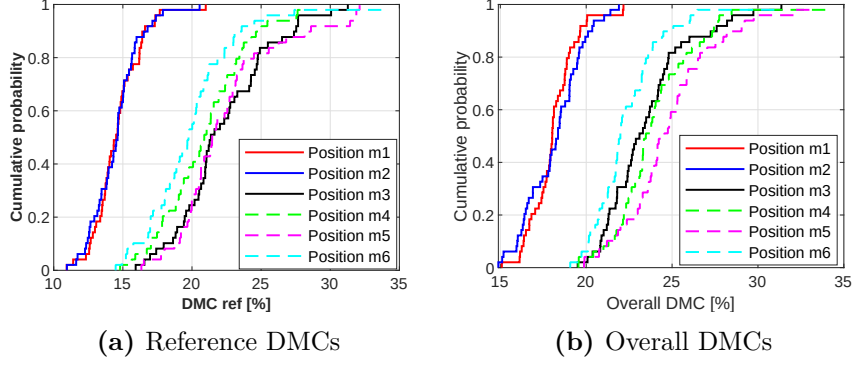


Figure 2.25: DMCs CDFs: reference (a) and overall (b) positions.

2.2.3.2 Indoor Open Office

Following (2.22), we computed the overall DMC (i.e., the average value over the full MISO links) at each RX position. In Fig. 2.26, we show the computed DMCs percentage values per position.

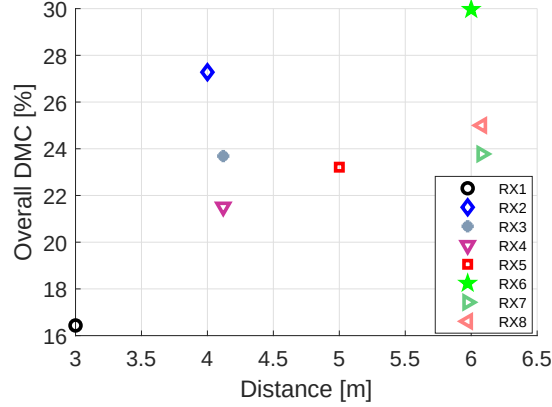


Figure 2.26: Overall DMCs per position.

2.2.3.3 Indoor Factory

Here we briefly present the DMCs in the InF environment. We consider the 49 sub-arrays at all the 20 positions (P1-P20). Fig. 2.27 shows the DMCs CDF curves for the different InF positions. Each of the reference DMCs curve at a certain RX position is obtained from the 49 DMCs

percentage values constituting the SISO link between the TX sub-array center and the RX position. For the overall DMCs, the average values over the full MISO links are considered.

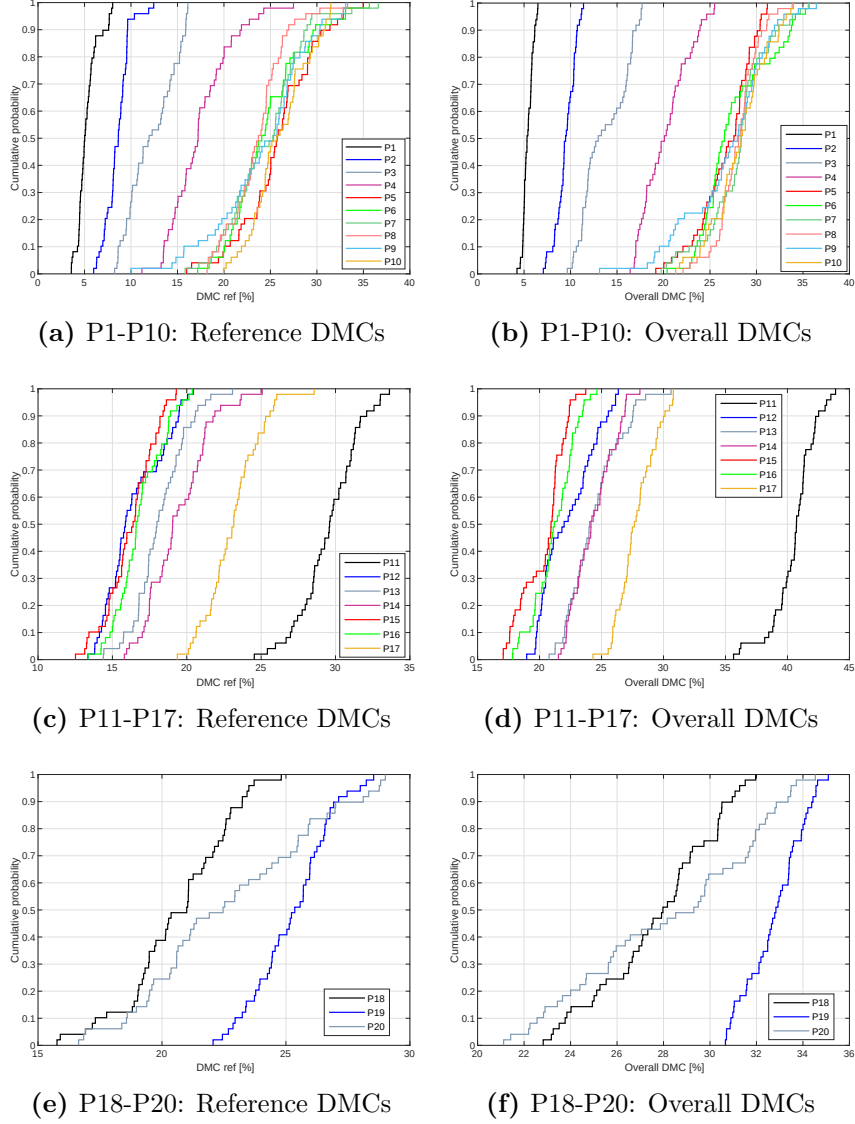


Figure 2.27: P1-P20 DMCs CDFs: reference (a), (c), (e) and overall (b), (d), (f) positions.

The DMCs generally appear to increase with TX-RX separation dis-

tance up to 5 m, and then they become independent of the TX-RX separation distance. This behaviour could be related to the fact that some of the first few RX positions are in the near-field of the 21×21 VPA. The Fraunhofer distance (far-field) is about 3.73 m when considering large array (21×21 VPA) and this decreases to about 0.04 m when considering a 3×3 sub-array. The quasi-NLOS and NLOS positions recorded the largest DMCs values compared to the LOS and OLOS conditions.

2.2.4 Investigation on indoor mmWave mMIMO channel correlation

Starting from measurement results, we investigate the channel correlation in frequency and delay domains over the large array employed on the transmitting side. For this purpose, the 21×21 large array was divided into 49 adjacent sub-arrays of 3×3 dimensions, as shown in Fig. 2.3(a). The main purpose is to investigate how different sub-arrays belonging to a large one are correlated. This investigation on channel stationarity is performed for the InLab and InF environments, where the massive 21×21 grid was scanned. We remark that for the InLab environment, we have MIMO links whereas for the InF environment, we have MISO links. This means that a combination of 81 SISO links exist between each RX grid position and a particular sub-array in the InLab. As for the InF, a combination of 9 SISO links exist between each RX position and a particular sub-array.

We computed the average maximum correlation amplitude in the frequency domain as follows:

$$\overline{\rho_{f,p,q}} = \mathbb{E} \left[\max_{\Delta f} \left| \frac{\mathbf{H}_{p,i}(f) \cdot \mathbf{H}_{q,i}(f + \Delta f)^*}{\sqrt{\mathbf{H}_{p,i}(f) \cdot \mathbf{H}_{p,i}(f)^*} \sqrt{\mathbf{H}_{q,i}(f) \cdot \mathbf{H}_{q,i}(f)^*}} \right| \right] \quad (2.23)$$

where $\mathbf{H}_{p,i}(f)$ is the channel transfer function related to the p -th sub-array and i -th MIMO or MISO link, and $(\cdot)^*$ denote the Hermitian transpose operator. In the following results we show the correlation between the central sub-array and the other sub-arrays over the large

array. For the InLab room, we can notice on Fig. 2.28 that the correlation is generally below 0.6, and for highly correlated sub-arrays we do not notice a symmetrical behaviour over the large surface.

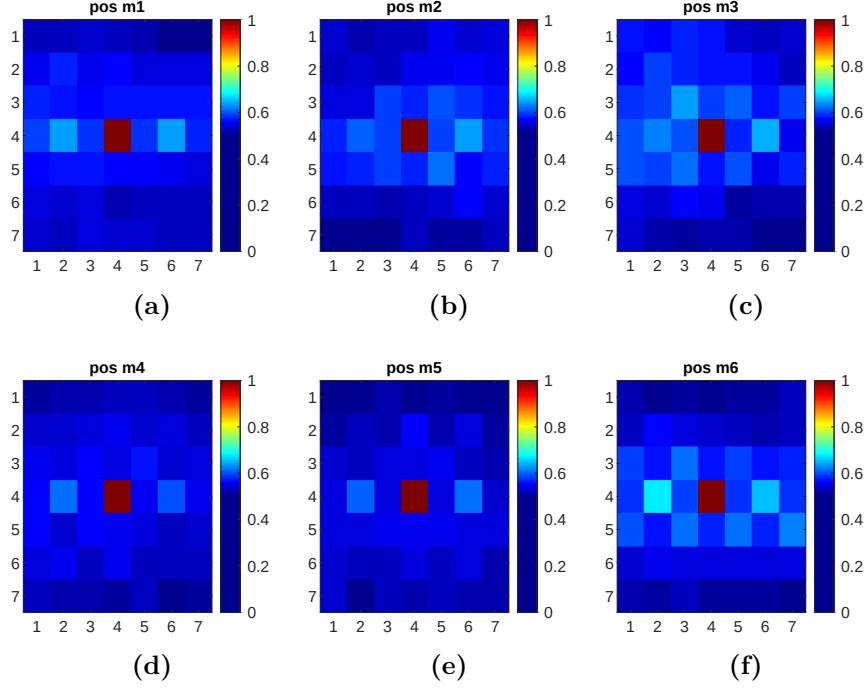


Figure 2.28: $\overline{\rho_{f,p,q}}$: InLab central sub-array vs 48 other sub-arrays including its autocorrelation at each receiver position.

For the InF environment, Fig. 2.29 and Fig. 2.30 show the channel correlation for the positions P1-P10 and P11-P20, respectively. We can observe that for positions P1-P10, generally the channel correlation is decreasing with this distance. Very high correlation values above 0.8 are obtained for the first 3 positions, and these values decrease to less than 0.3 at P10. For positions P11-P20, we can observe that position P11 in quasi-NLOS condition and positions P18-P20 in NLOS condition, have smaller channel correlation values than the positions in OLOS conditions. In both the InLab and the InF environments, the absence of a symmetrical behaviour over the large surface suggests the non-stationarity of the channel.

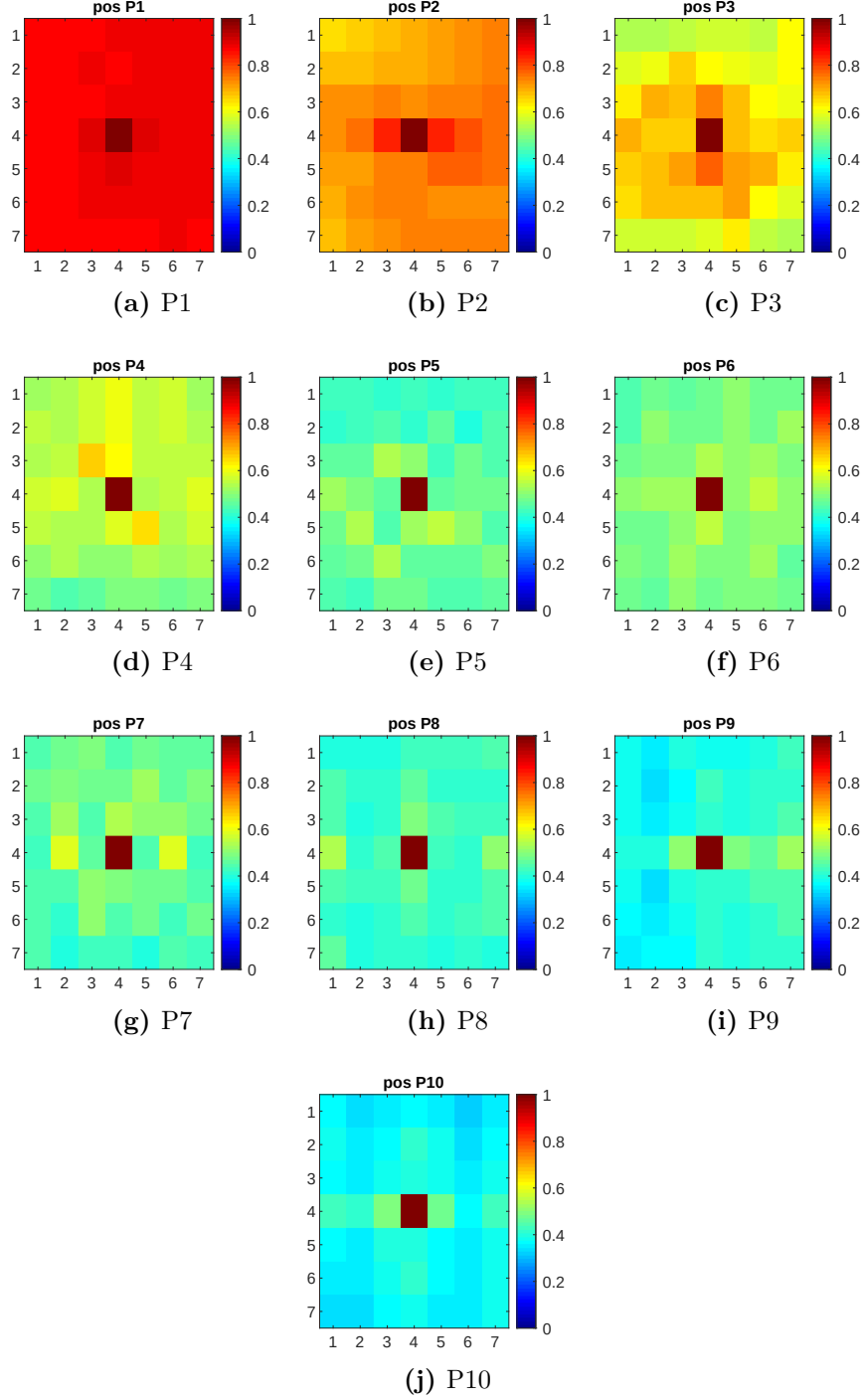


Figure 2.29: $\overline{\rho_{f,p,q}}$: InF central sub-array vs 48 other sub-arrays including its autocorrelation at each receiver position.

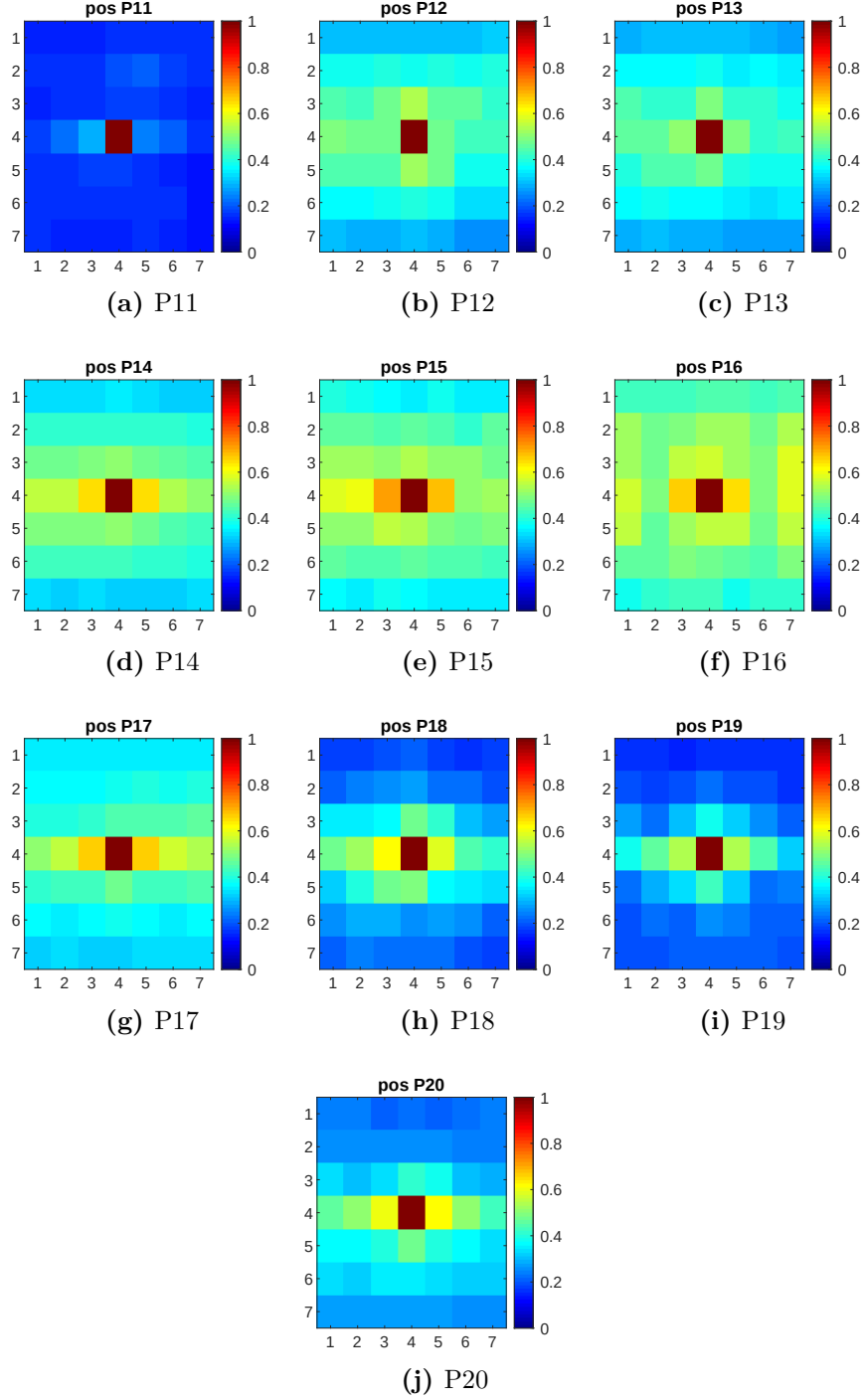


Figure 2.30: $\overline{\rho_{f,p,q}}$: InF central sub-array vs 48 other sub-arrays including its autocorrelation at each receiver position.

To further analyze this behaviour, we computed the correlation between different sub-arrays in the delay domain:

$$\overline{\rho_{\tau,p,q}} = \mathbb{E} \left[\max_{\Delta\tau} \frac{\mathbf{P}_{p,i}(\tau) \cdot \mathbf{P}_{q,i}(\tau + \Delta\tau)^T}{\sqrt{\mathbf{P}_{p,i}(\tau) \cdot \mathbf{P}_{p,i}(\tau)^T} \sqrt{\mathbf{P}_{q,i}(\tau) \cdot \mathbf{P}_{q,i}(\tau)^T}} \right] \quad (2.24)$$

where $\mathbf{P}_{p,i}(\tau)$ is the Power Delay Profile related to the p -th sub-array and i -th MIMO or MISO link, and $(\cdot)^T$ denote the transpose operator.

Two different cases were considered here. In the first case, $\overline{\rho_{\tau,p,q}}$ were computed including the LOS component using (2.24). Fig. 2.31 shows $\overline{\rho_{\tau,p,q}}$ when the central sub-array $\mathbf{P}_{p,i}(\tau)$ is cross-correlated with the other sub-arrays PDPs in the InLab.

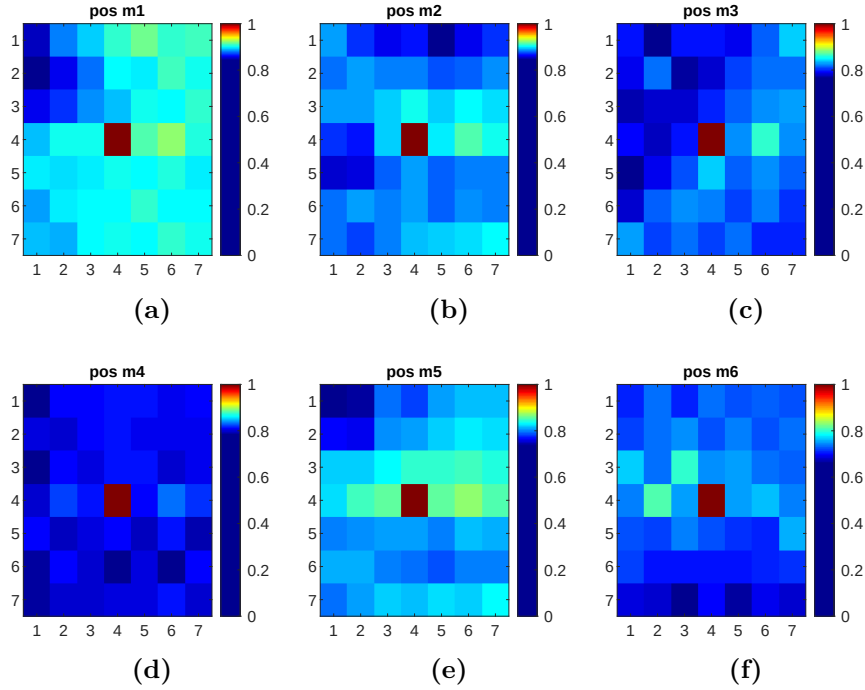
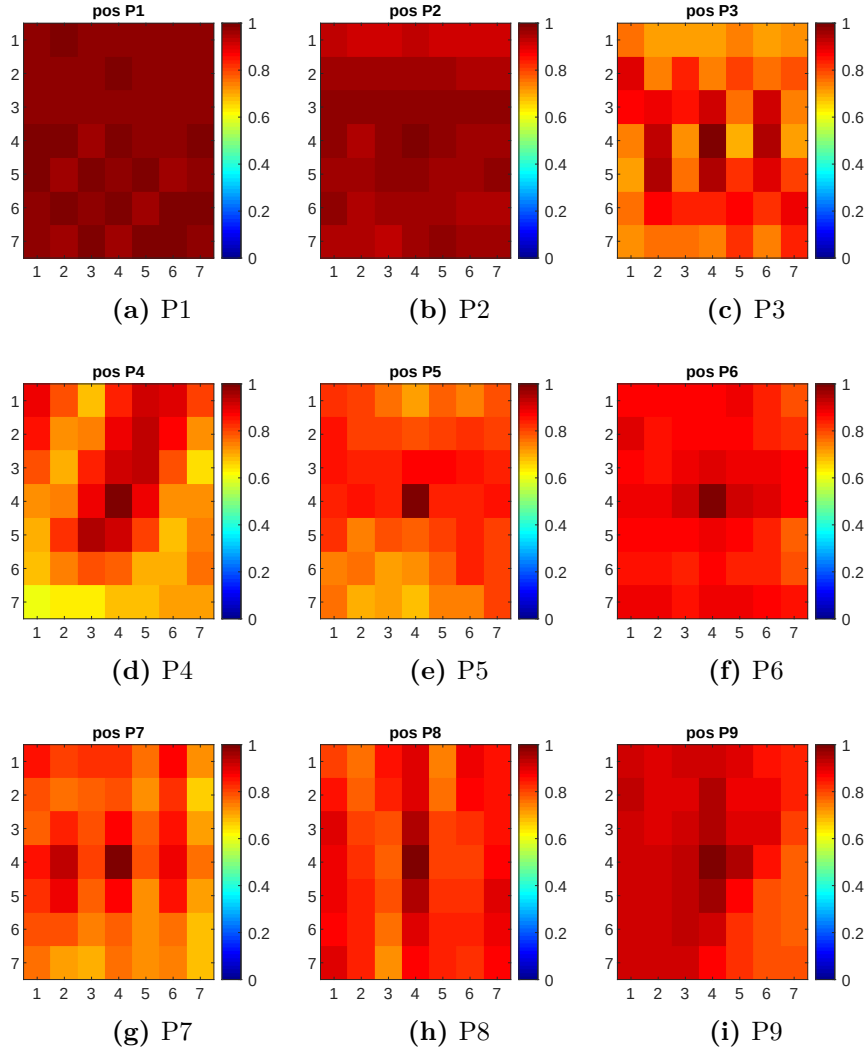
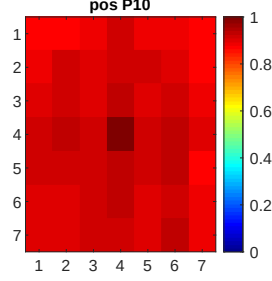


Figure 2.31: $\overline{\rho_{\tau,p,q}}$: InLab central sub-array vs 48 other sub-arrays including its auto-correlation at each receiver position.

It was observed that in considering the LOS component, the minimum $\overline{\rho_{\tau,p,q}}$ for the six receiver positions ranged from 0.66 to 0.84. Given the short distances of about 10 cm, traversed by the sub-arrays the channel correlation coefficients obtained are consistent with the findings in [89].

In the InF environments, we can see in Fig. 2.32, that the correlation values for positions P1-P10 are generally higher than those obtained in the InLab. This can be attributed to the difference in the types of links considered in the two environments.

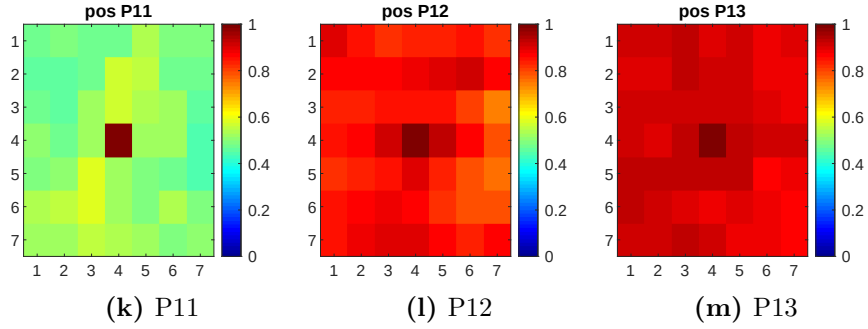




(j) P10

Figure 2.32: $\overline{\rho_{\tau,p,q}}$: InF Central sub-array vs 48 other sub-arrays including its auto-correlation at each receiver position.

Moving on to the InF environments, OLOS and NLOS positions P11-P20, we show in Fig. 2.33, the obtained $\overline{\rho_{\tau,p,q}}$ values. As already seen in the frequency domain, RXs in the NLOS tend to have smaller correlation values, with the exception of P20. Unlike the other NLOS positions (P18, P19 and P11), position P20 has very high correlation values and this is because of the presence of a stronger dominant peak at P20 than in the other positions. This is shown in Fig. 2.40.



(k) P11

(l) P12

(m) P13

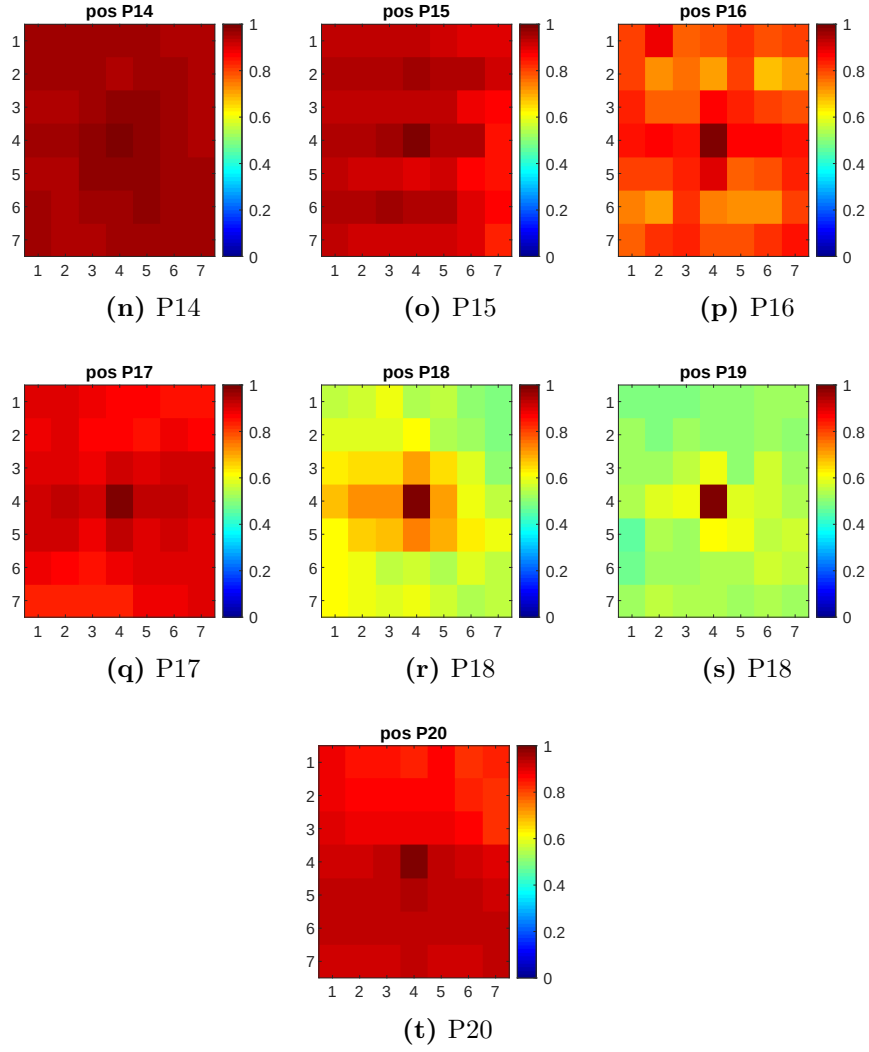


Figure 2.33: $\overline{\rho_{\tau,p,q}}$: InF central sub-array vs 48 other sub-arrays including its auto-correlation at each receiver position.

In the second case, the cross-correlations were computed excluding the LOS component, and we denote the normalized cross-correlation values as $\overline{\rho_{\tau,p,q}^{ExcLOS}}$. Fig. 2.34 shows the $\overline{\rho_{\tau,p,q}^{ExcLOS}}$ for the 6 receiver positions. The minimum $\overline{\rho_{\tau,p,q}^{ExcLOS}}$ values for the six receiver positions ranged from 0.54 to 0.65.

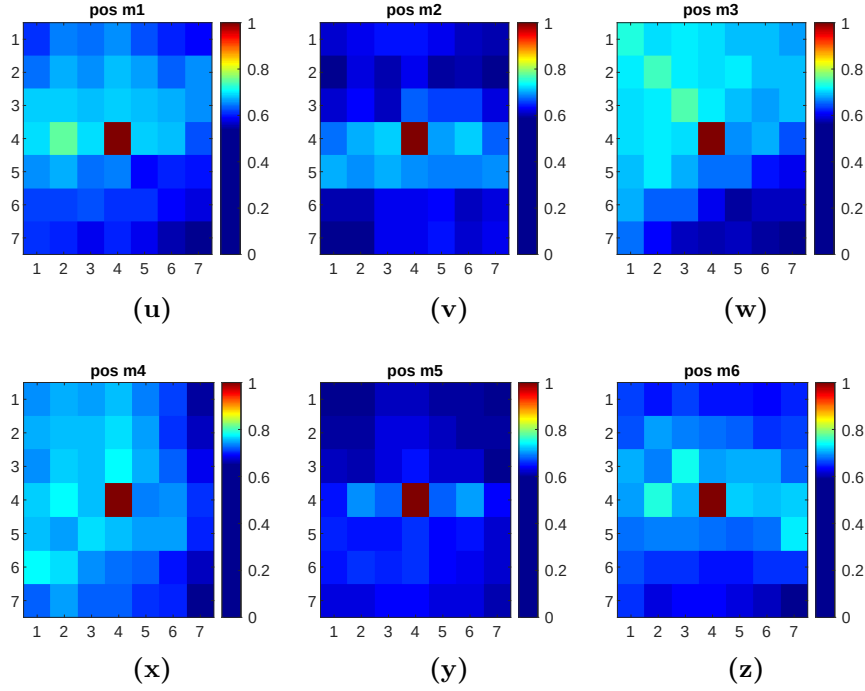


Figure 2.34: $\overline{\rho_{\tau,p,q}^{ExcLOS}}$: InLab central sub-array vs 48 other sub-arrays including its auto-correlation at each receiver position.

For the InF environments, P1-P10, Fig. 2.35 shows the correlation values after time gating the LOS component. The decrease in the correlation values signifies the importance of the LOS component in this mmWave channel.

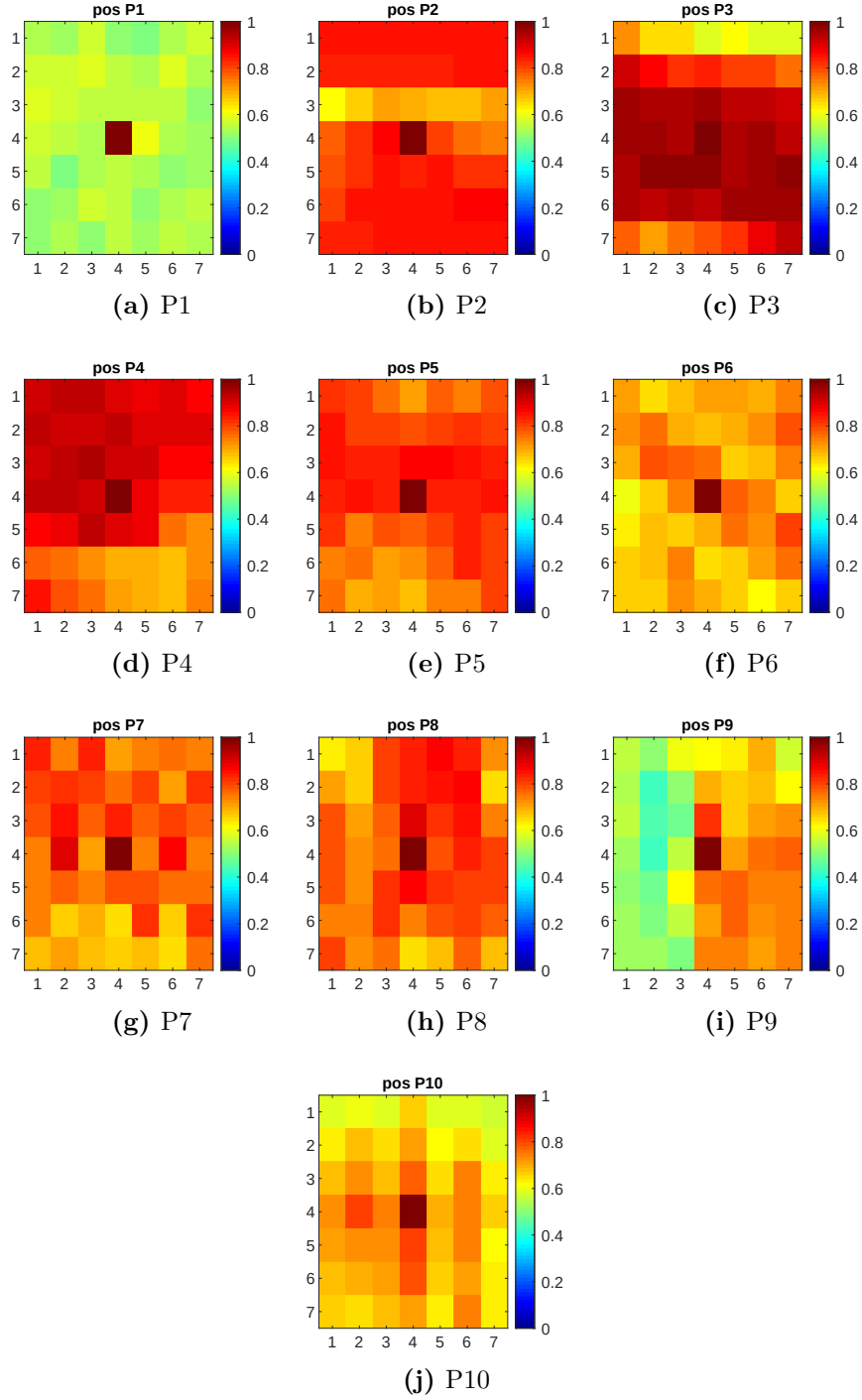


Figure 2.35: $\overline{\rho_{\tau,p,q}^{ExcLOS}}$: InF central sub-array vs 48 other sub-arrays including its auto-correlation at each receiver position.

In summary, we remark that in both environments, the LOS component contributes more to the correlation coefficients of the receivers who are closer to the transmitter than it does to the correlation coefficients of the receivers further from the transmitter. This remark emanates from the larger decrease in correlation values from $\overline{\rho_{\tau,p,q}}$ to $\overline{\rho_{\tau,p,q}^{ExcLOS}}$ for the closer positions compared to the further ones, in the InLab. Likewise, in the InF environments, the big decrease in the correlation values after excluding the LOS components manifests its significance. Generally, as observed in the InF environments, the channel correlation values decrease in the following order: from LOS to OLOS and then finally to NLOS conditions (which tend to have the least values).

To get further insights, the next steps considered were to extract the MPCs of each of the 49 sub-arrays at a particular position, identify the common paths among the sub-arrays following a joint temporal, power and angular thresholds criterion, and then analyze the MPCs distributions.

2.2.5 Analysis of Multipath Components Distributions Over a Large Array in Indoor mmWave Channels

2.2.5.1 Indoor Laboratory

The UWB SAGE algorithm was used for the MPCs estimation. MPCs of significant powers (10 dB above the noise floor) were considered in the InLab. When a massive 21×21 array was compared with the central 3×3 sub-array, it was observed that the LOS path remains the same despite the size of the array and this also holds true for the 49 sub-arrays at one particular receiver position. On the contrary, the size of the array has an impact on the secondary MPCs estimation [135]. The 49 sub-arrays of the massive array, do not see the same channel (shown by the superposed PDP plots of any two sub-arrays). Table 2.8 shows the range of the energy contribution of the LOS path for the 49 sub-arrays at each particular RX position. The least and the highest LOS component energy contributions among all 49 sub-arrays at all six

receiver positions were 26 % and 49%, respectively.

Table 2.8: InLab LOS MPCs energy contributions.

Position	Minimum value %	Maximum value %
Position $m1$	37	49
Position $m2$	36	49
Position $m3$	34	48
Position $m4$	33	44
Position $m5$	33	45
Position $m6$	26	35

With our focus placed on the 6 different receiver positions, we identify the common MPCs seen by the 49 sub-arrays at one particular receiver position. Let us define the l -th MPC of the p -th sub-array at a particular receiver position as follows (2.25):

$$\mathbf{MPC}_l^p = [\alpha_l^p, \tau_l^p, \phi_l^p]^T \quad (2.25)$$

where α_l^p , τ_l^p , ϕ_l^p are respectively, the amplitude, the delay and the azimuth angle of arrival of the l -th MPC of the p -th sub-array. Therefore in our case, we have $p = 1, \dots, P$ with $P = 49$, and $l = 1, \dots, L^p$ where L^p is the number of MPCs detected by considering the p -th sub-array. Hence the MPCs detected by the p -th sub-array are given by $\mathbf{MPC}^p = [\mathbf{MPC}_1^p, \mathbf{MPC}_2^p, \dots, \mathbf{MPC}_{L^p}^p]$. In order for the detected MPCs between the p -th and the q -th sub-arrays to be considered common, equation (2.26), given below, has to be met jointly and simultaneously:

$$\begin{aligned} |\tau_l^p - \tau_l^q| < \Delta\tau \cap ||\phi_l^p| - |\phi_l^q|| &\leq \Delta\phi \\ \cap ||(\alpha_l^p)^2| - |(\alpha_l^q)^2|| &< \Delta\xi \end{aligned} \quad (2.26)$$

where $\Delta\tau$, $\Delta\phi$ and $\Delta\xi$ are the delay threshold in $[ns]$, AOA threshold in $[^\circ]$ and power threshold in $[dB]$, respectively. Effectively, after the common paths identification, the p -th sub-array satisfies the following equation (2.27):

$$\sum_{l=1}^{L^p} \alpha_l \delta(\tau - \tau_l) \delta(\phi - \phi_l) = \sum_{l=1}^{L^c} \alpha_l \delta(\tau - \tau_l) \delta(\phi - \phi_l) + \sum_{l=L^c+1}^{L^p} \alpha_l \delta(\tau - \tau_l) \delta(\phi - \phi_l) \quad (2.27)$$

where L^p is the total number of MPCs at the p -th sub-array, L^c is the number of common paths found.

Basically, equation (2.26) is applied in such a way that each l -th MPC of the p -th sub-array is compared with all the L^q MPCs of the q -th sub-array (one at a time). In our work, for the delay threshold, we considered any two MPCs to be similar, if the absolute difference of the arrival delays is within 2 *ns*. This delay threshold accounts for the 1 *ns* delay bin width considered in the UWB SAGE algorithm as well as twice the 0.5 *ns* accounting for the furthest distance between two sub-arrays on the extremities of the massive array. Applying physical geometry to positions $m1$ and $m4$ for instance, ideally, two MPCs can be considered to be the same if the difference between their azimuth AOAs is about $\Delta\phi \simeq 2^\circ$. It has been seen in this work that applying this strict value results in some MPCs that via visual inspection are similar, being considered different. As a result, tuning of this parameter to $\Delta\phi = 5^\circ$ provides consistent results. It is important to remark that AOAs in our work were defined from -180° to 180° and in using (2.26), an extra step is needed to make sure that in the event of oppositely signed AOAs, only two MPCs whose AOAs are closer to 180° or to 0° could be considered common. Fig. 2.36 serve as an example of the detected common MPCs between two different sub-arrays. For the other positions, see the appendices section: Fig. B.1.1 and Fig. B.1.2. As for the MPCs powers, a difference of less than 3 *dB* between the two MPCs was considered permissible in order for the two MPCs to be deemed similar (common). The results showed that for example, the fourth MPCs in one sub-array can be the fifth MPCs in the other sub-array and so on.

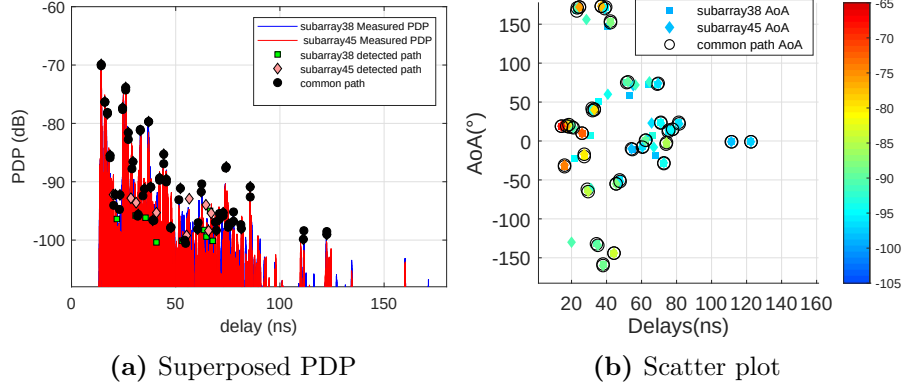


Figure 2.36: InLab position $m3$: Example superposed PDPs, detected and common MPCs and scatter plots.

The DS and AS values for the p -th sub-array are computed using (2.28) and (2.30), respectively.

$$DS^p = \sqrt{\frac{\sum_{l=1}^{L^p} (\tau_l^p - \tau_m^p)^2 (\alpha_l^p)^2}{\sum_{l=1}^{L^p} (\alpha_l^p)^2}} \quad (2.28)$$

where τ_m^p is the mean arrival delay of the multipaths and is computed as follows:

$$\tau_m^p = \frac{\sum_{l=1}^{L^p} (\alpha_l^p)^2 \tau_l^p}{\sum_{l=1}^{L^p} (\alpha_l^p)^2} \quad (2.29)$$

L^p , $(\alpha_l^p)^2$ and τ_l^p are the number of detected MPCs, the power of the l -th path and the arrival delay of the l -th path, respectively, for the p -th sub-array.

$$AS^p = \sqrt{-2 \ln \left(\left| \frac{\sum_{l=1}^{L^p} \exp(j\phi_l^p) (\alpha_l^p)^2}{\sum_{l=1}^{L^p} (\alpha_l^p)^2} \right| \right)} \quad (2.30)$$

where ϕ_l^p is the azimuth angle of arrival (or departure) of the l -th path at the p -th sub-array.

Respecting (2.26), consider for example one particular receiver position (position $m1$). Each of the 49 sub-arrays is compared with the

other sub-arrays (including self-comparison) in order to identify common paths. We call the sub-array that is being compared to the other sub-arrays the reference sub-array. This means that a total of 2401 comparisons are done for the position $m1$ (each of the 49 sub-arrays having been considered as a reference sub-array). This means that for each p -th reference sub-array, 49 sets of common paths will be identified. Each set contains the common MPCs identified between the reference sub-array and the other sub-array. For each set of common paths, we then compute the DS, the AS, using (2.28) and (2.30), replacing the superscript p with $pc=1,...,49$ where pc is the pc -th set of common paths obtained considering the p -th reference sub-array. The energy contributions of these common MPCs (η) with respect to the reference sub-array are also obtained following (2.31). We then proceed to generate the CDF of the 2401 sets at position $m1$ (e.g the red curve in Fig. 2.37(a) shows the common MPCs energy contributions). Excluding the reference sub-array's self-comparison results, the minimum common MPCs energy contribution is 43.4% while the maximum contribution is 99.4% for all the six receiver positions. Likewise, the minimum average common paths energy contribution was found to be 76.2% while the maximum average common paths contribution was 87.1%. Table 2.9 summarizes the range of the common path energy contributions for the 49 sub-arrays at a particular RX position.

From Fig. 2.37(b), we can observe that the difference between the common paths median DS and all paths median DS value ranges from 0.42 ns to 1.32 ns for all six positions. Similarly, the azimuth angle of arrival AS (Azimuth AOA) ranges from 2° to 6° for all the six receiver positions. With regards to the number of paths shown, the median number of common paths as a percentage of the median number of all the paths detected was within the range 46.9% to 59.2 %. The detailed per position statistics can be found in the appendices section: Fig. B.1.3.

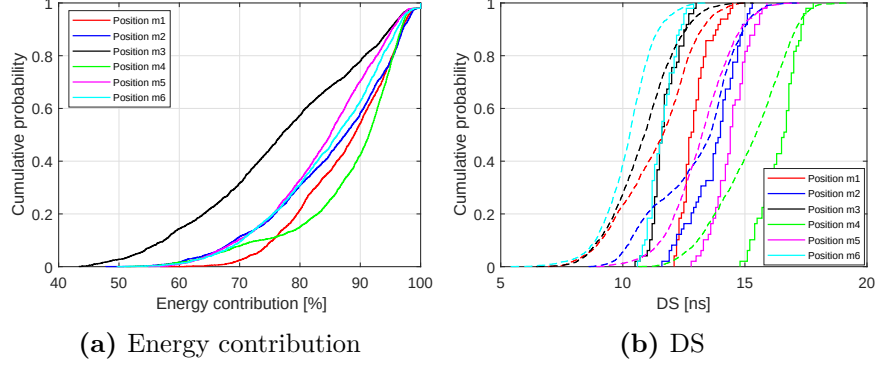


Figure 2.37: InLab: Common MPCs energy contributions (a) and DS position $m1$ - $m6$: Solid lines show all the MPCs statistics and the dotted lines show the common paths statistics.

Table 2.9: InLab: Common MPCs energy contributions.

Position	Minimum value %	Maximum value %	Mean value%
Position $m1$	56.8	99.4	87.1
Position $m2$	47.8	99.4	84.9
Position $m3$	43.4	99.3	76.2
Position $m4$	51.2	98.9	88
Position $m5$	54.8	98.7	83.3
Position $m6$	49.7	99.2	84.2

The results show that the common MPCs (which are numerically, 47% to 59% of L^p) have on average, an energy contribution higher (by a factor >2) than the energy contributions of the uncommon paths. The common MPCs are less spread both in the azimuth and in the elevation than the uncommon MPCs and they have shorter DS compared to the uncommon paths.

$$\eta^p(\%) = \frac{\sum_{l=1}^{L^c} (\alpha_l^{pc})^2}{\sum_{l=1}^{L^p} (\alpha_l^p)^2} \times 100 \quad (2.31)$$

where $(\alpha_l^{pc})^2$ is the l -th common MPC power, and $(\alpha_l^p)^2$ is the power of the l -th MPC of the p -th sub-array and $pc=1, \dots, 49$ where pc is the pc -th set of common paths obtained considering the p -th sub-array as the reference sub-array.

Having identified the common MPCs and the uncommon MPCs large scale parameters and their respective energy contributions at each particular receiver position, we will now look at the overall statistics. In essence, all the 6 receiver positions parameters (DS and AS) are combined into a single set of data. Table 2.10 shows the minimum, maximum and median values of the aforementioned parameters when different array sizes are considered. A comparison between the overall statistics before the common path identification and the overall statistics of the identified common paths in Fig. 2.38 shows that the common path DS and azimuth AS are smaller (on average by 1.2 *ns* and 3°, respectively). For overall elevation AS statistics, see Fig. B.1.4.

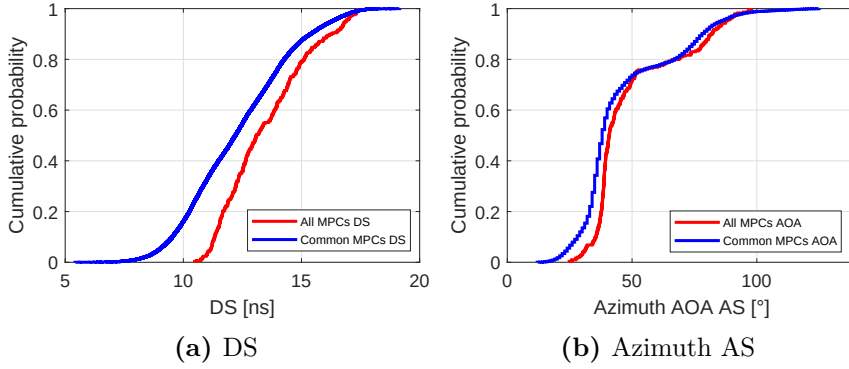
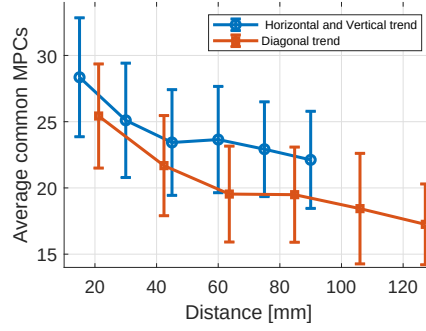


Figure 2.38: InLab: Overall common paths vs all paths statistics.

Fig. 2.39 shows the variation of the common paths number with distance over the array. The displacements were considered horizontally, vertically and diagonally. The minimum vertical or horizontal displacement distance is 15 mm ($\frac{3\lambda}{2}$) while the maximum vertical or horizontal displacement distance is 90 mm ($\frac{18\lambda}{2}$). Diagonally, the minimum displacement is 21.2 mm and the maximum displacement is 127.3 mm. We can clearly see from Fig. 2.39 that the number of common paths decreases with increase in distance.

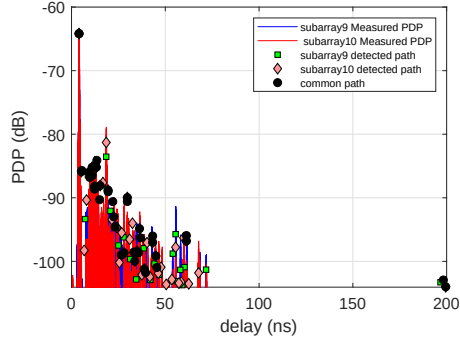
Table 2.10: InLab overall DS and AS statistics considering different TX array sizes.

Parameter	3×3 central sub-array	7×7 sub-array	21×21 massive array	49 (3×3) sub-arrays
Min DS [ns]	11.3	10.4	10.4	10.5
Max DS [ns]	17	16.9	15.6	17.8
Med DS [ns]	13.7	13.6	13	13.1
Min AOA AS [°]	30	29	34	25
Max AOA AS [°]	81	82	87	98
Med AOA AS [°]	41	39	42	41

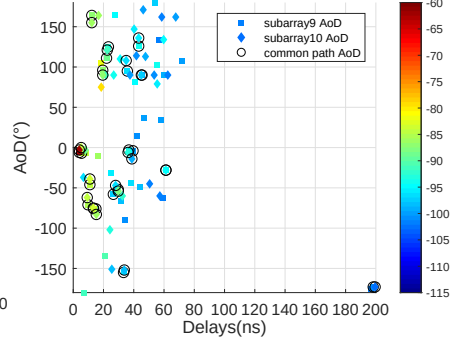
**Figure 2.39:** InLab: Overall average common path variation per distance over the massive array.

2.2.5.2 Indoor Factory

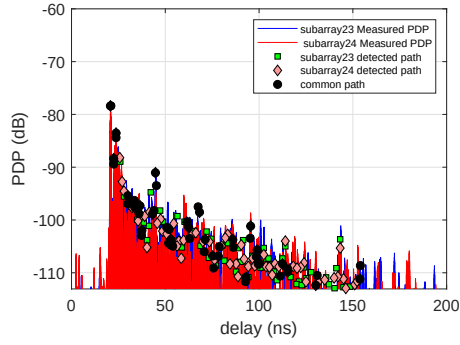
A similar analysis is carried out for the InF environments. We first start by identifying the common MPCs. With the exception of the angular threshold, the delay and power thresholds were similar to the InLab environments. However, for the angular threshold, the considered value was $\Delta\phi = 8^\circ$. The $\Delta\phi = 8^\circ$ threshold is governed by the maximum difference between the least LOS AOD and maximum LOS AOD of the 49 sub-arrays at any of the positions P1-P10. In Fig. 2.40 we show examples of sub-arrays superposed PDPs and scatter plots in the InF environment. Other position results can be found in the appendices section: Fig. B.2.1 and Fig. B.2.2.



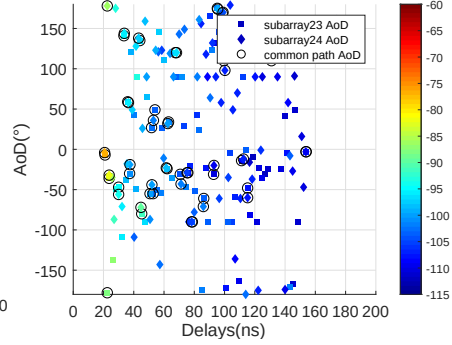
(a) Position P1: Superposed PDP



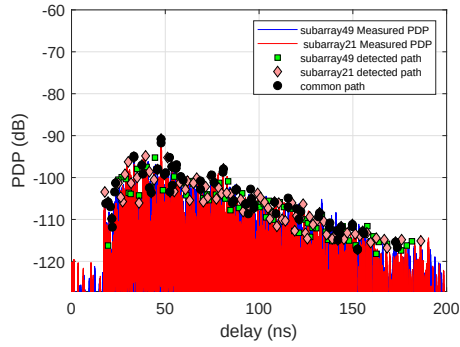
(b) Position P1: Scatter plot



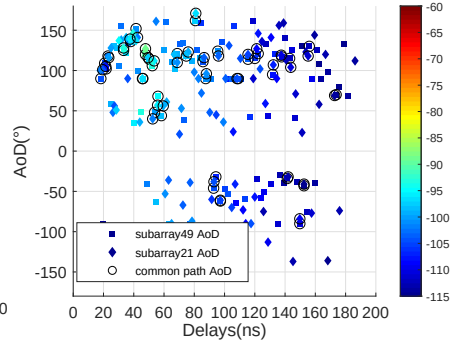
(c) Position P6: Superposed PDP



(d) Position P6: Scatter plot



(e) Position P11: Superposed PDP



(f) Position P11: Scatter plot

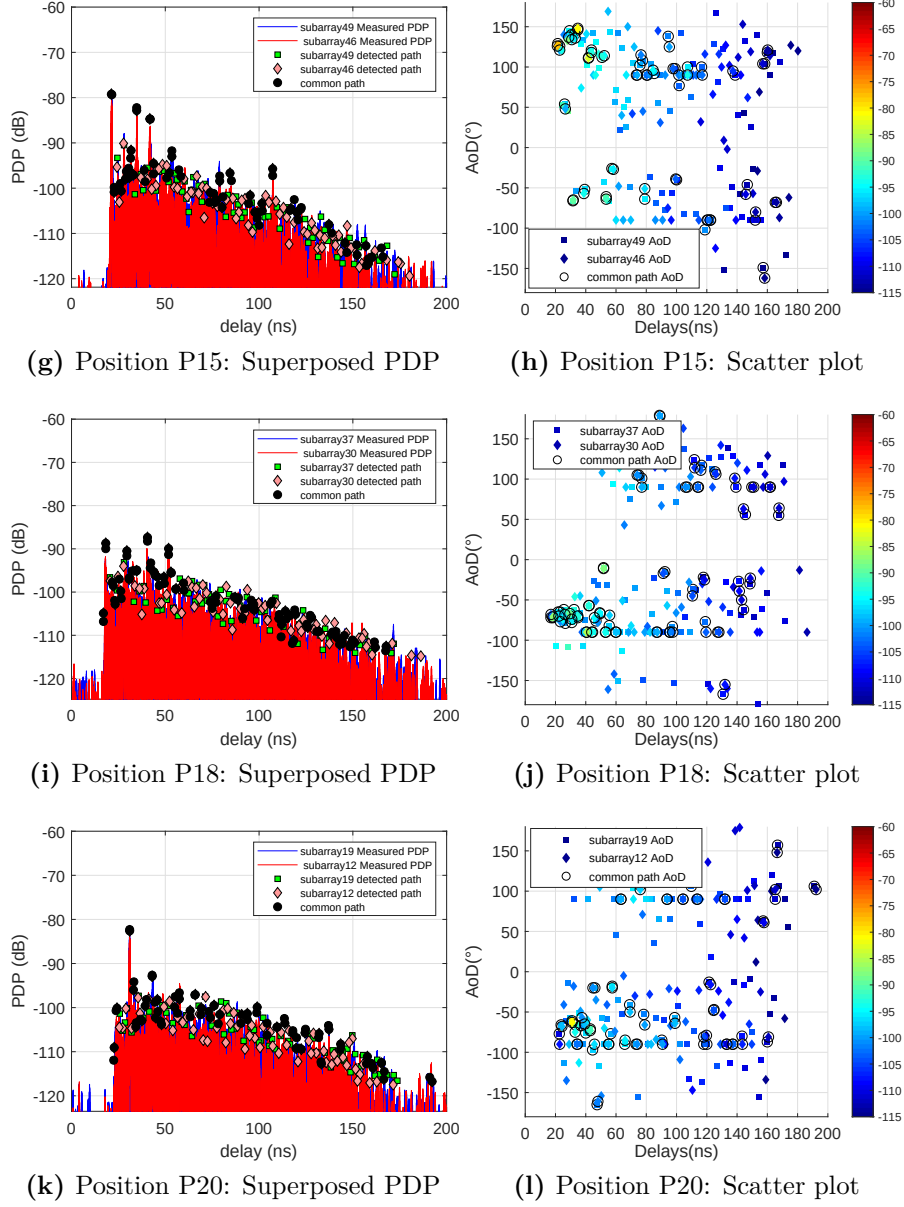


Figure 2.40: Example superposed PDPs, detected and common MPCs for the InF environment.

The common paths energy contribution statistics for the different positions are shown in Fig. 2.41. We can see that for P1-P10 measurements,

the position P1 has the highest common path contribution and this is attributed to the LOS path, which happens to be the strongest path. On average, the common path energy contribution ranges between 61-96.5 % for P1-P10. For P11-P17 the common path energy contribution ranges between 34-68 %, with position P11 which actually is in quasi-NLOS recording the least contribution. We can also see that for P18-P20, on average the common path energy contribution ranges between 45-48 %. The results suggests that, on average: the common paths in the LOS conditions contribute more energy compared to those in the OLOS and NLOS conditions, with the NLOS condition contributing the least. Finally, in Fig. 2.41(d), we can see that positions P1-P10 have higher common path contribution than positions P11-P20. This can be attributed to the strong or dominant LOS path, typical in mmWave channels.

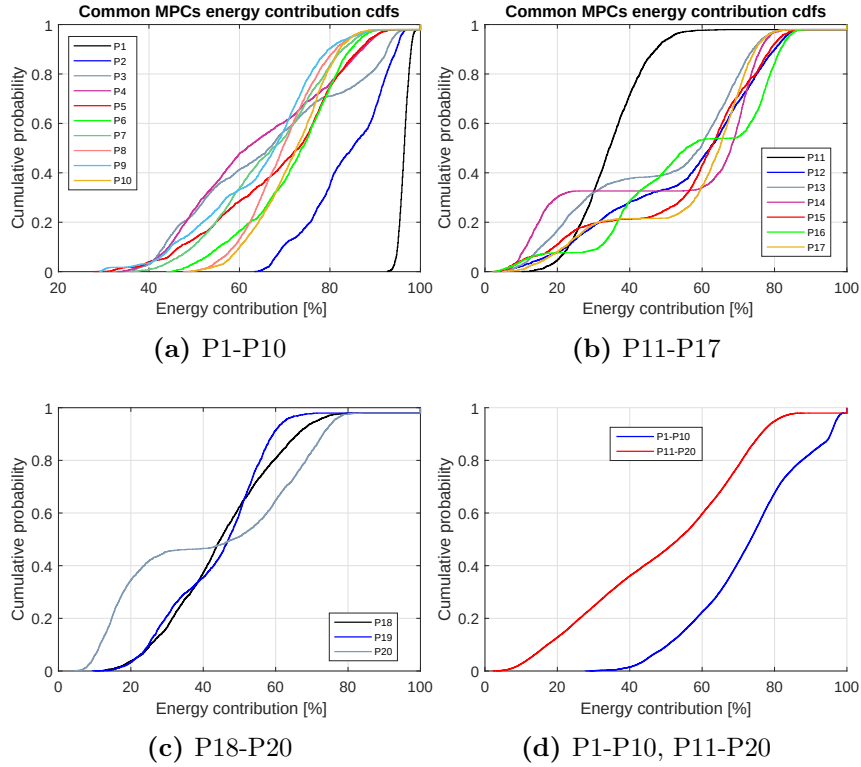


Figure 2.41: InF common MPCs energy contributions.

The overall InF environment statistics for the positions P1-P10, P11-P17 and P18-P20, are shown respectively, in figures Fig. 2.42, Fig. 2.43 and Fig. 2.44. Position specific results can be found in the appendices, in Fig. B.2.5, Fig. B.2.6 and Fig. B.2.7.

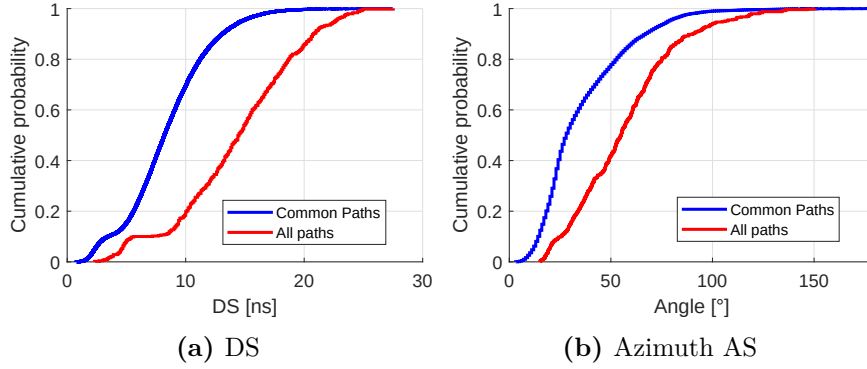


Figure 2.42: InF environments: P1-P10 Overall common paths vs all paths statistics.

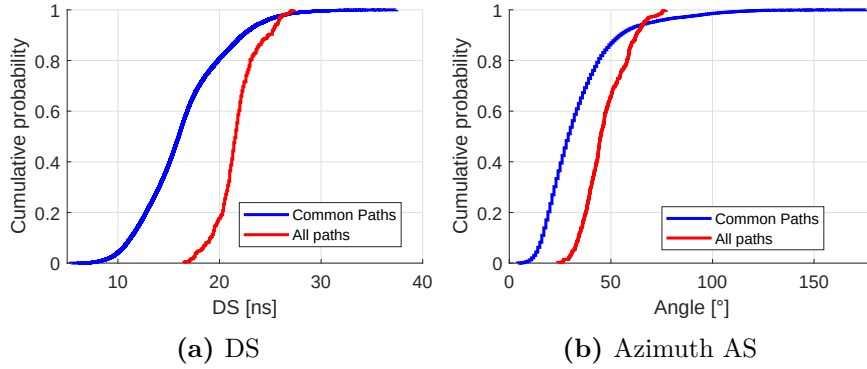


Figure 2.43: InF environments: P11-P17 Overall common paths vs all paths statistics.

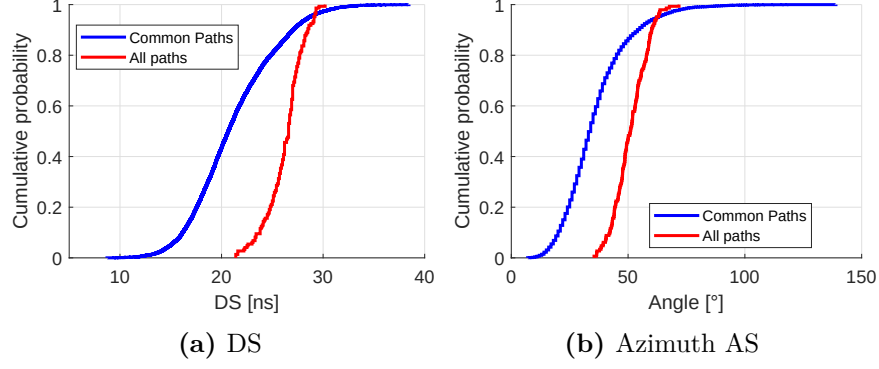


Figure 2.44: InF Environments: P18-P20 Overall common paths vs all paths statistics.

We can observe that in the InF environments, just like in the InLab, the common paths are less spread in delay than all paths. The common paths are more spread in the azimuth plane than they are spread in the elevation (see Fig. B.2.8 for overall elevation AS statistics). We remark that in the InF environments, the gap between the common paths statistics and all paths statistics is slightly larger than that of the InLab measurement campaign. Finally, in Fig. 2.45, we show the variation of the common paths number with distance over the array. We can observe that, even though common paths at P1-P10 are numerically fewer than the other positions, their energy contribution is more significant compared to the common paths obtained at the other positions.

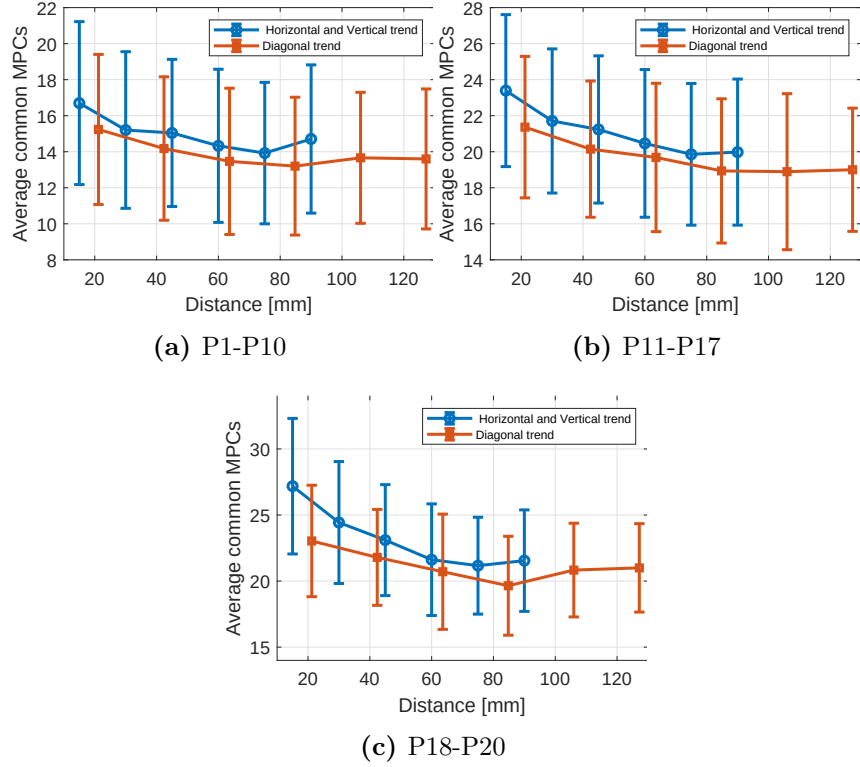


Figure 2.45: InF overall average common path variation per distance over the massive array.

2.3 Conclusions

In this chapter we have characterized and modelled different indoor mmWave mMIMO channels comprising either a $5 \times 5 \times 5$ or a 21×21 massive array.

Large scale parameters (path loss and delay spread) models have been derived for the InF indoor environments for different conditions. The impact of the array size on the channel characteristics was investigated. The MPCs are extracted using a high resolution algorithm. Basically, we observed that the estimation of the LOS component is almost unchanged when considering a massive array or a sub-array. On the contrary, the size of the array has an impact on the secondary multipath component estimation. Despite the fact that the energy contribution

of the secondary MPCs is relatively small, this difference leads to different overall delay and angular estimations. MPCs in the different indoor environments are clustered by means of the KPowerMeans algorithm. Corresponding spatio-temporal channel models were derived. The spatio-temporal channel models are in agreement with some of the findings in the literature. We then quantified the DMCs in the different investigated environments. Generally, the DMCs percentage contribution considering the reference or central point measurement is smaller than that of the average DMCs contribution over all the array elements. In all environments, DMCs values were between 4-43%. The DMCs were observed to increase with TX-RX separation distance up to 5 m, and then they become independent of the TX-RX separation distance. This behaviour could be related to the fact that some of the first few RX positions are in the near-field of the TX array. In the InF environments, the NLOS positions recorded the largest DMCs values compared to the other conditions. We also investigated the spatial channel correlation in both the frequency domain and the delay domain considering LOS, OLOS and NLOS scenarios. In both domains (with the delay domain clearly highlighting this), the normalized cross-correlation values do not have a symmetric behaviour over the large array, suggesting non-stationarity over the large array. Between the InLab and the InF environments, the spatial channel correlation values in both domains are generally smaller for the InLab than the InF environments. This is because the InLab consists of MIMO links compared to the MISO links of the InF environments. In the InF environments, spatial channel correlation values decrease in the following manner; receivers in LOS condition have generally higher correlation values, followed by receivers in the OLOS condition and finally the NLOS condition (with the exception of position P20). Looking at the PDP of position P20 in comparison with other NLOS positions, we have seen that position P20 has a very distinguished and more pronounced dominant peak than the other two positions and it is this peak that results in a higher spatial channel correlation in the temporal domain for position P20. Finally, we also analyzed the common MPCs distributions over a massive array in

both the InLab and InF indoor environments. A joint temporal, power and angular thresholds criterion was proposed to identify the common MPCs between different sub-arrays of a massive array. The results show that these common paths have an important energy contribution in the different propagation conditions considered. However, in order to fully catch the channel characteristics, the sub-array dependent paths, here called uncommon, should also be considered. The impact of these components was investigated for different sub-array sizes, showing that their contribution can reach up to 70% or 56.6% of the energy even in LOS, respectively, for the InF and InLab environments. A model based on only the common MPCs could lead to an underestimation of angular and delay spreads. The shorter delay spreads and smaller angular spreads for the common MPCs may suggest that efficient mmWave mMIMO systems exploiting hybrid beamforming based on sub-array division can be achieved. On the one hand, shorter delay spreads imply flat fading, which has an impact on wideband orthogonal frequency-division multiplexing (OFDM) systems, where analog beamformers can hardly have different weights across subcarriers. On the other hand, by taking advantage of a small angular spread at the base station sub-array, we can reduce the dimension of the effective instantaneous channel state information for digital beamforming within each coherent fading block. However, as already highlighted above, at some receiver positions, the uncommon paths energy contribution can be significant, therefore caution needs to be applied when designing such mmWave mMIMO systems employing sub-array based beamforming. Hence, these effects need to be carefully taken into account for mmWave MIMO channel characterization for indoor applications.

Chapter 3

Indoor mmWave Massive MIMO Channel Characterization and Modelling with T-RISs

The 5G and 6G key driving technologies include mMIMO, small cells technology and the exploitation of mmWave, among others. The synergy of the aforementioned technologies result in increased wireless propagation channel capacity and link reliability, enhanced security as well as the efficient saving of energy etc. mmWave mMIMO is mostly suited for small coverage areas, fewer users and low user mobility situations. Small cells technology, unlike conventional high power macro base stations which cover large geographical areas, involves the use of small and low power base stations to transmit signals. The small cells can be split into categories (femtocells, picocells and micro cells). The small cells technology finds applications in both indoor and outdoor environments. Advanced techniques like beamforming are employed in small cells technology through the use of smart antennas such as T-RISs.

In this chapter, we investigate the T-RISs beamscanning capabilities

and the impact of T-RISs beamforming on the indoor mmWave radio channel characteristics. For this purpose and in considering a T-RIS at the TX side, channel measurements were performed in the InLab, InOpOffice, InMixOffice, corridors and InF environments. The channel and antenna joint effect is investigated. For the T-RIS based channel measurements, statistical spatio-temporal channel modelling will also be performed for the different indoor environments.

The remainder of this chapter is outlined as follows: The two types of T-RISs used in our measurements are presented in section 3.1. Section 3.2 presents the channel measurement campaigns in the different environments. Section 3.3 presents the channel characterization results for the different investigated environments. In particular, the T-RISs beamscanning capabilities as well as the impact of beamforming on the large scale parameters are presented in the aforementioned section. Section 3.4 deals with the omnidirectional PDP synthesis followed by the derivation of the statistical spatio-temporal channel models in Section 3.5. Conclusions are finally given in Section 3.6.

3.1 Deployed T-RISs

In this section, we briefly present the two types of T-RISs used in our measurements.

3.1.1 Linearly polarized T-RIS

The employed T-RIS operates in the Ka-band. It is based on a 1-bit UC architecture. Two phase-states with a relative phase-shift of 180° are achieved by electronically changing the state of two PIN diodes integrated on the UC. The UC architecture is presented in Fig. 3.1(a) and consists of four metal layers (M1 – M4), two identical substrates of Rogers Duroid RT6002 and one bonding film of Arlon CuClad 6700. Fig. 3.1(b) shows the view of the T-RIS with the focal source and the steering logic. The transmitting layer (M4) is composed of a rectangular patch loaded by a U-shaped slot, while the receiving layer (M1) contains a rectangular patch loaded by an O-shaped slot and the two PIN diodes (D1 and D2). In the EM simulator, these active devices

are modelled as a lumped-element equivalent circuit extracted from the measurements and a gallium-arsenide block [136]. This active patch is connected to the passive one printed on (M4) with a metallized via hole placed at the center of the UC. A ground plane occupies one of the two intermediate metal layers (M3). The other inner layer (M2) contains the biasing lines. In the proposed UC structure, one PIN diode is biased in the forward state with a 10-mA current. The 1.3-V threshold voltage of this diode is sufficient to maintain the other diode, mounted in anti-parallel configuration, in its reverse state. Thus, only one bias line is necessary for each UC, facilitating thereby the layout and routing of the bias network in very large array configurations. The bias line is 100- μm wide and is connected to the active patch by using two symmetric metallic via connections. More details on the 1-bit unit-cell operational principle, model, parametric analysis, and simulation setup are detailed in [136]. The array can electronically steer the beam on a two dimensional window of $120^\circ \times 120^\circ$.

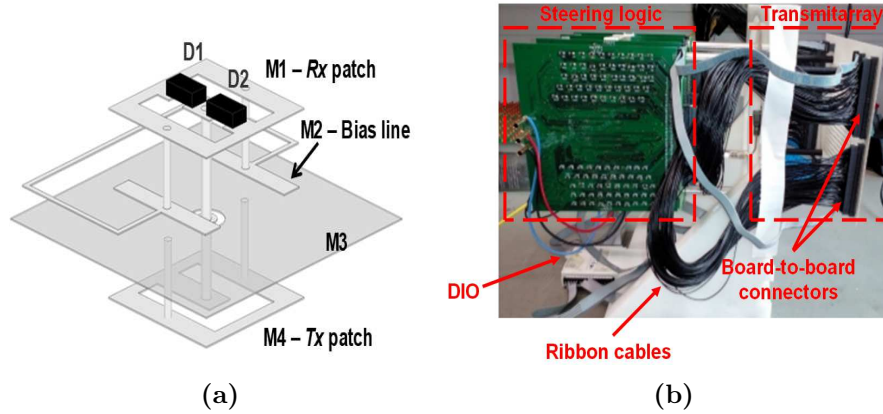


Figure 3.1: (a) Schematic view of the proposed 1-bit electronically reconfigurable unit cell based on PIN diodes, (b) view of the T-RIS with the focal source and the steering logic.

The T-RIS patterns are shown in Fig. 3.2. Supplementary information about the T-RIS can be found in the appendices section: Fig. A.3.1.

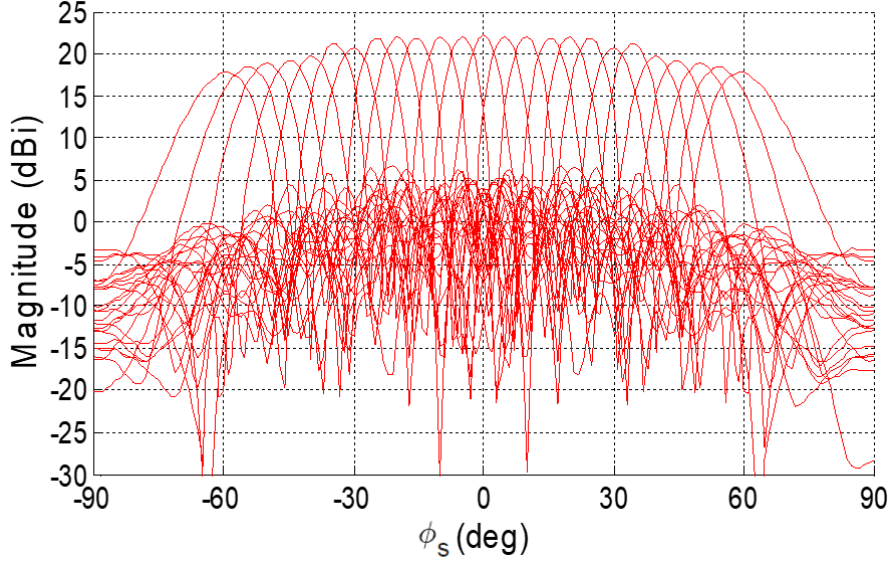


Figure 3.2: Linearly polarized T-RIS beam scans.

3.1.2 Circularly polarized T-RIS

This T-RIS is composed of 400-elements (or UCs) which are positioned in a 20×20 square aperture of size $10.2 \times 10.2 \text{ cm}^2$ [2], as shown in Fig. 3.3. It is based on linearly polarized 1-bit UCs with 180° phase-shifting capability. They permit the generation of either right hand (RH) or left hand (LH) circular polarizations depending on the phase distribution, despite a 3dB lower gain in comparison with an array composed of circularly-polarized UCs. In order to obtain circular polarization from the linearly polarized UCs, a sequential rotation is usually applied to the transmitting layer. In this particular T-RIS we employed, the active UC side loaded by p-i-n diodes is placed on the receiving layer and the rotation is applied to the transmitting layer (i.e passive UC side). In order to improve the tilting capabilities of the T-RIS, and prevent the appearance of grating lobes on diagonal planes, a *random* sequential rotation scheme is applied to the transmitting layer of the T-RIS. For more details about the designing of the T-RIS, refer to [2].

The phase compensation, i.e. the phase shift provided by each unit-

cell through a proper bias of the p-i-n diodes, is computed using an optimization tool. The combination of the receiving layer, the phase compensation and the rotation scheme of the patch elements on the transmitting layer gives the wanted phase distribution on the radiating aperture. In this architecture a 1-bit phase control is implemented, therefore it is possible to choose the phase of either 0° or 180° through two diodes. The T-RIS prototype and architecture are shown in Fig. 3.3.

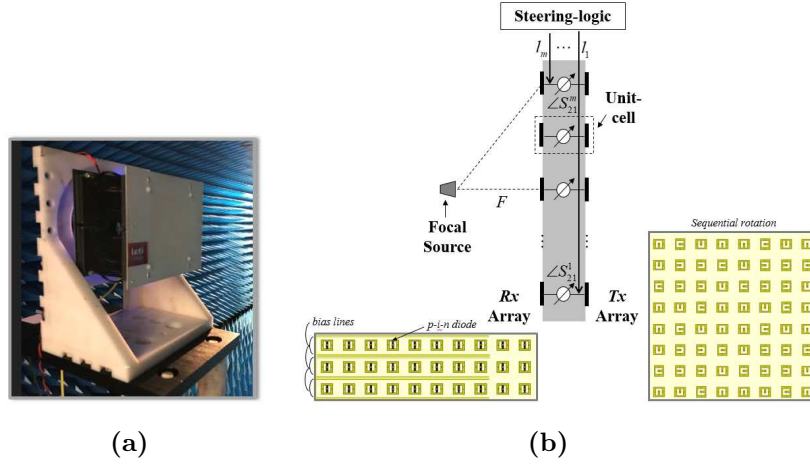


Figure 3.3: T-RIS [2]: prototype (a), architecture (b).

By changing the phase distribution, on the T-RIS we can electronically reconfigure the radiation pattern and realize beamsteering.

Once the phase distribution has been optimized, the T-RIS vector transfer function can be written as:

$$\mathbf{H}(f, \theta, \phi, \theta_s, \phi_s) = H_v(f, \theta, \phi, \theta_s, \phi_s) \widehat{a}_v \pm j H_h(f, \theta, \phi, \theta_s, \phi_s) \widehat{a}_h \quad (3.1)$$

where $H_v(f, \theta, \phi, \theta_s, \phi_s)$ is the vertical component and $H_h(f, \theta, \phi, \theta_s, \phi_s)$ is the horizontal component, θ, ϕ are the pattern elevation and azimuthal angles, respectively, θ_s, ϕ_s are the elevation and azimuthal steering angles, respectively. The maximum gain for $\phi_s = 0^\circ$ is 15.9 dBi and 18.7

dBic, respectively, while for a maximum steering angle of -60° the gain drops to 7.87 dBi and 11.94 dBic, respectively. The steering angle varies as a function of frequency, due to the beam squint, but the effect remains limited even for larger pointing angles. The T-RIS patterns are shown in Fig. 3.4. Supplementary information about the T-RIS can be found in the appendices Fig. A.2.1.

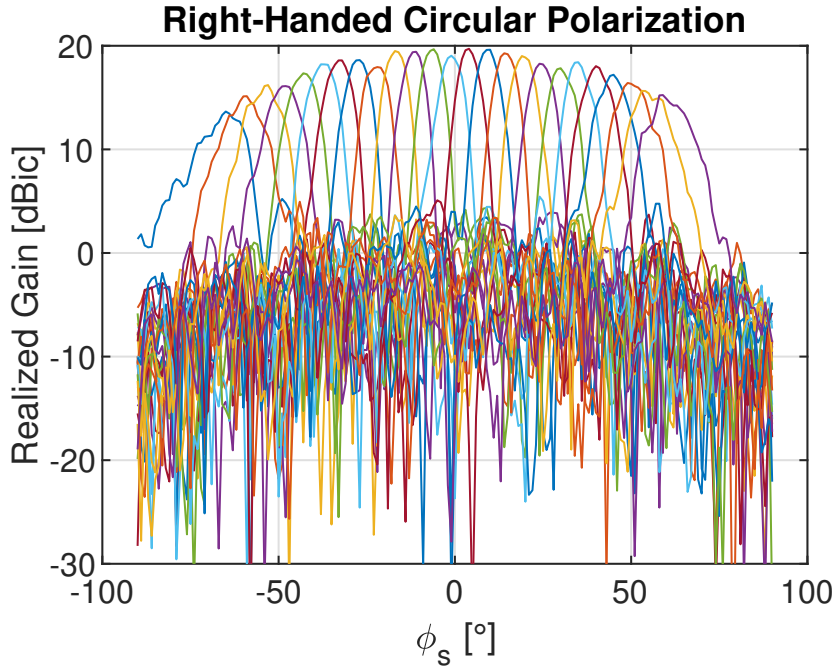


Figure 3.4: Circularly polarized T-RIS beam scans.

3.2 Channel Measurement Campaigns

The channel measurement campaigns were performed in different environments at CEA-Leti. In all environments, a vertically polarized monopole antenna (of measured gain 0 dBi) was considered at the RX side. At the TX side, either a linearly polarized or circularly polarized T-RIS is employed. Both the TX and RX antennas were at the same height above the ground. Measurements were performed in the frequency band 26-30 GHz, sweeping 801 frequency points. The transmitted power was 10 dBm. An external PC controls the measurement

instruments. The T-RIS scans the environment from -60° to 60° following a step of 5° . The general measurement setup is shown below in Fig. 3.5.

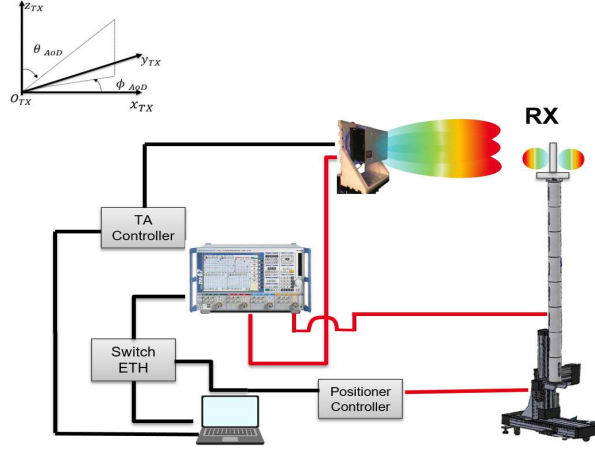


Figure 3.5: RIS-enabled channel measurement setup.

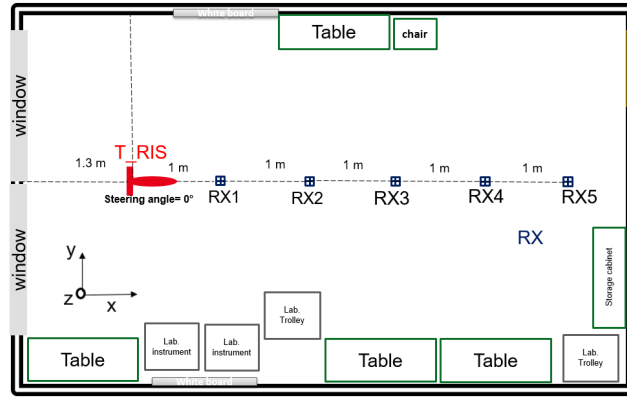
3.2.1 Indoor Laboratory

The linearly polarized T-RIS is considered here. The channel measurements were performed in an InLab at CEA-Leti. The dimensions of the room are $7 \text{ m} \times 4.3 \text{ m} \times 2.8 \text{ m}$. The room is furnished with three tables, a chair, a metallic storage cabinet, and a plastic drawer chest. Also present in the room is a channel sounder (the RX part and the TX part). The measurement setup follows the general setup (see Fig. 3.5) and is based on a VNA and an automatic positioner to control the receiving monopole antenna movements while scanning spatial grids. The measurement environments are shown in Fig. 3.6(a). The room has two white boards on two of its opposite walls. It also has a large glass window on one of its four walls as clearly depicted in the floor plans. Two different floor plans (Floor plans A and Floor plans B) were considered. Floor plans A are exactly the same as those shown in Fig. 2.3(b) but replacing the massive virtual array with the linearly polarized T-RIS. Fig. 3.6(b) shows the Floor plans B. The instruments are controlled by an external PC. As mentioned before, the T-RIS performed 25 beam

scans per each RX position. At each RX, 3×3 spatial grids were done in the x and y axes, considering a grid step of 5 mm. In essence, for each receiver position, e.g position $m1$, 225 channel measurements were performed. Both the TX and the RX were at a height of 1.54 m above the ground.



(a) Environment



(b) Floor plans B

Figure 3.6: InLab measurement environments and the floor plans.

3.2.2 Indoor Open Office

The circularly polarized T-RIS is considered here. The measurement setup is shown in Fig. 3.5. The measurement setup consists of a four-port VNA operating in the frequency range 24-40 GHz; one T-RIS (size 20×20 , 1 bit); one monopole antenna. The TX and the RX were

both at a height of 1.52 m above the ground. At the TX side, there is the circularly polarized T-RIS while on the RX side, a vertically polarized monopole antenna is considered. The T-RIS optimized gain in the broadside direction at 28 GHz was 18.7 dBic. The dimensions of the InLab were 72.41 m². The InOpOffice is furnished with tables, chairs, desktops, sofas, and a television as clearly depicted in Fig. 3.7. The floor plans considered are shown in Fig. 2.4, replacing the VCA with the circularly polarized T-RIS. The left walls of the room comprise mostly of glass windows and the right side walls also have a part with a glass window. On the roof, also present is a metallic positioner.



Figure 3.7: InLab measurement environments.

3.2.3 Indoor Mixed Office

The channel measurements were performed in InMixOffice rooms at CEA-Leti. The measurement setup is shown in Fig. 3.5. The circularly polarized T-RIS is considered here. In all InMixOffice environments channel measurements, 3×3 spatial grids in the x and y axes are scanned at the RX side. A grid step of a full wavelength (λ) was considered in all InMixOffice environments. The TX and the RX were both at a height of 1.52 m above the ground. The office room is virtually empty; it only has a storage unit shown in Fig. 3.8. Three different InMixOffice floor plans were considered. Floor plans 1 and Floor plans 2 were considered in the same office room.

In Floor plans 1 (see Fig. 3.8(a) and Fig. 3.9(a)), the T-RIS is very

close to the right corner (near the storage unit). This scenario, as shown in the floor plans, involves the T-RIS almost close to the right corner, where the storage unit is. The measurements reference position for Floor plans 1 is RX5.

In Floor plans 2 (see Fig. 3.8(b) and Fig. 3.9(b)), the T-RIS is on the left corner of the building. The measurements reference position for Floor plans 2 is RX3.

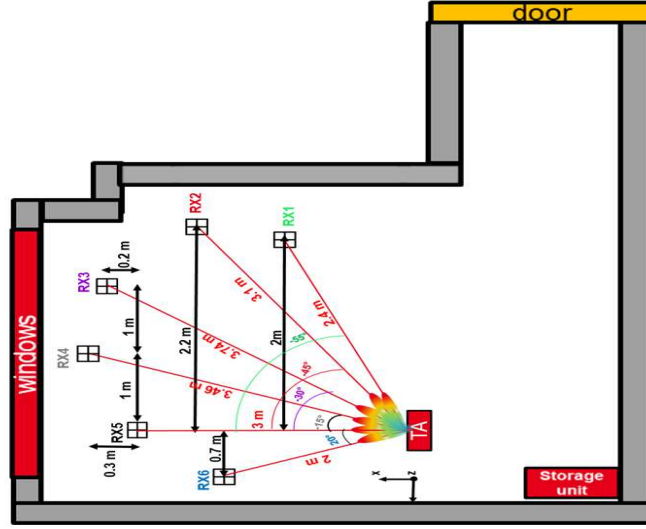


(a) FP1

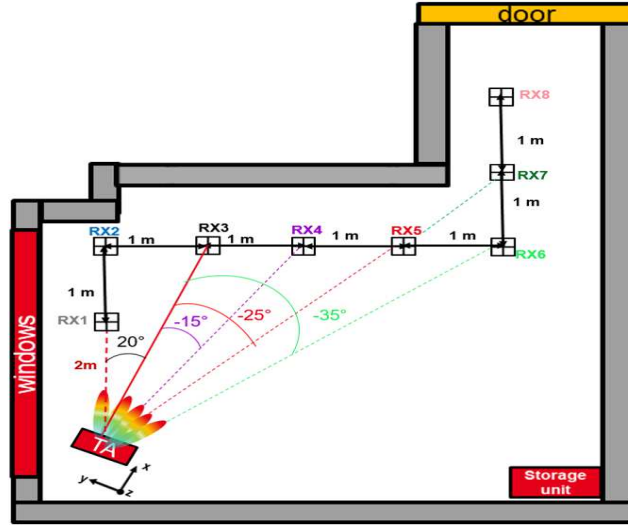


(b) FP2

Figure 3.8: InMixOffice measurement environments.



(a) Floor plans 1



(b) Floor plans 2

Figure 3.9: InMixOffice floor plans.

Floor plans 3 involve channel measurements from one office room (28.54 m^2) to another office room (25.34 m^2) via a corridor. This measurement campaign allows us to investigate the evolution of the PL and DS as RX positions move from one office room to the corridor and then eventually to another office room. The measurement environments and

floor plans are shown in Fig. 3.10.

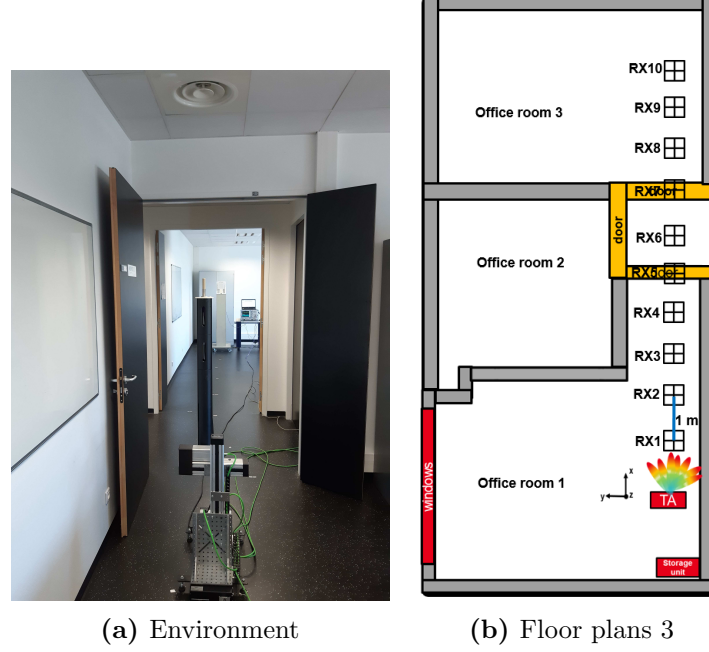


Figure 3.10: Measurement environment and floor plans for InMixOffice FP3.

3.2.4 Indoor Factory

The channel measurements were carried out in an InF environment considering the circularly polarized T-RIS at the TX side. At the RX side, a single monopole receiver was considered. Three propagation conditions were investigated, namely LOS, OLOS and NLOS. The measurement setup is similar to the one shown in Fig. 3.5. To increase the dynamic range for both the OLOS and NLOS conditions, a low noise amplifier of 20 dB was used at the RX side. Hence, attenuators in series are considered during the measurement calibration. Since the attenuators are not used in the actual measurement, their influence is de-embedded during postprocessing. The InF environment floor plans are shown in Fig. 2.6. Fig. 3.11 shows the photos of the 3 considered scenarios.



Figure 3.11: Pictures of the InF measurement environments.

3.3 Channel Characterization Results

In this section we discuss the channel measurement results. We highlight that the expected angles of arrival were computed using trigonometry (applied on the different floor plans). As for the expected LOS path power, the Friis equation is employed.

3.3.1 Indoor Laboratory

Fig. 3.12 shows the superposed PDPs at each grid center in the main lobe direction. The results clearly show the T-RIS beamscanning capabilities and the beamforming impact: maximizing the LOS path power at 0° for positions $m1$ and $m4$, 5° for $m2$ and $m5$, and 15° for $m3$ and $m6$, according to the scenario geometry.

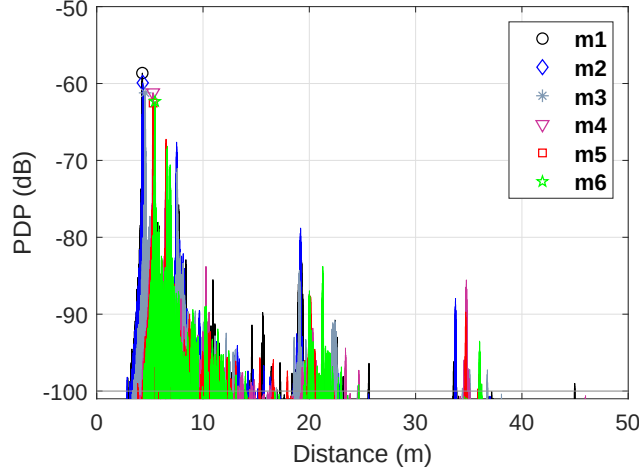


Figure 3.12: InLab FP A: Superposed PDPs for all receiver central grid positions in the mainlobe direction.

Table 3.1 resumes the measured LOS path power per steering angle for the different RX positions.

Table 3.1: InLab FP A: LOS path power [dB] vs. steering angle

Steering Angle ($^{\circ}$)	$m1$	$m2$	$m3$	$m4$	$m5$	$m6$
-25	-73.1	-74.9	-76.3	-78.8	-80.1	-80.9
-20	-80.4	-77.3	-77.5	-78.8	-79.8	-77.8
-15	-80	-69.7	-76.7	-82	-77.7	-78.1
-10	-72.6	-75.4	-71.5	-78.4	-75.1	-76.4
-5	-64.3	-79.8	-74.9	-68.8	-76.7	-74.9
0	-58.6	-65.2	-76.5	-63.4	-66.8	-76.2
5	-66.5	-60.7	-70.4	-69.2	-63.9	-78.4
10	-74.6	-63.1	-66.8	-78.2	-70.8	-66
15	-72.3	-65.3	-62.9	-70.4	-71.8	-63.4
20	-71.1	-67.2	-61.5	-75.8	-73.6	-65.8
25	-72	-66.7	-65.1	-73.3	-69.6	-66.5

The measured LOS path power in the expected AOD direction corresponds to the RX grids' centers. The measured LOS path power at a certain RX grid center and the average LOS power over the 9 RX grid positions in the expected AOD direction are not so different (< 1 dB).

The beamscanning capabilities and the beamforming impact is also witnessed by the CG (antenna embedded) per steering angle, shown in Fig. 3.13(a). It is evident from the aforementioned figure that the channel gain increases in the main lobe direction, which in essence translates to reduced path loss in this direction. Actually the path loss is reduced thanks to T-RIS beamforming capabilities, improving up to 12 *dB* of the overall link budget. Also it can be seen that antenna directivity and beamforming has a direct impact on the DS of the channel. When the receiver is in the T-RIS main lobe direction, the DS is comprised between 8 and 10 *ns*, while it is much more increased (up to 26 *ns*) when the beamsteering is performed in other directions. Fig. 3.13(b) shows the variation of the DS with the steering angle.

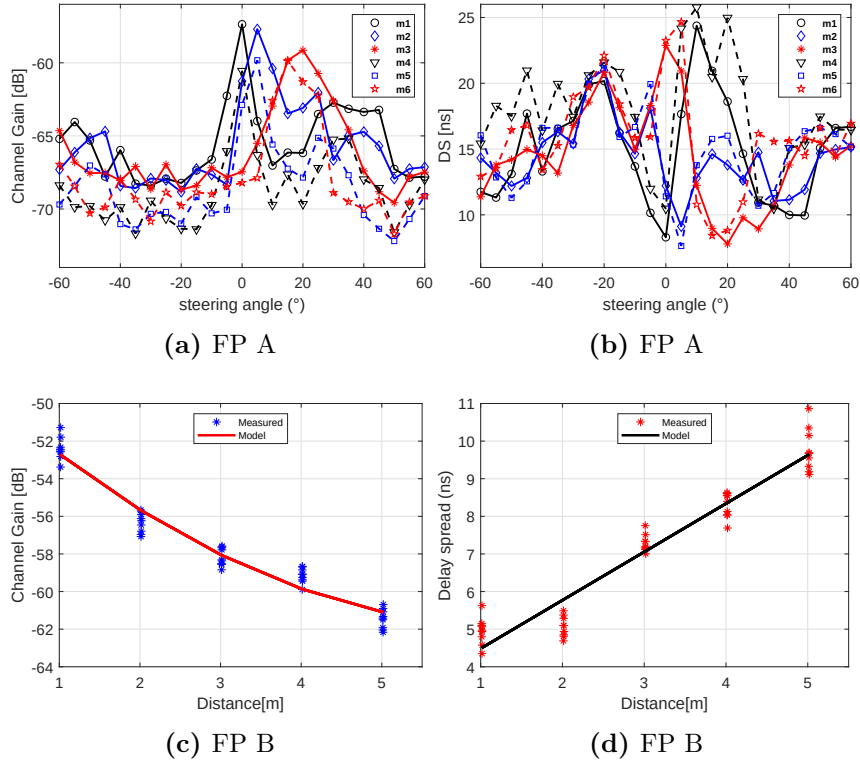


Figure 3.13: InLab channel gain (antenna embedded) and delay spread (a), (b) variation at each receiver position per steering angle, and (c), (d) models at main lobe direction $\phi_s = 0^\circ$.

Moving our attention to the Floor plans B, we can see in Fig. 3.13(c), that the channel gain decreases with increasing TX-RX separation distances along the direction $\phi_s = 0^\circ$. Likewise, Fig. 3.13(d) shows that the DS increases with TX-RX separation. The CG and DS model parameters are provided in Table 3.2. A path loss exponent of less than 2 is observed and this is common for indoor environments.

Table 3.2: InLab FP B: Antenna embedded CG and DS Model Parameters.

Scenario	$G_0[dB]$	n	$\sigma[dB]$	$a[ns/m]$	$b[ns]$	$\sigma_\tau[ns]$
Steering Angle= 0°	-52.3	1.23	0.6	1.29	3.2	1.84

3.3.2 Indoor Open Office

Fig. 3.14 shows the PDP when $\phi_s = 0^\circ$. At $\phi_s = 0^\circ$, the main beam is in the direction of receivers RX1, RX2, RX5 and RX6. As expected, the received power decreases with increasing transmitter-receiver separation distance.

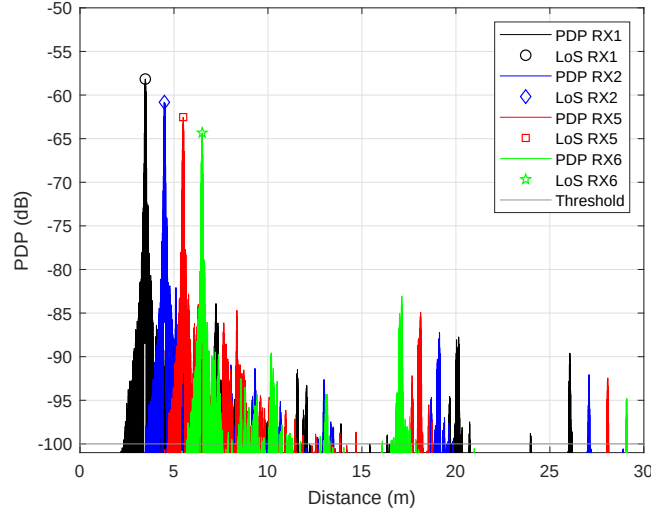


Figure 3.14: InOpOffice PDPs for RX1, RX2, RX5 and RX6 at $\phi_s = 0^\circ$.

From Fig. 3.15(a) and Fig. 3.15(b) showing the results for all the

eight RX positions, we see that as long as the RX is in the main lobe direction, the overall CG (antenna embedded) experienced is very high, thanks to the T-RIS directivity. For one TX-RX measured point (at each T-RIS steering angle), the overall CG is computed following equation (2.2). In particular, when the steering angle is $\phi_s = 0^\circ$, we can see that the receivers (RX1, RX2, RX5 and RX6) in the main beam direction have the highest overall CG and least DS values. For steering angles, $\phi_s = 15^\circ$ and $\phi_s = -15^\circ$, evidently, the receiver positions RX3 and RX4 which are in the main lobe direction record the highest overall CG and least DS values, respectively. The same behaviour is evidenced for $\phi_s = 10^\circ$ and $\phi_s = -10^\circ$ whereby the highest overall CG and least DS values are observed at receiver positions RX7 and RX8, respectively. We can clearly see from Fig. 3.15(b) that DS values as small as 6 ns are observed in the main lobe directions while values as high as 32 ns are observed in other directions. The values obtained are consistent with those found in the literature [137]. The small DS values in the main lobe direction are due to the narrow beam transmission which reduces the time dispersion [138].

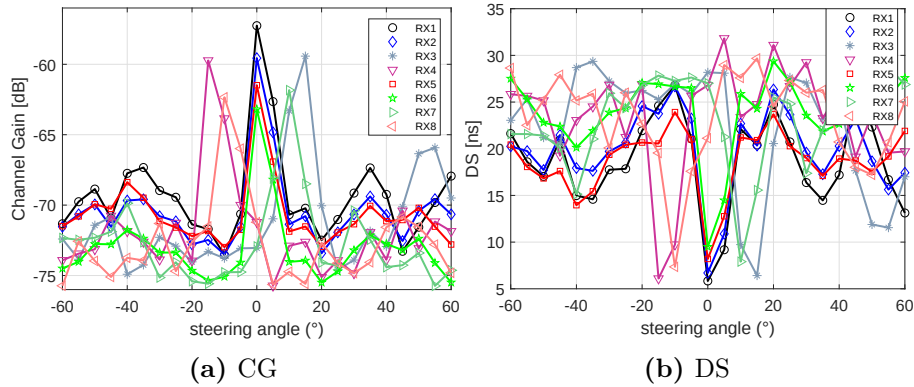


Figure 3.15: InOpOffice: Overall channel gain (antenna embedded) and delay spreads for all receiver positions.

Table 3.3 summarizes the expected and the measured angles of departure and LOS path powers, respectively. The measured LOS path

power in the expected AOD direction corresponds to the RX grids' centers. Similar to the InLab, the measured LOS path power at a certain RX grid center and the average LOS power over the 9 RX grid positions in the expected AOD direction are not so different.

Table 3.3: InOpOffice: LOS PATH RESULTS.

Position	AOD($^{\circ}$)	$\phi_s(^{\circ})$	Expected [dB]	Measured [dB]
RX1	0	0	-55	-58.3
RX2	0	0	-57.6	60.9
RX3	15	15	-57.8	-61.4
RX4	-15	-15	-57.8	-61.6
RX5	0	0	-59.5	-62.5
RX6	0	0	-61.1	-64.3
RX7	10	10	-61.2	-63.4
RX8	-10	-10	-61.2	-64.5

3.3.3 Indoor Mixed Office

Starting with Floor Plans 1, we have RX5 as the reference position. The highest CG (antenna embedded) and the least DS values are obtained at $\phi_s = 0^{\circ}$ for RX5. The same behaviour is observed for both Floor Plans 2 (whose reference position is RX3) and Floor Plans 3. Fig. 3.16 shows example PDPs for the FP1 and FP2. Likewise, Fig. 3.17 shows the example PDPs for the FP3. Significant reflections from the windows and the walls can be observed from the PDPs of the receivers. This is mainly because the receiver positions are very close to the windows and the walls as can be seen in the floor plans. Compared to the InOpOffice scenario, the immediate secondary MPCs for both FP1 and FP2 have higher intensities. This is mainly because of the proximity of the RX positions (in both cases) to the walls and windows.

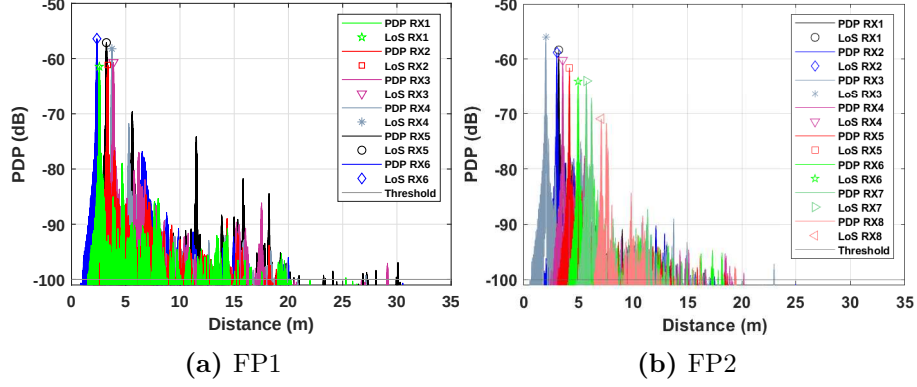


Figure 3.16: InMixOffice: FP1 and FP2 PDPs for all RXs grid centers in the main lobe directions.

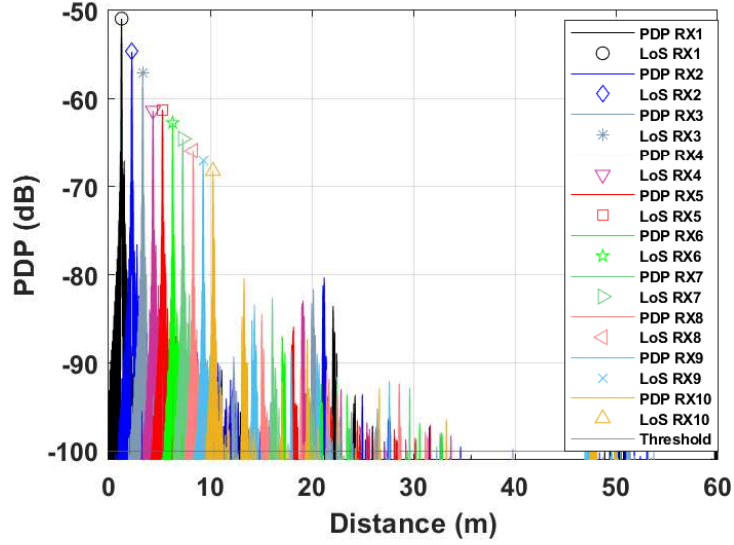


Figure 3.17: InMixOffice: FP3 PDPs for all RXs grid centers in the main lobe directions.

Fig. 3.18 summarizes the three floor plans average CG and DS variations per steering angle. The average value for a particular RX position is taken over the 9 grid positions scanned. The obtained results are consistent with the geometry of the room floor plans. The results show that the highest overall CG and the least DS is in the main lobe directions

for the same reasons already mentioned in the InOpOffice results.

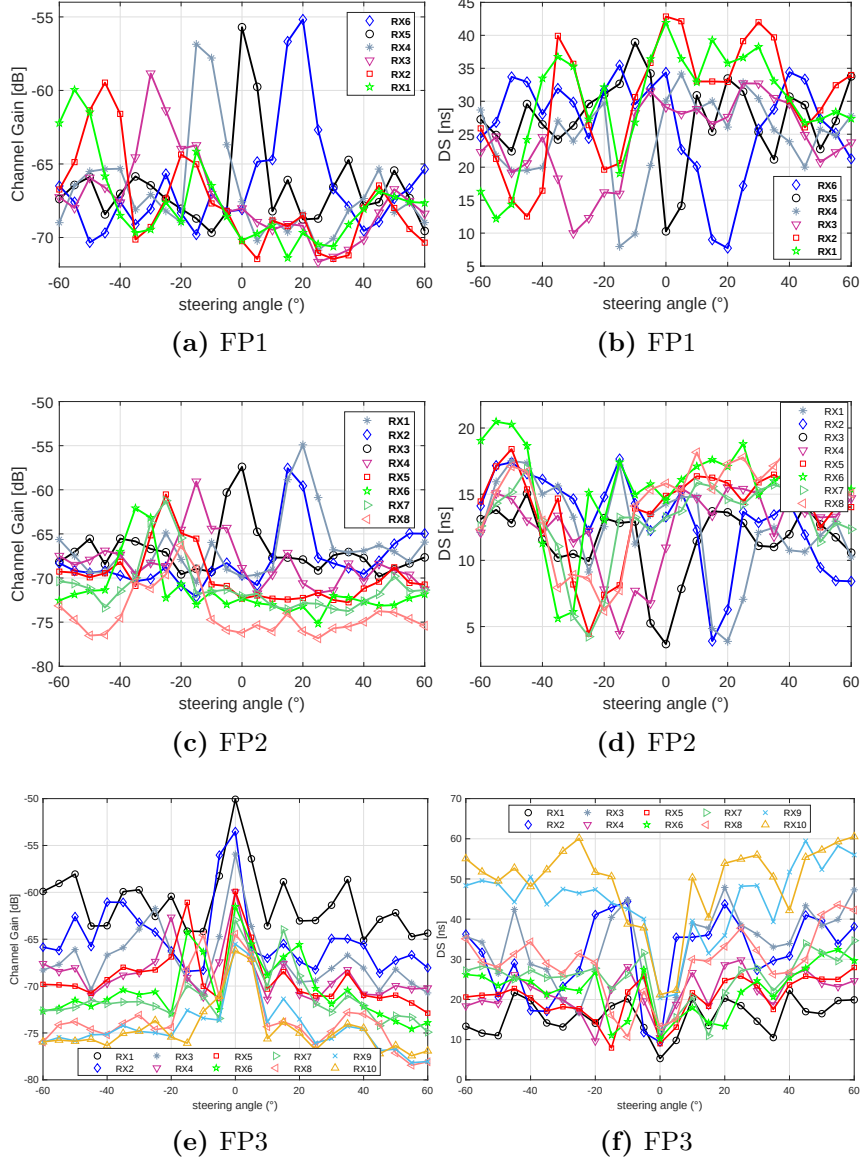


Figure 3.18: InMixOffice: Overall mean CG (antenna embedded) and delay spreads for all receiver positions.

In Table 3.4 and Table 3.5, we summarize the expected and the measured angles of departure and LOS path powers for the Floor Plans

1 and Floor Plans 2, respectively. We remind that the expected values are computed considering the room geometry (floor plans) and the Friis equation. The measured LOS path power in the expected AOD direction corresponds to the RX grids' centers. Similar to the InLab and InOpOffice, the measured LOS path power at a particular RX grid center and the average LOS power over the 9 RX grid positions in the expected AOD direction are not so different. We remark that for Floor Plans 2, the RX8 is actually in NLOS condition.

Table 3.4: InMixOffice FP1: LOS PATH RESULTS.

Position	AOD($^{\circ}$)	$\phi_s(^{\circ})$	Expected [dB]	Measured [dB]
RX1	-56	-55	-58.4	-61.3
RX2	-45	-45	-58.11	-60.9
RX3	-32	-30	-59.2	-60.6
RX4	-16.7	-15	-56.3	-57.9
RX5	0	0	-55	-56.8
RX6	21	20	-51.8	-56.1

Table 3.5: InMixOffice FP2: LOS PATH RESULTS.

Position	AOD($^{\circ}$)	$\phi_s(^{\circ})$	Expected [dB]	Measured [dB]
RX1	21.8	20	-51.9	-55.8
RX2	18	20	-55.4	-58.3
RX3	0	0	-55.6	-58.4
RX4	-15.7	-15	-56.7	-60
RX5	-27	-25	-59.6	-61.4
RX6	-35	-35	-61.7	-64
RX7	-27	-25	-62	-63.9
RX8	N/A	-20	N/A	-70.1

Focusing on the Floor Plans 3, in Fig. 3.19 we show the PL and DS along the direction $\phi_s = 0^{\circ}$. This scenario involves receiver positions located in two office rooms, passing via the corridor. We can indeed appreciate the improvement to the link budget brought about by the T-RIS as seen by the comparison with the free-space path loss. Similar

to the PL, the DS appear to increase with the increasing TX-RX distance. To model the path loss we employed the floating intercept point model [18, 19]. The T-RIS embedded PL and DS model parameters for this office room to corridor to another office room scenario are given in Table 3.6. We remark that in de-embedding the co-polarized T-RIS broadside gain pattern, the PL curve is almost similar (touches) to the free-space model.

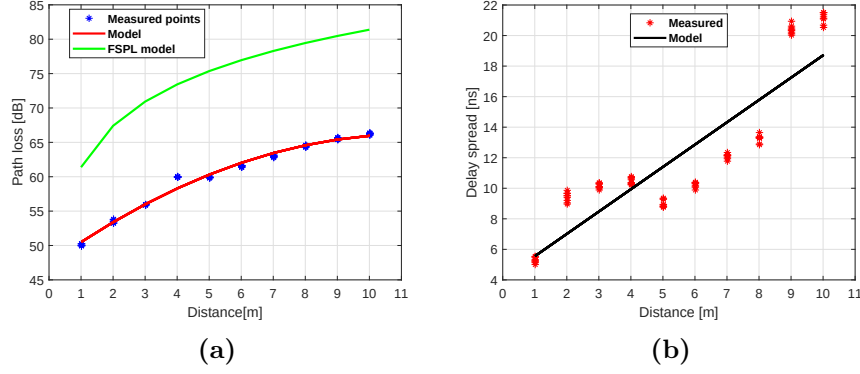


Figure 3.19: InMixOffice FP3: PL and DS models in the main lobe direction $\phi_s = 0^\circ$.

Table 3.6: InMixOffice FP3 Path Loss and Delay Spread Model Parameters.

Scenario	$PL_0[dB]$	n	$\sigma[dB]$	$a[ns/m]$	$b[ns]$	$\sigma_\tau[ns]$
T-RIS included	49.7	1.67	0.7	1.46	4.1	4.2

3.3.4 Indoor Factory

Here we discuss the results for the InF environment T-RIS channel measurement campaign. In Fig. 3.20, we show the superposed PDPs for the positions P1-P20. The PDP in the direction of the maximum received power is shown. We recall that in the InF environment, no spatial grids were scanned at the RX and therefore the PDPs shown correspond to the single measurement in the direction of the maximum

received power (unlike in some of the previous environments where the PDP for the RX grid center was shown).

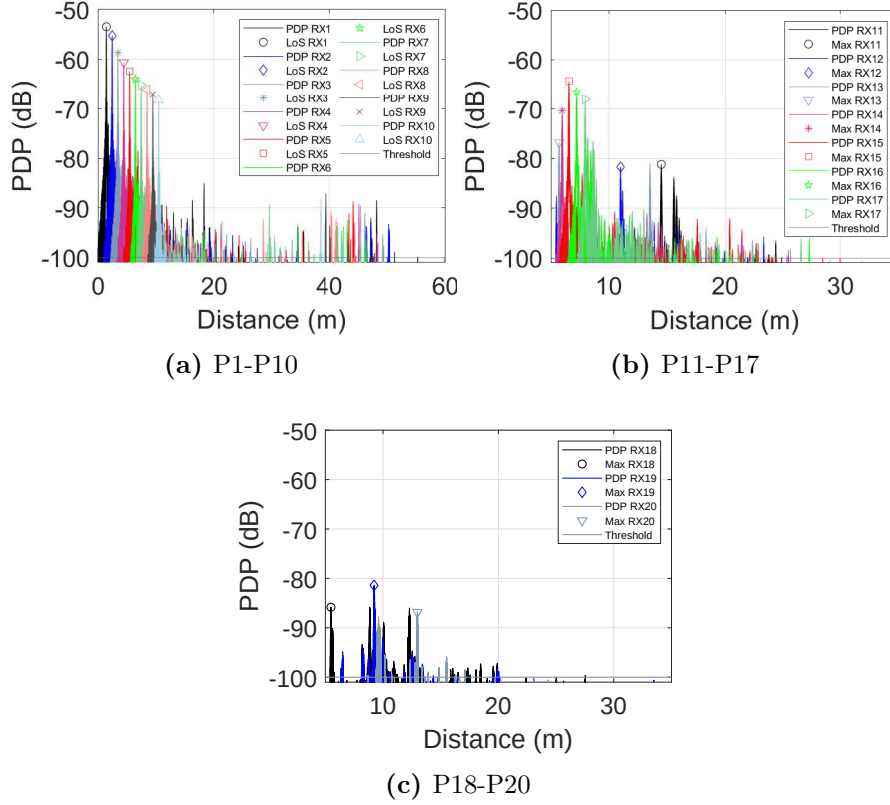


Figure 3.20: InF: Superposed PDPs for the positions P1-P20 in the direction of the maximum received power.

In Fig. 3.21, we can see that for positions P1-P10, the highest CG (antenna embedded) is obtained in the direction $\phi_s = 0^\circ$. For positions P11, P12, P13, P14, P15, P16 and P17, the highest CG is in the directions $\phi_s = 55^\circ$, $\phi_s = 30^\circ$, $\phi_s = 60^\circ$, $\phi_s = 60^\circ$, $\phi_s = 50^\circ$, $\phi_s = 45^\circ$, and $\phi_s = 40^\circ$, respectively. At position P12 we notice that in the directions $\phi_s = 55^\circ$ and $\phi_s = 60^\circ$, which geometrically are expected to record maximum powers, the channel gain is almost the same with that observed at $\phi_s = 30^\circ$. For positions P18, P19, P20, the highest CG is in the direction $\phi_s = -60^\circ$ for all the three positions. With regards to the

delay spread, Fig. 3.21 shows that the DSs appear to be inversely related to the CGs. In essence, very small delay spread values are observed in the directions of the highest CGs.

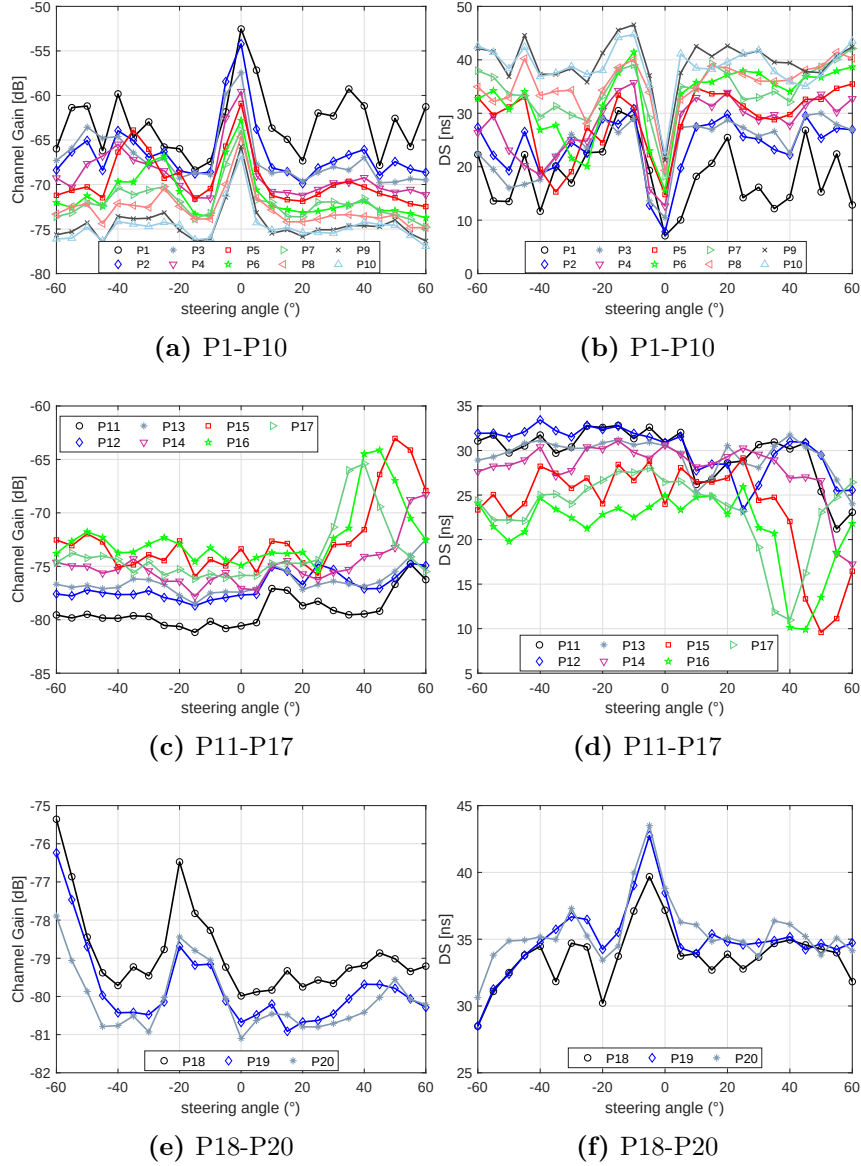


Figure 3.21: InF: CG and DS per steering angle for the LOS scenario.

Focusing on both the P1-P10 measurements and the P11-P17 mea-

measurements, Fig. 3.22 and Fig. 3.23 show the CG and DS models. In particular, Fig. 3.22(a) and (b) show the models in considering only the maximum CG over the measured BW while Fig. 3.22(c) and (d) show the models in considering the average CG over the measured BW. The models in Fig. 3.23(a) and (b) show the DS models and values are computed over the whole BW. What we can observe is that for the P1-P10 measurements, the channel gain is decreasing with the increasing TX-RX separation distance for the steering direction $\phi_s = 0^\circ$. However, for the P11-P17 measurements, we are considering the measurements corresponding to the maximum steering direction for each particular RX position. The CG is increasing with distance. This is because for positions P11-P17, the RX locations are in such a way that P11 is basically in a quasi-NLOS condition, and as we move to P17, the scenario becomes more and more OLOS with an observable dominant peak.

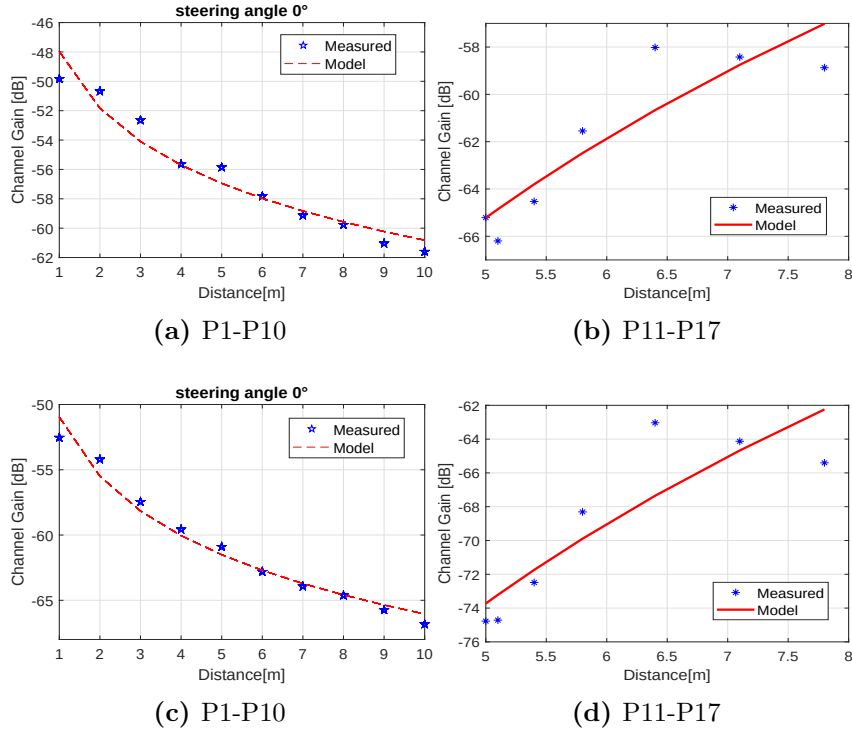


Figure 3.22: InF: maximum (a), (b) and mean (c), (d) CGs over BW.

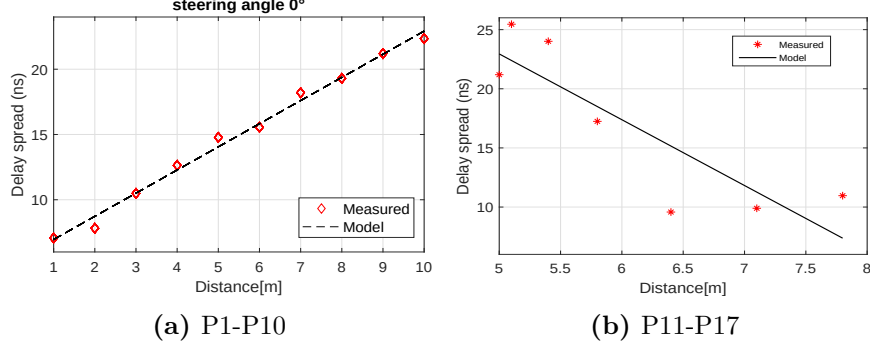


Figure 3.23: InF: Delay spread models.

Table 3.7 and Table 3.8, respectively, present the channel gain and the delay spread model parameters. We remind that these are T-RIS antenna embedded models.

Table 3.7: InF: Channel Gain Model Parameters.

Scenario	$G_0[dB]$	n	$\sigma[dB]$
P1-P10 (maximum over BW)	-48	1.28	1
P1-P10 (average over BW)	-51	1.51	0.8
P11-P17 (maximum over BW)	-94.9	-4.25	1.5
P11-P17 (average over BW)	-115.3	-5.95	2.4

Table 3.8: InF: Delay spread Model Parameters.

Scenario	$a[ns/m]$	$b[ns]$	$\sigma_\tau[ns]$
P1-P10	1.77	5.2	0.5
P11-P17	-4.4	45.5	3.9

3.4 Omnidirectional Power Delay Profile Synthesis from electronic T-RIS antenna

In the literature, channel modelling at mmWave is often based on mechanical steering of directive antennas. The measurements collected are

then used to obtain the omnidirectional power delay profile in order to retrieve the channel characteristics [90, 121, 125, 139]. In our work, we synthesize the omnidirectional power delay profile from channel measurements involving the electronic steering of a T-RIS. For a particular receiver position, the synthesis is done according to the following steps:

- Firstly, the measured CTF matrix, $\mathbf{H}(\phi_s, f)$ is a function of both the steering direction and frequency. $\mathbf{H}(\phi_s, f)$ has dimensions $[N_s \times N_f]$, where N_s is the number of scanning directions and N_f is the number of frequency points swept.
- Secondly, the steering direction and delay dependent channel impulse response matrix $\mathbf{h}(\phi_s, \tau)$ of dimensions $[N_s \times N_\tau]$ is computed following (3.2):

$$h(\phi_s, \tau) = \mathcal{F}^{-1}(W(f) \cdot H(\phi_s, f)) \quad (3.2)$$

where $W(-)$ is the Hamming window function, $H(\phi_s, f)$ is the measured channel transfer function, ϕ_s is the considered scanning direction, f is the frequency point index and $\mathcal{F}^{-1}$ is the inverse Fourier Transform.

- Thirdly, the PADP matrix, $\mathbf{PADP}(\phi_s, \tau)$ of dimensions $[N_s \times N_\tau]$ is obtained following:

$$\mathbf{PADP}(\phi_s, \tau) = |\mathbf{h}(\phi_s, \tau)|^{\circ 2} \quad (3.3)$$

where $\mathbf{PADP}(\phi_s, \tau)$ is the PADP matrix, $\mathbf{h}(\phi_s, \tau)$ is the channel impulse response matrix and $(\cdot)^{\circ}$ is the Hadamard power.

- Finally, the omnidirectional power delay profile vector, $\mathbf{PDP}(\tau)$ with dimensions $[1 \times N_\tau]$ is obtained from the marginal integral of the $\mathbf{PADP}(\phi_s, \tau)$, following:

$$\mathbf{PDP}(\tau) = \frac{1}{N_s} \sum_{s=1}^{N_s} \mathbf{PADP}(\phi_s, \tau) \quad (3.4)$$

The synthesized omnidirectional PDP is then used to detect paths following the algorithm proposed in [139]. In essence, L detectable paths and their corresponding delays τ_l where $l = 1, 2, 3, \dots, L$ are detected from the synthesized omnidirectional PDP. Each delay τ_l is mapped to a unique scanning angle (ϕ_s). The path detection algorithm [139] searches for a local maxima in the synthesized omnidirectional PDP by comparison with a threshold function defined as:

$$T(\tau) = \frac{\epsilon}{\Delta} \int_{\tau - \frac{\Delta}{2}}^{\tau + \frac{\Delta}{2}} PDP(x) dx \quad (3.5)$$

where Δ is a length of a sliding window over the delay and ϵ is an offset of the threshold to avoid detecting artifacts and noisy peaks. In the computations, we used $\epsilon = 1.8$ dB and $\Delta = 2.5$ ns (that is 10 times the delay resolution) after tuning. A peak at $\tau = \tau_l$ is identified as a specular path if $PDP(\tau_l) \geq T(\tau_l)$. For the identified paths, their azimuth of departures are estimated by searching a maximum of the PADP at the identified delays.

3.4.1 InOpOffice Results

Fig. 3.24 below shows an example of the synthesized omnidirectional PDP and the corresponding scatter plots in the InOpOffice. For other positions results, see Fig. C.1.1 and Fig. C.1.2.

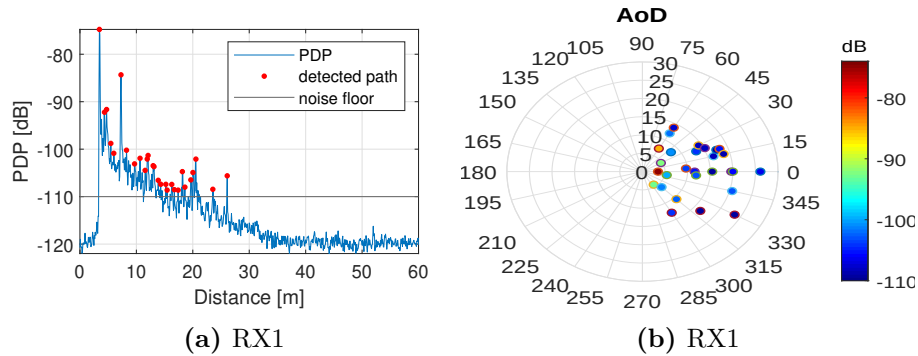


Figure 3.24: Example synthesized omnidirectional PDP and scatter plot at position RX1.

Fig. 3.25(a), (b), and (c), respectively, show the path loss, delay spread, and angular spread models. Fig. 3.25(d) shows the ratio of the specular power relative to the total power. The ratio of the specular power relative to the total power is computed in a similar manner as done in [139]. To model the path loss, we employed the floating intercept point model [18,19]. The path loss model parameters are provided in Table 3.9.

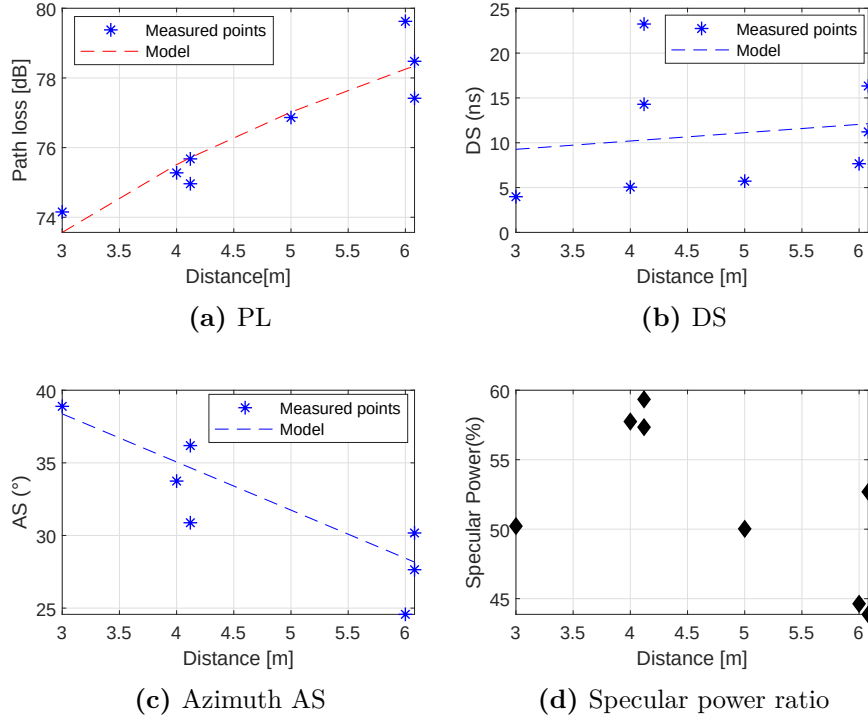


Figure 3.25: PL, DS, AS models and ratio of specular power relative to the total power.

Table 3.9: InOpOffice: T-RIS Path Loss Model Parameters.

Scenario T-RIS	$PL_0[dB]$	n	$\sigma[dB]$
TRIS setup	66.2	1.56	0.73

To model the delay spread and the angular spread we followed (3.6)

and (3.7), respectively.

$$\tau_{rms}[ns] = a.d + b + X_\tau \quad (3.6)$$

$$\phi_{rms}[^\circ] = c.d + e + X_\phi \quad (3.7)$$

where a and c represent the delay spread and the angular spread exponents, respectively, likewise b and e are the intercepts and X_τ and X_ϕ denote a zero mean Gaussian random variable with the standard deviation σ_τ or σ_ϕ and they represent the deviation of the delay and angular spreads from the models.

The delay spread and angular spread models are given in Table 3.10.

Table 3.10: InOpOffice: T-RIS Delay and Angular Spreads Model Parameters.

Scenario	$a[ns/m]$	$b[ns]$	$\sigma_\tau[ns]$	$c[^\circ/m]$	$e[^\circ]$	$\sigma_\phi[^\circ]$
TRIS scenario 1	0.93	6.5	6.6	-3.3	48.3	6.3

3.4.2 Indoor Mixed Office Results

Fig. 3.26 shows examples of the synthesized omnidirectional APDPs in the 3 different office environments floor plans. Each APDP at a particular RX position is obtained as the average of the 9 PDPs at that specific position (since 3×3 spatial grids were scanned at each RX). For other positions results considering FP1, see Fig. C.2.1 and Fig. C.2.2. For other positions results considering FP2, refer to Fig. C.3.1 and Fig. C.3.2. Likewise, for other positions results considering FP3, see Fig. C.4.1 and Fig. C.4.2.

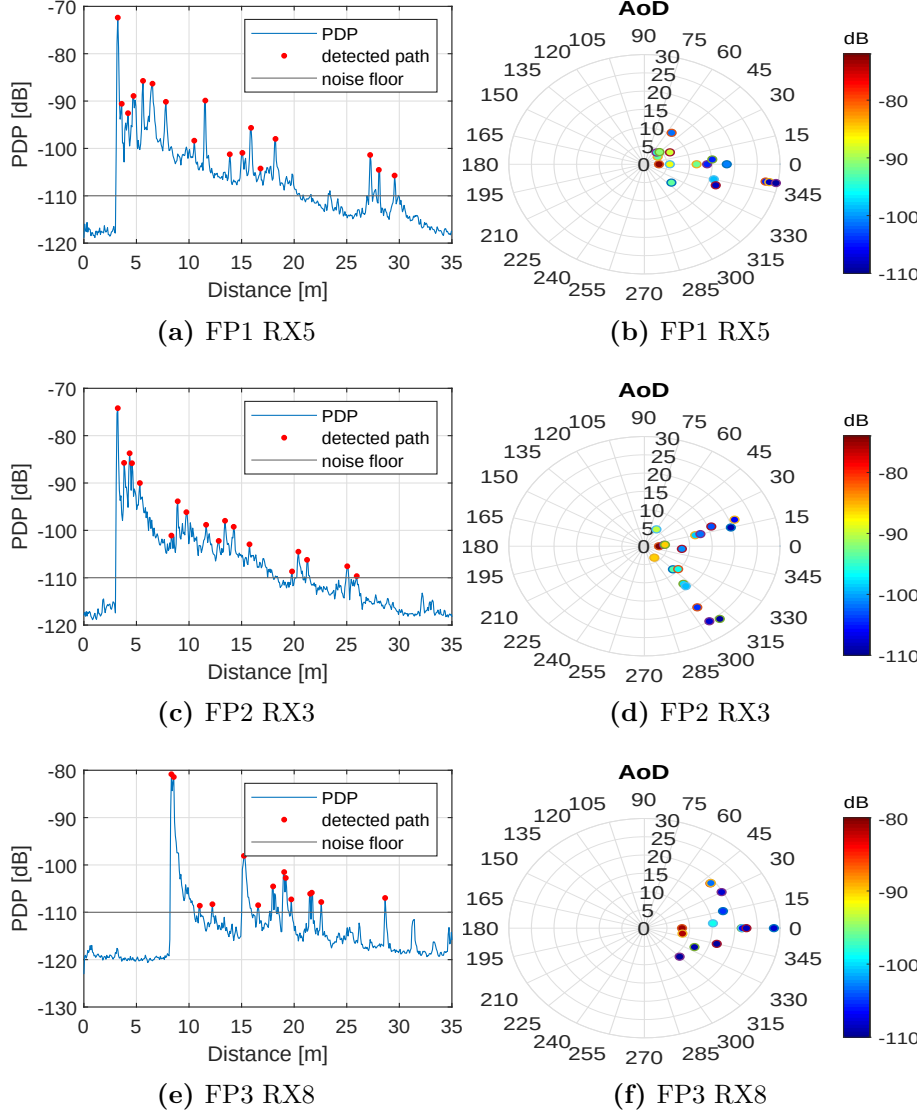


Figure 3.26: InMixOffice: Example synthesized omnidirectional APDPs and scatter plots for the office environments.

Fig. 3.27(a), (b) and (c) show the ratio of specular power relative to the total power for the 3 different floor plans. Fig. 3.27(d) shows the path loss model obtained from the detected MPCs. To model the path loss we employed the floating intercept point model [18,19]. The path loss model parameters are provided in Table 3.11

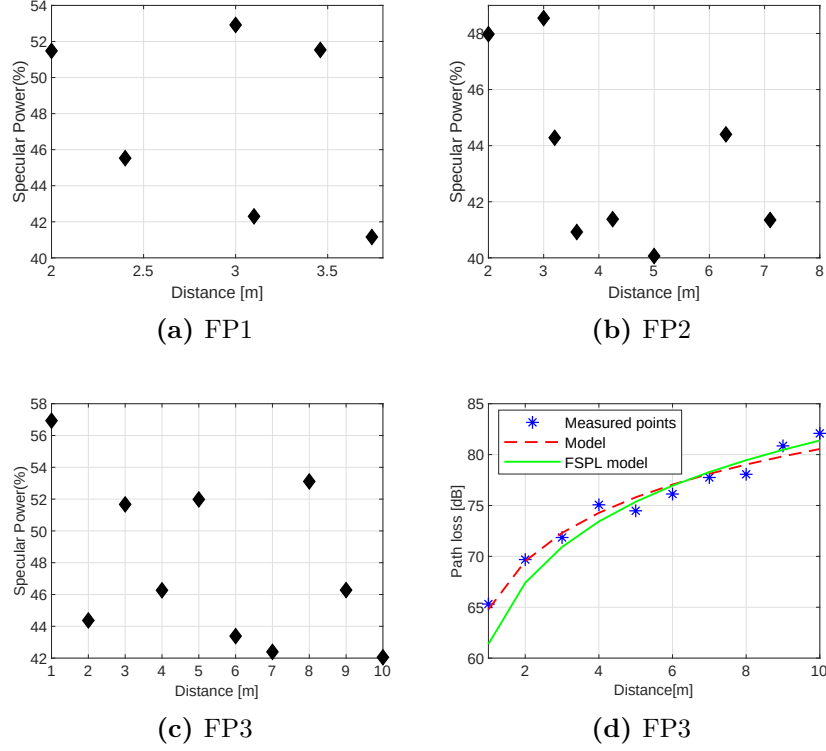


Figure 3.27: InMixOffice Ratio of specular power relative to the total power (a), (b), (c) at the different floor plans and (d) FP3 path loss model.

Table 3.11: FP3 Omnidirectional Path Loss Model Parameters.

Scenario	$PL_0[dB]$	n	$\sigma[dB]$
TRIS scenario 3	64.8	1.58	0.96

3.4.3 Indoor Factory Environments Results

Fig. 3.28 shows examples of the synthesized omnidirectional PDPs and scatter plots for different positions in the InF environments. For other positions results, see Fig. C.5.1 to Fig. C.5.4.

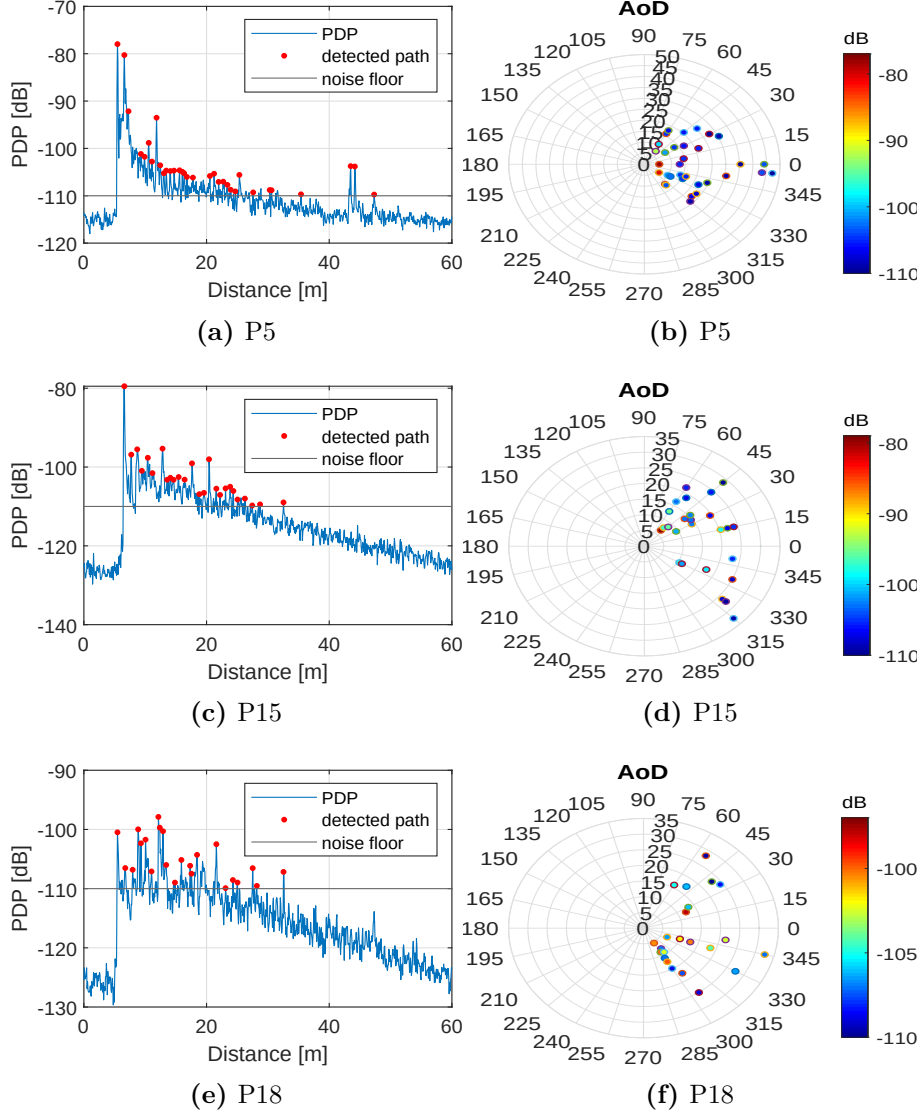


Figure 3.28: Example synthesized omnidirectional PDPs and scatter plots for the InF environments.

In Fig. 3.29(a) and (b) we show the ratio of specular power relative to the total power in the respective positions P1-P10 and P11-P17. Fig. 3.29(c) shows the path loss model for the positions P1-P10. The path loss model parameters are given in Table 3.12.

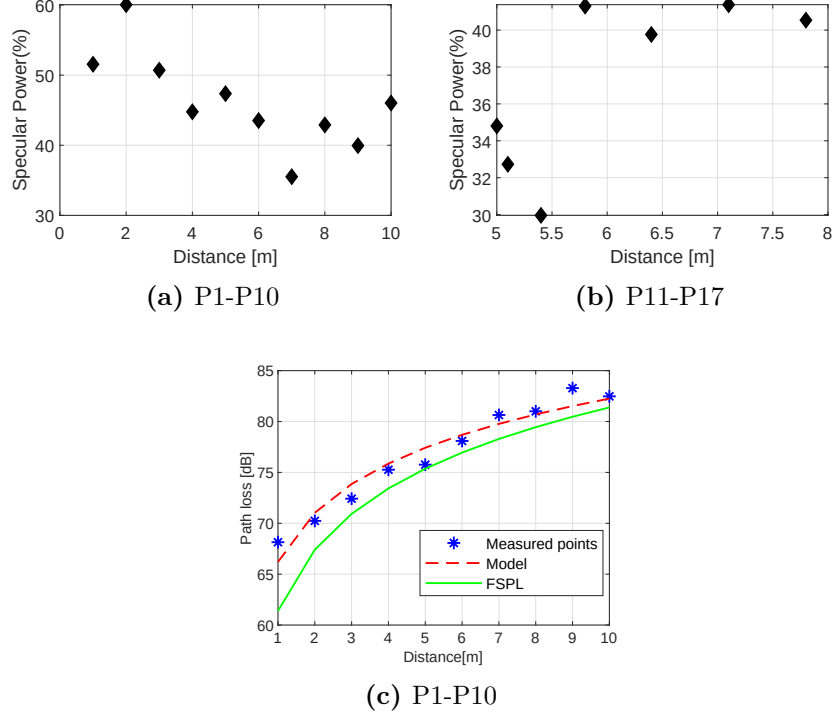


Figure 3.29: InF Ratio of specular power relative to the total power (a), (b) and (c) P1-P10 path loss model.

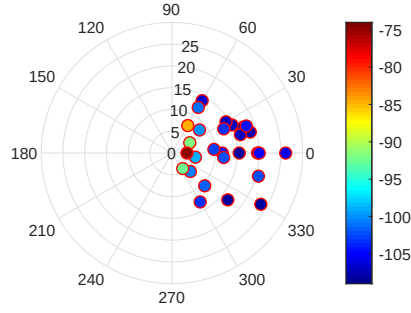
Table 3.12: InF P1-P10: T-RIS Path Loss Model Parameters.

P1-P10 T-RIS	$PL_0[dB]$	n	$\sigma[dB]$
TRIS setup	66.2	1.61	1.3

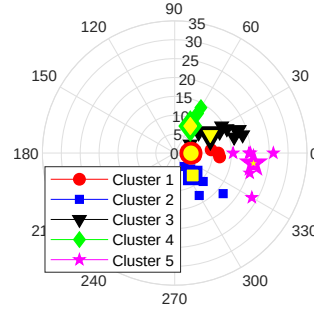
3.5 Statistical Spatio-Temporal Channel Models

This last step involves deriving the statistical spatio-temporal channel models based on the different T-RIS measurements. Having synthesized the omnidirectional PDPs and identified the temporal and angular parameters of the MPCs, we then proceed to apply the KPowerMeans algorithm (following exactly the same procedure already described in

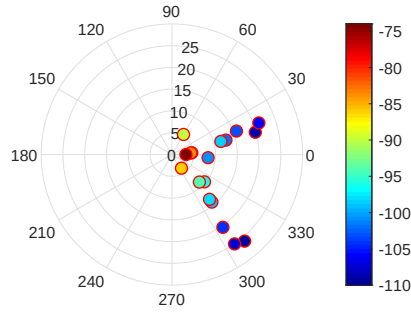
chapter 2) in order to identify the clusters. Examples of the identified clusters in the different environments can be seen in Fig. 3.30.



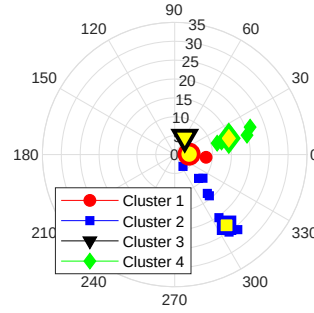
(a) InOpOffice RX1 omnidirectional



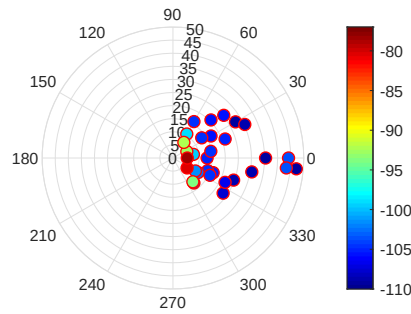
(b) InOpOffice RX1 clusters



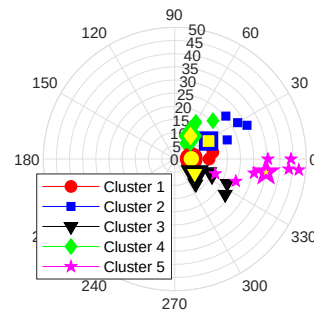
(c) InMixOffice FP2 RX3 omnidirectional



(d) InMixOffice FP2 RX3 clusters



(e) InF P5 omnidirectional



(f) InF P5 clusters

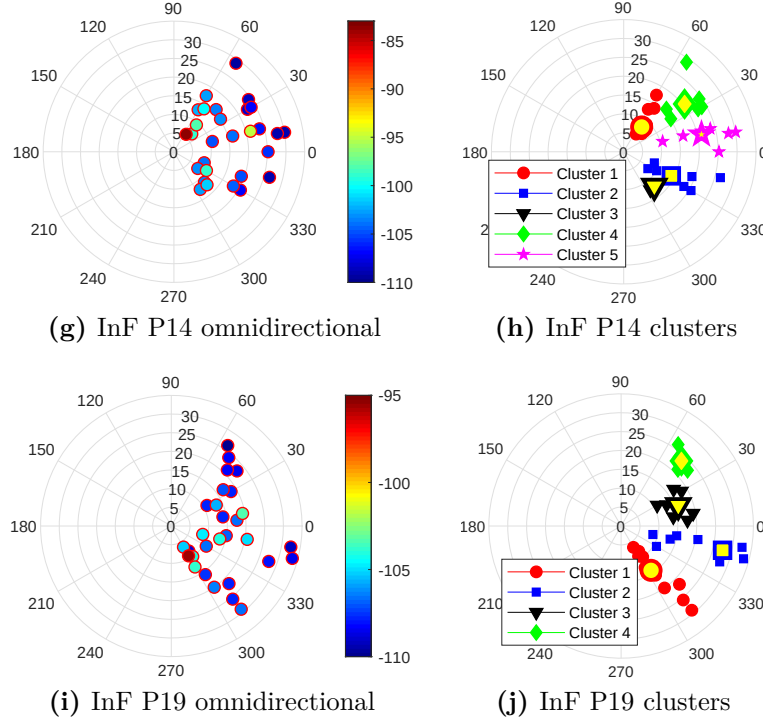


Figure 3.30: Omnidirectional MPCs and clusters at each RX position.

The extended SV channel model parameters are then derived for the different environments. See Table 3.13 for clusters and rays parameters.

Table 3.13: Decay rate and arrival rate of clusters and rays.

Scenario	$\Gamma[ns]$	$\gamma[ns]$	$\frac{1}{\Lambda}[ns]$	$\frac{1}{\lambda}[ns]$
InOpOffice T-RIS	17	24.1	7.6	9
InMixOffice T-RIS 24 RXs	17	23.9	11.2	9.4
InF T-RIS P1-P20	29.8	39	9.1	9
InF T-RIS P1-P10	14.5	41.6	6.6	10.1

Taking for example the T-RIS based channel modelling results (cluster parameters) for the InF T-RIS P1-P10, the InF T-RIS P1-P20, and comparing them with the VCA based measurements, we can see that the results are in agreement, with slight differences. The slight differences may be attributed to the fact that the T-RIS measurements did not

scan the full 360° plane. With the exception of InF T-RIS P1-P20, the CDFs of the clusters relative arrival angles for the other scenarios in Table 3.13 cannot be estimated by a single straight line but piecewise by three straight lines (each representing a uniform distribution interval). The correlation values for the time of arrival and the AOA of the clusters and rays ranged between (0.1 and 0.17) and (0.17 and 0.26), respectively. These small correlation values suggest the decorrelation between angle and time in either cases. Considering the Laplacian distribution with $\mu = 0$ to describe the pdf of the relative azimuth angles of arrivals of the rays, $\sigma = 42^\circ, 54^\circ, 62^\circ$ and 80° , respectively, for the InOpOffice, InMixOffice, InF P1-P20 and InF P1-P10.

3.6 Conclusions

In this chapter, we investigated the beamforming and beamscanning capabilities of T-RISs in the InLab, InOpOffice, InMixOffice, corridors and InF environments. The path loss and delay spread were observed to be greatly reduced for users located in the T-RIS main lobe direction. The small delay spread values in the main lobe direction are as a result of the narrow beam transmission which reduces the time dispersion. Likewise, the path losses in the main beam direction are reduced thanks to T-RIS beamforming capabilities, which leads to an improvement in the overall link budget. From the channel measurements, path loss exponents of less than 2 were observed in the different indoor mmWave channels. In indoor environments such as the corridors and the InF environments we analyzed, path loss exponents tend to be smaller than 2 due to the wave-guiding effect. As a last step, omnidirectional PDP synthesis was performed for the different T-RIS measurements. From the synthesized omnidirectional channels, path loss exponents of less than 2 were observed in the different indoor environments. Clusters were then identified in the different environments followed by statistical spatio-temporal channel modelling in the different environments. A comparison between the T-RIS based statistical spatio-temporal channel models and the massive array based statistical spatio-temporal channel models shows a good agreement in some environments.

Chapter 4

Impact of T-RIS on the geometrical structure of the channel

In this chapter, we investigate the impact of the T-RIS on the geometrical structure of the indoor mmWave mMIMO radio channel characteristics. For this purpose, two measurement campaigns were conducted by employing a T-RIS and a VCA. The InOpOffice and the InF environments were investigated. The VCA MPCs extraction was performed to embed the T-RIS antenna pattern and evaluate the effect on large-scale parameters such as the path loss, delay and angular spreads. In essence, we model separately the propagation channel and the antenna (T-RIS). We then embed the 2D and 3D antenna patterns into the propagation channel and then compare the resulting synthesized channels and models with the actual T-RIS measured channels and models.

The remainder of this chapter is outlined as follows: Section 4.1 focuses on the investigation of the impact of T-RIS on the geometrical structure of the InOpOffice and InF mmWave mMIMO channels. The results are presented in Section 4.2. Conclusions are given in Section 4.3.

4.1 Antenna embedding

The channel measurements were conducted in both the InOpOffice and InF environments. The measurement setups (Fig. 2.1 and Fig. 3.5) consist of a four-port VNA operating in the frequency range 24-40 GHz; one circularly polarized T-RIS (size 20×20 , 1 bit); two identical vertically polarized monopole antennas and an X-Y-Z positioner. The measurements were performed by employing either a T-RIS (Fig. 4.1 (a)) or a VCA antenna (Fig. 4.1 (b)) on the TX side while considering the same floor plans. The RX comprised a monopole antenna in both environments. To recap the floor plans and environments, see Fig. 2.4 and Fig. 2.5 for the InOpOffice. Likewise, for the InF, refer to Fig. 2.6 and Fig. 2.7.

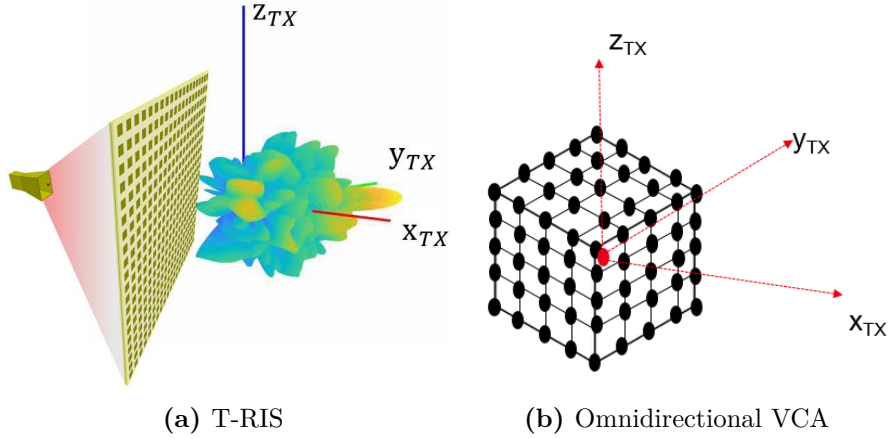


Figure 4.1: T-RIS based antenna (a) and VCA (b) schemas.

Multipath Estimation and RIS Pattern Embedding

Starting from the VCA channel measurements, the UWB SAGE algorithm [35] was used for the MPCs detection and channel parameters estimations. Only MPCs of significant power were considered in this work. The maximum number of resolvable MPCs to be estimated was set to 100. The stopping criteria was when more than 95 percent of the measured channel power had been estimated, or otherwise, when the maximum number of the resolvable MPCs had been reached.

Let us consider the angular dependent channel impulse response extracted from VCA measurements as:

$$h(\tau, \Omega_{AOD}, \Omega_{AOA}) = \sum_{l=1}^L \alpha_l \cdot \delta(\tau - \tau_l) \cdot \delta(\Omega_{AOD} - \Omega_{AOD,l}) \cdot \delta(\Omega_{AOA} - \Omega_{AOA,l}) \quad (4.1)$$

where the l -th MPC is characterized by its amplitude (α_l), delay (τ_l), angle of departure $\Omega_{AOD,l}$ and angle of arrival $\Omega_{AOA,l}$. Starting from this estimation, the objective is to embed the T-RIS effect into the channel and compare it with the real measured one with the T-RIS.

The T-RIS vector transfer function can be written as:

$$\mathbf{H}(f, \theta, \phi, \theta_s, \phi_s) = \sum_m \frac{\lambda}{4\pi r_m} e^{-\frac{j2\pi}{\lambda} r_m} \mathbf{H}_{FS}(\theta_{FS}^m, \phi_{FS}^m) \cdot \mathbf{H}_{RX,m}(\theta_{uc}^m, \phi_{uc}^m) \cdot S_{21}^m(f) \cdot \mathbf{H}_{TX,m}(\theta_{uc}^m, \phi_{uc}^m) \quad (4.2)$$

where $\mathbf{H}_{FS}(\theta_{FS}^m, \phi_{FS}^m)$ is the radiation pattern of the source illuminating the surface, $\mathbf{H}_{RX,m}(\theta_{uc}^m, \phi_{uc}^m)$, $\mathbf{H}_{TX,m}(\theta_{uc}^m, \phi_{uc}^m)$, respectively, represent the radiation patterns of the m -th unit-cell in the receiving side and of the m -th unit-cell in the transmitting side. r_m represents the distance between the source and the m -th unit-cell. Each unit cell will present a transmission coefficient $S_{21}^m(f)$, whose phase is controlled by a 1-bit PIN diode architecture, implementing either a 0° or 180° variation. f is the frequency index, θ, ϕ are the pattern elevation and azimuthal angles, respectively. Finally θ_s, ϕ_s are the elevation and azimuthal steering angles, obtained thanks to the phase distribution over the unit-cells.

Hence, for a given phase distribution on the T-RIS, i.e. for an aimed steering angle (θ_s, ϕ_s) , we can embed its effect on the channel by replacing in Eq. (4.1) the l -th MPC amplitude with:

$$\alpha_l^{emb} = \alpha_l \cdot H(f, \theta = \theta_{AOD,l}, \phi = \phi_{AOD,l}, \theta_s, \phi_s) \quad (4.3)$$

where $H(f, \theta = \theta_{AOD,l}, \phi = \phi_{AOD,l}, \theta_s, \phi_s)$ is the transfer function of the T-RIS from Eq. (4.2) in the given angle of departure $\Omega_{AOD,l} = (\theta_{AOD,l}, \phi_{AOD,l})$, neglecting here the polarization for simplicity of notation. In practice, given that we used on RX side a vertically polarized antenna, we consider in the following analysis the embedding with only the main polarization (given the small effect from the cross-polarised contribution).

4.2 Results: Measured Channel vs Synthesized Channels

In this section, we will discuss the main results obtained. In the InOpOffice, for receiver positions: RX1, RX2, RX5 and RX6, the steering angle $\phi_{s,max}$, corresponding to the main lobe direction where the maximum power is received, is $\phi_{s,max} = 0^\circ$, while for the receiver positions RX3, RX4, RX7 and RX8, the main beams are in the steering directions $\phi_{s,max} = 15^\circ, -15^\circ, 10^\circ$, and -10° , respectively. In [140], the T-RIS was found to decrease both the path loss and DS for all receiver positions in the main lobe direction. As an example we consider here the position RX5. Fig. 4.2 shows the UWB SAGE estimated MPCs, i.e. the PADP with omnidirectional antennas. We then consider T-RIS embedding in the full 3D plane or just 2D plane, hence forcing $\theta_{AOD,l} = 90^\circ$. Fig. 4.3(a) shows the 2D pattern embedding at the position RX5 for $\phi_{s,max} = 0^\circ$. We can see that the embedding process results in some significant paths, whose AODs do not lie within the T-RIS range $[-90^\circ : 1^\circ : 90^\circ]$, being eliminated. We can also see that the power of the MPCs whose AODs are within the half power beamwidth (HPBW) are amplified while those outside the HPBW are decreased when the embedding is performed using the radiation pattern for $\phi_{s,max} = 0^\circ$. A similar behaviour is observed for the other receiver positions when embedded with the radiation patterns corresponding to ϕ_s . Fig. 4.3(b) shows the 3D radiation pattern embedding ($\phi_{s,max} = 0^\circ$), which takes into account both the azimuth and elevation planes for the position RX5. We can notice that some significant paths whose AODs do not lie within the

T-RIS range $[-90^\circ : 1^\circ : 90^\circ]$ were eliminated. On top of this, we can clearly see in Fig. 4.3(b) that 3D embedding impacts the MPCs in both the azimuth and elevation planes. Considering the T-RIS patterns for $\phi_s = 50^\circ$ at the position RX5, we can see the 2D and 3D embedding results in Fig. 4.4. Indeed, the MPCs within the main beam direction are significantly impacted, highlighting the spatial filtering nature of the T-RIS.

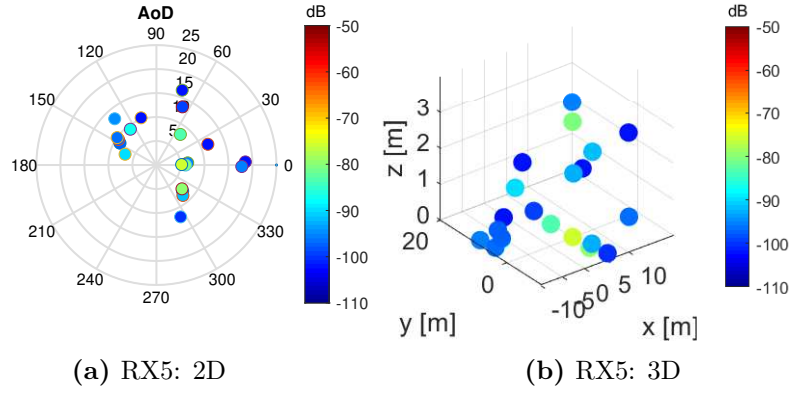


Figure 4.2: InOpOffice omnidirectional PADP extracted from VCA measurements.

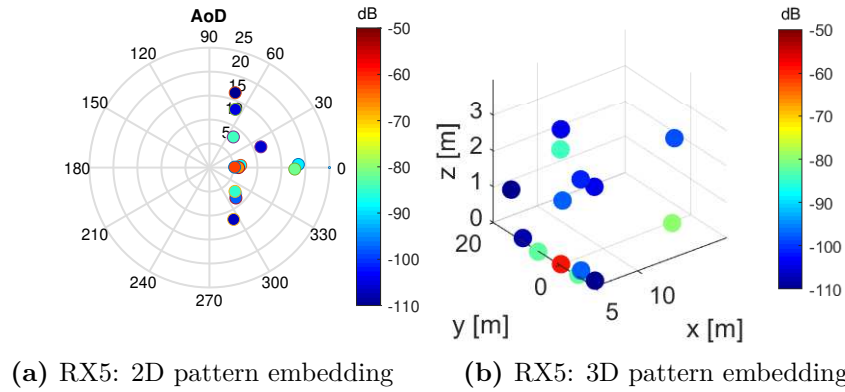
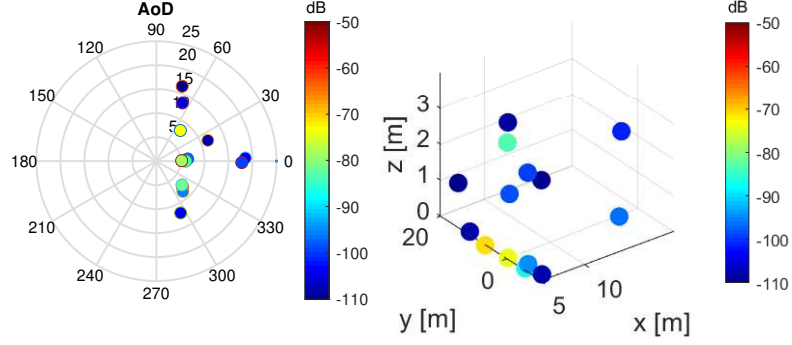


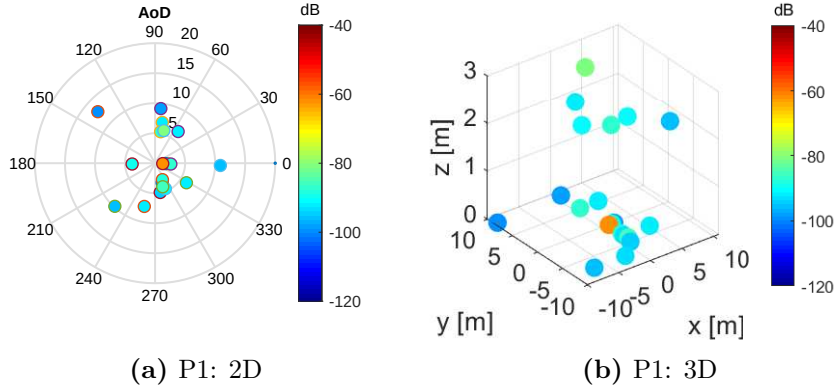
Figure 4.3: InOpOffice PADP with T-RIS embedding for $\phi_s = 0^\circ$.



(a) RX5: 2D pattern embedding (b) RX5: 3D pattern embedding

Figure 4.4: InOpOffice PADP with T-RIS embedding for $\phi_s = 50^\circ$.

Likewise, the same embedding process was performed for the different scenarios in the InF environments. From Fig. 4.5 to Fig. 4.16, we show examples of the VCA 2D and 3D extracted MPCs and the respective 2D and 3D embedding results per given steering angles.



(a) P1: 2D (b) P1: 3D

Figure 4.5: InF omnidirectional PADP extracted from VCA measurements.

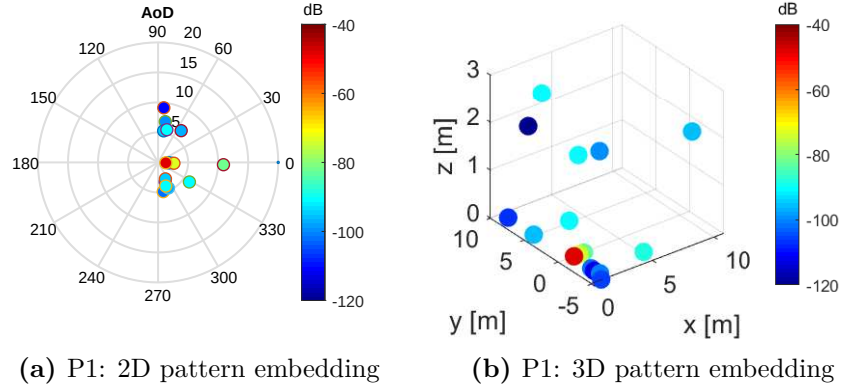


Figure 4.6: InF PADP with T-RIS embedding for $\phi_s = 0^\circ$.

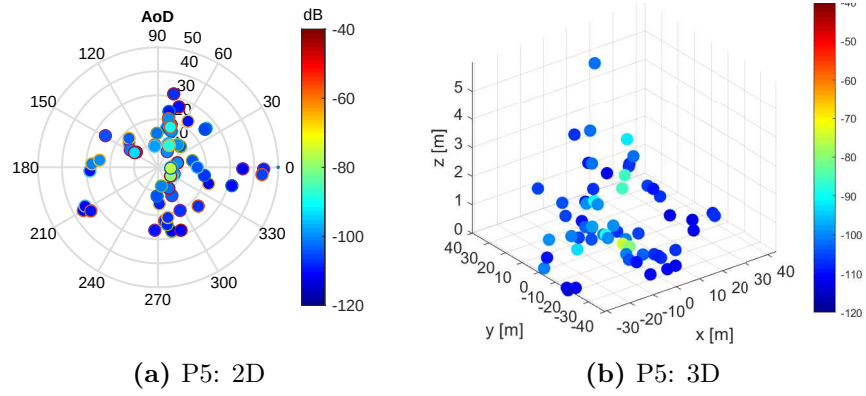


Figure 4.7: InF omnidirectional PADP extracted from VCA measurements.

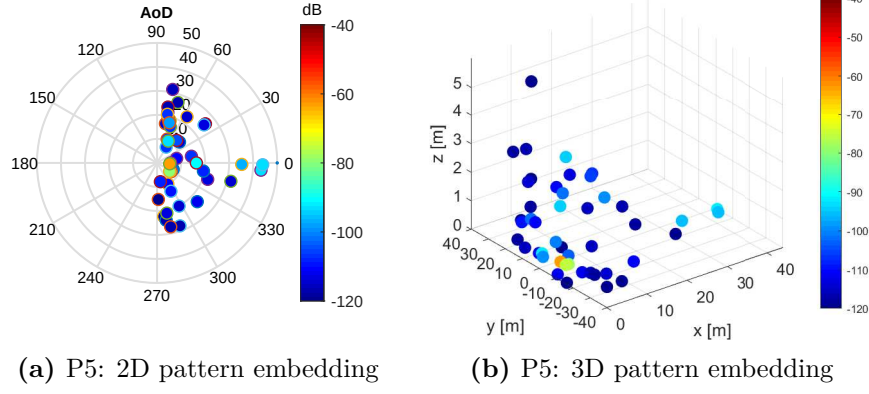


Figure 4.8: InF PADP with T-RIS embedding for $\phi_s = 0^\circ$.

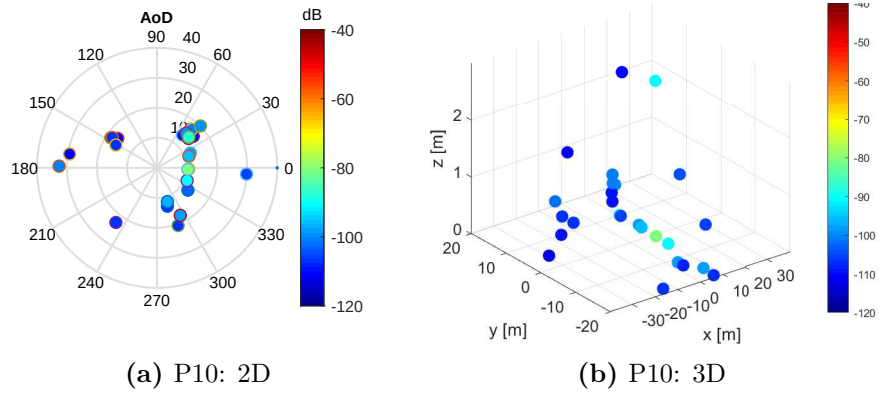


Figure 4.9: InF omnidirectional PADP extracted from VCA measurements.

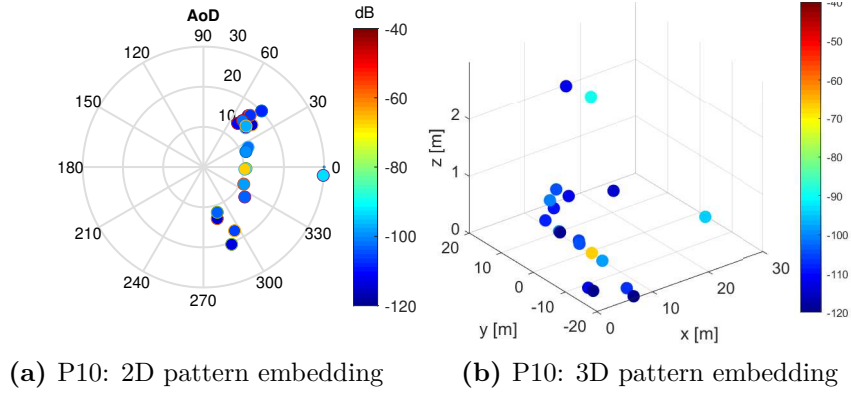


Figure 4.10: InF PADP with T-RIS embedding for $\phi_s = 0^\circ$.

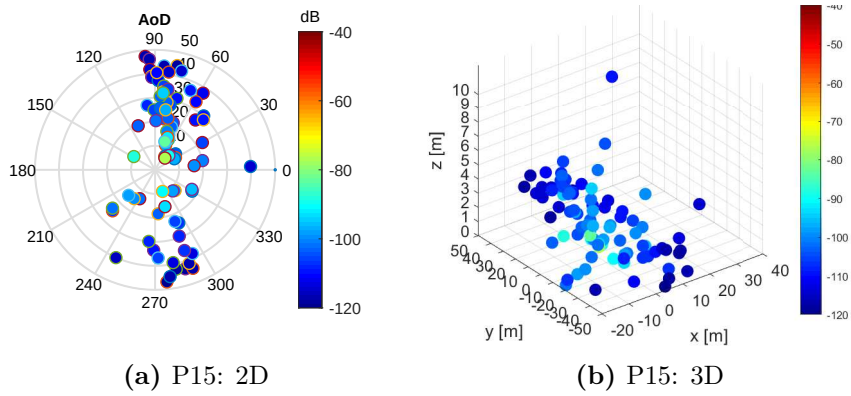


Figure 4.11: InF omnidirectional PADP extracted from VCA measurements.

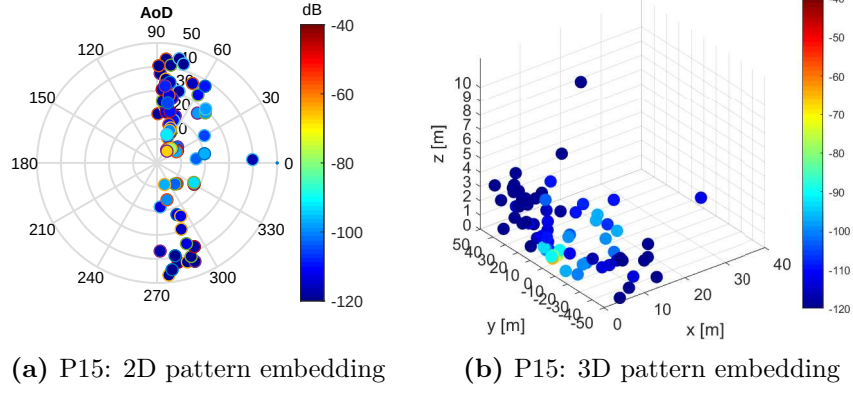


Figure 4.12: InF PADP with T-RIS embedding for $\phi_s = 50^\circ$.

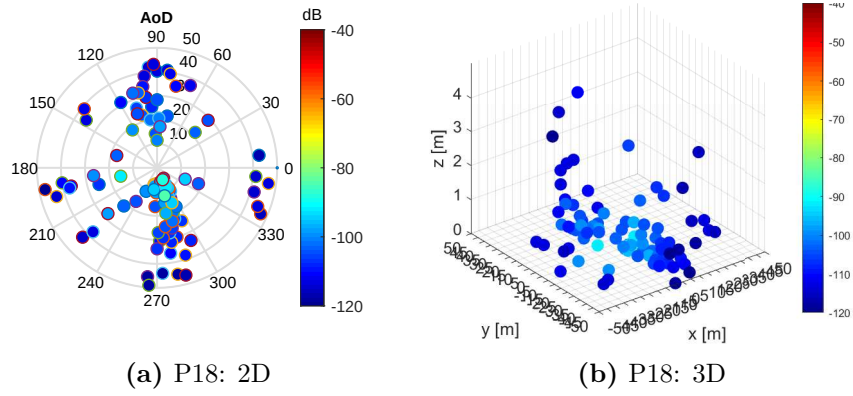


Figure 4.13: InF omnidirectional PADP extracted from VCA measurements.

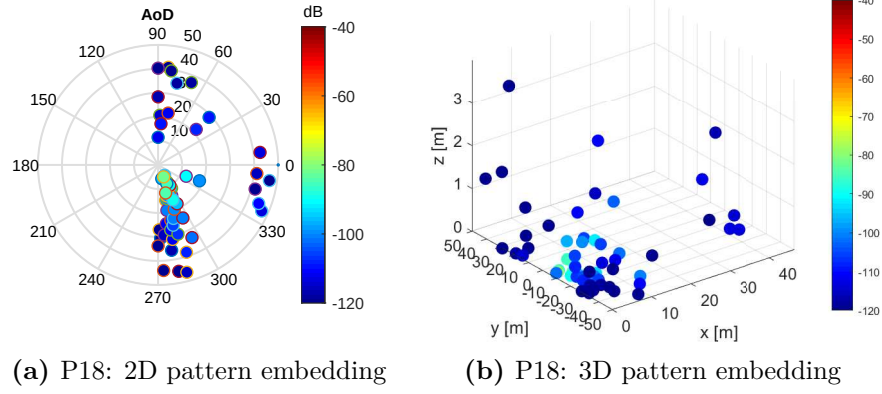


Figure 4.14: InF PADP with T-RIS embedding for $\phi_s = -60^\circ$.

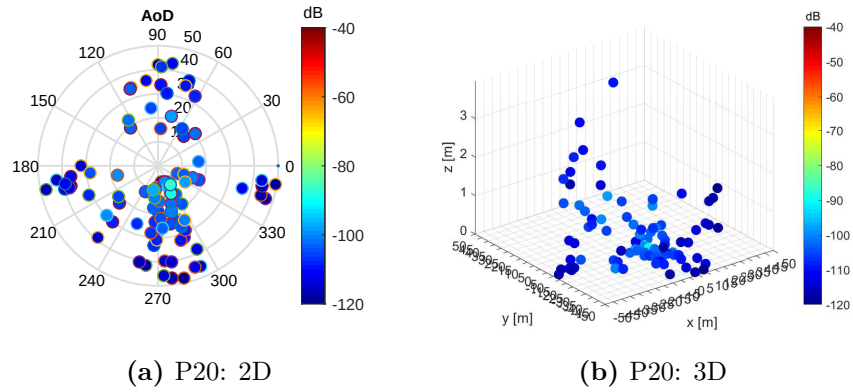


Figure 4.15: InF omnidirectional PADP extracted from VCA measurements.

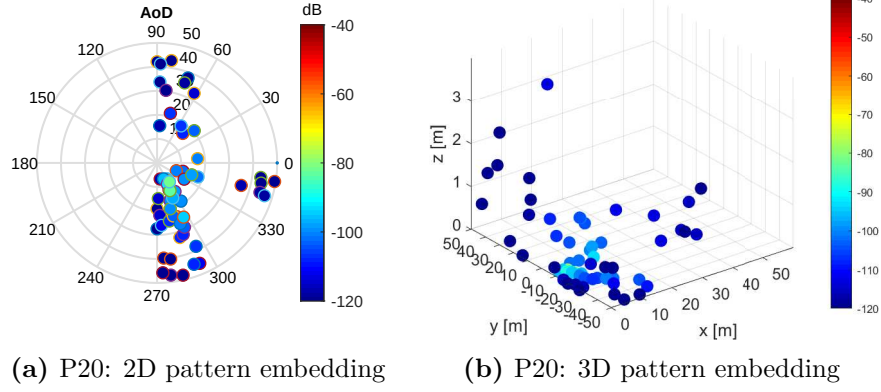


Figure 4.16: InF PADP with T-RIS embedding for $\phi_s = -60^\circ$.

For the InOpOffice, Fig. 4.17 shows the measured vs the embedding CG and DS per steering angles for a few positions.

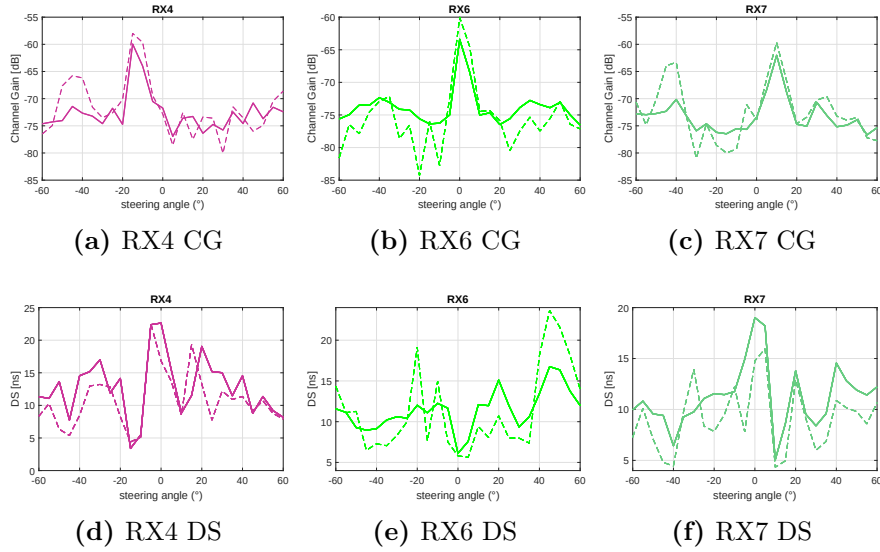


Figure 4.17: InOpOffice: Channel gain (a), (b), (c) and Delay spread (d), (e) and (f) as a function of steering angle: measured (solid) vs 3D T-RIS embedding (dotted line).

Likewise, Fig. 4.18 shows the similar comparison for different positions in the InF environments. With regards to both the CG and DS, we

can see that there is good correspondence between the actual measured channel and the synthesized channel. It is worth mentioning that there is a 3 dBi peak gain difference between the 2D T-RIS measured gain pattern and the 3D T-RIS simulated gain patterns, with the latter being higher.

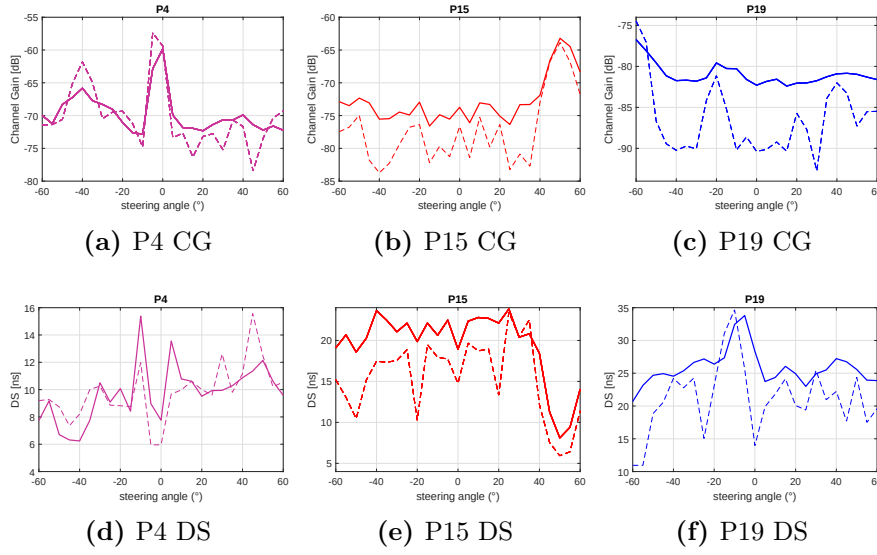


Figure 4.18: InF environments: Channel gain (a), (b), (c) and Delay spread (d), (e) and (f) as a function of steering angle: measured (solid) vs 3D T-RIS embedding (dotted line).

Fig. 4.19 shows a comparison of the actual T-RIS measured channel PDP envelope (in blue color) with the PDP envelopes of synthesized channels (in red, green and black colors) in the InOpOffice for position RX7. Likewise, Fig. 4.20 and Fig. 4.21 show the PDP envelopes for position P4 in the InF environments. The synthesized channels involve the plugging in or embedding of the measured 2D and simulated 3D T-RIS radiation patterns to the UWB SAGE extracted MPCs from the VCA measurement setup. From the aforementioned figures, we can observe that the 3D synthesized channel closely resembles the actual measured channel as it corrects the overestimation of secondary MPCs powers encountered in the 2D synthesized channels. As expected, 3D embedding

improves the quality of the model especially for secondary MPCs that could come at elevation angles far from the azimuth plane. However, the process here involves only the MPCs that are extracted from UWB SAGE, while it is well known that DMCs yield an important energy contribution [120]. Hence, here we artificially add the DMCs extracted from VCA measurements to add them to the 3D synthesized channel. We highlight that the added DMCs are angular-white. The PDP envelope in black corresponds to the result of adding DMCs from the high resolution algorithm estimation to the 3D synthesized channel.

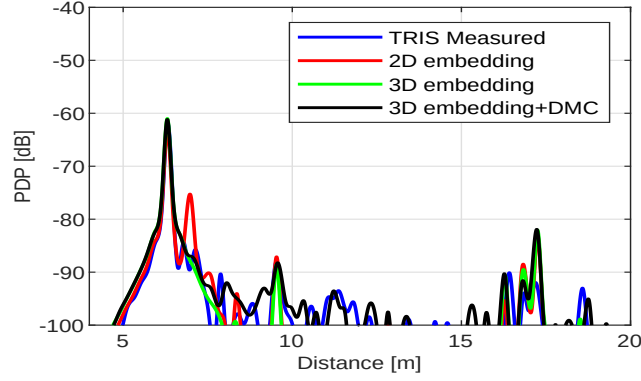
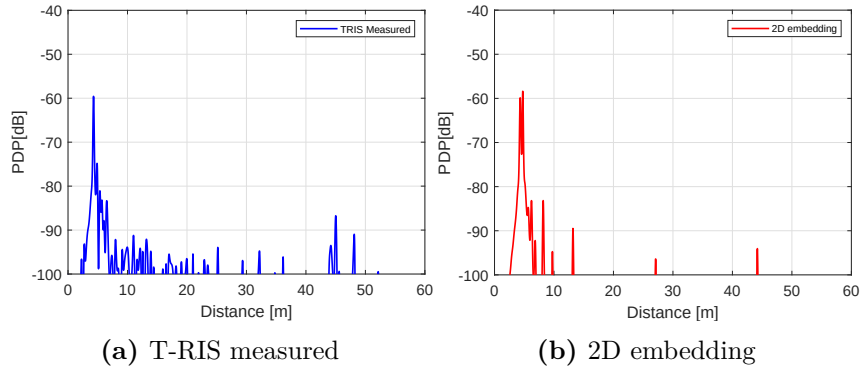


Figure 4.19: InOpOffice example of PDP comparison: actual measured PDP vs synthesized PDPs.



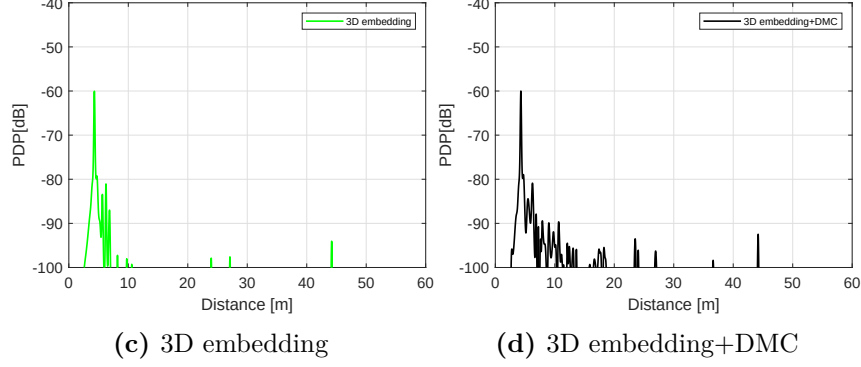


Figure 4.20: InF position P4 measured and synthesized PDPs.

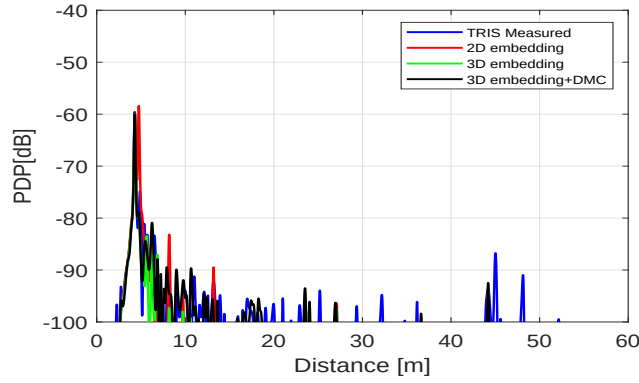


Figure 4.21: InF position P4 superposed T-RIS measured PDP vs synthesized PDPs.

Large Scale Parameters

We employed the conventional power law model given by equation (2.1) to model the distance dependent CG. Fig. 4.22 shows the CG comparison of the VCA measured channel, T-RIS measured channel and the synthesized channels in the direction of maximum gain for the InOpOffice channel measurements. Fig. 4.24 and Fig. 4.26, respectively, show the CG comparisons for positions P1-P10 and P11-P17 for the InF environments. We can see that the VCA measured channel comprises the least CG and this is due to the presence of high gain T-RIS in the other cases. We can also see that the synthesized channel (considering

the measured 2D T-RIS gain patterns), in red color, is lower compared to the actual measured T-RIS channel, in blue color, because the CG in the actual measured T-RIS channel includes the diffuse components which are not present in the synthesized channel. The CG model parameters for the different environments are given in Table 4.1, Table 4.3 and Table 4.5. For the InF, we recall that the models are derived from only the VCA channel measurements and this explains the slight numerical differences between the models derived in chapter 2 which considered the merged VCA and VPA channel measurements for modelling. We observe that adding back the angular-white DMCs to the 3D embedding channel results in an improvement of the CG model, but the DS appears to be slightly overestimated. To further improve the quality of fitness, a full angular distribution of DMCs may need to be considered.

Table 4.1: InOpOffice: CG Model Parameters.

Scenario	$G_0[dB]$	n	$\sigma[dB]$
VCA meas	-61.2	1.63	0.54
TRIS meas	-47.1	1.44	0.56
2D embedding	-49.9	1.54	1.1
3D embedding	-45.1	1.9	0.5
3D embedding +DMC	-46.7	1.4	0.8

Table 4.2: InOpOffice: DS Model Parameters.

Scenario	$a[ns/m]$	$b[ns]$	$\sigma_\tau[ns]$
VCA meas	0.33	9.6	1.54
TRIS meas	0.64	5.03	0.5
2D embedding	0.06	5.5	0.6
3D embedding	0.19	4	0.47
3D embedding + DMC	0.32	14.8	1.26

The DS is the square root of the second central moment of the PDP. For a multipath channel, the DS is a measure of duration of time over which most of the symbol energy from the transmitter arrives to the receiver. The DS is calculated using the mean delay (the first moment

Table 4.3: InF P1-P10: CG Model Parameters.

Scenario	$G_0[dB]$	n	$\sigma[dB]$
VCA meas	-60.5	1.73	1.08
TRIS meas	-48	1.28	1
2D embedding	-46.9	1.94	1.25
3D embedding	-48.1	1.9	0.67
3D embedding +DMC	-47.8	1.37	1.42

Table 4.4: Industry P1-P10: DS Model Parameters.

Scenario	$a[ns/m]$	$b[ns]$	$\sigma_\tau[ns]$
VCA meas	0.18	11.29	1.13
TRIS meas	1.77	5.2	0.5
2D embedding	-0.15	7.8	1.22
3D embedding	-0.1	7.4	1.47
3D embedding + DMC	0.79	23.6	4.3

Table 4.5: InF P11-P17: CG Model Parameters.

Scenario	$G_0[dB]$	n	$\sigma[dB]$
VCA meas	-96.1	-2.46	2.6
TRIS meas	-94.9	-4.25	1.5
2D embedding	-136.7	-8.32	3.3
3D embedding	-140.3	-8.9	4.7
3D embedding + DMC	-73.9	-1.6	1.6

Table 4.6: InF P11-P17: DS Model Parameters.

Scenario	$a[ns/m]$	$b[ns]$	$\sigma_\tau[ns]$
VCA meas	-2.27	35	1.7
TRIS meas	-4.4	45.5	3.9
2D embedding	-4.5	38.9	2.9
3D embedding	-3.6	32.2	2.8
3D embedding + DMC	-0.28	31.9	1.2

of the PDP). Fig. 4.23 and Table 4.2 show and present the DS models and parameters for the InOpOffice. Fig. 4.25 and Fig. 4.27, respectively, show the DS models for the InF environments positions P1-P10 and

P11-P17. The models parameters are shown in Table 4.4 and Table 4.6, respectively. With regards to the angular spreads, not reported here for sake of brevity, we observed, for example in the InOpOffice, that the VCA channel is more spread in the azimuth plane (reaching values of over 50°) and less spread in the elevation plane (values around 5°) whereas the T-RIS synthesized cases are characterized by small angular spreads in both planes (less than 10°).

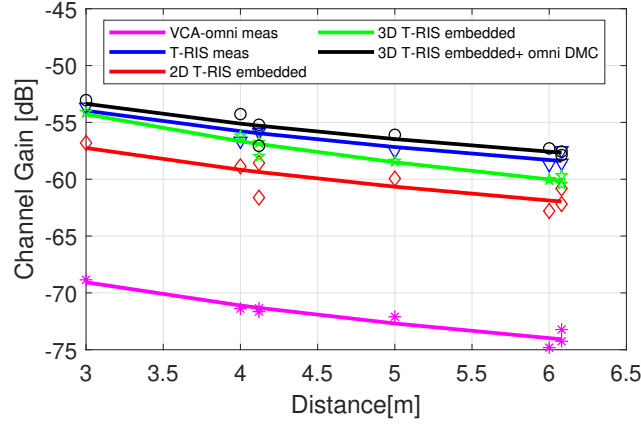


Figure 4.22: InOpOffice CG comparison in the direction of maximum gain: measurements vs models.

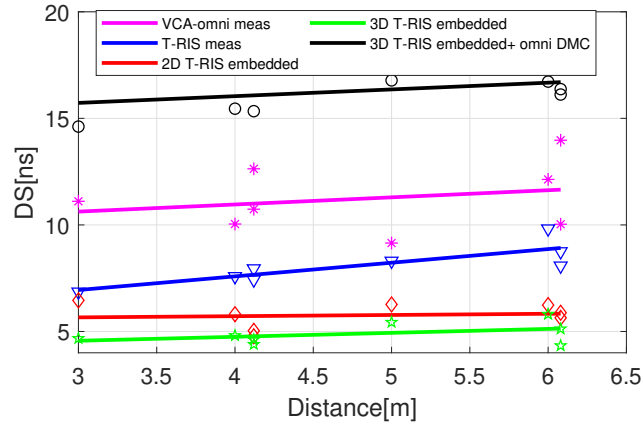


Figure 4.23: InOpOffice DS comparison in the direction of maximum gain: measurements vs models.

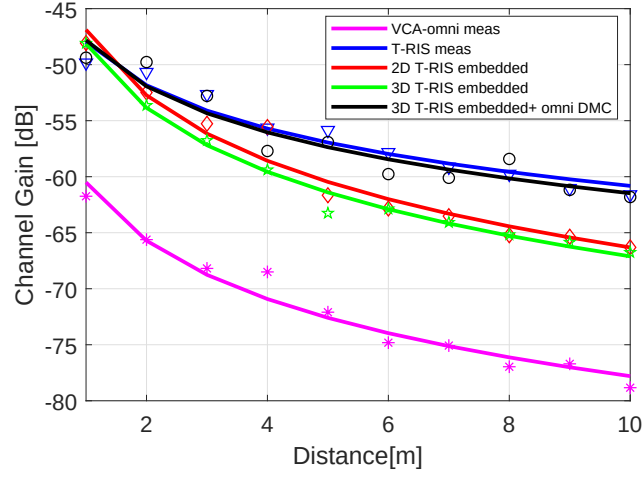


Figure 4.24: InF CG comparison (P1-P10) in the direction of maximum gain: measurements vs models.

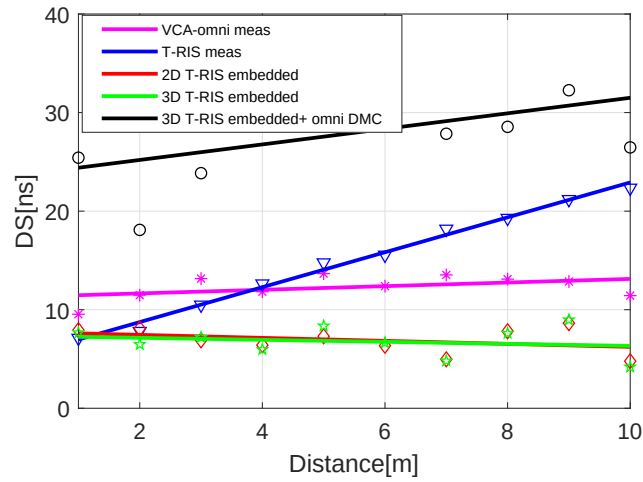


Figure 4.25: InF DS comparison (P1-P10) in the direction of maximum gain: measurements vs models.

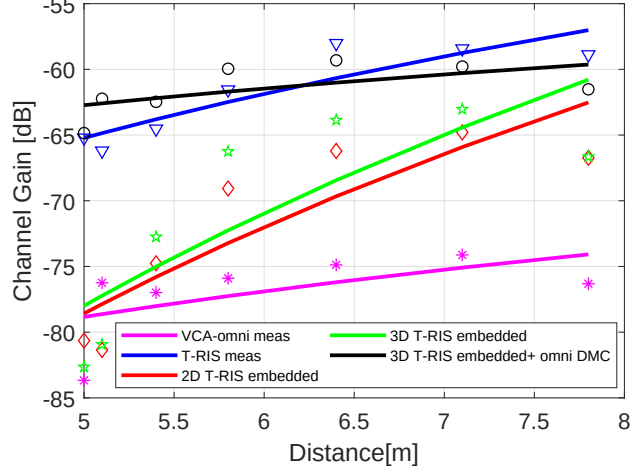


Figure 4.26: InF CG comparison (P11-P17) in the direction of maximum gain: measurements vs models.

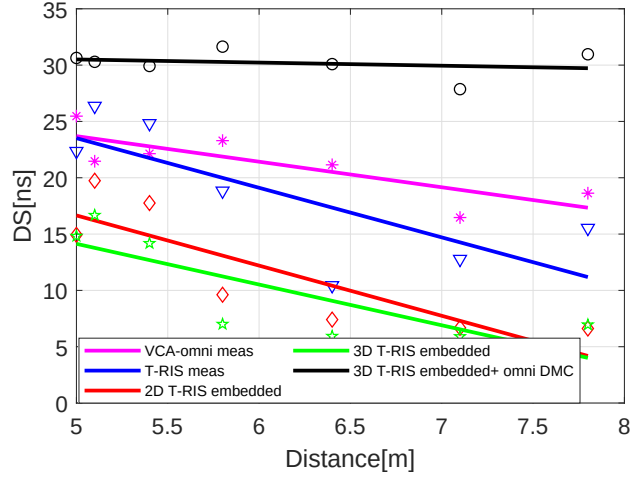


Figure 4.27: InF DS comparison (P11-P17) in the direction of maximum gain: measurements vs models.

4.3 Conclusions

In this chapter, we have evaluated how the structure of the channel is geometrically modified when a T-RIS (transmitting reconfigurable intelligent surface) is employed instead of a VCA (an omnidirectional monopole scanning spatial grids). Starting from the MPCs extracted

from the VCA measurement setups, we embedded the T-RIS radiation patterns for a given phase distribution and aimed steering angle. In our scenarios, the synthesized channel considering only the azimuth plane embedding (2D embedding) results in an overestimation of the powers of the secondary MPCs whose AODs are within the half power beamwidth of the T-RIS. Performing 3D embedding, the synthesized channel highly resembles the actual T-RIS measured channel, since elevation information can affect MPCs amplitude. The large scale parameters showed that the high gain and directivity of the T-RIS results in reduced path losses, delay and angular spreads. However, considering only specular components does not seem to fully reproduce the measured results. Including the angular-white DMCs to the 3D embedding channel improves the CG model.

Chapter 5

Conclusions and Perspectives

In the scope of 5G and 6G mmWave mMIMO channel modelling and performance evaluation, we have presented in this thesis, measurement based characterization and modelling of mmWave mMIMO channels. Channel measurements were performed in different InLab, InOpOffice, InMixOffice, corridor and InF environments. Massive virtual arrays or T-RISs were employed in these measurements.

For the massive arrays' channel measurements, we investigated the impact of the array size and geometry on the channel characteristics. MPCs were extracted by means of a high resolution algorithm. We observed that the estimation of the LOS component is almost unchanged when considering a massive array or a sub-array. On the contrary, the size of the array has an impact on the secondary multipath component estimation. Despite the fact that the energy contribution of the secondary MPCs is relatively small, this difference leads to different overall delay and angular estimations. DMCs were quantified in the different channel measurement environments. Spatial channel correlation over the massive array was also investigated in both the frequency domain and the delay domain. In both domains (with the delay domain clearly

highlighting this), the normalized crosscorrelation values do not have a symmetric behaviour over the large array, suggesting non-stationarity over the massive array. The LOS component was observed to strongly influence the correlation values in the delay domain. In most instances, it was also observed that the LOS component contributed more to the delay domain correlation values of users that were closer to the TX than the ones that were further. Generally, in a descending order, the correlation values were highest in LOS conditions, followed by OLOS and NLOS conditions. In view of hybrid beamforming approaches, where different sub-arrays can be exploited, we analyzed the MPCs distributions and similarities between different positions within the massive array. A joint temporal, power and angular thresholds criterion was proposed to identify common MPCs between different sub-arrays of the massive array. The results show that these common paths have an important energy contribution in the LOS, OLOS and NLOS scenarios considered. The energy contribution of common MPCs in LOS conditions is higher than that of the common MPCs in both OLOS and NLOS conditions, despite the fact that the common MPCs in LOS conditions may be numerically fewer than in the other conditions. This could be due to the very dominant LOS component in the investigated mmWave channels. However, in order to fully catch the channel characteristics, the sub-array dependent paths, here called uncommon, should also be considered. The impact of these common MPCs was investigated for different sub-array sizes, showing that their contribution can reach up to 70% or 56.6% of the energy even in LOS, respectively, for the InF and InLab environments. A model based on only the common MPCs could lead to an underestimation of angular and delay spreads. The shorter delay spreads and smaller angular spreads for the common MPCs may suggest that efficient mmWave mMIMO systems exploiting hybrid beamforming based on sub-array division can be achieved. On the one hand, shorter delay spreads imply flat fading, which has an impact on wideband orthogonal frequency-division multiplexing (OFDM) systems, where analog beamformers can hardly have different weights across subcarriers. On the other hand, by taking advantage of a small angular spread at the base station sub-array, we

can reduce the dimension of the effective instantaneous channel state information for digital beamforming within each coherent fading block. However, as already highlighted above, at some receiver positions, the uncommon paths energy contribution can be significant, therefore caution needs to be applied when designing such mmWave mMIMO systems employing sub-array based beamforming. Hence, these effects need to be carefully taken into account for mmWave MIMO channel characterization for indoor applications. We also derived different statistical spatio-temporal channel models for the different massive arrays' indoor measurements. From the extracted MPCs, clusters were identified by applying the KPowerMeans algorithm. Most of the time, five clusters were observed per position and it was the first cluster that carried most of the energy. Intracluster and intercluster parameters for the different indoor environments were determined and basically, rays were observed to decay slower than the clusters. The results were in line with some of the investigated environments by the IEEE 802.15.3c channel model subgroup.

For the T-RISs channel measurements, we investigated the T-RISs beam-scanning capabilities as well as the impact of beamforming on delay spread and path loss. It was observed that both the path loss and delay spread were significantly reduced for receivers in the T-RISs main lobe directions. The expected angles of departures, computed via trigonometry of the floor plans, were observed to coincide with the T-RIS expected main beam directions. The impact of smart antennas like T-RISs on the geometrical structure of the indoor mmWave mMIMO channel was also investigated. In essence, we investigate the impact of embedding either 2D or 3D T-RIS patterns on the propagation channel. The synthesized channel considering only the azimuth plane embedding (2D embedding) resulted in an overestimation of the powers of the secondary MPCs whose AODs are within the half power beamwidth of the T-RIS. By performing 3D embedding, the synthesized channel highly resembles the actual T-RIS measured channel since elevation information can affect MPCs amplitudes. The implication of not considering

DMCs in synthesized channels was also investigated. We observed that including the DMCs to the 3D embedding channel improves the channel gain model. The delay spread model is however slightly overestimated by including DMCs to the 3D embedding channel. Further analysis of the T-RISs measurements involved the omnidirectional PDP synthesis. MPCs power, delay and angular parameters are identified following an algorithm (presented in [139]) and clusters are then identified by applying the KPowerMeans algorithm [123]. Intracluster and intercluster parameters for the different indoor environments are determined. Similar to the massive array measurements, the results were found to be consistent with some of the investigated environments in the literature.

Comparing the T-RIS based statistical spatio-temporal channel modelling results with the massive virtual arrays' based statistical spatio-temporal channel modelling results, we observed a strong agreement in some of the considered environments, with slight differences. Some differences may be partially attributed to the fact that the T-RIS measurements did not scan the full 360° plane and also due to the changing side lobes at each scanning angle (unlike in mechanical steering of e.g horn antennas where the radiation pattern does not change per steering angle, different side lobes are observed per steering angle in electronic steering). Nevertheless, the close agreement between the two channel modelling approaches validates the channel modelling approaches. With regards to the path loss exponents, the indoor mmWave mMIMO channels based on both the massive virtual arrays and the T-RIS were characterized by path loss exponents of less than 2 and this can be attributed to the wave-guiding effect in the investigated environments. Indeed, the path loss was observed to increase with increasing TX-RX separation distance. The delay spreads were also observed to increase with increasing TX-RX separation distances in some of the environments considered.

Wireless channel modelling is a complicated process. The complexity arises from many factors that include the time-varying nature of the channels, the antenna polarization, correlation and configuration, the terminal heights, the displacement or mobility of terminals and obsta-

cles within the channel and its surroundings etc. Including the aforementioned factors may increase both the accuracy and the complexity of the channel models. Hence, a compromise between the channel model complexity and simplicity needs to be done since a very complicated to use but accurate channel model is equally as bad as an oversimplified and inaccurate one. Mobility in mmWave mMIMO is one of the most important challenges that will need to be addressed since at higher frequencies, the channel coherence time is much smaller. In order to extend the proposed channel models derived in our work, future perspectives include mmWave mMIMO channel measurements involving mobile scenarios. These scenarios should include: a moving TX and a fixed RX, a fixed TX and a moving RX and dual mobility (when both communicating nodes are moving). Dual mobility is typical of Device to Device (D2D) communications and these scenarios are characterized by a high doppler spread. Besides the increased challenges such as the scarcity and prohibitive costs of channel sounders supporting mMIMO measurements, performing dynamic channel measurements will lead to improved models that capture the time-varying nature of the mmWave mMIMO channels. With regards to DMCs, we have only quantified them in this work. Future work should include the comprehensive modelling of the DMCs in the different indoor environments. On top of this, it will be interesting to consider the full angular distribution of DMCs (and not just the angular-white DMCs as was done in this work) in the analysis of the impact of the T-RIS on the geometrical structure of the mmWave mMIMO channels.

List of Publications

Journal Papers

A. Mudonhi, R. D'Errico and C. Oestges, "Analysis of Multipath Components Distributions Over a Large Array in Indoor mmWave Channels," in *IEEE Transactions on Antennas and Propagation*, 2022.

A. Mudonhi, R. D'Errico and C. Oestges, "Channel modelling with T-RISs," to be submitted in *IEEE Transactions on Antennas and Propagation*, 2022.

Conference Papers

A. Mudonhi, M. Lotti, G. Makhoul, R. D'Errico and C. Oestges, "Mm-Wave Massive MIMO Channel Sounding in Industrial IoT Scenarios," *2022 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*, Grenoble, 2022, pp. 1-5.

A. Mudonhi, M. Lotti, A. Clemente, R. D'Errico and C. Oestges, "Impact of a Transmitting-RIS on the Geometrical Structure of Indoor mmWave Channels," *2022 16th European Conference on Antennas and Propagation (EuCAP)*, Madrid, 2022, pp. 1-5.

A. Mudonhi, M. Lotti, A. Clemente, R. D'Errico and C. Oestges, "RIS-enabled mmWave Channel Sounding Based on Electronically Reconfigurable Transmitarrays," *2021 15th European Conference on Antennas*

and Propagation (*EuCAP*), Düsseldorf, 2021, pp. 1-5.

A. Mudonhi, R. D’Errico and C. Oestges, "Indoor mmWave Channel Characterization with Large Virtual Antenna Arrays," 2020 *14th European Conference on Antennas and Propagation (EuCAP)*, Copenhagen, 2020, pp. 1-5.

IRACON-COST ¹ Conference

R. D’Errico, A. Clemente, F. Foglia Manzillo, M. Smierzchalski, A. Mudonhi, A. Guerra and F. Guidi, "Reconfigurable and Focused Surfaces and Channel Characterization at mmWave", *IRACON-COST*, CA15104 TD(20)12035, January 2020.

Project Deliverables

- H2020 RISE-6G Deliverable D3.1 “Preliminary RIS model and measurement campaigns”
- CRIIOT Deliverable D2.7 (a) “URLLC, mmW et redcap: proposition d’innovations”

¹IRACON-COST: The Inclusive Radio Communications (IRACON) concept defines those technologies aimed to support wireless connectivity at any rates, for any communicating units, and in any type of scenarios. The Wireless Internet of Things beyond 2020 will require revolutionary approaches in Radio Access technologies, networks and systems. Some theoretical foundations have to be revisited and breaking technologies are to be discovered during the coming decade.

The COST Action aims at scientific breakthroughs by introducing novel design and analysis methods for the 5th-generation (5G) and beyond-5G radio communication networks. Challenges include i) modelling the variety of radio channels that can be envisioned for future inclusive radio, ii) capacity, energy, mobility, latency, scalability at the physical layer and iii) network automation, moving nodes, cloud and virtualisation architectures at the network layer, as well as iv) experimental research addressing Over-the-Air testing, Internet of Things, localization and tracking and new radio access technologies.

Appendix A

Antennas Characteristics

Contents

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A.3 Linearly Polarized T-RIS	181

In this appendix, the different frequency characteristics of the monopole antennas as well as the different T-RIS characteristics are presented.

A.1 Monopole Antennas

The monopole antennas used in this work were vertically polarized. The monopole antenna patterns were measured in the anechoic chamber. In Fig. A.1.1, we show the measured azimuth and elevation gain patterns at 28 GHz considering co-polarization. Fig. A.1.2 shows the measured 3D monopole gain patterns at 28 GHz.

A.2 Circularly Polarized T-RIS

The circularly polarized T-RIS patterns were measured in the anechoic chamber for 25 scanning or steering angles, $\phi_s = -60^\circ : 5^\circ : 60^\circ$. Fig. A.2.1 shows the measured gain patterns of the T-RIS in the azimuth plane. We remark that the elevation scanning angle was always fixed at

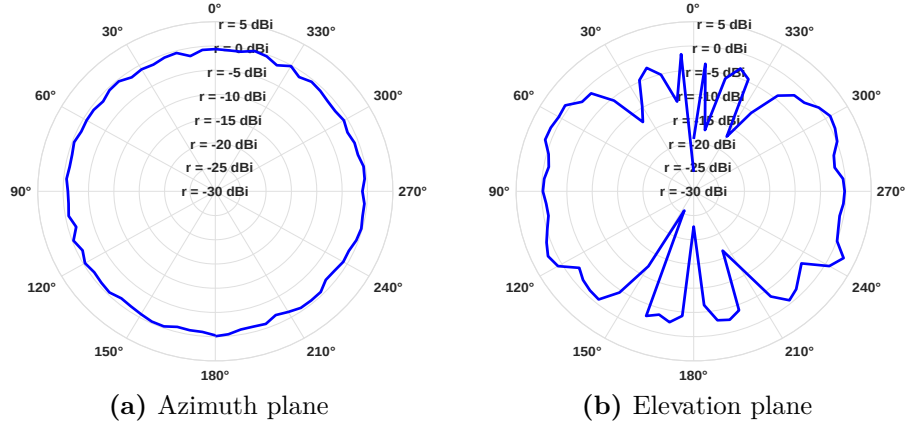


Figure A.1.1: Monopole antenna measured gains pattern in the Azimuth and Elevation planes.

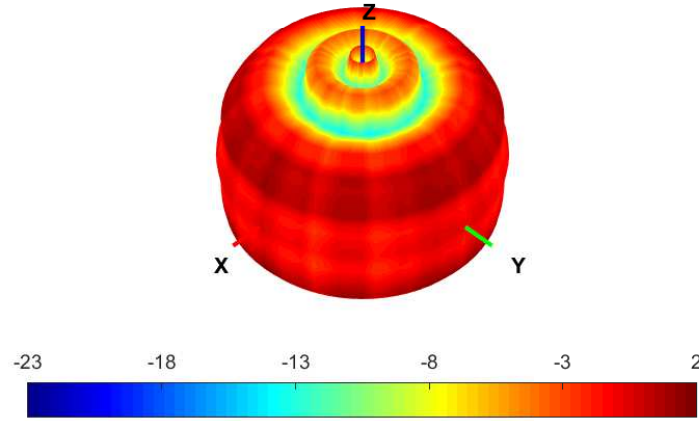


Figure A.1.2: Monopole antenna measured 3D gain pattern at 28 GHz.

90° that is $\theta_s = 90^\circ$. Fig. A.2.2 shows the beamsquint for the scanning or steering angles $\phi_s = 0^\circ, 30^\circ, -30^\circ, 45^\circ$. Finally, Figure. A.2.3 shows the 3D simulated gain pattern for the co-polarization component.

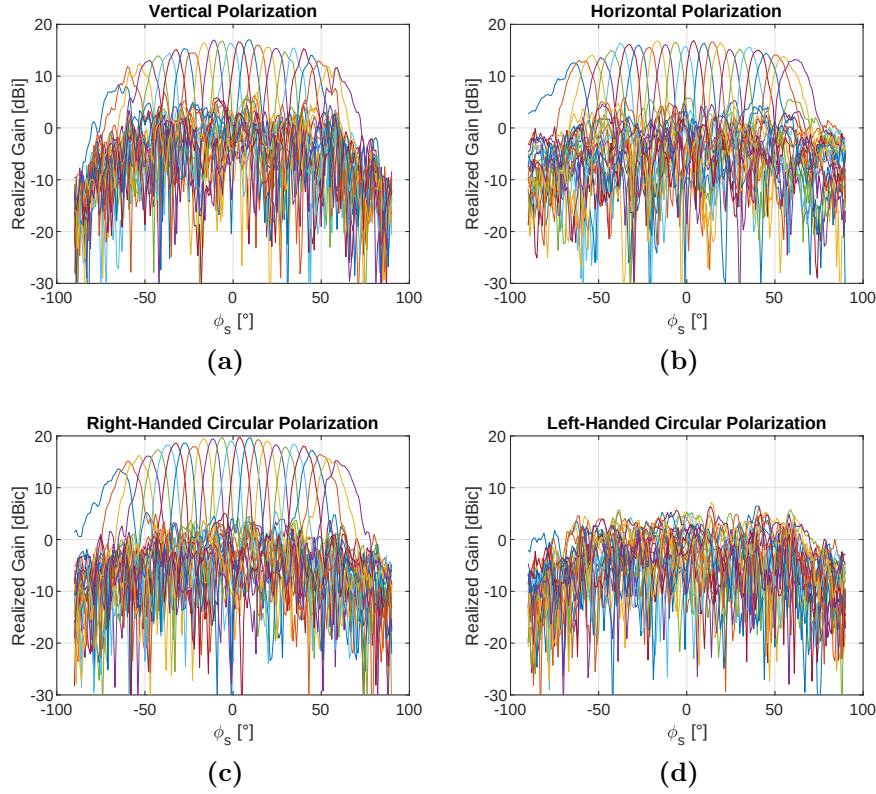


Figure A.2.1: Measured Gain patterns for the circularly polarized T-RIS at 28 GHz.

A.3 Linearly Polarized T-RIS

Fig.A.3.1(a) shows the T-RIS realized flat-lens array. The T-RIS operates in linear polarization at Ka-band. The flat-lens array is composed of 400 linearly polarized UCs (20×20 elements) with a total of 800 PIN diodes (Fig.A.3.1(b)) and is illuminated with a 10-dBi standard gain horn antenna. The flat-lens total size, including the 400 bias lines, is $196 \times 196 \text{ mm}^2$. Four board-to-board connectors are also integrated to connect the array to the steering logic. The measured broadside gain, computed as a function of the frequency in the range 26 to 32 GHz, is plotted in Fig. A.3.1(c). The peak-gain at 28 GHz is equal to 21.3 dBi. The gain variation on the band 26 to 31 GHz is in the range ± 1 dBi.

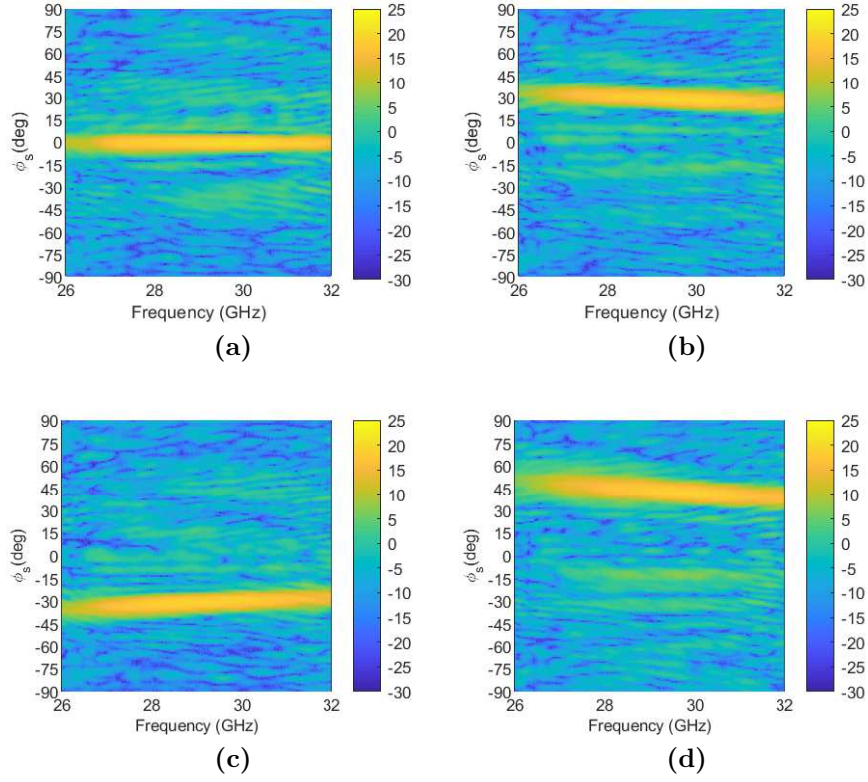


Figure A.2.2: Circularly polarized T-RIS beamsquint.

The co-polarized radiation patterns computed on the horizon cut plane as a function of the steering angle are plotted in Fig. A.3.1(d).

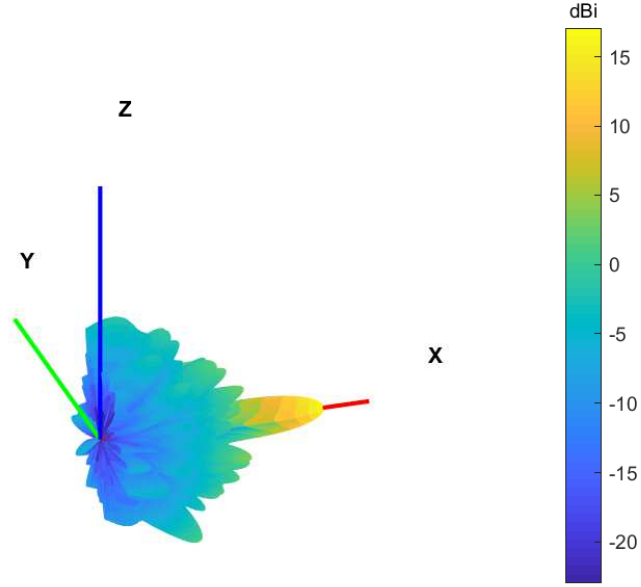


Figure A.2.3: Circularly polarized T-RIS 3D simulated co-polarization gain pattern.

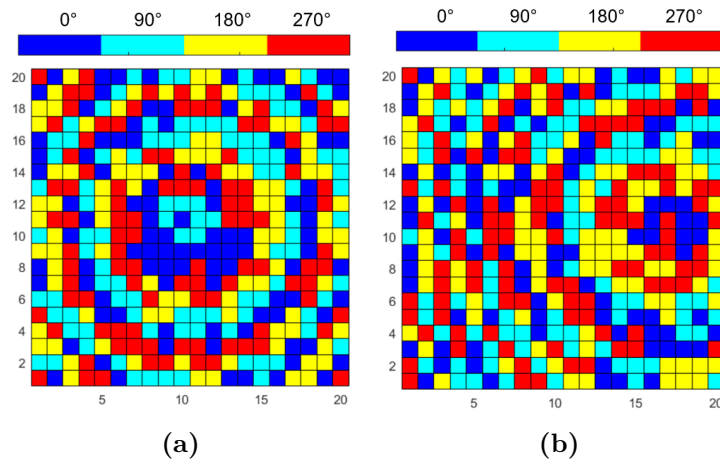


Figure A.2.4: Phase distribution (a), (b) for $\phi_s = 0^\circ$ and $\phi_s = 30^\circ$.

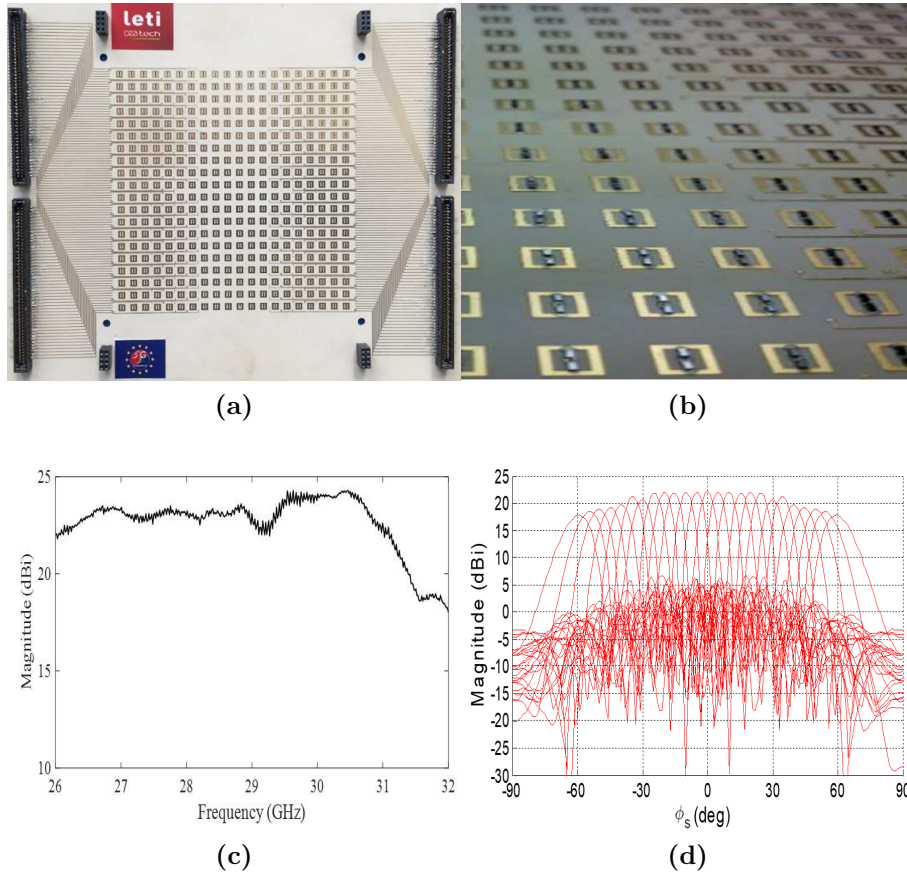


Figure A.3.1: (a) Flat-lens array, (b) zoom on the active layer with PIN diodes, (c) peak-gain at broadside as a function of the frequency, (d) beam-steering capability at 28 GHz.

Appendix **B**

Superposed PDPs and Scatter Plots

B.1 Indoor Laboratory

B.2 Indoor Factory

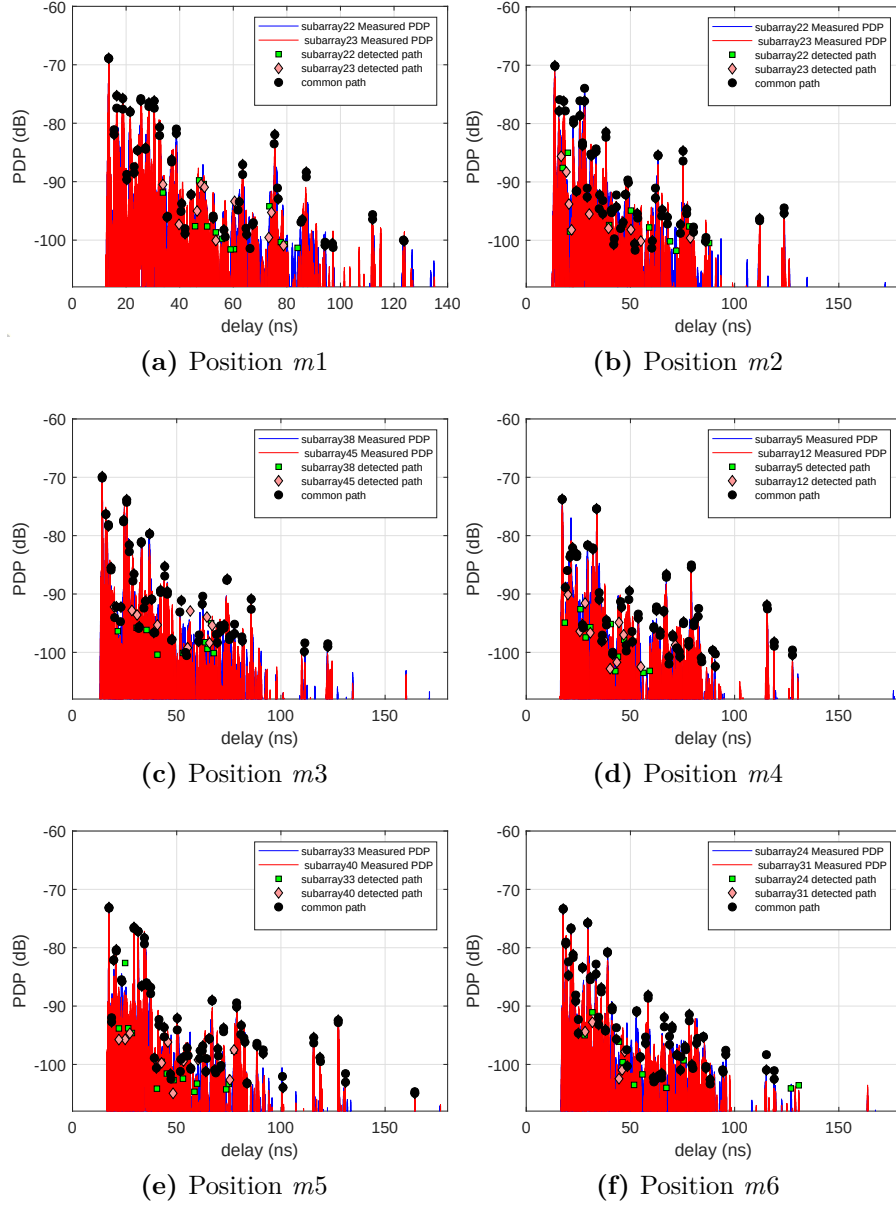


Figure B.1.1: InLab: Example superposed PDPs, detected and common MPCs for the 6 positions considered.

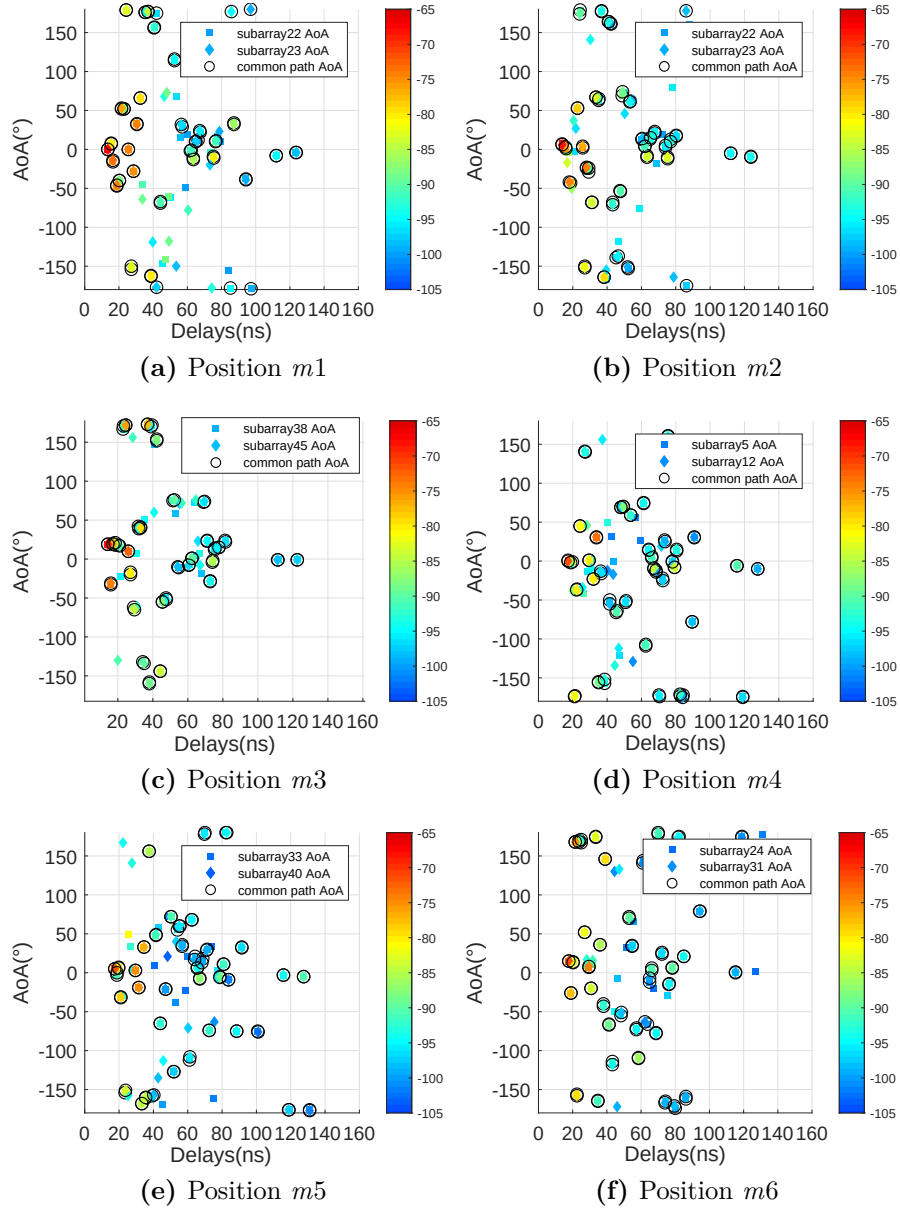


Figure B.1.2: InLab: Example scatter plots, detected and common MPCs for the 6 positions considered.

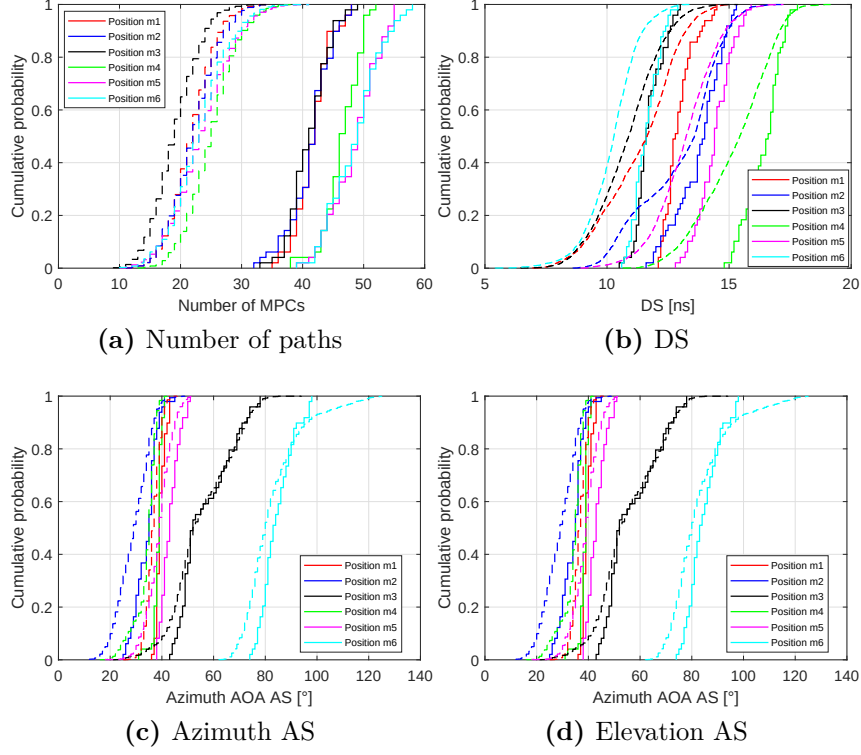


Figure B.1.3: InLab position $m1$ - $m6$: Solid lines show all the MPCs statistics and the dotted lines show the common paths statistics.

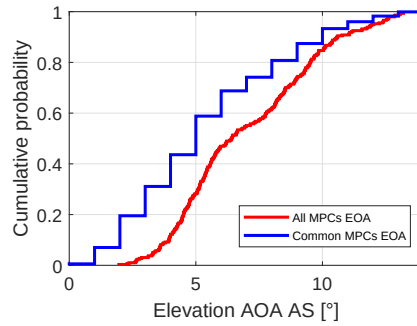
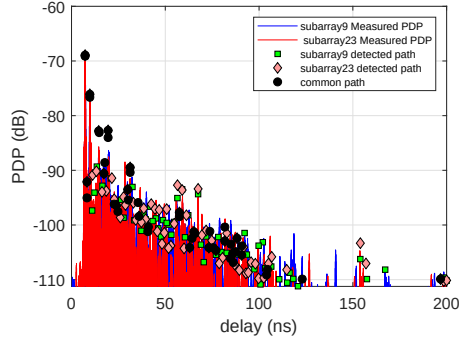
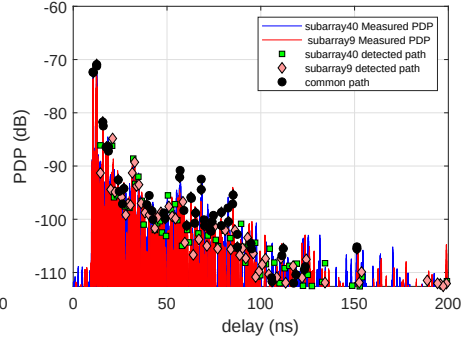


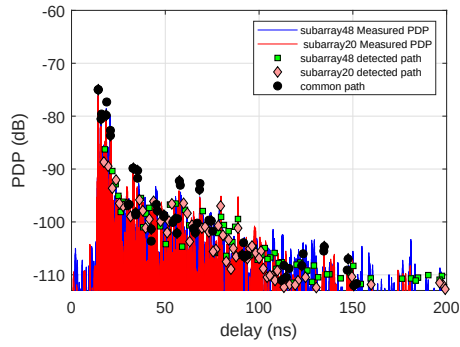
Figure B.1.4: InLab: Overall common paths vs all paths elevation AS statistics.



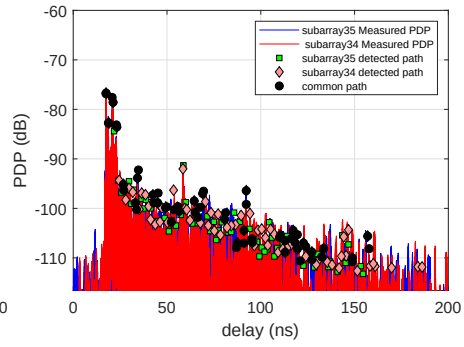
(a) Position P2



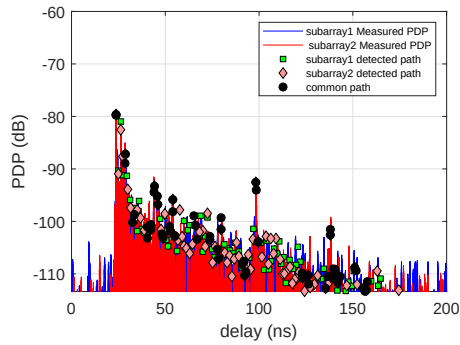
(b) Position P3



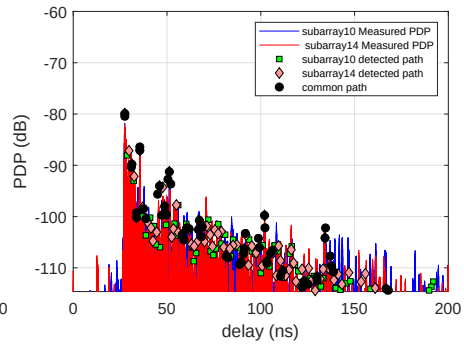
(c) Position P4



(d) Position P5



(e) Position P7



(f) Position P8

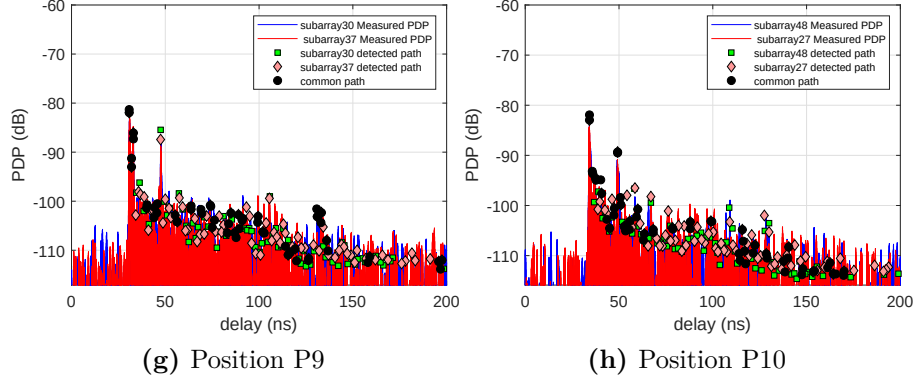
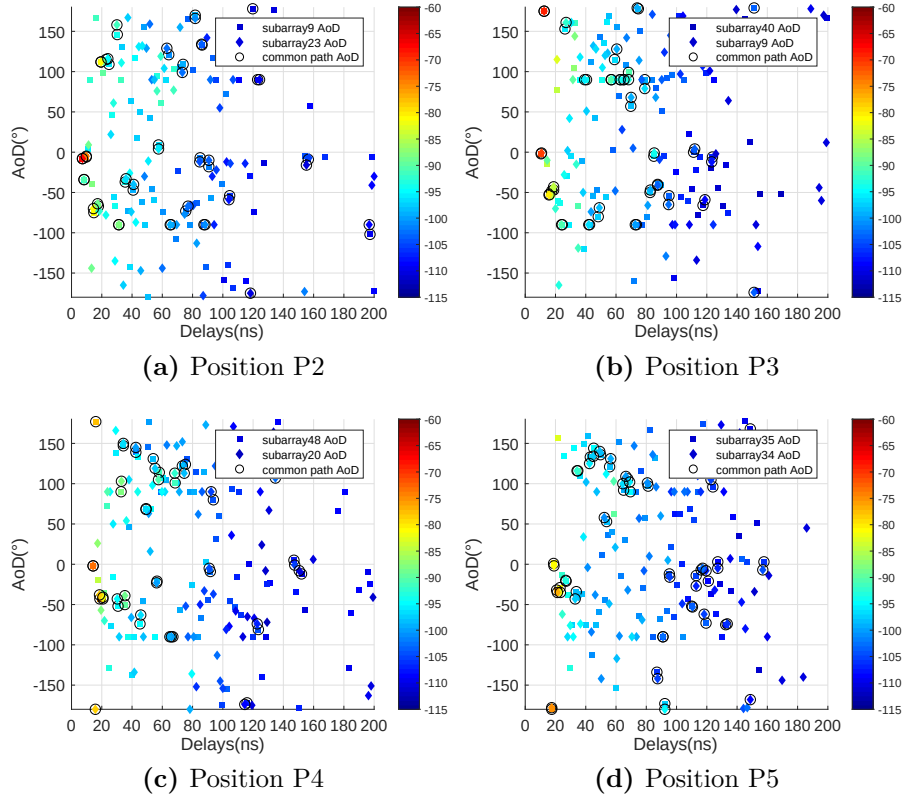


Figure B.2.1: InF P1-P10: Example superposed PDPs, detected and common MPCs for the LOS scenario.



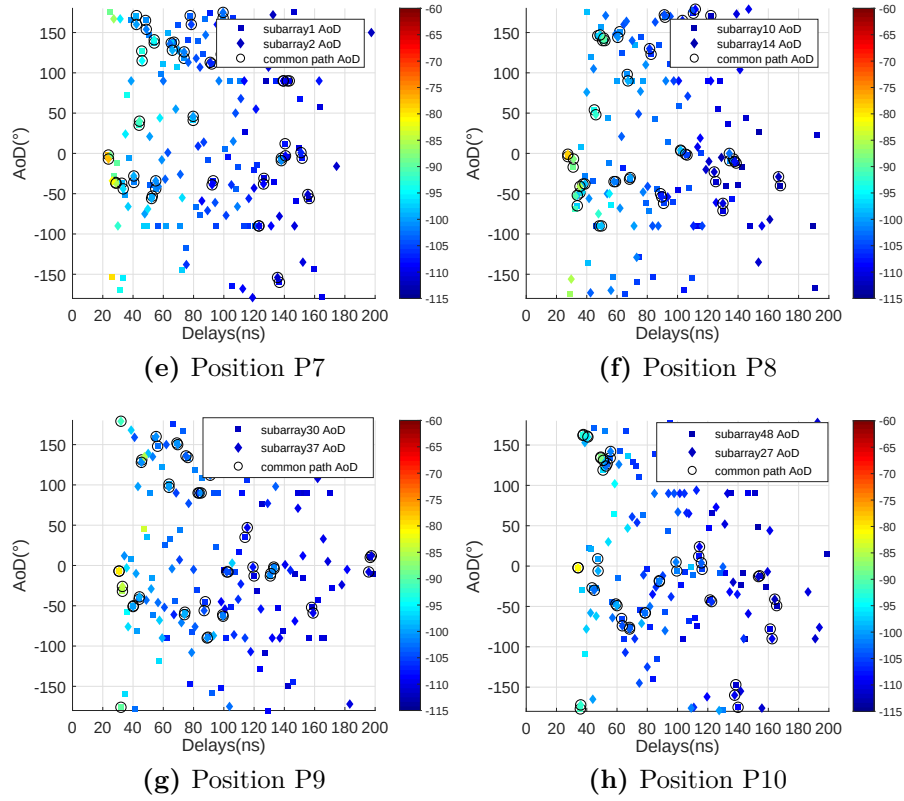


Figure B.2.2: InF P1-P10: Example scatter plots, detected and common MPCs for the LOS scenario.

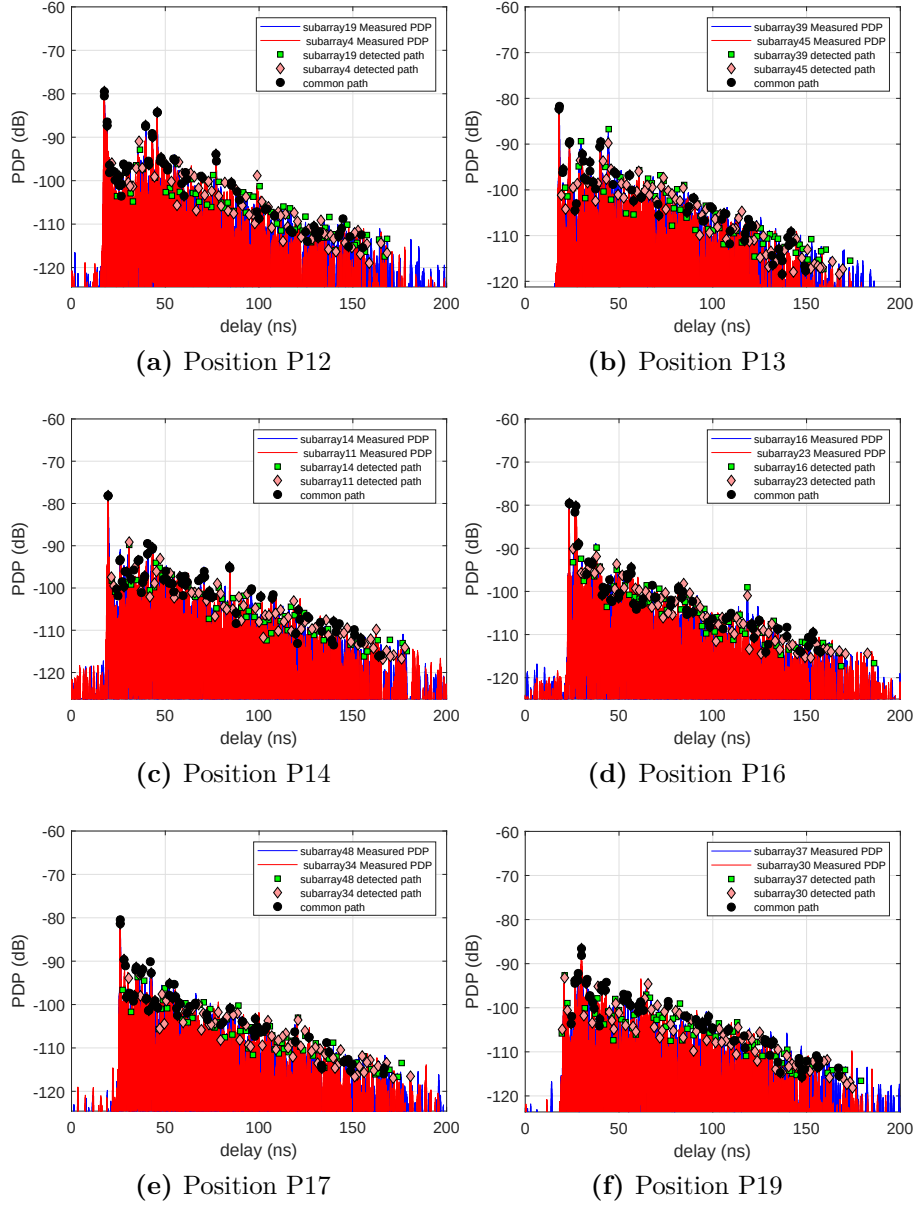


Figure B.2.3: InF P11-P20: Example superposed PDPs, detected and common MPCs.

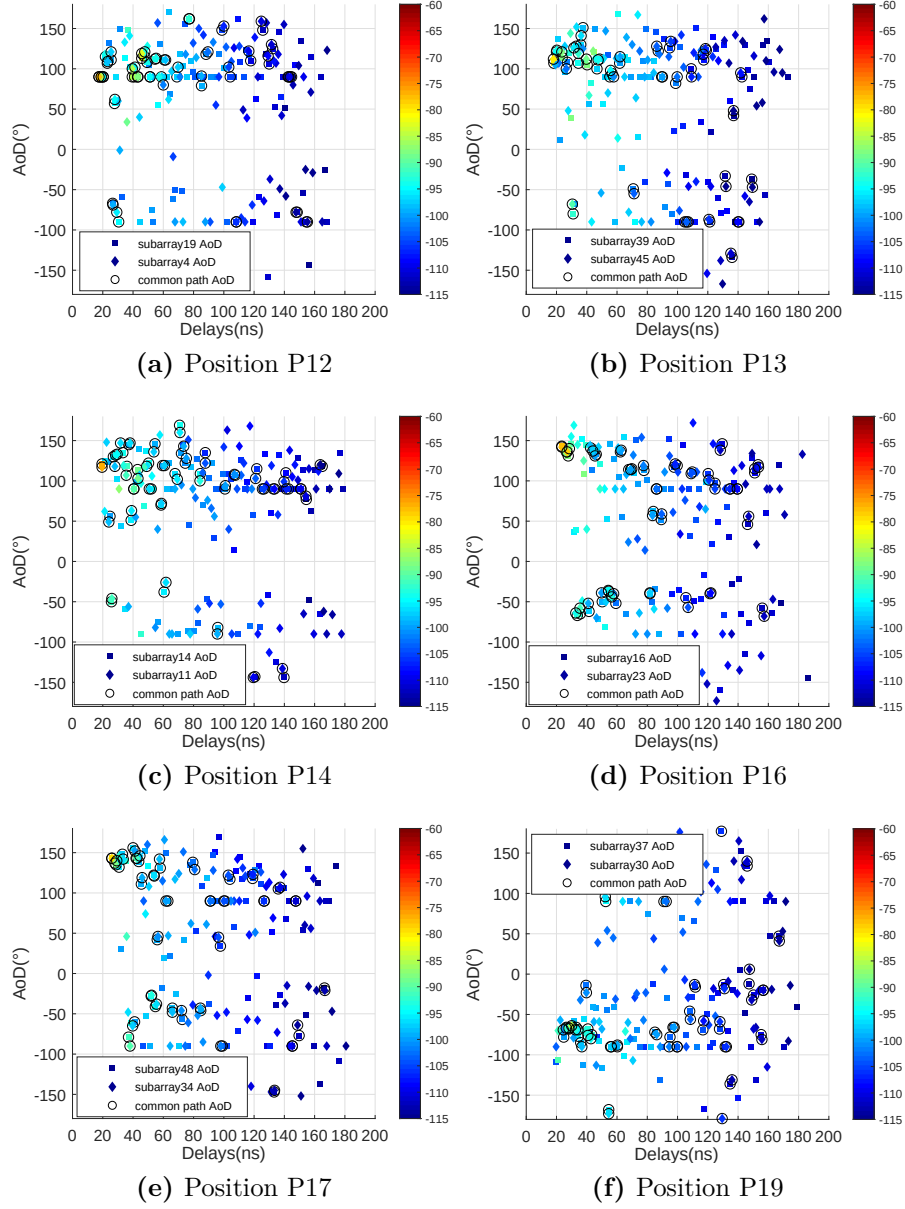


Figure B.2.4: InF P11-P20: Example scatter plots, detected and common MPCs.

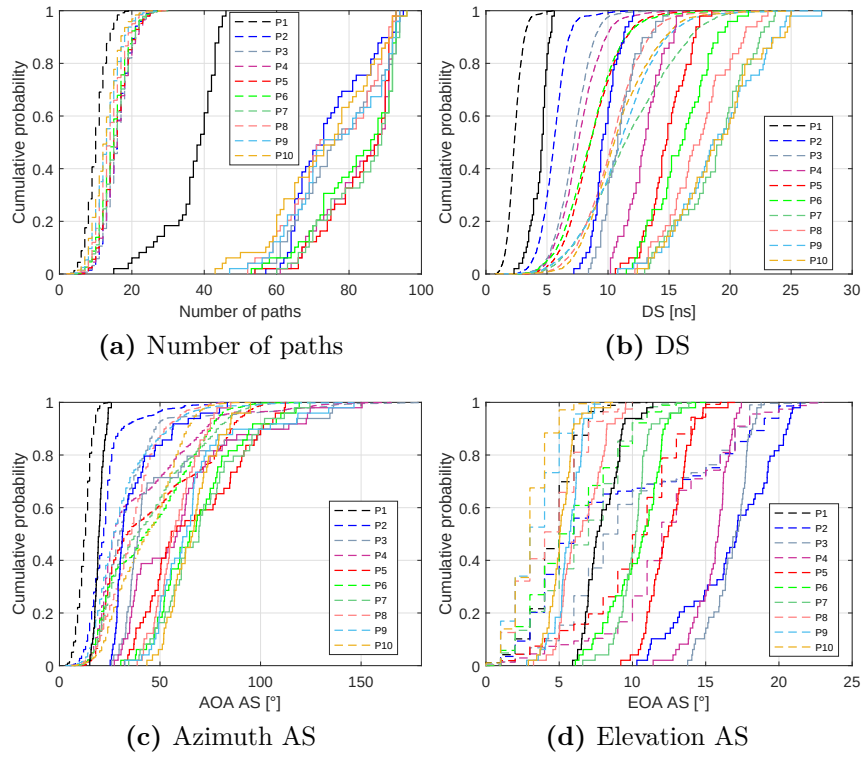


Figure B.2.5: InF P1-P10: Solid lines show all the MPCs statistics and the dotted lines show the common paths statistics.

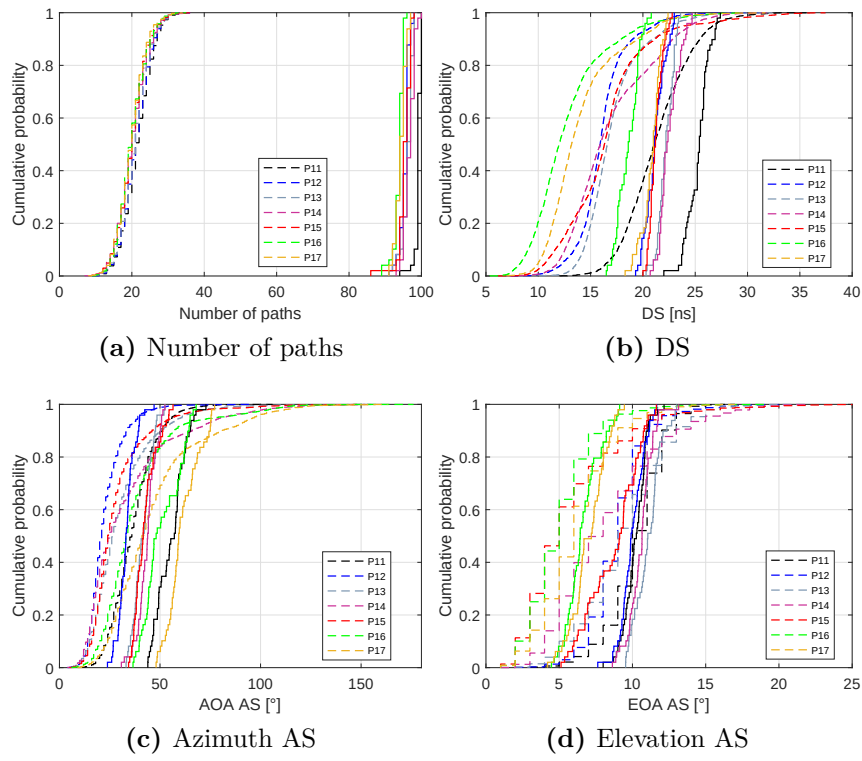


Figure B.2.6: InF P11-P17: Solid lines show all the MPCs statistics and the dotted lines show the common paths statistics.

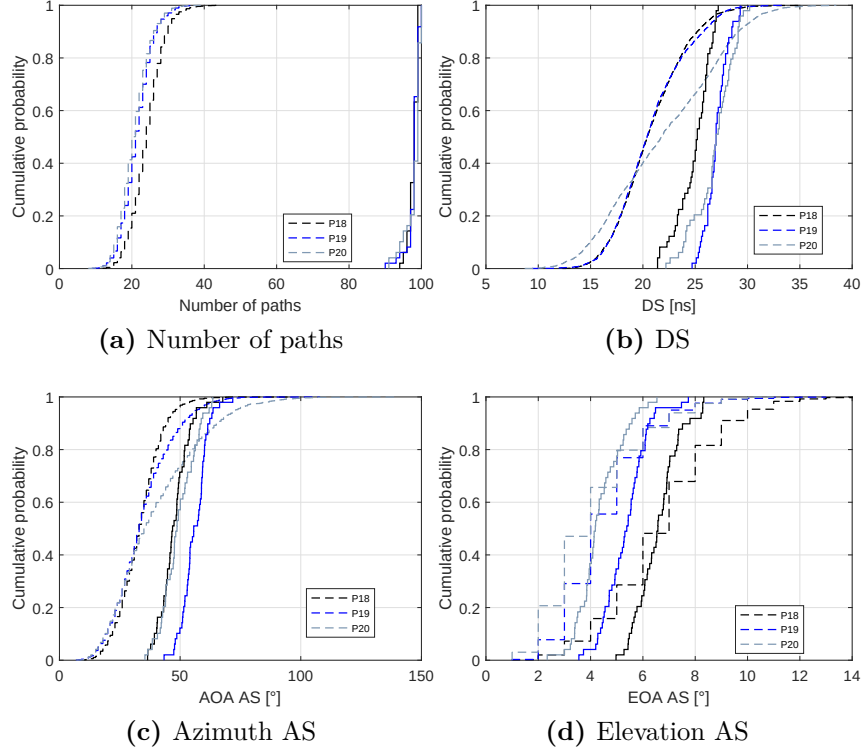


Figure B.2.7: InF P18-P20: Solid lines show all the MPCs statistics and the dotted lines show the common paths statistics.

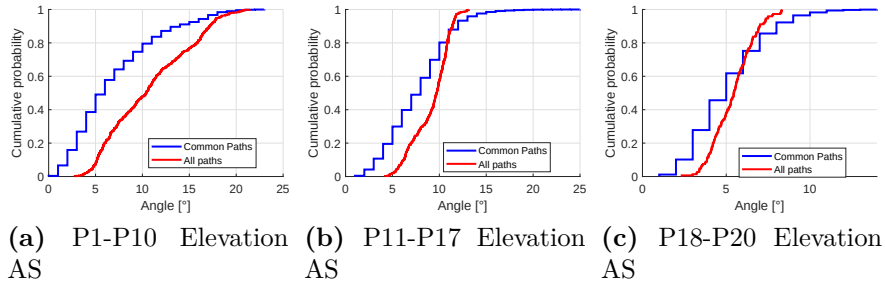


Figure B.2.8: InF environments: P1-P20 Overall common paths vs all paths statistics.

Appendix C

Omnidirectional PDPs and Polar plots

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B.2	Indoor Factory	185

C.1 Indoor Open Office

C.2 Indoor Mixed Office: Floor plans 1

C.3 Indoor Mixed Office: Floor plans 2

C.4 Indoor Mixed Office: Floor plans 3

C.5 Indoor Factory

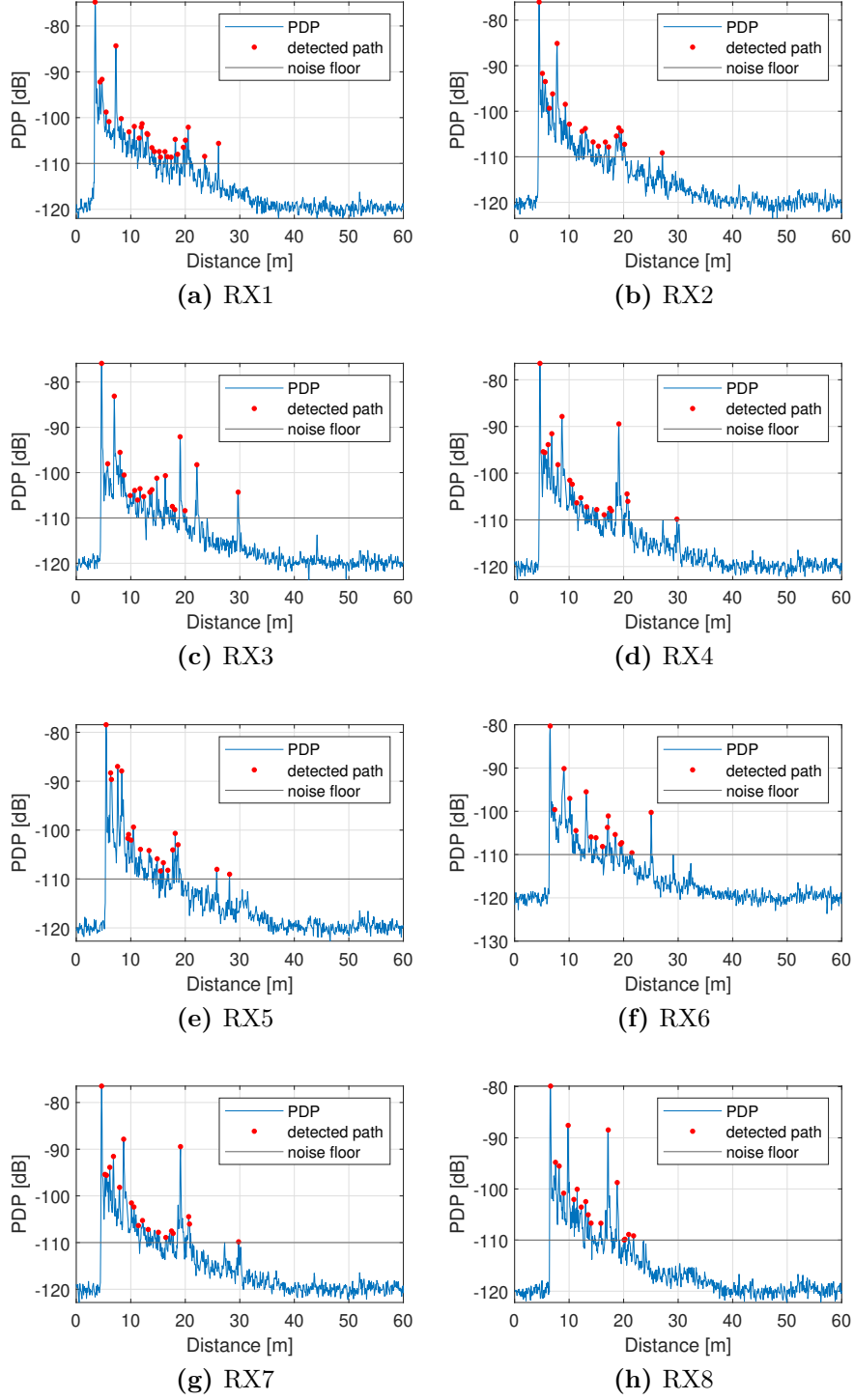


Figure C.1.1: InOpOffice omnidirectional PDPs at all receivers in the T-RIS setup.

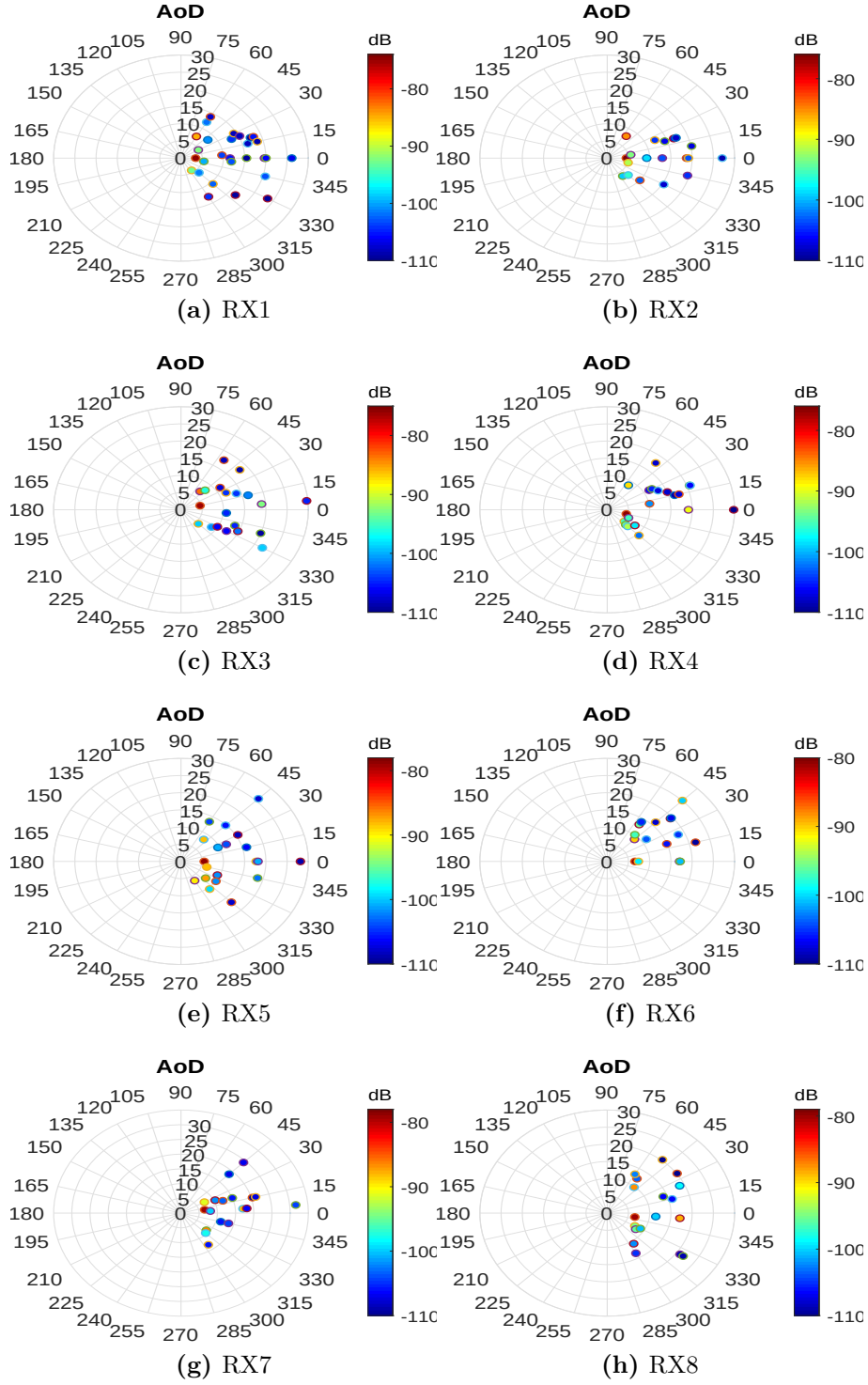


Figure C.1.2: InOpOffice polar plots at all receivers in the T-RIS setup.

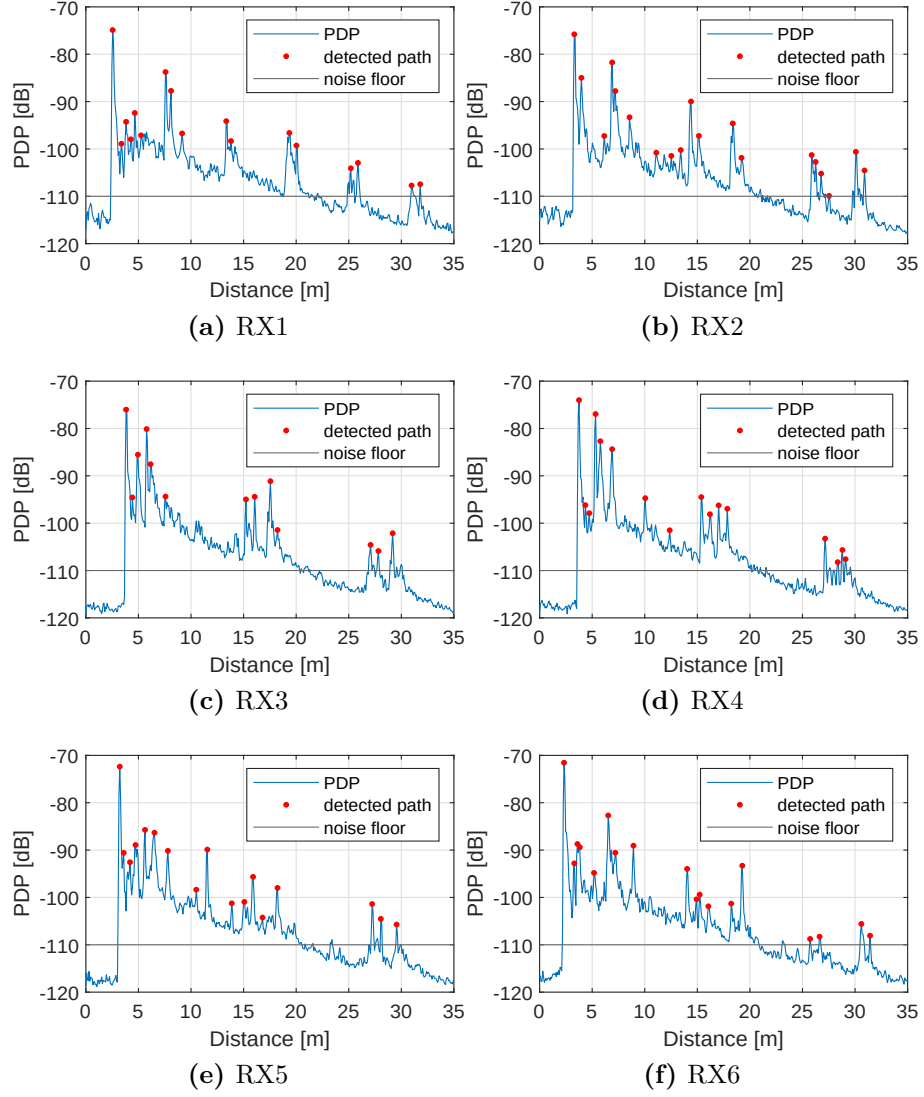


Figure C.2.1: InMixOffice FP1 omnidirectional APDPs at all 6 receivers positions.

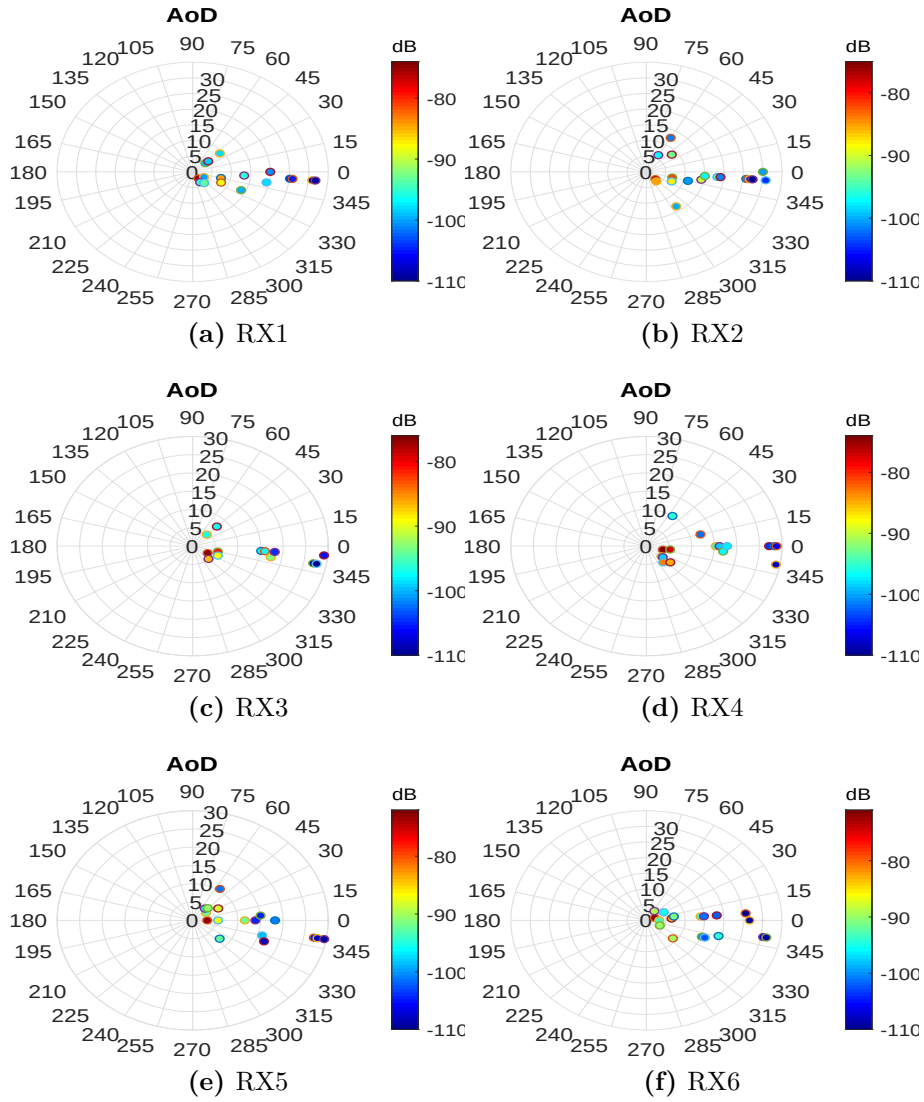


Figure C.2.2: InMixOffice FP1 polar plots at all 6 receiver positions.

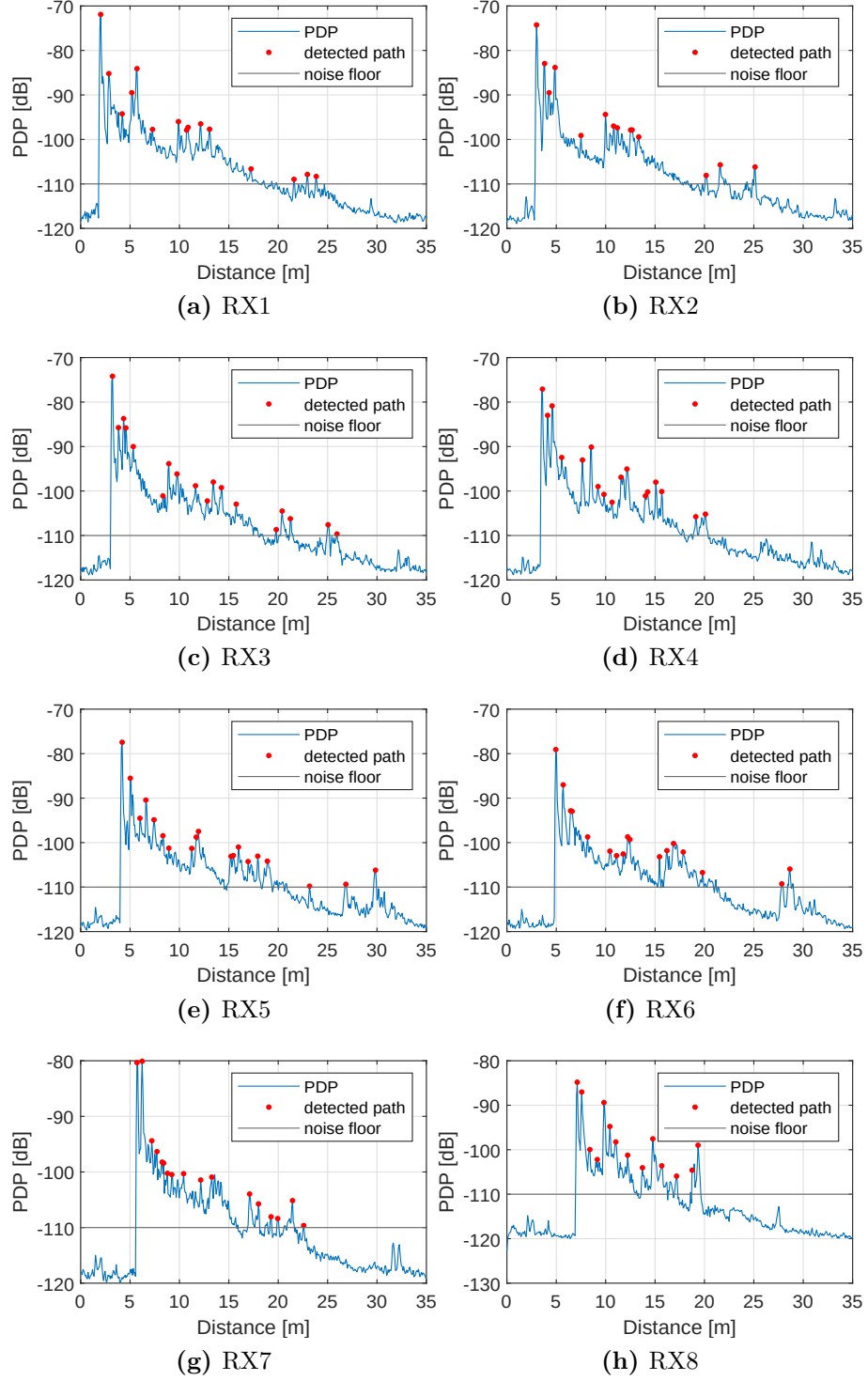


Figure C.3.1: InMixOffice FP2 omnidirectional APDPs at all 8 receivers positions.

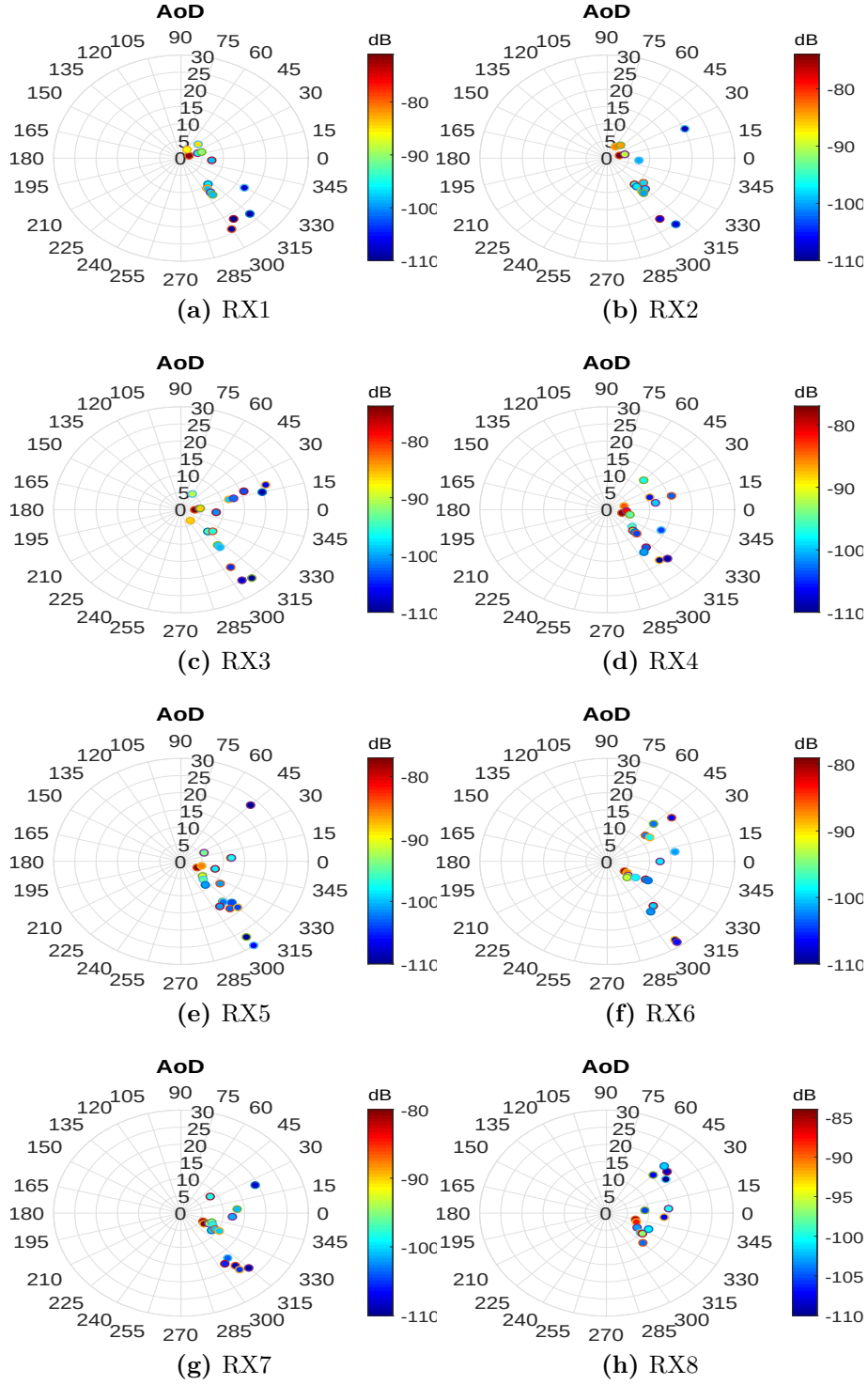
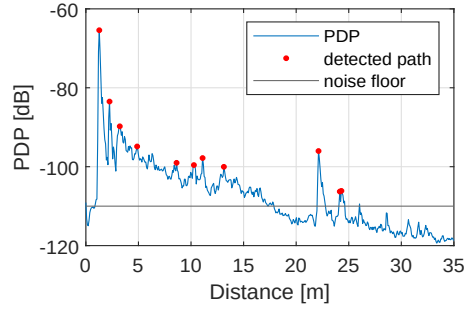
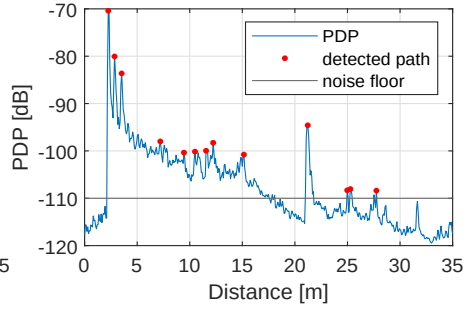


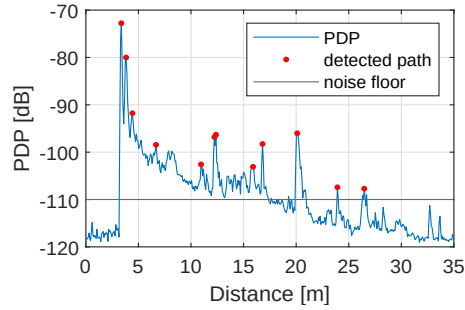
Figure C.3.2: InMixOffice FP2 polar plots at all 8 receiver positions.



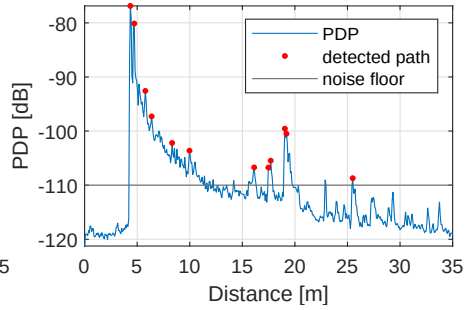
(a) RX1



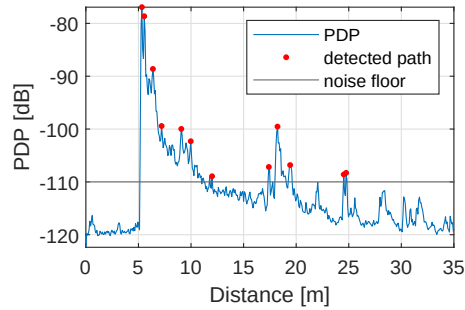
(b) RX2



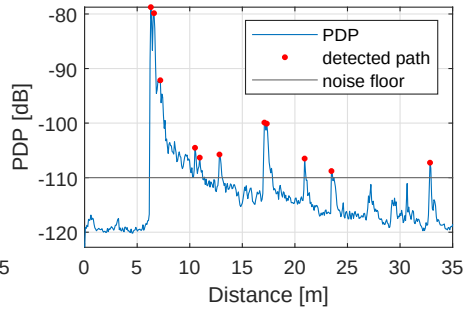
(c) RX3



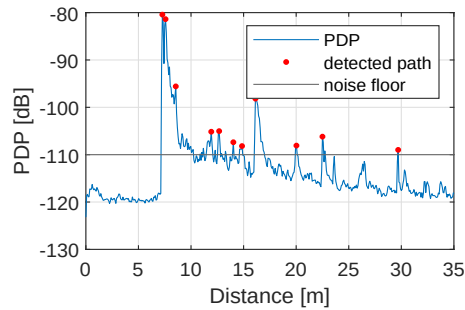
(d) RX4



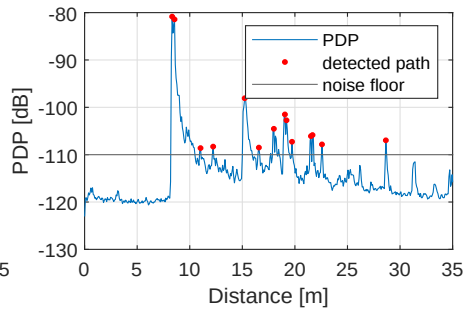
(e) RX5



(f) RX6



(g) RX7



(h) RX8

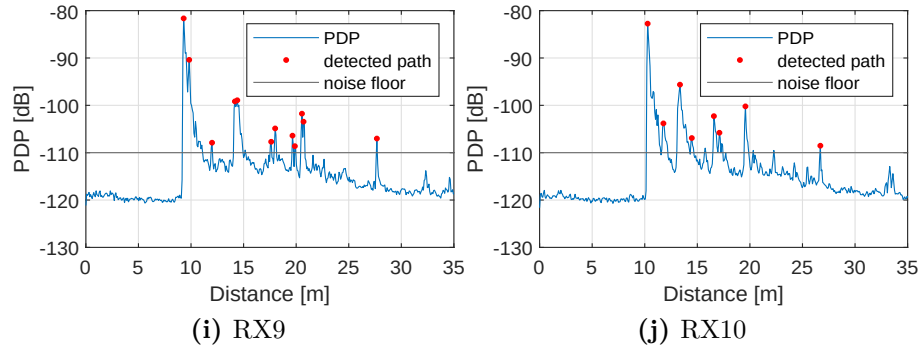
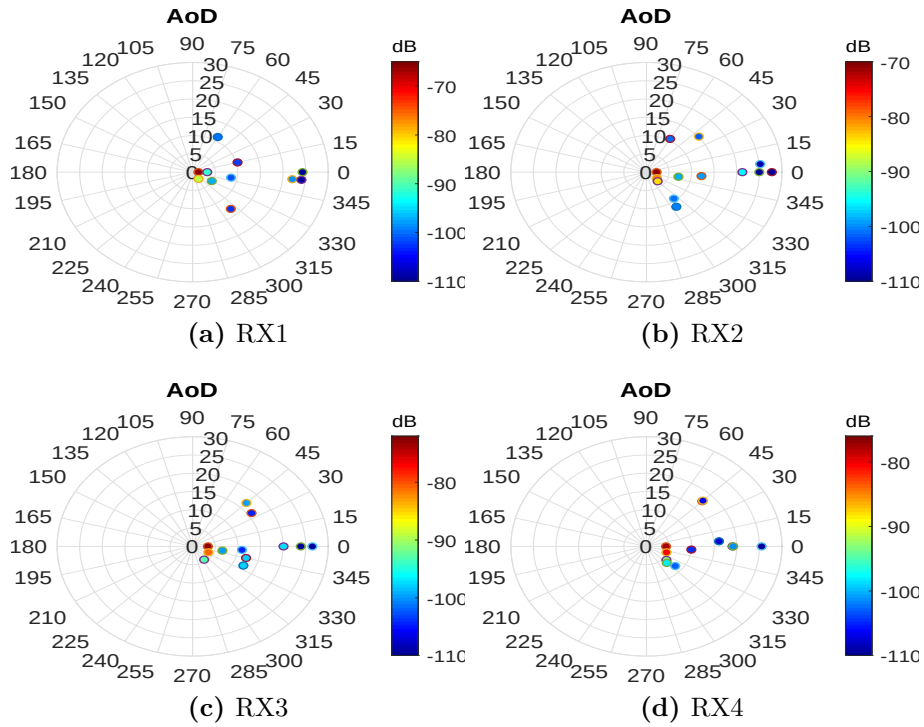


Figure C.4.1: InMixOffice FP3 omnidirectional APDPs at all 10 receivers positions.



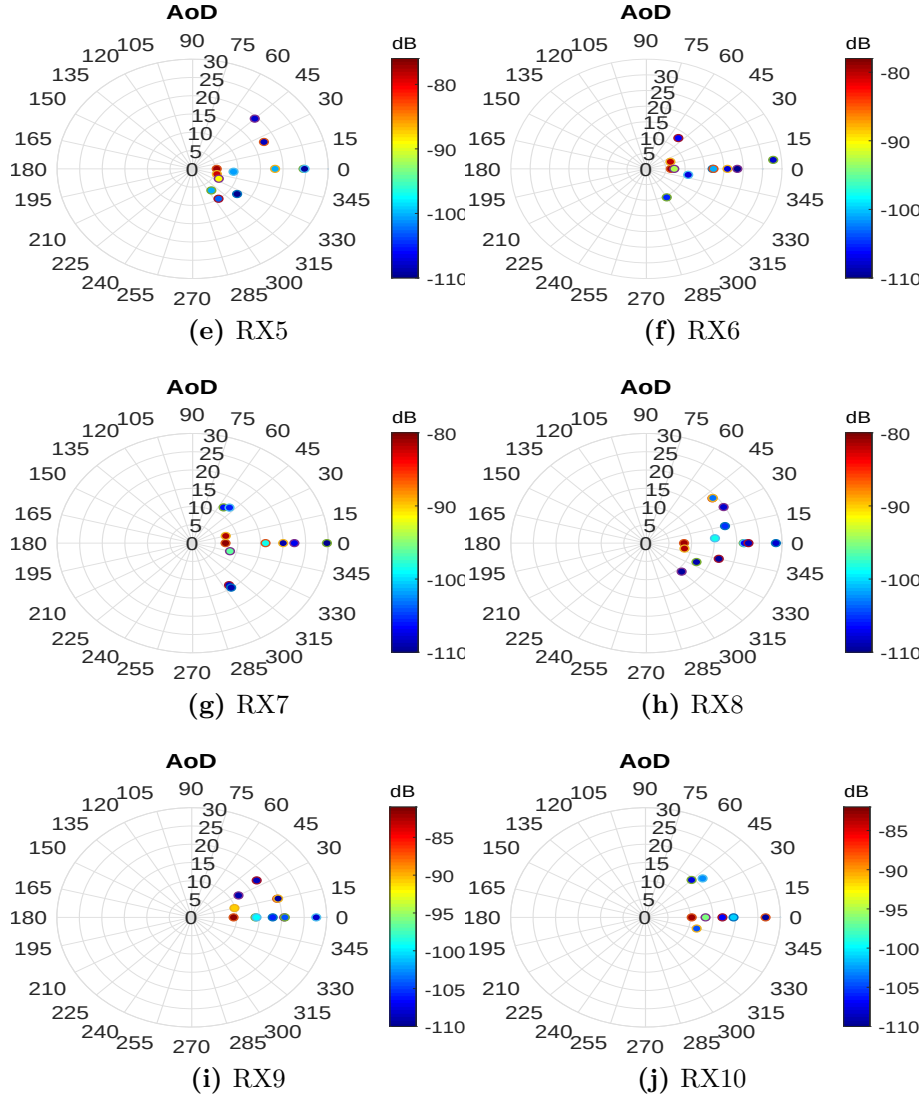
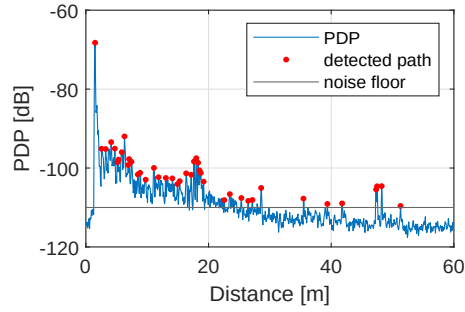
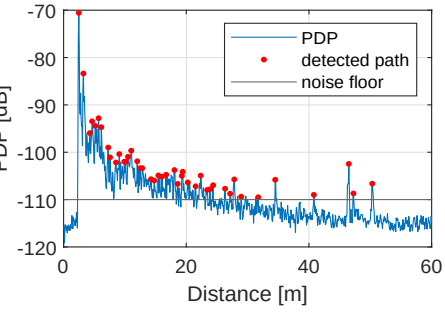


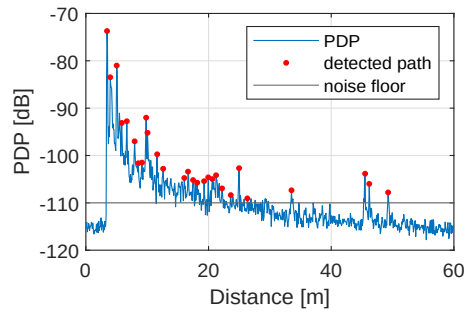
Figure C.4.2: InMixOffice FP3 polar plots at all 10 receiver positions.



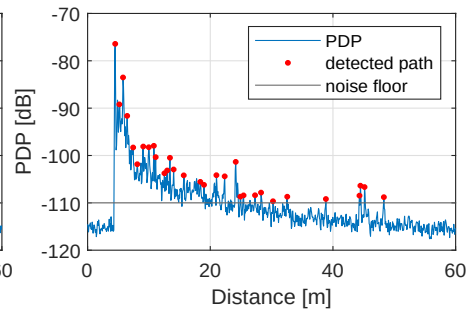
(a) P1



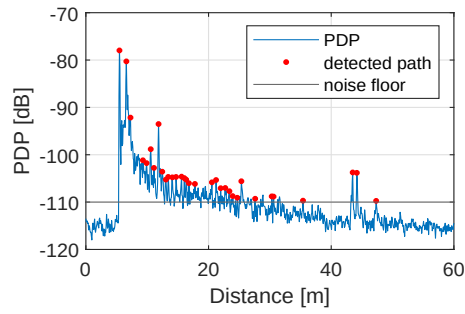
(b) P2



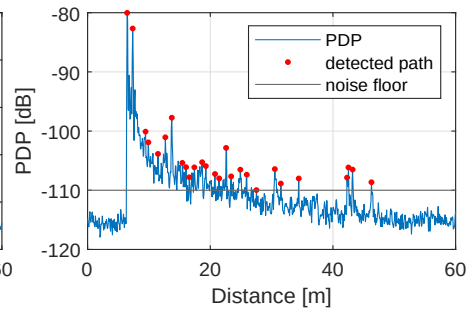
(c) P3



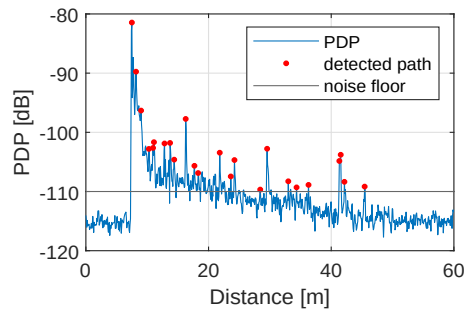
(d) P4



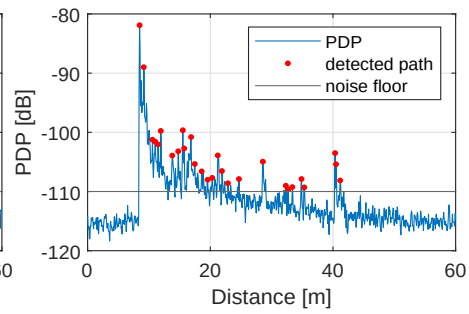
(e) P5



(f) P6



(g) P7



(h) P8

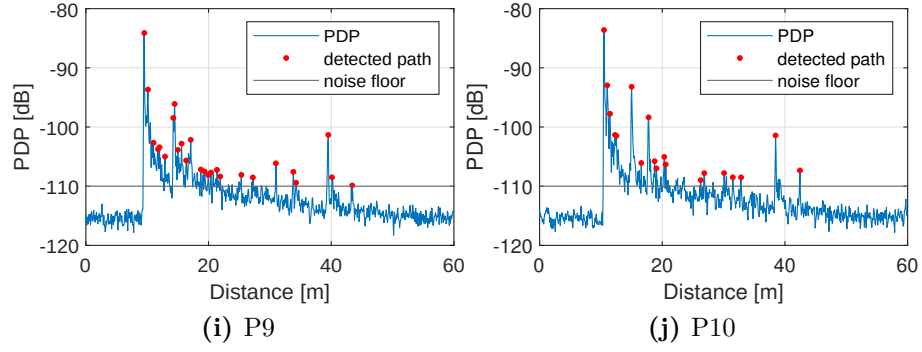
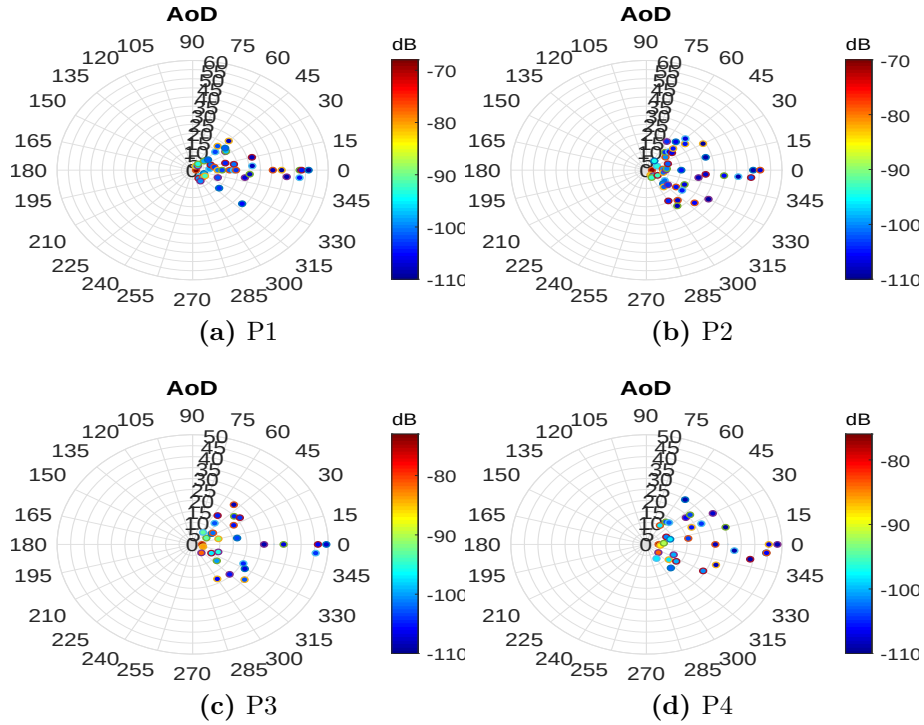


Figure C.5.1: InF P1-P10: Omnidirectional PDPs at all receivers for the LOS scenario.



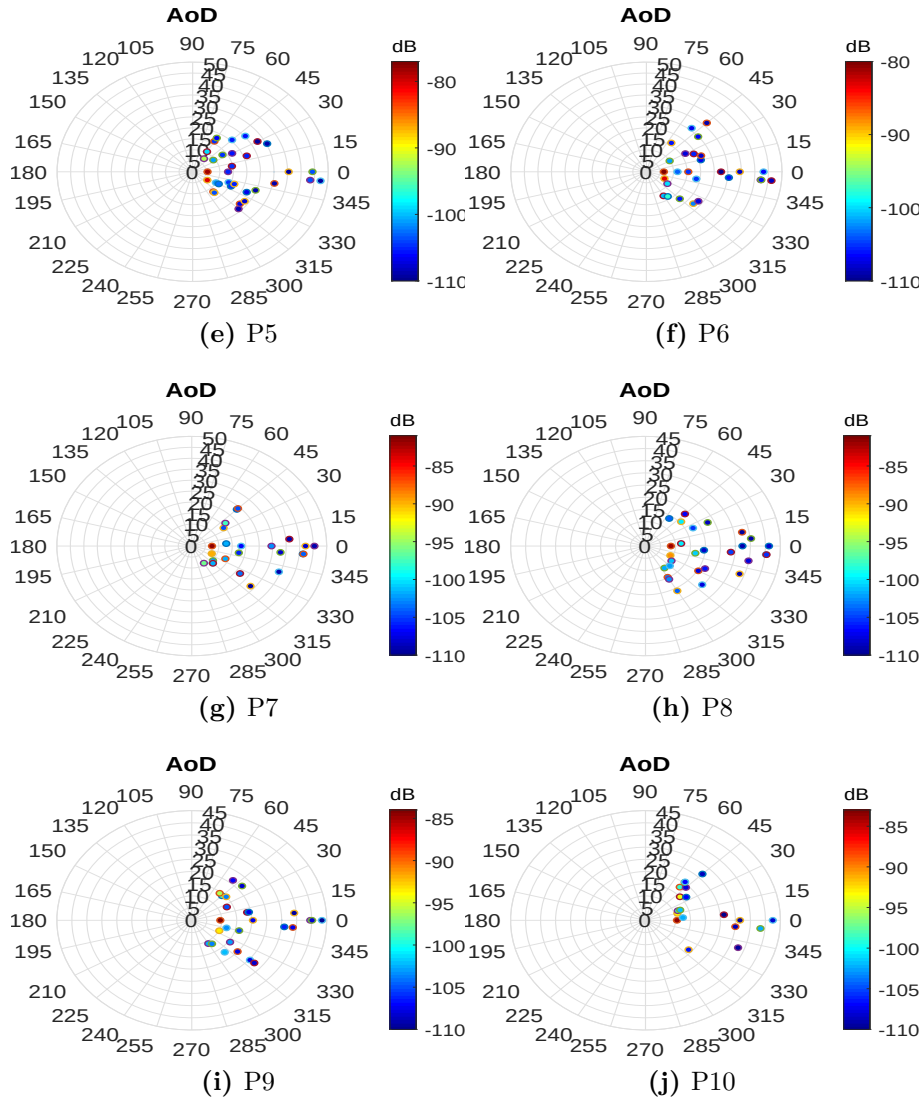
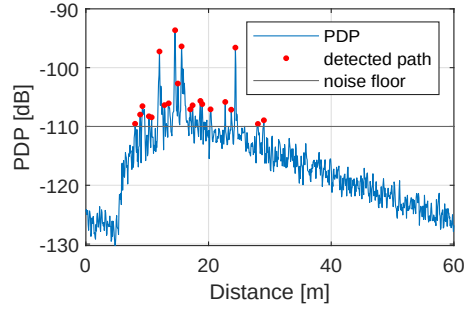
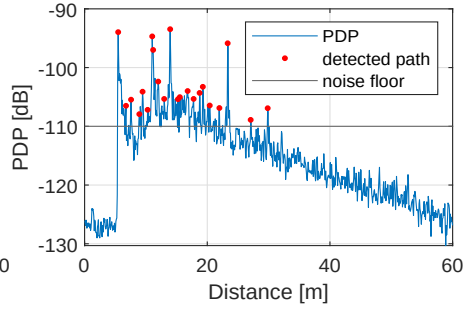


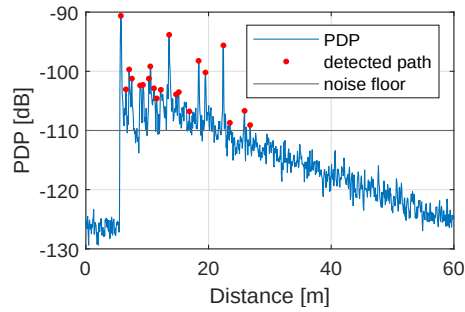
Figure C.5.2: InF P1-P10: Polar plots at all receivers for the LOS scenario.



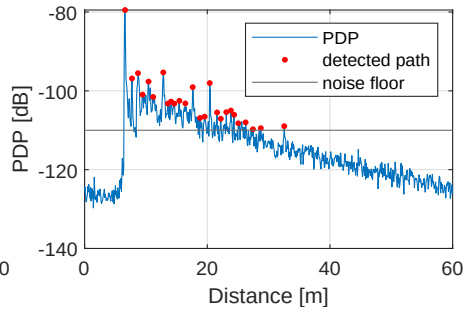
(a) P11



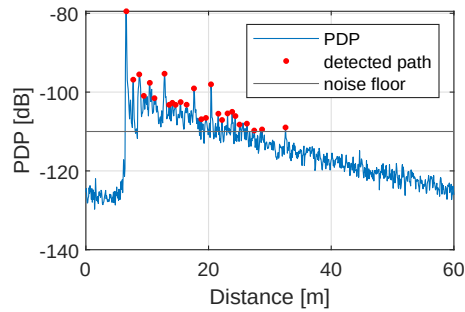
(b) P12



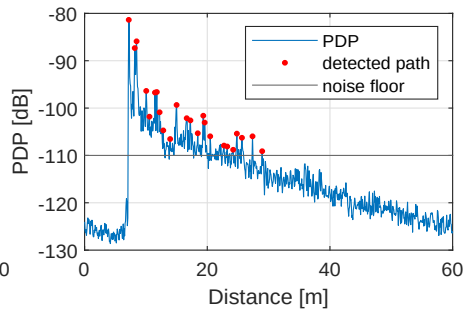
(c) P13



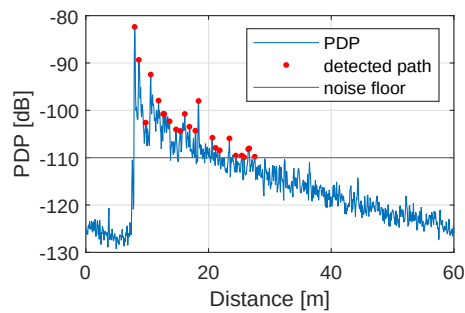
(d) P14



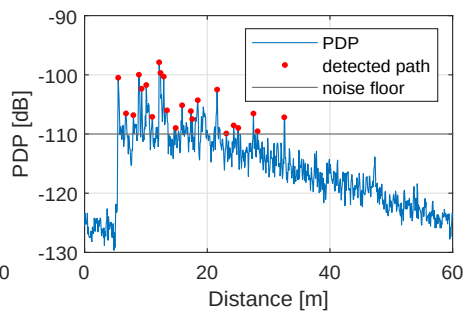
(e) P15



(f) P16



(g) P17



(h) P18

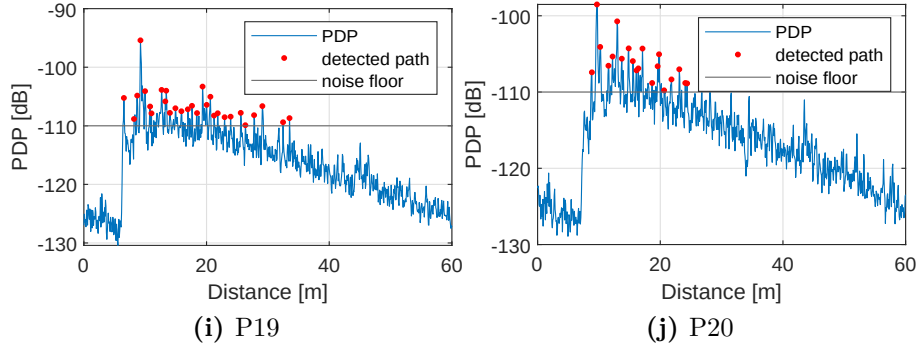
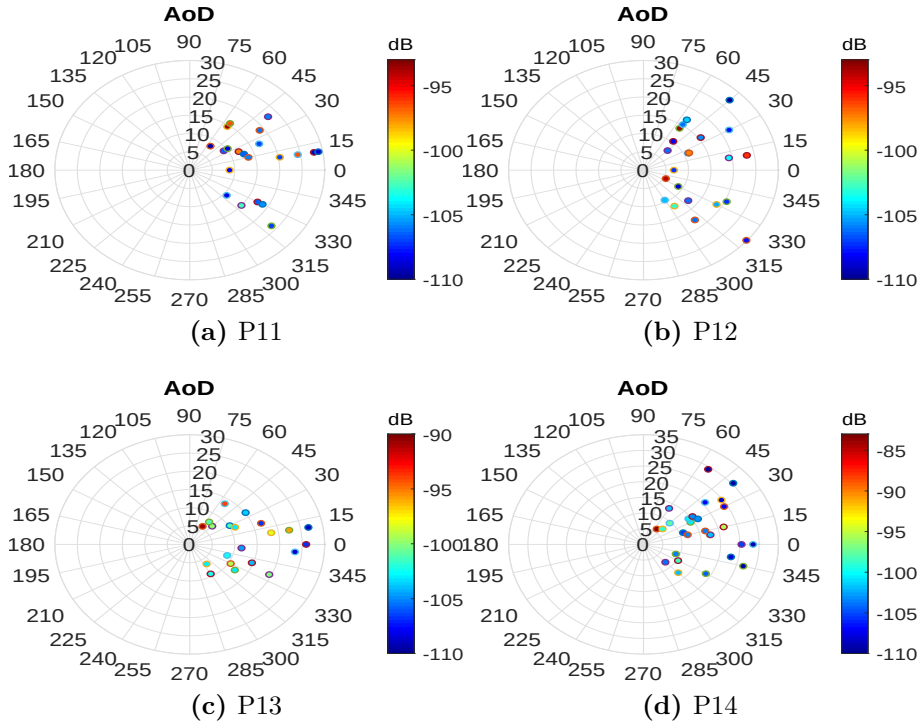


Figure C.5.3: InF P11-P20: Omnidirectional PDPs at all receivers for the OLOS scenario.



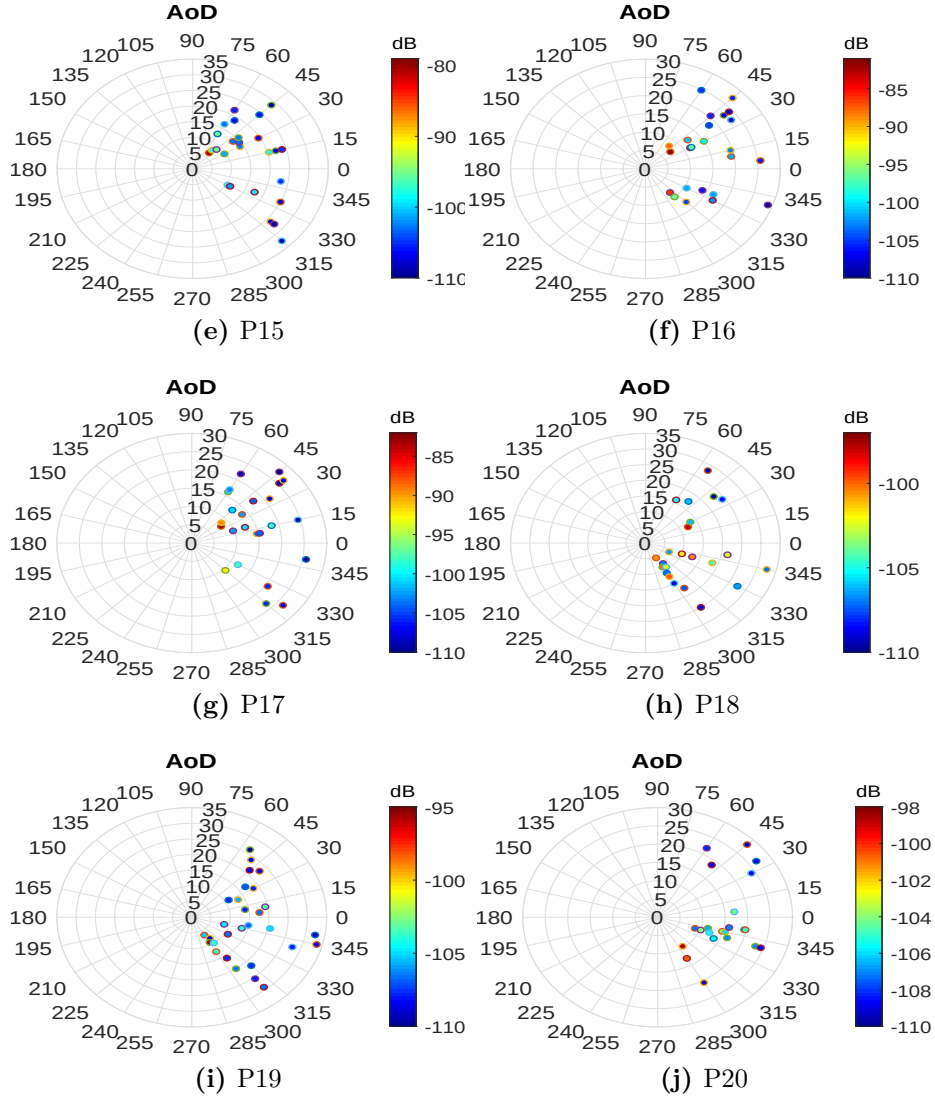


Figure C.5.4: InF P11-P20: Polar plots at all receivers for the OLOS scenario.

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