POWER CONSUMPTION TRADE-OFF IN CHANNEL ESTIMATION WITH HYBRID TRANSCEIVER

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ABSTRACT

The usage of massive antenna arrays coupled with millimeter-wave (mmW) transmissions has emerged as enabling technology of the fifth generation mobile communication standard, the 5G. This solution has great potentials to provide Gb/s data-rate and high cell capacity by leveraging the synergy amongst high resolution spatial filtering, adaptive beamforming and channel sparsity. One of the main challenges, however, is related to the implementation and digital processing as with a conventional transceiver architecture, an increase of the number of antennas implies more analog-to-digital (or digital-to-analog) converters, more power amplifiers and baseband units. Subsequently, the energy, factor-size and computational power requirements become impractical.

To counter these effects a hybrid transceiver design has been proposed, in which multiple analog front-ends are combined into a single (or multiple) baseband processing unit allowing the transceiver to reduce the complexity of the digital signal processing as well as the power consumption. In this Thesis we investigate different architecture models and evaluate the trade-off between energy consumption and performance in channel estimation. More specifically, we study a hybrid receiver model with 64 antenna elements, parallel digital paths and, for the channel estimation, we consider the adaptive-least absolute shrinkage and selection operator (A-LASSO) algorithm that leverages channel sparsity into the estimation.

Simulation results have shown that a transceiver architecture with only four base-bands performed best over the different cell sizes. Compared to the fully digital receiver this results in tenfold power consumption reduction according to analysis.

Keywords: Massive MIMO, 5G, Sparse channel estimation, LASSO, hybrid transceiver, RF, smart antennas
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## ABSTRACT

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FOREWORD

The research work for this master’s thesis was carried out at the Centre for Wireless Communications (CWC), Department of Communications Engineering (DCE), University of Oulu. The purpose of this thesis was to evaluate the performance of hybrid transceiver designs in terms of power consumption and channel estimation performance.

I would like to express thanks to my supervisors Prof. Aarno Pärssinen and Dr. Giuseppe Destino. Their valuable insights and directions gave me needful guidance to complete the research and write this thesis. I would also like to thank my fellow team members for a friendly working atmosphere.

A special thanks to my family and friends for their support.

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Tobias Ziegler
## ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>5G</td>
<td>fifth generation cellular standard</td>
</tr>
<tr>
<td>ADC</td>
<td>analog-to-digital converter</td>
</tr>
<tr>
<td>AF</td>
<td>array factor</td>
</tr>
<tr>
<td>AWGN</td>
<td>additive white gaussian noise</td>
</tr>
<tr>
<td>DAC</td>
<td>digital-to-analog converter</td>
</tr>
<tr>
<td>dBi</td>
<td>decibel-isotropic</td>
</tr>
<tr>
<td>DoA</td>
<td>Direction of Arrival</td>
</tr>
<tr>
<td>DoD</td>
<td>Direction of Departure</td>
</tr>
<tr>
<td>ITU</td>
<td>International Telecommunication Union</td>
</tr>
<tr>
<td>LO</td>
<td>local oscillator</td>
</tr>
<tr>
<td>LS</td>
<td>least square</td>
</tr>
<tr>
<td>LTE</td>
<td>Long Therm Evolution cellular standard</td>
</tr>
<tr>
<td>LTE-A</td>
<td>LTE-Advanced</td>
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<tr>
<td>MIMO</td>
<td>multiple input multiple outputs</td>
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<tr>
<td>MISO</td>
<td>Multiple Input Single Outputs</td>
</tr>
<tr>
<td>mmW</td>
<td>millimeter Wave</td>
</tr>
<tr>
<td>NP-hard</td>
<td>non-deterministic polynomial-time hard</td>
</tr>
<tr>
<td>OFDM</td>
<td>orthogonal frequency division multiplexing</td>
</tr>
<tr>
<td>QAM</td>
<td>quadrature amplitude modulated</td>
</tr>
<tr>
<td>QoS</td>
<td>quality of service</td>
</tr>
<tr>
<td>RF</td>
<td>radio frequency</td>
</tr>
<tr>
<td>RIP</td>
<td>Restricted Isometry Property</td>
</tr>
<tr>
<td>SIMO</td>
<td>Single Input Multiple Outputs</td>
</tr>
<tr>
<td>SNR</td>
<td>signal to noise ratio</td>
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<td>SVD</td>
<td>Singular value decomposition</td>
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1. INTRODUCTION

1.1. Background

Given the ever higher demands on data rate and unprecedented growth in the number of connected devices, the current fourth generation standards (LTE) will get to limits. To meet these new demands the industry and academia are working on specifications for the next generation of wireless standards. According to the International Telecommunication Union (ITU) recommendation the fifth generation cellular standard (5G) will provide a peak data rate of up to 20Gbps, 1ms end-to-end latency and a cell edge data rate of 1Gbps [1]. To meet those high demands there is a strong tendency towards millimeter-wave (mmW) communication. The main advantage of mmW communication is the possibility to allocate large bandwidths to the commercial sector which allows for very high data rates.

Figure 1: ITU 5G requirements [2]

The propagation channel for mmW communication is inherently different from those at lower frequencies. The mmW has a high penetration loss for most material which lead to a low power for multipath components propagation through walls. In addition to that, the wavelength gets smaller than most physical objects which reduced the effects of diffraction [3]. This gives the radio channel a quasi-optical behavior which can be used to estimate the channel more efficient [4]. With these propagation characteristics the transceiver requires highly directional and steerable antenna beams. To implement such a beamformer a large number of antennas need to be implemented into the device.
Fortunately, the high frequency allows for small antenna elements which enables the implementation of large antenna arrays into similar sized devices.

Compared to the current standards in broadband cellular systems the large available spectrum and use of massive multiple input multiple output (MIMO) communication allows a drastic increase in cell capacity [5]. The current state-of-the-art cellular standard long term evolution advanced (LTE-A) allows the use of limited MIMO up to 8by8 in the uplink and 4by4 in the downlink [6]. With conventional transceiver architectures, an increase in the number of antennas implies more baseband units and power amplifiers. This in turn increases the non signal dependent power consumption which drastically reduced the efficiency of the transceiver. In addition to that, the computational complexity increase the power consumption of the processing unit.

1.2. Thesis goal

To counter these effects a hybrid transceiver design has been proposed. In the hybrid transceiver multiple analog front-ends are combined into a single baseband processing unit, allowing the transceiver to reduce the complexity of the digital signal processing as well as the power consumption. The focus of this work is on the comparison of different hybrid architectures and their performance during channel estimation, as well as there power consumption. The comparison is made with a 64 antenna hybrid structure with different baseband configuration to evaluate the possibilities and limitations of hybrid designs for future implementations.

For the channel estimation the adaptive-least absolute shrinkage and selection operator (A-LASSO) algorithm is used to leverage channel sparsity during the estimation.

1.3. Thesis outlines

The general structure of the thesis is as follows:

Chapters 2 to 4 describe the theory and general implementation of the simulated models.

Chapters 5 and 6 define the concepts and algorithms used for the signal processing and channel estimation.

In Chapter 7 the specific implementation used for the simulations is described.

In Chapter 8 the simulation results are shown.

Chapter 9 shows the implications of the results and gives an overview over possible future works.
2. RADIO PROPAGATION CHANNEL AT HIGH CARRIER FREQUENCIES

The radio channel describes the electromagnetic propagation from the transmitter to the receiver. If the interfering objects and the receiver are placed far enough from the transmitting antenna, the propagation can be modeled with the far field assumption. This means that the wavefront from the transmitter antennas can be modeled as a single radiation pattern instead of multiple interfering wavefronts from individual antenna elements.

2.1. Free-space model

The simple model for radio propagation is the free-space model, in which only the distance between the transmitter and the receiver is considered. The electric field of the signal \( \cos(2\pi ft) \) in free-space is normally described as [7]

\[
E(f, t, r, k) = \frac{\Upsilon_e(k) \cos 2\pi f (t - \frac{r}{c})}{r},
\]

where \( r \) defines the distance from the transmitter antenna, \( t \) is the time, \( f \) is the transmitted frequency, \( c \) denotes the speed of light and \( \Upsilon_e(k) \) describes the radiation pattern of the transmitting antenna which depends on the direction of propagation \( k \) that can be defined as

\[
k = \frac{2\pi f}{c} \begin{bmatrix} \sin \Theta \cos \phi \\ \sin \Theta \sin \phi \\ \cos \Theta \end{bmatrix}
\]

where \( \phi \) defines the azimuth and \( \Theta \) is the elevation.

For this work the azimuth \( \phi \) defines the counterclockwise angle from the x-axis in the xy-plane and the elevation \( \Theta \) defines the angle from the xy-plane to the positive z-axis (see Figure 2).

![Figure 2: Relation between the spherical and Cartesian coordinates](image)
The transformation from the spherical to the Cartesian coordinate system is defined as

\[
x = r \sin \Theta \cos \phi \\
y = r \sin \Theta \sin \phi \\
z = r \cos \Theta
\]  
(3)

In Equation (1) it can be seen that the electric field decrease over distance relative to \( r^{-1} \) which results in a power decreases per \( m^2 \) relative to \( r^{-2} \). Integrated over a sphere around transmitter the power stays the same as the area of the sphere increase with \( r^2 \) over distance. Most current standards operate below 10GHz where the electromagnetic waves penetrate air almost without attenuation. At higher frequencies the water and oxygen molecules start absorbing some of the signal energy. The strength of this attenuation can be added to Equation (1) so that the free-space electric field \( \cos(2\pi ft) \) is defined as

\[
E(f, t, r, k) = \frac{\mathcal{E}_0(k) \cos 2\pi f(t - \frac{r}{c})}{r} \alpha(r, f),
\]  
(4)

where \( \alpha(r, f) \) defines the atmospheric attenuation at the frequency \( f \) and over the distance \( r \). The attenuation in the air for different frequencies can be seen in Figure 3.

![Figure 3: Average millimeter-wave atmospheric absorption [8] ©2009 IEEE](image)

Higher attenuation limits the propagation distance and with that the coverage area. For instance 60GHz systems are defined as short-range communication and thereby the main goal is to get high signal to noise ratio (SNR) over a short link [8]. These systems are usually used in a line of sight (LOS) or single reflection configuration. The limited propagation distance allows a high frequency reuse factor. In applications such as live video steaming within the same room the maximum distance is insignificant but the data throughput and latency are crucial. Other possible applications are in mobile virtual reality or remote desktop devices where the wireless link is limited to a single room [9].
In order to describe the channel between transmitting and receiving antenna ports, the radiation pattern of the receiving antenna needs to be taken into account and the transmitted signal needs to be excluded. Thus, we obtain

\[ H(f, r, k^{TX}, k^{RX}) = \frac{\gamma_e(k^{TX})\gamma_e(k^{RX})e^{-i2\pi f \frac{r}{c}}}{r} \alpha(r, f), \]  

(5)

where the superscript TX and RX refer to the to the the antennas at the transmitter and the receiver with their respective directions for the line of sight path. Note, that the equation assume the same antenna radiation pattern at the transmitter and the receiver. To show the performance of channel estimators the channels are often assumed to be time and frequency invariant.

### 2.2. Multipath propagation

In a typical indoor or urban environment, the electro-magnetic signal will encounter multiple objects that reflect, diffract or scatter the signal towards the receiver. Every copy of the transmitted signal that arrives to the receivers input has propagated through a different path form the transmitter. In this multipath environment the channel is the complex sum of all the propagation path channels. With independent phase shifts for every path the signals at the receiver can have a constructive or destructive interference depending on the relative phase shift.

To model the channel for a specific environment, the ray tracing model computes the signal strength and phase for every path and sums them together. Under the assumption of a time-invariant narrow-band channel the single antenna physical model with \( P \) paths yields

\[ h = \sum_{p=1}^{P} \gamma_e(k_p^{RX})l_p\gamma_e(k_p^{TX}), \]  

(6)

where \( k_p^{RX} \) and \( k_p^{TX} \) refer to the direction of arrival (DoA) and direction of departure (DoD) for the path and \( l_p \) defined the path loss, including the overall attenuations along the path \( p \) in a environment with \( P \) paths. The total arriving signal is the interference between all paths and there respective antenna gain.

This model is relatively accurate if the nearest scatterer is multiple wavelengths from the antenna and all the scatterers are large relative to the wavelength. This results in better performance for high frequency models due to the shorter wavelength which results in a quasi-optical behavior [4]. Also, due to the limited range of mmW transmission and relatively high attenuation in classical building materials [10] the number of paths that are detectable at the receiver is limited. This results in a sparse scattering environment for mmW transmission.

There has been several approaches to model a statistical channel at mmW frequencies in urban environment [11–13]. They generally use a path loss model that has been fit to some measured data in different cities. In general, the mmW propagation in outdoor environment can be modeled with simple statistical models, similar to those in current cellular standards. However the propagation loss through building materials is much higher than in traditional centimeter wave propagation [11]. There has been some measurement campaigns on the penetration of mmW into buildings and
the propagation within buildings [4, 10]. The measurements in [10] suggest that the communication through building material within modern building is possible while the penetration of outside walls and tainted glass is difficult.

2.3. MIMO channel model

For a multi-antenna design it is theoretically possible to create an independent ray trace simulation for every element of the antenna but this is in most cases not necessary. If the antenna elements of the same transceiver are in close proximity to each other it is possible to model the antenna and the far field channel separately.

More specifically, the single antenna channel model given in Equation (6) can be modified to include the local delays of the antenna elements in an array as follows:

$$H_{RF} = \sum_{p=1}^{P} v(k_p^{RX}, R^{RX})g_p^{RX}(k_p^{RX})l_p g_p^{TX}(k_p^{TX})v^H(k_p^{TX}, R^{TX}),$$  \hspace{1cm} (7)

where $[:]^H$ defines the complex conjugate transpose, $H_{RF} \in \mathbb{C}^{(M^{RX} \times M^{TX})}$ defines the channel matrix with $M^{TX}$ and $M^{RX}$ being the number of antennas at the transmitter and the receiver respectively and $v^T(k, R)$ beeing the wave vector function defined as

$$v^T(k, R) = e^{jk^T R},$$  \hspace{1cm} (8)

where $[:]^T$ defines the complex conjugate and $R \in \mathbb{R}^{3 \times M}$ is the matrix notation of the single antenna element position that are defined column wise indicating the Cartesian coordinates (relative to the antenna center) at the transmitter and the receiver respectively.

In full matrix notation the RF channel in Equation (7) can be described as

$$H_{RF} = V(K^{RX}, R^{RX})g_{e}(K^{RX})A_l g_{e}(K^{TX})V^H(K^{TX}, R^{TX}),$$  \hspace{1cm} (9)

where $A_l \in \mathbb{C}^{P \times P}$ is the path loss matrix defined as $A_l = diag([l_1, l_2, \ldots, l_P])$, $K \in \mathbb{R}^{3 \times P}$ is defined by $K = [k_1, k_2, \ldots, k_P]$ and $V \in \mathbb{C}^{M \times P}$ is the matrix notation of the wave vector function and is defined as

$$V^H(K, R) = e^{jK^T R},$$  \hspace{1cm} (10)
3. HYBRID RECEIVER

As in mmW communication the single antenna elements get smaller, a large number of antennas can be integrated into single device. This gives the opportunity, to consider a transceiver design based on massive MIMO technology. However, it is well known that with a conventional full-digital architecture, every antenna would need its own RF front-end as well as a separate baseband processing unit. Such a system is for most applications to complex, expensive and power consuming. Additionally, there is a problem of limited space, as the antenna elements start to get smaller than the transceiver chain, the transceiver does not fit behind the antenna array anymore. In this regard, a hybrid design is typically considered to reduce the complexity of the system while maintaining most of the performance [14–16]. The hybrid design used in this work combines several antennas after the RF front-end and feeds them to a single digital baseband. The proposed design can be seen in Figure 4. This design reduced the number of basebands and with that, the computational complexity while maintaining some of the flexibility of a fully digital array.

![Figure 4: Hybrid receiver](image)

The difficulty with the hybrid architecture is to leverage spatial diversity into the communication. The joint optimization of the analog beamformer and the digital beamformer is a problem that has not been solved so far. In most recent papers the problem has been simplified to a form, that known algorithms can optimally solve. For example, in [16] the assumption is, that every analog beamformer has enough antenna elements, so that the beams are non overlapping. This implies, that the digital beamformer is only used as a beam selector and the system can be optimized as parallel independent analog beamformers. In [15] it is considered, that all the RF-beamformers
are steered towards a single direction and, subsequently, it is necessary that the analog beams are wide enough for the required coverage. This in turn limits the number of antenna elements per analog beamformer. The optimization problem is then reduced to a digital beamformer with directional antennas and no adaptive analog beamforming. These two simplification are the extreme versions of the hybrid design and only perform optimally for very small or very large analog beamformers.

3.1. Architecture model

For a single transmission over a MIMO-OFDM channel the transmission can be described as

\[ y = H_{RF}x + \omega, \]  

where \( x \in \mathbb{C}^{M_{TX}} \), \( y \in \mathbb{C}^{M_{RX}} \) and \( \omega \sim \mathcal{N}(0, N_0I_{M_{RX}}) \) define the transmitted signal, received signal and additive white gaussian noise AWGN, respectively.

By including the beamformer for single symbol, Equation (11) can be written as

\[ \tilde{y} = w_{RX}^H H_{RF} w_{TX} \tilde{x} + w_{RX}^H \omega, \]

where \( \tilde{x} \) and \( \tilde{y} \) define the representation of the symbol at the transmitter and the receiver, \( w_{TX} \) defines the beamformer at the transmitter and \( w_{RX} \) defines the beamformer at the receiver. In the sequel we focus on the receiver beamformer \( w_{RX} \) and analyze the implications due to the hybrid architecture\(^1\). For the sake of clarity, we simplify the notation by replacing \( w_{RX} \) with \( w \).

The beamformer \( w \) defines all the complex operations between the symbol representation and the antenna port. By splitting the beamformer into analog and digital components, it yields

\[ w = w_{BB} A_T \text{diag}(w_{RF}), \]

where \( \text{diag}(\cdot) \) defines the diagonal matrix representation, \( w_{BB} \in \mathbb{C}^{N} \) and \( w_{RF} \in \mathbb{C}^{M} \) represent the digital and analog beamformer and \( A \in \mathbb{R}^{M \times N} \) is a block diagonal matrix that defines the configuration of the hybrid architecture with \( N \) and \( M \) defining the number on basebands and front-ends, respectively. More specifically, it defines how many antennas are combined after the analog beamformers to a single baseband unit. It results, that the analog beamformer is splitted into small, independent analog beamformers, which are combined with the digital beamformer. For the sake of illustration, an eight antenna combiner matrix is defined first with four basebands (\( A_4 \in \mathbb{R}^{8 \times 4} \)) and than with two basebands (\( A_2 \in \mathbb{R}^{8 \times 2} \))

\[ A_4^T := \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}, \quad A_2^T := \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{bmatrix}. \]

The columns of \( A \) define an analog combiner (summation) of all the front-ends that are non zero in the column.

\(^1\)We omit the analysis of the transmit beamformer as, the same model can be applied.
The single element of $w$ are computed as

$$w_n = w_{BB} a_n w_{RFn},$$  \hspace{1cm} (15)$$

where $a_n$ defines the $n$th row of the matrix $A$ and $w_{RFn}$ specifies the $n$th element of $w_{RF}$. As every element of $w$ is linearly dependent of a specific element of $w_{RF}$, $w$ can be controlled by only controlling the analog beamformer $w_{RF}$. Due to the fact that analog beamformers operate on the analog signal, they are constant over frequency, in addition the signal needs to be divided to multiple beamformers to introduce spatial multiplexing. On the other hand, digital beamformers operate on the OFDM symbols and might vary per subcarrier. There is also no loss in dividing the signal into multiple digital beamformers, which allows the use of spatial multiplexing without additional analog components or losses. For multiple implementations of the digital beamformers, in frequency or spatial multiplexing, the Equation (12) can be expanded to

$$\tilde{y} = W_{RX}^H H_{RF} W_{TX} \tilde{x} + W_{RX}^H \omega,$$  \hspace{1cm} (16)$$

where $\tilde{x} \in \mathbb{C}^S$ and $\tilde{y} \in \mathbb{C}^S$ are the representation of the S-parallel transmitted symbols at the transmitter and the receiver, $W_{RX} \in \mathbb{C}^{M_{RX} \times S}$ defines column wise the parallel beamformers at the receiver and $W_{TX} \in \mathbb{C}^{M_{TX} \times S}$ defines column wise the parallel beamformers at the transmitter.

The same expansion to parallel symbols can be made on Equation (13) which result in

$$W = W_{BB} A \text{diag} (w_{RF}),$$  \hspace{1cm} (17)$$

where $W_{BB} \in \mathbb{C}^{N \times S}$ contain a set of digital beamformers. The limitation in this kind of configuration with hybrid transceiver is, that the analog beamformer limits the directions where the digital beamformer can operate.

### 3.2. Power consumption model

The RF and analog power consumption of a transceiver is difficult to predict. As the design of amplifiers and waveforms for the hybrid design is an active research topic, the modeling of the transmitter power consumption was not attempted during this work. To still get an estimate of the reduction in power consumption, a model for a hybrid receiver which is mostly independent of the analog signal, was designed. The designed model does not include the power consumption of the digital signal processing unit and focus only on the consumption of in the analog components. There has been some implementations of mmW antenna arrays [17, 18] which are used for reference and simulation parameters in the model.

There are some component that are needed and do not depend on the number of antennas or the hybrid structure. The most power consuming of these is the frequency synthesizer($P_{SX}$). The power consumption of frequency synthesizers depends strongly on the frequency and bandwidth that is required. Other than that, the local oscillator (LO) and synchronization loop use additional power ($P_{LO}$), which does not depend on the size of the receiver. To distribute the LO frequency to all the parallel analog receiver units some additional power in the line drives ($P_{LOdist}$) in needed. The high
speed clock for the digital signals processing is not included in the model as it is
considered as a part of the digital signal processing unit.

The power consumption of the low noise amplifier as well as the per antenna phase
shifter are combined to a simple front end power consumption ($P_{FE}$). Similar to that
the down conversion and analog IQ filtering is combined to a single baseband power
consumption ($P_{BB}$). The model assumes that the signals between the front end and the
baseband are combined by using active combiners to compensate for additive losses
when analog beamformer gets larger. Those consume additional power ($P_{comb}$).

To get a good estimate of what the analog-to-digital converters (ADC) power con-
sumption would be it is important to define some requirements for the ADC first. The
sampling rate $f_s$ needs to be at least twice the bandwidth of the channel. By looking
at current trend in bandwidth development and the demanded data rates, the estimated
bandwidth for a 5G system is around 1GHz. This requires a ADC that has a sampling
rate of at least 2 gigasample per second. To do beamforming in the digital signal pro-
cessing the resolution of the ADC should be around 12bits. All this contributes to the
high power consumption ($P_{ADC}$) of the ADC used in this model.

The total power consumed by the analog part in the hybrid receiver is defined as

$$P_{RX} = NP_{FE} + (N - M)P_{comb} + (P_{BB} + P_{LOdist} + 2P_{ADC})M + P_{SX} + P_{LO}, \quad (18)$$

Note that every baseband requires two ADC’s to detect a quadrature amplitude mod-
ulated (QAM) signal, this results in the number of ADC’s being twice the number of
basebands. In the illustration of an analog beamformer in Figure 5 it can be seen, that
every baseband needs $N/M - 1$ combiners, which sums to a total of $N - M$ combiners.
In our model all the combiners are modeled as active combiners.

Figure 5: Structure of a single baseband receiver used in [17]©2011 IEEE
4. ANTENNA ARRAY THEORY

In the IEEE standard an antenna is defined as "That part of a transmitting or receiving system that is designed to radiate or to receive electromagnetic waves." [19]. In other words an antenna is a device that transforms electromagnetic waves in the air to electrical waves in a conductive medium. In this chapter the focus is not on the radiation mechanism, but on the far field radiation pattern and effects of multi-antenna designs [20, 21].

4.1. Radiation pattern

The radiation pattern $\Gamma_c(k)$ defines the gain of a antenna as a function of the wave vector $k$. This makes the radiation pattern only depend on the geometry of the antenna element and interfering object in close proximity such as the substrate. The gain does not depend on the modulation or strength of the signal. Tools such as CST Microwave Studio™ are specially designed to simulate the radiation pattern of antennas in a three dimensional environment. For this work a square patch antenna on a substrate has been simulated in CST Microwave Studio™. It is assumed that the effects of objects in the vicinity of the antenna as well as correlation between antenna elements in an antenna array are negligible.

![Figure 6: Single patch antenna pattern](image)

In Figure 6 an approximation of the antenna element as well as the simulated radiation pattern can be seen. The magnitude of the radiation pattern is defined in decibel-isotropic dBi which is in the definition of the antenna gain described as "The ratio
of the radiation intensity in a given direction to the radiation intensity that would be produced if the power accepted by the antenna were isotropically radiated." [19].

4.2. Antenna array gain

The array gain pattern is defined as

$$\mathcal{Y}(\mathbf{k}, \mathbf{w|R}) = \sum_{n=1}^{N} \mathcal{Y}_e^n(\mathbf{k}) w_n e^{-j\mathbf{k}^T \mathbf{r}_n},$$

(19)

where \( \mathcal{Y}_e^n \) defines the antenna pattern of the \( n \)th antenna element.

If all the antenna elements have the same single element pattern \( \mathcal{Y}_e \) the Equation (19) can be rewritten as

$$\mathcal{Y}(\mathbf{k}, \mathbf{w|R}) = \mathcal{Y}_e(\mathbf{k}) \sum_{n=1}^{N} w_n e^{-j\mathbf{k}^T \mathbf{r}_n},$$

(20)

which can be simplified to

$$\mathcal{Y}(\mathbf{k}, \mathbf{w|R}) = \mathcal{Y}_e(\mathbf{k}) AF(\mathbf{k}, \mathbf{w|R}),$$

(21)

where the Array factor function \( AF(\mathbf{k}, \mathbf{w|R}) \) described the array gain pattern for an omnidirectional antenna array. It is often used to describe the functionality of antenna arrays without considering a specific antenna element [7].

With a simple beamformer where

$$w_n = 1 \quad \forall n = 1, \ldots, N$$

(22)

the maximum gain of the antenna array is towards the broadside and increases linearly with the number of antenna elements

$$max(\mathcal{Y}(\mathbf{k}|\mathbf{w}, \mathbf{R})) = N\mathcal{Y}_e(\mathbf{k}),$$

(23)

while also increasing the directivity.

For illustration we assume a equally spaced antenna array of eight by eight antenna elements with element spacing of \( \lambda/2 \). By using the same patch antenna as in Figure 6 the broadside array pattern result in the pattern seen in Figure 7.
4.3. Phased array beamforming

The advantage of antenna arrays over other directional antennas is, that the gain pattern can be adjusted with the values of $w$. There are many different ways how to optimize the values for $w$ depending on the requirements for the gain pattern. The simplest beamformer is the phase array where the phase of every array element is set to maximize the array factor towards a specific direction. This optimization problem can be written as

$$ w = \arg \max_{w \in \mathbb{C}^N} |AF(w|k_d, R)| $$

subject to $|w_n| = 1 \quad \forall n = 1, \ldots, N$.

where $k_d$ is the wave vector for the desired direction. The optimization constraint indicates that $w$ is only depending on its phase so that

$$ w_n = 1 e^{j \beta_n}; $$

where $\beta_n$ defines the phase shift for the $n$th antenna element. Therefore, by using Equation (20) and Equation (25), the aforementioned optimization problem can be rewritten as

$$ b = \arg \max_{b \in \mathbb{R}^N} \left| \sum_{n=1}^{N} e^{j \beta_n} e^{-j k_d^T r_n} \right|, $$

where $b$ is the vector notation of the angles $\beta_n$. The sum of complex numbers is maximized if all numbers have the same complex angle. More specifically, we can
obtain a closed form solution of the optimization problem shown in Equation (26) by computing $\beta_n$ from

$$e^\alpha = e^{j\beta_n} e^{-jkd_n} \quad \forall n = 1, \ldots, N,$$

(27)

where $\alpha$ is an arbitrary fixed angle.

For example, with an angle of $\alpha = 0$ the beamformer parameters are

$$w = e^{jkd_R},$$

(28)

In Figure 8 the same antenna array as in Figure 7 has been steered towards $kd = k(30, 30)$. The maximum gain is a little lower than in the broadside case as the antenna element gain is a little lower towards $k_d$.

![Figure 8: 8by8 antenna array ($\Theta = 30, \phi = 30$)](image)

4.4. Beamformer amplitude control

There are several methods to improve on the beams shape by controlling the amplitude of the beamformer coefficients $w_n$. The dimensioning of these amplitude values has a lot of similarities with the design of filter coefficients. In [21] there has been two ways described to reduce the side lobes.

The first method is the binomial array where the amplitudes of the beamformer coefficients follows $(1 + x)^n - 1$. This binomial formula can be expanded into a series expansion where the amplitudes follow the Pascal’s triangle. The coefficients for different sized beam formers can be seen in the Pascal’s triangle Figure 9.
\[ n = 0: \quad 1 \]
\[ n = 1: \quad 1 \quad 1 \]
\[ n = 2: \quad 1 \quad 2 \quad 1 \]
\[ n = 3: \quad 1 \quad 3 \quad 3 \quad 1 \]
\[ n = 4: \quad 1 \quad 4 \quad 6 \quad 4 \quad 1 \]
\[ n = 5: \quad 1 \quad 5 \quad 10 \quad 10 \quad 5 \quad 1 \]
\[ n = 6: \quad 1 \quad 6 \quad 15 \quad 20 \quad 15 \quad 6 \quad 1 \]
\[ n = 7: \quad 1 \quad 7 \quad 21 \quad 25 \quad 25 \quad 21 \quad 7 \quad 1 \]

Figure 9: Pascal’s triangle

For the 8 by 8 example array these amplitudes go from 1 to 625. This will be too much dynamic range for most power amplifiers which makes this amplitude control scheme often not practical. Especially if the amplitude constraint is per antenna element the gain of the main beam gets reduced quite drastically. The gain pattern with the reduced side lobes can be seen in Figure 10. The cost for lower side lobes is a wider main beam with less gain towards the target direction \( k_d \).

Figure 10: 8by8 Binomial beam pattern (\( \Theta = 30 \), \( \phi = 30 \))

A tradeoff between the binomial design and no amplitude control is the Dolph-Chebychev amplitude control first described by Dolph in [22]. Similar to the classical Chebychev filter design the objective is to reduce the highest side lobe (ripple in filters) while minimizing the beam width. For the amplitude design the side lobe levels are
fixed to a desired level. The classical Chebychev polynomial has equal ripples with a peak magnitude of one in the range of -1 to 1 and are defined as

\[ T_0(z) = 1 \]
\[ T_1(z) = z \]
\[ T_n(z) = 2zT_{n-1}(z) - T_{n-2}(z) \quad n = 2, 3, \ldots \]

where \( z \in \mathbb{C} \) is the variable form the z-Transformation which is used to simplify the notation of the Parameters. The concept of the Dolph-Chebychev amplitude control is, to match the AF to the Chebychev polynomial, so that the desired ripple of magnitude one defines the side lobes of the beam. For a two dimensional array the factor is calculated for every dimension independently and then multiplied by each other to get the beamformers in two dimensions. For a linear eight antenna array with equal element spacing of \( \lambda/2 \) the AF can be written as

\[ AF = \sum_{n=1}^{4} w_n \cos[(2n - 1)\pi \cos \Theta/2], \]

By computing the z transformation and replacing \( \cos(u) \) with \( z/z_0 \), Equation (30) can be rewritten as

\[
AF = w_1 \cos(u) + w_2 \cos(3u) + w_3 \cos(5u) + w_4 \cos(7u) \\
= z/z_0[w_1 - 3w_2 + 5w_3 - 7w_4] + z^3/z_0^3[4w_2 - 20w_3 + 56w_4] \\
+ z^5/z_0^5[16w_3 - 112w_4] + z^7/z_0^7[64w_4],
\]

The variable \( z_0 \) is defined as the point where the side lobe reaches the eight Chebychev parameter

\[ S = T_8(z_0) \]

which defines

\[ z_0 = \cosh \left[ 1/7 \cosh^{-1}(S) \right], \]

For a side lobe of \( S = 10dB \) the variable \( z_0 \) is equal to 1,0928. With this value and the polynomial in Equation (31) the amplitudes for the different antenna elements can be calculated as

\[
T_7 = -7z + 56z^3 - 112z^5 + 64z^7 \\
T_7 = AF_8 \\
64z^7 = 64w_4/z_0^7 \quad w_4 = w_5 = 0.6187 \\
-112z^5 = 16w_3 - 112w_4/z_0^5 \quad w_3 = w_6 = 0.8315 \\
56z^3 = 4w_2 - 20w_3 + 56w_4/z_0^3 \quad w_2 = w_7 = 1.3598 \\
-7z = w_1 - 3w_2 + 5w_3 - 7w_4/z_0 \quad w_1 = w_8 = 1.8614
\]

With this beamformer the relative power levels between the highest and lowest antenna is reduced to 9.05 compared to the 625 for the binomial method. In Figure 11 the array gain pattern for a Dolph-Chebychev beamformer receiver with the same 8by8 antenna array can be seen. The Dolph-Chebychev amplitude control is only one in many
possibilities how to adjust the power of individual antennas to optimize the array pattern for different criteria.

Figure 11: 8by8 Dolph-Chebychev beam pattern ($\Theta = 30, \phi = 30$)
5. MIMO SIGNAL PROCESSING

It has been shown in several papers that a multi-antenna design has the potential to increase the link performance. There are different performance metrics depending on the use case. In some implementations the reliability and SNR are the most important values where in others the throughput needs to be maximized. In both cases a MIMO system can outperform a classical single antenna link. In this chapter, the difference between spatial diversity and spatial multiplexing is explained. The difference between the two ways is in simple terms, that in diversity the same symbol is sent towards all the paths in the channel while in multiplexing the goal is to sent different symbols over the different paths.

5.1. Spatial diversity

The concept of diversity is to sent redundant information across independent fading channels. The improvement in performance comes from the fact, that there is a low probability that all the channels, where the information is sent, are in deep fade. The redundant information can be created by simply repeating the transmitted symbol or by using codes that allow the receiver to reconstruct the transmitted data even if some parts of it are compromised or missing. Almost all current standards use diversity to compensate for fast fading channels as they are very difficult to measure in real time. In time or frequency diversity the performance only improves if the redundant information is sent over uncorrelated channels.

![Figure 12: SIMO channel diversity](image-url)

Figure 12: SIMO channel diversity

The simplest form of spatial diversity is that for example the receiver has a second antenna as can be seen in Figure 12. If the channels to the first antenna and that to the second antenna are uncorrelated the chance that both antennas are in a deep fade at the same time is smaller. This increase the reliability of the link without an increase in time or frequency usage. The diversity is indicated as the number of independent fading channels and would be in this case indicated as diversity 2. To further increase the diversity it is possible to add more receiver antennas. In a single input multiple output (SIMO) transmission the diversity is defined by the number receiver antennas.
For the reverse communication with multiple input single output (MISO) the number of independent fading channel is equal to the number of transmit antennas. This implies, that in the same configuration the up and down link have the same diversity as they have the same number of independent fading channels.

If we take the example of Figure 12 and add a second antenna at the transmitter the number of channels increased from two to four, as can be seen in Figure 13. In a MIMO system with uncorrelated channels the diversity is defined as number of transmit antennas times the number of receiver antennas.

![MIMO channel diversity](image)

Figure 13: MIMO channel diversity

The limitation of spatial diversity is that the antennas at the transmitter and the receiver are usually in close proximity. The antenna spacing is limited by the physical size of the device. This limited spacing yields a high correlation between the different channels and reduces the performance gained by diversity. In case of high correlation it is possible to use beamforming, also referred to as spatial filter, to reduce the impact of interference and noise.

### 5.2. Spatial multiplexing

For a fully digital receiver the MIMO transmission can be described according to the Equation (11) as

$$y = Hx + \omega,$$

where $H$ defines the channel between the digital-to-analog converter (DAC) and the analog-to-digital converter (ADC). The received noise signal is assumed as additive white gaussian noise (AWGN). The assumption of AWGN can be made if the noise is mostly thermal noise and amplified version there of.

The spectral efficiency of a AWGN channel can be computed as

$$C_{awgn} = \log (1 + SNR),$$

which defines the maximum achievable spectral efficiency through a single antenna AWGN channel [23]. To compute the spectral efficiency of the MIMO channel, the
idea is to decompose the MIMO channel into parallel AWGN channels. Hence, the spectral efficiency of a MIMO channel is given by

$$C_{MIMO} = \sum_{i=1}^{n_{min}} \log \left( 1 + \frac{P_i \lambda_i^2}{N_0} \right),$$

(37)

where \(n_{min}\) is equal to the rank of the channel matrix, \(\lambda_i\) define the singular values of the channel matrix, \(N_0 \in \mathbb{R}\) is the total received noise power and \(P_1, \ldots, P_{n_{min}}\) are the waterfilling power allocations:

$$P_i = \left( \mu - \frac{N_0}{\lambda_i^2} \right),$$

(38)

with \(\mu \in \mathbb{R}\) defined that the total power is limited [7]. Essentially the MIMO spectral efficiency is defined by decomposing the channel matrix into \(n_{min}\) parallel AWGN channels. This decomposition can be obtained from a the singular value decomposition of \(H\), i.e.,

$$H = U \Sigma V^H,$$

(39)

where \(U \in \mathbb{C}^{M_{RX} \times M_{RX}}\) and \(V \in \mathbb{C}^{M_{TX} \times M_{TX}}\) are rotation unitary matrices, consisting of the right and left singular vectors of \(H\) and \(\Sigma \in \mathbb{R}^{M_r \times M_t}\) is a rectangular matrix with the singular values \(\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_{n_{min}}\) of \(H\) on the main diagonal. As there are only \(n_{min}\) singular values the Equation (39) can be written as

$$H = \sum_{n=1}^{n_{min}} \lambda_n u_n v_n^H,$$

(40)

where \(u_n\) and \(v_n\) are the right and left singular vectors for the singular value \(\lambda_n\).

Recall that a unitary matrix \(U\) satisfies

$$U^T U = U U^T = I,$$

(41)

where \(I\) defines the identity matrix. If we define the pre-processing and post-processing as

$$\tilde{x} = V x$$

$$\tilde{y} = U^H y$$

$$\tilde{\omega} = U^H \omega,$$

(42)

the transmission in Equation (11) can be written as

$$\tilde{y} = U^H H V \tilde{x} + \tilde{\omega},$$

(43)

which can be simplified by including Equation (39) and the property in Equation (41) into

$$\tilde{y} = \Lambda \tilde{x} + \tilde{\omega},$$

(44)

which described in essence \(n_{min}\) parallel AWGN channels [7]. The concept behind MIMO capacity and spatial multiplexing is summarized in Figure 14.
In the single link MIMO theory the resource allocation over these parallel channels follow the waterfilling algorithm to achieve optimal performance. If the channel is extended to multiple users, the maximum overall throughput, which is still achieved with waterfilling, is often not the desired transmission scheme as a certain fairness between the users is normally desired. The optimal resource allocation is a active research topic as it is always a trade off between many different aspects such as quality of service (QoS), latency and power consumption [24–26].

Figure 14: MIMO spatial multiplexing [7]
6. SPARSE CHANNEL ESTIMATION WITH HYBRID TRANSCEIVERS

In the last decade, there has been extensive research in compressive sensing and sparse compression. In many modern engineering problems the cost of sensing at sufficient speed and accuracy exceeds the practicality. In most cases the sensing does not fully exploit the structure of the signal. For example a band limited contiguous signal can be transformed by the Fourier transformation into a sparse signal. If the dimension where the system is sparse is known the recovery of an under sampled signal can be achieved [27].

6.1. Compressed sensing of sparse signals

The compressed sensing can be understood as a recovery technique for a signal vector \( z \in \mathbb{C}^n \) from which only \( m \) linear projections have been sampled. The equations describing the sampling can be written as

\[
y = Tz,
\]

(45)

where \( T \in \mathbb{C}^{m \times n} \) and \( y \in \mathbb{C}^m \) with \( m < n \). This is an under determined system of equations as there is more unknown than equations. This means that the problem has an infinite number of solutions for the vector \( z \) and can only be determined if some additional constraints are introduced. The additional information used in compressed sensing is that the searched signal is structured and can be represented as a \( k \)-sparse linear transformation. \( k \)-sparse means that the signal has only \( k \) nonzero elements. To be sure that the signal can be recovered some additional constraints to the structure of \( T \) are needed.

Lets assume we have to sample a perfect band limited single-tone signal, which is represented in the Fourier domain as an all zero vector with only a single entry at frequency. The signal has a \( 1 \)-sparse representation in frequency. The sampling can be represented as

\[
x = A_{DFT} z_f,
\]

(46)

where \( z_f \) represents the frequency vector, \( A_{DFT} \) is the Fourier transformation matrix and \( x \) defines the samples in time. If it is known at the receiver that the signal is \( 1 \)-sparse, only a small number of samples are required to recover the frequency vector \( z_f \).

To recover the sparse signal \( z \) we have to find the solution where \( z \) has the minimum \( L_0 \) norm. The problem can be written as a classical optimization in the form of

\[
z = \arg \min_{z \in \mathbb{C}^n} ||z||_0 \quad \text{subject to} \quad y = Tz,
\]

(47)

where \( ||.||_q \) represent the q-norm. In [28], it has been shown that if \( m > 2k \) and \( z \) has \( k \)-sparse representation in the space spanned by the column of \( T \), then the solution to Equation (47) exists and is unique. Unfortunately, direct \( L_0 \) norm minimization is a non-deterministic polynomial-time (NP) hard problem.
The solution is to convert NP-hard problem into a convex optimization problem that can be solved with well known and efficient algorithms. The simplification that is usually used in compressed sensing, is that the L0 norm is replaced with a L1 norm. The equation in Equation (47) can be rewritten as

\[
    \mathbf{z} = \arg \min_{\mathbf{z} \in \mathbb{C}^m} ||\mathbf{z}||_1
    \]

subject to \( \mathbf{y} = \mathbf{Tz} \),

which is a convex problem that is capable of finding \( \mathbf{z} \) if the sensing matrix \( \mathbf{T} \) has some specific properties, namely described by the Restricted Isometry Property (RIP) [29]. The RIP basically define, that representation in the space spanned by the column of \( \mathbf{T} \) does not collapse or stretch to infinity. To verify that a matrix meets these additional constraint is also a NP-hard problem that is not feasible. Interestingly a random matrix \( \mathbf{T} \) has been shown to satisfy the constrained in RIP in all but a few cases. A more detailed description on the limitations of the L1 optimization in sparse sensing can be found in [27].

### 6.2. Application to channel estimation

To measure a MIMO channel with traditional channel estimators every link of the channel matrix \( \mathbf{H} \) need to be sounded and estimated separately. For a large number of antennas as in massive MIMO this kind of estimator will be to complicated and time consuming. For a large number of antennas and a limited number of propagation paths the channel matrix \( \mathbf{H} \) is sparse in the directions of arrival and departure for the different paths. In case of a sparse matrix the assumption is that every path comes from a different direction that can be sampled independently with spatial filtering (Beam-forming). The idea behind sparse channel estimation is to estimate the channel while taking advantage of the sparse representation of the channel in the spatial domain.

The basic concept of the algorithm used in this estimator, is to find the maximal sparse representation of the channel while minimizing the number of pilots that are used to find that estimation. Given that the pilots are known at the receiver and the channel has a sparse representation the problem can be stated as

\[
    \mathbf{z} = \arg \min_{\mathbf{z} \in \mathbb{C}^{2^N}} ||\mathbf{z}||_1 + \frac{1}{2} ||\mathbf{y} - (\mathbf{XW}_{TX} \otimes \mathbf{W}_{RX})\Psi\mathbf{z}||_2^2 ,
\]

where \( \mathbf{X} \) and \( \mathbf{Y} \) define the transmitted and received signals during the pilots sequence, \( \lambda \) defines the weighting between the sparsity and the least square (LS) optimization, \( \otimes \) defines the Kronecker product, \( \Psi \) is the dictionary that defines the supports of the sparse channel representation and \( \mathbf{z} \) is the sparse channel representation.

Equation (49) can be separated into the sparsity maximization \( ||\mathbf{z}||_1 \) and the LS-channel estimation. This optimization problem is well known in the literature as the Least Absolute Shrinkage and Selection Operator (LASSO) problem and numerous algorithms exist to compute the vector \( \mathbf{z} \).

The limitation in the LASSO optimization is, that the dictionary \( \Psi \) is assumed to be known. Similar to other sparse sensing problems the difficulty is to find the optimal support as well as the optimal sparse solution. During this simulation work the
Adaptive-LASSO algorithm has been used to jointly optimize the dictionary as well as the channel sparsity [30].

The basic concept behind the A-LASSO algorithm is to jointly optimize the sparse representation of the channel and find the ideal supports to do so. The algorithm first defines a dictionary of evenly distributed supports (called atoms in the paper). In the second step the supports, within the dictionary, that perform best in the LASSO optimization are computed. With these $L$-best supports a new dictionary is generated that creates supports around the $L$-best supports from the first iteration. The new dictionary can be seen as a focusing of the dictionary towards the supports that performed well in the previous iteration. The same process is repeated until all the supports in the dictionary are in tight clusters around the actual sparse supports of the channel. For the final channel estimate the dictionary supports are clustered and the center of these clusters is fixed as the support estimate of the algorithm.

![Figure 15: A-LASSO dictionary supports](image)

For our simulation the algorithm creates the dictionary over elevation and azimuth at the receiver and the transmitter. To illustrate the way the algorithm works the intermediate steps of the estimator implementation are shown in Figure 15. The dictionary during the simulation consists of 4096 supports which are evenly spaced in the four dimensions. This results in eight dictionary entries per angular direction. In Figure 15a the hundred best performing supports with their respective LASSO values are plot-
ted in two out of the four dimensions. Note that some of the values are on the same position as the supports are in four dimensions.

The 4096 supports for the second iteration are randomly distributed in the four dimensions around the 100-best supports selected in Figure 15a. From this new dictionary the best 100-best supports are selected again and can be seen in Figure 15b. The supports that are selected are clearly moving closer together and allow a higher resolution around channels ideal sparse support. The same plot has been made for three and four iterations (Figures 15c and 15d) where it can be seen that more than three iterations do not result in a significant improvement in a four dimensional A-LASSO algorithm. The final output of the algorithm is the mean support of the selected cluster values in the last iteration.
7. SIMULATOR CONFIGURATION

7.1. System model

For the simulations a single-link MIMO-OFDM communication is considered. The simulations are run at a center frequency of 26.5GHz with a bandwidth of 153.6MHz separated into 2048 subcarrier. Both the transmitter and the receiver have a hybrid structure which is described in more detail in Chapter 3. The transmitter and the receiver consist each of 64 antennas in a 16 by 4 equally spaced antenna array with an element spacing of $\lambda/2$ at the center frequency. The analog beamformer modeled is a phased array with no amplitude control.

The transmit power during the pilots is set to 30dBm per antenna, equally distributed over all the subcarriers. To keep the sampling time for the estimation at a single OFDM symbol the pilots are transmitted over parallel subcarriers. The assumption that the different subcarriers are seeing the same channel can be made, if all the pilot subcarriers are well within the coherence bandwidth. For a channel outside of the coherence bandwidth a separate channel estimation needs to be made. For this work it is assumed that all the pilots propagate through the same multipath channel.

![Free space loss](image)

Figure 16: Free space loss

To show the advantage of using antenna arrays Figure 16 shows the SNR over position with a single omnidirectional antenna at the transmitter and the receiver. In comparison the ideal configuration with 64 antenna element arrays and perfect alignment can be seen in Figure 17. The higher SNR with the use of the antenna array comes from the directive antenna pattern. With large antenna arrays it is possible to create very narrow beams that can yield a high SNR if they are perfectly aligned.
For every channel implementation the A-LASSO channel estimator estimates the direction of the strongest path at the transmitter and the receiver. With no prior information the algorithm spreads the analog beams over all the directions that are within the cell. Because of the implementation in the analog beamformer the receiver can only steer but not otherwise manipulate the analog beams. This can result in scenarios where the analog beams are too narrow to cover all the directions.

The A-LASSO algorithm on a single sample of evenly spread analog beams can estimate the rough direction of the beamformer but might not be able to achieve an accurate enough estimate to align pencil beams to communicate. To get a better estimate of the path direction the analog beamformers are steered towards the estimated direction from the first sample and a new sample is taken. This second iteration has a much higher resolution towards the direction where the initial estimation is placed and the A-LASSO algorithm can do a more accurate estimation of the direction.

To compare the performance between the different hybrid architectures the performance is evaluated compared to the energy consumption during the estimation. The power consumption is modeled with the model described in Section 3.2 and the parameters in Table 1 and multiplied with the sample time to compute the energy consumption during the estimation. This metric is useful to show the difference between architectures as well as to visualize the penalty of using multiple iterations.
Table 1: Power consumption model parameters

<table>
<thead>
<tr>
<th>Component</th>
<th>Parameter</th>
<th>Power consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front-end [17]</td>
<td>$P_{FE}$</td>
<td>56.25mW</td>
</tr>
<tr>
<td>Combiner [17]</td>
<td>$P_{comb}$</td>
<td>50mW</td>
</tr>
<tr>
<td>Baseband [17]</td>
<td>$P_{BB}$</td>
<td>250mW</td>
</tr>
<tr>
<td>ADC [31]</td>
<td>$P_{ADC}$</td>
<td>3500mW</td>
</tr>
<tr>
<td>Local oscillator [17]</td>
<td>$P_{LO}$</td>
<td>120mW</td>
</tr>
<tr>
<td>LO distribution [17]</td>
<td>$P_{LOdist}$</td>
<td>50mW</td>
</tr>
<tr>
<td>Frequency synthesizer [17]</td>
<td>$P_{SX}$</td>
<td>150mW</td>
</tr>
</tbody>
</table>

The interest in this work is on different configuration of the hybrid transceivers. To see how the hybrid configuration impacts performance the simulations all have been done for four different configurations. These configurations range from two basebands with 32 antennas per analog beamformer up to 16 basebands with only four antennas per analog beamformer. The four antenna configurations can be seen in Figure 18 where the same colored antenna elements are connected to one baseband.

![Figure 18: Simulated Hybrid antenna configurations](image)

(a) 2 basebands (2nBB)  
(b) 4 basebands (4nBB)  
(c) 8 basebands (8nBB)  
(d) 16 basebands (16nBB)

**7.2. Open air channel model with ground reflection**

For this simulations a simple open air model with a single ground reflection has been used (see Figure 19). The model uses a geometrical model to determine the length and direction of the LOS as well as the ground reflection, which allows the simulator to separately compute the channel for every path. The path loss over distance is modeled
as a simple free space loss without taking into account the atmospheric attenuation or reflection loss.

![Diagram of Openair channel with ground reflection](image)

**Figure 19:** Openair channel with ground reflection

To model the interference between the paths at the receiver the phase difference between the transmitter and the receiver need to be modeled. For an accurate modeling of the multipath interference in a reflected path the polarization of the antennas as well as the reflection characteristic would have to be considered. To show the impact of interference without accurate modeling of the phase shift of every reflection a random phase shift over every path has been introduced. For a two path model this can give some error in the simulation as the relative phase is completely random and does not depend on the position of the antennas. For a larger number of paths the random phase error gets averaged and the accuracy of the model will increase. For the purpose of this simulation the open air channel has been selected as a simplification to show the possibility in cell size and beam steering and not as an actual scenario where a hybrid transceiver would be implemented. With that in mind, the random phase gives a better estimate of the performance as it does not have specific areas where the two paths always interfere destructive or constructive.

In the simulations the antenna array of the transmitter and the receiver are oriented always towards the x or -x coordinate respectively and positioned at one meter off the ground. The transmitter is fixed and the receiver is randomly placed in a sector or ±45 degrees and a maximum distance of 500 meters. For every position and architecture the adaptive A-LASSO has been run with up to four iterations of analog beamforming adaption.

### 7.3. Performance metrics

The performance of a connection can be measured in many different metrics. In most cases the performance metric is the data throughput of the wireless link. With a single-link transmission the maximum channel throughput is directly proportional to the SNR so that it is possible to compare performances by comparing the SNR. There is a random generated noise for every channel instance to that the SNR depends also on the noise level in that particular instance.

The used setup for the channel estimation tries to estimate the direction of arrival and departure of the strongest path in the channels which is in our setup the LOS path. The channel implementation has some random components such as noise and individual phases.
To compare the performance of the estimator for different channels the reference SNR is defined as the SNR of the channel if the transmitter and the receiver steer their beamformer directly towards the LOS of the channel. This reference implementation implies a communication with perfect knowledge about the relative position.

The SNR over position for the reference implementation can be seen in Figure 20. The randomness of the SNR is from the random parameters in the channel implementation. It can be seen that the performance decreases over distance while even at 500 meter distance the SNR is around 15dB.

![Reference beamformer](image)

**Figure 20: Reference SNR for specific positions**

The performance is defined as the difference between the estimator SNR and the reference SNR. For example, if the estimator reaches 50% of the reference SNR the performance is going to be -3dB.
8. PERFORMANCE EVALUATION

To properly show the effects and limitations the performance is evaluated from different perspectives. First, we will look at the average performance over a fixed cell to compare the general performance of the different architectures and the iterative A-LASSO algorithm. This evaluation is done for normal and narrow cells to show the potential in the road or the corridor scenarios for the hybrid design. In the second section we will have a closer look on the beam shapes and the performance over position for specific architectures. The focus here is on the limitations of the hybrid designs due to the analog beam width and beam steering. In the third section the performance is evaluated over angles and distance, to show the tradeoff between range and cell width for the different architectures.

The original motivation for a hybrid design was the reduction in complexity and power consumption. To show the improvement in component count and power consumption in the receiver we will first show general comparison between the simulated implementations and a fully digital design (64nBB) in terms of component count and power consumption.

<table>
<thead>
<tr>
<th>Basebands</th>
<th>RF-front-end</th>
<th>Combiner</th>
<th>ADC’s</th>
<th>LO</th>
<th>Power consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>2nBB</td>
<td>64</td>
<td>61</td>
<td>4</td>
<td>1</td>
<td>15.0W</td>
</tr>
<tr>
<td>4nBB</td>
<td>64</td>
<td>59</td>
<td>8</td>
<td>1</td>
<td>29.7W</td>
</tr>
<tr>
<td>8nBB</td>
<td>64</td>
<td>55</td>
<td>16</td>
<td>1</td>
<td>59.1W</td>
</tr>
<tr>
<td>16nBB</td>
<td>64</td>
<td>47</td>
<td>32</td>
<td>1</td>
<td>118.0W</td>
</tr>
<tr>
<td>64nBB</td>
<td>64</td>
<td>0</td>
<td>128</td>
<td>1</td>
<td>471.1W</td>
</tr>
</tbody>
</table>

In Table 2 it can be seen that the power consumption for a two baseband receiver is only around 3.2% of the power compared to a fully digital receiver. However, the absolute power levels are of a state-of-the-art receiver [17] and shoulder be considered as reference for future implementations, as the computation does not consider future development of manufacturing processes.

8.1. Average performance over cells

To compare the performance over a cell we look at the normalized downlink SNR which is defined as the difference between the SNR with the estimated value and the reference implementation SNR. A normalized downlink SNR below -10dB means that practically none of the users have been detected.

8.1.1. General cell evaluation (90degree)

This first scenario is considered a general use case with a cell angle of ±45 degrees (Figure 21). The performance is averaged over hundred meter cells to show the per-
formance over distance and show the possible range of the different architectures. The colors represent the different simulated structures and the points of the same color represent the same architecture with a different number of estimations.

Over a short range (Figure 21b) the structures with a large number of basebands (8nBB and 16nBB) are performing well already in the first estimation and do not see a big improvement over multiple iterations. The architecture with four basebands on the other hand needs two iterations to reach its maximum performance. Only the 2nBB architecture does not reach a good performance even in the short range over this cell.

The maximum cell size with reasonable performance is somewhere between 200 and 300 meters as can be seen in (Figure 21b). For cell sizes above 300 meters the performance decrease well below acceptable levels. Over the cells where reliable communication is possible the architecture with four basebands outperforms the others.

8.1.2. Narrow corridor cell evaluation (30degree)

In the second scenario, we would like to show average over an angular cell range of only ±15 degrees (Figure 22). Scenarios like this can be found along the roads or in a corridor where all the users are within a specific direction. Same as in the first scenario the performance is averaged over hundred meter cells.

The biggest difference compared to the previous scenario is the performance of the two baseband structure. It can be seen, that it outperforms all the other receivers in almost every cell and is able to reliably estimate the channel until a range of 300 meters (see Figure 22d). There is also some improvement for the four baseband implementation especially for the first estimation. This shows that the ideal hybrid design always depends on the used scenario.

8.2. Positional performance for specific implementations

To visualize the effects that have lead to the performance values as given in the previous section, we would like to show the SNR behavior at different positions. The two considered structures are the two and four baseband implementation. They where selected, because they have performed the best in the previous section and have experienced the biggest improvement over multiple estimations.
Figure 21: Performance comparison for ± 45 degree
(a) Cell illustration

Trade-off between normalized downlink SNR and energy consumption
TX power = 30dBm TXant=64 RXant=64

(b) 0 to 100 meters

(c) 100 to 200 meters

(d) 200 to 300 meters

(e) 300 to 400 meters

(f) 400 to 500 meters

Figure 22: Performance comparison for ± 15 degree
8.2.1. Positional performance with a four baseband architecture (4nBB)

For the four baseband structure the SNR values for the scanning and the first three iterations of the adaptive analog beamformer can be seen in Figure 23. By looking at the change in SNR from the initial scan (Figure 23a) to the first estimation (Figure 23b) only the signals which have SNR around 5dB or above, can be detected by the estimator. To achieve that minimum SNR at the receiver some antenna gain is required at the transmitter as well as the receiver. The antenna gain is directly dependent on the number of elements that are combined. This also indicates, why the structures with more basebands where not able to detect the signal over longer distance.
The accuracy of the estimation not only depends on the SNR of the initial scan, but also on the number of overlapping beams towards the path during the sampling. This can be seen as worse estimations at the cell edges where only a single beam is covering the direction and there is no overlap. If the estimator is able to pick up the signal in the first estimation it will redirect all four analog beams towards the path. In the second sample the analog beams are all overlapping and the estimator is able to do an accurate estimation of the path direction if the path is within the beams (Figure 23c). Additional iterations of the channel sampling and estimation do not improve the performance significantly anymore as the estimation is relatively accurate for the detected signal and can not be improved for the non-detectable signals (see Figure 23d).
8.2.2. Positional performance with a two baseband architecture (2nBB)

To show the effects of the narrow analog beams more clearly the same plots as for the four baseband version can be seen in Figure 24 for two basebands. In Figure 24a it can be seen that the beams are already in the initial scan not able to cover more than half the cell angles. After the first estimation (Figure 24b) the steering directions of the two analog beams during the estimation can be seen clearly. The two beams have basically no overlap, what explains the limited performance towards the center of the cell. With the higher analog beamformer gain it is possible to estimate the channel over a longer range within the limited cell.
With only two analog beams having basically no overlap for the initial scanning the first estimation can be quite far from the target. This can be seen by the continues improvement over multiple iterations as can be seen in Figures 24c and 24d.

8.3. Performance over distance and angle

In Section 8.1 it has been shown that there is some dependency of the performance on the angular range and distance. To define the coverage that can be achieved with a specific hybrid structure the performance in angle and distance are evaluated independently as a continuous function. The plots use a moving average which averages the performance over a specific number of samples. This gives a smoother plot over the whole range but results in some inaccuracies towards the edge of the data which can be seen in both the distance and angular plots.

8.3.1. Performance over distance

For the performance over distance (Figure 25) the angles that are considered are limited to ±15 degrees as all hybrid architectures where able to cover that cell in that angular range.

As already mentioned the scanning SNR depends on the antenna array gain of the analog beams (see Figure 25a). It decreases over distance as can be expected due to the free space loss in the channel. Interesting here is the fact that the SNR for four and eight basebands are almost identical. This could come from the higher overlapping of the analog beams in the eight basebands scanning, that compensate for the lower array gain.

After the first estimation it can be seen that the range of the 16 baseband implementation is limited to a maximum of 100 meters and does not improve over multiple iterations. Similar to the SNR, the first channel estimation seen in Figure 25b performs almost identical for the four and eight basebands implementation, with a little bit longer range for the one with four basebands. With additional iterations of the estimator the four baseband implementation is able to leverage the overlapping of its beams, while the eight baseband version does not increase significantly due to its already good overlap in the initial scanning.

The most significant improvement over the adaptive iterations can be seen with the two baseband implementation. For the first estimation the performance is relatively low due to the fact that the estimator does not have sufficient overlap to accurately estimate users towards the center of the cell. Over multiple iterations it is able to outperform the other architectures and reach the maximum usable range of approximately 300 meters.
8.3.2. Performance over angular range

To evaluate the performance over angles independent of the distance the evaluated performances are limited to a cell of 100 meters.

In the scanning plot (Figure 26a) we can see that in the center of the angular range the SNR depends, similar to the previous section, only on the analog array gain. Towards the sides the limited angular range of the implementation with only two basebands can be seen.

For such a small distance all the estimators are able reach near optimum estimation if they can detect the signal. In the first estimation (Figure 26b) every receiver reaches a good performance, if the LOS path is within the angles where the analog beams overlap. It is clear that with more analog beams a wider area can be covered with overlapping beams. For the two baseband estimation a performance drop in the center of the range can be seen. This comes from the limited overlap the two analog beams of the initial scanner have towards the center of the range. Additional iterations improve the performance in the angle ranges where there has been no overlap of the analog beams (see Figures 26c and 26d). This performance continues to increase until the
range has reached the limits of the initial scanning beams. Any signal that has not been sampled by the initial beams can not be estimated even with multiple iterations of analog beam adaption.

<table>
<thead>
<tr>
<th>Angle [Deg]</th>
<th>SNR [dB]</th>
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<tbody>
<tr>
<td>-80</td>
<td></td>
</tr>
<tr>
<td>-60</td>
<td></td>
</tr>
<tr>
<td>-40</td>
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</tr>
<tr>
<td>60</td>
<td></td>
</tr>
<tr>
<td>80</td>
<td></td>
</tr>
</tbody>
</table>

Downlink SNR with initial beamforming over angle
TX power = 30dBm TXant=64 RXant=64
2nBB
4nBB
8nBB
16nBB

Trade-off between normalized downlink SNR and angle
TX power = 30dBm TXant=64 RXant=64

Figure 26: Performance over angle
9. CONCLUSION AND FUTURE TRENDS

Considering the trend in the current mmW research there is a high probability, that massive MIMO is going to be introduced in future cellular systems. In this thesis was shown the potential of hybrid designs to reduce power consumption in a massive MIMO implementation.

The proposed hybrid design combines analog and digital signal processing to reduce complexity and power consumption in a large antenna array. The design uses analog signal processing to do initial spatial filtering before the analog-to-digital conversion. In contrast to fully analog designs, the hybrid structure is still capable of using spatial multiplexing to serve multiple directions simultaneously.

The thesis has been focusing on the use of the limited spatial multiplexing in combination with the A-LASSO channel estimation algorithm to do efficient channel estimation. The simulations showed that for a single user case a limited number of basebands not only reduce the computational complexity, but also increase the maximal distance for accurate channel estimation. The simulations show that there is a trade-off between range and scanning angle that can be achieved with the same number of pilots.

For the simulated scenario with a $\pm 45$ degree cell the ideal configuration has four basebands with 16 antennas per baseband. As can be seen in Figure 18b every baseband has four antennas in azimuth. This yields a 3dB beamwidth for the analog beams of approximately 25 degree in azimuth [32]. For the initial scanning this means that the beams are less than a 3dB beamwidth apart. This results in a good coverage of the cell with some overlap towards every direction.

This implies, that for a good performance in a $\pm 45$ degree cell, the number of analog beamformers should be equal to the number of antennas per analog beamformer in the same dimension. If the cell gets narrower the number of antennas can be higher than the number of basebands. This effect has been shown in the corridor cell simulations. In this scenario the implementation with two basebands and 32 antennas per baseband (eight in azimuth) produce the best results.

To show the feasibility of the proposed design in a 5G system some additional simulations and tests are needed. As in a first step the simulations need to be extended to support more complex multipath environments as well as multiple users simultaneously. This requires some alterations in the algorithm, especially in the adaptive steering of the analog beams for multiple iterations. With the introduction of multiple users into the simulation the spatial multiplexing during communication needs to be optimized. Another challenge is the analog beam steering for the estimation of a frequency dependent wide band channel.

In general this thesis showed that the potential of simplifying the implementation and computation in massive MIMO systems with a hybrid design. The main challenge is to find the analog beam steering concept to optimally leverage the potential of the hybrid design. It has been shown that, even with a very rudimentary approach to the analog beam steering the hybrid design allows for efficient and fast channel estimation.
REFERENCES


