Channel Estimation and Receiver Design in Single- and Multiuser Multiantenna Systems

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Theses of the Dissertation Submitted for the Degree of Doctor of the Hungarian Academy of Sciences

Contents

Chapter 1
Objectives

Over the past decade, wireless technologies have become the primary enablers of mobile internet services, machine type communications and the networked society at large. It is envisioned that advanced wireless technologies of the networked society will not only provide high bit-rate mobile broadband services at low cost, but they will also enable vehicles, sensors and actuators to form the "Internet of Things". Ultimately, the Internet of Things will transform the way we live, interact, create businesses and manage virtually all segments of society.

Since the late 90's, Multiple Input Multiple Output (MIMO) systems have emerged as one of the prime wireless technologies for achieving high data rates and spectral efficiency, and at the same time improving the energy efficiency and reliability of commercially deployed cellular systems. Indeed, MIMO systems are recognized as the single most important technology components of the new generation of integrated cellular, local area and short range communication systems, which are commonly referred to as the 5th generation communication systems. This new generation of communication systems are the technological foundation of the Internet of Things and thereby the networked society.

Multiple antenna techniques offer the combination of three advantages over traditional Single Input Single Output (SISO) systems, namely the gains associated with diversity, increasing array size and their capability of spatially multiplexing multiple users. The aggregate effect of these gains is the order of magnitudes higher user bit rates than achievable by existing 3rd and 4th generation wireless standards in a spectrum and energy efficient manner.

The gains associated with multi-antenna systems strongly depend on the availability of Channel State Information (CSI) at the transmitter and the receiver. This key observation has served as the basic motivation of my research reported in the present dissertation and the associated publications. Specifically, due to their great impact on the achievable gains in MIMO systems, my research has focused on two key aspects of spectral and energy efficient communication by means of multiple antennas:

- How to model and analyze the inherent trade-off between spending time, frequency and power resources on acquiring CSI and on transmitting user data in multiple antenna systems ?
- How to design multiple antenna receivers that operate spectrum efficiently and provide high bit-rates to users when perfect CSI is not available ?

Within the broad field outlined by the above two research and system design questions, the objective of my research has been to develop mathematical models of single and multi-user systems, that provide exact results on the achievable mean squared error and spectral efficiency by multiple antenna cellular base stations. This objective was motivated by the desire of gaining insight in the achievable gains of multi-antenna systems, in which perfect CSI is not available. Interestingly, the intimate relationship between the amount of resources spent on CSI acquisition, the resources left for data transmission, and the associated CSI acquisition and receiver algorithms were not available in the literature prior to my research. Therefore, the main objective of my research has been to develop mathematical methodology and generate numerical results that fill this research gap. Ultimately, the objective of my research has been to develop rigorous methodology based on mathematical analysis and gain engineering insights by applying this methodology to the most important use cases of employing multi-antenna systems for high spectral efficiency.

Chapter 2
Technology Motivation and Problem Formulation

2.1 The Evolution of Multi-Antenna Systems: From Single User to Massive Multi-user Multiple Input Multiple Output Systems

Conventional communication systems equipped with a a single transmit antenna and a single receive antenna are called SISO communication systems (Figure 2.1, upper left). This intuitively clear terminology explicitly refers to a signal model that involves the convolution of the complex impulse response of the wireless channel (typically represented as a random variable h) and the single input x to model the single output y:

$$y = h \star x + n, \tag{2.1}$$

where n is complex baseband additive white Gaussian noise. The above equation is for a single realization of the complex single output y.

The value of multiple antenna systems as a means to improve communications, including improving the overall system capacity and transmission reliability, was recognized in the early ages of wireless communications. Specifically, adaptive transmit or receive beamforming by means of employing multiple antennas either at the transmitter or the receiver roots back to classic papers that appeared in the 1960s and 1970s [1, 2, 3]. In particular, Widrow *et al.* described the Least Mean Square (LMS) adaptive antenna array, which is a technique to adaptively determine the weights that are derived from the received signal to minimize the mean squared error (MSE) between the received signal and a reference (pilot) signal [1, 3]. Applebaum proposed a multiple antenna array structure that adaptively suppresses sidelobe energy when the desired signal's angle-of-arrival (AoA) is known, such as in a radar system.

Starting from the 1980's, there has been a renewed and increased interest in employing multiple antenna techniques in commercial systems, particularly mobile

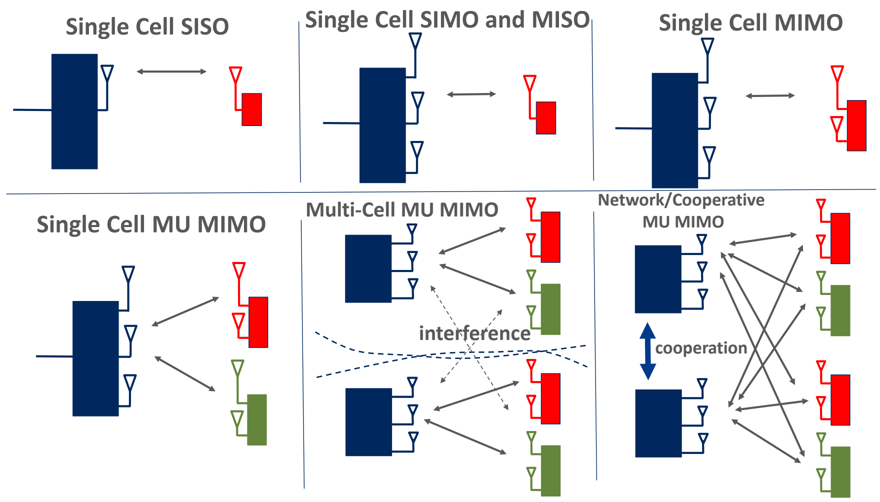

Fig. 2.1 The evolution of multiple antenna systems from single cell single input single output transmissions to cooperative network multiple input multiple output transmissions.

and cellular systems, where multipath and unintentional interference from simultaneously served users was the main and increasing concern [4]. However, it was not until the cost of digital signal processing was dramatically reduced and commercial wireless systems matured in the late 1990s that adaptive beamforming became commercially feasible, and large scale industrial interest has started to take off.

While traditional SISO systems exploit time- or frequency-domain processing and decoding of the transmitted and received data, the use of additional antenna elements at the cellular base station (BS) or user equipment (UE) side opens up the extra spatial dimension to signal precoding and detection. Depending on the availability of multiple antennas at the transmitter and the receiver, such techniques are classified as Single Input Multiple Output (SIMO), multiple input single output (MISO) or MIMO (Figure 2.1, upper middle and upper right). Specifically, space-time and space-frequency processing methods in SIMO, MISO and MIMO systems make use of the spatial dimension with the aim of improving the link's performance in terms of error rate, data rate or spectral and energy efficiency [3].

In the context of cellular networks, for example, in the scenario of a multi-antenna enabled BS communicating with a single antenna UE, the uplink (UL) and downlink (DL) are referred to as SIMO and MISO respectively. When a multi-antenna terminal is involved, a full MIMO link may be obtained, although the term MIMO is sometimes also used in a collective sense including SIMO and MISO as special cases.

A MIMO system, in which the transmitter and receiver are equipped with M and N antennas respectively, is conveniently characterized by the multi-dimensional version of (2.1) as follows:

$$\mathbf{y} = \underbrace{\mathbf{H}}_{N\times M}\underbrace{\mathbf{x}}_{M\times 1} + \underbrace{\mathbf{n}}_{N\times 1} \quad \in C^{N\times 1}, \tag{2.2}$$

where $\mathbf{x}$ and $\mathbf{y}$ represent the complex M and N dimensional input and output vectors of the MIMO system respectively.

While a point-to-point multiple-antenna link between a BS and a UE is referred to as Single-User Multiple Input Multiple Output (SU-MIMO), Multi-user Multiple Input Multiple Output (MU-MIMO) features several UEs communicating simultaneously using the same frequency- and time-domain resources (Figure 2.1, lower left). By extension, considering a multi-cell system, neighboring BSs sharing their antennas and forming a virtual MIMO system to communicate with the same set of UEs in different cells are called cooperative multi-point (CoMP) or network MIMO transmission/reception (Figure 2.1, lower middle and lower right).

2.2 Channel State Information Acquisition and Transceiver Design: Major Challenges in Multiple Input Multiple Output Systems

As noted, the spectral and energy-efficient operation of wireless systems in general, and multiple antenna systems in particular, relies on the acquisition of accurate channel state information at the transmitter (CSIT) and channel state information at the receiver (CSIR) [5]. The main reasons for this are that (1) transmitters of modern wireless systems adapt the transmitted signal characteristics to the prevailing channel conditions and (2) the effect of the channel on the transmitted signal must be estimated in order to recover the transmitted information. As long as the receiver accurately estimates how the channel modifies the transmitted signal, it can recover the signal from the impacts of the wireless channel. In practice, pilot signal-based data-aided techniques are used not only due to their superior performance in fast fading environments, but also due to their cost efficiency and inter-operability in commercial systems. Consequently, channel estimation methods have been studied extensively and a large number of schemes, including blind, data-aided, and decision-directed non-blind techniques, have been evaluated and proposed in the literature [6, 7, 8].

As the number of antennas at the BS and the simultaneously served users grows large, it is desirable to have pilot based schemes that are scalable in terms of the required pilot symbols and provide high quality CSI for UL data detection and DL precoding. To this end, MU-MIMO systems employing a large number of antennas typically rely on channel reciprocity and employ uplink pilots to acquire CSI at

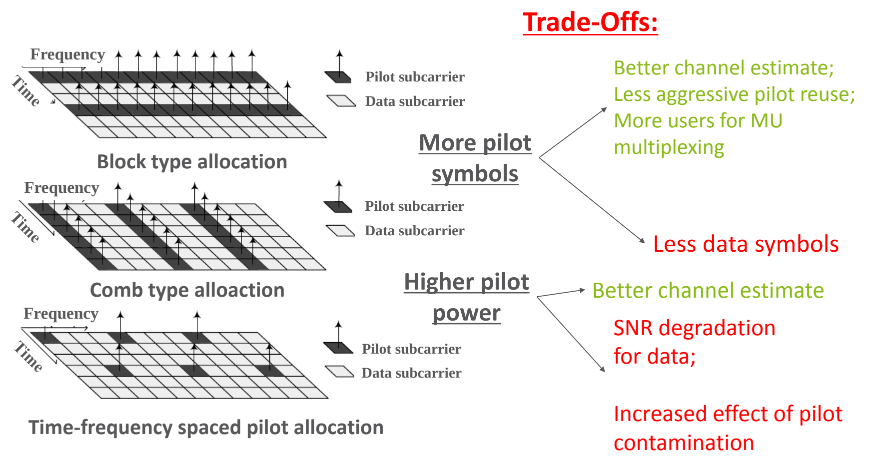

Fig. 2.2 Trade-offs associated with channel estimation, reference (pilot) signal design in MU-MIMO systems

BSs. Although solutions for non-reciprocal systems (such as systems operating in frequency division duplex (FDD) mode) are available [9], it is generally assumed that massive MIMO systems can advantageously operate in time division duplex (TDD) mode exploiting channel reciprocity [10, 11].

Pilot reuse generally causes contamination of the channel estimates, which is known as pilot contamination (PC) or pilot pollution. As there are a large number of channels to be estimated in MU-MIMO and massive MIMO systems, accurate CSI acquisition scaling with the number of BS antennas becomes a significant challenge due to the potentially limited number of pilots available. Indeed, PC limits the performance gains of non-cooperative MU-MIMO systems [10, 12]. Specifically, PC is known to cause a saturation effect in the signal-to-interference-plus-noise ratio (SINR) as the number of BS antennas increases to a very large value. This is in contrast to the PC exempt scenario where the SINR increases almost linearly with the number of antennas [12]. It is therefore clear that the trade-offs associated with the resources used for pilot signals and those reserved for data transmission is a key design aspect of modern wireless communication systems.

2.3 Fundamental Trade-Offs in the Design of Multi-user Multiple Input Multiple Output Systems

Although pilot-based CSI acquisition is advantageous in fast fading environments, its inherent trade-offs must be taken into account when designing channel estimation techniques for various purposes. These purposes include demodulation, precoding or beamforming, spatial multiplexing and other channel-dependent algorithms such as frequency selective scheduling or adaptive modulation and coding scheme (MCS) selection [13, 14, 15]. The inherent trade-offs between allocating resources to pilot and data symbols include the following, as illustrated in Figure 2.2:

- Increasing the power, time, or frequency resources to pilot signals improves the quality of the channel estimate, but leaves fewer resources for uplink or downlink data transmission [13, 14, 15].
- Constructing long pilot sequences (for example, employing orthogonal symbol sequences such as those based on the well-known Zadoff-Chu sequences in Long Term Evolution (LTE) systems) helps to avoid tight pilot reuse in multi-cell systems), helps to reduce or avoid inter-cell pilot interference. This is because long pilot sequences enable to construct a great number of orthogonal sequences and, consequently, help avoid pilot reuse in neighbor cells, and thereby address the root cause of PC. On the other hand, spending a greater number of symbols on pilots increases the pilot overhead and might violate the coherence bandwidth [15, 16].
- Specifically in MU-MIMO systems, increasing the number of orthogonal pilot sequences may increase the number of spatially multiplexed users at the expense of spending more symbols when creating the orthogonal sequences [13, 14].

In particular, increasing the pilot power increases the signal-to-noise ratio (SNR) of the received pilot signal, and thereby improves the quality of channel estimation in terms of the MSE of the channel estimate [17]. Unfortunately, increasing the pilot power may also lead to the SNR degradation of the data signals, and may exacerbate the PC problem in multi-cell scenarios [18]. In addition to these inherent trade-offs, the arrangement of the pilot symbols in the time, frequency, and spatial domains have been shown to have a significant impact on the performance of MU-MIMO and massive MIMO systems in practice, see for example [13, 14, 19].

Chapter 3
Research Methodology and Investigations

The motivations and objectives formulated in the preceding chapters determined the research directions, methodology and set the scope of the scientific investigations carried out in the course of the dissertation. The main objectives called for developing (i) mathematical models that facilitate the performance evaluation of MU-MIMO systems and (ii) methodologies that help determine key performance metrics both symbolically and numerically. Ultimately, the objective of my research was to propose mathematical models and methodology that help the design and evaluation of SU-MIMO and MU-MIMO systems that are more efficient – in terms of key performance indicators, such as MSE or spectral efficiency (SE) – than the currently deployed such systems.

In the area of resource management techniques applicable in MIMO systems, I initially focused on techniques that enable the efficient management of the transmitting power as a scarce resource. Specifically, I examined the impact of distributing the overall power budget available at the MIMO transmitter on the quality of channel state information acquisition and associated data communication. The mathematical models developed during these studies and their analysis lead to closed form results that capture the impact of distributing the available power budget between pilot and data signals on the mean squared error of the received data symbols. A particularly useful feature of these expressions is that they do not only capture the impact of the power distribution, but also the number of receive antennas. Subsequently, I examined the impact of the inevitable channel state information errors on the quality of data reception in terms of the mean square error of the received data symbols. In this regard, my ultimate goal was to design MIMO receiver structures that minimize the mean square error in the presence of channel state information errors. To this end, I applied the methodology of quadratic optimization, which enabled me to propose novel MIMO receiver structures. Indeed, these novel receiver structures provably minimize the mean square error of the received data symbols. By combining these two families of results, it became possible to determine the optimal receiver structure and the optimal pilot-to-data power ratio in the uplink of MIMO systems.

Next, I refined the mathematical models and associated analysis techniques to enhance their practical applicability. To this end, I extended the receiver models to explicitly capture the correlation among the receiver antennas. In practice, the correlation structure heavily depends on real-life antenna system parameters, such as antenna spacing, operational frequency or the statistics of the angle of arrival. Due to these extensions, I obtained results that allow to investigate the impact of antenna correlation on the quality of the received data symbols in terms of mean square error.

Since channel state information acquisition at the receiver involves the important trade-off between estimation quality and the complexity of the estimation algorithm, I proposed model extensions that explicitly capture the behavior of the popular least square and the minimum mean square estimators. I developed a technique that allows the derivation of the mean square error of the received data symbols when employing these channel estimation techniques.

Finally, I extended these results in the direction of establishing the receiver and the associated PDPR that are together able to minimize the MSE of the received data symbols. I verified and extended these results by means of computer simulations. These results clearly indicate that employing the optimal receiver and appropriately setting the Pilot-to-Data Power Ratio (PDPR) become more important as the number of receiver antennas increases. This result may seem surprising at first sight and has a large impact on the currently ongoing standardization of MU-MIMO systems, especially on the standardization of the pilot signals. Clearly, these standards play a key role not only in tuning the performance but also in ensuring the interoperability of modern SU-MIMO and MU-MIMO systems.

Chapter 4
Theses of the Dissertation

4.1 Notation and Terminology Used in the Theses

We consider the uplink transmission of a single cell single-user or multi-user (SU-MIMO or MU-MIMO) wireless system, in which the Mobile Stations (MSs) are equipped with a single transmit antenna. The single user or the multiple users is/are scheduled on multiple frequency channels that facilitates composing pilot sequences that consist of multiple pilot symbols and thereby facilitate creating orthogonal pilot sequences. Such set of frequency channels are also referred to as transmission or resource blocks. It is assumed that each MS employs an orthogonal pilot sequence, so that no interference between pilot signals is present in the system. This is a common assumption in single cell massive multi-user MIMO systems in which a single MS may have a single antenna [10]. The BS estimates the channel $\mathbf{h}$ (column vector of dimension N_r, where N_r is the number of receive antennas at the BS) by employing Least Square (LS) or minimum mean squared error (MMSE) channel estimators to initialize the linear MMSE equalizers for data detection.

4.2 Thesis I: Pilot-to-Data Power Ratio in Single User Systems

Thesis I considers a single input multiple output SIMO system in which the MS balances its PDPR, while the BS uses LS channel estimation to initialize its linear MMSE equalizer. It is important to emphasize that the term single user refers to a single scheduled user per frequency channel at a time, whereas hundreds of users can be served by using suitable time- and frequency domains schedulers. Thesis I is concerned with calculating the MSE of the uplink estimated data symbols based on the uplink received data signal and the available channel estimate by the multiple antenna BS.

4.2.1 Notation and Terminology Used in Thesis I

It is assumed that he channel is quasi-static frequency-flat within each resource block. Therefore, it is equivalent to model the whole pilot sequence as a single symbol per resource block with power P^p , while each data symbol is transmitted with power P.

Furthermore, we will use the following notation and terminology. Each MS transmits an orthogonal pilot symbol x_j that is received by the BS. Thus, the column vector of the received pilot signal at the BS from the j^{th} MS is:

$$\mathbf{y}_j^p = \sqrt{P_j^p}\alpha_j \mathbf{h}_j x_j + \mathbf{n}^p, \tag{4.1}$$

where we assume that $\mathbf{h}_j$ is a circular symmetric complex normal distributed vector with mean vector $\mathbf{0}$ and covariance matrix $\mathbf{C}_j$ (of size N_r), denoted as $\mathbf{h}_j \sim \mathcal{CN}(\mathbf{0}, \mathbf{C}_j)$, α_j accounts for the propagation loss, $\mathbf{n}^p \sim \mathcal{CN}(\mathbf{0}, \sigma^2\ \mathbf{I})$ is the contribution from additive Gaussian noise and the pilot symbol is scaled as $|x_j|^2 = 1, \forall j$. Since we assume orthogonal pilot sequences, the channel estimation process is independent for each MS and we therefore drop the index j. With a LS channel estimator, the BS estimates the channel based on (4.1) assuming

$$\hat{\mathbf{h}} = \frac{\mathbf{y}^p}{\sqrt{P^p}\alpha x},$$

that is:

$$\hat{\mathbf{h}} = \mathbf{h} + \frac{\mathbf{n}^p}{\sqrt{P^p}\alpha x}; \quad |x|^2 = 1. \tag{4.2}$$

It then follows that the estimated channel $\hat{\mathbf{h}}$ is distributed as follows:

$$\hat{\mathbf{h}} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}), \tag{4.3}$$

with $\mathbf{R} \triangleq \mathbb{E}\left\{\hat{\mathbf{h}}\hat{\mathbf{h}}^H\right\} = \mathbf{C} + \frac{\sigma^2}{P^p\alpha^2}\ \mathbf{I}$.

Furthermore, in this thesis, we will use the following notation. The channel estimation error $\mathbf{w} \triangleq \hat{\mathbf{h}} - \mathbf{h}$ is also normally distributed with a covariance inversely proportional to the employed pilot power:

$$\mathbf{w} \sim \mathcal{CN}(\mathbf{0}, \mathbf{C}_\mathbf{w}); \quad \mathbf{C}_\mathbf{w} \triangleq \frac{\sigma^2}{P^p\alpha^2}\ \mathbf{I}_{N_r}.$$

Equations (4.2)-(4.3) imply that $\mathbf{h}$ and $\hat{\mathbf{h}}$ are jointly circular symmetric complex Gaussian (multivariate normal) distributed random variables [20], [21]. Specifically, the covariance matrix of the joint probability density function (PDF) is composed by autocovariance matrices $\mathbf{C}_{\mathbf{h},\mathbf{h}}$, $\mathbf{C}_{\hat{\mathbf{h}},\hat{\mathbf{h}}}$ and cross covariance matrices $\mathbf{C}_{\mathbf{h},\hat{\mathbf{h}}}$, $\mathbf{C}_{\hat{\mathbf{h}},\mathbf{h}}$ as

$$\begin{bmatrix} \mathbf{C}_{\mathbf{h},\mathbf{h}} & \mathbf{C}_{\mathbf{h},\hat{\mathbf{h}}} \\ \mathbf{C}_{\hat{\mathbf{h}},\mathbf{h}} & \mathbf{C}_{\hat{\mathbf{h}},\hat{\mathbf{h}}} \end{bmatrix} = \begin{bmatrix} \mathbf{C} & \mathbf{C} \\ \mathbf{C} & \mathbf{R} \end{bmatrix},$$

and $\mathbf{R} = \mathbf{C} + \mathbf{C}_\mathbf{w}$.

From the joint PDF of $\mathbf{h}$ and $\hat{\mathbf{h}}$ the following conditional distributions are determined.

Result 4.2.1 *Given a random channel realization* $\mathbf{h}$*, the estimated channel* $\hat{\mathbf{h}}$ *conditioned to* $\mathbf{h}$ *can be shown to be distributed as*

$$(\hat{\mathbf{h}} \mid \mathbf{h}) \sim \mathbf{h} + \mathcal{CN}(\mathbf{0}, \mathbf{C_w}). \tag{4.4}$$

Result 4.2.2 *The distribution of the channel realization* $\mathbf{h}$ *conditioned to the estimate* $\hat{\mathbf{h}}$ *is normally distributed as follows:*

$$(\mathbf{h} \mid \hat{\mathbf{h}}) \sim \mathbf{D}\hat{\mathbf{h}} + \mathcal{CN}\Big(\mathbf{0}, \mathbf{Q}\Big), \tag{4.5}$$

where $\mathbf{D} = \mathbf{C}\mathbf{R}^{-1}$ *and* $\mathbf{Q} = \mathbf{C} - \mathbf{C}\mathbf{R}^{-1}\mathbf{C}$.

4.2.2 Thesis I

With the above terminology and notation, the main result is stated as follows.

Theorem 4.1. *In the case of* N_r *uncorrelated receiver antennas at the BS, the channel covariance matrix is diagonal in the form of* $\mathbf{C} = \varrho\mathbf{I}$*, where* $\varrho \in \mathbb{R}^+$*, and the covariance matrices* $\mathbf{D}$*,* $\mathbf{Q}$ *are* $\mathbf{D} = d\mathbf{I}$*,* $\mathbf{Q} = q\mathbf{I}$ *with* $d = \varrho(\varrho + \frac{\sigma^2}{P^p\alpha^2})^{-1}$*,* $q = \varrho(1-d)$*. Furthermore, the MSE of the equalized symbols is*

$$\begin{aligned}\mathbb{E}\{\mathrm{MSE}\} = d^2 N_r \Big(\mathcal{G}(a, 1+N_r) + pr\mathcal{G}(1+N_r, 1+N_r) - 1\Big) + \\ + \frac{b}{pr}\Big(\mathcal{G}(a, N_r) + pr\mathcal{G}(N_r, N_r) - 1\Big) - 2d \cdot \Big(pr\mathcal{G}(N_r, 1+N_r)\Big) + 1;\end{aligned}$$

where P *is the transmit power employed by the MS for transmitting the data symbols,* $p = \alpha^2 P$*,* $a = \sigma^2$*,* α *is the propagation loss,* σ^2 *is the noise power at the receive antenna,* $b = qp + \sigma^2$*,* $\mathbf{R} \triangleq \mathbb{E}\Big\{\hat{\mathbf{h}}\hat{\mathbf{h}}^H\Big\} = \mathbf{C} + \frac{\sigma^2}{P^p\alpha^2}\,\mathbf{I} = r\,\mathbf{I}$*, and*

$$\mathcal{G}(x, y) \triangleq \frac{1}{pr} e^{\frac{a}{pr}} x E_{in}\Big(y, \frac{a}{pr}\Big),$$

and $E_{in}(n, z) \triangleq \int_1^\infty e^{-zt}/t^n \, dt$ *is a standard exponential integral function.*

4.3 Thesis II: Minimum Mean Squared Error Receiver in the Presence of Channel State Information Errors

Thesis II is concerned with deriving an explicit formula for a receiver that minimizes the MSE of the estimated data symbols when the receiver has a non-perfect channel estimate. Thesis II also derives a closed form expression for the MSE when this optimum receiver is used, as a function of the number of receive antennas and the applied data and pilot power.

4.3.1 Notation and Terminology Used in Thesis II

Thesis II concerns the uplink of a MU-MIMO system, in which the MS transmit orthogonal pilot sequences $\mathbf{s} = \left[s_1, \ldots, s_{\tau_p}\right]^T \in \mathbb{C}^{\tau_p \times 1}$, in which each pilot symbol is scaled as $|s_i|^2 = 1$, for $i = 1, .., \tau_p$. The pilot sequences are constructed such that they remain orthogonal as long as the number of spatially multiplexed users is maximum τ_p. Specifically, without loss of generality, the number MU-MIMO users is $K \leq \tau_p$. In practice, $K \ll N_r$, where N_r is the number of antennas at the BS.

Thesis II is valid for the comb type arrangement of the pilot symbols [22]. Given F subcarriers in the coherence bandwidth, a fraction of τ_p subcarriers are allocated to the pilot and $F_d = F - \tau_p$ subcarriers are allocated to the data symbols. Each MS transmits at constant power P_{tot}, however, the transmission power can be distributed unequally in each subcarrier. In particular, considering a transmitted power P_p for each pilot symbol and P for each data symbol transmission, the sum constraint of $\tau_p P_p + (F - \tau_p)P = P_{tot}$ is enforced. Using the above notation and assumptions, the $N_r \times \tau_p$ matrix of the received pilot signal from a specific MS at the BS can be conveniently written as:

$$\mathbf{Y}^p = \alpha\sqrt{P_p}\mathbf{h}\mathbf{s}^T + \mathbf{N}, \tag{4.6}$$

where it is assumed that $\mathbf{h} \in \mathbb{C}^{N_r \times 1}$ is a circular symmetric complex normal distributed column vector with mean vector $\mathbf{0}$ and covariance matrix $\mathbf{C}$ (of size N_r), denoted as $\mathbf{h} \sim \mathcal{CN}(\mathbf{0}, \mathbf{C})$, α accounts for the propagation loss, $\mathbf{N} \in \mathbb{C}^{N_r \times \tau_p}$ is the spatially and temporally additive white Gaussian noise (AWGN) with element-wise variance σ_p^2, where the index p refers to the noise power on the received *pilot* signal.

For each MS, the BS utilizes pilot sequence orthogonality and estimates the channel by replacing $\mathbf{y}^p = \sqrt{P_p}\alpha\hat{\mathbf{h}}x$ based on (4.6) assuming:

$$\hat{\mathbf{h}} = \mathbf{h} + \mathbf{w} = \frac{1}{\alpha\sqrt{P_p}}\mathbf{Y}^p\mathbf{s}^*(\mathbf{s}^T\mathbf{s}^*)^{-1} = \mathbf{h} + \frac{1}{\alpha\sqrt{P_p}\tau_p}\mathbf{N}\mathbf{s}^*, \tag{4.7}$$

where $\mathbf{s}^* = \left[s_1^*, \ldots, s_{\tau_p}^*\right]^T \in \mathbb{C}^{\tau_p \times 1}$ denotes the vector of pilot symbols and $(\mathbf{s}^T\mathbf{s}^*) = \tau_p$. By considering $\mathbf{h} \sim \mathcal{CN}(\mathbf{0}, \mathbf{C})$, it follows that the estimated channel $\hat{\mathbf{h}}$ is a circular symmetric complex normal distributed vector $\hat{\mathbf{h}} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R})$, with

$$\mathbf{R} \triangleq \mathbb{E}\{\hat{\mathbf{h}}\hat{\mathbf{h}}^H\} = \mathbf{C} + \frac{\sigma_p^2}{\alpha^2 P_p \tau_p}\mathbf{I}_{N_r}. \tag{4.8}$$

The distribution of the channel realization $\mathbf{h}$ conditioned on the estimate $\hat{\mathbf{h}}$ is normally distributed and denoted as follows:

$$(\mathbf{h} \mid \hat{\mathbf{h}}) \sim \mathbf{D}\hat{\mathbf{h}} + \mathcal{CN}\left(\mathbf{0}, \mathbf{Q}\right), \tag{4.9}$$

where $\mathbf{D} \triangleq \mathbf{C}\mathbf{R}^{-1}$ and $\mathbf{Q} \triangleq \mathbf{C} - \mathbf{C}\mathbf{R}^{-1}\mathbf{C}$.

4.3.2 Thesis II

Using the above notation and terminology, we have the following results.

Let κ be the index of a tagged user in a MU-MIMO system of K users, $\kappa = 1 \ldots K$, and let $\mathbf{G}_\kappa^\star$ denote the receiver vector that minimizes the MSE of the estimated data symbols of the tagged user.

The optimal MU-MIMO receiver vector for User-κ is as follows:

Theorem 4.3.1 *The optimal* $\mathbf{G}_\kappa^\star$ *can be derived as:*

$$\mathbf{G}_\kappa^\star = \alpha_\kappa \sqrt{P_\kappa}\hat{\mathbf{h}}_\kappa^H \mathbf{D}_\kappa^H \cdot$$
$$\cdot \left(\alpha_\kappa^2 P_\kappa \left(\mathbf{D}_\kappa \hat{\mathbf{h}}_\kappa \hat{\mathbf{h}}_\kappa^H \mathbf{D}_\kappa{}^H + \mathbf{Q}_\kappa\right) + \sum_{k \neq \kappa}^{K} \alpha_k^2 P_k \mathbf{C}_k + \sigma_d^2 \mathbf{I}\right)^{-1}. \tag{4.10}$$

Next, it is of great interest to determine the MSE of the estimated data symbols when employing $\mathbf{G}_\kappa^\star$ as the receiver of the tagged user. To this end, the following result holds.

Theorem 4.3.2 *The unconditional* MSE *of the received data symbols of User-*κ *when the BS uses the optimal* $\mathbf{G}_\kappa^\star$ *receiver is as follows.*

$$
\begin{aligned}
&\mathrm{MSE} = \\
&s_\kappa \cdot \frac{N_r\left(-s_\kappa r + e^{\frac{b_\kappa}{s_\kappa r}}\left(b_\kappa + (1+N_r)s_\kappa r\right)E_{in}\left(1+N_r, \frac{b_\kappa}{s_\kappa r}\right)\right)}{s_\kappa^2 r} + \\
&+ b_\kappa \cdot \frac{-s_\kappa r + e^{\frac{b_\kappa}{s_\kappa r}}\left(b_\kappa + N_r s_\kappa r\right)E_{in}\left(N_r, \frac{b_\kappa}{s_\kappa r}\right)}{s_\kappa^2 r^2} - \\
&-2 \cdot e^{\frac{b_\kappa}{s_\kappa r}} N_r E_{in}\left(1+N_r, \frac{b_\kappa}{s_\kappa r}\right) + 1,
\end{aligned}
\tag{4.11}
$$

where $E_{in}(n,z) \triangleq \int_1^\infty e^{-zt}/t^n \, dt$ *is a standard exponential integral function.*

4.4 Thesis III: The Impact of Antenna Correlation on the Pilot-to-Data Power Ratio

Thesis III is concerned with determining the MSE of the estimated data symbols at multiple antenna receivers with correlated receive antenna structures. Specifically, Thesis III allows for an arbitrary correlation matrix structure at the multiple antenna receiver, derives a closed form expression for the MSE of the received data symbols as follows and thereby captures the tradeoff between the pilot and data power, with regards to the MSE of the equalized data symbols.

4.4.1 Notation and Terminology Used in Thesis III

The following notation is used to describe the conditional distributions of the actual and estimated channel between the served user and the multi-antenna BS. Given a random channel realization $\mathbf{h}$, the estimated channel $\hat{\mathbf{h}}$ conditioned to $\mathbf{h}$ is distributed as

$$
(\hat{\mathbf{h}} \mid \mathbf{h}) \sim \mathbf{h} + \mathcal{CN}(\mathbf{0}, \mathbf{R} - \mathbf{C}). \tag{4.12}
$$

Furthermore, the distribution of the channel realization $\mathbf{h}$ conditioned to the estimate $\hat{\mathbf{h}}$ is normally distributed as follows:

$$
(\mathbf{h} \mid \hat{\mathbf{h}}) \sim \mathbf{D}\hat{\mathbf{h}} + \mathcal{CN}\left(\mathbf{0}, \mathbf{Q}\right), \tag{4.13}
$$

where $\mathbf{D} = \mathbf{C}\mathbf{R}^{-1}$ and $\mathbf{Q} = \mathbf{C} - \mathbf{C}\mathbf{R}^{-1}\mathbf{C}$.

Furthermore, Thesis III uses the following notation. Let $\mathbf{C} = \mathbf{\Theta}^H \mathbf{S_C} \mathbf{\Theta}$ be the singular value decomposition of $\mathbf{C}$. Then $\mathbf{R} = \mathbf{\Theta}^H \mathbf{S_R} \mathbf{\Theta}$, $\mathbf{D} = \mathbf{\Theta}^H \mathbf{S_D} \mathbf{\Theta}$ and $\mathbf{Q} = \mathbf{\Theta}^H \mathbf{S_Q} \mathbf{\Theta}$ with $\mathbf{S_R} = \mathbf{S_C} + \frac{\sigma^2}{P_p \alpha^2} \mathbf{I}$, $\mathbf{S_D} = \mathbf{S_C} \mathbf{S_R}^{-1}$, and $\mathbf{S_Q} = \mathbf{S_C} - \mathbf{S_C} \mathbf{S_R}^{-1} \mathbf{S_C}$ where matrices $\mathbf{S}_\bullet$ are real non-negative diagonal matrices. Specifically, we will refer to the diagonal elements of $\mathbf{S_D}$ and $\mathbf{S_R}$ using the notations $d_k = \mathbf{S_D}_{kk}$ and $r_k = \mathbf{S_R}_{kk}$, respectively. Also, let $\mathbf{v} = \mathbf{\Theta}\hat{\mathbf{h}}$, then $\mathbf{v}$ is a random vector with distribution $\mathcal{CN}(\mathbf{0}, \mathbf{S_R})$, since

$$\begin{aligned}\mathbb{E}(\mathbf{v}\mathbf{v}^H) &= \mathbb{E}(\mathbf{\Theta}\hat{\mathbf{h}}\hat{\mathbf{h}}^H \mathbf{\Theta}^H) = \mathbf{\Theta}\mathbb{E}(\hat{\mathbf{h}}\hat{\mathbf{h}}^H)\mathbf{\Theta}^H = \\ &= \mathbf{\Theta}\mathbf{R}\mathbf{\Theta}^H = \mathbf{\Theta}\mathbf{\Theta}^H \mathbf{S_R} \mathbf{\Theta}\mathbf{\Theta}^H = \mathbf{S_R} \ .\end{aligned}$$

That is, the elements of $\mathbf{v}$ are independent, but they have different variances.

4.4.2 Thesis III

Using the above notation, the main result is stated as follows.

Theorem 4.4.1 *The mean square error (MSE) of the uplink received data with arbitrary covariance matrix* $\mathbf{C}$ *of the uplink channel can be calculated as*

$$\mathrm{MSE} = T_1 + T_2 + T_3 + 1, \tag{4.14}$$

where

$$\begin{aligned}T_1 = &\sum_k \sum_{\ell, \ell \neq k} d_k d_\ell \cdot \\ &\cdot \int_{x=0}^{\infty} x e^{-x\sigma^2/(\alpha^2 P)} \frac{1}{x + r_k} \frac{1}{x + r_\ell} \prod_i \frac{r_i}{x + r_i} \, dx + \\ &+ \sum_k d_k^2 \int_{x=0}^{\infty} x e^{-x\sigma^2/(\alpha^2 P)} \frac{2}{(x + r_k)^2} \prod_i \frac{r_i}{x + r_i} \, dx;\end{aligned}$$

$$T_2 = \frac{1}{\alpha^2 P} \sum_k m_k \int_{x=0}^{\infty} x e^{-x \frac{\sigma^2}{\alpha^2 P}} \frac{1}{x + r_k} \prod_i \frac{r_i}{x + r_i} dx;$$

and

$$T_3 = 2 \sum_k d_k \int_{x=0}^{\infty} e^{-x \frac{\sigma^2}{\alpha^2 P}} \frac{1}{x + r_k} \prod_i \frac{r_i}{x + r_i} dx,$$

where $\mathbf{S_M} \triangleq \alpha^2 P\mathbf{S_Q} + \sigma^2\mathbf{I}$ *is a diagonal matrix with diagonal elements* $m_k = \mathbf{S_M}_{kk} = \alpha^2 P q_k + \sigma^2$, *where* $q_k = \mathbf{S_Q}_{kk}$.

4.5 Thesis IV: Block and Comb Type Channel Estimation

Thesis IV derives analytical results for the spectral efficiency of MU-MIMO systems, in which the overall resources must be shared between channel estimation and data transmission. Specifically, using similar notation and terminology as Thesis II, Thesis IV shows that the spectral efficiency in MU-MIMO systems is not only a function of the PDPR, but it also depends on the specific channel estimation scheme, as given by the following results.

Theorem 4.5.1 (Spectral efficiency with LS estimation) *Assume* $\mathbf{C} = c\mathbf{I}_{N_r}$, *where* $c \in \mathbb{R}^+$, *then the average spectral efficiency with LS channel estimation and MMSE receiver is*

$$\bar{S}_{LS} = \frac{(\tau - \tau_p)}{\tau}\left(\frac{2\mathcal{G}(x_0) - \mathcal{G}(x_1) - \mathcal{G}(x_2)}{(N_r - 1)!} - \log(d-1)^2\right) \tag{4.15}$$

with $x_{1,2} = \frac{1}{2}\left(-\frac{2\sigma^2 - 2d\sigma^2 + b}{p(d-1)^2} \pm \sqrt{\left(\frac{2\sigma^2 - 2d\sigma^2 + b}{p(d-1)^2}\right)^2 - \frac{4\sigma^4}{p^2(d-1)^2}}\right)$, $x_0 = \frac{\sigma^2}{p}$, $p = \alpha^2 P$, $b = qp + \sigma^2$, $q = c(1 - c/r$, $r = c + \frac{\sigma^2}{\alpha^2 P_p \tau_p}$,
and where

$$\mathcal{G}(x) = \mathbf{MeijerG}_{2,3}^{1,3}\left(\begin{matrix} 0,1 \\ 0,0,N_r \end{matrix}\,\middle|\, \frac{x}{r}\right), \tag{4.16}$$

is the Meijer G-function.

Theorem 4.5.2 (Spectral efficiency with MMSE estimation) *Assume* $\mathbf{C} = c\mathbf{I}_{N_r}$, *where* $c \in \mathbb{R}^+$, *then the average spectral efficiency with MMSE channel estimation and MMSE receiver is*

$$\bar{S}_{MMSE} = \frac{(\tau - \tau_p)}{\tau}\left(\log(pb) + \frac{2\mathcal{G}(x_3) - \mathcal{G}(x_4)}{(N_r - 1)!}\right) \tag{4.17}$$

with $x_3 = \frac{\sigma^2}{p}$, $x_4 = \frac{\sigma^2}{pb}$, $b = qp + \sigma^2$, $q = \frac{\sigma^2 c}{\sigma^2 + \alpha^2 c P_p \tau_p}$, *and* $\mathcal{G}(x)$ *defined in 4.5.1.*

4.6 Thesis V: The Pilot-to-Data Power Ratio in Multiuser Systems

Thesis V derives analytical results for the MSE of the received data symbols and the overall spectral efficiency of MU-MIMO systems, in which the overall resources must be shared between channel estimation and data transmission, and the receive antennas are correlated according to an arbitrary correlation structure.

Let

$$\boldsymbol{\Psi}_\ell \triangleq \alpha_\ell^2 P_\ell \mathbf{Q}_\ell + \sum_{k\neq\ell}^{K} \alpha_k^2 P_k \mathbf{C}_k + \sigma_d^2 \mathbf{I}_{N_r}, \tag{4.18}$$

and

$$\boldsymbol{\Psi}_\ell = \boldsymbol{\Theta}_\ell^H \mathbf{S}_\ell \boldsymbol{\Theta}_\ell \tag{4.19}$$

denote the singular value decomposition (SVD) of $\boldsymbol{\Psi}_\ell$. Furthermore, define the linear transformed version of the estimated channel $\hat{\mathbf{h}}_\ell$ as:

$$\boldsymbol{\nu}_\ell \triangleq \mathbf{S}_\ell^{-1/2} \boldsymbol{\Theta}_\ell \mathbf{D}_\ell \hat{\mathbf{h}}_\ell, \tag{4.20}$$

and denote the distribution of $\boldsymbol{\nu}_\ell$ as:

$$\boldsymbol{\nu}_\ell \sim \mathcal{CN}(\mathbf{0}, \boldsymbol{\Omega}_\ell), \tag{4.21}$$

where

$$\boldsymbol{\Omega}_\ell \triangleq \mathbb{E}(\boldsymbol{\nu}_\ell \boldsymbol{\nu}_\ell^H) = \mathbf{S}_\ell^{-1/2} \boldsymbol{\Theta}_\ell \mathbf{D}_\ell \mathbf{R}_\ell \mathbf{D}_\ell^H \boldsymbol{\Theta}_\ell^H \mathbf{S}_\ell^{-1/2},$$

and denote the SVD of $\boldsymbol{\Omega}_\ell$:

$$\boldsymbol{\Omega}_\ell = \boldsymbol{\Theta}_{\boldsymbol{\Omega}_\ell}^H \mathbf{S}_{\boldsymbol{\Omega}\ell} \boldsymbol{\Theta}_{\boldsymbol{\Omega}\ell}, \tag{4.22}$$

where $\boldsymbol{\Theta}_{\boldsymbol{\Omega}\ell}$ is an orthogonal matrix.

Also, denote the linear transform of $\boldsymbol{\nu}_\ell$, with $\boldsymbol{\omega}_\ell$

$$\boldsymbol{\omega}_\ell \triangleq \boldsymbol{\Theta}_{\boldsymbol{\Omega}\ell} \boldsymbol{\nu}_\ell\ , \tag{4.23}$$

and its diagonal covariance matrix with $\mathbf{S}_{\boldsymbol{\Omega}}$.

With this notation, the MSE and the SE can be calculated as follows:

Theorem 4.6.1 *Denote the variance of ω_i with ξ_i^2. Then, $|\omega_i|^2$ is exponentially distributed with parameter $\lambda_i = 1/\xi_i^2$, and the mean squared error of the received data symbols can be calculated as:*

$$\text{MSE} = \int_x \frac{1}{\alpha_\ell^2 P_\ell x + 1} f(x) dx, \tag{4.24}$$

while the spectral efficiency can be calculated as:

$$\eta = -\int_x \log\left[\frac{1}{\alpha_\ell^2 P_\ell x + 1}\right] f(x)dx, \tag{4.25}$$

where α_ℓ *represents the large scale fading (path loss) of User-*ℓ*, and* $f(x)$ *is the the density function of* $\sum_{i=1}^{N_r} |\omega_i|^2$*:*

$$f(x) = e_1^T e^{\mathbf{A}x} e_{N_r} \lambda_{N_r}, \tag{4.26}$$

where e_i *is the i-th unit vector (whose only nonzero element is 1 at position i), and the matrix* $\mathbf{A}$ *is:*

$$\mathbf{A} = \begin{pmatrix} -\lambda_1 & \lambda_1 & & \\ & -\lambda_2 & \lambda_2 & \\ & & \ddots & \ddots \\ & & & -\lambda_{N_r} \end{pmatrix}. \tag{4.27}$$

For the special but important case, when all non-zero ξ_i (and λ_i) are distinct (different), we have the following result.

Proposition 4.6.2 *When all non-zero* ξ_i *(and* λ_i*) are distinct (different), then*

$$f(x) = \sum_{i=1}^{N} \frac{\lambda_i e^{-\lambda_i x}}{\prod_{j=1, j\neq i}^{N} \left(1 - \frac{\lambda_i}{\lambda_j}\right)}, \tag{4.28}$$

and the mean squared error can be calculated as:

$$\mathrm{MSE} = \sum_{i=1}^{N} \frac{-\lambda_i^{\frac{-N}{2}} e^{\frac{\lambda_i}{p}} E_{in}\left(1, \frac{-\lambda_i}{p}\right)}{p \prod_{j=1, j\neq i}^{N} \left(1 - \frac{\lambda_i}{\lambda_j}\right)}, \tag{4.29}$$

where $p = \alpha^2 P_\ell$*.*

The SE can be calculated as follows:

$$\eta = \sum_{i=1}^{N} \frac{-\lambda_i^{\frac{2-N}{2}} e^{\frac{\lambda_i}{p}} E_{in}\left(1, \frac{-\lambda_i}{p}\right)}{\prod_{j=1, j\neq i}^{N} \left(1 - \frac{\lambda_i}{\lambda_j}\right)}. \tag{4.30}$$

In the special but important when all variances of ω are equal, the following proposition holds

Proposition 4.6.3 *Suppose $\xi_i = \xi = \lambda^{-1/2}$, $\forall i \leq N$. Then, $f(x)$ follows the Erlang distribution as follows:*

$$f(x, N, \lambda) = \frac{\lambda^N x^{N-1} e^{-\lambda x}}{(N-1)!}, \tag{4.31}$$

and the MSE is given by:

$$\mathrm{MSE} = \frac{\lambda}{p} e^{\frac{\lambda}{p}} E_{in}\left(N, \frac{\lambda}{p}\right), \tag{4.32}$$

and the spectral efficiency can be calculated as:

$$\eta = \frac{\mathcal{G}(\frac{\lambda}{p})}{a^N (N-1)!}, \tag{4.33}$$

where

$$\mathcal{G}(x) \triangleq \mathbf{MeijerG}_{1,0}^{3,1}\left(\begin{matrix} -N_r; -(N_r-1) \\ -N_r, -N_r, 0; . \end{matrix} \middle| x \right), \tag{4.34}$$

is the Meijer G function.

Chapter 5
Publications Related to the Dissertation

5.1 Journal and Magazine Articles

- **[J1]** N. N. Moghadam, H. Shokri-Ghadikolaei, **G. Fodor**, M. Bengtsson, C. Fischione, "Pilot Precoding and Combining in Multiuser MIMO Networks", *IEEE Journal on Selected Areas in Communications*, Vol. 35, Issue 7, pp. 1632-1648, July 2017.
- **[J2] G. Fodor**, N. Rajatheva, W. Zirwas, L. Thiele, M. Kurras, K. Guo, A. Tölli, J. H. Sorensen, E. de Carvalho, "An Overview of Massive MIMO Technology Components in METIS", *IEEE Communications Magazine*, Vol. 55, Issue 6, pp. 155-161, June 2017.
- **[J3]** A. Orsino, A. Ometov, **G. Fodor**, D. Moltchanov, L. Militano, S. Andreev, O. N. C. Yilmaz, T. Tirronen, J. Torsner, G. Araniti, M. Dohler, and Y. Koucheryavy, "Effects of Heterogeneous Mobility on D2D- and Drone-Assisted Mission-Critical MTC in 5G", *IEEE Communications Magazine*, Vol. 55, Issue 2, pp. 79-87, February 2017.
- **[J4]** H. Shokri-Ghadikolaei, F. Boccardi, C. Fischione, **G. Fodor** and M. Zorzi, "Spectrum Sharing in mmWave Cellular Networks via Cell Association, Coordination, and Beamforming", *IEEE Journal on Selected Areas in Communications*, Vol. 34, Issue 11, pp. 2902-2917, 2016.
- **[J5]** F. Boccardi, H. Shokri-Ghadikolaei, **G. Fodor**, E. Erkip, C. Fischione, M. Kountouris, P. Popovski, and M. Zorzi, "Spectrum Pooling in MmWave Networks: Opportunities, Challenges, and Enablers", *IEEE Communications Magazine*, Vol. 54, Issue 11, pp. 33 - 39, November 2016.
- **[J6]** J. B. M. da Silva, **G. Fodor**, C. Fischione, "Spectral Efficient and Fair User Pairing for Full-Duplex Communication in Cellular Networks", *IEEE Transactions on Wireless Communications*, Vol. 15, Issue 11, pp. 7578 - 7593, August 2016.
- **[J7]** A. Ometov, A. Orsino, L. Militano, D. Moltchanov. G. Araniti, E. Olshannikova, **G. Fodor**, S. Andreev, T. Olsson, A. Iera, J. Torsner, Y. Koucheryavy, T. Mikkonen, "Towards Trusted, Social-Aware D2D Connectivity: Bridging Across

Technology and Sociality Realms", *IEEE Wireless Communications*, Vol. 3, Issue 4, pp. 103-111, August 2016.

- **[J8] G. Fodor**, S. Roger, N. Rajatheva, S. B. Slimane, T. Svensson, P. Popovski, J. M. B. da Silva Jr, S. Ali, "An Overview of Device-to-Device Communications Technology Components in METIS", *IEEE Access*, June 2016.
- **[J9]** G. Fodor, P. Di Marco and M. Telek, "On the Impact of Antenna Correlation and CSI Errors on the Pilot-to-Data Power Ratio", *IEEE Transactions on Communications*, Volume 64, Issue 6, pp. 2622-2633, April 2016.
- **[J10]** Jose Mairton B. da Silva and G. Fodor, "A Binary Power Control Scheme for D2D Communications", *IEEE Wireless Communications Letters*, September 2015.
- **[J11]** A. Abrardo, **G. Fodor** and B. Tola, "Network Coding Schemes for D2D Communications Based Relaying for Cellular Coverage Extension", *Wiley Transactions on Emerging Telecommunications Technologies*, November 2015.
- **[J12] G. Fodor**, P. D. Marco and M. Telek, "On Minimizing the MSE in the Presence of Channel State Information Errors", *IEEE Communications Letters*, June 2015.
- **[J13]** H. Shokri-Ghadikolaei, C. Fischione, **G. Fodor**, P. Popovski, M. Zorzi, "Milimeter Wave Cellular Networks: A MAC Layer Perspective", *IEEE Transactions on Communications*, July 2015.
- **[J14]** M. Belleschi, **G. Fodor**, D. D. Penda, A. Pradini, M. Johansson, A. Abrardo, "Benchmarking Practical RRM Algorithms for D2D Communications in LTE Advanced", *Wireless Personal Communications* (Springer), January 2015.

5.2 Conference Papers

- **[C1]** J. M. B. da Silva Jr., **G. Fodor**, C. Fischione, "On the Spectral Efficiency and Fairness in Full-Duplex Cellular Networks", *IEEE International Conference on Communications (ICC)*, Paris, France, 21-25 May 2017.
- **[C2]** K. Guo, S. Dai, C. Zhang, **G. Fodor**, G. H. Ascheid, "Massive MIMO Aided Multi-Pair Relaying with Underlaid D2D Communications", *European Wireless*, Dresden, Germany, 17-19 May 2017.
- **[C3]** N. N. Moghadam, H. Shokri-Ghadikolaei, **G. Fodor**, M. Bengtsson and C. Fischione, "Pilot Precoding and Combining in Multiuser MIMO Networks", *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, New Orleans, LA, USA, 5-9 March 2017.
- **[C4]** H. Shokri-Ghadikolaei, F. Boccardi, E. Erkip, C. Fischione, **G. Fodor**, M. Kountouris, P. Popovski, and M. Zorzi, "The Impact of Beamforming and Coordination on Spectrum Pooling in MmWave Cellular Networks", *IEEE Asilomar Conference on Signals, Systems and Computers*, Pacific Grove, CA, USA, 6-9 November 2016.

- **[C5]** J. M. B. da Silva Jr, Y. Xu, **G. Fodor** and C. Fischione, "Distributed Spectral Efficiency Maximization in Full Duplex Cellular Networks", *IEEE ICC Workshop on Novel Medium Access and Resource Allocation for 5G Networks*, Kuala Lumpur, Malaysia, 23-27 May 2016.
- **[C6]** L. Srikar Muppirisetty, H. Wymeersch, J. Karout, **G. Fodor**, "Location-Aided Pilot Contamination Elimination for Massive MIMO Systems", *IEEE Globecom*, San Diego, CA, USA, 6-10 December 2015.
- **[C7] G. Fodor**, P. Di Marco and M.Telek, "On the Impact of Antenna Correlation on the Pilot-Data Balance in Multiple Antenna Systems", *IEEE International Conference on Communications (ICC)*, London, UK, June 2015.
- **[C8]** A. Abrardo, **G. Fodor**, B. Tola, "Network Coding Schemes for D2D Communications Based Relaying for Cellular Coverage Extension", *IEEE Signal Processing Advancements for Wireless Communications (SPAWC)*, Stockholm, June 2015.
- **[C9]** V. Saxena, **G. Fodor**, E. Karipidis, "Mitigating Pilot Contamination by Pilot Reuse and Power Control Schemes for Massive MIMO Systems", *IEEE Vehicular Technology Conference (VTC) Spring*, Glasgow, Scotland, May 2015.
- **[C10]** J. M. B. da Silva Jr, **G. Fodor**, T. F. Maciel, "Performance Analysis of Network Assisted Two-Hop D2D Communications", *10th IEEE Broadband Wireless Access Workshop*, Austin, TX, USA, December 2014.
- **[C11] G. Fodor**, P. Di Marco, M. Telek, "Performance Analysis of Block and Comb Type Channel Estimation for Massive MIMO Systems", *First International Conference on 5G for Ubiquitous Connectivity*, Levi, Finland, November 2014.
- **[C12]** K. Guo, Y. Guo, **G. Fodor** and G. Ascheid, "Uplink Power Control with MMSE Receiver in Multicell Multi-User Massive MIMO Systems", *IEEE International Conference on Communications (ICC)*, Sydney, Australia, June 2014.
- **[C13] G. Fodor** and M. Telek, "On the Pilot-Data Trade-Off in Single Input Multiple Output Systems", *European Wireless*, Barcelona, Spain, May 2014.
- **[C14] G. Fodor**, A. Pradini and A. Gattami, "On Applying Network Coding in Network Assisted Device-to-Device Communications", *European Wireless*, Barcelona, Spain, May 2014.
- **[C15]** L. Qianxi, M. Qingyu, **G. Fodor** and N. Brahmi, "Clustering Schemes for D2D Communications Under Partial/No Network Coverage", IEEE Vehicular Technology Conference (VTC) Spring, Seoul, June 2014.
- **[C16]** A. Pradini, **G. Fodor**, G. Miao and M. Belleschi, "Near Optimal Practical Power Control Schemes for D2D Communications in Cellular Networks", *European Conference on Networks and Communications (EuCNC)*, Bologna, Italy, June 23-26, 2014.
- **[C17]** Q. Lu, Q. Miao, N. Brahmi and **G. Fodor**, "Radio Resource Management for Network Assisted D2D in Cellular Uplink", *IEEE and CIC International Conference on Communications in China (ICCC)*, Xian, China, 12-14 August 2013.

- **[C18] G. Fodor**, D. D. Penda, M. Belleschi, M. Johansson and A. Abrardo, "A Comparative Study of Power Control Approaches for Device-to-Device Communications", *IEEE International Conference on Communications (ICC)*, Budapest, Hungary, June 2013.
- **[C19]** A. Abrardo, M. Belleschi, **G. Fodor** and M. Moretti, "A Messages Passing Approach for Resource Allocation In Cellular OFDM Communications", *IEEE Global Communications Conference (Globecom)*, Anaheim, CA, USA, 3-7 December 2012.
- **[C20]** M. Fallgren, **G. Fodor** and A. Forsgren, "Optimization Approach to Joint Cell, Channel and Power Allocation in Wireless Communication Networks", *20th European Signal Processing Conference (EUSIPCO '12)*, Bucarest, Romania, August 27-31 2012.
- **[C21]** M. G. da S. Rego, T. F. Maciel, H. Barros, F. R. P. Cavalcanti and **G. Fodor**, "Performance Analysis of Power Control for Device-to-Device Communication in Cellular MIMO Systems", *2nd International Workshop on Self Organizing Networks, IWSoN*, Paris, France, August 28-31 2012.

Bibliography

[1] B. Widrow, P. E. Mantey, L. J. Griffiths, and B. B. Goode, “Adaptive antenna systems,” *Proceedings of the IEEE*, vol. 55, no. 12, pp. 2143–2159, December 1967.

[2] S. R. Applebaum, “Adaptive arrays,” *IEEE Transactions on Antennas and Propagation*, vol. 24, no. 5, pp. 585–598, September 1976.

[3] J. Winters, *Space-Time Wireless Systems – From Array Processing to MIMO Communications*, H. Bölcskei, D. Gesbert, C. B. Papadias, and A.-J. van der Veen, Eds. Cambridge University Press, 2006.

[4] J. H. Winters, “Optimum combining in digital mobile radio with cochannel interference,” *IEEE Journal on Selected Areas in Communications*, vol. 2, no. 4, pp. 528–539, April 1984.

[5] A. Goldsmith, S. A. Jafar, N. Jindal, and S. Vishwanath, “Capacity limits of mimo channels,” *IEEE Journal on Selected Areas of Communications*, vol. 21, no. 5, pp. 684–702, June 2003.

[6] M. K. Ozdemir and H. Arslan, “Channel estimation for wireless ofdm systems,” *IEEE Communications Surveys and Tutorials*, vol. 9, no. 2, pp. 18–48, 2007.

[7] S. Coleri, M. Ergen, A. Puri, and A. Bahai, “Channel estimation techniques based on pilot arrangement in ofdm systems,” *IEEE Transactions on Broadcasting*, vol. 48, no. 3, pp. 223–229, September 2002.

[8] Y.-H. Nam, Y. Akimoto, Y. Kim, M. i. Lee, K. Bhattad, and A. Ekpenyong, “Evolution of reference signals for lte-advanced systems,” *IEEE Communications Magazine*, vol. 5, no. 2, pp. 132–138, February 2012.

[9] J. Choi, T. Kim, D. J. Love, and J.-Y. Seol, “Exploiting the preferred domain of fdd massive mimo systems with uniform planar arrays,” in *IEEE International Conference on Communications*, London, UK, June 2015, pp. 3068–3073.

[10] T. Marzetta, “Noncooperative Cellular Wireless with Unlimited Numbers of Base Station Antennas,” *IEEE Trans. Wireless Comm.*, vol. 9, no. 11, pp. 3590–3600, 2010.

[11] F. Rusek, D. Persson, B. K.Lau, E. G. Larsson, T. L. Marzetta, O. Edfors, and F. Tufvesson, “Scaling Up MIMO - Opportunities and Challenges with Very Large Arrays,” *IEEE Signal Processing Magazine*, 2013.

[12] B. Gopalakrishnan and N. Jindal, "An analysis of pilot contamination on multiuser mimo cellular systems with many antennas," in *International Workshop on Signal Processing Advances in Wireless Communications*, San Francisco, June 2011, pp. 381–385.

[13] T. Kim and J. G. Andrews, "Optimal pilot-to-data power ratio for mimo-ofdm," *IEEE Globecom*, pp. 1481–1485, December 2005.

[14] ——, "Balancing pilot and data power for adaptive mimo-ofdm systems," *IEEE Globecom*, pp. 1–5, 2006.

[15] T. Marzetta, "How much training is needed for multiuser mimo ?" *IEEE Asilomar Conference on Signals, Systems and Computers (ACSSC)*, pp. 359–363, June 2006.

[16] N. Jindal and A. Lozano, "A Unified Treatment of Optimum Pilot Overhear in Multipath Fading Channels," *IEEE Transactions on Communications*, vol. 58, no. 10, pp. 2939–2948, October 2010.

[17] G. Fodor and M. Telek, "On the Pilot-Data Power Trade Off in Single Input Multiple Output Systems," *European Wireless '14*, vol. Barcelona, Spain, May 2014.

[18] K. Guo, Y. Guo, G. Fodor, and G. Ascheid, "Uplink power control with mmse receiver in multi-cell mu-massive-mimo systems," in *IEEE International Conference on Communications (ICC)*, 10-14 June 2014, pp. 5184–5190.

[19] H. Yin, D. Gesbert, M. Filippou, and Y. Liu, "A Coordinated Approach to Channel Estimation in Large-Scale Multiple-Antenna Systems," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 2, pp. 264–273, February 2013.

[20] S. M. Kay, *Fundamentals of Statistical Signal Processing, Vol. I: Estimation Theory*. Prentice Hall, 1993, no. ISBN: 0133457117.

[21] R. Gallager, "Circularly-Symmetric Gaussian Complex Vectors," *http://www.rle.mit.edu/rgallager/documents/CircSymGauss.pdf*, 2008.

[22] G. Fodor, P. D. Marco, and M. Telek, "Performance Analysis of Block and Comb Type Channel Estimation for Massive MIMO Systems," in *First International Conference on 5G*, Finland, November 2014.