Abstract—Hybrid beamforming provides a promising solution to achieve high data rate transmission at millimeter waves. Implementing hybrid beamforming at a transceiver based on available channel state information is a common solution. However, many reference methods ignore the complexity of channel estimation for large antenna arrays or subsequent steps, such as the singular value decomposition of a channel matrix. To this end, we present a low-complexity scheme that exploits implicit channel knowledge to facilitate the design of hybrid beamforming for frequency-selective fading channels. The implicit channel knowledge can be interpreted as couplings between all possible pairs of analog beamforming vectors at the transmitter and receiver over the surrounding channel. Instead of calculating mutual information between large antenna arrays, we focus on small-size coupling matrices between beam patterns selected by using appropriate key parameters as performance indicators. This converts the complicated hybrid beamforming problem to a much simpler one: it amounts to collecting different sets of the large-power coupling coefficients to construct multiple alternatives for an effective channel matrix. Then, the set yielding the largest Frobenius norm (or the largest absolute value of the determinant) of the effective channel provides the solution to the hybrid beamforming problem. It turns out that the proposed method does not require information on MIMO channel and can be simply implemented by the received correlated pilot signals that are supposed to be used for channel estimation.

Index Terms—millimeter wave, analog beam selection, hybrid beamforming, implicit channel state information, key parameters of hybrid beamforming gain, OFDM, MIMO.

I. INTRODUCTION

With the rapid increase of data rates in wireless communications, the problem of bandwidth shortage is getting more critical. Therefore, there is a growing interest in using millimeter wave (mmWave) for future wireless communications, taking advantage of an enormous amount of available spectrum at frequencies $>6$ GHz [1]. Measurements of mmWave channel characteristics presented in [2]-[5] show that the path loss in such an environment is very severe. In order to improve capacity and service quality, mmWave small-cell deployment together with beamforming for large antenna arrays is seen as a promising approach [6], [7]. When a system operates at mmWave frequency bands, it is infeasible to equip each antenna with its own radio frequency (RF) chain due to high implementation cost and power consumption. Accordingly, a combination of analog beamforming (operating in passband) [8], [9] and digital beamforming (operating in baseband) [10] can be one of the low-cost solutions, and this combination is commonly called hybrid beamforming [11]-[14].

In hybrid beamforming systems, although both analog and digital beamforming matrices use the same word beamforming, only the former has a specific geometrical meaning in the sense of directing or collecting energy towards specific directions by using antenna arrays. In contrast, the digital beamforming matrix has rather an algebraic meaning. In other words, it is more like a coefficient matrix. According to the functions of analog and digital beamforming, hybrid beamforming can be regarded as first converting an over-the-air large-scale MIMO channel matrix $\mathbf{H}$ in the spatial domain into an effective channel $\mathbf{H}_E$ of significantly smaller size\(^1\) in the angular domain by analog beamforming vectors. Then, one can further try linear combinations of analog beamforming vectors with entries of digital beamforming matrices as coefficients to maximize mutual information conditional on $\mathbf{H}_E$.

Unquestionably, it is intractable to deal with hybrid beamforming at a transmitter and a receiver simultaneously. To simplify the problem, one can assume that the channel state information (CSI) is available. Then, by utilizing the singular value decomposition (SVD) of the channel matrix, the problem of hybrid beamforming on both sides (i.e., finding the precoder and combiner) can be decoupled and formulated as two minimization problems [12], [15]-[18]. In addition, the properties of codebooks used for the analog beamforming are incorporated into the problem as an additional constraint. For frequency-flat fading channels, a single SVD computation suffices, while more than one becomes necessary to handle a multi-carrier modulation in frequency-selective fading channels. One can also decouple the transceiver by an assumption that either the transmitter or receiver employs fully digital beamforming to facilitate the problem-solving process [19]-[21]. Nevertheless, most previously proposed hybrid beamforming methods require channel knowledge and ignore the overhead of channel estimation for large-scale antenna arrays [22]-[25].

A feasible alternative that decouples the precoder and combiner is therefore introduced as follows. Generally speaking,

\(^{1}\text{The size of } \mathbf{H}_E \text{ is determined by the number of available RF chains on both sides; a more detailed description of this will be given in Section II.'}
given candidates for the analog beamforming vectors selected from codebooks on both sides, finding the corresponding optimal digital beamforming is trivial in the sense that it is almost equivalent to the conventional fully digital beamforming apart from different power constraints [26]. As a result, the critical issue of hybrid beamforming is definitely in analog beam selection. The work in [27] explains why analog beam selection based on the power of received correlated pilot signals is equivalent to the selection method by the orthogonal matching pursuit (OMP) algorithm [28]. It holds when the analog beamforming vectors are selected from orthogonal codebooks (intuitively such codebooks act as complete dictionaries in terms of compressed sensing techniques). However, the performance of the analog beam selection technique based on the received power can be further improved because the corresponding effective channel $H_E$ is not necessarily well-conditioned [29], [30]. In other words, the factor dominating the performance of hybrid beamforming is the singular values of $H_E$ rather than the received power.

To find an effective channel yielding the maximum throughput, one can reserve a few more candidates for the analog beamforming vectors corresponding to the large received power levels. Then, the subset of these candidates yielding the maximum throughput will provide the optimal solution to the hybrid beamforming problem. Again it is evident that the computational complexity exponentially increases as the size of the enlarged candidate set. Consequently, we have a strong motivation to find a relationship between the observations for the analog beam selection and key parameters of the hybrid beamforming gain. The relationship can be used to facilitate the process of determining the optimal analog beamforming vectors. First let us ask, what is actually the key quantity or parameter that leads to hybrid beamforming gain? Depending on the SNR, we find that it is either the Frobenius norm of the effective channel $H_E$ or the absolute value of the determinant of $H_E$. $H_E$ can be regarded as a coupling of the channel and analog beamforming on both sides. Such coupling coefficients can be obtained by transmitting known pilot signals and used for not only the analog beam selection but also constructing alternatives for $H_E$. Accordingly, estimates of the coupling coefficients yielding the maximum value of the key parameters give us the necessary information to optimally select the analog beamforming vectors.

The problem statements and contributions of the proposed algorithm are summarized as follows:

1) Most hybrid beamforming methods in the literature are implemented based on explicit CSI ($H$) but ignore the complexity of channel estimation or SVD. Therefore, this paper presents a method that uses implicit CSI (the received correlated pilots) to implement the hybrid beamforming and omit channel estimation for large antenna arrays.

2) To simplify the joint problem of the precoder and combiner, some previously proposed methods decouple these two by the assumption that either the transmitter or receiver employs fully digital beamforming. However, the assumption is not necessary. This paper shows that the precoder and combiner can be implemented simultaneously with reasonable complexity based on the estimates of the received power levels.

3) Compared with existing approaches, we formulate a different optimization problem by using the key parameters of hybrid beamforming gain, which significantly alleviates the complexity of hybrid beamforming problem.

The rest of the paper is organized as follows: Section II describes the system and mmWave frequency-selective channel models. Section III states the objective of hybrid beamforming problem. Based on the objective function, a hybrid beamforming algorithm based on implicit CSI is presented in Section IV. A theoretical analysis in terms of statistical properties of effective noise occurring in the proposed method is detailed in Section V. To support this analysis, simulation results are presented in Section VI, and we conclude our work in Section VII.

We use the following notations throughout this paper.

- $a$: A scalar
- $A$: A column vector
- $\mathbf{A}$: A matrix
- $\mathcal{A}$: A set
- $[\mathbf{A}]_{n,n}$: The $n$th diagonal element of $\mathbf{A}$
- $[\mathbf{A}]_{:,1:N}$: The first $N$ column vectors of $\mathbf{A}$
- $[\mathbf{A}]_{1:N,1:N}$: The $N \times N$ submatrix extracted from the upper-left corner of $\mathbf{A}$
- $\mathbf{A}^*$: The complex conjugate of $\mathbf{A}$
- $\mathbf{A}^H$: The Hermitian transpose of $\mathbf{A}$
- $\mathbf{A}^T$: The transpose of $\mathbf{A}$
- $\|\mathbf{A}\|_F$: The Frobenius norm of $\mathbf{A}$
- $\text{det}(\mathbf{A})$: The determinant of $\mathbf{A}$
- $\text{vec}(\mathbf{A})$: The vectorization of $\mathbf{A}$
- $[\mathbf{A} | \mathbf{B}]$: The horizontal concatenation
- $\mathbf{A} \otimes \mathbf{B}$: The Kronecker product of $\mathbf{A}$ and $\mathbf{B}$
- $\Re(\mathbf{A})$, $\Im(\mathbf{A})$: The real (or imaginary) part of $\mathbf{A}$
- $\mathbf{1}_N$: The $N \times N$ identity matrix
- $0_{N \times M}$: The $N \times M$ zero matrix
- $\mathbb{E}[\cdot]$: The expectation operator

II. System Model

A system has a transmitter with a uniform linear array (ULA) of $N_T$ elements and wants to communicate $N_S$ OFDM data streams to a receiver with an $N_R$-element ULA as shown in Fig. 1. At the transmitter, the $N_T$ antenna elements connect to a precoder $\mathbf{F}_P \mathbf{F}_B[k]$ at subcarrier $k = 0, \cdots, K - 1$, where $\mathbf{F}_P \in \mathbb{C}^{N_T \times N_{RF}}$ is the analog beamforming matrix implemented in passband as part of the RF front end and $\mathbf{F}_B[k] \in \mathbb{C}^{N_{RF} \times N_S}$ is the digital beamforming matrix in baseband. The value $K$ specifies the number of subcarriers in one OFDM symbol, and $N_{RF}$ denotes the number of available RF chains at both the transmitter and receiver. High implementation costs and power consumption impose hardware constraints on the analog beamforming ($\mathbf{F}_P$) so that it has fewer degrees of freedom than the digital beamforming ($\mathbf{F}_B[k]$). Specifically, first, $\mathbf{F}_P$ should be a constant matrix within (at least) one OFDM symbol, which requires certain coherence time of the channel. Second, the entries of $\mathbf{F}_P$ have equal magnitude because analog beamformers are typically
implemented by delay elements in the RF front end. The \(N_{RF}\) analog beamforming vectors of \(\mathbf{F}_P\) are selected from a predefined codebook \(\mathcal{F} = \{\mathbf{f}_n, n_f = 1, \ldots, N_F\}\) with the \(n_f^{th}\) member given by \[8\]

\[
\tilde{\mathbf{f}}_{n_f} = \frac{1}{\sqrt{N_T}} \left[ 1, e^{j \frac{2\pi}{\lambda_0} \sin(\phi_{T,n_f}) \Delta_d}, \ldots, e^{j \frac{2\pi}{\lambda_0} \sin(\phi_{T,n_f}) (N_T-1) \Delta_d} \right]^T,
\]

where \(\phi_{T,n_f}\) stands for the \(n_f^{th}\) candidate for the steering angles at the transmitter, \(\Delta_d = \lambda_0/2\) is the distance between two neighboring antennas, and \(\lambda_0\) is the wavelength at the carrier frequency. At the receiver, the combiner \(\mathbf{W}_P \mathbf{W}_B[k]\) has a similar structure as the precoder, where \(\mathbf{W}_P \in \mathbb{C}^{N_{RF} \times N_{RF}}\) and \(\mathbf{W}_B[k] \in \mathbb{C}^{N_{RF} \times N_{RF}}\) are the analog and digital beamforming matrices respectively. Also, the columns of \(\mathbf{W}_P\) are selected from the other codebook \(\mathcal{W} = \{\tilde{\mathbf{w}}_{n_w} \in \mathbb{C}^{N_{RF} \times 1}, n_w = 1, \ldots, N_W\}\), where the members of \(\mathcal{W}\) can be generated by the same rule as (1).

Via a coupling of the precoder, combiner, and a frequency-selective fading channel \(\mathbf{H}[k] \in \mathbb{C}^{N_{RF} \times N_T}\), the received signal \(\mathbf{r}[k] \in \mathbb{C}^{N_T \times 1}\) at subcarrier \(k\) can be written as

\[
\mathbf{r}[k] = \mathbf{W}_B^H[k] \mathbf{W}_P^H \mathbf{H}[k] \mathbf{F}_P \mathbf{F}_B[k] s[k] + \mathbf{W}_B^H[k] \mathbf{W}_P^H \mathbf{n}[k]
= \mathbf{W}_B^H[k] \mathbf{W}_P^H \mathbf{H}[k] s[k] + \mathbf{n}[k],
\]

where \(s[k] \in \mathbb{C}^{N_T \times 1}\) is the transmitted signal vector whose covariance matrix \(\mathbf{R}_s = E[s[k]s^H[k]]\) is assumed to be a diagonal matrix, and \(\mathbf{n}[k] \in \mathbb{C}^{N_T \times 1}\) is an \(N_T\)-dimensional circularly symmetric complex Gaussian (CSCG) random noise vector with mean \(0_{N_T} \times 1\) and covariance matrix \(\sigma_n^2 \mathbf{I}_{N_T}\). Furthermore, the precoded transmitted signal vector \(\mathbf{g}[k] \in \mathbb{C}^{N_T \times 1}\) and combined noise vector \(\mathbf{n}[k] \in \mathbb{C}^{N_T \times 1}\) are enforced to satisfy the following two conditions respectively: (1) constant transmit power on each subcarrier, and (2) the entries of \(\mathbf{n}[k]\) remain independent and identically distributed (i.i.d.), i.e.,

\[
\text{tr}(\mathbf{R}_s) = \text{tr}(\mathbf{F}_P \mathbf{F}_B[k] \mathbf{R}_s \mathbf{F}_P^H[k] \mathbf{F}_B^H[k]) = \text{tr}(\mathbf{R}_s), \quad \mathbf{R}_n = \sigma_n^2 \mathbf{W}_B^H[k] \mathbf{W}_P^H \mathbf{W}_B[k] = \sigma_n^2 \mathbf{I}_{N_T}. \tag{3}
\]

2We consider a stricter condition that the constant power is allocated per subcarrier instead of per OFDM symbol for the sake of low complexity.

Figure 1. A MIMO-OFDM transceiver has hybrid analog and digital beamforming (DBF) structures on both sides, where each analog beamforming vector is represented by multiple phase shifters connecting to one RF chain.

\[\]
• \( \phi_{D,c,r} \) is the angle of departure (AoD) of ray \( r \) in cluster \( c \), see Fig. 2. It is characterized by the mean \( \phi_{D,c} \), root mean square angular spread \( c_D \), and offset angle \( \Delta_r \) for ray \( r \), i.e.,

\[
\phi_{D,c,r} = \phi_{D,c} + c_D \Delta_r,
\]

where \( \phi_{D,c} \sim \mathcal{U}(-\pi/2,\pi/2) \), \( \Delta_r \), and \( c_D \) are respectively given in [5, Table 7.5-3] and [5, Table 7.5-6]. In the same way, one can generate the angle of arrival (AoA) \( \phi_{A,c,r} \).

• The array response vector of the ULA to an incident plane wave at the transmitter, \( \mathbf{a}_D(\phi_{A,c,r}) \), has \( N_T \) entries of equal magnitude and is a function of \( \phi_{A,c,r} \) only. It can be written as

\[
\mathbf{a}_D(\phi_{D,c,r}) = \frac{1}{\sqrt{N_T}} \left[ 1, e^{j \frac{2 \pi c_D}{\lambda} \sin(\phi_{D,c,r})}, \ldots, e^{j \frac{2 \pi c_D}{\lambda} \sin(\phi_{D,c,r}) (N_T - 1) \Delta_r} \right]^T.
\]

III. PROBLEM STATEMENT

In the beamforming system, the objective of the precoder \( \mathbf{F}_P \mathbf{F}_B[k] \forall k \) and the associated combiner \( \mathbf{W}_P \mathbf{W}_B[k] \forall k \) is to maximize the mutual information of the system subject to the power constraints on \( \mathbf{F}_P \), \( \mathbf{W}_P \), \( \mathbf{F}_B[k] \), and \( \mathbf{W}_B[k] \forall k \). That is, we seek matrices that solve

\[
\max_{\mathbf{F}_P, \mathbf{W}_P, (\mathbf{F}_B[k], \mathbf{W}_B[k]) \forall k} \sum_{k=0}^{K-1} \max_{\mathbf{f}_p, \mathbf{w}_p, \mathbf{f}_B[k], \mathbf{w}_B[k]} \text{I}(\mathbf{F}_P, \mathbf{W}_P, \mathbf{F}_B[k], \mathbf{W}_B[k]),
\]

\[
\text{s.t.} \quad \mathbf{f}_p, \mathbf{w}_p, \mathbf{f}_B[k], \mathbf{w}_B[k] \in \mathcal{W} \forall n_f, \quad \text{tr}(\mathbf{f}_p \mathbf{F}_B[k] \mathbf{R}_s \mathbf{f}_B[k] \mathbf{H}^H) = \text{tr}(\mathbf{R}_s) \forall k, \quad \mathbf{W}_B[k] \mathbf{W}_B[k] = \mathbf{I}_{N_S} \forall k,
\]

where \( \mathbf{f}_p, \mathbf{w}_p, \mathbf{f}_B[k], \mathbf{w}_B[k] \) are respectively the \( n_f \)th column vectors of \( \mathbf{F}_P \) and \( \mathbf{W}_P \), and the last two constraints are the consequences of (3) and (4). Assume that \( s[k] \) is a CSCG random vector with mean \( 0_{N_S \times 1} \), i.e., \( s[k] \sim \mathcal{CN}(0_{N_S \times 1}, \mathbf{R}_s) \), the mutual information of the system of the \( k \)th OFDM subchannel is given by [12], [19], [31], [32]

\[
\text{I}(\mathbf{F}_P, \mathbf{W}_P, \mathbf{F}_B[k], \mathbf{W}_B[k]) = \log_2 \det \left( \mathbf{I}_{N_S} + R_s^{-1} (\mathbf{W}_B[k] \mathbf{W}_B[k] \mathbf{H} \mathbf{W}_B[k] \mathbf{F}_B[k]) \cdot (\mathbf{W}_B[k] \mathbf{W}_B[k] \mathbf{H} \mathbf{W}_B[k] \mathbf{F}_B[k])^H \right).
\]

Moreover, we denote the solution of (8) by \( (\mathbf{F}_{P,\text{Opt}}, \mathbf{W}_{P,\text{Opt}}, (\mathbf{F}_{B,\text{Opt}}[k], \mathbf{W}_{B,\text{Opt}}[k]) \forall k) \).

If explicit CSI is available, the problem of the precoder and combiner can be solved by exploiting the SVD of the channel matrix [15], [19], [21]. In the paper, we consider a more pragmatic approach that channel knowledge is neither given nor estimated. To efficiently get the solution of (8) without the channel knowledge, we try an alternative expression of (8): given two sets \( \mathcal{I}_X \) and \( \mathcal{I}_W \), the maximum data rate of (8) is greater than or equal to

\[
I_{LM}(\mathbf{F}_P, \mathbf{W}_P) : \text{local maximum throughput}
\]

These two versions of the hybrid beamforming problem will have the same maximum throughput if \( \mathcal{I}_X \) and \( \mathcal{I}_W \) include \( \mathbf{F}_{P,\text{Opt}} \) and \( \mathbf{W}_{P,\text{Opt}} \) respectively.

The reformulated problem in (10) becomes simpler because, given \( \mathbf{F}_P \) and \( \mathbf{W}_P \), the inner problem (to obtain the local maximum throughput \( I_{LM}(\mathbf{F}_P, \mathbf{W}_P) \)) is similar to conventional fully digital beamforming designs subject to different power constraints [10], [26]. In other words, the critical issue of the hybrid beamforming is to solve the outer problem by an additional maximization over all members of \( \mathcal{I}_X \) and \( \mathcal{I}_W \). Therefore, the motivation is to find \( \mathcal{I}_X \) and \( \mathcal{I}_W \), which ideally include \( \mathbf{F}_{P,\text{Opt}} \), \( \mathbf{W}_{P,\text{Opt}} \), and perhaps few other candidates, and then select a pair \( (\mathbf{F}_P, \mathbf{W}_P) \) from \( \mathcal{I}_X \) and \( \mathcal{I}_W \) that leads to the maximum throughput.

IV. A HYBRID BEAMFORMING ALGORITHM BASED ON IMPLICIT CSI

In this section, we present how to use implicit CSI to find the optimal solution to the hybrid beamforming problem. In addition, key parameters of the hybrid beamforming gain are introduced to reduce the complexity of the problem.

A. Initial analog beam selection

To begin with, let us see how to obtain the sets \( \mathcal{I}_X \) and \( \mathcal{I}_W \) in (10) from the given codebooks \( \mathcal{F} \) and \( \mathcal{W} \). We call this step initial analog beam selection. By transmitting known pilot signals, we have the received pilot signals used for the initial analog beam selection. However, these received signals include the effect of analog beamforming because the hardware-constrained analog beamforming matrices \( \mathbf{F}_P \) and \( \mathbf{W}_P \) cannot be replaced by the identity matrices. As a result, one can simply assume that all the members of the codebooks \( \mathcal{F} = \{\mathbf{f}_n, n_f = 1, \cdots, N_F\} \) and \( \mathcal{W} = \{\mathbf{w}_n, n_w = 1, \cdots, N_W\} \) are trained by transmitting a training sequence \( \{s[k]\}_{k=0}^{K-1} \) that satisfies \( |s[k]|^2 = 1 \forall k \), as shown in Fig. 3. Then an
observation used for the analog beam selection at subcarrier $k$ for a specific beam pair $(\hat{f}_{nj}, \hat{w}_{nw})$ can be acquired by correlating the $k^{th}$ received pilot with its transmitted signal

$$y_{nw,nj}[k] = \frac{s^*[k]}{|s[k]|^2}(\hat{w}_{nw}^H \mathbf{H}[k] \hat{f}_{nj} s[k] + \hat{w}_{nw}^H n[k])$$

received pilot signal

$$= \hat{w}_{nw}^H \mathbf{H}[k] \hat{f}_{nj} + \frac{s^*[k]}{|s[k]|^2} \hat{w}_{nw}^H n[k]$$

(11)

$$= \hat{w}_{nw}^H \mathbf{H}[k] \hat{f}_{nj} + z_{nw,nj}[k].$$

Similar observations become available on all subcarriers and the effective noise $z_{nw,nj}[k]$ is random for a trained analog beam pair $(\hat{f}_{nj}, \hat{w}_{nw})$. The observation $y_{nw,nj}[k]$ can be viewed as implicit CSI, which is a coupling coefficient corresponding to a pair of analog beamforming vectors selected on both sides of the channel.

Borrowing the idea from our previous works in [27], [33], it shows that when $\mathcal{F}$ and $\mathcal{W}$ are orthogonal codebooks, the sum of the power of $K$ observations in one OFDM symbol can be directly used for the analog beam selection. Consequently, $M$ analog beam pairs (assume that $M \geq N_{RF}$, which will be explained later) can be selected individually and sequentially according to the sorted received energy estimates

$$\hat{(f_m, w_m)} = \arg \max_{\hat{f}_{nj} \in \mathcal{F}, \hat{w}_{nw} \in \mathcal{W}, \mathcal{W}'} \sum_{k=0}^{K-1} \left| y_{nw,nj}[k] \right|^2,$$

(12)

where $m = 1, \ldots, M$, $\mathcal{F}' = \{\hat{f}_n, n = 1, \ldots, m-1\}$ and $\mathcal{W}' = \{\hat{w}_n, n = 1, \ldots, m-1\}$ are the sets consisting of the selected analog beamforming vectors from iteration 1 to $m-1$.

We assume that $M \geq N_{RF}$ for the reason that the first $N_{RF}$ selected analog beam pairs according to the sorted values of $\sum_{k=0}^{K-1} |y_{nw,nj}[k]|^2$, where $n_w = 1, \ldots, N_W$ and $n_f = 1, \ldots, N_F$, may not be equal to the optimal solution $(\mathbf{F}_{P,Opt}$ and $\mathbf{W}_{P,Opt})$ because we do not yet consider the effect of digital beamforming during the analog beam selection phase. In addition, (12) is derived from the assumption that $\mathcal{F}$ and $\mathcal{W}$ are orthogonal codebooks. To find the optimal solution for any type of codebook (orthogonal or non-orthogonal), one has to further take into account linear combinations of $N_{RF}$ members chosen from $(\mathcal{F}_m \forall m)$ and $(\mathcal{W}_m \forall m)$ with coefficients in digital beamforming. To this end, we define two sets $\mathcal{I}_F$ and $\mathcal{I}_W$ consisting of $(\hat{f}_m, \hat{w}_m)$ and $(\tilde{f}_m, \tilde{w}_m)$, respectively, which can be written as

$$\mathcal{I}_F = \{\mathbf{F}_{P,i_f}, i_f = 1, \ldots, I_F\},$$

$$\mathcal{I}_W = \{\mathbf{W}_{P,i_w}, i_w = 1, \ldots, I_W\},$$

(13)

where the cardinality $I_F = I_W = \binom{M}{N_{RF}}$ of both sets is given by the binomial coefficient. The notations $\mathbf{F}_{P,i_f}$ and $\mathbf{W}_{P,i_w}$ respectively denote the $i_f^{th}$ and $i_w^{th}$ candidates for the analog beamforming matrices $\mathbf{F}_P$ and $\mathbf{W}_P$. When $M$ becomes large, there is a high probability that $\mathcal{I}_F$ and $\mathcal{I}_W$ include the global optimum solution $(\mathbf{F}_{P,Opt}$ and $\mathbf{W}_{P,Opt})$.

Schematic example: To illustrate the concept, let us consider a scenario with $N_T = N_R = 8$ antenna elements, codebook sizes $N_F = N_W = 8$, the same orthogonal codebook $\mathcal{F} = \mathcal{W}$ at the transmitter and receiver with the candidates for steering angles given by $\{-90^\circ, 90^\circ\}$, $-48.59^\circ, 30^\circ, -14.48^\circ, 0^\circ, 14.48^\circ, 30^\circ, 48.59^\circ\}$, and $N_{RF} = 2$ available RF chains to transmit $N_S = 2$ data streams at SNR = 5 dB.

The channel realization as depicted in Fig. 4 has two paths. In Fig. 4(a), two analog beam pairs selected according to (12) steer towards these two paths (highlighted in red). Before digital beamforming comes into play, the analog beamforming
vectors would be used with the same weighting. If more than \(N_{RF} = 2\) analog beam pairs are reserved, more options with digital beamforming can be explored. In this example, with \(M = 4\), we have \(I_F = I_W = \binom{4}{2} = 6\) members in both \(I_F\) and \(I_W\), see Fig. 5. We enumerate them explicitly as

\[I_F = \{ F_{P,i_f,i_f} \mid i_f = 1, \ldots, 6 \}, \]
\[I_W = \{ W_{P,i_w,i_w} \mid i_w = 1, \ldots, 6 \}. \]

For instance, \(\tilde{F}_{P,1} = [\tilde{f}_1, \tilde{f}_6]\) and \(\tilde{W}_{P,1} = [\tilde{w}_3, \tilde{w}_4]\). Therefore, one can try 36 pairs, \(\{ (F_{P,i_f,i_f}, W_{P,i_w,i_w}) \mid \forall i_f, i_w \}\), to determine the optimal weights of digital beamformers and the corresponding analog beamforming matrices, which will be detailed in the following subsections. In general, there will be a competition between spatial multiplexing gain over different propagation paths and power gain available from the dominant path. In this case, the two analog beam pairs highlighted in blue in Fig. 4(b) steer to the dominant path and lead to higher spectral efficiency. However, which beamforming strategy yields higher throughput in any specific case is not clear beforehand.

### B. Digital beamforming

After the initial analog beam selection, we are in possession of the two sets \(I_F\) and \(I_W\) that contain the candidates for \(F_P\) and \(W_P\), and the objective is to efficiently find the optimal solution. Before going into the detail of our proposed scheme, let us review the relationship between the analog and digital beamforming. Given one particular choice \((\tilde{F}_{P,i_f}, \tilde{W}_{P,i_w})\) selected from the candidate sets \(I_F\) and \(I_W\), it is clear that the goal of digital beamforming is to maximize the local maximum throughput \(I_{LM}(F_{P,i_f}, W_{P,i_w})\), as defined in (10), with the objective function expressed as

\[
\max_{(F_P[k], W_P[k]) \in \forall k} \sum_{k=0}^{K-1} I(F_{P,i_1}, W_{P,i_2}, F_B[k], W_B[k])
\]

\[
= \sum_{k=0}^{K-1} \max_{F_B[k], W_B[k]} I(F_{P,i_1}, W_{P,i_2}, F_B[k], W_B[k]),
\]

where \(I(F_{P,i_1}, W_{P,i_2}, F_B[k], W_B[k])\) is given by (9) with \(F_P = F_{P,i_1}\) and \(W_P = W_{P,i_2}\). As a result, the digital beamforming problem at subcarrier \(k\) can be formulated as a throughput maximization problem subject to the power constraints, which can be stated as

\[
(F_{B,i}[k], W_{B,i}[k]) = \arg \max_{F_B[k], W_B[k]} I(F_{P,i_1}, W_{P,i_2}, F_B[k], W_B[k])
\]

subject to

\[
\begin{align*}
\text{tr}(F_{P,i_1} W_{P,i_2} F_B[k] F_{P,i_1}^H) = & \text{tr}(R_s), \\
W_B[H][k] W_{P,i_2} W_{P,i_2} W_B[k] = & I_{NS},
\end{align*}
\]

where \(i = (i_1-1)I_W+i_{i_2}\) is an index specifying the combined members of \(I_F\) and \(I_W\). To proceed, we take advantage of the mathematical results in Appendix A and have

\[
F_{B,i}[k] = (F_{P,i_1} W_{P,i_2})^{-0.5} [V_{E,i}[k]]_{1:1:1:NS},
\]
\[
W_{B,i}[k] = (W_{P,i_2} W_{P,i_2})^{-0.5} [U_{E,i}[k]]_{1:1:1:NS},
\]

where the columns of \(V_{E,i}[k]\) and \(U_{E,i}[k]\) are respectively the right- and left-singular vectors of the effective channel matrix defined by

\[
H_{E,i}[k] = (W_{P,i_2} W_{P,i_2})^{-0.5} W_{P,i_2} H[k] F_{P,i_1} (F_{P,i_1} W_{P,i_2})^{-0.5}.
\]

### C. Key parameters of hybrid beamforming gain

As mentioned above, given a pair of members selected from \(I_F\) and \(I_W\), \((F_{P,i_1}, W_{P,i_2})\), we have the corresponding optimal digital beamforming matrices \((F_{B,i}[k], W_{B,i}[k])\) \(\forall k\). Accordingly, the local maximum throughput is given by

\[
I_{LM}(F_{P,i_1}, W_{P,i_2})
= \sum_{k=0}^{K-1} \sum_{n=1}^{N_s} \text{log}_2 \left( 1 + \frac{1}{\sigma_n^2} \mathbf{E}_i[k]_{n,n_s} \mathbf{R}_s_{n,n_s} \right),
\]

where the diagonal elements of \(\mathbf{E}_i[k]\) are the singular values of the effective channel \(H_{E,i}[k]\) \(\forall k\). Based on the candidate set \(\{ F_{P,i_1}, W_{P,i_2} \mid \forall i_1, i_2 \}\), the pair leading to the maximum throughput provides the best approximation of the global optimal analog beamforming matrices, that is, the solution to the hybrid beamforming problem in (10), written as

\[
(F_P, W_P) = \arg \max_{(F_P[k], W_P[k]) \in \forall k} I_{LM}(F_{P,i_1}, W_{P,i_2}).
\]

However, this way of solving the problem requires the SVD of \(\{H_{E,i}[k]\}_{k=0}^{K-1}\) to obtain \(I_{LM}(F_{P,i_1}, W_{P,i_2})\) for each pair, which means that we have to repeat the calculation as many as \(\binom{M}{2}\) times.

Alternatives that can reduce the potentially large computational burden are necessary. We ask ourselves what are the crucial parameter(s) or indicator(s) that actually determine the throughput. To answer this question, let \(R_s = \frac{1}{\sigma_n} I_{NS}\) (equal power allocation) so that the maximum spectral efficiency at subcarrier \(k\) becomes

\[
I(F_{P,i_1}, W_{P,i_2}, F_{B,i}[k], W_{B,i}[k])
= \sum_{n=1}^{N_s} \text{log}_2 \left( 1 + \frac{1}{N_s \sigma_n^2} \mathbf{E}_i[k]_{n,n_s} \right),
\]

\[
= \sum_{n=1}^{N_s} \left( 1 + \gamma \mathbf{E}_i[k]_{n,n_s} \right).
\]

It is simpler to find the key parameter of the hybrid beamforming gain in the high and low SNR regimes. At low SNR
\( (\gamma \to 0) \), using the fact that \( \log(1 + x) \approx \gamma x \) as \( \gamma \to 0 \), the achievable spectral efficiency in (21) can be approximated by

\[
I(\mathbf{F}_{P,ij}, \mathbf{W}_{P,iw}, \mathbf{F}_{B,i}[k], \mathbf{W}_{B,i}[k]) \approx \gamma \sum_{n_s=1}^{N_S} \left\| \mathbf{H}_{E,i}[k] \right\|_F^2
\]

\[
\leq \left\| \mathbf{H}_{E,i}[k] \right\|_F^2
\]

(22)

with equality in (a) if \( N_{RF} = N_S \). For the case of \( N_{RF} > N_S \), \( \left\| \mathbf{H}_{E,i}[k] \right\|_F^2 \) corresponds to the sum of all \( N_{RF} \) (instead of only the \( N_S \) strongest) eigenvalues of \( \mathbf{H}_{E,i}[k] \mathbf{H}_{E,i}^H[k] \). Assuming that the sum of the weaker \( N_{RF} - N_S \) eigenvalues of \( \mathbf{H}_{E,i}[k] \mathbf{H}_{E,i}^H[k] \) is small, the approximation of \( \sum_{n_s=1}^{N_S} \left[ \Sigma^2_{E,i}[k] \right]_{n_s,n_s} \) by \( \left\| \mathbf{H}_{E,i}[k] \right\|_F^2 \) seems to be valid for most cases of interest.

On the other hand, in the high SNR regime \( (\gamma \to \infty) \), using \( \log(1 + x) \approx \log x \) as \( \gamma \to \infty \), the achievable spectral efficiency in (21) is approximated by

\[
I(\mathbf{F}_{P,ij}, \mathbf{W}_{P,iw}, \mathbf{F}_{B,i}[k], \mathbf{W}_{B,i}[k]) \approx \gamma \sum_{n_s=1}^{N_S} \log_2 \left( \gamma \left[ \Sigma^2_{E,i}[k] \right]_{n_s,n_s} \right)
\]

\[
= \log_2 \left( \gamma^{N_S} \right) + \log_2 \left( \prod_{n_s=1}^{N_S} \left[ \Sigma^2_{E,i}[k] \right]_{n_s,n_s} \right)
\]

\[
\leq \log_2 \left( \gamma^{N_S} \right) + \log_2 \left( \left\| \mathbf{H}_{E,i}[k] \right\|_F^2 \right)
\]

which holds with equality in (b) if \( N_{RF} = N_S \). When the number \( CR \) of propagation paths is much larger than the number \( N_{RF} \) of RF chains, it is reasonable to conclude that \( \det(\mathbf{H}_{E,i}[k]) \neq 0 \), i.e., \( \text{rank}(\mathbf{H}_{E,i}[k]) = N_{RF} \).

As we have seen, either the Frobenius norm of the effective channel matrix or the absolute value of the determinant of the effective channel matrix acts as the key parameter for the system throughput. The discussion focuses on the high and low SNR regimes, and we will provide more details on approximation error in the numerical results.

### D. Hybrid Beamforming Based on Implicit CSI

In this subsection, we will introduce how to use the coupling coefficients (or implicit CSI) to obtain the effective channel matrix \( \mathbf{H}_{E,i}[k] \). Once we have \( \mathbf{H}_{E,i}[k] \), the solution of the hybrid beamforming problem can be efficiently found by using the key parameters. First, let us show the effective channel matrices presented in (18) and approximate the elements of the matrix \( \mathbf{W}_{P,iw}^H \mathbf{H}_{E,i}[k] \mathbf{F}_{P,ij} \) by the coupling coefficients as the following equations:

\[
\mathbf{H}_{E,i}[k] \approx \left( \mathbf{W}_{P,iw}^H \mathbf{W}_{P,iw} \right)^{-0.5} \mathbf{W}_{P,iw}^H \mathbf{H}_{E,i}[k] \mathbf{F}_{P,ij} \left( \mathbf{F}_{P,ij}^H \mathbf{W}_{P,iw} \right)^{-0.5}
\]

\[
\approx \left( \mathbf{W}_{P,iw}^H \mathbf{W}_{P,iw} \right)^{-0.5} \mathbf{Y}_i[k] \left( \mathbf{F}_{P,ij}^H \mathbf{F}_{P,ij} \right)^{-0.5}
\]

\[
\approx \left( \mathbf{Y}_i[k] \mathbf{F}_{P,ij} \right)^{-0.5}
\]

(24)

where the elements of \( \mathbf{Y}_i[k] \) can be collected from the coupling coefficients [33]. For example, when \( \mathbf{F}_{P,ij} = [\mathbf{f}_1, \ldots, \mathbf{f}_{N_{RF}}] \) and \( \mathbf{W}_{P,iw} = [\mathbf{w}_1, \ldots, \mathbf{w}_{N_{RF}}] \), where \( \mathbf{f}_{n_{RF}} \) is the \( n_{RF} \) column of \( \mathbf{F} \) and \( \mathbf{w}_{n_{RF}} \) is the \( n_{RF} \) column of \( \mathbf{W} \), one has

\[
\mathbf{Y}_i[k] = \begin{bmatrix}
y_{1,1}[k] & \cdots & y_{1,N_{RF}}[k] \\
\vdots & \ddots & \vdots \\
y_{N_{RF},1}[k] & \cdots & y_{N_{RF},N_{RF}}[k]
\end{bmatrix}
\]

(25)

Therefore, given a pair \( (\mathbf{F}_{P,ij}, \mathbf{W}_{P,iw}) \) selected from \( \mathcal{I}_\mathcal{F} \) and \( \mathcal{I}_\mathcal{W} \), we can rapidly obtain the approximation of \( \mathbf{H}_{E,i}[k] \), denoted by \( \hat{\mathbf{H}}_{E,i}[k] \) in (24).

In brief, the proposed solution can be stated as follows: first obtain the candidate sets \( (\mathcal{I}_\mathcal{F} \text{ and } \mathcal{I}_\mathcal{W}) \) and the approximation of \( \mathbf{H}_{E,i}[k] \) from the observations (or coupling coefficients) \( \{y_{n_{RF},n_{RF}}[k] \forall n_{RF}, n_{RF}\} \), and then solve the max-minimization problem in (20), which can be rewritten as

\[
\left( \hat{i}_f, \hat{i}_w \right) = \arg \max_{\mathbf{F}_{P,ij} \in \mathcal{I}_\mathcal{F}, \mathbf{W}_{P,iw} \in \mathcal{I}_\mathcal{W}} I_{LM}(\mathbf{F}_{P,ij}, \mathbf{W}_{P,iw})
\]

\[
\approx \arg \max_{\mathbf{F}_{P,ij} \in \mathcal{I}_\mathcal{F}, \mathbf{W}_{P,iw} \in \mathcal{I}_\mathcal{W}} \sum_{k=0}^{K-1} f \left( \hat{\mathbf{H}}_{E,i}[k] \right),
\]

(26)

where \( f(\hat{\mathbf{H}}_{E,i}[k]) \) denotes the analog beam selection criterion using (21), (22), or \( |\det(\mathbf{H}_{E,i}[k])| \) in (23), with the argument \( \mathbf{H}_{E,i}[k] \) and \( \hat{\mathbf{H}}_{E,i}[k] \) and \( \mathbf{U}_{E,i}[k] \mathbf{S}_{E,i}[k] \mathbf{V}_{E,i}^H[k] \), given by

\[
f \left( \mathbf{H}_{E,i}[k] \right) = \begin{cases}
\sum_{n_s=1}^{N_S} \log_2 \left( 1 + \gamma \left[ \Sigma^2_{E,i}[k] \right]_{n_s,n_s} \right), & \text{w/ approx. as } \gamma \to 0 \\
\left\| \mathbf{H}_{E,i}[k] \right\|_F^2 & \text{w/ approx. as } \gamma \to \infty 
\end{cases}
\]

(27)

Next, according to the selected index pair \( (\hat{i}_f, \hat{i}_w) \), the selected analog and corresponding digital beamforming matrices are given by

\[
\hat{\mathbf{F}}_{P} = \mathbf{F}_{P,\hat{i}_f},
\]

\[
\hat{\mathbf{W}}_{P} = \mathbf{W}_{P,\hat{i}_w},
\]

\[
\hat{\mathbf{F}}_{B}[k] = (\hat{\mathbf{F}}_{P}^H \hat{\mathbf{F}}_{P})^{-0.5} \hat{\mathbf{V}}_{E,i}[k]_{1:N_S},
\]

\[
\hat{\mathbf{W}}_{B}[k] = (\hat{\mathbf{W}}_{P}^H \hat{\mathbf{W}}_{P})^{-0.5} \hat{\mathbf{U}}_{E,i}[k]_{1:N_S},
\]

(28)

where \( \hat{i} = (\hat{i}_f - 1)I_W + \hat{i}_w \) and \( \hat{\mathbf{U}}_{E,i}[k] \mathbf{S}_{E,i}[k] \mathbf{V}_{E,i}^H[k] = \text{SVD}(\hat{\mathbf{H}}_{E,i}[k]) \).

The pseudocode of the proposed hybrid beamforming algorithm based on implicit CSI is shown in Algorithm 1. The advantages of the proposed algorithm are: (1) channel estimation for large antenna arrays can be omitted, and (2) even though the set sizes of \( \mathcal{I}_\mathcal{F} \) and \( \mathcal{I}_\mathcal{W} \) are large, the computational overhead is minor. At low SNR, we just need to
calculate the Frobenius norm of the effective channel matrices, whose elements can be easily obtained from the observations \( \{ y_{n,w,n_f} | \forall n, n_f, k \} \).

In (21), we simply assume that the transmit power is equally allocated to \( N_S \) data streams to facilitate the process of finding the key parameters. Once we find the analog and digital beamforming matrices, the global maximum throughput can be further improved by optimizing the power allocation (i.e., by a water-filling power allocation scheme [26]) for \( N_S \) data streams according to the effective channel condition.

V. ANALYSIS OF THE PROPOSED HYBRID BEAMFORMING ALGORITHM

In the section, we focus on the statistical analysis of using the Frobenius norm of the effective channel as the key parameter at low SNR. Starting from (24), \( \tilde{H}_{E,i}[k] \) can be expressed as a noisy version of the true effective channel as

\[
\begin{align*}
\tilde{H}_{E,i}[k] & \equiv \text{SVD} \left( \tilde{W}_{P,i}^H \tilde{W}_{P,iw} \right)^{0.5} \tilde{Y}_{E,i}[k] \tilde{F}_{P,i}^T \tilde{F}_{P,i}^{-0.5} \\
& = \tilde{W}_{P,i}^H \tilde{W}_{P,iw} \tilde{H}_{E,i}[k] \tilde{F}_{P,i}^T \tilde{F}_{P,i}^{-0.5} \\
& + \left( \tilde{W}_{P,i}^H \tilde{W}_{P,iw} \right)^{0.5} \tilde{Z}_{E,i}[k] \tilde{F}_{P,i}^T \tilde{F}_{P,i}^{-0.5} \\
& = \tilde{H}_{E,i}[k] + \tilde{Z}_{E,i}[k],
\end{align*}
\]

where the multivariate distribution of the \( N_{RF}^2 \)-dimensional random vector \( \tilde{Z}_{E,i}[k] \) can be written as (see Appendix B)

\[
\tilde{Z}_{E,i}[k] \sim \mathcal{CN} \left( 0_{N_{RF}^2 \times 1}, \sigma_n^2 \left( \left( \tilde{F}_{P,i}^T \tilde{F}_{P,i} \right)^{-1} \otimes \left( \tilde{W}_{P,iw}^H \tilde{W}_{P,iw} \right)^{-1} \right) \right).
\]

From (29), we have \( \| \tilde{H}_{E,i}[k] \|^2_F \) given by

\[
\| \tilde{H}_{E,i}[k] \|^2_F = \| H_{E,i}[k] \|^2_F + 2 \cdot \Re \left( (H_{E,i}^H[k] Z_{E,i}[k]) \right).
\]

To analyze the noise effect, we introduce the quantities \( U \) and \( V \), conditional on a channel state \( H'[k] \) and an analog beamforming pair \( \tilde{F}_{P,i}^T \tilde{W}_{P,iw} \), given by

\[
\begin{align*}
U & = \| Z_{E,i}[k] \|^2_F, \\
V & = 2 \cdot \Re \left( (H_{E,i}^H[k] Z_{E,i}[k]) \right).
\end{align*}
\]

where

\[
\begin{align*}
H_{E,i}[k] & = \left( \tilde{W}_{P,iw}^H \tilde{W}_{P,iw} \right)^{0.5} H'[k] \tilde{F}_{P,iw} \left( \tilde{F}_{P,iw}^T \tilde{F}_{P,iw} \right)^{-0.5}, \\
& \text{and then pursue the analysis of } U \text{ and } V \text{ for orthogonal and non-orthogonal codebooks.}
\end{align*}
\]

A. Orthogonal codebooks

When the columns of \( \tilde{F}_{P,i} \) and the columns of \( \tilde{W}_{P,iw} \) are mutually orthogonal respectively, from (30) we know that the elements of \( \text{vec}(Z_{E,i}[k]) \) have the same normal distribution with mean zero and variance \( \sigma_n^2 \), \( \text{vec}(Z_{E,i}[k]) \sim \mathcal{CN}(0_{N_{RF}^2 \times 1}, \sigma_n^2 I_{N_{RF}^2}) \). Therefore, \( U \) is the sum of the absolute squares of \( N_{RF} \) i.i.d. Gaussian random variables, which follows a Gamma distribution with shape parameter \( N_{RF}^2 \) and scale parameter \( \sigma_n^2 : \)

\[
U = \sum_{i=1}^{N_{RF}} \sum_{j=1}^{N_{RF}} \Re \left( \left( Z_{E,i}[k] \right)_{i,j} \right)^2 + 3 \left( \left( Z_{E,i}[k] \right)_{i,j} \right)^2 \sim \Gamma \left( \frac{1}{2}, \sigma_n^2 \right)
\]

In addition, \( V \) is normally distributed with mean zero and variance \( 2\sigma_n^2 \| H_{E,i}^H[k] \|^2_F \).

B. Non-orthogonal codebooks

When the columns of \( \tilde{F}_{P,i}^T \) or the columns of \( \tilde{W}_{P,iw} \) are not mutually orthogonal, the elements of \( \text{vec}(Z_{E,i}[k]) \) in (30) are not i.i.d. anymore. In this case, there are no closed-form expressions for the probability distributions of \( U \) and \( V \). Accordingly, we only derive and state \( \mathbb{E}[U] \), \( \text{Var}(U) \), and \( \mathbb{E}[V] \) in this section. These are given by (see Appendix C)

\[
\begin{align*}
\mathbb{E}[U] & = \sigma_n^2 \cdot \text{tr} \left( \left( \tilde{F}_{P,i}^T \tilde{F}_{P,i} \right)^{-1} \right) \text{tr} \left( \left( \tilde{W}_{P,iw}^H \tilde{W}_{P,iw} \right)^{-1} \right), \\
\text{Var}(U) & = \text{tr}(\Psi R_{R_{tv}}) - \mathbb{E}[U]^2,
\end{align*}
\]

where

\[
\Psi = \left( \tilde{F}_{P,i}^T \tilde{F}_{P,i} \right)^{-1} \otimes \left( \tilde{W}_{P,iw}^H \tilde{W}_{P,iw} \right)^{-1} \otimes \left( \tilde{W}_{P,iw}^H \tilde{W}_{P,iw} \right)^{-1}
\]
the errors between the right singular vectors and the precoder is to minimize the sum of the squared Frobenius norms of carriers. In the reference method, given the channel matrices, comparison and extended it from single carrier to multiple carriers. This implies that

\[
\mathbf{R}_{\mathbf{z}_v} = \mathbb{E}[(\text{vec}(\mathbf{Z}[k]) \otimes \text{vec}(\mathbf{Z}[k]))(\text{vec}(\mathbf{Z}[k]) \otimes \text{vec}(\mathbf{Z}[k]))^H],
\]

\[
\mathbf{z}_v[k] \in \mathbb{C}^{N_R \times 1} \quad \mathbf{z}_v[k] \quad (38)
\]

and \( \mathbb{E}[V] = 0 \). Unfortunately, we did not find a closed-form expression for \( \text{Var}(V) \). From the analysis results, it is clear that when we use non-orthogonal codebooks, the distributions of \( U \) and \( V \) vary with different candidates for analog beamforming matrices. This implies that \( \| \mathbf{H}_{E,i}[k] \|_F^2 \) in (31) may become unreliable because of the non-i.i.d. noise signals.

VI. SIMULATION RESULTS

The system parameters used in the simulations are listed below. In addition, the SNR in linear scale is given by \( \text{SNR} = \frac{\rho}{N_R N_N} \), where \( \rho \) is the average received power.

- Number of antennas: \( N_T = N_R = 32 \)
- Number of RF chains: \( N_{RF} = 2 \)
- Number of data streams: \( N_S = 2 \)
- Length of a training sequence: \( K = 512 \)
- Number of clusters: \( C = 5 \) (1 LoS and 4 NLoS clusters)
- Number of rays per cluster: \( R = 8 \)

We chose the work in [15] that implements hybrid beamforming based on explicit CSI as a reference method for comparison and extended it from single carrier to multiple carriers. In the reference method, given the channel matrices, \( \mathbf{H}[k] = \mathbf{U}[k] \mathbf{\Sigma}[k] \mathbf{V}^H[k] \forall k \), the goal of the precoder design is to minimize the sum of the squared Frobenius norms of the errors between the right singular vectors and the precoder across all subcarriers:

\[
(\mathbf{F}_p, \mathbf{F}_B[k] \forall k) = \arg \min_{\mathbf{F}_p, \mathbf{F}_B[k] \forall k} \sum_{k=0}^{K-1} \left\| \mathbf{V}[k] \right\|_{2,1: N_S} - \mathbf{F}_p \mathbf{F}_B[k] \|_F^2,
\]

\[
\text{s.t. } \left\{ \mathbf{f}_{r,n_f} \in \mathcal{F} \forall n_f, \left\| \mathbf{F}_p \mathbf{F}_B[k] \right\|_F^2 = N_S \forall k. \right. \]

The problem can be solved by the OMP algorithm [28] and the pseudocode is given in Algorithm 2. Similarly, given \( \left[ \mathbf{U}[k] \right]_{1:1, N_S} \), we have the corresponding solution to the combiner, denoted by \( (\mathbf{W}_p, \mathbf{W}_B[k] \forall k) \).

Comparing Algorithm 1 with Algorithm 2, we know that the first algorithm uses the received coupling coefficients as the inputs, while the second uses the singular vectors of the channel as the inputs. The coupling coefficients are commonly used for channel estimation [17], [22], but in this paper we use them to directly implement the hybrid beamforming on both sides. As a result, we can get rid of the overhead of channel estimation.

To clearly present the difference in throughput in the simulation results, the calculated throughput values are normalized by the throughput achieved by fully digital beamforming (DBF), i.e.,

\[
I_{DBF} = \sum_{k=0}^{K-1} \sum_{n_s=1}^{N_S} \log_2 \left( 1 + \frac{\gamma}{\| \mathbf{\Sigma}_2^2[k] \|_{n_s, n_s} } \right),
\]

\[ \text{(40)} \]

where \( \gamma = \frac{1}{\text{SNR}} \) and the diagonal entries of \( \mathbf{\Sigma}_2^2[k] \) are the eigenvalues of \( \mathbf{H}[k] \mathbf{H}^H[k] \). The spectral efficiency of the fully digital beamforming system \( (I_{DBF}/K) \) from SNR = -20 dB to 30 dB (step by 5 dB) is: \( \{0.05, 0.14, 0.41, 1.03, 2.17, 3.77, 5.79, 8.17, 10.91, 13.95, 17.13\} \) in bit/Hz. In what follows, a complete analysis with respect to three different codebooks, whose coherence values are 0, 0.12, and 0.99, is provided.\(^4\)

A. Orthogonal codebooks

Assume that the codebooks \( \mathcal{F} \) and \( \mathcal{W} \) have the same number \( N_F = N_W = 32 \) of candidates for the analog beamforming vectors. When \( \mathcal{F} \) and \( \mathcal{W} \) are orthogonal codebooks, the 32 candidates for the steering spatial frequency are equally distributed in the spatial frequency domain and the corresponding steering angles are: \( \left\{ 180^\circ \cdot \sin^{-1} \left( \frac{(n_f - 1) \cdot \pi}{16} \right) \right\}_{n_f = 1, \ldots, 32} \right\} \).\(^{35}\)

In Fig. 6, we evaluate the achievable data rates with \( M = 2, 3, 4, 5 \) initially selected analog beam pairs in the proposed method, and more details of these curves are stated as follows:

- \( I_{P_{\text{rel}}}(\mathbf{E}_{\text{ig}}, M = 2, 3, 4, 5) \) is calculated by

\[
I_{P_{\text{rel}}} = \sum_{k=0}^{K-1} I(\mathbf{F}_p, \mathbf{W}_p, \mathbf{F}_B[k], \mathbf{W}_B[k]),
\]

\[ \text{(41)} \]

where \( (\mathbf{F}_p, \mathbf{W}_p, \mathbf{F}_B[k], \mathbf{W}_B[k]) \) is the output of Algorithm 1 with the beam selection criterion \( f(\mathbf{H}_{E,i}[k]) = \sum_{n_s=1}^{N_S} \log_2 (1 + \gamma |\mathbf{\Sigma}_2^2[k]|_{n_s, n_s} ) \) in Step 6 in the algorithm. In the phase of initial analog beam selection, we reserve \( M = 2, 3, 4, 5 \) initially selected analog beam pairs.

- \( I_{P_{\text{rel}}}(\mathbf{E}_{\text{ig}}, NF, M = 2, 3, 4, 5) \) is calculated in the same way as \( I_{P_{\text{rel}}}(\mathbf{E}_{\text{ig}}, M = 2, 3, 4, 5) \) but with noise-free observations. That is to say, the inputs of Algorithm 1, \( \left\{ y_{n_w, n_f, n} \right\} \forall n_w, n_f, k \), do not take into account the noise effect.

\(^4\)The coherence of a codebook \( \mathcal{F} \) is defined as \( \max_{i<j} |\mathbf{\mathbf{f}_i}^H \mathbf{f}_j| \|\mathbf{f}_i\|_2 \|\mathbf{f}_j\|_2 \) [34].
As shown in Fig. 6, in the low SNR regime, the beam selection performance more or less suffers from the noise effect. When SNR > 0 dB, the noisy observations are reliable enough to achieve almost the same throughput as that by using the noise-free observations. In addition, when M > 5, the achievable data rates are almost the same as the curves with M = 5 (although they are not shown in the figure). For the sake of low complexity, it is not necessary to take more than M = 5 candidates into account because most observations are dominated by noise signals except for those corresponding to the already selected analog beamforming vectors.

Comparisons between the proposed and reference methods are shown in Fig. 7. To better compare our approach with the reference method, we choose the curves \( I_{\text{Ref}} (Eig, NF, M = 2, 3, 4, 5) \) in Fig. 6, whose inputs are noise-free observations. Furthermore, the reference curve denoted by \( I_{\text{Ref}} \) is calculated by

\[
I_{\text{Ref}} = \sum_{k=0}^{K-1} I(\hat{F}_P, \hat{W}_P, \hat{F}_B[k], \hat{W}_B[k]),
\]

where \((\hat{F}_P, \hat{W}_P, \hat{F}_B[k], \hat{W}_B[k])\) is obtained from Algorithm 2 with the inputs \( \{V[k]|v\} \) and \( \{U[k]|v\} \). Data rates achieved by the reference and proposed methods shown in Fig. 7 are normalized by \( I_{\text{DBF}} \), i.e., \( I_{\text{Ref}} / I_{\text{DBF}} \) and \( I_{\text{Pro}} / I_{\text{DBF}} \). In the figure, we can find that the curves \( I_{\text{Pro}} (Eig, NF, M = 3, 4, 5) \) achieve higher data rates than \( I_{\text{Ref}} \). Although these two methods use different ways to implement the hybrid beamforming, we try an explanation based on some assumptions. Assume that these two schemes find the same \( N_{RF} \) analog beam pairs (i.e., \( \hat{F}_P = F_P \) and \( \hat{W}_P = W_P \)), which means that they have the same effective channel \( H_E[k] = [H_E^H[k]F_P] = [W_P^H[k]F_P] \). In this case, Algorithm 1 uses the SVD of effective channel matrices.

\[ ^5 \text{The number “} M - N_{RF} \text{” can be interpreted as a degree of diversity. As it is well known from other diversity techniques, the gain in performance decays more or less quickly with the increasing degrees of diversity.} \]

From [26], we know that this solution is optimal. In contrast, the digital beamforming in Algorithm 2 Step 9 uses the least-squares solution, which is sub-optimal. When we reserve more candidates (\( M > N_{RF} \)), it has a high probability that both algorithms find the same \( N_{RF} \) analog beam pairs. If so, Algorithm 1 theoretically outperforms Algorithm 2.

Next, approximation results of \( I_{\text{Pro}} (Eig, M = 3) \) by using the key parameters are shown in Fig. 8, where

- \( I_{\text{Pro}} (Fro, M = 3) \) and \( I_{\text{Pro}} (Det, M = 3) \) use beam selection criteria \( f(H_E[i]|k] = ||H_E[i]|^2_F \) and \( f(H_E[i]|k] = \det(H_E[i]|)^2 \), respectively, in Algorithm 1 Step 6.

When SNR < 5 dB, \( I_{\text{Pro}} (Fro, M = 3) \) achieves almost the same throughput as \( I_{\text{Pro}} (Eig, M = 3) \). When 5 dB < SNR < 20 dB, both key parameters cannot perfectly yield the same data rates as \( I_{\text{Pro}} (Eig, M = 3) \), but the relative loss amounts to at most a few percentages. From Fig. 6, Fig. 7, and Fig. 8, we can find that if the system operates in the SNR range of 0 to 5 dB, the Frobenius norm of the estimated effective
channel works pretty well.

B. Non-orthogonal codebooks

Now assume that \( \mathcal{F} \) and \( \mathcal{W} \) are non-orthogonal codebooks. As mentioned in Section V, if the columns of \( \mathcal{F} \) or \( \mathcal{W} \) are not mutually orthogonal, some highly correlated columns (e.g., \( |f_{i,2}|, |f_{i,3}| \approx 0.99, i \neq j \)) may make the effective noise level unacceptably large, and the estimated effective channel becomes unreliable accordingly. Here we use two non-orthogonal codebooks to characterize the noise effect:

- The first non-orthogonal codebook has \( N_F = N_W = 36 \) columns and the corresponding 36 steering angles are: \( \left\{ \frac{180^\circ}{\pi} \sin^{-1} \left( \frac{(n_f - 18)}{18} \right), n_f = 1, \cdots, 36 \right\} \). The coherence of the codebook is 0.12, which implies a weakly coherent codebook.
- The second non-orthogonal codebook has larger coherence than the first one. It has \( N_F = N_W = 32 \) columns and the corresponding 32 steering angles are: \( \left\{ -90^\circ + \frac{180^\circ}{N_F} n_f, n_f = 1, \cdots, 32 \right\} \). This codebook design leads to the coherence of 0.99 that implies a strongly coherent codebook.

In Fig. 9, when using the weakly coherent codebook (coherence = 0.12) at the transmitter and receiver, the throughput shown in the curve \( I_{Pr0}(Eig, M = 3) \) can be further improved compared with \( I_{Pr0}(Eig, M = 2) \), which means that, in (29), the effect of the correlated columns of the weakly coherent codebook on \( \mathbf{H}_{E,i}[k] \) is minor. Also, the approximations of \( I_{Pr0}(Eig, M = 3) \) by using the key parameters shown in the curves \( I_{Pr0}(Fro, M = 3) \) at low SNR and \( I_{Pr0}(Det, M = 3) \) at high SNR are quite accurate and only with small differences in the SNR range of 0 to 20 dB. Compared with the results shown in Fig. 8 with the orthogonal codebook, although the approximations in the case of the weakly coherent codebook become slightly worse, the achievable throughput overall becomes better since there are four additional candidates in the weakly coherent codebook.

With the other non-orthogonal codebook whose coherence is 0.99, see Fig. 10, unfortunately the throughput degrades with the increasing \( M \) when SNR < 10 dB. From (30), it is clear that, when we select some highly correlated columns of the codebook, that the variances of the elements of vec(\( \mathbf{Z}_{E,i}[k] \)) are increased leads to unreliable estimates of the effective channel, especially in the low SNR regime. With larger \( M \), it has a higher probability of selecting these unreliable estimates.

In Fig. 9 and Fig. 10, when SNR > 5 dB, the gap between \( I_{Pr0}(Eig, M = 3) \) and \( I_{Pr0}(Fro, M = 3) \) is obvious, but it is not clear that either the approximation error between (21) and (22) or the effective noise dominates the performance loss. To this end, we further provide Fig. 11 to show the approximation error, which are calculated by the following steps. First, using Algorithm 1 with the noise-free observations and selection criterion \( f(\mathbf{H}_{E,i}[k]) = \sum_{n_s=1}^{N_s} \log_2 (1 + \gamma [\mathbf{Z}_{E,i}[k]]_{n_s,n_s}) \) to obtain \( \hat{\mathbf{F}}_P, \hat{\mathbf{W}}_P \) and the corresponding noise-free effective channel matrix written as

\[
\mathbf{H}_{E,i}[k] = (\mathbf{W}_P^H \hat{\mathbf{W}}_P)^{-0.5} \hat{\mathbf{W}}_P^H \mathbf{H}[k] \hat{\mathbf{F}}_P (\hat{\mathbf{F}}_P^H \hat{\mathbf{F}}_P)^{-0.5}.
\]

Then using \( \mathbf{H}_{E,i}[k] \) to calculate the approximation error between (21) and (22) given by
\[
\epsilon = \frac{1}{K} \mathbb{E}\left[ \sum_{k=0}^{K-1} \sum_{n_s=1}^{N_S} \log_2 \left( 1 + \gamma \frac{\mathbf{H}_{E,i}[k]^H \mathbf{H}_{E,i}[k]}{\sigma_n^2} \right) \right] 
\]
\[
\approx \frac{\gamma}{\ln(2)} \cdot \frac{1}{K} \mathbb{E}\left[ \sum_{k=0}^{K-1} \frac{1}{\sigma_n^2} \mathbf{H}_{E,i}[k]^H \mathbf{H}_{E,i}[k] \right] 
\]

where the diagonal elements of \( \mathbf{\Sigma}_{E,i}^2 \) are the eigenvalues of \( \mathbf{H}_{E,i} \mathbf{H}_{E,i}^H \). Repeating the steps with the two non-orthogonal codebooks yields the approximation errors shown in Fig. 11. The approximation error is proportional to the SNR value (or \( \gamma \)). As a result, at high SNR, the gaps between \( I_{\text{pro}}(E_{i}, M=3) \) and \( I_{\text{pro}}(F_{i}, M=3) \) in Fig. 9 and Fig. 10 become obvious. At low SNR, because the approximation error between (21) and (22) is small, we can also use the analysis results of (22) in Section V-A and Section V-B to explain the noise effect on \( I_{\text{pro}}(E_{i}, M=2,3) \) with the orthogonal and non-orthogonal codebooks. Moreover, at low SNR, the approximation error between \( I_{\text{pro}}(E_{i}, M=3) \) and \( I_{\text{pro}}(F_{i}, M=3) \) with the strongly coherent codebook in Fig. 10 seems larger than the approximation error with the weakly coherent codebook in Fig. 9. Nevertheless, from Fig. 11, we can find that without considering the noise effect on the coupling coefficients, the approximation error with the strongly coherent codebook is even smaller than the results with the orthogonal codebook.

In the numerical results, we use these three different types of codebooks to analyze the performance of the proposed method. Generally speaking, the proposed method works well for orthogonal and weakly coherent codebooks.

VII. CONCLUSION

This paper presents a novel strategy for the implementation of hybrid beamforming. It shows that hybrid beamforming matrices at the transmitter and receiver can be easily implemented based on the received coupling coefficients so that channel estimation and singular value decomposition for large antenna arrays are unnecessary. The idea behind this approach is simple: efficiently evaluating the key parameters of the hybrid beamforming gain, such as the Frobenius norm of the effective channel or the absolute value of the determinant of the effective channel. Since the key parameters are functions of the effective channel matrix, which has a much smaller size typically, it is not difficult to try a (small) set of possible alternatives to find a reasonable approximation of the optimal hybrid beamforming matrices. The improvement achieved by additional alternatives can be viewed as a diversity effect that is available from multiple different pairs of array patterns. Moreover, the effective channel matrix can be obtained from the estimated coupling coefficients. This avoids acquiring explicit channel estimates and knowledge of the specific angles of propagation paths. In turns out that implicit channel knowledge in the sense of which beam pairs produce the strongest coupling between the transmitter and receiver is sufficient. Compared with hybrid beamforming methods based on the explicit CSI, the proposed algorithm facilitates the low-complexity hybrid beamforming implementation and should be even robust to deviations from certain desired ideal beam patterns, which is a weak point of all methods based on compressed sensing techniques.

APPENDIX A

DERIVATION OF \( \hat{\mathbf{F}}_{B,i}[k] \) AND \( \hat{\mathbf{W}}_{B,i}[k] \)

In the problem (15), if there exists \( \mathbf{W}_B[k] \) such that
\[
\mathbf{W}_B^H[k] \mathbf{W}_B[k] = \mathbf{I}_{N_R},
\]
one can define a matrix \( \mathbf{Q}_W[k] = (\mathbf{W}_B[k] \mathbf{W}_B[k])^{-0.5} \mathbf{W}_B[k] \), which is equivalent to \( \mathbf{W}_B[k] = (\mathbf{W}_B[k] \mathbf{W}_B[k])^{-0.5} \mathbf{Q}_W[k] \). Replacing \( \mathbf{W}_B[k] \) in (45) by \( (\mathbf{W}_B[k] \mathbf{W}_B[k])^{-0.5} \mathbf{Q}_W[k] \) leads to \( \mathbf{Q}_W[k] \mathbf{Q}_W[k] = \mathbf{I}_{N_R} \) so that the columns of \( \mathbf{Q}_W[k] \) are mutually orthogonal. Similarly, if there exists \( \mathbf{F}_B[k] \) that satisfies the other power constraint at the transmitter, we can define another matrix \( \mathbf{Q}_F[k] = (\mathbf{F}_B[k] \mathbf{F}_B[k])^{-0.5} \mathbf{F}_B[k] \), which is equivalent to \( \mathbf{F}_B[k] = (\mathbf{F}_B[k] \mathbf{F}_B[k])^{-0.5} \mathbf{Q}_F[k] \).

Given \( \mathbf{W}_B[k] = (\mathbf{W}_B[k] \mathbf{W}_B[k])^{-0.5} \mathbf{Q}_W[k] \) and \( \mathbf{F}_B[k] = (\mathbf{F}_B[k] \mathbf{F}_B[k])^{-0.5} \mathbf{Q}_F[k] \), the objective function of the problem therefore becomes
\[
I(\mathbf{F}_{P,i}, \mathbf{W}_{P,i}, \mathbf{F}_B[k], \mathbf{W}_B[k]) = \log_2 \det \left( \mathbf{I}_{N_R} + \frac{1}{\sigma_n^2} \mathbf{Q}_W[k] \mathbf{H}_{E,i}[k] \mathbf{Q}_F[k] \mathbf{R}_s \mathbf{Q}_F[k] \mathbf{H}_{E,i}[k] \mathbf{Q}_W[k] \right),
\]
where \( \mathbf{H}_{E,i}[k], i = (i-1)N_T + i_w, \) is the effective channel as defined as
\[
\mathbf{H}_{E,i}[k] \triangleq (\mathbf{W}_{P,i} \mathbf{W}_{P,i}^H)^{-0.5} \mathbf{W}_{P,i}^H \mathbf{H}_{E,i}[k] \mathbf{F}_{P,i} \mathbf{F}_{P,i}^H)^{-0.5}.
\]
Let the SVD of \( \mathbf{H}_{E,i}[k] \) be
\[
\mathbf{U}_E[i][k] \mathbf{S}_{E,i}[k] \mathbf{V}_E^H[i][k],
\]
the corresponding mutual information is bounded by
\[
I(\mathbf{F}_{P,i}, \mathbf{W}_{P,i}, \mathbf{F}_B[k], \mathbf{W}_B[k]) \leq \sum_{n_s=1}^{N_S} \log_2 \left( 1 + \frac{1}{\sigma_n^2} \mathbf{S}_{E,i}[k] \mathbf{U}_E[i][k] \right),
\]
where equality holds if \( \mathbf{R}_s \) is a diagonal matrix, \( \mathbf{Q}_W[k] = [\mathbf{U}_E[i][k]]_{1:1;N_S}, \) where the columns of \( \mathbf{Q}_W[k] \) are mutually orthogonal as required, and \( \mathbf{Q}_F[k] = [\mathbf{V}_E[i][k]]_{1:1;N_S}, \) which satisfies the condition \( \text{tr}(\mathbf{F}_{P,i} \mathbf{F}_{P,i}^H[k] \mathbf{R}_s \mathbf{F}_{P,i} \mathbf{F}_{P,i}^H[k]) = \text{tr}(\mathbf{R}_s) \) when \( \mathbf{F}_B[k] = (\mathbf{F}_{P,i} \mathbf{F}_{P,i}^H)^{-0.5} \mathbf{Q}_F[k] \). As a result, the solution to the maximization problem is given by
\[
\hat{\mathbf{F}}_{B,i}[k] = (\mathbf{F}_{P,i} \mathbf{F}_{P,i}^H)^{-0.5} \mathbf{Q}_F[k],
\]
\[
\hat{\mathbf{W}}_{B,i}[k] = (\mathbf{W}_{P,i} \mathbf{W}_{P,i}^H)^{-0.5} [\mathbf{U}_E[i][k]]_{1:1;N_S}.
\]
**APPENDIX B**

*DERIVATION OF THE COVARIANCE MATRIX OF $\text{vec}(Z_{E,i}[k])$*

Let us repeat (28) that $Z_{E,i}[k] = (W_{P,i}^H W_{P,iw}^{-0.5} Z_{F,i} [F_{P,i}^T F_{P,i}]^{-0.5})$, where the elements of $Z_{E,i}[k]$ have the same normal distribution with mean zero and variance $\sigma_n^2$. To find the covariance between the elements of $Z_{E,i}[k]$, we vectorize $Z_{E,i}[k]$ as

$$\text{vec}(Z_{E,i}[k]) = \left( (F_{P,i}^H F_{P,i})^{-0.5} \right)^T \otimes (W_{P,iw}^H W_{P,iw}^{-0.5}) \text{vec}(Z[k]) = \left( (F_{P,i}^T F_{P,i})^{-0.5} \otimes (W_{P,iw}^H W_{P,iw})^{-0.5} \right) \text{vec}(Z[k]),$$

and the covariance matrix of $\text{vec}(Z_{E,i}[k])$ is given by (46).

**APPENDIX C**

*DERIVATION OF $E[U]$ AND $\text{Var}(U)$ FOR NON-ORTHOGONAL CODEBOOKS*

By the definition of $U$ in (32), one has the mean and variance of $U$ given by

$$E[U] = E\left[ \text{vec}(Z_{E,i}[k])^T \right]_F = E\left[ \text{vec}(Z_{E,i}[k]) \text{vec}(Z_{E,i}[k])^H \right] = \sigma_n^2 \text{tr} \left( (F_{P,i}^T F_{P,i})^{-1} \right) \text{tr} \left( (W_{P,iw}^H W_{P,iw})^{-1} \right)$$

and $\text{Var}(U)$ in (47).

**REFERENCES**


\( R_{Z_E,i} \triangleq E \left[ \text{vec}(Z_{E,i}[k])\text{vec}(Z_{E,i}[k])^H \right] \\
= E \left[ \left( (F_{P,i}^T F_{P,i}^*)^{-0.5} \otimes (W_{P,iw}^H W_{P,iw}^{-0.5}) \right) \text{vec}(Z[k]) (Z[k])^H \left( (F_{P,i}^T F_{P,i}^*)^{-0.5} \otimes (W_{P,iw}^H W_{P,iw}^{-0.5}) \right)^H \right] \\
= \sigma_n^2 \left( (F_{P,i}^T F_{P,i}^*)^{-1} \otimes (W_{P,iw}^H W_{P,iw}^{-1}) \right) \\
(46) \\
\text{Var}(U) = E \left[ U^2 \right] - E \left[ U \right]^2 = E \left[ \| Z_{E,i} \|_{\text{F}}^2 \right] - E \left[ U \right]^2 \\
= E \left[ \text{tr} \left( \left( (F_{P,i}^T F_{P,i}^*)^{-1} \otimes (W_{P,iw}^H W_{P,iw}^{-1}) \right) (Z[k]) (Z[k])^H \right) \right] \\
= \text{tr} \left( \Psi \cdot \text{E} \left[ (\text{vec}(Z[k]) (Z[k])^H) \otimes (\text{vec}(Z[k]) (Z[k])^H) \right] \right) \\
= \text{tr} \left( \Psi \cdot R_{ZY} \right) - E \left[ U \right]^2 \\
(47) \\
\textbf{Hsiao-Lan Chiang} received the M.S. degree from the Institute of Electronics Engineering, National Chiao Tung University, Taiwan, in 2007. From 2007 to 2014, she was an algorithm development engineer with MediaTek, Taiwan, and Industrial Technology Research Institute, Taiwan. She is now pursuing the Ph.D. degree at the Institute of Communications Engineering, Technische Universität Dresden, Germany. Her research interests lie in the areas of digital signal processing and wireless communications, including millimeter wave beamforming, channel estimation, and MIMO techniques.

\textbf{Wolfgang Rave} is a senior lecturer at the Vodafone Chair Mobile Communications Systems of Technische Universität (TU) Dresden. He received the diploma and Ph.D. degrees in materials science for electrical engineering from the University of Erlangen-Nürnberg as well as a habilitation degree in electrical engineering from TU Dresden for work on numerical micromagnetics. Since joining the Vodafone Chair in 1999, his research has focused on the application of signal processing techniques to different problems in the context of mobile communications, such as spatial multiplexing, the compensation of RF impairments in OFDM, UWB communications, and aspects of estimation and detection theory.

\textbf{Gerhard Fettweis} earned his Ph.D. under H. Meyr’s supervision from RWTH Aachen in 1990. After one year at IBM Research in San Jose, CA, he moved to TCSI Inc., Berkeley, CA. Since 1994, he has been a Vodafone Chair Professor at TU Dresden, Germany, with currently 20 companies from Asia/Europe/US sponsoring his research on wireless transmission and chip design. He coordinates 2 DFG centers at TU Dresden, cfAED and HAEC. Gerhard is an IEEE Fellow, member of acatech. He has an honorary doctorate from TU Tampere and has received multiple awards. In Dresden he has spun-out ten startups, and setup funded projects of more than EUR 1/3 billion volume. He has helped organizing IEEE conferences, most notably as TPC Chair of IEEE ICC 2009, IEEE TTM 2012, and General Chair of VTC Spring 2013. He remains active within IEEE.

\textbf{Tobias Kadur} received his Dipl.-Ing. degree in electrical engineering from Technische Universität Dresden, Dresden, Germany, in 2013. During his studies, he focused on wireless communications. Since 2014, he has been a Research Associate at the Vodafone Chair at TU Dresden. He is now pursuing his Ph.D. degree. His research interests focus on millimeter wave communications and beamforming.