Joint Hybrid RF/Baseband Transceiver design for Multi-User MIMO Downlink in Millimeter Wave Communication System

Deepa Jagyasi and P. Ubaidulla
Signal Processing and Communication Research Center (SPCRC),
International Institute of Information Technology (IIIT), Hyderabad, India.
Email: jagyasi.deepa@research.iiit.ac.in, ubaidulla@ieee.org

***Abstract*—Millimeter wave (mmWave) communication systems employ hybrid RF/baseband transceivers that divide the spatial signal processing into radio frequency and baseband domains in order to reduce the hardware complexity resulting from the use of large number of antennas elements. In this paper, we consider two designs for hybrid multi-user MIMO downlink that minimizes the sum mean square error (SMSE), based on perfect channel knowledge (non-robust design) and transceiver design considering the channel imperfections (robust design). In the robust design, the channel state information (CSI) is assumed to be perturbed by estimation error and follows Gaussian distribution with known error variance. In both the designs, reduced hardware complexity is achieved by analog-digital hybrid processing by using orthogonal matching pursuit (OMP)-based sparse signal processing. We evaluate the performance of both the proposed schemes based on various parameters and also compare it with conventional fully-digital system. We present numerical results over various dictionaries. The comparison results show that robust design is resilient to the presence of CSI errors. Furthermore, we also demonstrate the convergence of both the proposed algorithms to a limit even though global convergence is hard to prove due to non convex nature of overall optimization problem.**

I. Introduction

With the ever-increasing data traffic, currently available spectrum for commercial wireless systems is depleting at a tremendous rate. Hence, a need for increase in available spectrum arises for future cellular communication. Millimeter wave (mmWave) frequency band (3-300 GHz) offers a huge unlicensed spectrum supporting multigigabit-per-second data rate and is becoming the point of interest amongst researchers for next generation communication [1]. Due to smaller wavelength at mmWave frequencies, large number of antennas can be packed into very small units that enables higher beamforming and spatial multiplexing gains, making MIMO a key technique for system design. However, due to high cost and power consumption of RF chains at these frequencies, the conventional fully-digital design with dedicated RF chain for each antenna element become impractical [2], [3]. Thus there arises a need for reduction in hardware complexity while designing mmWave system. As a result, mmWave system employs hybrid analog-digital processing in which the entire precoding operation is decomposed into an analog RF beamformer and a digital baseband processor. The single-user hybrid precoding in mmWave system has been studied in [4], [5]. Hybrid precoding using sparse approximation for point to point communication is reported in [6]. In [7], hybrid processing using orthogonal matching pursuit (OMP)-based sparse technique is presented for a mmWave interference channel. OMP is a well known signal processing method and has been extensively studied in literature. In OMP-based hybrid precoding algorithm, RF beamforming vectors are selected from dictionaries using MMSE criterion and corresponding baseband filter is obtained as a least-squares solution [8].

In this paper, we first propose a non-robust hybrid transceiver design for multi-user MIMO downlink mmWave system. More specifically, we assume that both the base station (BS) and user equipments (UE's) have multiple antennas with total number of RF chains less than total number of antennas. We propose to jointly design the hybrid precoder and receive filters. In literature, the joint transceiver designs have been well investigated for conventional fully-digital MIMO system [9]. In this paper, we formulate a joint optimization problem minimizing SMSE constrained on total transmit power at BS. Due to the non-convex nature of formulated problem, global convergence is not guaranteed but we show that the proposed algorithm converges to a limit and obtain the near optimal solution. Later, we apply OMP-based sparse approximation to obtain the low complexity hybrid design. We design this system by considering the availability of perfect CSI. However, various factors like feedback delays, quantization errors, *etc.*, can introduce errors in CSI degrading the performance of the system. Effects of imperfect CSI on the performance of MIMO system is discussed in [10]. This motivates us to extend our design to a robust case where we design a transceiver that is resilient to CSI errors. We compare the proposed designs with each other and also with a conventional fully-digital system over different parameters and numerical results are discussed in later sections. The rest of the paper is organized as follows. Sec. II describes the system model. The proposed low complexity designs are discussed in Sec. III. Sec. IV presents the simulation results. Finally, conclusion is given in Sec. V.

This work was supported in part by the Visvesvaraya Young Faculty Research Fellowship, Department of Electronics and Information Technology (DeitY), Government of India.

978-1-5386-3531-5/17/$31.00

Notations: Throughout this paper, we use bold-faced lowercase letters to denote column vectors and bold-faced uppercase letters to denote matrices. $\underline{\mathbf{X}}$ and $\overline{\mathbf{X}}$ implies that the variable $\mathbf{X}$ corresponds to the baseband and RF block respectively. $\text{tr}(\cdot)$, $\mathbb{E}\{\cdot\}$, $\|\cdot\|_0$ and $\|\cdot\|_F$ denotes the trace operator, expectation operator, 0-norm and Frobenius-norm respectively.

II. System Model

We consider a multi-user MIMO downlink mmWave system as shown in Fig. 1. Let $\mathbf{d}_k$ be the data intended for the k^{th} user with N_{sk} parallel data streams. Thus, the total data transmitted by BS is given as $\mathbf{d} = [\mathbf{d}_1^T \mathbf{d}_2^T..\mathbf{d}_K^T]^T$. It is assumed that the BS is equipped with nTx transmit antennas and each user equipment (UE) has nRx receive antennas. To reduce the hardware complexity, the BS and UE's are equipped with hybrid precoders and combiners respectively. Let $\overline{N}_t \times N_{sk}$ matrix $\underline{\mathbf{V}}_k$ denotes the digital baseband precoder and $nTx \times \overline{N}_t$ matrix $\overline{\mathbf{V}}_k$ denotes the RF beamformer for the k^{th} user, where $\overline{N}_t$ is the number of RF chains, with $N_{sk} \leq \overline{N}_t < nTx$. Received signal y_k at k^{th} UE is passed through an RF beamfomer denoted by $\overline{N}_r \times nRx$ matrix $\overline{\mathbf{R}}_k$ followed by a baseband combiner denoted by the $N_{sk} \times \overline{N}_r$ matrix $\underline{\mathbf{R}}_k$, where $\overline{N}_r$ is th RF chains such that, $N_{sk} \leq \overline{N}_r < nRx$ Let $\mathbf{V}_k^o$ and $\mathbf{R}_k^o$ denote the optimal precoder and receive filter for the k^{th} user in the conventional MIMO system *i.e.,* when, number of RF chains are aimed to be equal to the total number of antennas. Then, we design the hybrid filters to satisfy $\mathbf{V}_k^o = \underline{\mathbf{V}}_k \overline{\mathbf{V}}_k$ and $\mathbf{R}_k^o = \underline{\mathbf{R}}_k^H \overline{\mathbf{R}}_k^H$. Thus the signal estimated by any user k is given by,

$$\widehat{\mathbf{d}}_k = \mathbf{R}_k^o \Bigg(\mathbf{C}_k \sum_{i=1}^{K} \mathbf{V}_i^o \mathbf{d}_i + \mathbf{n}_k \Bigg), \quad (1)$$

where, $\mathbf{C}_k$ is channel estimate available at the k^{th} user and $\mathbf{n}_k$ is the additive white Gaussian noise at the receivers i.e., $\mathbf{n}_k \in \mathbb{C}^{nRx \text{ x } 1}$ with $\mathbf{n}_k \sim \mathcal{CN}(0, \sigma^2 \mathbb{I}_{nRx})$ for $k = 1, 2, \cdots, K$.

Due to high free-space pathloss and the use of large tightly-packed antenna at mmWave frequencies, a 2D narrowband parametric clustered channel model is adopted. We consider extended Saleh-Valenzuela model [11], in which the channel matrix $\mathbf{C}_k$, from BS to k^{th} UE can be characterized as follows,

$$\mathbf{C}_k = \gamma \sum_{m=1}^{N_{cl}} \sum_{n=1}^{N_{ray}} \alpha_{mn} \mathbf{a}_r\big(\phi_{mn}^r, \theta_{mn}^r\big) \mathbf{a}_t\big(\phi_{mn}^t, \theta_{mn}^t\big), \quad (2)$$

where, N_{ray} is the number of rays in N_{cl} clusters and, the normalization factor $\gamma = \sqrt{\frac{nTxnRx}{N_{cl} N_{ray}}}$ is such that it satisfies $\text{E}\big[||\mathbf{C}_\text{k}||_\text{F}^2\big] = \text{nTx} \times \text{nRx}$. α_{mn} denotes the complex gain of n^{th} ray in m^{th} cluster and is assumed to be i.i.d. and complex Gaussian random variables with zero mean and variance $\sigma_\alpha^2 \sim \mathcal{N}(0, \sigma_\alpha^2)$. $\mathbf{a}_t\big(\phi_{mn}^t, \theta_{mn}^t\big)$ and $\mathbf{a}_r\big(\phi_{mn}^r, \theta_{mn}^r\big)$ are the array response vectors at the transmitter and receiver respectively, and $\phi_{mn}^t, \theta_{mn}^t$ and $\phi_{mn}^r, \theta_{mn}^r$ are azimuthal and elevation angle for transmit and receive antennas respectively, where,

$$\mathbf{a}(\phi_{mn}, \theta_{mn}) = \frac{1}{\sqrt{nTx}} \big[\exp^{\iota m \times \frac{2\pi}{\lambda} \text{d}(\sin(\phi))} \big]^T. \quad (3)$$

We assume the transmitters possess only imperfect knowledge of the channel state, thus, the actual CSI can be modeled as,

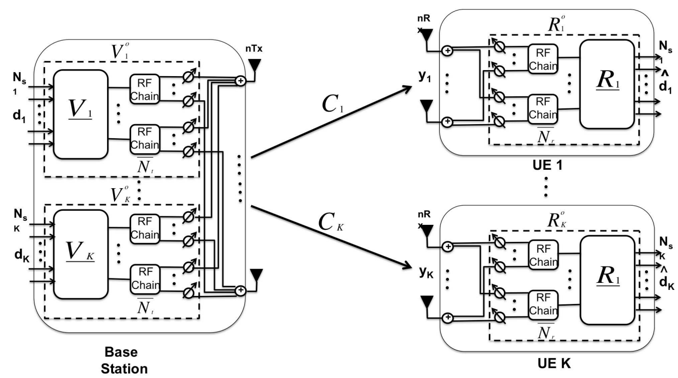

Fig. 1. Hybrid K-user MIMO Downlink mmWave Communication System.

$$\mathbf{C} = \widehat{\mathbf{C}} + \mathbf{\Delta}, \quad (4)$$

where $\widehat{\mathbf{C}}$ is the estimated CSI and $\mathbf{\Delta} \sim \mathcal{N}(0, \sigma_E^2)$ denote the corresponding error in the CSI.

III. Low-complexity Hybrid Transceiver Designs for mmWave system

In this section, we present designs of two multi-user MIMO downlink mmWave systems which differ in the knowledge of available CSI. For both the designs, we first obtain the optimal (fully-digital) precoding matrices $\{V_k^o\}, \{k = 1, 2.., K\}$ at BS and receive filter matrices $\{\mathbf{R}_k^o\}, \{k = 1, 2.., K\}$ for all UE's. We further decompose these optimal matrices into hybrid analog-digital processors that consist of reduced number of RF chains by incorporating OMP-based sparse signal processing technique into the design.

A. Non-Robust Transceiver Design for mmWave System

Non-Robust transceivers for mmWave system are designed by assuming that the channel is perfectly known to BS and UEs. We initially obtain optimal precoder and receiver filter matrices by formulating a joint optimization problem that minimizes the SMSE under the constraint of total transmit power at the BS. Thus, following the system architecture in Fig. 1, and assuming perfect CSI, SMSE can be given as,

$$\begin{aligned} \text{MSE}_k &= \mathbb{E}\{\|\widehat{\mathbf{d}}_k - \mathbf{d}_k\|^2\} \\ &= \mathbb{E}\Bigg[\text{tr}\Bigg(\mathbf{R}_k \widehat{\mathbf{C}}_k \big(\sum_{i=1}^{K} \mathbf{V}_i \mathbf{V}_i^H\big) \widehat{\mathbf{C}}_k^H \mathbf{R}_k^H + \sigma_n^2 \mathbf{R}_k \mathbf{R}_k^H - \\ &\quad \mathbf{V}_k^H \widehat{\mathbf{C}}_k^H \mathbf{R}_k^H - \mathbf{R}_k \widehat{\mathbf{C}}_k \mathbf{V}_k + \mathbf{I}\Bigg)\Bigg]. \end{aligned} \quad (5)$$

Thus, the joint transceiver design problem is formulated as,

$$\min_{\{\mathbf{V_k}\},\{\mathbf{R_k}\}} \sum_{k=1}^{K} \text{MSE}_k, \quad \textit{subject to: } \text{tr}\big(\sum_{k=1}^{K} \mathbf{V}_k^H \mathbf{V}_k\big) \leq P, \quad (6)$$

where, P is the upper limit on the total transmit power at the BS. This optimization problem can be solved using the Karush-Kuhn-Tucker conditions to be satisfied by the optimal solution. The Lagrangian associated with the optimization problem can be expressed as,

$$L(\mathbf{V}_k; \mathbf{R}_k; \lambda) = \sum_{k=1}^{K} \text{MSE}_k + \lambda \Bigg[\sum_{k=1}^{K} \text{tr}(\mathbf{V}_\text{k}^\text{H} \mathbf{V}_\text{k}) - \text{P} \Bigg], \quad (7)$$

where, λ is the Lagrangian variable. It can be observed that

TABLE I

Iterative algorithm computing $\mathbf{V}^o$ and $\mathbf{R}^o$ for power optimization
1. Initialize n = 0, $\mathbf{V}_k(0) \quad \forall k \in \{1,..K\}$.
2. Update $\mathbf{R}_k(n+1)$ using $\mathbf{V}_k(n)$,
3. Solve for λ_k:
$\mathbf{V}_k(\tilde{\lambda}) = \Big[\sum_{i=1}^{K} \widehat{\mathbf{C}}_i^H \mathbf{R}_i^H(n+1)\mathbf{R}_i(n+1)\widehat{\mathbf{C}}_i + \tilde{\lambda}\mathbf{I}+$
$\alpha\sigma_E^2 \mathrm{tr}\big(\mathbf{R}_k^H(n+1)\mathbf{R}_k(n+1)\big)\mathbf{I}\Big]^{-1}\widehat{\mathbf{C}}_k^H\mathbf{R}_k(n+1)^H,$
$\lambda(n+1) = \Big[\{\tilde{\lambda}\vert \text{ such that } \mathrm{tr}\big(\sum_{k=1}^{K}\mathbf{V}_k(\tilde{\lambda})^H\mathbf{V}_k(\tilde{\lambda})\big) = P\}\Big]_+.$
4. Update $\mathbf{V}_k(n+1)$ using $\mathbf{R}_k(n+1)$ and $\lambda_k(n+1)$,
5. Repeat 2,3,4 until convergence.
Non-Robust System : $\alpha = 0$;
Robust System: $\alpha = 1$.

SMSE function is not jointly convex in the optimization variables, but it is convex in $\{\mathbf{V}_k\}$ for fixed values of $\{\mathbf{R}_k\}$ and *vice versa*. Based on this, we obtain the solution by the coordinate descent method, wherein the minimization is performed *w.r.t.* one variable while keeping the other variables fixed. Thus, the optimal values for $\mathbf{V}_k^o$ and $\mathbf{R}_k^o$, $\{k = 1, 2.., K\}$ are obtained iteratively. Considering the minimization *w.r.t.* $\mathbf{V}_k$ while keeping $\mathbf{R_k}$ fixed, we set,

$$\frac{\partial L}{\partial \mathbf{V}_k^H} = \big(\sum_{i=1}^{K} \widehat{\mathbf{C}}_i^H \mathbf{R}_i^H \mathbf{R}_i \widehat{\mathbf{C}}_i + \lambda \mathbf{I}\big)\mathbf{V}_k - \widehat{\mathbf{C}}_k^H \mathbf{R}_k^H = 0.$$

Solving, we obtain the optimal precoder matrices $\mathbf{V}_k$ as,

$$\mathbf{V}_k = \big(\sum_{i=1}^{K} \widehat{\mathbf{C}}_i^H \mathbf{R}_i^H \mathbf{R}_i \widehat{\mathbf{C}}_i + \lambda \mathbf{I}\big)^{-1} \mathbf{C}_k^H \mathbf{R}_k^H. \tag{8}$$

Similarly, minimizing Lagrangian in (7) with respect to $\mathbf{R}_k$ while keeping $\mathbf{V}_k$ fixed, we get,

$$\frac{\partial L}{\partial \mathbf{R}_k^H} = \mathbf{R}_k \widehat{\mathbf{C}}_k \big(\sum_{i=1}^{K} \mathbf{V}_i \mathbf{V}_i^H\big) \widehat{\mathbf{C}}_k^H \mathbf{R}_k^H + \sigma_n^2 \mathbf{R}_k - \mathbf{V}_k^H \widehat{\mathbf{C}}_k^H,$$

thus, the optimal receive filter matrix $\mathbf{R}_k$ can be given as,

$$\mathbf{R}_k = \mathbf{V}_k^H \widehat{\mathbf{C}}_k^H \left(\widehat{\mathbf{C}}_k \big(\sum_{i=1}^{K} \mathbf{V}_i \mathbf{V}_i^H\big) \widehat{\mathbf{C}}_k^H + \sigma_n^2 \mathbf{I}\right)^{-1}. \tag{9}$$

From the expression for optimal precoder and receive filter in (8) and (9), as both are interdependent on each other, we obtain the values iteratively. The detailed iterative algorithm for obtaining the optimal values is discussed in Table I. Since the objective decreases with each iteration, and it is lower-bounded, the objective tends to limit as the number of iteration increases. Thus, even though the global convergence is not guaranteed, it is observed that SMSE is monotonically diminishing with each iteration. Result showing the convergence of the algorithm is discussed in section IV. Once we obtain the optimal transceiver matrices, we introduce hybrid architecture by decomposing these optimal filters into digital baseband and analog RF beamforming matrices. We achieve this by using the OMP-based sparse approximation technique. The details of this hybrid design are discussed later in section III-C.

B. Robust Transceiver Design for mmWave System

In order to mitigate the effect of CSI errors, we propose a robust transceiver design by considering the CSI errors in the channel, assuming that these errors are stochastically distributed Gaussian random variables with known error variance. Let the CSI error variance be σ_E^2. Thus, the channel for the robust transceiver design can be given by (4). Hence, the SMSE for robust transceiver design can be given as,

$$\begin{aligned}
\mathrm{MSE}_k &= \mathbb{E}\{\|\widehat{\mathbf{d}}_k - \mathbf{d}_k\|^2\}, \\
&= \mathbb{E}\Big[\mathrm{tr}\Big(\mathbf{R}_k\big(\widehat{\mathbf{C}}_k + \boldsymbol{\Delta}\big)\big(\sum_{i=1}^{K}\mathbf{V}_i\mathbf{V}_i^H\big)\big(\widehat{\mathbf{C}}_k + \boldsymbol{\Delta}\big)^H\mathbf{R}_k^H + \\
&\quad \sigma_n^2\mathbf{R}_k\mathbf{R}_k^H - \mathbf{V}_k^H\big(\widehat{\mathbf{C}}_k + \boldsymbol{\Delta}\big)^H\mathbf{R}_k^H - \mathbf{R}_k\big(\widehat{\mathbf{C}}_k + \boldsymbol{\Delta}\big)\mathbf{V}_k + \mathbf{I}\Big)\Big], \\
&= \mathrm{tr}\Big(\mathbf{R}_k\widehat{\mathbf{C}}_k\big(\sum_{i=1}^{K}\mathbf{V}_i\mathbf{V}_i^H\big)\widehat{\mathbf{C}}_k^H\mathbf{R}_k^H - (\mathbf{R}_k\widehat{\mathbf{C}}_k\mathbf{V}_k + \mathbf{V}_k^H\widehat{\mathbf{C}}_k^H\mathbf{R}_k^H) \\
&\quad + \sigma_n^2\mathbf{R}_k\mathbf{R}_k^H + \mathbf{I}\Big) + \sigma_E^2\big(\sum_{i=1}^{K}\mathrm{tr}(\mathbf{V}_i\mathbf{V}_i^H)\big)\mathrm{tr}(\mathbf{R}_k^H\mathbf{R}_k).
\end{aligned} \tag{10}$$

Following the similar approach as in previous subsection, and solving for $\{\mathbf{V}_k\}$ and $\{\mathbf{R}_k\}$, we get the expressions for robust optimal precoder and receive filter matrices as,

$$\mathbf{V}_k = \Big[\sum_{i=1}^{K}\widehat{\mathbf{C}}_i^H\mathbf{R}_i^H\mathbf{R}_i\widehat{\mathbf{C}}_i + \lambda_k\mathbf{I} + \sigma_E^2\mathrm{tr}\big(\mathbf{R}_\mathrm{k}^\mathrm{H}\mathbf{R}_\mathrm{k}\big)\mathbf{I}\Big]^{-1}\widehat{\mathbf{C}}_\mathrm{k}^\mathrm{H}\mathbf{R}_\mathrm{k}^\mathrm{H}, \tag{11}$$

and,

$$\mathbf{R}_k = \mathbf{V}_k^H\widehat{\mathbf{C}}_k^H\big(\widehat{\mathbf{C}}_k\sum_{i=1}^{K}(\mathbf{V}_i\mathbf{V}_i^H)\widehat{\mathbf{C}}_k^H + \sigma_n^2\mathbf{I} + \sigma_E^2\sum_{i=1}^{K}(\mathbf{V}_i\mathbf{V}_i^H)\big)^{-1}. \tag{12}$$

By incorporating the errors in the overall design problem and minimizing the modified problem, we obtain the robust filters that are resilient to erroneous CSI. However, we adopt the similar approach as in the non-robust design to obtain transceiver matrices as given in Table I. Again, we decompose this optimal design to a hybrid design by using OMP sparse signal processing technique discussed in following subsection.

C. Hybrid OMP-Based Precoding/Receive Filter Design

We obtain the decomposed hybrid RF/baseband matrices by using Orthogonal Matching Pursuit (OMP) sparse approximation technique. OMP is a greedy algorithm that constructs the sparse approximation through an iterative process. At each iteration, the residue is reduced, which starts out being equal to the full complexity optimal matrices, by appropriately selecting the column vectors from the predefined set of dictionaries. OMP is a well known signal processing algorithm, and has been extensively studied in literature for various applications [8], [12]. To obtain the decomposed matrices, for the given optimal matrices in (8), (9) and (11), (12); we select the RF beamforming vectors from dictionary that is most strongly correlated to the residue computed at each iteration and obtain the baseband matrices by solving the least square problem. Thus, we can obtain decomposed non-robust precoding and receive filter matrices by decomposing (8) and (11), whereas, robust matrices can be obtained by applying OMP on (9) and (12). Moreover, same algorithm is used to obtain hybrid precoders and hybrid receive filters for both the designs. Thus, by decomposing appropriate optimal receive filters, the optimal receive filter matrix can be rewritten as,

$$\mathbf{R}_k^o = \mathbf{\Gamma}_{\mathbf{y}_k}\mathbf{\Gamma}_{\mathbf{y}_k\mathbf{s}_k}^{-1}, \tag{13}$$

TABLE II

OMP-based iterative algorithm for robust MSE optimization

Require $\mathbf{P}_k^o, \mathbf{\Phi}, \mathbf{S}_{BF}$

1: $\overline{\mathbf{Q}}_k = [\,]$
2: $\mathbf{A}_0 = \mathbf{P}_k^o$
3: for $i = 1$ to $\overline{N}$ do
4: $\mathbf{\Psi}_{i-1} = (\mathbf{\Phi}\mathbf{S}_{BF})^H(\mathbf{\Phi}\mathbf{A}_{i-1})$
5: $\underline{l = arg\ max_{m=1\ldots M}}(\mathbf{\Psi}_{i-1}\mathbf{\Psi}_{i-1}^H)_{m,m}$
6: $\overline{\mathbf{Q}}_k = [\overline{\mathbf{Q}}_k|\mathbf{\Phi}(:,k)]$
7: $\underline{\mathbf{Q}}_k = (\overline{\mathbf{Q}}_k^H\overline{\mathbf{Q}}_k)^{-1}\overline{\mathbf{Q}}_k^H\mathbf{P}_k^o$
8: $\mathbf{A}_i = \frac{\mathbf{P}_k^o - \overline{\mathbf{Q}}_k\underline{\mathbf{Q}}_k}{\|\mathbf{P}_k^o - \overline{\mathbf{Q}}_k\underline{\mathbf{Q}}_k\|_F}$
9: end for
10: $\underline{\mathbf{Q}} = \sqrt{N_s}\frac{\underline{\mathbf{Q}}}{\|\overline{\mathbf{Q}}\underline{\mathbf{Q}}^H\|_F}$, when $\zeta = 1$
11: return $\overline{\mathbf{Q}}, \underline{\mathbf{Q}}$

Precoder: $\overline{N} = \overline{N}_t, \mathbf{P}^o = \mathbf{V}^o, \mathbf{\Phi} = \mathbf{\Gamma}_{\mathbf{y}_k^r}^{\frac{1}{2}}, \zeta = 1,$
$\overline{\mathbf{Q}} = \overline{\mathbf{V}}$, and $\underline{\mathbf{Q}} = \underline{\mathbf{V}}$

Receive filter: $\overline{N} = \overline{N}_r, \mathbf{P}^o = \mathbf{R}^{oH}, \mathbf{\Phi} = \mathbf{\Gamma}_{\mathbf{y}_k}^{\frac{1}{2}}, \zeta = 0,$,
$\overline{\mathbf{Q}} = \overline{\mathbf{R}}$, and $\underline{\mathbf{Q}} = \underline{\mathbf{R}}$

where $\mathbf{\Gamma}_{\mathbf{y}_k} = \mathbb{E}[\mathbf{y}_k\mathbf{y}_k^H]$ and $\mathbf{\Gamma}_{\mathbf{y}_k\mathbf{d}_k} = \mathbb{E}[\mathbf{y}_k\mathbf{d}_k^H]$. The baseband receive filter matrix can be written as,

$$\underline{\mathbf{R}}_k^o = \mathbf{\Gamma}_{\mathbf{z}_k}^{-1}\mathbf{\Gamma}_{\mathbf{z}_k\mathbf{d}_k} = \left(\overline{\mathbf{R}}_k^H\mathbf{\Gamma}_{\mathbf{y}_k}\overline{\mathbf{R}}_k\right)^{-1}\overline{\mathbf{R}}_k^H\mathbf{\Gamma}_{\mathbf{y}_k\mathbf{d}_k}, \quad (14)$$

where $\mathbf{\Gamma}_{\mathbf{z}_k} = \mathbb{E}[\mathbf{z}_k\mathbf{y}_k^H]$ and $\mathbf{\Gamma}_{\mathbf{z}_k\mathbf{d}_k} = \mathbb{E}[\mathbf{z}_k\mathbf{d}_k^H]$. RF beamforming matrix can be formulated as,

$$\overline{\mathbf{R}}_k^o = \underset{\overline{\mathbf{R}}_k}{\operatorname{argmin}}\,\mathbb{E}\|\mathbf{d}_k - \underline{\mathbf{R}}_k^{oH}\overline{\mathbf{R}}_k\|^2, \quad (15)$$

which can be rewritten as,

$$\overline{\mathbf{R}}_k^o = \underset{\overline{\mathbf{R}}_k^o}{\operatorname{argmin}}\,\|\mathbf{\Gamma}_{\mathbf{y}_k}^{\frac{1}{2}}\mathbf{R}_k^o - \mathbf{\Gamma}_{\mathbf{y}_k}^{\frac{1}{2}}\overline{\mathbf{R}}_k\underline{\mathbf{R}}_k^o\|_F^2. \quad (16)$$

Introducing dictionary $\mathbf{S}_{BF}$, the optimization problem for a sparse receive filter can be rephrased as,

$$\underline{\tilde{\mathbf{R}}}_k^o = \underset{\tilde{\mathbf{R}}_k}{\operatorname{argmin}}\,\|\mathbf{\Gamma}_{\mathbf{y}_k}^{\frac{1}{2}}\mathbf{R}_k^o - \mathbf{\Gamma}_{\mathbf{y}_k}^{\frac{1}{2}}\mathbf{S}_{BF}\underline{\tilde{\mathbf{R}}}_k^o\|_F^2, \quad (17)$$

$$s.t.\ \|\text{diag}\,(\underline{\tilde{\mathbf{R}}}_k^o\underline{\tilde{\mathbf{R}}}_k^{oH})\|_0 = \overline{N}_r.$$

Similarly, the optimization problem for designing sparse precoder matrix can be written as,

$$\overline{\mathbf{V}}_k^o = \underset{\overline{\mathbf{V}}_k}{\operatorname{argmin}}\,\|\mathbf{\Gamma}_{\mathbf{y}_k^r}^{\frac{1}{2}}\mathbf{V}_k^o - \mathbf{\Gamma}_{y_k^r}^{\frac{1}{2}}\overline{\mathbf{V}}_k\underline{\mathbf{V}}_k^o\|_F^2, \quad (18)$$

and with the introduced dictionary,

$$\overline{\mathbf{V}}_k^o = \underset{\tilde{\mathbf{V}}_k}{\operatorname{argmin}}\,\|\mathbf{\Gamma}_{\mathbf{y}_k^r}^{\frac{1}{2}}\mathbf{V}_k^o - \mathbf{\Gamma}_{\mathbf{y}_k^r}^{\frac{1}{2}}\mathbf{S}_{BF}\tilde{\mathbf{V}}_k^o\|_F^2, \quad (19)$$

$$\text{s.t.}\quad \|\text{diag}\,(\underline{\tilde{\mathbf{V}}}_k^o\underline{\tilde{\mathbf{V}}}_k^{oH})\|_0 = \overline{N}_t \text{ and } \|\underline{\tilde{\mathbf{V}}}_k\|_F^2 = \|\mathbf{V}_k^o\|_F^2.$$

To solve this optimization problem, the RF beamforming matrix is selected from the set of candidate vectors $\mathbf{S}_{BF}$. At each iteration, the effective residue is updated, hence, minimizing the overall error with each iteration. A generalized OMP based iterative algorithm discussing the computation steps for jointly designing the RF and baseband hybrid filters at Tx and Rx is given in Table II. The set of candidate beamforming vectors are acquired from different dictionary sets. In this paper we evaluate the performance of both the proposed designs over different dictionaries including, eigen beamforming, discrete Fourier transform (DFT), discrete Cosine transform (DCT), discrete Hadamard transform (DHT) and antenna selection beamforming.

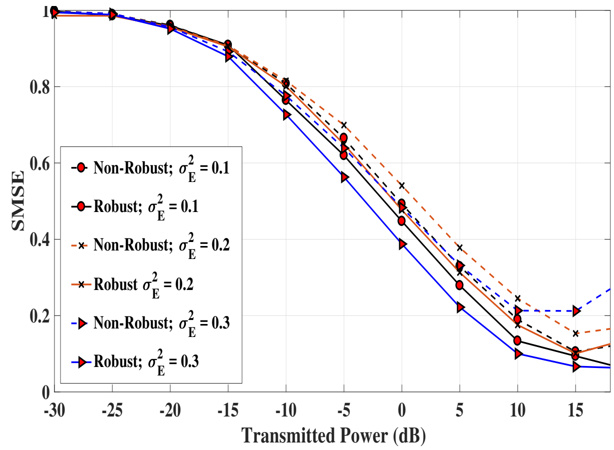

Fig. 2. SMSE Vs Transmitted Power for robust(solid line) and non-robust design(dashed line), for $K = 2$ for varying error variance σ_E^2.

IV. Simulation Results

In this section, we demonstrate the performance of both the proposed non-robust and robust multi-user MIMO downlink mmWave system designs. We compare both the designs based on different performance parameters such as, SMSE, sum-rate and bit error rate (BER). The designs are tested for multiple beamforming techniques. We also compare the performance of both the proposed systems to a conventional fully-digital system ($\overline{N_t} = nTx$ and, $\overline{N_r} = nRx$). Throughout our simulations, we assume $\{K \in 2, 4\}$ UEs in downlink channel with transceivers equipped with $nTx = 16$ and $nRx = 8$ number of Tx and Rx antennas respectively. The RF chain associated with BS and each UE is respectively $\overline{N}_t = 8$ and $\overline{N}_r = 4$, hence achieving half of the hardware complexity as compared to conventional fully-digital system. The channel assumed is Saleh-Valenzuela channel model with uniform linear antenna arrays with inter-element spacing as $\lambda/2$. The number of clusters and number of rays are assumed to be $N_{cl} \in \{4, 6\}$ and $N_{ray} = 5$ respectively. The stochastic errors in CSI are modeled as Gaussian random vector with zero mean and varying $\sigma_E^2 \in \{0.1, 0.15, 0.2, 0.25, 0.3\}$. BPSK modulation scheme is assumed for generation of data. All the simulations parameters have been tested for $N = 10000$ data samples. Multiple beamforming techniques are considered for performance evaluation as discussed in III-C.

We compare the performance for both the proposed designs in terms of SMSE versus varying transmit power in Fig 2. SMSE value are obtained for different error variance σ_E^2, and it is observed that the robust design achieves lower SMSE as compared to non-robust design for all values of σ_E^2. Moreover, with increasing σ_E^2, the difference between the robust and non robust plots increases, with robust system resulting in lower SMSE with increasing value of σ_E^2. Convergence of the proposed robust iterative algorithm is illustrated in Fig. 3, where rapid convergence in less than five iterations is observed. We also compare both the proposed designs with conventional fully-digital systems for BER and sum-rate performance as demonstrated in Fig. 4 and Fig. 5 respectively. In Fig. 4, it is observed that both the hybrid robust and

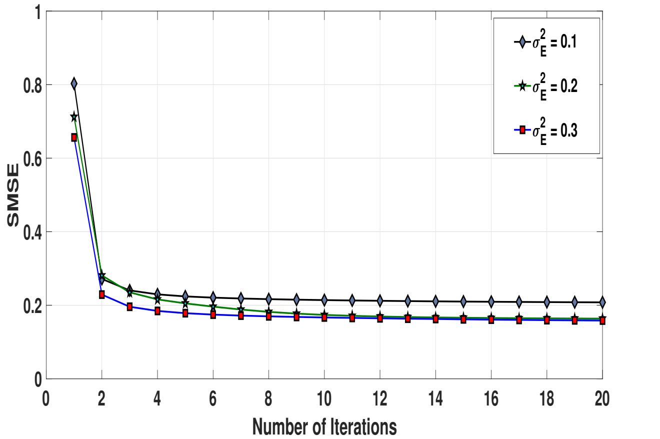

Fig. 3. Convergence behavior of robust design for transmit power = 10dB.

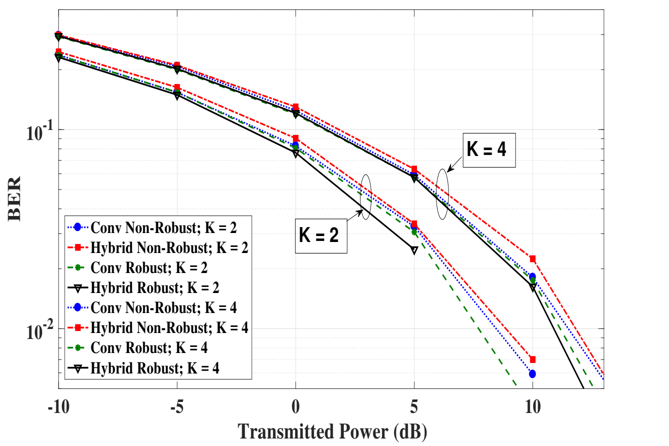

Fig. 4. Average BER Vs Transmitted Power comparing robust(solid line), non-robust(dashed line) and conventional design(dotted line).

non-robust systems with half complexity achieves equivalent performances as compared to full-complexity conventional robust and non-robust systems respectively. The plot (Fig. 4) also demonstrates the effect of varying number of users in downlink channel and we observe that BER increases with increasing number of users due to increasing interference from other UEs in the channel. Simulations over various dictionaries has been performed and results are shown in Fig. 5. Eigen beamforming shows the best result and can achieve the sum-rate that is equivalent to fully-digital system for both the proposed designs. However, it can be observed that the sum-rate for non-robust system is considerable less for all dictionaries as compared to robust system hence, demonstrating the robust design to be highly resilient to errors in CSI.

V. Conclusion

In this paper, we proposed low-complexity non-robust and robust hybrid transceiver designs for multi-user MIMO downlink mmWave communication system based on SMSE criterion by considering the difference in CSI knowledge. The low-complexity hybrid architecture was achieved by using the OMP-based sparse signal processing. We compared the performance of both the proposed systems amongst each other and to a conventional fully-digital transceiver design. Simulation results show that both the proposed designs achieve

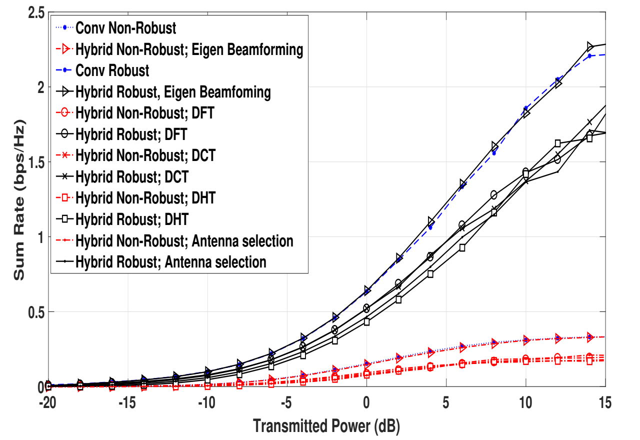

Fig. 5. Sum rate Vs Transmitted Power comparing robust, non-robust and conventional design for dictionaries.

comparable performance with half the hardware complexity as compared to fully-digital design. However, the robust system performs better that non-robust system, as it has been designed by considering the CSI errors and hence is resilient to the channel imperfections. Performance was evaluated over multiple dictionaries considered for RF beamforming and it has been observed that, eigen beamforming shows best performance over others.

References

[1] Y. Niu, Y. Li, D. Jin, L. Su, and A. V. Vasilakos, "A survey of millimeter wave communications (mmWave) for 5G: opportunities and challenges," *Wireless Networks*, vol. 21, no. 8, pp. 2657–2676, 2015.

[2] T. S. Rappaport, S. Sun, R. Mayzus, H. Zhao, Y. Azar, K. Wang, G. N. Wong, J. K. Schulz, M. Samimi, and F. Gutierrez, "Millimeter wave mobile communications for 5G Cellular: It will work!" *IEEE Access*, vol. 1, pp. 335–349, 2013.

[3] Z. Pi and F. Khan, "An introduction to millimeter-wave mobile broadband systems," *IEEE Communications Magazine*, vol. 49, no. 6, pp. 101–107, June 2011.

[4] O. E. Ayach, R. W. Heath, S. Abu-Surra, S. Rajagopal, and Z. Pi, "Low complexity precoding for large millimeter wave MIMO systems," in *Proc. IEEE International Conference on Communications (ICC)*, June 2012, pp. 3724–3729.

[5] J. Nsenga, A. Bourdoux, W. V. Thillo, V. Ramon, and F. Horlin, "Joint tx/rx analog linear transformation for maximizing the capacity at 60 GHz," in *Proc. IEEE International Conference on Communications (ICC)*, June 2011, pp. 1–5.

[6] O. E. Ayach, S. Rajagopal, S. Abu-Surra, Z. Pi, and R. W. Heath, "Spatially sparse precoding in millimeter wave MIMO systems," *IEEE Transactions on Wireless Communications*, vol. 13, no. 3, pp. 1499–1513, March 2014.

[7] D. Jagyasi and P. Ubaidulla, "Low-complexity transceiver design for multi-user millimeter wave communication systems under imperfect csi," in *Proc. IEEE 84th Vehicular Technology Conference (VTC-Fall)*, Sept 2016, pp. 1–5.

[8] T. T. Cai and L. Wang, "Orthogonal matching pursuit for sparse signal recovery with noise," *IEEE Transactions on Information Theory*, vol. 57, no. 7, pp. 4680–4688, July 2011.

[9] P. Ubaidulla and A. Chockalingam, "Robust transceiver design for multiuser MIMO downlink," in *Proc. IEEE Global Telecommunications Conference (GLOBECOM)*, Nov 2008, pp. 1–5.

[10] A. Leke and J. M. Cioffi, "Impact of imperfect channel knowledge on the performance of multicarrier systems," in *Proc. IEEE Global Telecommunications Conference (GLOBECOM)*, vol. 2, 1998, pp. 951–955 vol.2.

[11] T. S. Rappaport, R. W. Heath Jr, R. C. Daniels, and J. N. Murdock, *Millimeter wave wireless communications*. Pearson Education, 2014.

[12] J. A. Tropp and S. J. Wright, "Computational methods for sparse solution of linear inverse problems," *Proceedings of the IEEE*, vol. 98, no. 6, pp. 948–958, June 2010.