Energy-Efficient Hybrid Transceiver Designs for Millimeter Wave Communication Systems

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Energy-Efficient Hybrid Transceiver Designs for Millimeter Wave Communication Systems

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***Abstract*—In this paper, we consider the design of low-complexity analog-digital hybrid transceivers for a multi-input multi-output (MIMO) millimeter wave (mmWave) communication system operating in a $K-$user interference channel. Our objective is to achieve the energy efficiency by minimizing overall transmit power required for achieving a target mean-square error (MSE) at the receivers. We propose two transceiver designs based on the quality of the available channel state information (CSI). We first present a design that minimizes total transmit power assuming the availability of perfect channel knowledge. Later, we extend it to a robust transceiver design by considering imperfections in CSI. The proposed designs achieve reduced hardware and computational complexity by forming hybrid architecture using sparse signal processing. Hence, achieving similar MSE with lower energy consumption. We evaluate the performance of both the proposed schemes based on various parameters. Furthermore, we demonstrate the resilience of the robust design in presence of errors in CSI and performance of both the designs with various dictionaries.**

I. Introduction

Millimeter wave (mmWave) communication is expected to be an inevitable component of the suite of technologies for next generation cellular systems, harnessing which opens up availability of abundant spectral resource [1], [2]. The potential benefits are however accompanied by various challenges such as increased free space path loss, less significant scattering, pronounced coverage and blockage holes [3]. Some of these challenges can be overcome by beamforming or precoding data on large-scale antenna arrays, making multiple-input multiple-output (MIMO) a key technique for mmWave systems. Conventional full-complexity MIMO schemes use one radio frequency (RF) chain per antenna. However, dedicating a separate RF chain for each antenna will lead to high power consumption in mmWave systems. It is thus imperative to reduce the power consumption by reducing number of RF chains compared to the number of antenna elements in order to make the system less complex and amenable to practical implementation. Adapting hybrid architecture that processes data in two sequential phases, *viz.*, digital baseband processing followed by analog beamforming [3], can reduce the hardware complexity in mmWave systems. Some recent results point to the effectiveness of such techniques [4], [5]. We propose to develop energy efficient and practically realizable hybrid transceivers using sparse signal processing technique. Specifically, we adopt orthogonal matching pursuit (OMP) algorithm to achieve significant reduction in hardware complexity [6]. Another factor that affects the system performance is the quality of the available CSI. Various factors such as feedback delays, estimation error, pilot contamination, can introduce errors in CSI estimation. Systems developed assuming the perfect knowledge of CSI are likely to suffer performance degradation in the presence of errors [7]. Thus in practice, systems that are resilient to such errors are highly desirable.

In this paper, we propose two hybrid transceiver designs with reduced hardware complexity for multi-user interference channel. We first introduce a low complexity design that assumes the availability of perfect channel knowledge. This will be referred as non-robust design in rest of the paper. Later, we propose a robust design by considering the imperfections in the CSI. This design makes use of suitably modified performance metrics to combat the effect of errors in available CSI on the system performance. In each of the proposed designs, we first jointly design full-digital optimal precoder and receive filters, by minimizing total transmit power. Resultant optimal filters have high hardware and computational complexity due to large number of antennas in mmWave systems. However, we partition the overall processing to digital baseband and analog radio frequency (RF) processing by using sparse approximation, hence achieving reduced-complexity. We carry out the performance evaluation of both the schemes with extensive simulations over various parameter values and demonstrate the comparison results later in the paper. The rest of this paper is organized as follows. System and channel model is described in Section II. The proposed designs are discussed in Section III. Section IV presents the simulation results. Finally, Section V concludes this paper.

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

II. System and Channel Model

A. System Model

We consider a $K-$user interference channel with hybrid transceivers as shown in Fig. 1. Each transmitter transmits N_S symbols over nTx antennas and each receiver is equipped with nRx antennas. The signal transmitted by the kth transmitter is denoted by an N_s-dimensional column vector $\mathbf{d}_k$. The

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number of RF chains associated with each transmitter and receiver are $\overline{N}_t$ and $\overline{N}_r$, respectively, where $N_s \leq \overline{N}_t < nTx$ and $N_s \leq \overline{N}_r < nRx$. The $\overline{N}_t \times N_s$ matrix $\underline{\mathbf{V}}_k$ denotes the digital baseband precoder and the $N_t \times \overline{N}_t$ matrix $\overline{\mathbf{V}}_k$ denotes the RF beamformer at the kth transmitter. On the receiver side, the signal vector received by the k^{th} receiver is passed through a RF beamfomer denoted by $nRx \times \overline{N}_r$ matrix $\overline{\mathbf{R}}_k$ followed by a baseband combiner denoted by the $\overline{N}_r \times N_s$ matrix $\underline{\mathbf{R}}_k$. Let $\mathbf{V}_k^o$ and $\mathbf{R}_k^o$ denote the optimal precoder and receive filter in the conventional MIMO interference channel. Then, we design the hybrid filters to satisfy the following: $\mathbf{V}_k^o = \overline{\mathbf{V}}_k \underline{\mathbf{V}}_k$ and $\mathbf{R}_k^o = \underline{\mathbf{R}}_k^H \overline{\mathbf{R}}_k^H$. Following the above system model, the estimate of the transmitted data can be given by,

$$\widehat{\mathbf{d}}_k = \underline{\mathbf{R}}_k^H \overline{\mathbf{R}}_k^H \mathbf{y}_k. \tag{1}$$

B. Channel Model

We consider an extended Saleh-Valenzuela model [8], in which the channel matrix $\mathbf{C}_{kj}$, from j^{th} transmitter to k^{th} receiver can be characterized as follows,

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

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 $\mathrm{E}\big[||\mathbf{C}_{\mathrm{kj}}{}_{\mathrm{F}}^{2}||\big] = \mathrm{nTx} \times \mathrm{nRx}$. 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 $\sim \mathcal{N}(0, \sigma_\alpha^2)$. $\mathbf{a}_t\big(\phi_{mn}^{t(j)}, \theta_{mn}^{t(j)}\big)$ and $\mathbf{a}_r\big(\phi_{mn}^{r(k)}, \theta_{mn}^{r(k)}\big)$ are the array response vectors and $\phi_{mn}^{t(j)}, \theta_{mn}^{t(j)}$ and $\phi_{mn}^{r(j)}, \theta_{mn}^{r(j)}$ are azimuthal and elevation angle for transmit and receive antennas respectively, such that,

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

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

$$\mathbf{C} = \widehat{\mathbf{C}} + \mathbf{\Delta}, \tag{4}$$

where $\widehat{\mathbf{C}}$ is the estimated CSI available and $\mathbf{\Delta} \sim \mathcal{N}(0, \sigma_E^2)$ denote the corresponding error in the CSI. The additive noise at the receivers is white Gaussian noise, 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 $k = 1, 2, \cdots, K$.

III. Low-complexity Hybrid Transceiver Designs

In this section, we present two hybrid mmWave system designs that minimizes total transmit power under perfect and imperfect channel state knowledge. Solving the corresponding optimization problem, we obtain the optimal full-complexity precoding and receive filter matrices $\mathbf{V}_k^o$ and $\mathbf{R}_k^o$ respectively. Subsequently, we obtain the low complexity hybrid precoders and receive filters from the optimal matrices using the OMP-based sparse approximation technique.

A. Full-Complexity Precoder and Receive Filter Design

We aim to design a set of optimal precoder and receive filter matrices $\{\mathbf{V}_k^o, \mathbf{R}_k^o\}, k = 1...K$, to minimize total transmit power constrained on MSE where,MSE at the k^{th} user is,

$$\begin{aligned}
\mathrm{MSE}_k &= \mathbb{E}[||\widehat{\mathbf{d}}_k - \mathbf{d}_k||^2] \\
&= \mathbb{E}\Big[\mathrm{tr}\Big(\Big(\big(\mathbf{R}_K(\widehat{\mathbf{C}}_{kk} + \alpha\mathbf{\Delta})\mathbf{V}_k - \mathbf{I}\big)\mathbf{d}_k \\
&\quad + \mathbf{R}_k \sum_{i=1}^{K} (\widehat{\mathbf{C}}_{ki} + \alpha\mathbf{\Delta})\mathbf{V}_i\mathbf{d}_i + \mathbf{R}_k\mathbf{n}_k\Big)\Big(\big(\mathbf{R}_K(\widehat{\mathbf{C}}_{kk} + \alpha\mathbf{\Delta})\mathbf{V}_k - \mathbf{I}\big)\mathbf{d}_k \\
&\quad + \mathbf{R}_k \sum_{i=1}^{K} (\widehat{\mathbf{C}}_{ki} + \alpha\mathbf{\Delta})\mathbf{V}_i\mathbf{d}_i + \mathbf{R}_k\mathbf{n}_k\Big)^H\Big)\Big] \\
&= \mathrm{tr}\Big(\mathbf{R}_k \sum_{i=1}^{K} (\widehat{\mathbf{C}}_{ki}\mathbf{V}_i\mathbf{V}_i^H\widehat{\mathbf{C}}_{ki}^H)\mathbf{R}_k^H - (\mathbf{R}_k\widehat{\mathbf{C}}_{kk}\mathbf{V}_k + \mathbf{V}_k^H\widehat{\mathbf{C}}_{kk}^H\mathbf{R}_k^H) \\
&\quad + \sigma_n^2\mathbf{R}_k\mathbf{R}_k^H + \mathbf{I}\Big) + \mathbb{E}\Big[\mathrm{tr}\Big(\mathbf{R}_\mathrm{k}\big(\sum_{\mathrm{i}=1}^{\mathrm{K}} (\alpha\mathbf{\Delta})\mathbf{V}_\mathrm{i}\mathbf{V}_\mathrm{i}^\mathrm{H}(\alpha\mathbf{\Delta}^\mathrm{H})\big)\mathbf{R}_\mathrm{k}^\mathrm{H}\Big)\Big].
\end{aligned} \tag{5}$$

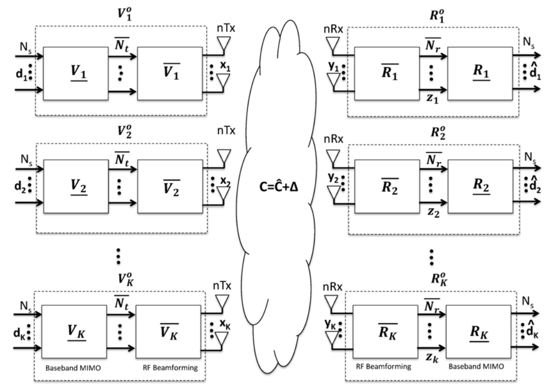

Fig. 1. mmWave Hybrid MIMO processor with K user interference channel.

The above equation is a generalized representation for MSE such that for $\alpha = 0$ and $\alpha = 1$, it represents the MSE for perfect and erroneousness CSI respectively. In order to further simplify (5), we use a Lemma in [7], which states that for any random matrix $\mathbf{X}$ with $\mathbb{E}\{\mathbf{X}\mathbf{X}^H\} = \sigma^2\mathbf{I}$, and matrices $\mathbf{U}$ and $\mathbf{Z}$ of appropriate dimensions, the following equality holds:

$$\mathbb{E}[tr(\mathbf{X}\mathbf{U}\mathbf{X}^H\mathbf{Z})] = \mathbb{E}[tr(\mathbf{X}^H\mathbf{Z}\mathbf{X}\mathbf{U})] = \sigma^2 tr(\mathbf{U})tr(\mathbf{Z}). \tag{6}$$

Employing the above result in (5) the sum-MSE for a $K-$user interference channel can be expressed as,

$$\begin{aligned}
\sum_{k=1}^{K} \mathrm{MSE_k} &= \mathrm{tr}\Big(\sum_{k=1}^{K} \mathbf{R}_k \sum_{i=1}^{K} \widehat{\mathbf{C}}_{ki}\mathbf{V}_i\mathbf{V}_i^H\widehat{\mathbf{C}}_{ki}^H\mathbf{R}_k^H \\
&\quad - \sum_{k=1}^{K} (\mathbf{R}_k\widehat{\mathbf{C}}_{kk}\mathbf{V}_k + \mathbf{V}_k^H\widehat{\mathbf{C}}_{kk}^H\mathbf{R}_k^H) + \sum_{k=1}^{K} \sigma_n^2\mathbf{R}_k\mathbf{R}_k^H + K\mathbf{I}\Big) \\
&\quad + \alpha \sum_{k=1}^{K}\sum_{i=1}^{K} \sigma_E^2 \mathrm{tr}(\mathbf{V}_i\mathbf{V}_i^H)\mathrm{tr}(\mathbf{R}_k^H\mathbf{R}_k).
\end{aligned} \tag{7}$$

The optimization problem can be mathematically given as,

$$\min_{\{\mathbf{V_k}\},\{\mathbf{R_k}\}} \quad \sum_{k=1}^{K} \mathrm{tr}(\mathbf{V}_k^H\mathbf{V}_k) \tag{8}$$

$$\text{subject to:} \quad \mathrm{MSE}_k \leq T_k, \forall k \in \{1..K\},$$

where MSE_k is given as in equation (7) and T_k is the upper bound on MSE for the k^{th} user. This optimization problem can be solved using the Karush-Kuhn-Tucker conditions to be satisfied by the optimal solution. The Langrangian associated with (8) is given by,

$$L(V_k, R_k, \lambda_k) = \sum_{k=1}^{K} \mathrm{tr}(\mathbf{V}_\mathrm{k}^\mathrm{H}\mathbf{V}_\mathrm{k}) + \sum_{\mathrm{k}=1}^{\mathrm{K}} \lambda_\mathrm{k}[\mathrm{MSE_k} - \mathrm{T_k}], \tag{9}$$

where λ_k, $k = 1, 2, \cdots, K$ are Lagrangian variables. It can be observed that the formulated problem 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 verse*. Based on this, we

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:
   $\mathbf{V}_k(\lambda_k^-) = \left(\mathbf{I} + \lambda_k \sum_{i=1}^{K} \widehat{\mathbf{C}}_{ik}^H \mathbf{R}_i^H(n+1)\mathbf{R}_i(n+1)\widehat{\mathbf{C}}_{ik}\right)^{-1}$
   $\times\left(\lambda_k \widehat{\mathbf{C}}_{kk}^H \mathbf{R}_k^H(n+1) - \alpha(\sigma_E^2 \sum_{i=1}^{K} \mathrm{tr}(\mathbf{R}_k^H(n+1)\mathbf{R}_k(n+1)))\right)$
   $\lambda_k(n+1) = \left[\{\tilde{\lambda_k} | \text{ such that } \mathrm{MSE}_k = \mathrm{T}\}\right]_+$
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: $\alpha = 1$

obtain a solution by coordinate descent method, wherein the minimization is performed w.r.t. one variable while keeping other variables fixed. Thus, the optimal values $\mathbf{V}^o$ and $\mathbf{R}^o$ are obtained iteratively. Solving (8) based on different available CSI, two corresponding transceiver designs are developed and the details are discussed in subsequent subsections.

1) Non-Robust Design: In this section, we assume that the CSI is globally and perfectly available. We jointly design optimal filters, by considering expected values of the optimization objective and constraints. Solving (9), the Lagrangian associated with non-robust transceiver design can be given as,

$$L = \sum_{k=1}^{K} tr(\mathbf{V}_k\mathbf{V}_k^H) + \sum_{k=1}^{K} \lambda_k \Big\{ tr\big[\mathbf{R}_k(\sum_{i=1}^{K} \widehat{\mathbf{C}}_{ki}\mathbf{V}_i\mathbf{V}_i^H \widehat{\mathbf{C}}_{ki}^H)\mathbf{R}_k^H - (\mathbf{R}_k\widehat{\mathbf{C}}_{kk}\mathbf{V}_k + \mathbf{V}_k^H\widehat{\mathbf{C}}_{kk}^H\mathbf{R}_k^H) + \mathbf{I} + \sigma_n^2\mathbf{R}_k\mathbf{R}_k^H\big]\Big\}. \quad (10)$$

Differentiating it w.r.t. $\mathbf{V}_k^*$, and $\mathbf{R}_k^*$ respectively and equating to 0, we obtain the corresponding full-complexity precoding and receive filter matrices as follows,

$$\frac{\partial L}{\partial \mathbf{V}_k^*} = 0, \qquad \forall k \in (1...K). \quad (11)$$

And,

$$\frac{\partial L}{\partial \mathbf{R}_k^*} = 0, \qquad \forall k \in (1...K). \quad (12)$$

Thus, the precoding matrix for a given $\mathbf{R}_k$ and receive filter matrix for given $\mathbf{V}_k$ can be given by,

$$\mathbf{V}_k^o = (\mathbf{I} + \lambda_k \sum_{i=1}^{K} \widehat{\mathbf{C}}_{ik}^H \mathbf{R}_i^H \mathbf{R}_i \widehat{\mathbf{C}}_{ik})^{-1} \widehat{\mathbf{C}}_{kk}^H \mathbf{R}_k^H. \quad (13)$$

$$\mathbf{R}_k^o = \mathbf{V}_k^H \widehat{\mathbf{C}}_{kk}^H (\sum_{i=1}^{K} \widehat{\mathbf{C}}_{ki}\mathbf{V}_i\mathbf{V}_i^H\widehat{\mathbf{C}}_{ki}^H + \sigma_n^2 I)^{-1}. \quad (14)$$

2) Robust Design: For this design, we consider the channel model given in (4) and design the system by considering the imperfections in the available channel knowledge. Following the similar approach as in the previous subsection, we obtain the solutions for robust optimal precoding and receive filters.Formulating and solving the optimization problem for the robust design, expressions for full-complexity optimal $\mathbf{V_k^o}$ and $\mathbf{R_k^o}$ are as given below,

$$\mathbf{V}_k^o = (\mathbf{I} + \lambda_k \sum_{i=1}^{K} \widehat{\mathbf{C}}_{ik}^H \mathbf{R}_i^H \mathbf{R}_i \widehat{\mathbf{C}}_{ik})^{-1} (\widehat{\mathbf{C}}_{kk}^H \mathbf{R}_k^H - \sigma_E^2 \sum_{i=1}^{K} \mathrm{tr}(\mathbf{R}_k^H \mathbf{R}_k)), \quad (15)$$

TABLE II

OMP-based iterative algorithm for robust MSE optimization

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

$\overline{\mathbf{Q}}_k = [\ ]$
$\mathbf{A}_0 = \mathbf{P}_k^o$
for $i = 1$ to $\overline{N}$ do
    $\mathbf{\Psi}_{i-1} = (\mathbf{\Phi}\mathbf{S}_{BF})^H(\mathbf{\Phi}\mathbf{A}_{i-1})$
    $\underline{l = arg\ max_{m=1...M}}(\mathbf{\Psi}_{i-1}\mathbf{\Psi}_{i-1}^H)_{m,m}$
    $\overline{\mathbf{Q}}_k = [\overline{\mathbf{Q}}_k | \mathbf{\Phi}(:,k)]$
    $\underline{\mathbf{Q}}_k = (\overline{\mathbf{Q}}_k^H \overline{\mathbf{Q}}_k)^{-1} \overline{\mathbf{Q}}_k^H \mathbf{P}_k^o$
    $\mathbf{A}_i = \frac{\mathbf{P}_k^o - \overline{\mathbf{Q}}_k \underline{\mathbf{Q}}_k}{\|\mathbf{P}_k^o - \overline{\mathbf{Q}}_k \underline{\mathbf{Q}}_k\|_F}$
end for
$\underline{\mathbf{Q}} = \sqrt{N_s}\frac{\underline{\mathbf{Q}}}{\|\overline{\mathbf{Q}}\underline{\mathbf{Q}}^H\|_F}$, when $\zeta = 1$
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 $\underline{\mathbf{Q}} = \underline{\mathbf{R}}$

$$\mathbf{R}_k^o = (\mathbf{V}_k^H \widehat{\mathbf{C}}_{kk}^H - \sigma_E^2 \sum_{i=1}^{K} \mathbf{V}_i \mathbf{V}_i^H) (\sum_{i=1}^{K} \widehat{\mathbf{C}}_{ki}\mathbf{V}_i\mathbf{V}_i^H\widehat{\mathbf{C}}_{ki}^H + \sigma_n^2\mathbf{I})^{-1}. \quad (16)$$

The generalized iterative algorithm for both the designs obtained in subsections 1 and 2 are given in Table. I.

B. Hybrid OMP-Based Precoder and Receive Filter Design

Orthogonal Matching Pursuit (OMP) for sparse approximation is a greedy approach that iteratively updates the initial zero estimates by minimizing the approximation cost w.r.t. all the currently selected coefficients. OMP is a well known signal processing algorithm, and has been extensively studied in literature for various applications [9]–[11]. It leads to reduced complexity implementation for mmWave systems. We use the OMP algorithm in order to decompose the optimal full-complexity matrices $\{\mathbf{V}_k^o\}$ and $\{\mathbf{R}_k^o\}$, into their corresponding baseband and RF processing matrices. The baseband and RF matrices are realized by decomposing optimal solution as $\mathbf{V}_k^o = \overline{\mathbf{V}}_k\underline{\mathbf{V}}_k$ and $\mathbf{R}_k^o = \underline{\mathbf{R}}_k^H \overline{\mathbf{R}}_k^H$. A generalized detailed 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 details of design are discussed in following subsections.

1) Design of Hybrid Receive Filters in MIMO Systems: In this section, we seek to design hybrid combiners $\overline{\mathbf{R}}_\mathbf{k}$, $\underline{\mathbf{R}}_\mathbf{k}$ that minimizes residue between optimal and decomposed matrices. Let, $\mathbf{\Gamma}_{\mathbf{y}_k} = \mathbb{E}[\mathbf{y}_k\mathbf{y}_k^H]$ and $\mathbf{\Gamma}_{\mathbf{y}_k\widehat{\mathbf{d}}_k} = \mathbb{E}[\mathbf{y}_k\widehat{\mathbf{d}}_k]$, where, $\widehat{\mathbf{d}}_k = \mathbf{R^o}^H\mathbf{y}_k$. Thus,

$$\mathbf{\Gamma}_{\mathbf{y}_k\widehat{\mathbf{d}}_k} = \mathbb{E}[\mathbf{y}_k\mathbf{y}_k^H\mathbf{R}^o], \quad (17)$$

$$\mathbf{\Gamma}_{\mathbf{y}_k\widehat{\mathbf{d}}_k} = \mathbf{\Gamma}_{\mathbf{y}_k}\mathbf{R}^o. \quad (18)$$

Hence, for the receiver design problem, the optimal solution in (14) or (16) can be rewritten as,

$$\mathbf{R}_k^o = \mathbf{\Gamma}_{\mathbf{y}_k}^{-1}\mathbf{\Gamma}_{\mathbf{y}_k\widehat{\mathbf{d}}_k^H}, \quad (19)$$

Similarly, the baseband receive filter matrix can be given by,

$$\underline{\mathbf{R}}_k^o = \mathbf{\Gamma}_{\mathbf{z}_k}^{-1}\mathbf{\Gamma}_{\mathbf{z}_k\widehat{\mathbf{d}}_k} = (\overline{\mathbf{R}}_k^H\mathbf{\Gamma}_{\mathbf{y}_k}\overline{\mathbf{R}}_k)^{-1}\overline{\mathbf{R}}_k^H\mathbf{\Gamma}_{\mathbf{y}_k\widehat{\mathbf{d}}_k}, \quad (20)$$

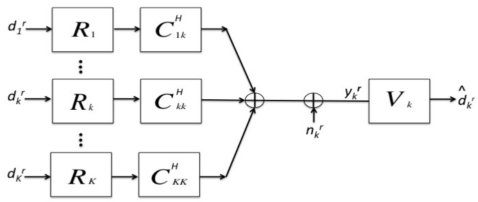

Fig. 2. Equivalent system for modeling reverse interference channel.

where $\mathbf{\Gamma}_{\mathbf{z}_k} = \mathbb{E}[\mathbf{z}_k\mathbf{z}_k^H]$ and $\mathbf{\Gamma}_{\mathbf{z}_k\widehat{\mathbf{d}}_k} = \mathbb{E}[\mathbf{z}_k\widehat{\mathbf{d}}_k^H]$. The OMP sparse problem for receiver can be formulated as,

$$\overline{\mathbf{R}}_k^o = \underset{\overline{\mathbf{R}}_k}{\operatorname{argmin}}\, \mathbb{E}\|\mathbf{d}_k - \underline{\mathbf{R}}_k^{o\,H}\overline{\mathbf{R}}_k\mathbf{y}_k\|^2, \tag{21}$$

Equation (21) is the standard form to which OMP algorithm can be applied, which can be rewritten as,

$$\overline{\mathbf{R}}_k^o = \underset{\overline{\mathbf{R}}_k^o}{\operatorname{argmin}}\, \|\mathbf{\Gamma}^{\frac{1}{2}}_{\mathbf{y}_k}\mathbf{R}_k^o - \mathbf{\Gamma}^{\frac{1}{2}}_{\mathbf{y}_k}\overline{\mathbf{R}}_k\underline{\mathbf{R}}_k^o\|_F^2. \tag{22}$$

Introducing a dictionary $\mathbf{S}_{BF}$, where dictionary constitutes a set of candidate beamforming vectors which can be used for RF design, the optimization problem can be rephrased as,

$$\tilde{\underline{\mathbf{R}}}_k^o = \underset{\tilde{\underline{\mathbf{R}}}_k}{\operatorname{argmin}}\, \|\mathbf{\Gamma}^{\frac{1}{2}}_{\mathbf{y}_k}\mathbf{R}_k^o - \mathbf{\Gamma}^{\frac{1}{2}}_{\mathbf{y}_k}\mathbf{S}_{BF}\tilde{\underline{\mathbf{R}}}_k^o\|_F^2, \tag{23}$$

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

2) Design of Hybrid Precoder in MIMO Systems: In order to design hybrid precoder matrices, we consider the equivalent system for modeling reverse MIMO interference channel as shown in Fig. 2 . The optimal precoders of forward system can be obtained from optimal receive filters of the reverse system. Thus for any k^{th} user in reverse system, the transceivers are considered to have $\mathbf{R}_k$ and $\mathbf{V}_k$ as their precoding and receive filter units respectively. The interference channel is modeled as C_{ik}^H from i^{th} transmitter to k^{th} receiver for any $i \neq k$ and $\mathbf{n}_k^r$ is considered as the additive white Gaussian noise at the receiver $\mathbf{n}_k \in \mathbb{C}^{nTx \times 1}$. Thus the received signal for the reverse system $\mathbf{y_k^r}$ can be given by,

$$\mathbf{y}_k^r = \mathbf{C}_{kk}^H\mathbf{R}_k\mathbf{d}_k^r + \sum_{i\neq k}^{K}\mathbf{C}_{ik}^H\mathbf{R}_i\mathbf{d}_k^r + \mathbf{n}_k^r. \tag{24}$$

And the signal estimate for reverse channel can be given by $\widehat{\mathbf{d}}_k^r = \underline{\mathbf{V}}_k^H\mathbf{y}_k^r$. Thus, the optimization problem for $\overline{\mathbf{V}}_k^o$ can be written as,

$$\overline{\mathbf{V}}_k^o = \underset{\overline{\mathbf{V}}_k}{\operatorname{argmin}}\, \|\mathbf{\Gamma}^{\frac{1}{2}}_{\mathbf{y}_k^r}\mathbf{V}_k^o - \mathbf{\Gamma}^{\frac{1}{2}}_{y_k^r}\overline{\mathbf{V}}_k\underline{\mathbf{V}}_k^o\|_F^2, \tag{25}$$

where, $\mathbf{\Gamma}_{\mathbf{y}_k^r} = \mathbb{E}[\mathbf{y}_k^r\mathbf{y}_k^{r\,H}]$, $\mathbf{\Gamma}_{\mathbf{y}_k^r\widehat{\mathbf{d}}_k} = \mathbb{E}[\mathbf{y}_k^r\widehat{\mathbf{d}}_k^H]$, and the baseband precoder $\underline{\mathbf{V}}_k^o = (\overline{\mathbf{V}}_k\mathbf{\Gamma}_{\mathbf{y_k^r}}\overline{\mathbf{V}}_k)^{-1}\overline{\mathbf{V}}_k^H\mathbf{\Gamma}_{\mathbf{y}_k^r\widehat{\mathbf{d}}_k^r}$. Hence, OMP sparse problem for hybrid precoders can be written as,

$$\overline{\mathbf{V}}_k^o = \underset{\tilde{\mathbf{V}}_k}{\operatorname{argmin}}\, \|\mathbf{\Gamma}^{\frac{1}{2}}_{\mathbf{y}_k^r}\mathbf{V}_k^o - \mathbf{\Gamma}^{\frac{1}{2}}_{\mathbf{y}_k^r}\mathbf{S}_{BF}\tilde{\mathbf{V}}_k^o\|_F^2, \tag{26}$$

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

We solve the optimization problems iteratively by minimizing the overall error to obtain hybrid matrices as given in Table. II. We consider eigen beamforming, discrete Fourier transform(DFT), discrete Cosine transform(DCT), discrete Hadamard transform(DHT) and antenna selection beamforming linear dictionaries for performance evaluation. Eigen beamforming is most complex of all above mentioned dictionaries and consists of eigenvectors of $\mathbf{\Gamma}_{\mathbf{y}_k}$. However, it offers the perfect decomposition as proved in lemma-2 in [12], and hence offers a very good performance. Whereas, DFT, DCT and DHT dictionaries can be designed by using the columns of Fourier transform, Cosine transform and Hadamard transform matrices respectively. However, in case of implementation complexity, antenna selection beamforming method is considered to be simplest of all, as it can be implemented by using a switching circuit, where the dictionary consisting of columns of I_{nRx} can be considered.

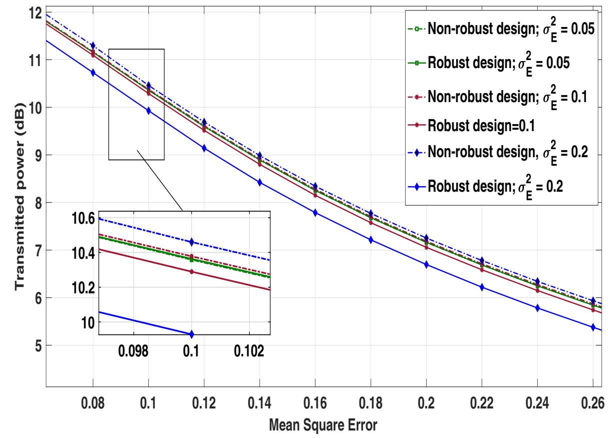

Fig. 3. Comparison of total transmit power performance for non-robust (dashed line) and robust (solid line) against varying MSE.

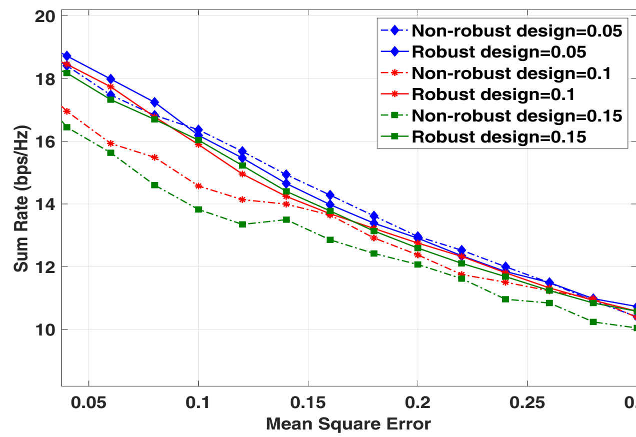

Fig. 4. Comparison of sum-rate performance Vs MSE for robust(solid line) and non-robust(dashed line).

IV. Performance Evaluation

In this section, we demonstrate the performance of both the proposed non-robust and robust mmWave system designs. We evaluate and compare the performance in terms of total transmit power and sum-rate. Sum-rate is given by, $\rho = \sum_{k=1}^{K}\log_2|\mathbf{I} + \text{SINR}_k|$ where $\text{SINR}_k = \frac{\mathbf{R}_k\mathbf{C}_k\mathbf{V}_k\mathbf{V}_k^H\mathbf{C}_k^H\mathbf{R}_k^H}{\mathbf{R}_k\beta_k\mathbf{R}_k^H}$ and $\beta_k = \sigma_n^2\mathbf{I} + \sum_{l=1}^{k}\mathbf{C}_{kl}\mathbf{V}_l\mathbf{V}_l^H\mathbf{C}_{kl}^H - \mathbf{C}_{kk}\mathbf{V}_k\mathbf{V}_k^H\mathbf{C}_{kk}^H$.

A. Simulation Parameters

The simulation environment is assumed to have $K = 4$ users, where data is sequentially processed in parallel $N_s = 2$

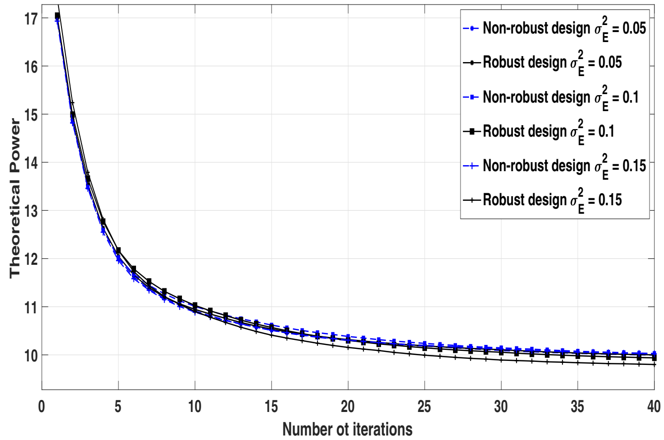

Fig. 5. Convergence behavior of non-robust Vs robust design for K=4.

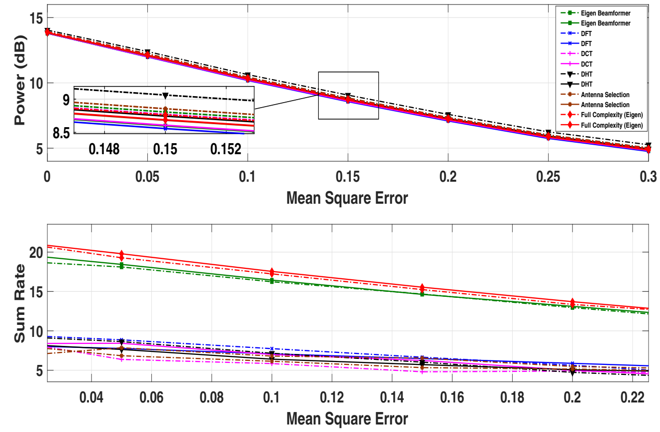

Fig. 6. Transmit power and sum-rate for robust(solid line) and non-robust design(dashed line) Vs MSE for different dictionaries.

transmission streams. BPSK modulation scheme is assumed for data generation. We assume $nTx = nRx = 20$ antennas associated with $\overline{N}_t = \overline{N}_r = 5$ RF chains, achieving the reduced complexity by factor of 4. The channel assumed is Saleh-Valenzuela channel for uniform linear antenna array with $\lambda/2$ inter-element spacing, $N_{cl} \in \{4, 6\}$ and $N_{ray} = 5$. The CSI errors are modeled as Gaussian random vector with zero mean and varying $\sigma_E^2 \in \{0.5, 1, 1.5\}$. Multiple beamforming techniques are considered as discussed in III-B.

B. Simulation Results

In Fig. 3 and 4, we compare the performance of proposed designs in terms of total transmit power and sum-rate respectively over a range of MSE for varying error variance σ_E^2. As seen in Fig. 3, power requirement decreases with increasing MSE. It is also observed that robust scheme require lesser transmit power as compared to non-robust scheme. From Fig. 4, sum-rate is higher for robust system as compared to non-robust design for all error variance. Hence from above results, it is observed that the robust scheme performs better than the non-robust. The robust design is observed to perform better as its optimization problem already considers the channel impairments hence obtaining better solutions and combating the effect of errors in available CSI knowledge as compared to non-robust scheme. We also observe the convergence of the proposed iterative algorithm against varying error variance in Fig. 5. Simulations for various dictionaries has been performed for range of MSE with fixed $\sigma_E^2 = 0.1$ and shown in the Fig. 6. It is observed that eigen dictionary outperforms over other dictionaries in both the cases. Other dictionaries show good performance, with slightly better results for robust design. But, considering their simple implementation they can be chosen for applications having non-critical criterion.

V. Conclusion

In this paper, we proposed two low-complexity analog-digital hybrid mmWave communication system designs(non-robust and robust), where, complexity was reduced by a factor of 4 as compared to fully-complex traditional MIMO system. Both the designs were proposed for K-user MIMO interference channel assuming the availability of different CSI knowledge minimizing total transmit power at mmWave frequencies. The robust design demonstrates the resilience to erroneous CSI as compared to non-robust design. Convergence of the proposed algorithm to a limit was demonstrated. We adopted OMP-based sparse approximation technique to obtain the RF-baseband decomposition of the optimal transmit and receiver processing matrices. Performance for both the schemes was compared for various parameters. Simulation results show that the proposed robust hybrid system outperforms the non-robust hybrid design in the presence of erroneous CSI.

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