MSE-Based Transceiver Designs for RIS-Aided Communications With Hardware Impairments

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Abstract—It is challenging to precisely configure the phase shifts of the reflecting elements at the reconfigurable intelligent surface (RIS) due to inherent hardware impairments (HIs). In this letter, the mean square error (MSE) performance is investigated in an RIS-aided single-user multiple-input multiple-output (MIMO) communication system with transceiver HIs and RIS phase noise. We aim to jointly optimize the transmit precoder, linear received equalizer, and RIS reflecting matrices to minimize the MSE. To tackle this problem, an iterative algorithm is proposed, wherein the beamforming matrices are alternately optimized. Specifically, for the beamforming optimization subproblem, we derive the closed-form expression of the optimal precoder and equalizer matrices. Then, for the phase optimization subproblem, we propose an efficient algorithm based on the majorization-minimization (MM) method. Simulation results show that the proposed MSE-based RIS-aided transceiver scheme dramatically outperforms the conventional system algorithms that do not consider HIs at both the transceiver and the RIS.

Index Terms—Reconfigurable intelligent surface (RIS), hardware impairments (HIs), mean square error (MSE), majorization-minimization (MM).

I. INTRODUCTION

THANKS to its appealing advantages of enhancing the system energy efficiency, reconfigurable intelligent surface (RIS) has attracted extensive research attention in both academia and industry [1], [2]. For RIS-aided communication systems, the transceiver design has been studied in [3]–[6]. Specifically, the authors in [4] investigated the weighted sum secrecy rate maximization problem by jointly optimizing the active transmit beamforming and passive reflecting phase shifts. Furthermore, the authors in [5] and [6] considered similar design problems for RIS-aided single-user multiple-input single-output (MISO), and single-user multiple-input multiple-output (MIMO) systems, respectively, with an aim of minimizing the mean square error (MSE).

However, all the above contributions assumed ideal transceiver hardware and perfect RIS phase-shifting without considering hardware impairments (HIs). The transceiver HIs and RIS phase errors always exist in actual systems, limiting channel capacity, particularly in the high-power region, and degrading beamforming gains. Unfortunately, the compensation algorithms cannot completely eliminate these impairments because of the time-varying hardware characteristics. As a result, several researches have studied the impact of HIs at both the transceiver and the RIS in various RIS-aided scenarios. The authors in [7] investigated the joint calibration of the direction-independent and direction-dependent phase errors for an RIS-aided millimeter-wave system on the system performance. Besides, an RIS-aided MISO system was studied based on statistical channel state information (CSI) in [8] to maximize the system sum rate with the consideration of HIs at both transceiver and the RIS. However, in these contributions [7]–[9], users are equipped with single antenna and the impact of transceiver HIs and RIS phase noise on an RIS-aided MIMO system has not been investigated.

In this letter, we study the transceiver design for an RIS-aided single-user MIMO communication system with transceiver HIs and RIS phase noise. We jointly optimize the transmit precoder, the received equalizer, and the RIS reflecting matrices to minimize the MSE of this system. The proposed optimization problem is tackled by using alternating optimization (AO) method based on Lagrange dual and majorization-minimization (MM) techniques. Simulation results show that the performance advantage of the proposed transceiver design scheme and reveal the importance of considering HIs impact on the transceiver design.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider an RIS-aided downlink communication system consisting of one $N_t$-antenna base station (BS), one $M$-element RIS, and one $N_r$-antenna user. Let $s \in \mathbb{C}^{d \times 1}$ denote the datastreams from the BS satisfying $\mathbb{E}|s|^2 = 0$, $\mathbb{E}[ss^H] = \mathbf{I}_d$, where $d$ is the number of data streams. The undistorted transmit vector $x \in \mathbb{C}^{N_t \times 1}$ is given by

$$x = Ws,$$

where $W \in \mathbb{C}^{N_t \times d}$ is the precoder matrix at the BS. The signal transmitted by the BS is given by

$$\hat{x} = x + z_x,$$

where $z_x \in \mathbb{C}^{N_t \times 1}$ represents the transmit distortion noise which is independent of $s$. More specifically, $z_x$ follows the independent zero-mean Gaussian random distribution, i.e., $z_x \sim \mathcal{CN}(0, \kappa_0 \text{diag}\{WW^H\})$, where $\kappa_0 \in (0, 1)$ denotes the normalized variance of the transmit distortion noise. We adopt the channel estimation methods for RIS-aided systems in [10] and thus we assume that the perfect CSI is available at the transmitter. The received signal at the user is expressed as

$$y = (H_d^H + H_d^H \Theta \hat{H}_t)x + z_d + n_d = \tilde{y} + z_d + n_d,$$
where $H_d \in \mathbb{C}^{N_t \times N_r}$ is the user-to-BS channel, $H_e \in \mathbb{C}^{M \times N_r}$ is the user-to-RIS channel, and $H_t \in \mathbb{C}^{M \times N_t}$ is the BS-to-RIS channel. $\Theta = \text{diag}(e^{j\theta_1}, e^{j\theta_2}, \ldots, e^{j\theta_M})$ is the diagonal reflection matrix of the RIS with $\theta_m \in [0, 2\pi)$ $(m = 1, 2, \ldots, M)$, and $n_d \sim \mathcal{CN}(0, \sigma_n^2 I)$ represents the thermal additive white Gaussian noise (AWGN). $z_d \in \mathbb{C}^{N_t \times 1}$ denotes the received distortion noise independent of $\gamma$ and the variance of $z_d$ is proportional to the undistorted received signal power, i.e., $z_d \sim \mathcal{CN}(0, \kappa_d)$, where $\kappa_d \in (0, 1)$ is the normalized ratio of distorted noise to undistorted received signal power. $\hat{\Theta} = \text{diag}(e^{j\hat{\theta}_1}, e^{j\hat{\theta}_2}, \ldots, e^{j\hat{\theta}_M})$ is the random phase noise matrix, wherein $\zeta_m$ is each RIS element’s phase noise caused by RIS HIs.

It is assumed that the linear equalizer matrix $C \in \mathbb{C}^{d \times N_t}$ is used to equalize the received signal. The estimated signal at the user is given by

$$s = Cy = C[(H_d^H + H_t^H \hat{\Theta}H_t)(W_s + z_s) + z_d + n_d].$$

(4)

Thus, the MSE of this system is defined as follows

$$\text{MSE} = \mathbb{E}[[\hat{s} - s]^2] = \mathbb{E}_{\hat{\Theta}}[\text{tr}((\hat{s} - s)(\hat{s} - s)^H)].$$

(5)

We assume that the phase noise variable $\varepsilon$ follows a zero-mean Von Mises Distributions with a concentration parameter $\varsigma$ [11]. We can obtain

$$\mathbb{E}(e^{j\varepsilon}) = \frac{I_1(\varsigma)}{I_0(\varsigma)} \triangleq \rho_1,$$

(6)

where $I_n(\varsigma)$ represents the modified Bessel function of the first kind and order $n$. Then we derive the mean of the random phase noise matrix as follows

$$\mathbb{E}(\hat{\Theta}) = \mathbb{E}(\text{diag}(e^{j\hat{\theta}_1}, e^{j\hat{\theta}_2}, \ldots, e^{j\hat{\theta}_M})) = \text{diag}(\mathbb{E}(e^{j\hat{\theta}_1}), \mathbb{E}(e^{j\hat{\theta}_2}), \ldots, \mathbb{E}(e^{j\hat{\theta}_M})) = \rho_1 I_M.$$  

(8)

To simplify the Eq. (5), we introduce an arbitrary square matrix $\Pi \in \mathbb{C}^{M \times M}$ to represent the combination of variables $W, C$ and $\Theta$, which can be defined as follows

$$\Pi = \begin{bmatrix}
\pi_{11} & \pi_{12} & \cdots & \pi_{1M} \\
\pi_{21} & \pi_{22} & \cdots & \pi_{2M} \\
\vdots & \vdots & \ddots & \vdots \\
\pi_{M1} & \pi_{M2} & \cdots & \pi_{MM}
\end{bmatrix}.$$  

(9)

From (6) and (9), we can obtain the equivalent phase noise autocorrelation matrix as (10).

$$\mathbb{E}_{\hat{\Theta}}[\hat{\Theta}\Pi^H\hat{\Theta}] = \rho_1^2 \Pi + (1 - \rho_1^2) \text{diag}(\Pi).$$

(10)

By using (6), (8) and (10), Eq.(5) can be further simplified as (7), as shown at the bottom of the next page, where

$$Y = \kappa_s\kappa_d C \text{diag}(H_d^H + \rho H_t^H \Theta H_t) \text{diag} \left\{ (WW^H)^{H}(H_d^H + \rho H_t^H \Theta H_t)^H \right\} C^H$$

is the covariance of the transmitted distortion noise and ignored since the multiplication of $\kappa_s$ and $\kappa_d$ is very small.

In this letter, we aim to minimize the MSE in Eq. (7) by jointly optimizing the transmit precoder $W$, the linear received equalizer $C$, and the RIS reflecting phase $\Theta$ while guaranteeing the power constraint at the BS and the unit-modulus constraints at the RIS. The optimization problem is formulated as follows

$$\min_{\Theta, W, C} \text{MSE}$$

(11a)

$$\text{s.t. } \text{tr}([\mathbb{E}[xx^H]]) \leq \tau,$$

(11b)

$$0 \leq \theta_m \leq 2\pi, m = 1, \cdots, M.$$  

(11c)

Constraint (11b) is the average transmit power constraint, by the way the maximum transmit power at the BS. In the following, we adopt an AO method to solve this problem.

III. ALGORITHM DESIGN

A. Transceiver Optimization

Firstly, we update the linear received equalizer $C$ with given precoder $W$ and RIS reflecting matrix $\Theta$. For convenience, we define $\tilde{H} \triangleq H_d^H + \rho H_t^H \Theta H_t$, $N_x \triangleq \tilde{H}W W^H H_d^H$, $N_c \triangleq \tilde{H}d \text{diag}(WW^H)H_d^H$, $N_i \triangleq H_tWW^H H_d^H$, and $N_r \triangleq H_t \text{diag}(WW^H)H_d^H$. With given $W$ and $\Theta$, Problem (11) can be rewritten as

$$\min_{C} \text{MSE}_c,$$

(12)

where $\text{MSE}_c$ is given in (13), as shown at the bottom of the next page. Note that Problem (12) is unconstrained. Therefore, the optimal $C_{opt}$ can be obtained by setting the first-order derivative of $\text{MSE}_c$ with respect to $C$ to zero, as follows

$$C_{opt} = \frac{\text{tr}(WW^H)}{\text{tr}(WW^H)^{H}N_x + \kappa_c N_c + \kappa_d \text{diag}(N_i)} + \frac{1}{\rho_1^2 + 1} \times \text{tr}(H_t \text{diag}(N_i) \Theta H_t),$$

$$\text{tr}(H_t \text{diag}(N_i) \Theta H_t),$$

(14)

Secondly, with given equalizer $C$ and RIS reflecting matrix $\Theta$, we optimize the precoder $W$. However, it is difficult to optimize $W$ directly because the precoder $W$ exists in the trace of Eq. (7) has different forms in terms of the tiers of the ‘diag’ calculation, such as $\text{diag}(WW^H)$, $\text{diag}(H_t \text{diag}(WW^H)H_d^H)$ and $\text{diag}(H_t \text{diag}(H_tWW^H H_d^H)^H)\Theta H_t).$. Then we derive the two significant properties $\text{tr}(\text{Adag}(B)C^H) = \text{tr}(\text{Bdiag}(C^H A^H))$ and $\text{tr}(\text{Adag}(\text{Bdiag}(C^H B^H) A^H)) = \text{tr}(\text{Cdiag}(\text{Bdiag}(A^H A) B^H))$. Based on these properties, we can optimize the optimization variable $W$ in (7) by separating it from the diagonal transformation. Then Problem (11) can be formulated as

$$\min_{W} \text{MSE}_w,$$

(15)

$$\text{s.t. } \text{tr}([\mathbb{E}[xx^H]]) \leq \tau,$$

where

$$\text{tr}([\mathbb{E}[xx^H]]) = \text{tr}(WW^H + \kappa_s \text{diag}(WW^H))$$

$$= (1 + \kappa_s) \text{tr}(WW^H),$$

and $\text{MSE}_w$ is given in (16), as shown at the bottom of the next page. Obviously, Problem (15) is convex and its optimal $W_{opt}$ can be obtained by resorting to the Karush-Kuhn-Tucker (KKT) conditions. Specifically, the Lagrangian function of Problem (15) is given by

$$\mathcal{L} = \text{MSE}_w + \lambda(\text{tr}[\mathbb{E}[xx^H]]) - \tau,$$

$$= \text{MSE}_w + \lambda(1 + \kappa_s)(\text{tr}(WW^H) - \frac{\tau}{1 + \kappa_s}),$$

where $\lambda$ is the Lagrangian multiplier. The KKT conditions can be formulated as

$$\frac{\partial \mathcal{L}}{\partial W} = 0,$$

(17a)

$$\lambda \geq 0, \quad \text{tr}(WW^H) \leq \frac{\tau}{1 + \kappa_s},$$

(17b)
Then (17a) can be formulated as
\[
\frac{\partial L}{\partial \mathbf{w}} = \mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H} \mathbf{W} + \kappa_d \text{diag}(\mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H}) \mathbf{W} + \kappa_a \mathbf{H}^\mathsf{H} \times \text{diag}(\mathbf{C}^\mathsf{H} \mathbf{C}) \mathbf{H} \mathbf{W} - \mathbf{H}^\mathsf{H} \mathbf{C} (1 + \tau)^2 \times \text{diag}(\mathbf{H}^\mathsf{H} \mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H}) \mathbf{W} + \kappa_a (1 - \tau)^2 \times \text{diag}(\mathbf{H}^\mathsf{H} \mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H}) \mathbf{W},
\]
where (b) is from \( \frac{\partial (\mathbf{Z} \mathbf{A}^\mathsf{H} \mathbf{B})}{\partial Z} = \mathbf{B} \mathbf{A} \). Thus, we can obtain the closed-form solution of the optimal \( \mathbf{W} \)
\[
\mathbf{W}^{\text{opt}} = \mathbf{A} + (1 + \kappa_a) \mathbf{I} - 1 \mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H},
\]
where
\[
\mathbf{A} = \mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H} + \kappa_d \text{diag}(\mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H}) + \kappa_a \mathbf{H}^\mathsf{H} \times \text{diag}(\mathbf{C}^\mathsf{H} \mathbf{C}) \mathbf{H} + (1 - \tau)^2 \mathbf{H}^\mathsf{H} \times \text{diag}(\mathbf{H}^\mathsf{H} \mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H}) \mathbf{W} + \kappa_a (1 - \tau)^2 \times \text{diag}(\mathbf{H}^\mathsf{H} \mathbf{H}^\mathsf{H} \mathbf{C} \mathbf{H}) \mathbf{W}.
\]
We define \( \Omega \triangleq H \circ \text{diag} \{ WW^H \} \)
\( H_c \circ \text{diag} \{ WW^H \} \), \( \Psi \triangleq H \circ \text{diag} \{ WW^H \} \)
\( H_c \circ \text{diag} \{ WW^H \} \), \( T \triangleq H \circ \text{diag} \{ CH^H \} \)
\( H_c \circ \text{diag} \{ CH^H \} \), and \( V \triangleq H \circ \text{diag} \{ CH^H \} \).
Denote the set of diagonal elements of \( \Omega, \Psi, T, V \) by \( \omega, \psi, t, v \), respectively, given by \( \omega = [\Omega_{1,1}, \ldots, \Omega_{M,M}]^T \), \( \psi = [\Psi_{1,1}, \ldots, \Psi_{M,M}]^T \), \( t = [T_{1,1}, \ldots, T_{M,M}]^T \) and \( v = [V_{1,1}, \ldots, V_{M,M}]^T \).

By using \( \text{tr} (\Theta^H \circ B \circ C^T \theta) \), where \( \circ \) is Hadamard product operation, the objective function shown in (24) can be reformulated as (25), as shown at the bottom of the next page, where

\[
\Xi = \rho^2 [H_c \circ \text{diag} \{ WW^H \} \circ (H \circ \text{diag} \{ WW^H \} H_t^H)^T] + (1 - \rho^2) [H_c \circ \text{diag} \{ WW^H \} \circ (H \circ \text{diag} \{ WW^H \} H_t^H)^T] + \rho^2 \kappa_s (H_c \circ \text{diag} \{ WW^H \} \circ (H \circ \text{diag} \{ WW^H \} H_t^H)^T] + \kappa_s (1 - \rho^2) [H \circ \text{diag} \{ CH^H \} \circ (H \circ \text{diag} \{ CH^H \} H_t^H)^T] + \rho^2 \kappa_d (H \circ \text{diag} \{ CH^H \} \circ (H \circ \text{diag} \{ CH^H \} H_t^H)^T] + \kappa_d (1 - \rho^2) [H_c \circ \text{diag} \{ CH^H \} \circ (H \circ \text{diag} \{ CH^H \} H_t^H)^T],
\]

\[
Q = \omega^* + \kappa_s \psi^* + \kappa_d t^* - v^*.
\]

Define \( \phi_m = e^{i \theta_m}, \forall m, \) and \( \theta = [\phi_1, \ldots, \phi_M]^T \).
Problem (23) can be rewritten as

\[
\begin{align}
\min_{\theta} f(\theta) &= \theta^H \Xi \theta + 2 \rho \text{Re}(\theta^H Q) & (27a) \\
\text{s.t.} \quad |\phi_m| = 1, m = 1, \ldots, M. & (27b)
\end{align}
\]
Due to the unit modulus constraints in (27b), Problem (27) is a nonconvex problem. In the following, we provide a Majorization-Minimization (MM) algorithm to solve this problem. Denote the solution of \( f(\theta) \) and the objective function value of Problem (27) at the \( t \)-th iteration by \( \theta^t \) and \( f(\theta^t) \), respectively. It can be observed from Problem (27) that \( \Xi \) is a Hermitian matrix. Utilizing the Claim 1 of [12], we have

\[
\theta^H \Xi \theta \leq \theta^H \Lambda \theta + 2 \rho \text{Re}(\theta^H (\Xi - \Lambda) \theta^t) + (\theta^t)^H (\Xi - \Xi) \theta^t
\]

where \( \Lambda \) should satisfy \( \Lambda \succeq \Xi \). Let \( \Lambda = \lambda_{\max}(\Xi) I \), where \( \lambda_{\max}(\Xi) \) is the largest eigenvalue of matrix \( \Xi \). The consequence of \( \theta^H \Lambda \theta \) is a constant due to \( \theta^H \Theta = M \). In addition, \( (\theta^t)^H (\Xi - \Xi) \theta^t \) is also a constant since vector \( \theta^t \) is known at the \( t \)-th iteration. Problem (27) at the \((t+1)\)-th iteration is given by

\[
\begin{align}
\max_{\theta} & 2 \rho \text{Re}(\theta^H u^t) & (29a) \\
\text{s.t.} \quad |\phi_m| = 1, m = 1, \ldots, M. & (29b)
\end{align}
\]
where \( u^t = -(\Xi - \lambda_{\max}(\Xi) I \theta^t) - \rho Q \).
The closed-form solution of Problem (29) can be derived as

\[
(\theta^{t+1})^* = e^{\arg(u^t)}.
\]

Based on the above subsections, the overall AO algorithm to solve Problem (11) is summarized in Algorithm 1.

**Algorithm 1: Algorithm to Solve Problem (11)**

1. Initialization: Randomly initialize \( \theta \) and \( W \). Normalize \( W \) to meet the power constraint and set \( \Theta^1 = \text{diag}(\theta^1) \). Set the iteration number \( t = 1 \) and the convergence accuracy \( \epsilon \rightarrow 0 \).
2. repeat
3. Update \( \Theta^t \) with fixed \( W^t \) and \( \Theta^t \) according to (14).
4. Update \( W^{t+1} \) with fixed \( \Theta^t \) and \( C^t \) according to (18).
5. Update \( \Theta^{t+1} \) with fixed \( W^{t+1} \) and \( C^1 \) by (30) and recover \( \Theta^{t+1} \) from \( \Theta^t \), set \( t \leftarrow t + 1 \).
6. until the difference of MSE in two iterations less than \( \epsilon \).

IV. Numerical Results

In this section, we evaluate the performance of the proposed algorithm for an RIS-aided single-user MIMO system with HIs impact. The normalized mean squared error (NMSE) is defined as \( \text{NMSE} = \frac{\text{MSE}}{\sigma^2} \). We set the locations of the BS and the RIS as \((0, 0)\) and \((10, 0)\), respectively. The large-scale path loss is modeled as \( PL = -30 - 10 \log_{10} (d) \), where \( d \) is the path-loss exponent and the distance of the transmission link, respectively. We set the path-loss exponent of line-of-sight (LoS) channel and non-LoS channel as 2 and 3.75, respectively. The small-scale fading is assumed to be Rician fading, i.e., \( H = \sqrt{\frac{\beta}{\beta+1}} H^{\text{LoS}} + \sqrt{\frac{1}{\beta+1}} H^{\text{NLoS}} \), where \( \beta \) is the Rician factor, and \( H^{\text{LoS}} \) and \( H^{\text{NLoS}} \) represent the deterministic line of sight (LoS) channel and non-LoS channel components, respectively. The \( H^{\text{LoS}} \) is given by \( H^{\text{LoS}} = a_r (\nu, \gamma) a_\ell (\nu, \gamma) H_r \), where \( a_\ell (\nu, \gamma) \) is the steering vector of uniform planar array (UPA) with \( \nu \) (resp. \( \gamma \)), and \( \nu \) (resp. \( \gamma \)).
representing the azimuth (resp. elevation) angles of departure and arrival for the LoS component, respectively. The other simulation parameters are set as follows: Rician factor of $\beta = 10$; thermal noise power density of $-104$ dBm/Hz, system bandwidth of $B = 1$ MHz, the number of transmit antennas of $N_t = 8$; the number of receive antennas of $N_r = 4$; the number of data steams of $d = 4$; the parameter of the phase noise of $\rho = 20$, and the error tolerance of $\epsilon = 10^{-5}$. In order to show the performance of the proposed system model more clearly, the following five schemes are compared: 1) RIS with HIs: the proposed design; 2) RIS without HIs: conventional design in an RIS-aided system without HIs; 3) No-RIS with HIs: conventional transceiver design considering HIs impact in a single-user MIMO system without an RIS; 4) Randphase-RIS with HIs: the phase shifts of the reflecting elements are randomly set and we only optimize the beamforming matrices at the BS and user; 5) Naive design: in this scheme, we consider an RIS-aided system with HIs. However, we adopt the existing methods that ignore the HIs. Then, we plug the obtained solutions into the actual RIS-aided system with HIs. This scheme is used to demonstrate the advantages of considering HIs in the system design.

Fig. 1 shows the NMSE of different schemes versus the number of RIS reflecting elements when $\kappa_s = 0.1$ and $\kappa_d = 0.1$. It can be seen that the NMSE value decreases with the increase of the number of reflecting elements $M$. Furthermore, the proposed scheme outperforms the naive design. The reason is that the naive design does not take the HIs into consideration that exists in real communication systems. It reveals that ignoring HIs will result in system performance degradation, thereby indicating the significance of transceiver design for RIS-aided systems by considering HIs. In addition, the dashed lines show the impact of RIS phase shift noise on the downlink NMSE. It is obvious that a higher $\varsigma$ leads to reduced NMSE. It is because that $\epsilon$ decreases as $\varsigma$ increases. When $\varsigma \to \infty$, then $\epsilon \to 0$, $\rho \to 1$ which means the ideal RIS hardware.

Fig. 2 compares the NMSE of various schemes versus $\kappa_s$ when $M = 40$. We can find that the NMSE performance deteriorates as $\kappa_s$ increases by taking into account the HIs. This is because the distortion noise power caused by hardware increases when $\kappa_s$ is large, which leads to large NMSE value. The proposed RIS-aided scheme outperforms randphase RIS sheme and no-RIS sheme under the same $\kappa_s$ when considering HIs. In addition, compared with the perfect hardware conditions, a large $\kappa_s$ brings a large NMSE performance loss.

V. CONCLUSION

In this letter, we investigated the transceiver design for an RIS-aided single-user MIMO communication system with imperfect HIs. We aimed to minimize the MSE by jointly optimizing the precoding matrix at the transmitter, decoding matrix at the receiver and the phase shifts matrices at the RIS. To tackle this non-convex problem, the algorithm based on the Lagrangian dual method and MM algorithm was proposed. Simulation results showed that the efficiency of our proposed algorithm and the significance of considering HIs in the transceiver design for RIS-aided system.

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