Massive multiple-input multiple-output channel estimation under hardware and channel impairments

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ABSTRACT

Hardware problems are the most detrimental issues to channel estimates in wireless communication systems. Because of the enormous number of antennas at the base station (BS) in cellular massive multiple-input multiple-output (MIMO) systems and because one radio frequency (RF) chain per antenna is required, hardware impairments in such systems will be quite severe. Many research publications have used a quality-cost tradeoff to adjust for RF unit hardware issues. In this study, we have taken a different approach by reducing the error floor caused by impairments in the predicted channels. Here are two steps to remedy the problem. In phase 1, a single active user channel in a single cell was calculated statistically rather than parametrically. In phase 2, a convex optimization approach was used to regularize the estimated channel in phase 1 to reduce error and provide a robust channel estimate. The results of our proposed procedure are measured by the normalized minimum mean squared error (NMSE) versus a range from the effective signal-to-noise ratio, and it shows a significant reduction (nearly one order of magnitude) in the error floor as compared with the conventional one, especially at high signal-to-noise ratio (SNR) in the range of (20 dB-30 dB). Simulation results were extracted in MATLAB R2020a.

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1. INTRODUCTION

Massive multiple-input multiple-output (MIMO) systems are appreciated as an emerging key technology for future generations of wireless communication systems [1]–[8]. In most academic wireless communication research, an ideal hardware transceiver is assumed with a negligible hardware impact on the transmitted and received signals. In such a classical setup, both transmitter and receiver hardware components are characterized as a memoryless linear filter model. In other words, the transmitter correctly modulates its analog passband signal from the complex samples of its baseband signal, while the receiver demodulates and samples its received signal synchronously with the transmitter.

However, the transceiver hardware in wireless communication systems is always non-ideal and the classical operations in ideal systems are not satisfied in practice [9]. In terms of power consumption and cost view, designing a massive MIMO system with a single radio frequency (RF) chain per antenna will lead to higher power consumption and expensive cost. Hence, a cost-quality trade-off policy should be followed, that is, the cost of realization of such systems will be M_j times than that have been needed for the conventional systems with only one RF chain. Hence, lower-quality hardware components with a compensation procedure may be used for saving costs.

In effect, the aggregate non-linear impact of the various non-ideal hardware in the RF chain is called hardware impairments [10]–[15]. Because of the hardware impairments, there is a mismatch between the received signal and the baseband signal on the transceiver hardware ends. Different modeling systems with analog and/or digital algorithms such as in [16]–[18] and the references therein, have been issued to compensate for these nonlinearities problems and reduce their impact on the performance of the communication system. But none of these algorithms have completely fixed these problems in practice. In other words, residual impairments [19] still exist in many of these modeling systems raised either by inaccuracies in the design or by the destructive nature of some hardware impairments.

In this paper, a single-user single-cell massive MIMO scenario has been considered under two impairment effects, the non-ideal hardware impairments, and the imperfection knowledge of the covariance matrices at the base station (BS) [20]–[22]. However, motivated by the fact that the channels estimated under such impairments have a large error floor, especially at high signal-to-noise ratio (SNR) [23], two phases of a procedure have been proposed here to estimate the channels under these conditions. In phase 1, the channels were statistically estimated based on many signal observations at the BS, exploiting the ergodicity of the channels and the low of the large number. In phase 2, to investigate a robust channel estimate with minimum error, a convex optimization method was applied to regularize the estimated channels in phase 1. Our results have been validated with conventional (parametric) channel estimation based on the local scattering model [24]. The results have shown a significant reduction in terms of floor error quantity at high SNR.

The paper is organized as follows: in section 2, the concepts under the hood like residual impairments of the non-linear model, the uplink transmission model, and the channel estimation with hardware distortion have been studied in detail. Our proposed model has been explained in section 3, and the results and their analysis have been discussed in section 4. Finally, the paper is concluded in section 5.

2. METHOD AND MODELS

2.1. Residual impairments model (Bussgangs' model)

Bussgang theorem [25] suppose that if the complex Gaussian random variable like $s \sim \mathbb{C}_{\mathcal{N}}(0, p)$ is fed into a distorting device with a non-linear memoryless function g(.), then the output of this device will no longer be Gaussian, that is if $y = g(s)$, then y will be a non-Gaussian random variable, and both s and y can be cross-correlated as in (1).

$$y = \frac{\mathrm{E}\{ys^*\}}{p} s + \eta \tag{1}$$

where the term $\mathrm{E}\{ys^*\}/p$ is a constant ratio that defines the *correlation ratio* between the output y and input variable s. The additive factor, η, is a nonlinear term that defines the impact of the hardware device on the input s. Based on the Bussgang analysis, if we assumed $\mathrm{E}\{|ys^*|^2\}/\mathrm{E}\{s^2\} = \rho$ as a constant factor, and using this notation in (1), we can now generalize a consistent and analytical model to describe the aggregate effect of residual impairments on the RF signals. Hence, the input-output model that fully characterizes the detrimental impact of the residual hardware impairments in the communication system as in (2).

$$y = \sqrt{\rho}\, s + \eta \tag{2}$$

where s and y are assumed with equal power p. However, the power of the distortion term can be calculated from (2) as follows: $\{|\,\eta|^2\} = E\{|y|^2\} - \rho\, E\{|\,s|^2\} \rightarrow \{|\,\eta|^2\} = (1-\rho)p$, that is $\eta \sim \mathbb{C}_{\mathcal{N}}(0, (1-\rho)p)$. Thus, the power of the distortion term is related to the input power p with a scaling factor $(1-\rho)$. That means, the additive distortion term is a power-dependent factor, in contrast to the classical additive receiver noise σ^2 which is independent of the input power p. However, the constant factor, $\rho \in (0, 1]$, represents the hardware quality factor that can be used to measure the level of impairment of hardware devices at the transmitter and receiver as follows: when $\rho = 1$, the output will be the same as the input, that is, $y = s$, i.e., the distortion term $(\{|\,\eta|^2\} = 0\})$, this is the case of ideal hardware. Otherwise, when $\rho = 0$, the distortion term will be $\eta \sim \mathbb{C}_{\mathcal{N}}(0, p)$ which is the same Gaussian distribution as the input. The latter case represents the worst-case condition, i.e., the input s is completely distorted at the output of the non-linear device.

2.2. Uplink transmission model

In this section, we will study the aggregate impact of the hardware impairments on the RF signal from both the BS and terminal user (TU) transceivers, in addition to the propagation channel impact. In a multi-user scenario, assume the transmitted signal by an arbitrary TU k located in cell j is $s_{jk} \sim \mathbb{C}_{\mathcal{N}}(0, p_{jk})$.

Following the model in (2), the complex Gaussian signal will be distorted by the non-ideal hardware of the TU device and then transmitted over the channel as $\sqrt{\rho_t^{TU}}\, s_{jk} + \eta_{jk}^{TU}$ instead of s_{jk}. The scaling factor ρ_t^{TU} denotes the quality of the TU device, and for tractable notation, it is assumed to be the same for all TUs in the network. The additive factor η_{jk}^{TU} determines the transmitter hardware distortion, which can be distributed as $\eta_{jk}^{TU} \sim \mathbb{C}_{\mathcal{N}}(0, (1-\rho_t^{TU})p_{jk})$. In general, the received planner array signals that reach the M_j antennas at the BS j from all TUs in the network are as in (3).

$$\breve{y}_j = \sum_{\ell=1}^{L} \sum_{i=1}^{K_\ell} \mathrm{h}_{\ell i}^{j} \left(\sqrt{\rho_t^{TU}}\, s_{\ell i} + \eta_{\ell i}^{TU}\right) \tag{3}$$

where L denotes the number of cells in the network, and K_ℓ refers to the total number of TUs in each cell in the network. However, for a given set of channel realizations $\{\mathrm{h}_{\ell i}^{j}\}$ within an arbitrary coherence block, the analog signal $\breve{y}_j$ represents a complex Gaussian signal that has zero mean and a conditional correlation matrix which can be given as in (4).

$$\mathbb{E}\left\{\breve{y}_j\, \breve{y}_j^{H} \middle| \{\mathrm{h}_{\ell i}^{j}\}\right\} = \sum_{\ell=1}^{L} \sum_{i=1}^{K_\ell} p_{\ell i}\, \mathrm{h}_{\ell i}^{j} \left(\mathrm{h}_{\ell i}^{j}\right)^{H} \tag{4}$$

However, since $\mathbb{E}\left\{\left|\sqrt{\rho_t^{TU}}\, s_{\ell i} + \eta_{\ell i}^{TU}\right|^2\right\} = p_{\ell i}$. Therefore, it can once again apply the model in (2) to determine the impact of hardware impairments at the receiver end (the BS). Thus, the signal $\breve{y}_j$ is replaced by $\sqrt{\rho_r^{BS}}\, \breve{y}_j + \eta_j^{BS}$, where $\rho_r^{BS} \in (0,1]$ denotes the quality of the hardware of the BS j which is also assumed to be the same for all BSs, and $\eta_j^{BS} \in \mathbb{C}^{M_j}$ is the hardware distortion term of the BS j. For analytical convenience, it has been assumed that the distortion terms between the different RF chains that attached to the M_j receive antennas are independent. In general, the marginal signal $y_j \in \mathbb{C}^{M_j}$ that is received from the UL transmission at BS j can be modeled as in (5).

$$y_j = \sqrt{\rho_r^{BS}} \left(\sum_{\ell=1}^{L} \sum_{i=1}^{K_\ell} \mathrm{h}_{\ell i}^{j} \left(\sqrt{\rho_t^{TU}}\, s_{\ell i} + \eta_{\ell i}^{TU}\right)\right) + \eta_j^{BS} + \mathrm{n}_j \tag{5}$$

where n_j is the White Gaussian (WG) noise that has been added at the BS j . Finally, the signal y_j represents a complex baseband signal that will be used in the following channel estimation model.

2.3. Channel estimation model under hardware distortion

In this section, an uplink channel estimation model for the signal in (5) will be derived under non-ideal transceiver hardware based on the received signal $\mathrm{Y}_j^{p} \in \mathbb{C}^{M_j \times \tau_p}$. To this end, let $s_{\ell i} = \sqrt{p_{\ell i}}\varphi_{\ell i} \in \mathbb{C}^{\tau_p}$, represents the transmitted pilot sequence used by a TU i in cell ℓ. Hence, the uplink transmission model in (5) over τ_p transmission instances will be given as in (6).

$$\mathrm{Y}_j^{p} = \sqrt{\rho_r^{BS}} \left(\sum_{\ell=1}^{L} \sum_{i=1}^{K_\ell} \mathrm{h}_{\ell i}^{j} \left(\sqrt{p_{\ell i}\, \rho_t^{TU}}\, \varphi_{\ell i}^{T} + (\eta_{\ell i}^{TU})^{T}\right)\right) + G_j^{BS} + \mathrm{N}_j^{p} \tag{6}$$

where $\mathrm{N}_j^{p} \in \mathbb{C}^{M_j \times \tau_p}$ is the additive noise on the M_j receive antennas with $i.i.d$ elements and are distributed as $\sim \mathbb{C}_{\mathcal{N}}(0, \sigma_{UL}^2)$, the term $G_j^{BS} \in \mathbb{C}^{M_j \times \tau_p}$ is the receiver hardware distortion matrix, each column of which takes the same distribution as η_j^{BS} in (5), while $\eta_{\ell i}^{TU} \in \mathbb{C}^{\tau_p}$ represents the transmitter distortion that contains τ_p transmission realizations from $\eta_{\ell i}^{TU}$ in (5). However, to estimate the channel of a TU i in cell ℓ at the BS j, the BS first correlates signal Y_j^{p} with the pilot sequence $\varphi_{\ell i}$ of the desired TU and yields the processed signal $y_{j\ell i}^{p} = \mathrm{Y}_j^{p}\varphi_{\ell i}^{*}$. For an instant, to estimate the channel of the kth TU in cell j at the BS j, the received signal will be written as in (7).

$$\begin{aligned} y_{jjk}^{p} = \mathrm{Y}_j^{p}\varphi_{jk}^{*} = \underbrace{\sqrt{p_{jk}\, \rho_t^{TU}\rho_r^{BS}}\tau_p\, \mathrm{h}_{jk}^{j}}_{Desired\ pilot} + \underbrace{\sum_{(\ell,i)\in\mathcal{P}_{jk}\setminus(j,k)} \sqrt{p_{\ell i}\, \rho_t^{TU}\rho_r^{BS}}\tau_p\, \mathrm{h}_{\ell i}^{j}}_{interfering\ pilots} + \\ \underbrace{\sum_{\ell=1}^{L} \sum_{i=1}^{K_\ell} \sqrt{\rho_r^{BS}}\, \mathrm{h}_{\ell i}^{j}\, (\eta_{\ell i}^{TU})^{T}\varphi_{jk}^{*}}_{Transmitter\ distortion} + \underbrace{G_j^{BS}\varphi_{jk}^{*}}_{Receiver\ distortion} + \underbrace{\mathrm{N}_j^{p}\varphi_{jk}^{*}}_{Noise} \end{aligned} \tag{7}$$

where τ_p results from multiplying $\varphi_{\ell i}^T \varphi_{jk}^*$ when $\varphi_{\ell i}^T = \varphi_{jk}^T$. The set $\mathcal{P}_{jk}$ denotes for all users using pilot sequences as the pilot sequence φ_{jk} of the desired TU k in cell j. Since $\|\varphi_{jk}\|^2 = \tau_p$. The last three terms in (7) will be distributed as follows: $\mathrm{N}_j^p \varphi_{jk}^* \sim \mathbb{C}_{\mathcal{N}}\left(0, \sigma_{UL}^2 \tau_p \mathrm{I}_{M_j}\right)$, $(\eta_{\ell i}^{TU})^T \varphi_{jk}^* \sim \mathbb{C}_{\mathcal{N}}(0, \tau_p(1-\rho_t^{TU}) p_{jk})$, and $G_j^{BS} \varphi_{jk}^* \sim \mathbb{C}_{\mathcal{N}}(0_{M_j}, \tau_p \mathrm{D}_{j,\{\mathrm{h}\}})$ for given channel realizations. It is seen from (7) that the processed signal y_{jjk}^p is affected by an aggregate distortion from the transmitter and receiver hardware of all signaling transmissions in the entire network. Since these distortions are almost surely non-orthogonal to their pilot sequence, this implies that there are pilot contaminations between every TUs in the network. However, according to the Bussgang theorem, the processed signal y_{jjk}^p in (7) represents a non-Gaussian signal. Therefore, a suboptimal estimator will be used here instead of the exact one. In other words, a linear minimum mean squared error (LMMSE) estimator with a little performance loss will be used instead of the optimal MMSE estimator. In general, based on the processed signal $y_{j\ell i}^p = \mathrm{Y}_j^p \varphi_{\ell i}^*$ the linear LMMSE estimator [24] $\hat{\mathrm{h}}_{\ell i}^j$ can be given as in (8).

$$\hat{\mathrm{h}}_{\ell i}^j = \sqrt{p_{\ell i}\, \rho_t^{TU} \rho_r^{BS}} \mathrm{R}_{\ell i}^j \Psi_{\ell i}^j y_{j\ell i}^p \tag{8}$$

where $\mathrm{R}_{\ell i}^j \in \mathbb{C}^{M_j \times M_j}$ denotes the covariance matrix of $\mathrm{h}_{\ell i}^j$, and $\Psi_{\ell i}^j$ refers to the overall effects from all interfering TU, the additive receiver noise, and hardware distortions caused by pilot signaling of all TUs in the entire network, it is written as in (9).

$$\Psi_{\ell i}^j = \Big(\sum_{(\ell,i)\in\mathcal{P}_{jk}\setminus(j,k)} p_{\ell i}\, \rho_t^{TU} \rho_r^{BS} \tau_p\, \mathrm{R}_{\ell i}^j + \sigma_{UL}^2 \mathrm{I}_{M_j} + \sum_{\ell=1}^{L} \sum_{i=1}^{K_\ell} p_{\ell i}(1 - \rho_t^{TU}) \rho_r^{BS}\, \mathrm{R}_{\ell i}^j + \sum_{\ell=1}^{L} \sum_{i=1}^{K_\ell} p_{\ell i}(1-\rho_r^{BS})\, \mathrm{D}_{\mathrm{R}_{\ell i}^j}\Big)^{-1} \tag{9}$$

where

$$\mathrm{D}_{\mathrm{R}_{\ell i}^j} = \mathrm{diag}\left([\mathrm{R}_{\ell i}^j]_{11}, \dots, [\mathrm{R}_{\ell i}^j]_{M_j M_j}\right) \tag{10}$$

represents a diagonal matrix that contains diagonal elements from $\mathrm{R}_{\ell i}^j$. However, the estimator that gives a minimum mean squared error minimum mean squared error (MSE) $\mathbb{E}\{\|\mathrm{h}_{\ell i}^j - \hat{\mathrm{h}}_{\ell i}^j\|^2\}$ is the best estimator that can be used, the difference $\mathrm{h}_{\ell i}^j - \hat{\mathrm{h}}_{\ell i}^j$ represents the estimation error $\tilde{\mathrm{h}}_{\ell i}^j$ that has a correlation matrix $\mathrm{C}_{\ell i}^j = \mathbb{E}\left\{\tilde{\mathrm{h}}_{\ell i}^j (\tilde{\mathrm{h}}_{\ell i}^j)^H\right\}$ given as in (11).

$$\mathrm{C}_{\ell i}^j = \mathrm{R}_{\ell i}^j - p_{\ell i}\, \rho_t^{TU} \rho_r^{BS} \tau_p\, \mathrm{R}_{\ell i}^j \Psi_{\ell i}^j \mathrm{R}_{\ell i}^j \tag{11}$$

while the correlation matrix of the linear estimator $\hat{\mathrm{h}}_{\ell i}^j$ calculated as in (12).

$$\mathbb{E}\left\{\hat{\mathrm{h}}_{\ell i}^j \left(\hat{\mathrm{h}}_{\ell i}^j\right)^H\right\} = \mathrm{R}_{\ell i}^j - \mathrm{C}_{\ell i}^j = p_{\ell i}\, \rho_t^{TU} \rho_r^{BS} \tau_p\, \mathrm{R}_{\ell i}^j \Psi_{\ell i}^j \mathrm{R}_{\ell i}^j \tag{12}$$

It is noticed from (8) that the correlation matrix of the linear estimator $\hat{\mathrm{h}}_{\ell i}^j$ is fully dependent on the second-order statistics of all TUs in the network, which means that the BS can determine the LMMSE estimator $\hat{\mathrm{h}}_{\ell i}^j$ only when it knows the correlation matrices $\mathrm{R}_{\ell i}^j$ and $\Psi_{\ell i}^j$ including the scaling quantity $p_{\ell i}\, \rho_t^{TU} \rho_r^{BS} \tau_p$. However, the BS in practice has imperfect or no prior knowledge of this statistical information and therefore should be statistically estimated based on the random matrix theory.

2.4. Hardware distortions impact

In this section, a single cell single active TU scenario has been tested to show how hardware impairments impact the estimated channel in section 2.3, the channel between the TU and the BS is denoted by $\mathrm{h} \sim \mathbb{C}_{\mathcal{N}}(0_M, \mathrm{R})$, where $\mathrm{R} \in \mathbb{C}^{M\times M}$, is the semi-definite covariance matrix. Following (11), the correlation matrix of the error for a single user scenario is given as in (13).

$$\mathrm{C} = \mathrm{R} - p\, \rho_t^{TU} \rho_r^{BS} \tau_p\, \mathrm{R}\Psi\mathrm{R} \tag{13}$$

Where

$$\Psi=\left(p\left(1+\rho_t^{TU}(\tau_p-1)\right)\rho_r^{BS}\mathrm{R}+p(1-\rho_r^{BS})\mathrm{D_R}+\sigma_{UL}^2\mathrm{I}_M\right)^{-1} \tag{14}$$

The Ψ expression in (14) shows the distortion effect of the transceiver's hardware in the desired TU and the BS, which is different from the case when having ideal hardware i.e. $\rho_t^{TU}=\rho_r^{BS}=1$. Sub. (14) in (13) and take the limits when p goes to infinity the correlation matrix of the error becomes as in (15).

$$\mathrm{C}=\mathrm{R}-\mathrm{R}\left(\frac{1+\rho_t^{TU}(\tau_p-1)}{\rho_t^{TU}\tau_p}\mathrm{R}+\frac{(1-\rho_r^{BS})}{\rho_t^{TU}\rho_r^{BS}\tau_p}\mathrm{D_R}\right)^{-1}\mathrm{R} \tag{15}$$

For a special case of $\mathrm{R}=\beta\mathrm{I}_M$, the correlation matrix of the error in (15) simplifies to:

$$\mathrm{C}=\beta\mathrm{I}_M-\frac{\beta^2}{\frac{1+\rho_t^{TU}(\tau_p-1)}{\rho_t^{TU}\tau_p}\beta+\frac{(1-\rho_r^{BS})}{\rho_t^{TU}\rho_r^{BS}\tau_p}\beta}\mathrm{I}_M=\frac{\beta(1-\rho_t^{TU}\rho_r^{BS})}{1+\rho_t^{TU}\rho_r^{BS}(\tau_p-1)} \tag{16}$$

The last expression in front of I_M represents the aggregate error floor term of the transceiver's hardware at the BS and the TU device. As seen in (16), the error floor is constrained by the hardware quality ρ_t^{TU} and ρ_r^{BS}, the pilot length τ_p, and the average gain of the channel β. Hence, one can use these parameters to optimize the error floor at the BS.

The normalized mean squared error normalized minimum mean squared error (NMSE) $=\mathrm{tr(C)/tr(R)}$ in Figure 1 has been used in [24] to show how the hardware distortion affects the estimated channel when using "the local scattering model" with angular standard deviation (ASD) $=10^{\circ}$ and a uniform distributed nominal angle. NMSE curves are averaged over a range from the effective SNR for $\tau_p=10$ lengths and with different hardware constants, as illustrated in Figure 1.

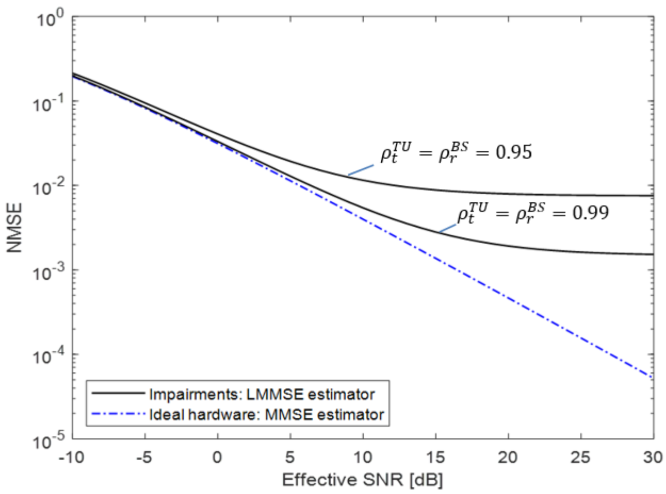

Figure 1. The normalized MSE of the conventional channel estimation using the local scattering model in [24] with equal hardware quality at the transceiver ends

3. PROPOSED APPROACH

In motivation with the fact that the BS can estimate the channel $\mathrm{h}_{\ell i}^{j}$ only when it knows the correlation matrices $\mathrm{R}_{\ell i}^{j}$ and $\Psi_{\ell i}^{j}$ which in practice are unknown at the BS. Therefore, in this section, the methods of two phases have been suggested to estimate the channels under such consideration. In phase 1, the channel $\mathrm{h}_{\ell i}^{j}$ statistically estimated based on many observations of the signals in (6) exploiting the channel ergodicity characteristics and the low of the large number. A sample covariance matrix from the random matrix theory of the desired TU channel would be estimated first, then a convex optimization method will be applied to regularize the covariance matrices in phase 1. In the present work, two imperfection conditions, the hardware distortions, and the unknown statistics of the channel at the BS have been jointly considered.

3.1. Phase 1: sample covariance matrix estimation
3.1.1. $\boldsymbol{\Psi}_{\ell \mathbf{i}}^{\jmath\ (\text{sample})}$ estimation
In this part, the BS needs to see many observations from $y_{\jmath\ell i}^{p}$ as $y_{\jmath\ell i}^{p}[1], \dots, y_{\jmath\ell i}^{p}[N_{\Psi}]$, where N_{Ψ} refers to the total number of signal observations, assumed the coherence time is large enough to include many channel realizations, then the sample matrix can then be given as in (17):

$$\widehat{\Psi}_{\ell i}^{\jmath\ (sample)} = \frac{1}{N_{\Psi}} \sum_{n=1}^{N_{\Psi}} y_{\jmath\ell i}^{p}[n] \left(y_{\jmath\ell i}^{p}[n] \right)^{H} \tag{17}$$

and according to the large number low, i.e., when $N_{\Psi} \rightarrow \infty$, then as in (18).

$$\left[\frac{1}{N_{\Psi}} \sum_{n=1}^{N_{\Psi}} y_{\jmath\ell i}^{p}[n] \left(y_{\jmath\ell i}^{p}[n] \right)^{H} \right]_{m,m} \xrightarrow{a.s} [\Psi_{\ell i}^{\jmath}]_{m,m} \tag{18}$$

which is a diagonal element from the sample covariance matrix in (17).

3.1.2. $\mathbf{R}_{\ell \mathbf{i}}^{\jmath\ (\text{sample})}$ estimation
In this part, the same approach above can be followed with two stages of a procedure as in [21]. In the first stage, the BS first estimate the $\Psi_{\ell i}^{\jmath\ (sample)}$ that determined for all TUs in the network, including the desired TU. In the second stage, the BS gives extra pilots to the interfering users and used their observations to estimate $\mathrm{R}_{\ell i}^{\jmath\ (sample)}$ as in (19).

$$\widehat{\mathrm{R}}_{\ell i}^{\jmath\ (sample)} = \widehat{\Psi}_{\ell i}^{\jmath\ (sample)} - \widehat{\Psi}_{\ell i,-k}^{\jmath\ (sample)} \tag{19}$$

where $\widehat{\Psi}_{\ell i}^{\jmath\ (sample)}$ is the already computed matrix and $\widehat{\Psi}_{\ell i,-k}^{\jmath\ (sample)}$ is the sample covariance matrix of the interfering TUs with additional pilots.

3.2. Phase 2: convex optimization of sample covariance matrices
Due to the estimation error in all elements of the sample covariance matrices estimated in phase 1; a convex optimization method will be used here to obtain a better estimate, where the statistical sample covariance matrices are regularized with its diagonal matrices to reduce the error as follows:

$$\widehat{\Psi}_{\ell i}^{\jmath}(c) = c\, \widehat{\Psi}_{\ell i}^{\jmath\ (sample)} + (1-c) \widehat{\Psi}_{\ell i}^{\jmath\ (diagonal)} \tag{20}$$

$$\widehat{\mathrm{R}}_{\ell i}^{\jmath}(\alpha) = \alpha \widehat{\mathrm{R}}_{\ell i}^{\jmath\ (sample)} + (1-\alpha) \widehat{\mathrm{R}}_{\ell i}^{\jmath\ (diagonal)} \tag{21}$$

where c and α denote the regularization factors. The diagonal elements of the $\widehat{\mathrm{R}}_{\ell i}^{\jmath}(\alpha)$ and $\widehat{\Psi}_{\ell i}^{\jmath}(c)$ are the same as in $\widehat{\mathrm{R}}_{\ell i}^{\jmath\ (diagonal)}$ and $\widehat{\Psi}_{\ell i}^{\jmath\ (diagonal)}$ respectively, while the elements in the off-diagonal locations are regularized corresponding to c and $\alpha \in [0,1]$. This might be important for the estimating model in (8) since it uses the covariance matrices to estimate the channel $\mathrm{h}_{\ell i}^{\jmath}$. Thus, (8) can be rewritten in terms of the regularized covariance matrices as in (22).

$$\widehat{\mathrm{h}}_{\ell i}^{\jmath}(\alpha, c) = \sqrt{p_{\ell i}\, \rho_t^{TU} \rho_r^{BS}}\, \widehat{\mathrm{R}}_{\ell i}^{\jmath}(\alpha) \widehat{\Psi}_{\ell i}^{\jmath}(c)\, y_{\jmath\ell i}^{p} \tag{22}$$

Then, the $\mathrm{NMSE} = \mathrm{tr(C)/tr(R)}$ for a single-TU single-cell scenario can be applied to compare the obtained results with the standard results in Figure 1.

4. RESULT AND ANALYSIS
For performance evaluation, the average NMSE curves in Figure 1 of the local scattering model have been considered as the standard results [24] that can be used to validate our results in Figures 2 and 3. It has been assumed that the NMSE curves in Figure 1 are averaged over different nominal angles of the TU in the cell ($0^{\circ} - 360^{\circ}$) with Gaussian distribution and angular standard deviation ($ASD = 10^{\circ}$) using $M = 100$ antennas at the BS. Figure 1 illustrates the NMSE curves as a function of the effective SNR (p/σ_{UL}^{2}) with a pilot sequence $\tau_p = 10$ and different

hardware constants as follows, $\rho_t^{TU} = \rho_r^{BS} = 0.99$ and $\rho_t^{TU} = \rho_r^{BS} = 0.95$ in case of hardware distortions, and $\rho_t^{TU} = \rho_r^{BS} = 1$ in case of ideal hardware. Figure 1 emphasizes that there is an error floor in the estimated channels, particularly in the range of (20 dB and 30 dB) SNR, while it is small at low SNR values. On the other hand, hardware impairments show a substantial impact on the estimated channels when the quality of hardware components decreases, particularly at $\rho_t^{TU} = \rho_r^{BS} = 0.95$. In the present work, an optimized channel estimation method was proposed to reduce the error floor in the NMSE curves at high SNR. We first take advantage of the random matrix theory to estimate the channels statistically based on the sample covariance matrix method under imperfect statistical information, then a convex optimization procedure has been applied to regularize the estimated sample covariance matrices of the estimated channels. Our results illustrated in Figure 2 show the average NMSE curves for the estimated channels under the joint impact of hardware impairments and imperfection knowledge of the channels at the BS. It shows how the practical channels are closely aligned to the standard NMSE curves of the local scattering model in Figure 1. On the other hand, Figure 3 shows the optimized NMSE curves when the convex optimization procedure was applied to the sample covariance matrices in Figure 2. As a result, the error floor in Figure 3 is significantly reduced when the hardware quality $\rho_t^{TU} = \rho_r^{BS} = 0.99$, while it is slightly better than before in the case of $\rho_t^{TU} = \rho_r^{BS} = 0.95$. On the other hand, it is noticed that the NMSE curve when $\rho_t^{TU} = \rho_r^{BS} = 0.99$ is closely aligned to the ideal hardware case of $\rho_t^{TU} = \rho_r^{BS} = 1$, which means that less quality hardware components can be used now at the BS with only a little performance loss in the channel estimation.

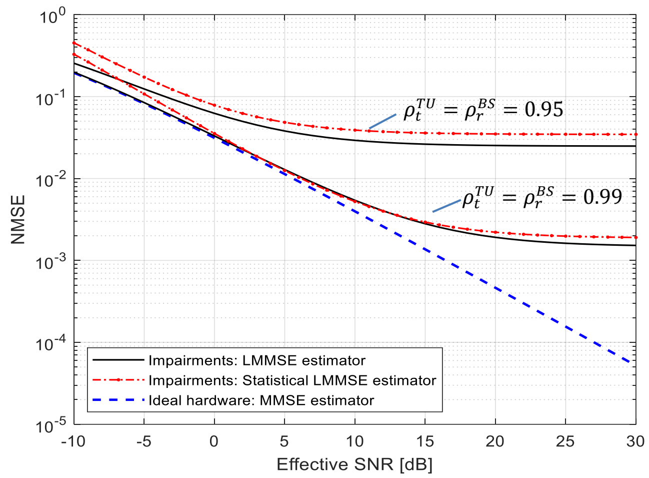

Figure 2. The normalized MSE of the statistical channel estimation using the sample covariance matrix in phase 1 with equal hardware quality at the transceiver ends

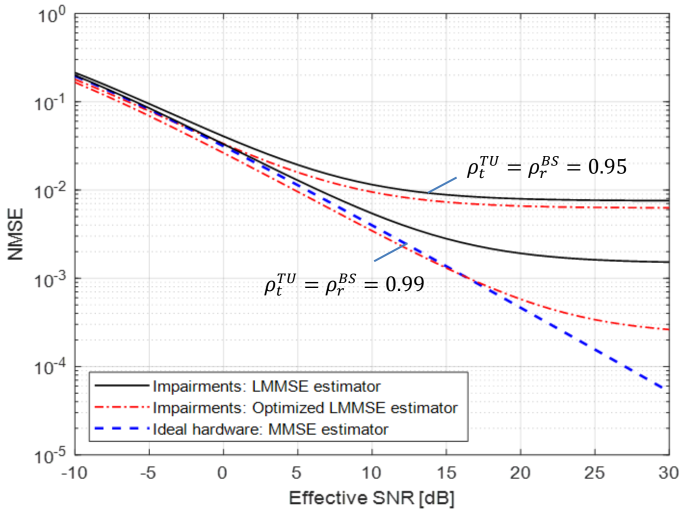

Figure 3. The normalized MSE of the optimized channel estimation using the convex optimization method in phase 2 with equal hardware quality at the transceiver ends

5. CONCLUSION

In this research, a channel estimate approach for large MIMO systems was suggested under two situations of impairment: the non-ideal hardware impairments at the transceiver ends of the transmitter and receiver, and the impairments caused by the BS's insufficient statistical information. We estimated the channels jointly under these conditions, regularized them, then compared them to the typical result from the local scattering model. In terms of hardware quality constants, the results show that our proposed technique beats the usual one in terms of lowering the error floor (almost by an order of magnitude).

REFERENCES

[1] E. G. Larsson, O. Edfors, F. Tufvesson, and T. L. Marzetta, "Massive MIMO for next generation wireless systems," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 186–195, Feb. 2014, doi: 10.1109/MCOM.2014.6736761.

[2] E. Björnson, E. G. Larsson, and T. L. Marzetta, "Massive MIMO: ten myths and one critical question," *IEEE Communications Magazine*, vol. 54, no. 2, pp. 114–123, Feb. 2016, doi: 10.1109/MCOM.2016.7402270.

[3] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overview of massive MIMO: benefits and challenges," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 742–758, Oct. 2014, doi: 10.1109/JSTSP.2014.2317671.

[4] T. L. Marzetta, "Massive MIMO: an introduction," *Bell Labs Technical Journal*, vol. 20, pp. 11–22, 2015, doi: 10.15325/BLTJ.2015.2407793.

[5] F. Rusek, D. Persson, B. K. Lau, E. G. Larsson, T. L. Marzetta, and F. Tufvesson, "Scaling up MIMO: opportunities and challenges with very large arrays," *IEEE Signal Processing Magazine*, vol. 30, no. 1, pp. 40–60, Jan. 2013, doi: 10.1109/MSP.2011.2178495.

[6] M. K. Hussein and N. N. Khamiss, "Integrating millimeter wave with hybrid precoding multiuser massive MIMO for 5G communication," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 18, no. 1, pp. 90-98, Feb. 2020, doi: 10.12928/telkomnika.v18i1.13674.

[7] M. K. Bhatt, B. S. Sedani, and K. Borisagar, "Performance analysis of massive multiple input multiple output for high speed railway," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 6, pp. 5180–5188, Dec. 2021, doi: 10.11591/ijece.v11i6.pp5180-5188.

[8] H. A. Atallah, S. Almutairi, A. B. A.- Rahman, and M. Elwekeil, "Promoting fractional frequency reuse performance for combating pilot contamination in massive multiple input multiple output," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 3, pp. 2681-2688, Jun. 2022, doi: 10.11591/ijece.v12i3.pp2681-2688.

[9] T. Schenk, *RF imperfections in high-rate wireless systems: impact and digital compensation*. Dorrdrecht, Netherlands: Springer Science & Business Media, 2008.

[10] U. Gustavsson *et al.*, "On the impact of hardware impairments on massive MIMO," in *2014 IEEE Globecom Workshops (GC Wkshps)*, Dec. 2014, pp. 294–300, doi: 10.1109/GLOCOMW.2014.7063447.

[11] C. Mollen, U. Gustavsson, T. Eriksson, and E. G. Larsson, "Impact of spatial filtering on distortion from low-noise amplifiers in massive MIMO base stations," *IEEE Transactions on Communications*, vol. 66, no. 12, pp. 6050–6067, Dec. 2018, doi: 10.1109/TCOMM.2018.2850331.

[12] S. Jacobsson, G. Durisi, M. Coldrey, U. Gustavsson, and C. Studer, "Throughput analysis of massive MIMO uplink with low-resolution ADCs," *IEEE Transactions on Wireless Communications*, vol. 16, no. 6, pp. 4038–4051, Jun. 2017, doi: 10.1109/TWC.2017.2691318.

[13] E. Bjornson, J. Hoydis, M. Kountouris, and M. Debbah, "Massive MIMO systems with non-ideal hardware: energy efficiency, estimation, and capacity limits," *IEEE Transactions on Information Theory*, vol. 60, no. 11, pp. 7112–7139, Nov. 2014, doi: 10.1109/TIT.2014.2354403.

[14] Q. Zhang, T. Q. S. Quek, and S. Jin, "Scaling analysis for massive MIMO systems with hardware impairments in rician fading," *IEEE Transactions on Wireless Communications*, vol. 17, no. 7, pp. 4536–4549, Jul. 2018, doi: 10.1109/TWC.2018.2827068.

[15] E. Bjornson, L. Sanguinetti, and J. Hoydis, "Hardware distortion correlation has negligible impact on UL massive MIMO spectral efficiency," *IEEE Transactions on Communications*, vol. 67, no. 2, pp. 1085–1098, Feb. 2019, doi: 10.1109/TCOMM.2018.2877331.

[16] F. Horlin and A. Bourdoux, *Digital compensation for analog front-ends: a new approach to wireless transceiver design*. West Sussex, England: John Wiley & Sons, 2008.

[17] M. Valkama, "RF impairment compensation for future radio systems," in *Multi-Mode/Multi-Band RF Transceivers for Wireless Communications*, Hoboken, NJ, USA: John Wiley & Sons, Inc., 2010, pp. 451–496.

[18] M. Wenk, "MIMO-OFDM-testbed: challenges, implementations, and measurement results: challenges, implementations, and measurement results," ETH Zuerich, 2010.

[19] A. Papazafeiropoulos, B. Clerckx, and T. Ratnarajah, "Rate-splitting to mitigate residual Transceiver hardware impairments in massive MIMO systems," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 9, pp. 8196–8211, Sep. 2017, doi: 10.1109/TVT.2017.2691014.

[20] E. Bjornson, L. Sanguinetti, and M. Debbah, "Massive MIMO with imperfect channel covariance information," in *2016 50th Asilomar Conference on Signals, Systems and Computers*, Nov. 2016, pp. 974–978, doi: 10.1109/ACSSC.2016.7869195.

[21] A. K. Kocharlakota, K. Upadhya, and S. A. Vorobyov, "On achievable rates for massive MIMO system with imperfect channel covariance information," in *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2019, pp. 4504–4508, doi: 10.1109/ICASSP.2019.8682163.

[22] N. Shariati, E. Bjornson, M. Bengtsson, and M. Debbah, "Low-complexity polynomial channel estimation in large-scale MIMO with arbitrary statistics," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 815–830, Oct. 2014, doi: 10.1109/JSTSP.2014.2316063.

[23] F. Athley, G. Durisi, and U. Gustavsson, "Analysis of massive MIMO with hardware impairments and different channel models," in *2015 9th European Conference on Antennas and Propagation (EuCAP)*, 2015, pp. 1–5.

[24] E. Björnson, J. Hoydis, and L. Sanguinetti, "Massive MIMO networks: spectral, energy, and hardware efficiency," *Foundations and Trends® in Signal Processing*, vol. 11, no. 3–4, pp. 154–655, 2017, doi: 10.1561/2000000093.

[25] J. J. Bussgang, "Crosscorrelation functions of amplitude-distorted Gaussian signals," Cambridge, Massachusetts, 1952.

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