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Joint data power control and LSFD design in distributed cell-free massive MIMO under non-ideal UE hardware

Ning Li[1*] and Pingzhi Fan[1]

*Correspondence: lining@my.swjtu.edu.cn

[1] Institute of Mobile Communications, Southwest Jiaotong University, Chengdu 610031, Sichuan, China

Abstract

This paper investigates distributed cell-free massive multiple-input multiple-output with non-ideal user equipment hardware under spatially correlated channels. By employing the use-and-then-forget technique, a lower capacity bound is derived based on the established generalized UE hardware impairments model. In addition, maximum ratio combining can be used to derive a closed-form expression of the spectral efficiency (SE), which offers novel insights into the impact of non-ideal UE hardware on network performance. Furthermore, a max–min SE fairness problem with UE hardware impairments is established where the optimization variables are data power and large-scale fading decoding (LSFD) vectors. Since this is a non-convex problem, we devise an iterative alternating optimization algorithm based on the bisection search to acquire the globally optimal solution. Numerical results indicate that the recommended joint data power control and LSFD design algorithm provides higher SE for the weakest UE, thus significantly enhancing the total SE of the network.

Keywords: Cell-free mMIMO, Non-ideal UE hardware, Spatially correlated channels, Spectral efficiency, Iterative alternating optimization

1 Introduction

Massive multiple-input multiple-output (mMIMO) and its evolution ultra-mMIMO provide high data rate services by spatial multiplexing and advanced signal processing [1]. The traditional mMIMO network is based on cellular architecture, which makes the data rate vary widely. In contrast, the recent emergence of user-centric cell-free (CF) mMIMO may suppress inter-cell interference to provide a consistently very high data rate [2]. CF networks can be divided into distributed operation and centralized operation [3]. Since centralized operation has higher computational complexity and increases the operating burden of the central processing unit (CPU), this paper concentrates on the distributed CF mMIMO network.

Most existing works study transceiver hardware impairments based on spatially uncorrelated channel models [4–7]. The uplink capacity of CF mMIMO with non-ideal hardware for four receiver cooperation is investigated in [4], and it is pointed out that hardware impairments at user equipments (UEs) significantly impact the uplink average

spectral efficiency (SE) compared to hardware impairments at access points (APs). The uplink achievable rate of CF mMIMO with constrained fronthaul and hardware limitations is analyzed and optimized in [5]. Uplink CF mMIMO under hardware imperfections is investigated in [6], and a power optimization approach is designed to maximize the total SE. The performances of distributed mMIMO and small cell networks under hardware and channel imperfections are analyzed and compared in [7]. However, the practical channels are usually spatially correlated in multiple antennas [8]. As far as we know, few existing works analyze and optimize CF mMIMO with non-ideal hardware under spatially correlated channels. Only two works analyze CF mMIMO with hardware imperfections in spatially correlated channels [9, 10]. Since UE hardware impairment constrains the performance of the network [11], we will investigate how UE hardware impairment affects the performance of distributed CF mMIMO with spatially correlated channels.

One of the most critical factors for optimizing CF networks is max–min fairness, which attempts to optimize the lowest SE across all UEs. A Max–min SE fairness optimization problem with uplink data power constraints was addressed in [12] using meta-heuristics. The joint data power control and large-scale fading decoding (LSFD) design approach proposed in [13] effectively improves the total SE of cellular mMIMO networks. However, we concentrate on the problem of maximizing SE for the weakest UEs. The max–min fairness issue in CF mMIMO with wireless power transfer is addressed in [14] using an alternating optimization method. Inspired by [13, 14], the max–min SE fairness with data power and LSFD vectors constraints is considered in this paper and benchmarked with max–min fairness power control [15] and fractional power control [16], respectively.

1.1 Major contributions

The following are the major contributions of this paper:

- Through an established UE hardware impairment model, the LMMSE estimator is utilized to obtain the uplink channel state information of the distributed CF mMIMO network, revealing a non-zero estimation error floor caused by non-ideal UE hardware. Furthermore, we discuss schemes for reducing the estimation error floor.
- The lower bound of the uplink ergodic channel capacity is established, and the optimal LSFD detection scheme is derived. Furthermore, with the help of MR combining, a closed form for the uplink SE can be obtained, which offers profound insights into the impact of non-ideal UE hardware on network performance.
- A joint data power control and LSFD design algorithm is proposed to maximize the SE of the UE with the lowest SE. Finally, simulation results demonstrate that the proposed algorithm not only provides higher SE for the weakest UE but also significantly enhances the overall SE of the network.

1.2 Paper outline and notation

The remainder of this paper is structured as follows. Section 2 describes the CF mMIMO network model and discusses the uplink channel acquisition and the decoding of uplink data. Section 3 establishes the lower bound of the ergodic channel capacity for the distributed CF mMIMO network and obtains the optimal LSFD detection scheme and the

closed-form expression of SE. The proposed method for joint data power control and LSFD design is presented in Sect. 4. Section 5 provides a numerical evaluation and comparison of the performance of the proposed algorithm. Finally, the major conclusions of this paper are summarized in Sect. 6. The "Appendix" includes detailed proofs.

Notation In column vectors and matrices, boldfaced lowercase and uppercase letters are utilized. $\mathbf{I}$ stands for the identity matrix, and $\mathrm{diag}(\lambda_1, \ldots, \lambda_N)$ is a diagonal matrix whose main diagonal elements are $\lambda_1, \ldots, \lambda_N$. $\mathrm{tr}(\mathbf{X})$ represents the trace of square matrix $\mathbf{X}$. Let $\mathbf{X}^*$ represent the complex conjugate operation of $\mathbf{X}$. $\mathbf{X}^{\mathrm{T}}$ and $\mathbf{X}^{\mathrm{H}}$ correspond to the transpose and Hermitian transpose operations of matrice $\mathbf{X}$. A complex Gaussian stochastic vector $\mathbf{x}$ is represented by $\mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{R})$, where the mean is 0 and $\mathbf{R}$ denotes the correlation matrix. The expected value of a stochastic vector $\mathbf{x}$ can be indicated by $\mathbb{E}\{\mathbf{x}\}$.

2 Network model

This paper considers a distributed CF mMIMO network under non-ideal UE hardware, where K UEs configured with a single antenna are served by L dispersed APs and N antennas are installed on each AP. Each AP is linked via a fronthaul to the CPU in charge of AP collaboration. The non-ideal UE hardware can be described as the intended signal power of ideal hardware multiplied by $\sqrt{1-\epsilon^2}$, where $0 \leq \epsilon < 1$ measures the hardware impairment level and can be referred to as the hardware impairment factor, with the addition of the Gaussian distortion noise [17]. The channel vector for spatially correlated Rayleigh fading from UE k to AP l is $\mathbf{h}_{lk} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{R}_{lk})$, where $\mathbf{R}_{lk} \in \mathbb{C}^{N\times N}$ denotes the spatial correlation matrix and $\beta_{lk} \triangleq \mathrm{tr}(\mathbf{R}_{lk})/N$ can be defined as the large-scale fading coefficient. Uplink transmission devotes τ_p samples to uplink pilot signaling and $\tau_u = \tau_c - \tau_p$ samples to uplink data signals, with τ_c samples per coherence block.

2.1 Uplink channel acquisition

Let $s_i \in \mathbb{C}$ denote an arbitrary signal sent by UE i and assume its power $\mathbb{E}\{|s_i|^2\} = p_i$. Assuming a set of τ_p mutually orthogonal pilot signals $\boldsymbol{\phi}_1, \ldots, \boldsymbol{\phi}_{\tau_p}$ to estimate the channel of an extensive network with $K > \tau_p$. The pilot sequence of UE k is symbolized by $\boldsymbol{\phi}_k \in \mathbb{C}^{\tau_p}$ with $\|\boldsymbol{\phi}_k\|^2 = \tau_p$. Set $\mathcal{P}_k = \left\{i : \boldsymbol{\phi}_i = \boldsymbol{\phi}_k, i = 1, \ldots, K\right\}$ is a collection of all UEs assigned to the same pilot sequence as UE k. The signal $\mathbf{Y}_l^p \in \mathbb{C}^{N\times\tau_p}$ received at AP l can be represented as

$$\mathbf{Y}_l^p = \sum_{i=1}^{K} \mathbf{h}_{li}\left(\sqrt{p_i\left(1-\epsilon^2\right)}\boldsymbol{\phi}_i^{\mathrm{T}} + \mathbf{e}_i^{\mathrm{T}}\right) + \mathbf{N}_l^p, \tag{1}$$

where the transmitter distortion is denoted as $\mathbf{e}_i \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_{\tau_p}, \epsilon^2 p_i \mathbf{I}_{\tau_p})$. The additive receiver noise is $\mathbf{N}_l^p \in \mathbb{C}^{N\times\tau_p}$, with a distribution of $\mathcal{N}_{\mathbb{C}}\left(0, \sigma^2\right)$ for each element. The AP l can multiply the pilot sequence $\boldsymbol{\phi}_k$ of UE k with $\mathbf{Y}_l^p$ to obtain the processed received pilot signal $\mathbf{y}_{lk}^p \in \mathbb{C}^N$ as

$$\mathbf{y}_{lk}^p = \mathbf{Y}_l^p\boldsymbol{\phi}_k^* = \sqrt{p_k\left(1-\epsilon^2\right)}\tau_p\mathbf{h}_{lk} + \sum_{i=1}^{K}\mathbf{h}_{li}\mathbf{e}_i^{\mathrm{T}}\boldsymbol{\phi}_k^* + \sum_{i\in\mathcal{P}_k\setminus\{k\}}\sqrt{p_i\left(1-\epsilon^2\right)}\tau_p\mathbf{h}_{li} + \mathbf{N}_l^p\boldsymbol{\phi}_k^*. \tag{2}$$

By minimizing the mean-squared error (MSE) $\mathbb{E}\{\|\mathbf{h}_{lk} - \hat{\mathbf{h}}_{lk}\|^2\}$, it is possible to calculate the linear MMSE (LMMSE) estimate of $\mathbf{h}_{lk}$ as

$$\hat{\mathbf{h}}_{lk} = \sqrt{p_k\left(1-\epsilon^2\right)}\mathbf{R}_{lk}\mathbf{\Psi}_{lk}^{-1}\mathbf{y}_{lk}^{p}, \tag{3}$$

where

$$\mathbf{\Psi}_{lk} = \sum_{i\in\mathcal{P}_k} p_i\left(1-\epsilon^2\right)\tau_p\mathbf{R}_{li} + \sum_{i=1}^{K}\epsilon^2 p_i\mathbf{R}_{li} + \sigma^2\mathbf{I}_N. \tag{4}$$

The channel estimation $\hat{\mathbf{h}}_{lk}$ and the estimation error $\tilde{\mathbf{h}}_{lk} = \mathbf{h}_{lk} - \hat{\mathbf{h}}_{lk}$ are uncorrelated and have the distributions $\hat{\mathbf{h}}_{lk} \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \hat{\mathbf{R}}_{lk}\right)$ and $\tilde{\mathbf{h}}_{lk} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{C}_{lk})$, where the covariance matrices are

$$\hat{\mathbf{R}}_{lk} = \mathbb{E}\left\{\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\} = p_k\left(1-\epsilon^2\right)\tau_p\mathbf{R}_{lk}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}, \tag{5}$$

$$\mathbf{C}_{lk} = \mathbb{E}\{\tilde{\mathbf{h}}_{lk}\tilde{\mathbf{h}}_{lk}^{\mathrm{H}}\} = \mathbf{R}_{lk} - p_k\left(1-\epsilon^2\right)\tau_p\mathbf{R}_{lk}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}. \tag{6}$$

To measure the impact of non-ideal UE hardware on channel estimation, we assume that there is only one UE and one AP in the distributed CF mMIMO network. Then, the estimation error covariance matrix in (6) becomes

$$\mathbf{C}_{lk} = \mathbf{R}_{lk} - p_k\left(1-\epsilon^2\right)\tau_p\mathbf{R}_{lk}\left(p_k\mathbf{R}_{lk}\left(\tau_p - \epsilon^2\tau_p + \epsilon^2\right) + \sigma^2\mathbf{I}_N\right)^{-1}\mathbf{R}_{lk} \tag{7}$$

When $p_k \to \infty$, the estimation error covariance matrix in (7) approaches

$$\mathbf{C}_{lk} = \frac{\epsilon^2}{\left(1-\epsilon^2\right)\tau_p + \epsilon^2}\mathbf{R}_{lk} \tag{8}$$

It can be seen from (8) that UE hardware impairments cause a non-zero estimation error floor under a high signal-to-noise ratio (SNR). Furthermore, we find that the estimation error floor can be reduced by increasing the pilot length τ_p.To measure estimation accuracy, we define normalized mean squared error (NMSE) as

$$\mathrm{NMSE}_{lk} = \frac{\mathbb{E}\left\{\left\|\mathbf{h}_{lk} - \hat{\mathbf{h}}_{lk}\right\|^2\right\}}{\mathbb{E}\left\{\|\mathbf{h}_{lk}\|^2\right\}} = \frac{\mathrm{tr}(\mathbf{C}_{lk})}{\mathrm{tr}(\mathbf{R}_{lk})} = 1 - \frac{p_k\left(1-\epsilon^2\right)\tau_p\mathrm{tr}\left(\mathbf{R}_{lk}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}\right)}{\mathrm{tr}(\mathbf{R}_{lk})} \tag{9}$$

It is noted that the value of NMSE_{lk} ranges between 0 (perfect estimation) and 1.

2.2 Uplink data decoding

The signal $\mathbf{y}_l \in \mathbb{C}^N$ received at AP l during the uplink data transfer phase is modeled as

$$\mathbf{y}_l = \sum_{i=1}^{K}\mathbf{h}_{li}\left(\sqrt{1-\epsilon^2}s_i + e_i\right) + \mathbf{n}_l, \tag{10}$$

where $\mathbf{n}_l \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \sigma^2 \mathbf{I}_N\right)$ indicates the noise vector and $s_i \sim \mathcal{N}_{\mathbb{C}}(0, p_i)$ designates the payload data signal with power p_i sent by UE i. By taking the inner product of the combining vector $\mathbf{v}_{lk}$ and $\mathbf{y}_l$, AP l can acquire the local decoded signal of UE k as

$$\check{s}_{lk} \triangleq \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{y}_l = \sqrt{1-\epsilon^2} \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{lk} s_k + \sqrt{1-\epsilon^2} \sum_{i=1, i \neq k}^{K} \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{li} s_i + \sum_{i=1}^{K} \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{li} e_i + \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{n}_l, \tag{11}$$

where the combining vector $\mathbf{v}_{lk}$ is a function of channel estimation. According to [18], the following three combining schemes of maximum ratio (MR), regularized zero-forcing (RZF), and minimum mean squared error (MMSE) for uplink data decoding are considered:

$$\mathbf{v}_{lk} = \begin{cases} \hat{\mathbf{h}}_{lk} & \text{MRC}, \\ \left(\sum_{i=1}^{K} p_i \hat{\mathbf{h}}_{li} \hat{\mathbf{h}}_{li}^{\mathrm{H}} + \sigma^2 \mathbf{I}_N \right)^{-1} \hat{\mathbf{h}}_{lk} & \text{RZF}, \\ \left(\sum_{i=1}^{K} p_i \left(\hat{\mathbf{h}}_{li} \hat{\mathbf{h}}_{li}^{\mathrm{H}} + \mathbf{C}_{li} \right) + \sigma^2 \mathbf{I}_N \right)^{-1} \hat{\mathbf{h}}_{lk} & \text{MMSE}. \end{cases} \tag{12}$$

Then the CPU assigns weight $a_{lk} \in \mathbb{C}$ to the local decoded signal $\check{s}_{lk}$ to obtain the final decoded signal of UE k as

$$\begin{aligned} \hat{s}_k = & \sqrt{1-\epsilon^2} \left(\sum_{l=1}^{L} a_{lk}^* \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{lk} \right) s_k + \sum_{l=1}^{L} a_{lk}^* \left(\sum_{i=1}^{K} \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{li} e_i \right) \\ & + \sqrt{1-\epsilon^2} \sum_{l=1}^{L} a_{lk}^* \left(\sum_{i=1, i \neq k}^{K} \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{li} s_i \right) + \sum_{l=1}^{L} a_{lk}^* \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{n}_l. \end{aligned} \tag{13}$$

3 Uplink spectral efficiency

By adding and subtracting $\sqrt{1-\epsilon^2} \sum_{l=1}^{L} a_{lk}^* \mathbb{E}\{\mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{lk}\} s_k$, the final decoded signal of UE k in (13) can be rewritten and simplified as

$$\hat{s}_k = \mathrm{D}_k s_k + \mathrm{B}_k s_k + \sum_{i=1, i \neq k}^{K} \mathrm{I}_{ki} s_i + \sum_{i=1}^{K} \mathrm{T}_{ki} e_i + n_k', \tag{14}$$

where n_k' stands for the noise. D_k, B_k, I_{ki}, T_{ki}, and n_k' are respectively provided by the following:

$$\mathrm{D}_k = \sqrt{1-\epsilon^2} \sum_{l=1}^{L} a_{lk}^* \mathbb{E}\left\{ \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{lk} \right\}, \tag{15}$$

$$\mathrm{B}_k = \sqrt{1-\epsilon^2} \sum_{l=1}^{L} a_{lk}^* \left(\mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{lk} - \mathbb{E}\left\{ \mathbf{v}_{lk}^{\mathrm{H}} \mathbf{h}_{lk} \right\} \right), \tag{16}$$

$$\mathrm{I}_{ki} = \sqrt{1-\epsilon^2}\sum_{l=1}^{L} a_{lk}^{*}\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{h}_{li}, \tag{17}$$

$$\mathrm{T}_{ki} = \sum_{l=1}^{L} a_{lk}^{*}\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{h}_{li},\ n_k' = \sum_{l=1}^{L} a_{lk}^{*}\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{n}_l. \tag{18}$$

In order to maintain conciseness, the following vectors and matrices are defined:

$$\mathbf{a}_k = [a_{1k}\ \ldots\ a_{Lk}]^{\mathrm{T}} \in \mathbb{C}^L, \tag{19}$$

$$\mathbf{b}_k = [b_{1k}\ldots b_{Lk}]^{\mathrm{T}} \in \mathbb{C}^L, b_{lk} = \mathbb{E}\left\{\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{h}_{lk}\right\}, \tag{20}$$

$$\mathbf{F}_{ki} \in \mathbb{C}^{L\times L}, f_{ki}^{ll'} = \mathbb{E}\left\{\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{h}_{li}\mathbf{h}_{l'i}^{\mathrm{H}}\mathbf{v}_{l'k}\right\}, \tag{21}$$

$$\mathbf{N}_k \in \mathbb{C}^{L\times L}, n_{lk} = \mathbb{E}\{|\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{n}_l|^2\}. \tag{22}$$

where $\mathbf{a}_k$ is called the LSFD vector, the element in row l and column l' of $\mathbf{F}_{ki}$ is $f_{ki}^{ll'}$, and n_{lk} is the lth diagonal element of the diagonal matrix $\mathbf{N}_k$.

3.1 Ergodic capacity analysis

We can obtain the following theorem by employing the use-and-then-forget (UatF) technique [15]. In the UatF technique, the channel estimate can be only used to calculate the receive combining scheme, and then the channel estimate is effectively "forgotten" before data signal detection.

Theorem 1 *The uplink ergodic channel capacity of UE k in a distributed CF mMIMO network is lower bounded as*

$$\mathrm{C}^{\mathrm{CF}} \geq \mathrm{SE}_k^{\mathrm{CF}} = \frac{\tau_u}{\tau_c}\log_2\left(1+\mathrm{SINR}_k^{\mathrm{CF}}\right), \tag{23}$$

with

$$\mathrm{SINR}_k^{\mathrm{CF}} = \frac{\left(1-\epsilon^2\right)p_k\left|\mathbf{a}_k^{\mathrm{H}}\mathbf{b}_k\right|^2}{\mathbf{a}_k^{\mathrm{H}}\left(\sum_{i=1}^{K} p_i\mathbf{F}_{ki} - \left(1-\epsilon^2\right)p_k\mathbf{b}_k\mathbf{b}_k^{\mathrm{H}} + \mathbf{N}_k\right)\mathbf{a}_k}, \tag{24}$$

where

$$\mathbf{N}_k = \sigma^2\mathrm{diag}\left(\mathbb{E}\{\|\mathbf{v}_{1k}\|^2\},\ldots,\mathbb{E}\{\|\mathbf{v}_{Lk}\|^2\}\right). \tag{25}$$

and the expectation operation is for all sources of randomness.

Proof

The proof can be done by treating $\sum_{i=1}^{K} \mathrm{T}_{ki} e_i$ *as an interference and using the same method as [3, Prop. 2].* □

It is worth noting that the $\mathrm{SINR}_k^{\mathrm{CF}}$ in (24) represents a generalized Rayleigh quotient concerning $\mathbf{a}_k$. Consequently, it is possible to maximize the effective $\mathrm{SINR}_k^{\mathrm{CF}}$ by utilizing [8, Lemma B.10], and the optimum $\mathbf{a}_k$ may be achieved concurrently, as shown below.

Corollary 1 *The optimal LSFD vector of UE k is*

$$\mathbf{a}_k^{\mathrm{opt}} = \left(\sum_{i=1}^{K} p_i \mathbf{F}_{ki} + \mathbf{N}_k \right)^{-1} \mathbf{b}_k, \tag{26}$$

which achieves the maximum effective $\mathrm{SINR}_k^{\mathrm{CF}}$ *as*

$$\mathrm{SINR}_k^{\mathrm{CF}} = \left(1-\epsilon^2\right) p_k \mathbf{b}_k^{\mathrm{H}} \left(\sum_{i=1}^{K} p_i \mathbf{F}_{ki} - \left(1-\epsilon^2\right) p_k \mathbf{b}_k \mathbf{b}_k^{\mathrm{H}} + \mathbf{N}_k \right) \mathbf{b}_k. \tag{27}$$

It can be seen that this corollary determines the optimal LSFD vector for a distributed CF mMIMO network with UE hardware impairments.

3.2 Closed-form SE expression

To gain insights into UE hardware impairments, the following corollary provides a closed-form SE based on MR combining.

Corollary 2 *By using MR combining with* $\mathbf{v}_{lk} = \hat{\mathbf{h}}_{lk}$*, the expectations in* (24) *are*

$$b_{lk} = p_k \left(1-\epsilon^2\right) \tau_p \mathrm{tr}\left(\mathbf{R}_{lk} \mathbf{\Psi}_{lk}^{-1} \mathbf{R}_{lk} \right), \tag{28}$$

$$n_{lk} = \sigma^2 p_k \left(1-\epsilon^2\right) \tau_p \mathrm{tr}\left(\mathbf{R}_{lk} \mathbf{\Psi}_{lk}^{-1} \mathbf{R}_{lk} \right), \tag{29}$$

$$f_{ki}^{ll} = \mathrm{tr}\left(\mathbf{R}_{li} \hat{\mathbf{R}}_{lk} \right) + \mathbb{I}_{i \in \mathcal{P}_k} p_k p_i \left(1-\epsilon^2\right)^2 \tau_p^2 \left| \mathrm{tr}\left(\mathbf{R}_{li} \mathbf{\Psi}_{lk}^{-1} \mathbf{R}_{lk} \right) \right|^2, \tag{30}$$

$$f_{ki}^{ll'} = \mathbb{I}_{i \in \mathcal{P}_k} p_k p_i \left(1-\epsilon^2\right)^2 \tau_p^2 \mathrm{tr}\left(\mathbf{R}_{li} \mathbf{\Psi}_{lk}^{-1} \mathbf{R}_{lk} \right) \mathrm{tr}\left(\mathbf{R}_{l'i} \mathbf{\Psi}_{l'k}^{-1} \mathbf{R}_{l'k} \right), \tag{31}$$

where $l' \neq l$. $\mathbb{I}_{i \in \mathcal{P}_k} = 1$ *for* $i \in \mathcal{P}_k$ *and zero otherwise.*

Proof

The proof is presented in "Appendix". □

4 Methods

This section investigates how to maximize the worst UE performance.The choice between high and low power regimes in distributed CF mMIMO systems involves a trade-off between SE and other factors such as interference, energy consumption, and coverage area. A high power regime improves SE by enhancing signal strength and enabling higher-order modulation, which is beneficial for coverage but comes with the drawbacks of increased interference and higher energy consumption. On the other hand, a low power regime reduces interference and is more energy-efficient, yet it may compromise SE due to weaker signal penetration and the necessity for lower-order modulation. Therefore, achieving the optimal SE requires a balanced approach, often involving dynamic power control that intelligently adapts to changing network conditions and UE needs, striving to optimize network performance while managing interference and energy considerations.

Algorithm 1 Joint data power and LSFD vectors optimization algorithm for the solution of the max–min fairness in (36).

Input: Hardware impairment ϵ, maximum power $p_{\max}$, solution accuracy ε.
Output: Minimum SINR γ^{opt}, data power coefficients $\{p_k^{\text{opt}}\}$, LSFD vectors $\{\mathbf{a}_k^{\text{opt}}\}$.
Initialization: Initialize $\mathbf{a}_k$ as the vector of all ones for $k = 1, \ldots, K$. Set $\gamma_{\min} = 0$ and $\gamma_{\max} = \min_k \text{SINR}_k^{\text{CF}\star}$, respectively. Set the solution accuracy $\varepsilon > 0$ and the uplink power control coefficient p_k^{opt} to 0 for all k.
while $t_{\max} - t_{\min} > \epsilon$ **do**
  $\gamma \leftarrow \frac{\gamma_{\min}+\gamma_{\max}}{2}$.
  Solve the following convex problem and by taking γ and $\{\mathbf{a}_k\}$ as constant.

$$\begin{aligned} \underset{\{p_k\}}{\text{minimize}} \quad & \sum_{k=1}^{K} p_k, \\ \text{subject to} \quad & (1+\gamma)\left(1-\epsilon^2\right) p_k |\mathbf{a}_k^{\text{H}} \mathbf{b}_k|^2 - \gamma \sum_{i=1}^{K} p_i \mathbf{a}_k^{\text{H}} \mathbf{F}_{ki} \mathbf{a}_k \\ & - \gamma \mathbf{a}_k^{\text{H}} \mathbf{N}_k \mathbf{a}_k \geq 0, \quad k = 1, \ldots, K, \\ & 0 \leq p_k \leq p_{\max}, \quad k = 1, \ldots, K. \end{aligned} \tag{32}$$

  if (32) is feasible **then**
    • $\gamma_{\min} \leftarrow \gamma$.
    • $p_k^{\text{opt}} \leftarrow p_k$ for all k, which is a feasible solution of (32).
    • Update LSFD vector $\mathbf{a}_k^{\text{opt}}$.
  else
    $\gamma_{\max} \leftarrow \gamma$.
  end if
end while

4.1 Joint data power control and LSFD design

In a CF mMIMO network, different UEs might experience various channel conditions. Some UEs might be near APs (strong UEs), while others are far away (weaker UEs). Power control adjusts the transmission power for each UE based on its channel conditions. LSFD is a technique that focuses on decoding the transmitted signals in a way that

accounts for large-scale fading effects, such as path loss and shadowing. By taking these factors into account, LSFD can significantly improve the SNR at the receiver end. The combination of joint data power control and LSFD provides a comprehensive approach to maximizing SE for the weakest UEs. Power control ensures that users are transmitting at the optimal power levels, while LSFD optimizes the signal processing at the receiver end. Therefore, the problem of maximizing the lowest SE among all UEs by setting the optimization variables as data power and LSFD vectors can be formulated as follows:

$$\underset{\{\mathbf{a}_k, p_k\}, \gamma}{\text{maximize}} \quad \gamma, \tag{33}$$

$$\text{subject to} \;\; \mathrm{SINR}_k^{\mathrm{CF}}(\mathbf{a}_k, \{p_i\}) \geq \gamma, \quad k = 1, \ldots, K, \tag{34}$$

$$0 \leq p_k \leq p_{\max}, \;\; k = 1, \ldots, K, \tag{35}$$

where $\mathrm{SINR}_k^{\mathrm{CF}}$ is described in (24) and γ is the lowest effective SINR achievable by all UEs. Since the above optimization problem is non-convex, it can be transformed and equivalent to

$$\underset{\{p_k\}}{\text{minimize}} \;\; \sum_{k=1}^{K} p_k, \tag{36}$$

$$\begin{aligned} \text{subject to} \;\; & (1+\gamma)\left(1-\epsilon^2\right) p_k \left|\mathbf{a}_k^{\mathrm{H}} \mathbf{b}_k\right|^2 - \gamma \sum_{i=1}^{K} p_i \mathbf{a}_k^{\mathrm{H}} \mathbf{F}_{ki} \mathbf{a}_k \\ & - \gamma \mathbf{a}_k^{\mathrm{H}} \mathbf{N}_k \mathbf{a}_k \geq 0, \quad k = 1, \ldots, K, \end{aligned} \tag{37}$$

$$0 \leq p_k \leq p_{\max}, \quad k = 1, \ldots, K. \tag{38}$$

Based on the bisection search approach, an iterative alternating optimization algorithm considering both the data power and the LSFD vectors is presented in Algorithm 1, where $\gamma_{\max} = \min_k \mathrm{SINR}_k^{\mathrm{CF}\star}$ is the SINR that maximizes the weakest UE after ignoring all interference.

4.2 Two benchmarks

To evaluate the effectiveness of the recommended algorithm, two benchmarks are therefore considered:

4.2.1 Uplink power control

Only the power constraints are considered and the fixed-point algorithm is used to address the problem of max–min fairness (MMF) in [15], so we call it MMF power control for comparison.

4.2.2 Fractional power control

In accordance with the fractional power control (FPC) approach [16], UE k selects the uplink data transmission power as

$$p_k = p_{\max} \frac{\left(\sum_{l=1}^{L} \beta_{lk}\right)^{\vartheta}}{\max_{i\in\{1,\ldots,K\}} \left(\sum_{l=1}^{L} \beta_{li}\right)^{\vartheta}}, \tag{39}$$

where ϑ is an index to adjust the received power, and we take two typical values of $\vartheta = 0.5$ and $\vartheta = -0.5$ for comparison.

5 Results and discussion

This section numerically demonstrates how non-ideal UE hardware impacts the performance of a distributed CF mMIMO network. For a reasonable comparison, we use the same network configuration values from [3, 15], with $K = 40$ UEs, $L = 100$ APs, and $N = 4$ antennas setup on each AP in a 1×1 km square region. Network parameters are assumed to be $\tau_p = 10$, $\tau_c = 200$, $p_{\max} = 100$ mW, 20 MHz bandwidth, and the receiver noise power is $\sigma^2 = -96$ dBm. We set the hardware impairment factor ϵ to 0, 0.05, and 0.1 according to the typical values of UE hardware impairments in LTE [19].

5.1 Channel acquisition

Figure 1 shows the NMSE as a function of effective SNR p_k/σ^2 for different pilot lengths τ_p. It can be seen that UE hardware impairments cause error floors in channel estimation under high SNR. Furthermore, the impact of UE hardware impairments is minor at low SNR, but significant at high SNR. Reducing the hardware impairment factor can lower the error floor and enhance the corresponding effective SNR. This is because reducing the hardware impairment factor can decrease the additional distortion noise, thereby increasing the accuracy of the estimation. Note that increasing the pilot length τ_p can reduce the error floor, thereby validating the correctness of our analysis.

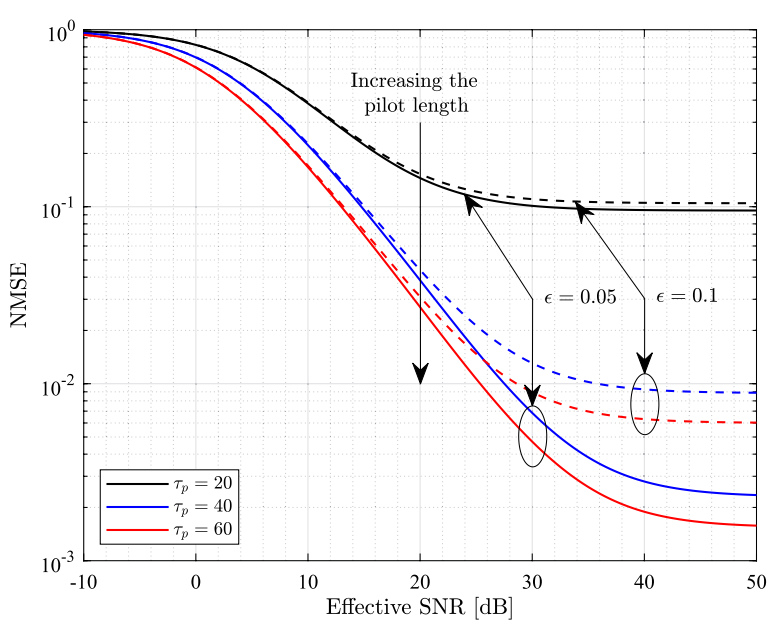

Fig. 1 NMSE as a function of effective SNR for different pilot lengths τ_p

5.2 Spectral efficiency

Figure 2 shows how the average uplink total SE for various combining schemes and hardware impairments varies with the number of UEs. MMSE combining provides the largest total SE. The low-complexity RZF combining provides basically the same sum SE as MMSE when the number of UEs is small. However, as the number of UEs increases, the sum SE provided by MMSE gradually exceeds that of RZF. MR provides nearly half of the total SE compared to MMSE and RZF.

Figure 3 illustrates the effect of pilot sequence length τ_p on sum SE under various hardware impairments. When K is kept fixed, the sum SE reaches its maximum value as the pilot sequence length increases to 10 because increasing τ_p decreases pilot contamination. However, as τ_p continues to increase, the sum SE gradually decreases because increasing τ_p reduces the uplink transmission data sample space τ_u, and the improved channel estimation quality is not enough to improve the performance loss caused by the pre-log factor τ_u/τ_c. Interestingly, when the pilot sequence length exceeds 10, low-complexity RZF and MMSE yield nearly the same sum SE.

Figure 4 exhibits the cumulative distribution function (CDF) of the uplink SE with MMSE combining under different optimization and power control schemes. At the 90% likely SE value, compared with MMF power control, the proposed joint optimization design scheme improves SE by 35.82% with perfect hardware and increases by 33.51% and 27.74% for 0.05 and 0.1 hardware impairment factors, respectively. Note that as the hardware impairment decreases, the proposed joint optimization scheme improves SE higher. When fractional power control is employed, UEs with more favorable channel circumstances can boost their transmission power by setting $\vartheta = 0.5$. Conversely, $\vartheta = -0.5$ gets nearly the same SE as MMF power control for the unluckiest UE.

Figure 5 is a bar graph displaying the sum SE with MMSE combining under MMF power control and proposed joint optimization schemes. Compared with MMF power

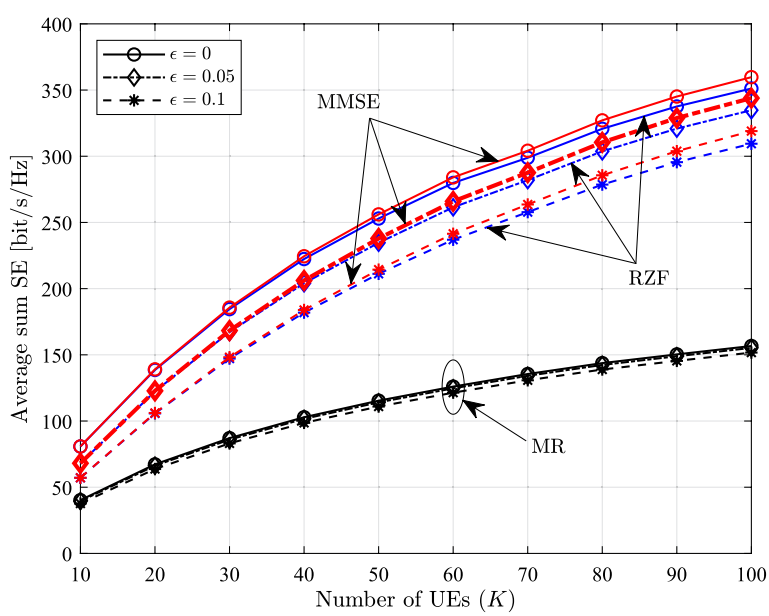

Fig. 2 Average uplink sum SE as a function of the number of UEs K with different hardware impairments in distributed CF mMIMO under various combining schemes

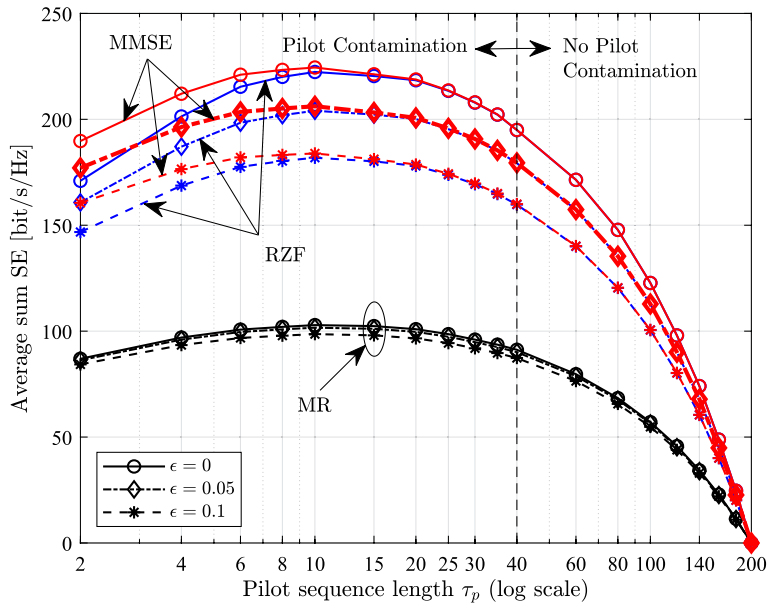

Fig. 3 Average uplink sum SE as a function of pilot sequence length τ_p for various combining schemes in distributed CF mMIMO under different hardware impairments

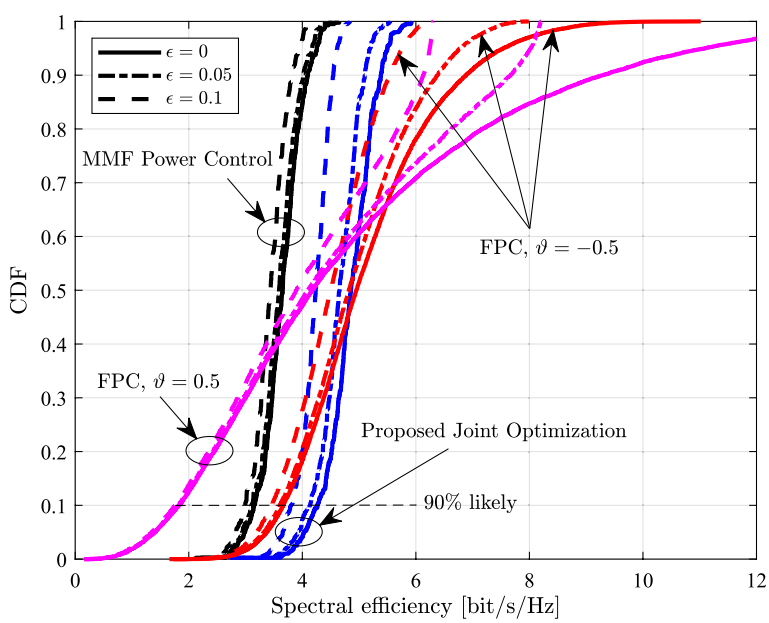

Fig. 4 CDF of the uplink SE for different optimization and power control schemes when using MMSE combining scheme under various hardware impairments

control, the proposed joint optimization scheme improves sum SE by 33.14% under perfect hardware and 29.64% and 23% under hardware damage factors of 0.05 and 0.1, respectively. Note that with the increase of hardware damage, the magnitude of SE improved by the proposed joint optimization scheme gradually decreases. This is because increased hardware impairments drastically degrade channel estimation quality, impacting network performance.

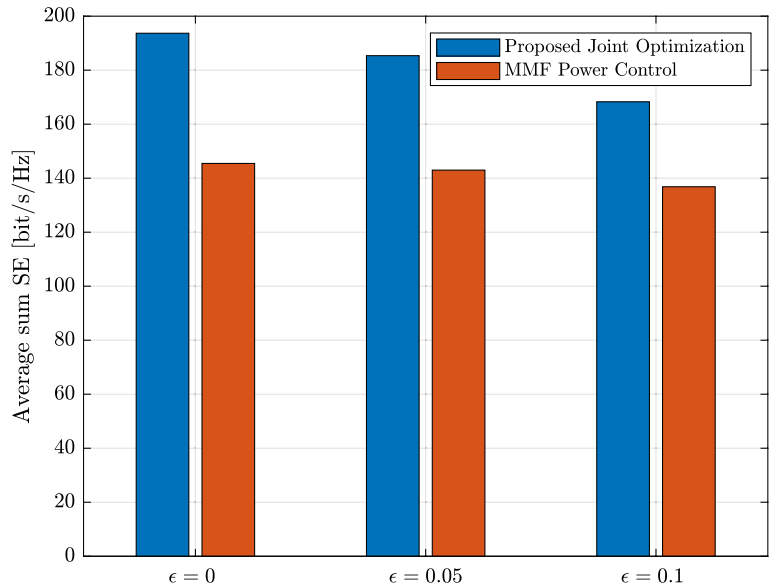

Fig. 5 Average uplink sum SE for MMF power control and proposed joint optimization approaches when using MMSE combining scheme under different hardware impairments

6 Conclusion

This paper derives a lower bound channel capacity for a distributed CF mMIMO network with UE hardware impairments. By employing MR combining, a closed-form SE expression is obtained, which provides more information and insight into the effects of hardware limitations and the design of network parameters. By jointly considering the data power and LSFD vectors, a max–min SE fairness problem with UE hardware impairments is formulated and solved. Numerical results prove that, compared to MMF power control, the proposed joint optimization scheme enhances the SE of the weakest UE and significantly improves the sum SE of the entire network. For instance, our results show an improvement of 35.82% in SE for the weakest UE with perfect hardware and an improvement of 33.14% in sum SE.

Appendix: Proof of Corollary 2

Employing the characteristics of the MMSE estimator, the expectations are calculated directly. The element b_{lk} in $\mathbf{b}_k$ can be computed by

$$\begin{aligned} b_{lk} &= \mathbb{E}\left\{\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{h}_{lk}\right\} = \mathbb{E}\left\{\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\mathbf{h}_{lk}\right\} \overset{(a)}{=} \mathbb{E}\left\{\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\hat{\mathbf{h}}_{lk}\right\} \\ &\overset{(b)}{=} \mathrm{tr}\left(\mathbb{E}\left\{\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) \overset{(c)}{=} p_k\left(1-\epsilon^2\right)\tau_p \mathrm{tr}\left(\mathbf{R}_{lk}\boldsymbol{\Psi}_{lk}^{-1}\mathbf{R}_{lk}\right) \end{aligned} \tag{40}$$

where (a) follows from $\mathbf{h}_{lk} = \hat{\mathbf{h}}_{lk} + \tilde{\mathbf{h}}_{lk}$ and the fact that $\mathbb{E}\{\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\tilde{\mathbf{h}}_{lk}\} = 0$. Since both the channel estimation and the estimation error have zero mean and are uncorrelated. Then, (b) is derived from the identity of the matrix $\mathrm{tr}(\mathbf{AB}) = \mathrm{tr}(\mathbf{BA})$ and (c) utilizes (6). Similarly,

$$n_{lk} = \mathbb{E}\left\{\left|\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{n}_l\right|^2\right\} = \sigma^2 \mathrm{tr}\left(\mathbb{E}\left\{\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) = \sigma^2 p_k\left(1-\epsilon^2\right)\tau_p \mathrm{tr}\left(\mathbf{R}_{lk}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}\right) \tag{41}$$

We divide the elements in $\mathbf{F}_{ki}$ into two parts according to whether l' is equal to l or not. We first calculate the case of $l' = l$. If $i \notin \mathcal{P}_k$, we can employ the uncorrelated of $\hat{\mathbf{h}}_{lk}$ and $\mathbf{h}_{li}$ to acquire

$$f_{ki}^{ll} = \mathbb{E}\left\{\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\mathbf{h}_{li}\mathbf{h}_{li}^{\mathrm{H}}\hat{\mathbf{h}}_{lk}\right\} = \mathrm{tr}\left(\mathbb{E}\left\{\mathbf{h}_{li}\mathbf{h}_{li}^{\mathrm{H}}\right\}\mathbb{E}\left\{\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) = \mathrm{tr}\left(\mathbf{R}_{li}\hat{\mathbf{R}}_{lk}\right) \tag{42}$$

If $i \in \mathcal{P}_k$, it is observed that

$$f_{ki}^{ll} = \mathrm{tr}\left(\mathbb{E}\left\{\mathbf{h}_{li}\mathbf{h}_{li}^{\mathrm{H}}\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) = \mathrm{tr}\left(\mathbb{E}\left\{\hat{\mathbf{h}}_{li}\hat{\mathbf{h}}_{li}^{\mathrm{H}}\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) + \mathrm{tr}\left(\mathbb{E}\left\{\tilde{\mathbf{h}}_{li}\tilde{\mathbf{h}}_{li}^{\mathrm{H}}\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) \tag{43}$$

where the last equality is derived by extending the expression and eliminating two cross-terms, which are 0 as a result of the estimate and the estimation error being uncorrelated and having zero mean. The second term becomes

$$\mathrm{tr}\left(\mathbb{E}\left\{\tilde{\mathbf{h}}_{li}\tilde{\mathbf{h}}_{li}^{\mathrm{H}}\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) = \mathrm{tr}\left(\mathbf{C}_{li}\hat{\mathbf{R}}_{lk}\right) \tag{44}$$

where the equality utilizes the uncorrelated between the estimate and estimation error. The first term is computed as

$$\mathrm{tr}\left(\mathbb{E}\left\{\hat{\mathbf{h}}_{li}\hat{\mathbf{h}}_{li}^{\mathrm{H}}\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) = \mathbb{E}\left\{\left|\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\hat{\mathbf{h}}_{li}\right|^2\right\} \tag{45}$$

we note that $\hat{\mathbf{h}}_{li} = \sqrt{p_i\left(1-\epsilon^2\right)}\mathbf{R}_{li}\mathbf{\Psi}_{lk}^{-1}\mathbf{y}_{lk}^{p}$ and $\hat{\mathbf{h}}_{li} \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \hat{\mathbf{R}}_{li}\right)$, where $\hat{\mathbf{R}}_{li} = p_i\left(1-\epsilon^2\right)\tau_p\mathbf{R}_{li}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{li}$. Using [20, Lemma 5] and the notation to get

$$\mathbf{R}_x^{\frac{1}{2}} = \sqrt{p_k\left(1-\epsilon^2\right)\tau_p}\mathbf{R}_{lk}\left(\mathbf{\Psi}_{lk}^{-1}\right)^{\frac{1}{2}}, \bar{\mathbf{x}} = \mathbf{0} \tag{46}$$

$$\mathbf{R}_y^{\frac{1}{2}} = \sqrt{p_i\left(1-\varepsilon^2\right)\tau_p}\mathbf{R}_{li}\left(\mathbf{\Psi}_{lk}^{-1}\right)^{\frac{1}{2}}, \bar{\mathbf{y}} = \mathbf{0} \tag{47}$$

Hence, the first term in (43) can be calculated as

$$\mathbb{E}\{|\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\hat{\mathbf{h}}_{li}|^2\} = p_k p_i\left(1-\epsilon^2\right)^2\tau_p^2\left|\mathrm{tr}\left(\mathbf{R}_{li}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}\right)\right|^2 + \mathrm{tr}\left((\mathbf{R}_{li} - \mathbf{C}_{li})\hat{\mathbf{R}}_{lk}\right) \tag{48}$$

By substituting (44) and (48) into (43), we finally obtain

$$f_{ki}^{ll} = p_k p_i\left(1-\epsilon^2\right)^2\tau_p^2\left|\mathrm{tr}\left(\mathbf{R}_{li}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}\right)\right|^2 + \mathrm{tr}\left(\mathbf{R}_{li}\hat{\mathbf{R}}_{lk}\right) \tag{49}$$

Let $\underset{i\in P_k}{\mathbb{I}}$ be denoted as 1 when $i \in \mathcal{P}_k$ and 0 otherwise. Therefore, when $l' = l$, f_{ki}^{ll} is calculated as

$$f_{ki}^{ll} = \mathrm{tr}\left(\mathbf{R}_{li}\hat{\mathbf{R}}_{lk}\right) + \underset{i\in\mathcal{P}_k}{\mathbb{I}} p_k p_i\left(1-\epsilon^2\right)^2\tau_p^2\left|\mathrm{tr}\left(\mathbf{R}_{li}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}\right)\right|^2 \tag{50}$$

Next, we calculate the case of $l' \neq l$. If $i \notin \mathcal{P}_k$, we can employ the independence of the channels of different APs to obtain $f_{ki}^{ll'} = 0$. If $i \in \mathcal{P}_k$, we note that $\hat{\mathbf{h}}_{li} = \sqrt{\frac{p_i}{p_k}}\mathbf{R}_{li}\mathbf{R}_{lk}^{-1}\hat{\mathbf{h}}_{lk}$ and calculate $\mathbb{E}\{\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{h}_{li}\}$ as

$$\begin{aligned}\mathbb{E}\left\{\mathbf{v}_{lk}^{\mathrm{H}}\mathbf{h}_{li}\right\} &= \mathrm{tr}\left(\mathbb{E}\left\{\hat{\mathbf{h}}_{li}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) = \mathrm{tr}\left(\mathbb{E}\left\{\sqrt{\frac{p_i}{p_k}}\mathbf{R}_{li}\mathbf{R}_{lk}^{-1}\hat{\mathbf{h}}_{lk}\hat{\mathbf{h}}_{lk}^{\mathrm{H}}\right\}\right) \\ &= \sqrt{p_k p_i}\left(1-\epsilon^2\right)\tau_p \mathrm{tr}\left(\mathbf{R}_{li}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}\right)\end{aligned} \tag{51}$$

Therefore, when $l' \neq l$, $f_{ki}^{ll'}$ is calculated as

$$f_{ki}^{ll'} = \mathop{\mathbb{I}}_{i\in\mathcal{P}_k} p_k p_i \left(1-\epsilon^2\right)^2 \tau_p^2 \mathrm{tr}\left(\mathbf{R}_{li}\mathbf{\Psi}_{lk}^{-1}\mathbf{R}_{lk}\right)\mathrm{tr}\left(\mathbf{R}_{l'i}\mathbf{\Psi}_{l'k}^{-1}\mathbf{R}_{l'k}\right) \tag{52}$$

This finishes the proof of Corollary 2.

Abbreviations

mMIMO	Massive multiple-input multiple-output
UE	User equipment
SE	Spectral efficiency
LSFD	Large-scale fading decoding
CF	Cell-free
AP	Access point
MSE	Mean-squared error
MMSE	Minimum mean squared error
LMMSE	Linear MMSE
SNR	Signal-to-noise ratio
RZF	Regularized zero-forcing
MR	Maximum ratio
UatF	Use-and-then-forget
MMF	Max–min fairness
FPC	Fractional power control

Authors' contribution
All authors have contributed to this research work, read and approved the final manuscript.

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Code availability
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Declarations

Ethics approval and consent to participate
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Consent for publication
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Competing interests
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