LOCALLY OPTIMAL FUSION RULE DESIGN FOR FRONTHAUL-EFFICIENT CELL-FREE MASSIVE MIMO NETWORKS WITH CENTRALIZED UPLINK PROCESSING

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ABSTRACT

In cell-free massive multiple-input multiple-output networks, centralized processing has been shown to significantly improve performance compared to distributed processing. However, centralization requires excessive network resources. This limitation can be addressed by fusion-based centralized processing, where access points (APs) fuse their received signals before forwarding them to the central processing unit. However, existing works either employ heuristic fusion rules that are not optimized with respect to any performance metric, thereby limiting performance, or assume perfect channel state information (CSI). In this paper, we propose a novel fusion rule design under imperfect CSI, in which the APs locally maximize the Médard lower bound of the mutual information between the fused received signals and the user equipment data signals to obtain the local fusion rule. The corresponding optimization problem is then solved using Riemannian conjugate gradient descent. Numerical experiments demonstrate that the proposed fusion rule design significantly outperforms the state-of-the-art and approaches centralized performance.

***Index Terms*—** Cell-free massive MIMO, centralized processing, Riemannian optimization, spectral efficiency.

1. INTRODUCTION

In a cell-free massive multiple-input multiple-output (CFmMIMO) network, geographically distributed access points (APs) jointly serve the user equipments (UEs), eliminating cell boundaries and providing uniform quality of service to all UEs in the network [1]. Owing to these attributes, CFmMIMO is widely regarded as a promising technology for next-generation wireless communication networks [2, 3].

In uplink **centralized operation** of CFmMIMO, the APs send their raw received signals to the central processing unit (CPU), which combines them to detect the data signals of the UEs [4]. Centralized operation has been shown to significantly improve spectral efficiency (SE) performance compared to distributed operation [4], in which the first APs obtain local estimates of the UE data signals using minimum mean-squared error (MMSE)-based combining and then send these to the CPU for statistics-based detection [5]. However, centralization requires excessive fronthaul overhead and high computational complexity [3]. Various approaches have been investigated to address this limitation, such as [6–8], in which different uplink schemes are proposed to reduce resource requirements.

An alternative strategy is **fusion-based centralized operation**, in which the APs first fuse their received signals using a specific fusion rule, estimate the fused channels, and then forward the fused signals and channel estimates to the CPU for data detection. This operation has been considered in [9] under the massive MIMO decentralized baseband processing paradigm and in [10], where the fusion rule is designed to maximize the sum rate of a CFmMIMO network. However, both works assume perfect channel state information (CSI). Heuristic fusion rule designs have been proposed in [11] and [12], where the fusion is constructed from the UE channels and the eigenvectors of the received signal covariance matrix, respectively. However, these heuristic designs may ultimately limit overall performance.

In this paper, we propose a locally optimal fusion rule design for fusion-based centralized operation under imperfect CSI. Specifically, we first derive closed-form expressions for the fused channel estimates, their associated estimation errors, and the corresponding covariance matrices. These expressions are then used to formulate the Médard MI lower-bound [13] maximization problem, which we solve using Riemannian conjugate gradient descent to obtain the locally optimal fusion rule. Numerical experiments demonstrate that the proposed fusion rule significantly outperforms the state-of-the-art and approaches centralized performance.

2. CELL-FREE MASSIVE MIMO SIGNAL MODEL

We consider a user-centric CFmMIMO system with L APs, each equipped with N antennas, and K single-antenna UEs. Each UE k is served by a subset of APs, denoted by $\mathcal{A}_k$, and each AP l serves a subset of UEs, denoted by $\mathcal{U}_l$. An AP-UE association algorithm is described in [5, Sec. V.A]. The APs are connected to the CPU through ideal fronthaul links.

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We denote the channel between UE k and AP l by $\mathbf{h}_{l,k} \in \mathbb{C}^N$. The channels are assumed to be constant over coherence blocks of τ_c samples. The pilot and uplink data transmission phases use τ_p and $\tau_u = \tau_c - \tau_p$ samples, respectively.

2.1. Channel Model and Channel Estimation

The channel between UE k and AP l is assumed to be a zero-mean circularly symmetric complex Gaussian random vector with covariance matrix $\mathbf{R}_{l,k} \in \mathbb{C}^{N \times N}$, i.e., $\mathbf{h}_{l,k} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_N, \mathbf{R}_{l,k})$. The covariance matrices are assumed to remain constant over a large number of coherence blocks [14].

We assume that each UE is assigned one τ_p-dimensional pilot signal out of τ_p mutually orthogonal pilot signals; a pilot assignment algorithm is described in [5, Sec. V.A]. In the pilot transmission phase, AP l despreads its received signal with the pilot signal of UE k to obtain the MMSE channel estimate $\widehat{\mathbf{h}}_{l,k} \in \mathbb{C}^N$, given by [5]

$$\widehat{\mathbf{h}}_{l,k} = \sqrt{p_k \tau_p}\, \mathbf{R}_{l,k} \boldsymbol{\Psi}_{l,t_k}^{-1} \mathbf{y}_{l,t_k}^{\mathrm{p}}, \tag{1}$$

where p_k is the transmission power of UE k, $t_k \in \{1, \ldots, \tau_p\}$ is the pilot index of UE k, $\mathbf{y}_{l,t_k}^{\mathrm{p}} \in \mathbb{C}^N$ is the despread signal vector, given by,

$$\mathbf{y}_{l,t_k}^{\mathrm{p}} = \sum_{i \in \mathcal{P}_k} \sqrt{p_i \tau_p} \mathbf{h}_{l,i} + \mathbf{n}_{l,t_k}, \tag{2}$$

with $\mathcal{P}_k$ being the set of UEs with the same pilot signal as UE k (including UE k itself) and $\mathbf{n}_{l,t_k} \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}_N, \sigma^2 \mathbf{I}_N\right)$, and $\boldsymbol{\Psi}_{l,t_k} \in \mathbb{C}^{N \times N}$ is the covariance matrix of the despread signal vector, given by

$$\boldsymbol{\Psi}_{l,t_k} = \mathbb{E}\{\mathbf{y}_{l,t_k}^{\mathrm{p}} (\mathbf{y}_{l,t_k}^{\mathrm{p}})^H\} = \sum_{i \in \mathcal{P}_k} p_i \tau_p \mathbf{R}_{l,i} + \sigma^2 \mathbf{I}_N. \tag{3}$$

The channel estimation error $\widetilde{\mathbf{h}}_{l,k} = \mathbf{h}_{l,k} - \widehat{\mathbf{h}}_{l,k}$ is distributed as $\widetilde{\mathbf{h}}_{l,k} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_N, \mathbf{C}_{l,k})$, where $\mathbf{C}_{l,k} \in \mathbb{C}^{N \times N}$ is given by

$$\mathbf{C}_{l,k} = \mathbf{R}_{l,k} - p_k \tau_p \mathbf{R}_{l,k} \boldsymbol{\Psi}_{l,t_k}^{-1} \mathbf{R}_{l,k}. \tag{4}$$

Note that AP l requires knowledge of the covariance matrices $\boldsymbol{\Psi}_{l,t_k}$ and $\mathbf{R}_{l,k}$ for channel estimation, which are assumed to be available; see [15, 16] for methods to estimate them.

2.2. Data Transmission and Centralized Operation

In the uplink, AP l receives the signal vector $\mathbf{y}_l \in \mathbb{C}^N$, given by

$$\mathbf{y}_l = \sum_{k=1}^{K} \mathbf{h}_{l,k} s_k + \mathbf{n}_l, \tag{5}$$

where $s_k \sim \mathcal{N}_{\mathbb{C}}(0, p_k)$ denotes the data signal of UE k, and $\mathbf{n}_l \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}_N, \sigma^2 \mathbf{I}_N\right)$ is the independent receiver noise. Here, we define the matrix $\mathbf{D}_{l,k}$, which is the identity $\mathbf{I}_N$ if UE k is served by AP l and the all zeros matrix $\mathbf{0}_{N \times N}$ otherwise, and $\mathbf{D}_k = \mathrm{blkdiag}\{\mathbf{D}_{l,k}\}_{l=1}^{L} \in \mathbb{C}^{LN \times LN}$.

In **centralized operation** [4], the CPU receives the AP signals and concatenates them to obtain a long vector $\mathbf{y} = \left[\mathbf{y}_1^T \ \ldots \ \mathbf{y}_L^T\right]^T \in \mathbb{C}^{LN}$, which can be written as

$$\mathbf{y} = \sum_{k=1}^{K} \mathbf{h}_k s_k + \mathbf{n}, \tag{6}$$

where $\mathbf{h}_k = \left[\mathbf{h}_{1,k}^T \ \ldots \ \mathbf{h}_{L,k}^T\right]^T \in \mathbb{C}^{LN}$ is the collective channel of UE k, and $\mathbf{n} = \left[\mathbf{n}_1^T \ \ldots \ \mathbf{n}_L^T\right]^T$. The CPU then estimates the signal s_k using the partial MMSE (P-MMSE) combiner $\mathbf{v}_k \in \mathbb{C}^{LN}$, which is given by [5]

$$\mathbf{v}_k = p_k \left(\sum_{i \in \mathcal{S}_k} p_i \mathbf{D}_k (\widehat{\mathbf{h}}_i \widehat{\mathbf{h}}_i^H + \mathbf{C}_i) \mathbf{D}_k + \sigma^2 \mathbf{I}_{LN} \right)^{-1} \mathbf{D}_k \widehat{\mathbf{h}}_k. \tag{7}$$

where $\mathcal{S}_k = \bigcup_{l \in \mathcal{A}_k} \mathcal{U}_l$ is the set of all the UEs that are served by at least one AP that also serves UE k, $\mathbf{C}_i = \mathrm{blkdiag}\{\mathbf{C}_{l,i}\}_{l=1}^{L} \in \mathbb{C}^{LN \times LN}$, and $\widehat{\mathbf{h}}_k = \left[\widehat{\mathbf{h}}_{1,k}^T \ \ldots \ \widehat{\mathbf{h}}_{L,k}^T\right]^T \in \mathbb{C}^{LN}$. The achievable SE for UE k is given by [4]

$$\mathrm{SE}_k = \frac{\tau_u}{\tau_c} \mathbb{E}\left\{\log_2\left(1 + \mathrm{SINR}_k\right)\right\}, \tag{8}$$

where

$$\mathrm{SINR}_k = \frac{p_k \left| \mathbf{v}_k^H \mathbf{D}_k \widehat{\mathbf{h}}_k \right|^2}{\sum\limits_{i \neq k} p_i \left| \mathbf{v}_k^H \mathbf{D}_k \widehat{\mathbf{h}}_i \right|^2 + \mathbf{v}_k^H \mathbf{Z}_k \mathbf{v}_k + \sigma^2 \left\| \mathbf{D}_k \mathbf{v}_k \right\|^2}, \tag{9}$$

with $\mathbf{Z}_k = \sum_{i=1}^{K} p_i \mathbf{D}_k \mathbf{C}_i \mathbf{D}_k$.

3. FUSION-BASED CENTRALIZED OPERATION AND FUSION RULE DESIGN

In this section, we describe the fusion-based centralized operation, derive closed-form expressions for the fused channel estimates and their statistics, and formulate an optimization problem from which we derive the locally optimal fusion rule.

3.1. Fusion-Based Centralized Operation

In fusion-based centralized operation, AP l fuses its N-dimensional despread signal vector $\mathbf{y}_{l,t_k}^{\mathrm{p}}$ in (2) using a fusion rule $\mathbf{V}_l \in \mathbb{C}^{N \times Q}$, with $Q < N$, and obtains the Q-dimensional fused despread signal vector $\widetilde{\mathbf{y}}_{l,t_k}^{\mathrm{p}} \in \mathbb{C}^Q$, which can be written as

$$\widetilde{\mathbf{y}}_{l,t_k}^{\mathrm{p}} = \mathbf{V}_l^H \mathbf{y}_{l,t_k}^{\mathrm{p}} = \sum_{i \in \mathcal{P}_k} \sqrt{p_i \tau_p} \mathbf{z}_{l,i} + \widetilde{\mathbf{n}}_{l,t_k}, \tag{10}$$

where $\mathbf{z}_{l,k} = \mathbf{V}_l^H \mathbf{h}_{l,k} \in \mathbb{C}^Q$ is the fused channel between UE k and AP l, and $\widetilde{\mathbf{n}}_{l,t_k} = \mathbf{V}_l^H \mathbf{n}_{l,t_k}$. AP l then uses this fused

despread signal vector to estimate the fused channel of UE k. The MMSE estimate of the fused channel $\widehat{\mathbf{z}}_{l,k} \in \mathbb{C}^Q$ is given by

$$\widehat{\mathbf{z}}_{l,k} = \sqrt{p_k \tau_p} \widetilde{\mathbf{R}}_{l,k} \widetilde{\mathbf{\Psi}}_{l,t_k}^{-1} \widetilde{\mathbf{y}}_{l,t_k}^{\mathrm{p}} \,, \tag{11}$$

where $\widetilde{\mathbf{R}}_{l,k} = \mathbf{V}_l^H \mathbf{R}_{l,k} \mathbf{V}_l$ and $\widetilde{\mathbf{\Psi}}_{l,t_k} = \mathbf{V}_l^H \mathbf{\Psi}_{l,t_k} \mathbf{V}_l$. The associated estimation error $\widetilde{\mathbf{z}}_{l,k} = \mathbf{z}_{l,k} - \widehat{\mathbf{z}}_{l,k}$ is distributed as $\widetilde{\mathbf{z}}_{l,k} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_Q, \widetilde{\mathbf{C}}_{l,k})$, where $\widetilde{\mathbf{C}}_{l,k} \in \mathbb{C}^{Q \times Q}$ is given by

$$\widetilde{\mathbf{C}}_{l,k} = \widetilde{\mathbf{R}}_{l,k} - p_k \tau_p \widetilde{\mathbf{R}}_{l,k} \widetilde{\mathbf{\Psi}}_{l,t_k}^{-1} \widetilde{\mathbf{R}}_{l,k} \,. \tag{12}$$

AP l also fuses its N-dimensional received signal vector $\mathbf{y}_l$ in (5) using the same fusion rule $\mathbf{V}_l$ to obtain the Q-dimensional fused signal vector $\widetilde{\mathbf{y}}_l \in \mathbb{C}^Q$, which can be written as

$$\widetilde{\mathbf{y}}_l = \mathbf{V}_l^H \mathbf{y}_l = \sum_{k=1}^{K} \mathbf{z}_{l,k} s_k + \widetilde{\mathbf{n}}_l \,, \tag{13}$$

where $\widetilde{\mathbf{n}}_l = \mathbf{V}_l^H \mathbf{n}_l$. AP l then sends its fused signal vector in (13) and the fused channel estimates in (11) (for $k \in \mathcal{U}_l$) to the CPU for data detection. The CPU then has access to $\widetilde{\mathbf{y}} = \left[\widetilde{\mathbf{y}}_1^T \ \ldots \ \widetilde{\mathbf{y}}_L^T\right]^T \in \mathbb{C}^{LQ}$, which can be written as

$$\widetilde{\mathbf{y}} = \sum_{k=1}^{K} \mathbf{z}_k s_k + \widetilde{\mathbf{n}} \,, \tag{14}$$

where $\mathbf{z}_k = \left[\mathbf{z}_{1,k}^T \ \ldots \ \mathbf{z}_{L,k}^T\right]^T$ and $\widetilde{\mathbf{n}} = \left[\widetilde{\mathbf{n}}_1^T \ \ldots \ \widetilde{\mathbf{n}}_L^T\right]^T$. Subsequently, the CPU detects the signal s_k using the fusion-based P-MMSE (FP-MMSE) combiner $\widetilde{\mathbf{v}}_k \in \mathbb{C}^{LQ}$, given by

$$\widetilde{\mathbf{v}}_k = p_k \left(\sum_{i \in \mathcal{S}_k} p_i \widetilde{\mathbf{D}}_k (\widehat{\mathbf{z}}_i \widehat{\mathbf{z}}_i^H + \widetilde{\mathbf{C}}_i) \widetilde{\mathbf{D}}_k + \sigma^2 \overline{\mathbf{V}}_k \right)^{-1} \widetilde{\mathbf{D}}_k \widehat{\mathbf{z}}_k \,, \tag{15}$$

where $\widehat{\mathbf{z}}_k = \left[\widehat{\mathbf{z}}_{1,k}^T \ldots \widehat{\mathbf{z}}_{L,k}^T\right]^T$, $\widetilde{\mathbf{C}}_i = \mathrm{blkdiag}\{\widetilde{\mathbf{C}}_{l,i}\}_{l=1}^L$, $\overline{\mathbf{V}}_k = \mathrm{blkdiag}\{\widetilde{\mathbf{D}}_{l,k} \mathbf{V}_l^H \mathbf{V}_l \widetilde{\mathbf{D}}_{l,k}\}_{l=1}^L$, and $\widetilde{\mathbf{D}}_k = \mathrm{blkdiag}\{\widetilde{\mathbf{D}}_{l,k}\}_{l=1}^L$, with $\widetilde{\mathbf{D}}_{l,k}$ the identity $\mathbf{I}_Q$ if UE k is served by AP l and all zeros matrix $\mathbf{0}_{Q \times Q}$ otherwise. From (15), it is seen that the CPU requires access to the block-diagonal matrices $\{\widetilde{\mathbf{C}}_i\}_{i \in \mathcal{S}_k}$ and $\overline{\mathbf{V}}_k$ to compute the FP-MMSE combiner. Consequently, AP l forwards its corresponding contributions to the CPU. The achievable SE of UE k in the fusion-based centralized operation is identical to (8), with the raw channel estimates replaced by their fused counterparts, and with the corresponding covariance matrices of the estimation errors. Note that fusion-based centralized operation decreases the fronthaul overhead roughly by a factor of N/Q compared to the centralized operation, and the CPU computational complexity is $\mathcal{O}(L^3 Q^3)$, which is smaller than that of centralized operation $\mathcal{O}(L^3 N^3)$, especially for $Q \ll N$.

3.2. Proposed Fusion Rule Design

We start from (13) and we write the Médard lower bound [13] of the MI between the fused signal vector $\widetilde{\mathbf{y}}_l$ in (13) and the data signals $\mathbf{s} = \left[s_1 \ldots s_k\right]^T \in \mathbb{C}^K$ as

$$\mathcal{I}\left(\widetilde{\mathbf{y}}_l \,;\, \mathbf{s} \,|\, \mathbf{V}_l\right) \geq \log_2 \left| \mathbf{I}_Q + \mathbf{\Sigma}_{EN}^{-1} \mathbf{\Sigma}_D \right| \,, \tag{16}$$

where

$$\mathbf{\Sigma}_{EN} = \sum_{k \in \mathcal{U}_l} p_k \widetilde{\mathbf{C}}_{l,k} + \sigma^2 \mathbf{V}_l^H \mathbf{V}_l \tag{17}$$

is the covariance matrix of the effective noise (EN), and

$$\mathbf{\Sigma}_D = \sum_{k \in \mathcal{U}_l} p_k \widehat{\mathbf{z}}_{l,k} \widehat{\mathbf{z}}_{l,k}^H \tag{18}$$

is the covariance matrix of the desired (D) component. Note that the Médard lower bound is tight for Gaussian data signals, as assumed here, and for small channel estimation MSE [13], which is expected in a CFmMIMO network since the APs are typically close to their serving UEs. The MI in (16) quantifies how much information the fused signal vector $\widetilde{\mathbf{y}}_l$ carries about the data signals $\{s_k\}_{k=1}^K$. Motivated by this observation, AP l maximizes the MI lower bound in (16) with respect to $\mathbf{V}_l$, by solving the optimization problem

$$\underset{\mathbf{V}_l \in \mathbb{C}^{N \times Q}}{\text{maximize}} \quad \log_2 \left| \mathbf{\Sigma}_D + \mathbf{\Sigma}_{EN} \right| - \log_2 \left| \mathbf{\Sigma}_{EN} \right| \tag{19a}$$

$$\text{subject to} \quad \mathbf{V}_l^H \mathbf{V}_l = \mathbf{I}_Q \,, \tag{19b}$$

where we have added the constraint (19b) to remove the subspace ambiguity in $\mathbf{V}_l$. Note that the constrained problem (19) can be viewed as an unconstrained problem over the Stiefel manifold $\mathcal{M} = \{\mathbf{V}_l \in \mathbb{C}^{N \times Q} : \mathbf{V}_l^H \mathbf{V}_l = \mathbf{I}_Q\}$ [17], which allows the constraint (19b) to be satisfied at every iteration, rather than being enforced through penalty terms or explicit projections after each update. This avoids the additional parameter tuning, which is typically required for Euclidean methods, and yields faster and numerically stable convergence [17, Ch. 4]. The transformed Riemannian optimization problem is given by

$$\underset{\mathbf{V}_l \in \mathcal{M}}{\text{maximize}} \quad \log_2 \left| \mathbf{\Sigma}_D + \mathbf{\Sigma}_{EN} \right| - \log_2 \left| \mathbf{\Sigma}_{EN} \right| \,, \tag{20}$$

and we propose to solve it using conjugate gradient descent [18].

4. NUMERICAL EXPERIMENTS

In this section, we compare the fusion-based centralized operation using the proposed fusion rule with the centralized operation [4], and the state-of-the-art fusion rule design in [12]. Specifically, [12] proposes a fusion rule constructed from the Q eigenvectors corresponding to the Q largest eigenvalues of the covariance matrix of the received signal, $\mathbb{E}\{\mathbf{y}_l \mathbf{y}_l^H\}$.

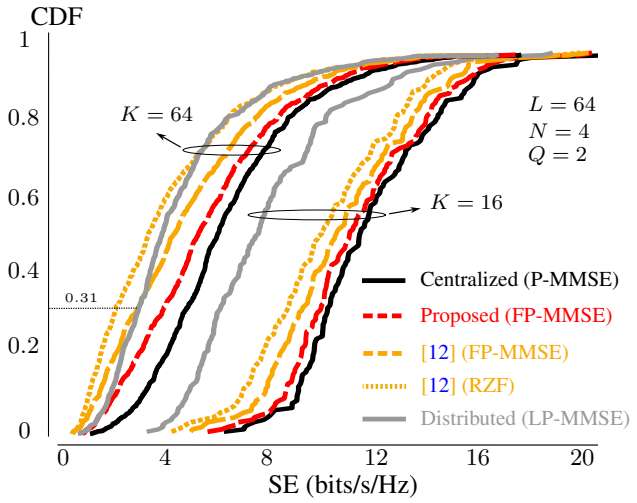

Fig. 1. Per-UE SE for $L = 64$, $N = 4$, $Q = 2$, and $K = \{16, 64\}$. The proposed fusion rule significantly outperforms the fusion of [12], even with FP-MMSE combining.

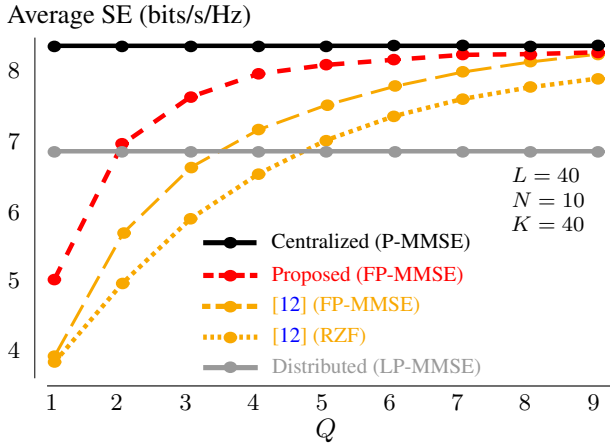

Fig. 2. Average SE for $L = 40$, $K = 40$, $N = 10$, and varying Q. The proposed fusion rule and the fusion in [12] achieve near-centralized performance for $Q = 6$ and $Q = 8$, respectively.

Moreover, the regularized zero-forcing (RZF) combiner was originally used in [12], where the channel estimation errors are not considered in the CPU data detection. We compare our proposed fusion rule, together with FP-MMSE combining, against [12] using both RZF and FP-MMSE combining. Lastly, we compare all methods with the local P-MMSE (LP-MMSE)-based distributed operation [5].

We consider a CFmMIMO network in a simulated square area of 2×2 km^2, and we set $\tau_c = 200$, $\tau_p = 10$, $p_k = p = 100$ mW, and $\sigma^2 = -94$ dBm. Moreover, we use the same propagation model as in [19, Sec. 2.5]. The AP-UE association and the pilot assignment are jointly implemented as described in [5, Sec. V.A].

In Fig. 1, we plot the cumulative distribution function (CDF) of the per-UE SE, for $L = 64$, $N = 4$, $Q = 2$, and $K = \{16, 64\}$. It is seen that the proposed fusion rule significantly outperforms the fusion in [12], especially for a larger number of UEs ($K = 64$), and achieves near-centralized performance with only half the fronthaul overhead compared to centralized operation. Interestingly, for $K = 64$, the fusion of [12] achieves smaller SE compared to distributed operation for almost 31% of the UEs. The proposed fusion rule consistently outperforms the distributed operation. In Fig. 2, we plot the average SE for $L = 40$, $K = 40$, $N = 10$, and varying Q. All curves are monotonically increasing with Q, reflecting the expected performance gain from using a higher-dimensional fused signal vector, albeit at the cost of increased fronthaul overhead. It is shown that the proposed fusion rule achieves distributed performance for small $Q = 2$, whereas the fusion in [12] requires $Q > 3$ for the same performance. Moreover, the proposed fusion rule achieves near-centralized performance for $Q = 6$, whereas the fusion in [12] achieves the same performance for $Q = 8$. For $Q < 8$, the proposed fusion rule significantly outperforms the fusion in [12]. In Fig. 3, we plot the average objective value of (20) over $L = 10$ APs against the iteration count, using $K = 10$, $N = 4$, and $Q = \{1, 2, 3\}$. It is seen that after a few iterations, convergence is reached. The objective value converges to larger values for larger Q, which is explained by the fact that more information can be carried by the Q-dimensional fused signal vector when Q increases.

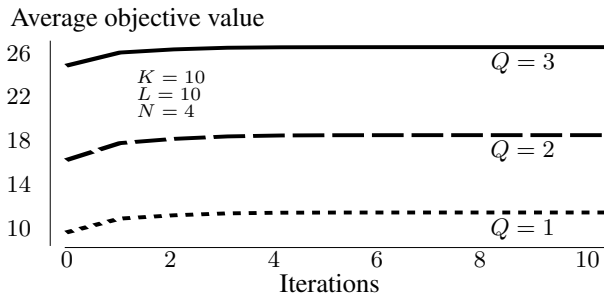

Fig. 3. Convergence of the proposed fusion rule design for $L = 10$, $K = 10$, $N = 4$, and $Q = \{1, 2, 3\}$. Convergence is reached after a few iterations.

5. CONCLUSION

In this paper, we have proposed a locally optimal fusion rule design for fusion-based centralized uplink processing. In this design, each AP computes the fusion rule by maximizing the Médard lower bound of MI between the fused received signal vector and the UE data signals. Numerical experiments demonstrate that the proposed fusion rule design significantly outperforms the state-of-the-art designs and approaches centralized performance for moderate values of the fused signal vector dimension. Future work will consider limited fronthaul capacity, as well as globally optimal fusion rules and fusion rules with AP-specific reduced dimensions.

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