

# Iterative Detection and Decoding for Cell-Free Massive MIMO Using LDPC Codes

Tonny Ssettumba, Roberto B. Di Renna, Lukas T. N. Landau and Rodrigo C. de Lamare

**Abstract**—This paper proposes an iterative detection and decoding (IDD) scheme for a cell free massive multiple input multiple output (CF-mMIMO) system. Users send coded data to the access points (APs), which is jointly detected at central processing unit (CPU). The symbols are exchanged iteratively in the form of log likelihood ratios (LLRs) between the detector and the low-density parity check codes (LDPC) decoder, increasing the coded system’s performance. We propose a list-based multi-feedback diversity with successive interference cancellation (MF-SIC) to improve the performance of the CF-mMIMO. Furthermore, the proposed detector is compared with the parallel interference cancellation (PIC) and MF-PIC schemes. Finally, the bit error rate (BER) performance of CF-mMIMO is compared with the co-located mMIMO (Col-mMIMO).

**Keywords**— Iterative detection and decoding, MMSE-SIC, MF-SIC, Cell-free Massive MIMO, co-located MIMO.

## I. INTRODUCTION

Massive multiple-input multiple-output (mMIMO) is a multi-user communications solution that involves a large number of antennas to provide service to multiple users. The large antenna array yields high throughput and also improves the propagation conditions because of the channel hardening property [1], [3]. mMIMO leverages on the assumption that users have a single-antenna whereby there are significantly more antennas at the Base Station (BS) than the number of served users [3]. The signals transmitted by the users to the receiver overlap, resulting in multi-user interference at the receiver. These interfering signals cannot be easily demodulated at the receiver, which call for techniques that can separate such signals [4]. The major aim is to reduce the Euclidean distance between the transmitted signal and the estimate of the received signal [5]. Several works have studied optimal detection techniques to improve the performance of mMIMO. However, the complexity of such schemes increases with the modulation order and the number of antennas [5]. Furthermore, sub-optimal detectors that use iterative detection and decoding (IDD) that utilise non-linear techniques such as minimum mean square error with successive interference cancellation (MMSE-SIC) and parallel interference cancellation (PIC) have been studied in different works [1], [2], [5], [6]. These schemes have been found to achieve close to optimal bit error rate (BER) performance.

The key aspect in IDD based strategies is the exchange of soft information between the soft detector and the decoder in

terms of likelihood ratios (LLRs). After some iterations, the decoder sends the interleaved posterior probabilities (extrinsic) information to the soft detector in form of feedback [6], [7]. The use of codes that use message passing such as low-density parity check codes (LDPC) and turbo codes has been studied in several works [8].

Prior works on IDD that employ channel codes that use message passing such LDPC and turbo codes include the work in [1]–[7]. Such code designs are less complex which simplifies communication system. The use of list-based detection approaches such as: Multiple-feedback (MF) with SIC (MF-SIC) and multiple-branch-MF processing with SIC (MB-MF-SIC) detection schemes have been applied in MIMO architectures to lower the BER [5], [6]. Such schemes achieve close to optimal performance and also reduce the brief error propagation that is prevalent when using SIC based detection. In [7], the uplink of a CF-mMIMO network has been studied. The access points (APs) are assumed to locally implement soft MIMO detection and then share the resulting bit LLRs on the front-haul link without exchanges between the detector and the decoder. The CPU was used to decode the data while the non-linear processing at the APs consisted of the approximate computation of the posterior density for each received data bit. Moreover, the detection was performed via Partial Marginalization.

In this work, we present an IDD scheme for CF-mMIMO systems, which unlike the work in [7], employs message passing. In particular, we propose list-based MF-SIC detectors based on soft interference cancellation for a centralized CF-mMIMO network. To the best of the authors’ knowledge, no such detector has been presented in the previous works for the CF-mMIMO architecture. Moreover, the use of message passing strategies can significantly reduce the BER. Therefore, the main contributions of this paper are summarized as follows. First, a list-based soft MF-SIC detector is proposed for the CF-mMIMO architecture. This proposed approach gives lower BER values at the same computation complexity as the traditional SIC scheme. Secondly, the proposed detector is compared with other detectors such as the linear MMSE, SIC, PIC and MF-PIC. Thirdly, the impact of increasing the IDD iterations is examined. Finally, the CF-mMIMO architecture is compared with the co-located mMIMO (Col-mMIMO) system in terms of the BER performance. The CF-mMIMO significantly achieves lower BER values than the Col-mMIMO.

The rest of this paper is organized as follows: Section II presents the system model and the statistical analysis. The proposed MF-SIC and MF-PIC detectors are presented in III.

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Section IV discusses the IDD scheme. Simulation results and discussions are presented in V. Finally, concluding remarks are given in section VI.

**Symbol notations:** We use lower/upper bold case symbols to represent vectors/matrices, respectively. The Hermitian transpose operator is denoted by  $(\cdot)^H$ .

## II. PROPOSED SYSTEM MODEL

The proposed low complexity IDD scheme for CF-mMIMO systems is shown in Fig. 1. Particularly, an LDPC-coded CF-mMIMO system comprising of  $L$  APs,  $K$  single antenna user equipments (UEs), a joint detector at the CPU and an LDPC decoder is considered. The data are first encoded (Enc) by an

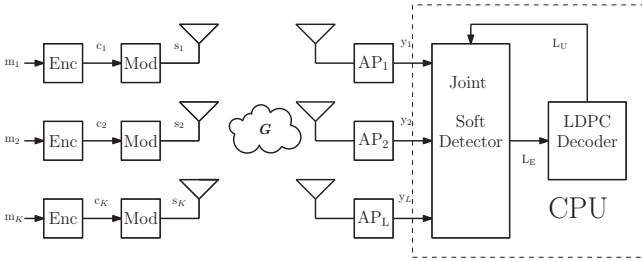


Fig. 1: Block diagram of a communication system with an IDD scheme.

LDPC encoder having a code rate  $R$ . This encoded sequence is then modulated (Mod) to complex symbols with a complex constellation of  $2^{M_c}$  possible signal points and average energy  $E_s$ . The coded data is then transmitted by  $K$  UEs through the channel  $\mathbf{G}$  to the APs.

We assume a centralized user-centric CF-mMIMO scenario, where the CPU does soft processing and joint detection on the received signal vectors from the APs. Then the CPU sends these soft outputs  $L_E$  in the form of LLRs to the LDPC decoder. The decoder adopts an iterative strategy by sending extrinsic information  $L_U$  to the CPU which improves the performance of the entire network. Additionally, the performance of the proposed detector is examined for the case with no iterations and the case with iterations. The channel coefficients between the  $l$ -th AP and the  $k$ -th UE are given by [9]

$$g_{k,l} = \sqrt{\beta_{k,l}} h_{k,l}, \quad (1)$$

where  $\beta_{k,l}$  is the large-scale (LS) fading coefficients as a result of path loss (PL) and shadowing. The small scale fading coefficients are given by  $h_{k,l}$ , that are independent and identically distributed (i.i.d.) Gaussian random variables with variance  $\mathbb{E}\{h_{k,l}^* h_{k,l}\} = 1$ .

The LS fading coefficient are assumed to be deterministic and can be obtained using the three-slope PL model [9]. More precisely, the PL exponent is 3.5 if the distance  $d_{kl}$  between the  $k$ -th UE and  $l$ -th AP is greater than  $d_1$ , equals 2 if  $d_1 \geq d_{kl} > d_0$ , and equals 0 if  $d_{kl} \leq d_0$ , for some  $d_0$  and  $d_1$ . For  $d_{kl} > d_1$ , the Hata-COST231 propagation model is applied. The PL  $PL_{kl}$  in dBs between the  $k$ -th UE and  $l$ -th AP can

be given such as

$$PL_{kl} = \begin{cases} -\Lambda - 35 \log(d_{kl}), & d_{kl} > d_1 \\ -\Lambda - 15 \log(d_1) - 20 \log(d_{kl}), & d_0 < d_{kl} \leq d_1 \\ -\Lambda - 15 \log(d_1) - 20 \log(d_0), & \text{if } d_{kl} \leq d_0 \end{cases} \quad (2)$$

The parameter  $\Lambda$  is given by

$$\Lambda \triangleq 46.3 + 33.9 \log_{10}(f) - 13.82 \log_{10}(h_{AP}) - (1.1 \log_{10}(f) - 0.7)h_u + (1.56 \log_{10}(f) - 0.8), \quad (3)$$

where  $f$  is the carrier frequency (in MHz),  $h_u$  and  $h_{AP}$  are the antenna heights of the UE and AP, respectively. The LS coefficient  $\beta_{kl}$  models the PL and shadow fading that is given by

$$\beta_{lk} = PL_{kl} \times 10^{\sigma_{sh} \zeta_{lk}}. \quad (4)$$

Where  $10^{\sigma_{sh} \zeta_{lk}}$  denotes the shadowing with standard deviation  $\sigma_{sh}$ , and  $\zeta_{lk} \sim N(0, 1)$ . The received signal  $\mathbf{y}$  at the joint soft detector is given by

$$\mathbf{y} = \mathbf{G}\mathbf{s} + \mathbf{n}, \quad (5)$$

where  $\mathbf{G} \in \mathbb{C}^{L \times K}$  is the channel matrix comprising of both small scale and LS fading coefficients.  $\mathbf{s} = [s_1, s_2, \dots, s_{k-1}, s_k, s_{k+1}, \dots, s_K]$ ,  $\mathbf{n}$  is the additive white Gaussian noise sample (AWGN) with zero mean and unit variance.

### A. MMSE soft cancellation detectors

For simplicity of analysis, we consider sub-optimal detectors which consists of PIC/SIC followed by an MMSE filter. The detector first forms soft estimates of the transmitted symbols by computing the symbol mean  $\bar{s}_j$  based on the available a-priori information from the decoder [3]

$$\bar{s}_j = \sum_{s \in A} s P(s_j = s), \quad (6)$$

where  $A$  is the complex constellation set. By assuming statistical independence of bits within the same symbol as in [3], the a-priori probabilities are calculated from the extrinsic LLRs provided by the LDPC decoder as

$$P(s_j = s) = \prod_{l=1}^{M_c} [1 + \exp(-s^{b_l} L_c(b_{(j-1)M_c+l}))]^{-1}, \quad (7)$$

where  $s^{b_l} \in (+1, -1)$  denotes the value of the  $l$ -th bit of symbol  $s$ ,  $L_c(b_i)$  denotes the extrinsic LLR of the  $i$ -th bit computed by the LDPC decoder in the previous iteration. We define  $L_c(b_i) = 0$  at the first iteration since the only available belief is from the channel. For the  $k$ -th user, the soft interference from the other  $K - 1$  users is canceled according to PIC to obtain

$$\mathbf{y}_k = s_k \mathbf{g}_k + \sum_{j=1, j \neq k}^K (s_j - \bar{s}_j) \mathbf{g}_j + \mathbf{n}. \quad (8)$$

For SIC, the soft interference from the other  $K - 1$  users is canceled to obtain

$$\mathbf{y}_k = \mathbf{y} - \sum_{j=1}^{K-1} \bar{s}_j \mathbf{g}_j. \quad (9)$$

Using (8), a symbol estimate  $\hat{s}_k$  of the transmitted symbol on the  $k$ -th UE is obtained by applying a linear filter  $\mathbf{w}_k$  to  $\mathbf{y}_k$  such as

$$\begin{aligned} \hat{s}_k &= \mathbf{w}_k^H \mathbf{y}_k \\ &= (\mathbf{w}_k^H \mathbf{g}_k) s_k + \sum_{j=1, j \neq k}^K (\mathbf{w}_k^H \mathbf{g}_j) (s_j - \bar{s}_j) + \mathbf{w}_k^H \mathbf{n}, \end{aligned} \quad (10)$$

where  $\mathbf{w}_k$  is chosen to minimize the mean square error (MSE) between the transmitter symbol  $s_k$  and the filter output  $\hat{s}_k$  and depends on the variance of the symbols used in the cancellation step. Due to paper size limitation, the estimated symbol while using the SIC can be obtained using a similar approach applied for the PIC. In [1], [3] it is shown that the corresponding linear filter is given by

$$\mathbf{w}_k = \left( \frac{\sigma_n^2}{E_s} \mathbf{I} + \mathbf{G} \Delta_k \mathbf{G}^H \right)^{-1} \mathbf{g}_k, \quad (11)$$

with

$$\Delta_k = \text{diag} \left[ \frac{\sigma_{s_1}^2}{E_s}, \dots, \frac{\sigma_{s_{k-1}}^2}{E_s}, 1, \frac{\sigma_{s_{k+1}}^2}{E_s}, \dots, \frac{\sigma_{s_K}^2}{E_s} \right], \quad (12)$$

where  $\sigma_{s_i}^2$  is the variance of the  $i$ -th user symbol computed as

$$\sigma_{s_i}^2 = \sum_{s \in \mathcal{A}} |s - \bar{s}_i|^2 P(s_i = s). \quad (13)$$

### III. PROPOSED MULTI-FEEDBACK DETECTION-SIC

In this section, we describe the operation of the proposed list-based detection scheme

#### A. MF-SIC Design

The block diagram of the proposed MF-SIC is shown in Fig. 2. The design leverages on feedback diversity by choosing a set of constellation candidates when the previously detected symbol is considered to be unreliable [5]. A shadow area constraint (SAC) is introduced in order to obtain an optimal feedback candidate. This helps to reduce the computation complexity in the search space, by avoiding it from growing exponentially. One of the positive attributes of such a selection criterion, is that there is no need for redundant processing when reliable decisions are made. Additionally, the proposed MF-SIC scheme mitigates error propagation that usually occurs when SIC-based approaches are used for detection. The procedure for detecting  $\hat{s}_k$  for the  $k$ -th user is described following a similar procedure presented in [9]. The  $k$ -th user soft estimate is obtained by  $u_k = \mathbf{w}_k^H \tilde{\mathbf{y}}_k$  where the  $L_{AP} \times 1$  MMSE filter vector  $\mathbf{w}_k = (\bar{\mathbf{G}}_k \bar{\mathbf{G}}_k^H + \frac{\sigma_n^2}{E_s} \mathbf{I})^{-1} \mathbf{g}_k$ .  $\bar{\mathbf{G}}_k$  represents the matrix obtained by stacking the columns  $k, k+1, \dots, K$  of  $\mathbf{G}$  and  $\tilde{\mathbf{y}}_k = \mathbf{y} - \sum_{t=1}^{k-1} \mathbf{g}_t \hat{s}_t$  denotes the received vector after performing cancellation of the  $k-1$  previously detected symbols. The soft estimate  $u_k$  for each

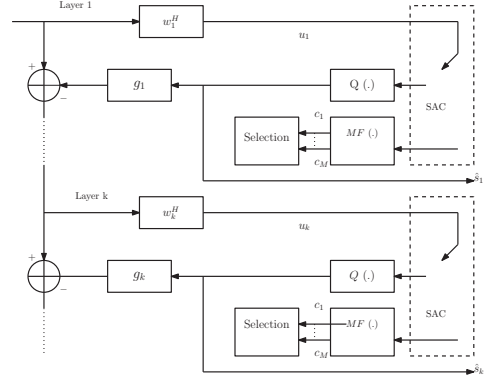


Fig. 2: Block diagram of a the Proposed MF-SIC detector.

layer is examined by the SAC to determine if this decision is reliable according to

$$d_k = |u_k - \nu_f|, \quad (14)$$

where  $\nu_f = \arg \min_{\nu_f \in \mathcal{A}} \left\{ |u_k - \nu_f| \right\}$  denotes the closest constellation point to the  $k$ -th user soft estimate  $u_k$ . If  $d_k > d_{\text{th}}$  the decision is considered to be unreliable and the selected constellation point is dropped into the shadow area of the constellation map. Parameter  $d_{\text{th}}$  is the predefined threshold euclidean distance to guarantee reliability of the selected symbol [5]. If the soft estimate  $u_k$  is deemed to be a reliable estimate for user  $k$ , the MF-SIC algorithm performs a hard slice as in the conventional SIC approach [5], [6]. In this case,  $\hat{s}_k = Q(u_k)$  is the estimated symbol, where  $Q(\cdot)$  is the quantization notation which maps to the constellation symbol closest to  $u_k$ .

Otherwise, the decision is deemed unreliable. In this case, a candidate set  $\mathcal{L} = \{c_1, c_2, \dots, c_m, \dots, c_M\} \subseteq \mathcal{A}$  is generated, which consists of the  $M$  constellation points closest to  $u_k$ . The number of candidate points  $M$  is given by the QPSK symbols. As a result, there is a trade-off between performance and complexity. The algorithm selects an optimal candidate  $c_{m,\text{opt}}$  from a pool of  $\mathcal{L}$  candidates. As a result, the unreliable choice  $Q(u_k)$  is substituted by a hard decision, and  $\hat{s}_k = c_{m,\text{opt}}$  is obtained. It should be noted that the MF-SIC algorithm's performance benefits are based on the assumption that  $c_{m,\text{opt}}$  is correctly selected. The following is a summary of the MF-SIC selection algorithm: To begin, the selection vectors  $\phi^1, \phi^2, \dots, \phi^m, \dots, \phi^M$  must be defined.

The size of these selection vectors is equal to the number of the constellation candidates that are used every time a decision is considered unreliable. For example, for the  $k$ -th layer, a  $K \times 1$  vector  $\phi^m = [\hat{s}_1, \dots, \hat{s}_{k-1}, c_m, \phi_{k+1}^m, \dots, \phi_q^m, \dots, \phi_K^m]^T$  which is a potential choice corresponding to  $c_m$  in the  $k$ -th user consists of the following items: (a) The previously estimated symbols  $\hat{s}_1, \hat{s}_2, \dots, \hat{s}_{k-1}$ . (b) The candidate symbol  $c_m$  obtained from the constellation for subtracting a decision that was considered unreliable  $Q(u_k)$  of the  $k$ -th user. (c) Using (a) and (b) as the previous decisions, detection of the next user data  $k+1, \dots, q, \dots, K$ -th is performed by the SIC

approach. Mathematically, the choice  $\phi^m$  is given by [9]

$$\phi_q^m = Q(\mathbf{w}_q^H \hat{\mathbf{y}}_q^m), \quad (15)$$

where the index  $q$  denotes a given UE between the  $(k+1)$ -th and the  $K$ -th UE,

$$\hat{\mathbf{y}}_q^m = \tilde{\mathbf{y}}_k - \mathbf{g}_k c_m - \sum_{p=k+1}^{q-1} \mathbf{g}_p \phi_p^m. \quad (16)$$

A key attribute of the proposed MF-SIC algorithm is the same MMSE filter  $\mathbf{w}_k$  that is used for all the constellation candidates. Therefore, the proposed algorithm has the same computational complexity as the conventional SIC. The optimal candidate  $m, \text{opt}$  is selected according to the local maximum likelihood (ML) rule given by

$$m, \text{opt} = \arg \min_{1 \leq m \leq M} \|\mathbf{y} - \mathbf{G}\phi^m\|^2. \quad (17)$$

#### IV. ITERATIVE DETECTION AND DECODING

In this section, the MMSE-based detectors are presented for the IDD scheme as shown in Fig. 1, consisting of a joint detector and an LDPC decoder. Due to paper size limitation, the operation is explained based on the MMSE detector given in (11). The received signal at the output of the filter, contains the desired symbol, residual co-user interference and noise. We use similar assumptions given in [1], [3], [10] to approximate the  $\hat{s}_k$  as an AWGN channel given by

$$\hat{s}_k = \mu_k s_k + z_k, \quad (18)$$

where  $\mu_k = \mathbb{E}\{\hat{s}_k s_k^*\}$ . The parameter  $z_k$  is a zero-mean AWGN variable. Using similar procedures as in [1], the parameter  $\mu_k$  is given by

$$\mu_k = \mathbf{g}_k^H \left( \frac{\sigma_n^2}{E_s} \mathbf{I} + \mathbf{G} \Delta_k \mathbf{G}^H \right)^{-1} \mathbf{g}_k. \quad (19)$$

The variance of  $\hat{s}_k$  variance  $\lambda_k^2$  is given by

$$\lambda_k^2 = \mathbb{E}\{\mu_k - \mu_k^2\}, \quad (20)$$

The extrinsic LLR computed by the detector for the  $l$ -th bit  $l \in \{1, 2, \dots, M_c\}$  of the symbol  $s_k$  transmitted by the  $k$ -th user is [1], [3]

$$L_D(b_{(k-1)M_c+l}) = \log \frac{\sum_{s \in A_l^{+1}} f(\hat{s}_k|s) P(s)}{\sum_{s \in A_l^{-1}} f(\hat{s}_k|s) P(s)} - L_c(b_{(k-1)M_c+l}), \quad (21)$$

where  $A_l^{+1}$  is the set of  $2^{M_c-1}$  hypothesis  $s$  for which the  $l$ -th bit is  $+1$ . The a-priori probability  $P(s)$  is given by (7). The approximation of the likelihood function [3]  $f(\hat{s}_k|s)$  is given by

$$f(\hat{s}_k|s) \simeq \frac{1}{\pi \lambda_k^2} \exp\left(-\frac{1}{\lambda_k^2} |\hat{s}_k - \mu_k s|^2\right). \quad (22)$$

#### A. Decoder Algorithm

The soft beliefs are exchanged between the proposed detectors and the decoder in an iterative manner. The traditional sum product algorithm (SPA) suffers from performance degradation

caused by the tangent function especially in the error-rate floor region [10]. Therefore, we use the box-plus SPA in this paper because it yields less complex approximations. The decoder is made up of two stages namely: The single parity check (SPC) stage and the repetition stage. The LLR sent from check node  $(CN)_J$  to variable node  $(VN)_i$  is computed as

$$L_{j \rightarrow i} = \boxplus_{i' \in N(j) \setminus i} L_{i' \rightarrow j}. \quad (23)$$

As shorthand, we use  $L_1 \boxplus L_2$  to denote the computation of  $L(L_1 \oplus L_2)$ . The LLR is computed by

$$\begin{aligned} L_1 \boxplus L_2 &= \log \left( \frac{1 + e^{L_1+L_2}}{e^{L_1} + e^{L_2}} \right), \\ &= \text{sign}(L_1) \text{sign}(L_2) \min(|L_1|, |L_2|) \\ &\quad + \log \left( 1 + e^{-|L_1+L_2|} \right) - \log \left( 1 + e^{-|L_1-L_2|} \right). \end{aligned} \quad (24)$$

The LLR from  $VN_i$  to  $CN_j$  is given by

$$L_{i \rightarrow j} = L_i + \sum_{j' \in N(i) \setminus j} L_{j' \rightarrow i}, \quad (25)$$

where the parameter  $L_i$  denotes the LLR at  $VN_i$ ,  $j' \in N(i) \setminus j$  denotes all CNs connected to  $VN_i$  except  $CN_j$ .

#### V. SIMULATION RESULTS AND DISCUSSION

In this section, the BER performance of the proposed soft detectors is presented for the CF-mMIMO and Col-mMIMO settings. The CF-mMIMO channel exhibits high PL values due to LS fading coefficients. Thus, the SNR definition is given by

$$SNR = \frac{\text{tr}(\sigma_s^2 \mathbf{G} \mathbf{G}^H) R}{L_{AP} K_{UE} \sigma_w^2}, \quad (26)$$

The simulation parameters are varied as follows: We consider a cell-free environment with a square of dimensions  $D \times D =$ , where  $D = 1$  km. Distances  $d_0$  and  $d_1$  are 10 m and 50 m, respectively.  $h_{AP} = 15$  m,  $h_u = 1.65$  m,  $f = 1900$  MHz,  $d_{th} = 0.38$ , LDPC code with code word length 256 bits,  $M = 128$  parity check bits and  $N - M$  message bits. The code rate  $R = \frac{1}{2}$ . The maximum number of inner iterations is set to 10. The signal power  $\sigma_s^2 = 1$  and the simulations are run for  $10^3$  channel realizations. The modulation scheme used is quadrature phase shift keying (QPSK). Figure 3 presents the BER versus the SNR as the number of IDD iterations are increased. It can be visualized that increasing IDD iterations yields lower BER. This is because more a posterior information is exchanged between the joint detector and decoder as the iterations increase, which improves the system performance. The number of iterations do not cause any marginal effect on the linear MMSE filter without cancellation because there is no  $\Delta_k$  in this filter which is needed for the IDD to improve the performance. Fig. 4 presents the BER versus the SNR for the CF-mMIMO system model for different values of  $L$  and the studied soft detectors for two IDD iterations. The PIC and MF-PIC achieves the lowest BER values, followed by MF-SIC, SIC, MMSE, in that order. Additionally, increasing  $L$  and  $K$  reduces the BER. Also, the performance benefit between conventional PIC and MF-PIC is negligible. Figure 5 presents

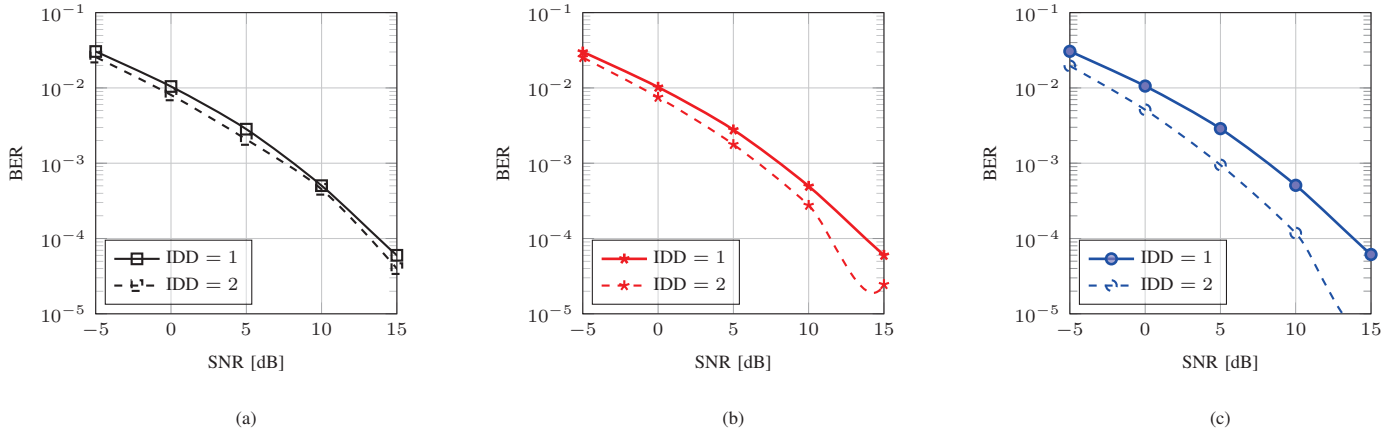


Fig. 3: BER versus SNR for CF-mMIMO for (a) SIC, (b) MF-SIC and (c) PIC with  $L = 100$ ,  $K = 40$ , while varying the number of IDD iterations.

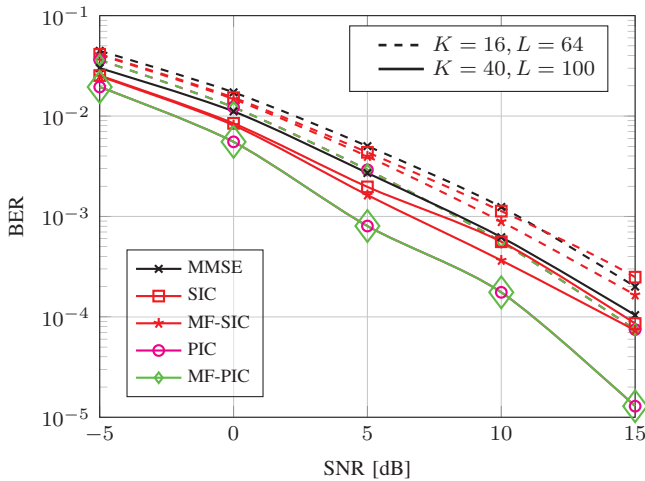


Fig. 4: BER versus SNR for CF-mMIMO for the different detectors.

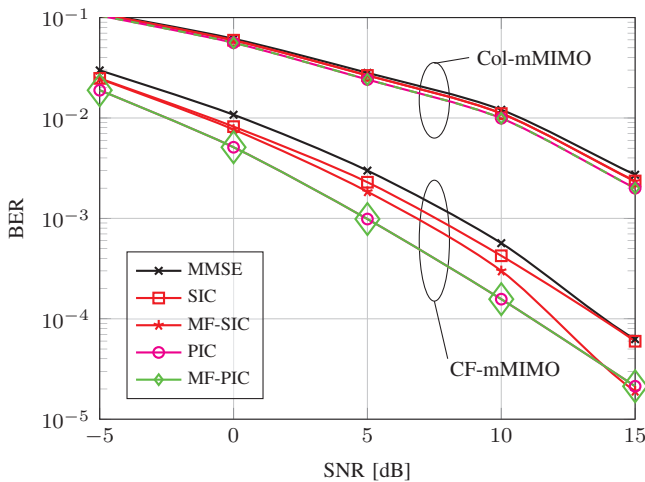


Fig. 5: BER versus SNR for CF-mMIMO and Col-mMIMO with  $L = 100$ ,  $K = 40$ ,  $IDD = 2$ , single Base Station (BS) with 100 antennas.

BER versus SNR while comparing the CF-mMIMO and Col-mMIMO architectures. It can be shown that the CF-mMIMO achieves low BER compared to the Col-mMIMO. This is due to the distributed nature of CF-mMIMO which improves the performance of the entire coverage area.

## VI. CONCLUDING REMARKS

In this paper, we have proposed list-based detectors for CF-mMIMO architectures. Specifically, an IDD scheme using LDPC codes has been studied. Additionally, the performance of the proposed MF-SIC/PIC schemes has been compared with other detectors. The proposed MF-PIC achieves lower BER values as compared to SIC scheme. Finally, increasing IDD iterations significantly reduces the BER.

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