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Hardware evaluation of interference alignment algorithms using USRPs for beyond 5G networks

David Alejandro Urquiza Villalonga*, Alejandro López Barrios *, M. Julia Fernández-Getino García*

*Department of Signal Theory and Communications, Universidad Carlos III de Madrid, 28911, Madrid, Spain
daurquiza@tsc.uc3m.es, alejandro.l.barrios@alumnos.uc3m.es, mjulia@tsc.uc3m.es

Abstract—Network densification is a key technology to achieve the spectral efficiency (SE) expected in 5G wireless networks and beyond. However, the proximity between transmitters and receivers increases the interference levels, becoming a major drawback. To overcome this problem, several interference management techniques have been proposed to increase the signal-to-interference-plus-noise ratio (SINR). Interference alignment (IA) algorithms have been extensively studied due to their capability to achieve optimal degrees of freedom (DoFs) in interference channels (ICs). Nevertheless, most of the works are limited to a purely theoretical analysis based on non-realistic assumptions such as perfect channel state information (CSI) and the synchronization of all nodes in the network. To the best of our knowledge, only a few articles address the IA implementation using reconfigurable hardware. To cover this lack, this paper proposes a practical design of the IA algorithm based on the SINR maximization, known as MAX-SINR, considering a multiuser IC. Each transmitter and receiver is implemented on the National Instruments USRP-2942. A practical solution for the channel estimation and synchronization stages in an IC, that are usually omitted in theoretical works, is developed. The performance of the proposed implementation is shown in terms of the SINR gain, SE, and bit error rate (BER). Unlike previous works, all the results are based on real measurements providing valuable insights into the performance of IA algorithms.

Index Terms—Interference alignment (IA), multi-user interference channels (ICs), universal software radio peripheral (USRP).

I. INTRODUCTION

Ultra-dense networks (UDNs) have emerged in the last decade as a promising solution to achieve the high spectral efficiency (SE) values demanded by 5G and beyond (B5G) wireless networks. The main idea is to provide short-range communications to multiple users through the deployment of small cells (SCs) in the coverage area of the traditional macrocells. Consequently, the signal-to-noise ratio (SNR) is increased even when the small base stations (SBSs) keep a low transmission power [1].

However, the proximity between SBSs and user equipments (UEs) also implies an increment in the interference levels. This represents a major drawback that has attracted a lot of attention in the scientific community. To overcome this

problem, several advanced interference management techniques have been studied. In this scenario of densification, interference alignment (IA) algorithms have been proposed to cancel multiple interfering transmissions with optimal degrees of freedom (DoFs) performance in interference channels (ICs) [2], [3]. IA is supported on the availability of multiple antennas in a multiple-input multiple-output (MIMO) system. The main idea is to compute the precoding and combining matrices at the transmitter and receiver side, respectively, to align the interference in a subspace orthogonal to the desired signal subspace. Then, the interference is eliminated by multiplying the received signal by the combining matrix.

A closed-form solution for the IA matrices design has been only proposed for an IC composed of three users [2]. In the case of denser networks, several linear iterative algorithms have been developed based on interference leakage (IL) minimization [4]–[6], optimization of the mean square error (MSE) between the transmitted and received signal [7], and the signal-to-interference-plus-noise ratio (SINR) maximization, known as MAX-SINR [5]. It has been proved that MAX-SINR achieves higher performance than algorithms based on IL minimization for low and moderate SNR values.

The main drawback of IA algorithms is the requirement of the channel state information (CSI) of the entire network at both the transmitter and receiver sides. This is very difficult to obtain in practical implementations due to the coordination between SBSs and UEs to estimate the channels. Indeed, the IA performance is affected in real scenarios by an imperfect CSI caused by channel estimation errors, feedback delay that leads to outdated CSI at the transmitter side, and quantization errors in the feedback link [3]. These issues have been extensively studied in several theoretical works through retrospective IA schemes, robust IA algorithms against channel estimation errors, and blind IA techniques [8], [9].

Although several works study the IA algorithms in a theoretical approach, to the best of our knowledge, only a few articles address the IA implementation using reconfigurable hardware. The feasibility of applying IA algorithms in a practical system to reduce interference is shown in [10] by using universal software radio peripherals (USRPs). The IA closed-form solution for the particular case of three users is tested in [11]. First, the CSI of the entire network is estimated during a training stage. Then, this information is used to compute the IA matrices. This investigation has been extended

by the same authors in [12]–[14] following the same hardware setup and design methodology. The impact of CSI errors on the IA performance is analyzed in [12]. This study is limited to illustrating the effects on the sum-rate of using IA matrices computed with an outdated CSI. However, the performance is just shown in terms of the theoretical sum-rate for MIMO systems using the estimated channels, noise power, and the IA precoding/combining matrices. A real measurement of the SINR at the receiver side and how the use of outdated CSI affects this SINR gain is omitted. Then, the implementation of IA on a multicarrier transmission is obtained in [13]. A performance comparison of IA methods and its applicability to indoor scenarios are studied in [14].

In these previous papers, it is assumed that the estimated channel at each user is shared through a TCP/IP connection with a central workstation where the IA matrices are computed. On the contrary, a fully distributed system with over-the-air feedback is proposed in [15]. The authors develop a master-slave synchronization method to coordinate all the nodes. Additionally, the tradeoff between the number of iterations and performance of the IL minimization method [4] is analyzed. The effects on SE performance of the errors introduced by an analog and quantized digital feedback are also evaluated. Nevertheless, the obtained results are limited to showing SE values using theoretical equations. On the contrary, a more practical analysis based on the bit error rate (BER) is missing. Recently, a real-time testbed has been developed in [16] to evaluate IA algorithms in heterogeneous networks. However, details regarding the implementation of synchronism, channel estimation, and feedback stages are not provided.

Based on the results achieved by these previous solutions, several issues need further study. The efficient coordination between the network users to properly align the interference is still an open problem. The channel estimation and synchronization stages require further improvements to reduce overhead and avoid imperfect CSI. Furthermore, the results presented are limited to offering an analysis of the SE versus SNR. Nevertheless, a study of the BER considering different levels of interference is not illustrated.

A. Contributions

This paper proposes a novel approach for the practical implementation of IA techniques using USRPs. The proposed solution is based on the MAX-SINR IA algorithm to manage the interference in multi-user MIMO ICs. A practical strategy for the channel estimation and synchronization stages in an IC that are usually omitted in theoretical works is described. The least square (LS) method is implemented for the channel estimation. The time synchronization step is based on the Schmidl and Cox algorithm [17]. A detailed description of the structure of the training sequence used for synchronization and channel estimation is provided to serve as a guideline for future designs. The performance of the proposed implementation is evaluated in terms of the SINR gain, SE, and BER for a 3-user IC. All the results are based on real measurements obtained at

the receiver side with each USRP. Unlike previous works, the performance metrics are obtained for several values of SINR measured at the input of the receiver. Therefore, a practical study of the performance of the IA technique in a network with different levels of interference is provided. Furthermore, although previous articles are only limited to analyzing the SE of the system, in this work, the BER obtained with each receiver is also illustrated. The BER is the main parameter to prove that the stages of channel estimation, synchronization, and interference cancellation with the MAX-SINR algorithm are properly designed.

The obtained results provide valuable insights of the IA performance in real ICs. The sensitivity of the IA algorithms against imperfect CSI is proved with real data. Furthermore, the SINR and SE gain obtained with the MAX-SINR algorithm justify its application in multi-user ICs. Although the proposed implementation is evaluated for a particular 3-user IC, it is easily scalable to a denser network. The results shown in this work serve as a baseline to characterize the UDNs foreseen in 5G/B5G systems.

B. Organization

The remainder of the paper is structured as follows. The system model is detailed in Section II. The proposed implementation of the IA algorithm using USRPs is explained in Section III. The results are presented and discussed in Section IV. Finally, Section V concludes the paper.

C. Notation

In this paper, boldface lower-case letters are used for vectors, while boldface upper-case letters are used for matrices. $\mathbf{A}^H$ and $\mathbf{A}^{-1}$ represent the conjugate transpose, and inverse of matrix $\mathbf{A}$, respectively. $\|\mathbf{a}\|$ is the Euclidean norm of vector $\mathbf{a}$. $|a|$ is the modulus of the complex number a. $\mathbb{C}^{N \times M}$ is the space of complex $N \times M$ matrices. $\mathcal{CN}\left(\mu, \sigma^2\right)$ is the complex Gaussian distribution with mean μ and variance σ^2. $\mathbf{I}_N$ is the $N \times N$ identity matrix.

II. SYSTEM MODEL

A downlink K-user MIMO IC system is considered, as illustrated in Fig. 1. In particular, an IC composed of $K = 3$ pairs of transmitters and receivers equipped with $N_t = 2$ and $N_r = 2$ antennas, respectively, is assumed. Each transmitter sends a single data stream to its corresponding receiver but interferes with the remaining $K - 1$ unintended users. The interference in the network is managed by the precoding and combining vectors based on IA algorithms.

Considering a flat fading channel, the signal at the k-th receiver for any time index, can be written as

$$\hat{\mathbf{s}}_k = \overbrace{\mathbf{u}_k^H \mathbf{H}_{kk} \mathbf{w}_k s_k}^{\text{useful signal}} + \mathbf{u}_k^H \overbrace{\sum_{j=1, j \neq k}^{K} \mathbf{H}_{kj} \mathbf{w}_j s_j}^{\text{interference}} + \overbrace{\mathbf{u}_k^H \mathbf{n}_k}^{\text{noise}}, \quad (1)$$

where $s_k \in \mathbb{C}$ denotes the modulated symbol with a power $P_k = |s_k|^2$, and $\mathbf{w}_k \in \mathbb{C}^{N_t \times 1}$ is the precoding vector. The
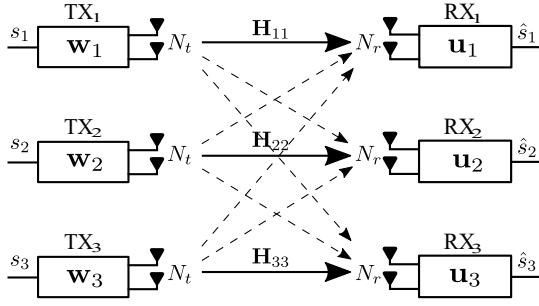
Fig. 1. Block diagram of the K-user MIMO interference channel system.

channel matrix between the j-th transmitter and the k-th receiver, $\forall k, j \in \{1, 2, ..., K\}$, is denoted by $\mathbf{H}_{kj} \in \mathbb{C}^{N_r \times N_t}$. At the receiver side, the combining vector $\mathbf{u}_k \in \mathbb{C}^{N_r \times 1}$ is applied to force the interference terms in (1) to zero and to recover the desired signal without errors. Finally, $\mathbf{n}_k$ represents the additive white Gaussian noise (AWGN) $\left(\mathbf{n}_k \sim \mathcal{CN}(\mathbf{0}, \sigma_{n_k}^2 \mathbf{I}_{N_r}) \right)$.

The main goal of this paper is to obtain a hardware implementation of the precoding and combining vectors based on the MAX-SINR algorithm [5] to maximize the SE of the network, known as sum-SE. This is formally denoted as

$$\max_{\mathbf{u}_k, \mathbf{w}_k} \quad \sum_{k=1}^{K} R_k \qquad (2)$$

$$s.t. \quad \|\mathbf{w}_k\|^2 = \|\mathbf{u}_k\|^2 = 1, \qquad (2a)$$

where the SE achieved at the k-th receiver is given by the Shannon equation $R_k = \log_2 \left(1 + SINR_k\right)$. The SINR is computed as follows [5]

$$SINR_k = \frac{\left| \mathbf{u}_k^H \mathbf{H}_{kk} \mathbf{w}_k \right|^2 P_k}{\mathbf{u}_k^H \mathbf{B}_k \mathbf{u}_k}, \qquad (3)$$

where $\mathbf{B}_k = \sum_{j=1, j \neq k}^{K} P_j \mathbf{H}_{kj} \mathbf{w}_j \mathbf{w}_j^H \mathbf{H}_{kj}^H + \sigma_{n_k}^2 \mathbf{I}_{N_r}$ is the interference-plus-noise covariance matrix. The MAX-SINR algorithm [5] assumes the channel reciprocity to alternatively design $\mathbf{u}_k$ and $\mathbf{w}_k$ such that the SINR of the system increases at each iteration. The process starts by fixing a precoding vector and computing the combining vector that maximizes (3) as [5]

$$\mathbf{u}_k = \frac{(\mathbf{B}_k)^{-1} \mathbf{H}_{kk} \mathbf{w}_k}{\left\| (\mathbf{B}_k)^{-1} \mathbf{H}_{kk} \mathbf{w}_k \right\|}. \qquad (4)$$

According to the channel reciprocity, the inverse channel between the k-th receiver and the j-th transmitter is given by $\overleftarrow{\mathbf{H}}_{jk} = \mathbf{H}_{kj}^H$. Therefore, $\mathbf{w}_j$ is designed to maximize the SINR in the inverse channel for the combining vector computed in the previous step as [5]

$$\mathbf{w}_j = \frac{(\mathbf{Q}_j)^{-1} \mathbf{H}_{jj}^H \mathbf{u}_k}{\left\| (\mathbf{Q}_j)^{-1} \mathbf{H}_{jj}^H \mathbf{u}_k \right\|}, \qquad (5)$$

where $\mathbf{Q}_j = \sum_{k=1, k \neq j}^{K} P_k \mathbf{H}_{kj}^H \mathbf{u}_k \mathbf{u}_k^H \mathbf{H}_{kj} + \sigma_{n_j}^2 \mathbf{I}_{N_t}$ is the interference-plus-noise covariance matrix at the inverse channel.

The precoding and combining vectors are alternatively updated in an iterative process until the SINR converges to a local maximum or until a given number of iterations is reached. Given the non-convex nature of the optimization problem, convergence to a global optimum is not guaranteed. From the equations above, it can be noted that computing $\mathbf{u}_k$ and $\mathbf{w}_k$ requires that each transmitter and receiver knows all the channel matrices of the system. With this aim, a channel estimation stage that involves the coordination among all nodes is needed. The major problem is the increment of training signals leading to a reduction of the transmission efficiency. The next section deals with this problem following a practical approach.

III. PROPOSED IMPLEMENTATION

The proposed IA implementation is based on the K-user IC shown in Fig. 1. Each transmitter and receiver is implemented on the National Instruments (NI) USRP-2942, which supports a MIMO configuration with two antennas. This is a commonly used software-programmable device for testing and validating wireless communications systems. The USRPs are programmed by using the NI Labview 2021 software. Each node is connected through a Gigabit Ethernet link to a central processing unit (CPU) which is used to control the six USRPs. However, completely independent processing chains are implemented to emulate a practical deployment of a communication network.

The major implementation issue is that the MAX-SINR algorithm requires a complete knowledge of the CSI. To overcome this problem, the proposed design is divided into two stages. First, a training stage is implemented in the downlink to estimate the direct and interference channels matrices (i.e., $\mathbf{H}_{kk}$ and $\mathbf{H}_{kj}$, respectively, $\forall k, j \in \{1, 2..., K\}$). Each transmitter sends a known training sequence (TS) which is used by the receivers to perform time synchronization and channel estimation. Based on the estimated CSI, the CPU computes the precoding and combining vectors with the MAX-SINR algorithm.

Then, a communication stage is implemented where each transmitter sends a single precoded data stream to its corresponding receiver. A TS is added as a preamble to synchronize each receiver with its corresponding transmitter. Finally, the interference is reduced by the combining vector and the received data is properly recovered. The length of the data packet is limited by the channel coherence time. After this time, the training stage is repeated to avoid outdated CSI with the consequent interference misalignment.

A. Training stage

Fig. 2 shows the structure of the training stage. Each transmitter sends the TS per antenna orthogonally in the time domain. The TS is used for two purposes: synchronization and channel estimation. To avoid a carrier frequency offset, an external oscillator is used to share the same signal clock with all USRPs. Nevertheless, a time synchronization block is required to detect the start of the frame. With this aim, an
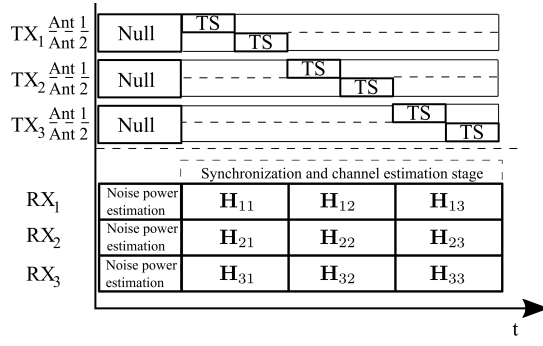
Fig. 2.   Training package structure.

Fig. 3.   Measured and simulated SINR after multiplying the received signal by the IA combining vector vs SINR before the combiner.

adaptation of the Schmidl and Cox method [17] for a single carrier frequency is implemented.

Based on the IEEE 802.11a preamble described in [18], the TS is composed of a frame of $N_{ss} = 16$ identical short symbols (SS) with low cross-correlation with the transmitted data symbols. Each SS is formed as an 11-length Barker´s code leading to a TS with a length of $L = 176$ symbols. The higher the length of this sequence, the higher the probability of correctly detecting the synchronism for a wide range of SNR. However, a higher overhead is generated. Therefore, the selected length guarantees a good tradeoff between performance and transmission efficiency. The main idea is to obtain a sequence with repeated patterns in the time domain to detect its presence by applying an auto-correlation. With this aim, the received signal in a window of length L is auto-correlated with a delayed window of the same length. A threshold ζ is set to find the position of the maximum value of the auto-correlation. The selection of the threshold is crucial to guarantee the proper performance of the synchronization. In [17], a relation between the threshold and SNR is proved as $\zeta = \left(\frac{SNR}{1+SNR} \right)^2$. To fix this threshold, the SNR is estimated by first computing the noise power in the interval of Fig. 2 where all transmitters are silent. Then, the received power is estimated with the received TS.

Assuming that the receiver knows the TS and the start of the received frame is correctly detected with the synchronization step, an LS method is applied for channel estimation. Since the transmitters send their TS orthogonally in the time domain, each receiver estimates the channel matrix with the active transmitter at each time interval as shown in Fig. 2. Finally, the precoding and combining vectors are computed by the MAX-SINR expressions (4) and (5).

Although the proposed design has been implemented for a particular 3-user IC, it is easily scalable to a denser network. The maximum number of users that can be managed depends on the values of N_t and N_r according to the theoretical feasibility conditions of IA algorithms. In this sense, a denser network requires higher spatial dimensions to align the interference. This is achieved by adding more antennas. However, an increment in the number of users and antennas leads to a longer training stage. A total of $N_t K$ TSs transmission intervals are required 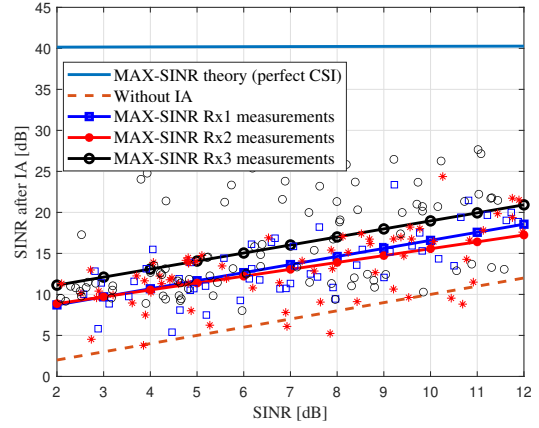to acquire the global CSI of the entire network. Therefore, the maximum number of users that can be coordinated is also related to channel variability.

B. Communication stage

This stage is addressed to establish the communication between the K transmitter/receiver pairs of the network avoiding interference between them. The transmitted data symbols are generated using a pseudo-noise (PN) bit generator block which can be configured to obtain a Galois or a Fibonacci sequence with different orders (e.g., orders 5 to 31). The sequence of bits is modulated by using a QPSK constellation. Similar to the training stage, a predefined TS is added to the header of the data packet to synchronize the receiver with the transmitter and hence, to detect the start of the data frame. The received signal is multiplied by the combining vector to reduce the interference signals and to recover the desired data symbols. The performance of the proposed implementation is evaluated in the next section.

IV.   MEASUREMENT SETUP AND RESULTS

The proposed implementation is validated for a K-user MIMO IC with $K = 3$, and $N_t = N_r = 2$. Each transmitter and receiver are implemented on a USRP-2942. The CPU is configured over a workstation with an Intel Core i7-10750H processor working at 2.6 GHz. An Octoclock CDA-2990 is used as an external clock to avoid frequency offset. The QPSK data symbols are transmitted over a central frequency of 1 GHz. The USRPs are distributed in an indoor laboratory. The interference levels are controlled by modifying the transmission powers of the interfering transmitters leading to a scenario with different SINR values. The performance of our proposal is measured in terms of the SINR gain, SE, and BER. All the figures are obtained by performing several measurements at each receiver in the communication stage.

Fig. 3 shows the SINR measured after multiplying the received signal by the combining vector versus the SINR at the input of the receiver, i.e., before the combiner. Each

SINR value is an instantaneous estimation per receiver obtained during the communication stage before and after the combining vector block. The interference power is estimated by first measuring the power of the received data packet. Then, the noise and desired signal power, which have been previously measured during the training stage, are subtracted leading to the interference level estimation. A linear fit of the corresponding measured data is also illustrated with a marked solid line. The unmarked solid line represents the theoretical SINR achieved with the MAX-SINR algorithm [5]. This is our benchmark because it is obtained by simulation in Matlab assuming perfect CSI. On the contrary, the unmarked dashed line shows the SINR without applying an IA stage which corresponds with an SINR gain of 0 dB. The simulation results are averaged over the three receivers and 100 channel realizations. The simulation parameters are fixed according to the experimentally measured data (e.g., $\sigma_n^2 = 4.6 \cdot 10^{-9}$, $P_t = 50 \cdot 10^{-3}$). The channel is modeled as a Rayleigh block fading where each entry is assumed to be independent and identically distributed (i.i.d) with zero mean and variance 10^{-3}. It can be observed that with the theoretical IA, a constant SINR value is obtained after the combining vector for the entire SINR range measured before the combiner. This is because IA algorithms with perfect CSI are capable of reducing the interference levels below the noise variance. Consequently, a system limited by noise is obtained after the combiner. Furthermore, Fig. 3 depicts how the SINR values increase after applying the IA stage with the proposed design. It can be noted that an averaged SINR gain of 9 dB is achieved by the receiver 3. This proves that the IA implementation described in this paper reduces the interference levels of the network providing a suitable design for ICs.

Although the interference is significantly decreased with our proposal, the measured SINR values are still below the theoretical MAX-SINR line. This is because the performance of the proposed hardware implementation is affected by channel estimation errors and non-instantaneous CSI that can not be avoided in a practical scenario. Fig. 3 reveals with real measurements that the IA algorithm is highly sensitive to imperfect CSI. Therefore, the channel estimation stage and update rate of the IA matrices must be meticulously designed according to the coherence time.

To provide further details about the performance achieved by the proposed design, Fig. 4 shows the SE per receiver in an SINR range between 2 to 12 dB. The SE values are obtained by applying the Shannon equation with the measured SINR. Similar to Fig. 3, the unmarked solid line represents the theoretical MAX-SINR algorithm which is our benchmark. The dashed line is the averaged SE of the singular value decomposition (SVD) method obtained by simulation assuming perfect CSI. It is well-known that SVD is the optimal solution only for a single-user MIMO (SU-MIMO) system without interfering signals [19]. It can be observed that the SE obtained with the proposed implementation is higher than the SVD even when SVD is designed assuming perfect CSI. This result proves the importance of implementing a
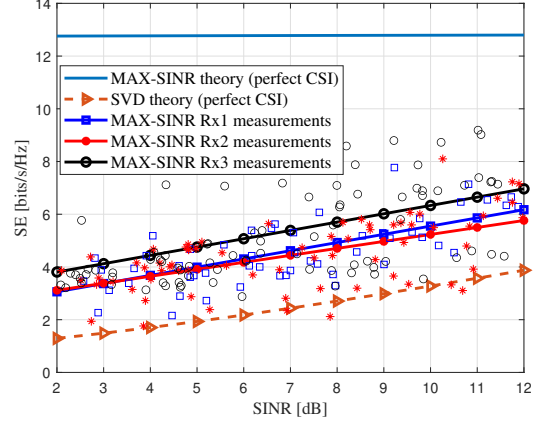

Fig. 4.   Measured and simulated SE vs SINR before the combiner.

technique that considers the effects of interference in a multi-user IC. Therefore, MAX-SINR algorithm is a great solution to improve the capacity of future ultra-dense wireless networks.

Fig. 5 shows the BER achieved by the three users versus the SINR measured before the combiner. The BER is obtained during the communication stage by averaging over several experiments and without applying any channel coding technique. At each experiment, the BER is also averaged over a transmission time long enough to meet the Monte Carlo confidence criteria. The BER is the main parameter to illustrate the correct performance of the system. With this figure, it is possible to evaluate that the stages of channel estimation, synchronization, and IA are properly designed to reach BER values up to 10^{-6}.

V. Conclusions

This work proposes a practical implementation of the MAX-SINR IA algorithm for a multi-user MIMO IC using the NI USRP-2942. The proposed solution is divided into a training and a communication stage. First, the training stage is used for synchronization, channel estimation, and IA computation. Then, the communication of $K = 3$ pairs of transmitters and receivers using the same time/frequency resources is achieved by applying the IA vectors to cancel the interference and recover the desired data. It is observed that channel estimation is a crucial step for the computation of the precoding and combining IA vectors. It is proved with real measured results that IA algorithms are highly sensitive to imperfect CSI. Furthermore, it is also shown the SINR gain and SE improvement obtained with IA algorithms over traditional precoding techniques such as SVD. This study provides a better understanding of the benefits of IA strategies to enhance the system performance in multi-user MIMO ICs over precoding techniques that neglect inter-user interference control. The obtained results provide valuable insights into the IA capabilities serving as a baseline to manage higher interference levels foreseen in 5G and B5G wireless networks.
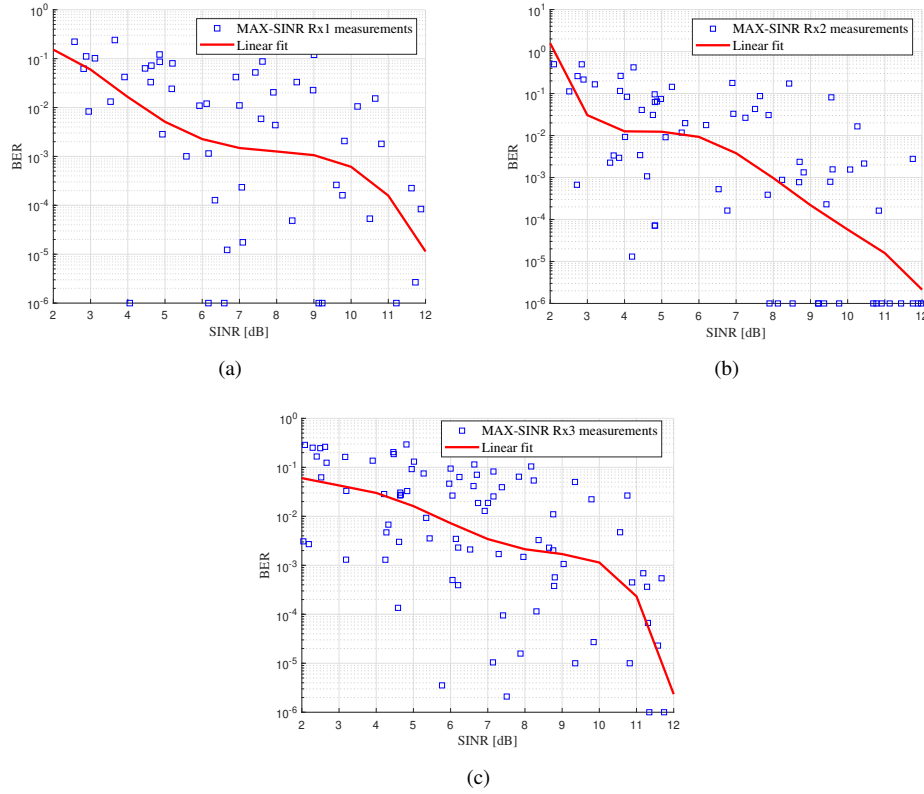
Fig. 5.   Measured BER vs SINR before the combiner achieved by; (a) Receiver-1; (b) Receiver-2; and (c) Receiver-3.

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