Experimental Performance Evaluation of Cell-Free Massive MIMO Systems Using COTS RRU With OTA Reciprocity Calibration and Phase Synchronization

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Abstract—Downlink coherent multiuser transmission is an essential technique for cell-free massive multiple-input multiple-output (MIMO) systems, and the availability of channel state information (CSI) at the transmitter is a basic requirement. To avoid CSI feedback in a time-division duplex system, the uplink channel parameters should be calibrated to obtain the downlink CSI due to the radio frequency circuit mismatch of the transceiver. In this paper, a design of a reference signal for over-the-air reciprocity calibration is proposed. The frequency domain generated reference signals can make full use of the flexible frame structure of the fifth-generation (5G) new radio, which can be completely transparent to commercial off-the-shelf (COTS) remote radio units (RRU) and commercial user equipments. To further obtain the calibration of multiple RRUs, an interleaved RRU grouping with a genetic algorithm is proposed, and an averaged Argos calibration algorithm is also presented. We develop a cell-free massive MIMO prototype system with COTS RRUs, demonstrate the statistical characteristics of the calibration error and the effectiveness of the calibration algorithm, and evaluate the impact of the calibration delay on the different cooperative transmission schemes.

Index Terms—Cell-free massive MIMO, distributed MIMO, OTA reciprocity calibration, phase synchronization.

Spectral efficiency (SE) is one of the key parameter indicators in the design of cellular mobile communication systems. For the fifth-generation (5G) system with massive multiple-input multiple-output (MIMO) technology [1], the SE can be increased to more than 50 bps/Hz. By using the remote radio units (RRUs) deployed in the existing cellular systems and introducing a coordinated multipoint (CoMP) transmission technique, the SE can be further increased. The related technologies are also referred to as distributed MIMO, cooperative MIMO, multiple transmission and reception points (multi-TRP), or cell-free massive MIMO (CF-mMIMO) [2]. CF-mMIMO can be viewed as an evolution of distributed MIMO or CoMP [3]. It employs scalable implementation to achieve coordinated multiuser transmission, thereby substantially improving SE [4], [5], [6], [7], [8], [9], [10]. The combination of CF-mMIMO with millimeter-wave or terahertz massive MIMO allows for ultra-high peak rates while improving SE [11], [12]. Therefore, CF-mMIMO has been considered an enabling technology for the sixth-generation (6G) [2].

In uplink CF-mMIMO systems, a distributed joint receiver can be implemented with very low complexity [9], [10]. For the downlink, coherent joint transmission (CJT) is adopted to achieve space-division multiplexing, which usually relies on known downlink channel state information (CSI) at the central processing unit (CPU). Exploiting the reciprocity of the over-the-air (OTA) channels in a time-division duplex (TDD) system, the feedback of the downlink CSI can be avoided, and then the signaling overhead can be reduced. However, in a practical system, the overall channels are composed of OTA propagation coefficients and the transmission coefficients introduced by the radio frequency (RF) transceivers. Since the RF transmitter and receiver have different transmission coefficients, the overall uplink and downlink channels are not reciprocal in practice. The mismatches in downlink-uplink channels include amplitude and phase mismatches. [13] showed that the downlink performance loss of a CF-mMIMO system is large when the phase mismatch is...
greater than 15°. One of the factors delaying the application of the CoMP technique in commercial fourth-generation (4G) and 5G systems was the reciprocity calibration or phase synchronization between distributed RRUs. A working group of 3GPP is studying the coherent transmission of multi-TRP for 5G new radio (NR) release 18 [14], and the reciprocity calibration (or phase synchronization in some literature) of the downlink-uplink channels is a critical issue. Therefore, OTA reciprocity calibration is a crucial technique in future 6G-oriented CF-mMIMO [15], [16].

There are two main types of calibration methods, namely, hardware calibration and OTA calibration. The former requires an additional reference antenna, while the latter does not require extra hardware. Both methods have been extensively studied in TDD massive MIMO [17], [18], [19]. However, unlike in the centralized massive MIMO system, multiple RRUs are physically deployed at different locations in a CF-mMIMO system; therefore, OTA calibration is desirable. OTA calibration can be achieved by transmitting known reference signals between RRUs or between RRUs and user equipments (UEs). The former is referred to as self-calibration, and the latter is named UE-assisted calibration. Both algorithms can obtain the calibration coefficients of the RRUs, whereas self-calibration is preferable since it is transparent\(^1\) to the UE. With uplink CSI and the calibration coefficients obtained from the collected calibration signals, coherent transmission can be achieved by using the calibrated downlink precoding [20].

OTA reciprocity calibration has been widely studied for distributed MIMO. [21] investigated the calibration of multiple remote radio units (RRUs) and proposed a cluster-based calibration method. To date, distributed MIMO has been experimentally studied in WiFi/long-term evolution (LTE) networks. References [22] and [23] implemented WiFi-based distributed MIMO, in which AirSync used the out-of-band signals for synchronization and MegaMIMO used a primary device with multiple secondary devices for synchronization. In [24], a hierarchical synchronization architecture was proposed for the phase synchronization of the whole network. The design in [24] is compatible with a 5G small cell and has been verified on an LTE system. However, the method in [24] requires the deployment of virtual UEs to support calibration. References [25] and [26] implemented a distributed MIMO system using the open-air-interface platform and proposed a primary-secondary calibration algorithm and a fast calibration method with RRU grouping, which can complete the calibration within 20 milliseconds. In [27], a distributed MIMO system was implemented, and a weighted least squares calibration method was proposed with CSI feedback from the UE.

For 5G evolution or 6G systems, calibration signals should be standardized to enable interoperability between devices. In addition, to realize cell-free networking, it is necessary to further study an ultrafast calibration method with low complexity and low overhead. Furthermore, there are no publicly available performance evaluations of experimental systems for CF-mMIMO with scalable precoding and imperfect calibration. The main research contributions of this study are summarized as follows:

1) We propose a group-based fast OTA reciprocity calibration scheme with a genetic algorithm-aided RRU grouping and a 5G NR compatible calibration reference signal (CARS). Different from [24], [25], [26], and [27], the calibration process does not require UE feedback, transparently supports both commercial off-the-shelf (COTS) RRUs and commercial UEs, and is especially suitable for the RRU implemented following the specification of open radio access network (ORAN) [28]. The CARS can achieve the calibration of up to 64 antennas on four orthogonal frequency-division multiplexing (OFDM [29], [30]) symbols in one slot (for example, approximately 134 \(\mu\)s for a 30 kHz subcarrier spacing).

2) This study proposes an improved Argos calibration method suitable for CF-mMIMO, which can make full use of the wireless links between multiple RRUs to improve the calibration accuracy and reduce the calibration complexity.

3) In this study, a CF-mMIMO prototype system with the 5G COTS RRU is developed, which is fully compatible with 5G commercial UEs. With the prototype UEs, the calibration coefficients obtained from the experimental system are analyzed and evaluated, including the statistical characteristics of the calibration errors and the performances of different calibration algorithms. Based on the testbed, we present the performance evaluations of the centralized and distributed precoders for downlink CF-mMIMO.

The paper is organized as follows: Section II presents the 5G NR compatible CARS, the group-based calibration algorithm is investigated in Section III, and Section IV presents the experimental verification results, followed by the conclusion of this study in Section V.

The notation conventions in this paper are as follows: Matrices and vectors are denoted by bold italic uppercase and lowercase letters, respectively; \(\text{diag}(x)\) is a diagonal matrix with \(x\) on its diagonal; \(\text{diag}(A)\) denotes a vector with the main diagonal of \(A\); \((\cdot)^H\), \((\cdot)^T\), and \((\cdot)^*\) represent Hermitian transpose, transpose, and conjugate, respectively; \(\circ\) represents Hadamard multiplication of two matrices; and \(\odot\) denotes an element-wise division of two matrices.

II. RRU GROUPING AND DESIGN OF A 5G NR-COMPATIBLE CALIBRATION SIGNAL

In a CF-mMIMO system, all of the RRUs should be calibrated for dynamic downlink coherent transmission. Location-based clustering is usually an effective way to reduce the calibration dimension for a CF-mMIMO system with a large number of RRUs. In [21], intercluster relative calibration and intracluster least squares calibration were proposed. An alternative transmission of the calibration signals was presented for

\(^1\)In this paper, ‘transparency’ means that a commercial UE (or COTS RRU) can benefit from coherent precoding with TDD calibration without being aware of how it is accomplished.
the calibration of RRU s in a cluster. The method exhibits an optimal performance but has a large calibration time.

In this study, the RRU s in a cluster are divided into two groups, and spatial-domain orthogonal calibration signals are transmitted between the two groups, thereby reducing the calibration time. In this section, we study an optimal RRU grouping and then design a 5G NR-compatible calibration signal for the two groups.

A. Interleaved RRU Grouping With Genetic Algorithm

In [25], a group-based calibration was proposed. However, the authors did not provide an effective method to obtain the optimal grouping. Intuitively, to obtain a better calibration signal-to-noise ratio (SNR), the two groups of RRU s should be interleaved together as much as possible. Note that when the RRU s are deployed, the calibration SNR between RRU s is mostly related to the large-scale fading, which is the relative distance between the RRU s. To achieve a better performance of the group-based calibration, we minimize the sum of the distances between the two groups of RRU s. Therefore, we formulate the minimization problem as follows:

\[
\min \sum_{p \in \mathcal{P}} \sum_{q \in \mathcal{Q}} d_{p,q} \tag{1}
\]

s.t. \( \mathcal{P} \cup \mathcal{Q} = T \) and \( \mathcal{P} \cap \mathcal{Q} = \emptyset \) and \( ||\mathcal{P}|-|\mathcal{Q}|| \leq 1 \)

where \( T \) is a set of all RRU s, the antennas are divided into two sets \( \mathcal{P} \) and \( \mathcal{Q} \), in which there are \( M \) antennas in group \( \mathcal{P} \) and \( N \) antennas in group \( \mathcal{Q} \), and \( d_{p,q} \) is the distance between antenna \( p \) in group \( \mathcal{P} \) and antenna \( q \) in group \( \mathcal{Q} \). Note that to simplify the problem, the difference in the number of RRU s in the two sets is less than or equal to one. With this constraint, the numbers of RRU s in the two groups are balanced.

When the number of RRU s is not large, we can use an exhaustive search to obtain the optimal solution to the optimization problem (1). However, when the number of RRU s is large, the complexity is high. Fortunately, the grouping is performed just once after the deployment of the RRU s. This optimization problem can be described by binary variables and then solved by a genetic algorithm (GA). A genetic algorithm is a heuristic search inspired by the process of natural selection, which is commonly used to generate high-quality solutions to optimization and search problems by relying on bioinspired operators such as mutation, crossover, and selection [31], [32].

In this paper, all \( N_{RRU} \) RRU s (here \( N_{RRU} = M + N \)) are divided into two groups. The population size is set to the number of RRU \( N_{RRU} \) and the offspringsize is set to \( N_{OS} = 0.8N_{RRU} \). The individual gene sequences of populations are represented as \( N_{RRU} \)-bit binary numbers, where the bit position indicates the RRU index, a bit value of 1 indicates that the RRU corresponding to this bit location is divided into RRU group 1, and conversely, a bit value of 0 indicates that the corresponding RRU is divided into RRU group 2. The individual’s fitness function is the reciprocal of the objective function (1). For each iteration, we use the fitness function to calculate the cumulative probability, use the roulette wheel method to randomly select \( N_{OS} \) candidates for crossover variation and gene mutation with a certain probability (5%) to obtain \( N_{OS} \) offsprings, calculate the individual fitness of each parent and offspring, and then select \( N_{RRU} \) optimal individuals as the next generation population to enter the next iteration. Since the objective function is executed \( N_{OS} \) times for each iteration, the complexity of the GA is about \( O(M_{iter}N_{RRU}) \), where \( M_{iter} \) is the number of iterations.

After the RRU grouping, we can send multiantenna orthogonal pilots to each other between the two groups, enabling a fast calibration. However, current 5G standards do not explicitly support RRU s sending signals to each other. Fortunately, we can take advantage of the dynamically configurable frame structure of 5G NR to achieve this functionality.

B. Slot Configuration for Calibration of RRU Groups

Figure 1 shows a frame configuration with a period of 2.5ms. The special slot (S-slot) is well-designed to perform a calibration of the two RRU groups. The S-slot configuration of Group 1 is a conventional pattern with a single guard period (GP), and the configuration of Group 2 is with two GPs. Because of the different positions of the downlink-uplink switching points in the S-slots for the two RRU groups, we can transmit and receive reference signals between the RRU groups. As can be seen from the figure, at the 5th and 6th
symbols of the S-slot, the RRUs in Group 1 are transmitting CARS, and the RRUs in Group 2 are receiving. Similarly, the RRUs in Group 1 are receiving when the RRUs in Group 2 are transmitting CARS at the 7th and 8th symbols. Therefore, we can achieve the transmission and reception of calibration signals between the two groups. Note that the CPU should not schedule UEs on these symbols. In addition, since 5G NR supports the dynamic configuration of a subframe through downlink control information, we can configure S-slots as mentioned above according to the calibration period. For the normal slot, all the RRUs can be configured with a common S-slot to avoid cross-link interference.

To evaluate the calibration performance, we also insert the downlink CSI-RS and the uplink sounding reference signal (SRS) into the S-slot to measure the downlink-uplink CSI between the CPU and the UEs.

C. CARS Design Considering Uplink Timing Advance

In the 5G-NR system, considering the propagation delay and the TDD switching time, [33] requires an uplink timing advance; as a result, the uplink and downlink are staggered by approximately 13 µs (for the Sub6 GHz band). As shown in Figure 2, the RRUs in Group 2 start to receive 13 µs in the GP in advance. A commercial UE knows the timing advance, whereas the commercial RRUs in Group 1 have their timing. If the RRUs in Group 1 just transmit CARS in the 6th symbol, the RRU Group 2 cannot receive the correct signal. Therefore, the two groups of RRUs are misaligned when transmitting signals to each other with the configuration of the S-slot in Figure 1.

Note that when the baseband unit can process time-domain OFDM symbols and adjust the TDD switch point, we can transmit and receive CARS in GP. However, for some commercial RRUs, such as those using the Option 7-2 standard [34], the RRU has the functions of low-level physical layer processing, including fast Fourier transform (FFT) /inverse fast Fourier transform (IFFT), cyclic prefix (CP) addition and removal, and phase compensation. This type of COTS RRU only receives the downlink frequency-domain signals from the baseband unit and transmits the uplink frequency-domain signals to the baseband unit. Therefore, it is necessary to design a frequency-domain calibration signal that considers the standardization issue.

To ensure that the CPU receives a correct calibration signal, we propose a two-symbol frequency-domain CARS. A set of multiantenna orthogonal reference signals is designed according to the number of antennas in the two RRU groups. The frequency-domain reference signal $\text{CARS}_i$ for the $i$th antenna is expressed as

$$x_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,N_{\text{FFT}}}]^T,$$

where $N_{\text{FFT}}$ is the length of the FFT, and the $n$-th element of the corresponding $\text{CARS}_2$ is given by

$$\tilde{x}_{i,n} = x_{i,n} \exp \left( \frac{2\pi L_{\text{CP}}}{N_{\text{FFT}}} n \right),$$

That is, each sample undergoes an $L_{\text{CP}}$ phase shift. After FFT, and an addition of a CP, the two symbols have the characteristics shown in Figure 3; that is, the valid data of the former symbol is the CP of the $N_{\text{FFT}}$ samples of the latter symbol.

With the above design, the RRUs start to receive the calibration signal in the first time-domain symbol with a receiving length of $N_{\text{FFT}} + L_{\text{CP}}$; then, after removing the CP, a complete reference signal can be obtained. Note that there is a certain shift between the received calibration sequence and the original calibration sequence, and we can recover it by the phase rotation in the frequency domain. Therefore, the design can be completely transparent to the RRU in Option 7-2 format [34]. With the CARS shown in Figure 3, we have a complete OFDM symbol at the receiver for calibration.

Commercial RRUs with multiple antennas for small-cell systems generally do not have internal calibration, so all the antennas of the RRUs should transmit calibration signals. When there is a large number of RRUs, the calibration signals should be orthogonal to obtain optimal channel estimations. Taking the SRS in 5G NR as an example, one OFDM symbol can support up to 16 antenna ports. Even 32 antenna ports can be multiplexed considering that the coverage area of small cells is usually small and that the calibration coefficients vary little in the frequency domain. Therefore, with the slot configuration shown in Figure 1, we can achieve the calibration of a total of 64 antennas in two sets on four OFDM symbols. Considering a subcarrier spacing of 30 kHz, the time consumption of the calibration is approximately 134 µs.

Finally, the CARS can be reused between clusters by using a similar idea of pilot reuse [35], [36], and the calibration between the clusters can be implemented according to [21] and [37].

III. GROUP-BASED CALIBRATION METHOD

To further improve the calibration accuracy with low complexity, in this section, we study the group-based calibration algorithms, including the traditional total least-square (TLS) and an improved Argos algorithm.
A. TLS Calibration Algorithm

Based on the calibration signals transmitted to each other, each receiver first performs a channel estimation to obtain the frequency-domain channel matrices between the two RRU groups. The channel matrices on a subcarrier between the two RRU groups are denoted as $H_1$ and $H_2$, which can be modeled as follows:

$$H_1 = C_{rx,2}HC_{tx,1},$$

$$H_2 = C_{tx,2}H^T_{tx,2},$$

(4)

(5)

where $H$ is the OTA channel matrix between RRU Group 2 and RRU Group 1; $C_{tx,1}$ and $C_{tx,2}$ are the RF mismatch coefficients of the receiving and transmitting RRUs in Group 1, respectively; and $C_{rx,2}$ and $C_{tx,2}$ are the RF mismatch coefficients of the receiving and transmitting RRUs in Group 2, respectively, each of which is modeled as a diagonal matrix. The following calibration matrices are defined

$$C_1 = C_{tx,1}C_{tx,1}^{-1},$$

$$C_2 = C_{tx,2}C_{tx,2}^{-1}.$$  

(6)

(7)

These are the calibration coefficients of the RRUs in Group 1 and Group 2. According to the above calibration matrix, the following equation is true

$$H_1C_1 = C_2H_2^T.$$  

(8)

The calibration vectors are defined as

$$c_1 = \text{diag}(C_1), \quad c_2 = \text{diag}(C_2),$$

$$c_1 = [c_{1,1} \cdots c_{1,M}]^T, \quad c_2 = [c_{2,1} \cdots c_{2,N}]^T.$$  

Then, the calibration vector of all RRUs can be expressed as

$$c_{cal} = [c_1^T, c_2^T]^T.$$  

According to (8), in the presence of noise, we can establish the following TLS optimization objective function [21], [38]:

$$\arg \min_{c_{cal}} \|H_1C_1 - C_2H_2^T\|^2_s.t.\|c_{cal}\|^2 = 1.$$  

(9)

The calibration model described in (9) is the same as the UE-assisted calibration model proposed in [38]. The above objective function can be expressed as

$$J(c_1, c_2) = \|H_1C_1 - C_2H_2^T\|^2 = \text{Tr}(C_1^H H_1^H H_1C_1 + C_2H_2^T H_2^H C_2^H$$

$$- C_2H_2^T C_1^{-1} H_1^H - H_1C_1H_2^HC_2^H).$$  

(10)

It is noted that the following is true:

$$\text{Tr}(C_1^H H_1^H H_1 C_1) = c_1^H \text{diag}(\text{diag}(H_1^H H_1)) c_1,$$

$$\text{Tr}(C_1^H H_1^H H_1 C_1) = c_1^H \text{diag}(H_1^H) c_1,$$

$$\text{Tr}(C_1^H H_1^H H_1 C_1) = c_1^H (H_1^H \odot H_1) c_1,$$

$$\text{Tr}(C_1^H H_1^H H_1 C_1) = c_1^H (H_1^H \odot H_1) c_1.$$  

Therefore,

$$J(c_1, c_2) = c_1^H A c_{cal},$$

where

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix},$$

$$A_{11} = \text{diag}(\text{diag}(H_1^H H_1)), \quad A_{22} = \text{diag}(\text{diag}(H_2^H H_2)),$$

$$A_{12} = -H_2 \odot H_1^H, \quad A_{21} = H_2^H \odot H_1^H.$$  

Then, the optimization objective function can be rewritten as

$$\min_{c_{cal}} c_{cal}^H A c_{cal}$$

$$\text{s.t.} \|c_{cal}\|^2 = 1.$$  

(11)

According to [21], the optimal solution of $c_{cal}$ is the eigenvector corresponding to the minimum eigenvalue of $A$, so that we may obtain the calibration coefficients of all the RRUs.

Note that the TLS calibration requires an eigenvalue decomposition of $A$ with the computation complexity $O((M + N)^3)$.

B. Averaged Argos Calibration Algorithm

To reduce the complexity of implementation, we propose an improved Argos calibration. For simplicity of the following description, the channel noise is neglected. Based on the two sets of channel matrices, we have the following:

$$\Theta_1 = H_1 \odot H_2^T,$$

where $\odot$ represents the division of the corresponding elements of the two matrices. Therefore, the above equation can be expressed as

$$\Theta_1 = c_2 [\text{diag}(C_1^{-1})]^T = \begin{bmatrix} c_{2,1} & c_{1,1} & \cdots & c_{2,1} \\ c_{2,1} & c_{1,1} & \cdots & c_{2,1} \\ \vdots & \vdots & \ddots & \vdots \\ c_{2,N} & c_{1,N} & \cdots & c_{2,N} \\ c_{1,1} & c_{1,2} & \cdots & c_{1,M} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ c_{1,M} & c_{1,M} & \cdots & c_{1,N} \end{bmatrix},$$

(12)

where $\text{diag}(C_{1}^{-1})$ is the reciprocal of each element of the vector $c_1$. The matrix $\Theta_1$ is a rank-1 matrix. We define the following matrix

$$\Theta_2 = H_2 \odot H_1^T = c_1 [\text{diag}(C_{1}^{-1})]^T$$

$$= \begin{bmatrix} c_{1,1} & c_{1,1} & \cdots & c_{1,1} \\ c_{1,2} & c_{1,2} & \cdots & c_{1,2} \\ \vdots & \vdots & \ddots & \vdots \\ c_{1,M} & c_{1,M} & \cdots & c_{1,N} \end{bmatrix},$$

(13)

where $\text{diag}(C_{1}^{-1})$ is a diagonal matrix formed by the reciprocal of each element of the vector $c_1$.

Consider the $N$th antenna of Group 2 as a reference antenna to describe the proposed calibration algorithm. The last column
of $\Theta_2$ is defined as $\vartheta$. Then, each column of $\Theta_2$ is multiplied by the corresponding diagonal element of $\Theta_1$ to obtain

$$\hat{\Theta}_2 = \Theta_2 \text{diag} \left[ \text{diag} \left( \Theta_1 \right) \right].$$

Then, we construct the following matrix

$$\Theta = \begin{bmatrix} \hat{\Theta}_2 \\ \Theta_1 \end{bmatrix} \text{diag} \left( \vartheta \right).$$

It can be seen that all columns of $\Theta$ are equal to $c_{\text{cal}}/c_{2,N}$ except the last column containing all ones (in practice, the last row can be directly assigned to 1 and is not involved in the calculation). We can average the matrix by column to obtain the final calibration coefficient.

However, in a practical system, the channel estimation is not perfect, and especially in a distributed MIMO system, when the distance between two RRUs is too large, the calibration signal experiences severe fading, resulting in a poor SNR, which eventually affects the accuracy of the calibration. If some solutions deviate too much from the normal value, the averaging in the above algorithm inevitably leads to performance degradation, so some anomalous solutions must be removed. Therefore, the following operations are performed for $\Theta_1$ and $\Theta_2$:

1) Find antenna $i$ in Group 1 that has the smallest sum of the distances from all antennas in Group 2 and find antenna $j$ in Group 2 that has the smallest sum of the distances from all antennas in group 1.
2) Find all the RRU pairs in RRU Group 1 and RRU Group 2 with an SNR less than a specified threshold. For example, assume that the SNR between antenna pair $(p, q)$ is less than a given threshold, where $p$ is an antenna in Group 1 and $q$ is an antenna in Group 2; then, let $[\Theta_1]_{i,p} = 0$ and $[\Theta_2]_{j,q} = 0$. Note that the zero-setting operation is not performed on the $j$th row of $\Theta_1$ or the $i$th row of $\Theta_2$.

Based on the above results, matrices $\Theta_2$ and $\Theta_1$ are calibrated for the $j$th and $i$th rows, respectively, and then averaged. The Argos algorithm for multiantenna averaging requires $2MN$ divisions, $2MN$ multiplications, and $MN$ additions for calibration, showing a lower complexity and an easier hardware implementation than TLS.

C. Simulation Results

Figure 4 shows the phase errors (in degrees) of the calibration coefficients for different system configurations with different calibration algorithms. In the simulation, the amplitude of the RF gain follows a log-normal distribution with a variance of 1 dB, and the phase follows a continuous uniform distribution on the interval $(-\pi, \pi)$. In the simulation, there are two RRUs, each with 8 (or 16) antennas. The inter-RRU channel is modeled by an independent and identically distributed (i.i.d.) Rayleigh fading. Considering that the amplitude error of the calibration coefficient has a minor impact on overall performance [13], [39], we are only concerned about phase error. To evaluate the accuracy of phase calibration, we normalize the calibration coefficients relative to a specific antenna.

From Figure 4, it can be seen that TLS significantly outperforms Argos and has an average phase error of less than 1° at a calibration SNR of 25 dB. Argos with a single reference antenna has poor calibration performance, with an error of approximately 4° at a calibration SNR of 31 dB. After averaging over multiple antennas, the calibration performance of Argos is improved; for example, an SNR gain of more than 8 dB is obtained for averaging eight antennas. Considering the complexity and accuracy, we can use the method of averaging over multiple antennas to improve the calibration accuracy of Argos in a practical system.

Next, we will demonstrate the performance of GA-based grouping and the averaged Argos algorithm considering the practical deployment of RRUs. For large-scale fading, we utilize the following model [40]:

$$\lambda(d) = 2\lambda_1 \left[ 1 + \left( 1 + d/d_0 \right)^\alpha \right]^{-1},$$

where $\lambda$ denotes the path loss at the reference point, which is given by

$$\lambda_{dB} = -34.5 - 20\log_{10}(d_0) - N_{NF} - 10\log_{10}(N_{BW}) - N_0.$$ 

The reference distance $d_0$ is 10 meters. $N_{NF}$ denotes the noise figure, which is set to 9 dB, $N_0$ is the thermal noise power density with -174 dBm/Hz, and the system bandwidth $N_{BW}$ is 1 MHz. The total number of RRUs is 8. Each RRU is with a single antenna. The path loss exponent $\alpha$ is set to 3.7. The RRU positions are randomly generated within a circle with a radius of 200 meters for 300 iterations; the corresponding large-scale fading is randomly generated 300 times for each.

From the simulation results in Figure 5, it can be seen that the performance of the TLS algorithm has been improved after a GA-based grouping. For a calibration power of 26 dBm, the performance was improved by about 20% compared with the random grouping. It is also demonstrated that for practical deployment, direct averaging is not the best option. We can select appropriate channels with the method in subsection III-B to obtain significant performance improvements.

IV. OTA CALIBRATION TEST RESULTS OF A CF-mMIMO SYSTEM

A. Prototype System

Figure 6 shows the CF-mMIMO prototype system. The test environment is shown in Figure 7. Low-cost RRUs for
5G indoor coverage are used. The system operates in the 4.9 GHz band with a bandwidth of 100 MHz. There are four RRUs and four UEs in the system, and the number of antennas of each RRU/UE is four. An evolved common public radio interface (eCPRI) is used between the RRU and the fronthaul accelerator card, which complies with the open radio access network (ORAN). The fronthaul between RRU and CPU follows the ORAN specification [28]. To reduce the fronthaul throughput, block-floating compression is adopted, and data compression methods should be further studied to achieve a better complexity and performance tradeoff [41]. The CPU provides time synchronization and the reference clock for multiple RRUs by using IEEE 1588 precision time protocol (IEEE 1588 PTP) and synchronous Ethernet (SyncE) protocol. Each RRU has an independent local oscillator (LO), but the four RF chains in one RRU share the same LO. The prototype UE uses a similar hardware platform to the CPU.

We divide the four RRUs on the CPU side into two groups and use the frame structure shown in Figure 1. The calibration signal between the two RRU groups is the same as the uplink SRS, which occupies 272 resource blocks (RBs). The channel estimation in this study adopts a Wiener interpolation based on the uniform power delay profile. For downlink channel estimation, we adopt the CSI-RS with 16 orthogonal ports.

In the practical system, it is difficult to obtain the perfect calibration coefficients of each RRU; consequently, a reasonable baseline is very important to evaluate the experimental performance. In the prototype system, for the UE-assisted calibration, we consider two RRU groups and 16 antennas per group, whereas, for the self-calibration of the two RRU groups, there are 8 antennas per group. As shown in Figure 4, UE-assisted calibration has better performance. Moreover, for the UE-assisted calibration, the CPU has both uplink and downlink channels, and then it is regarded as perfect CSI feedback. Therefore, we finally select UE-assisted TLS as the baseline.

In the following, we evaluate the experimental data in detail in terms of the time-frequency characteristics of the calibration coefficients, statistical characteristics of the calibration error, the performance of the calibration algorithms, and CF-mMIMO downlink performance. Unless stated otherwise, the calibration algorithm is a TLS-based self-calibration.

B. Time-Frequency Characteristics of the Calibration Coefficients

We divide the four RRUs in the system into two groups. The antennas of the two RRUs in Group 1 are numbered one to four for RRU1 and five to eight for RRU2, and the antennas of the two RRUs in Group 2 are numbered nine to twelve for RRU3 and thirteen to sixteen for RRU4. We normalize the calibration coefficients relative to that of the last antenna so that the 16th antenna has a calibration coefficient of 1.

In the prototype system, a common SyncE reference clock (10 MHz) is distributed to multiple RRUs, and an LO signal is generated through a phase-locked loop (PLL) for an RF transceiver. Due to the limitation of PLL implementation, the LO signal will have phase drift, which causes a variation in channel gain and calibration coefficient accordingly. Figure 8a shows the phase change of the calibration coefficient with time for the four antennas of RRU1 on a certain subcarrier. Due to the LO phase drift, the phases of the calibration coefficients of the RRU on a given subcarrier drift with time, and it is centered on the median with a range of about $-30^\circ$ and $+30^\circ$.

The range of the phase drift is related to the implementation of reference clock synchronization [42]. Since the four channels in the RRU have a common LO, they are synchronous, and the phases of the calibration coefficients of the RRU have a fixed phase difference. The phase difference in the RRU remains unchanged over a long period (with an observation time of 250 ms). Usually, the phase difference varies in minutes, depending on the environment and temperature.

For sub-6GHz systems, the LO phase drift has a small variation within a slot. Since each slot has demodulation reference signals, usually the phase drift has little impact on the uplink coherent joint reception. However, considering that the SRS period usually spans multiple slots, as shown in Figure 8b, at an interval of 7.5 ms (15 slots for 30 kHz subcarrier spacing), phase variation of a calibration coefficient exceeds $20^\circ$, which will significantly degrade the performance of some reciprocity-based downlink CIT, as demonstrated later.

Figure 8c shows the variation of the calibration coefficients with time for one antenna of each RRU. There is not only a fixed phase difference but also phase asynchrony between RRUs. In addition, since we use the 16th antenna as a reference, the phase of the calibration coefficient of the 13th
antenna varies little, and the phase change is within ±1.5°. Figure 8d shows the polar plot of the calibration coefficients for one antenna of each RRU. It is also seen that the phase rotation is approximately between −30° and +30° around its median. Next, we study the frequency domain performance of the calibration coefficients. The calibration signals are transmitted over the air, the delay between the transmission and reception is reciprocal, and theoretically, the calibration algorithm can eliminate the OTA timing delay. However, in the prototype system, although the RRUs recover the timing from IEEE 1588 PTP, they still have very small timing differences. As shown in Figure 8e, the phase of the calibration coefficients varies linearly with the subcarrier. The results show that the calibration coefficients of both the UE-assisted calibration and the self-calibration involve a timing delay which is demonstrated as a linear phase shift in the frequency domain. In this paper, the timing delay is referred to as the 16th antenna and usually remains constant for a long time. The delays involved in the calibration coefficients of antenna five and thirteen are about 0.15 ns and -0.33 ns respectively, and the delays for antenna one and nine are close to one sample (about 8 ns). Fluctuations in the calibration coefficients of adjacent subbands are not easily observed for antennas 1 and 9. It can be seen from antennas 5 and 13 that there are also certain fluctuations in different subbands, for example, up to approximately 2° for six adjacent RBs (with a bandwidth of approximately 2 MHz).

Remark 1: With a common reference clock, there is no carrier frequency offset (CFO) for the RRUs in the prototype system2. We can see that the phase of the calibration coefficient for a given subcarrier varies in the range of ±30° with a long-term constant value as the center. The phase drift introduced by the imperfect synchronization of each RRU is inevitable, and it is relatively large in one frame (10 ms) for the current COTS RRU. In this case, we may need to transmit CARS for a short period to obtain an accurate phase synchronization. The problem of LO phase drift is related to the design of PLL. If RRU has the capability of LO phase tracking [43], [44], we can reduce the overhead of the OTA calibration. The LO phase drift is also related to the synchronization of the reference clock. Using a high accuracy synchronization scheme named white rabbit [42], the range of phase drift can be reduced to within about ±5°.

Remark 2: Due to the excellent coherence between the multiple channels of the RRU, the phase differences of the calibration coefficients are almost constant (the phase error is within ±1.5°) for a long time. When the RRU is capable of self-calibration (for example, the commercial massive MIMO RRU), for each RRU, we just need to estimate one calibration coefficient. Then, the overhead of the OTA calibration can be reduced, or with the same overhead, we can calibrate more RRUs. Since the average value of the phase of the calibration coefficient remains constant over a long period, we can use it as a long-time calibration coefficient. In this case, the overhead of the CARS will be significantly reduced, but the phase error (here, the phase error is within ±30° in this paper) should be considered when designing the joint multiuser precoding.

Remark 3: Considering that the calibration coefficients vary less over a few RBs, we can increase the subcarrier bandwidth of the CARS. For example, using a subcarrier spacing of 120 kHz, it is possible to put one CARS into a GP

Limited by the current COTS RRU, the overhead of the CARSs in this study is still high. However, it is feasible to further reduce the overhead by considering the above discussion.

C. Calibration Error Analysis

Using the UE-assisted TLS calibration as a baseline, we compared the performance of the self-calibration in the CPU. Let the UE-assisted calibration coefficient be X and the calibration coefficient of the self-calibration be Y; then, we define the following variables:

\[ \theta = \text{angle}(Y/X), \quad \rho = |Y/X|, \]

where \( \theta \) and \( \rho \) denote the phase and magnitude of the error, respectively.

Considering that the calibration errors of the four antennas in each RRU have the same statistical characteristics, we treat them as one random variable. Figure 9a shows the statistical characteristics of the calibration errors of the four RRUs. It can be seen that the phase of the calibration error approximately follows a normal distribution and that the amplitude can be approximated to a lognormal distribution; this is consistent with the theoretical result of [45]. As seen in Figure 9b, the magnitude of the calibration error is small, less than 0.3 dB. Since the amplitude error is small and has little impact on the system performance, we focus on the statistical characteristics of the phase error in the following.

Figure 10 shows the performance of the calibration coefficient errors of the four RRUs on different subbands. We average the absolute values of the phases of the calibration errors on the same subcarrier and find that the maximum calibration error is approximately 4°. The averaged absolute phase errors over frequency and time for the four RRUs are 1.53°, 1.08°, 1.23°, and 1.25°. From Figure 4, we can see...
that for an SNR of 19 dB, the performance gap between a TLS with eight antennas and 16 antennas is approximately 1°. Then, if the calibration SNRs for UE-assisted calibration and self-calibration are the same, the averaged phase error for TLS-based self-calibration of RRU \( 2 \) is approximately 3°. Figure 11a gives the cumulative distribution function (CDF) of the absolute values of the phases of the calibration errors for all antennas of all the RRUs. It can be seen that the proposed averaged Argos algorithm has a much better performance than that of traditional Argos, and the performance is very close to the TLS. Then, the averaged Argos algorithm can achieve a good tradeoff between complexity and performance.

In practical systems, because of the signal processing delay or the large calibration period, the calibration coefficients calculated in the S-slot are usually applied to the downlink slots with a certain delay. Therefore, in Figure 11b we evaluate...
Fig. 9. Statistical characteristics of the calibration coefficients: (a) Phase PDF of the calibration error. (b) Amplitude PDF of the calibration error.

Fig. 10. The phase calibration errors of the four RRUs on different subbands.

the CDF of the absolute value of the phase of the calibration error in the presence of the calibration delay. Even a delay of 5 ms causes a large phase error, with 5% of the channels having a phase error of more than 10°, while a delay of 10 ms results in 10% of the channels having a calibration coefficient phase error of more than 15°. The results imply that even if the channel is static and the OTA channel is reciprocal, the phase of the baseband channel gain will change significantly after a few milliseconds due to the carrier phase drift.

Remark 4: The calibration coefficients of the RRU change significantly with time due to the phase drift of the independent LO of each RRU. Therefore, it is necessary to further evaluate the impact of calibration delay on system performance.

D. Comparison of the SE Performance of the System With 16 Downlink Data Streams

We first evaluate the total SE of transmitting 16 downlink data streams using joint zero-forcing (ZF) precoding. The CPU uses the calibration coefficients and the uplink channels to obtain the downlink channels and further calculate the ZF precoding. The signal to interference plus noise (SINR) of each data stream is calculated from the downlink equivalent channel to obtain the total SE. We consider the following four cases: UE-assisted TLS calibration (which can be regarded as the ideal downlink CSI feedback, referred to as UE-assisted TLS), TLS self-calibration (referred to as TLS), averaged Argos self-calibration (referred to as averaged Argos), and Argos self-calibration (referred to as Argos).

Figure 12a shows the total SE of the 16 data streams without considering the calibration delay. With a 10% outage probability, compared to the UE-assisted TLS, the TLS, the averaged Argos, and the Argos algorithms have performance losses of 18%, 37%, and 72%, respectively.

Figure 12b presents the total SE considering a calibration delay of 5 ms and 10 ms, under which even the performance loss of the TLS reaches 46% and 64%, respectively, and the performance loss of the averaged Argos further increases.

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Fig. 12. SE of full cooperation: (a) calibration without delay. (b) calibration with delays.

Figure 13 shows the relationship between the average SE and the calibration delay. As the calibration delay increases, the performance loss is significant due to the calibration error. As discussed in the previous subsections, the calibration errors introduced by the calibration algorithm and the calibration delay will lead to large phase errors of the CSIs obtained based on reciprocity, which consequently deteriorates the performance of the downlink CJT.

Remark 5: Cooperative downlink coherent multiuser transmission is susceptible to calibration errors in the case of full spatial multiplexing, and even a small calibration delay has a significant impact on the system performance. When the overhead of CARS is acceptable, we should minimize the time interval of calibration/phase synchronization, and improve the real-time performance of precoding. Moreover, we should take into account the statistical characteristics of the phase error of the calibration coefficient for robust precoder design.

E. Comparison of the SE Performance With Scalable Precoding Algorithms

Scalability is an important feature of CF-mMIMO systems. The definition of scalability for CF-mMIMO systems is given in [5], including scalable transceivers and power control algorithms. In [46] and [47], a new scalable architecture of CF-mMIMO was proposed, where an edge distributed unit (EDU) connecting multiple RRRs is introduced to obtain a better tradeoff between the capability of joint processing and the scalability of the transceiver. For downlink transmission, scalable precoding means that the precoding matrix is computed at each RRU/EDU with the local CSI between the RRU itself and the UEs it serves, and there is no requirement for CSI exchanging between RRRs/EDUs. When the number of UEs is remained fixed, the complexity of joint processing with scalable precoding increases only linearly with the number of RRRs. Maximum-ratio transmission (MRT) and local regularized zero-forcing (L-RZF) are two typical scalable precoding approaches [5].

For CF-mMIMO, we usually assume that the number of UEs is much smaller than the total antenna number of RRRs. Therefore, we evaluate the performance of the system using scalable precoding when one antenna is used for each prototype UE. Due to the poor performance of the Argos algorithm, in this subsection, we just show the SE performances of CF-mMIMO with the following three calibration algorithms: the UE-assisted TLS, the TLS, and the averaged Argos. We consider three commonly used precoding schemes, namely, MRT, L-RZF, and joint processing-regularized zero-forcing (JP-RZF) [4].

Figure 14 shows the CDF of the SE of the different precoding schemes without delay. Relatively speaking, the system performance is less affected by the calibration error due to the small number of spatial data streams. The performance of these calibration algorithms is nearly the same as that of MRT precoding. The calibration error has little impact on the performance of L-RZF and JP-RZF. Figure 15 shows the impact of a calibration delay on JP-RZF. The 10-ms and 20-ms delays have a significant impact on the performance of JP-RZF. For the TLS, with an outage probability of 10%, the 10-ms and 20-ms delays lead to performance losses of 29% and 41%, respectively.

Figure 16 shows the performance of L-RZF with a 20 ms calibration delay. Since each RRU is equipped with four antennas with a common LO and the phase changes synchronously, the L-RZF with four layers can successfully suppress the interference. As has been pointed out (see Remark 2), the average value of the phase between RRRs remains constant for a long time, and the phase drift is in the range of (-π/6, π/6). In Appendix A, we prove that for a small range of phase drift, the performance loss of local precoding can be omitted.
Therefore, the L-RZF is not sensitive to the phase drift of the calibration coefficients between RRUs. Figure 17 illustrates the impact of a 20-ms calibration delay on L-RZF and JP-RZF, and there is little difference in the performances of the two in this case.

Figure 18 illustrates the relationship between the average SE and the calibration delay. The performance of L-RZF is the worst but is nearly unaffected by the calibration delay. We also show the performance of a cell-free system with EDUs [47]. We divide the four RRUs into two groups, with two RRUs in each group, and the RRUs are connected to the EDUs in which the uplink coordinated reception and the downlink L-RZF precoding are implemented. The use of this scheme leads to a better performance than that of L-RZF implemented in RRUs, and the EDU-based L-RZF even outperforms JP-RZF when the calibration delay is large. However, the L-RZF implemented by EDUs remains susceptible to calibration errors.

Remark 6: When the overhead of real-time calibration is unacceptable, we should consider long-term calibration, that is, we only estimate the average value of the calibration coefficient over time for each subband. In this condition, when the number of downlink data streams is less than or equal to the number of antennas of each RRU, the system performance of the L-RZF is robust to the phase error. However, when the number of downlink data streams is large (well beyond the number of antennas per RRU), according to the analysis in [13], the performance of distributed transceivers will deteriorate severely due to the large phase error of the calibration coefficient. Therefore, to achieve more spatial multiplexing gains, we should equip more antennas per RRU with excellent coherence or design distributed robust precoder with multiple RRUs jointly as in [46] and [48].

V. CONCLUSION

In this study, TDD OTA calibration and phase synchronization techniques for 6G-oriented CF-mMIMO have been investigated. First, an OTA reciprocity CARS compatible with the 5G frame structure was designed that is transparent to commercial UEs and RRUs and enables fast self-calibration of the RRUs. The averaged Argos calibration was proposed for a group-based calibration, which can achieve a good tradeoff between complexity and performance. We have developed
a CF-mMIMO prototype platform based on 5G commercial COTS RRRUs. Based on the testbed, the time-frequency characteristics of the calibration coefficients, the statistical characteristics of the calibration error, and the performances of centralized and local precoding were studied. From the experimental results, we have the following main findings for downlink CJT of CF-mMIMO:

- For the ORAN RRRUs synchronized by IEEE 1588 PTP and SyncE, the LO phase drift is a serious problem. With long-term calibration, the multiplexing gain of the CF-mMIMO system will be significantly reduced. The centralized CJTs of multiple RRRUs are very sensitive to the phase error introduced by the OTA calibration and synchronization. High-precision synchronization is necessary to improve the performance of CF-mMIMO, and robust precoding that takes into account the phase error characteristics is also essential.

- Fully distributed precoding is insensitive to LO phase drift of each antenna in the same RRU is the same (see Figure 8a). For simplicity of analysis, we consider local ZF precoding. Then, there is no interlayer interference for L-ZF. The SNR loss at the receiver can be expressed as follows:

$$
\delta = \frac{1}{L^2} \sum_{n=1}^{L} e^{i\theta_n} \left( e^{i\theta_n} \theta_{max} \right).
$$

where

$$
\theta_n \sim (-\theta_{max}, \theta_{max}).
$$

We have

$$
E \left( \sum_{n=1}^{L} e^{i\theta_n} \right)^2 = \sum_{n=1}^{L} \sum_{m=1}^{L} E \left[ e^{i(\theta_n - \theta_m)} \right]
$$

For $\theta_n \neq \theta_m$, we have the following

$$
E \left[ e^{i(\theta_n - \theta_m)} \right] = \frac{1}{4\theta_{max}^2} \int_{-\theta_{max}}^{\theta_{max}} e^{-i\theta_n} d\theta_n \int_{-\theta_{max}}^{\theta_{max}} e^{-i\theta_m} d\theta_m
$$

Then, we obtain

$$
\delta = \frac{\sin^2 (\theta_{max})}{\theta_{max}^2} + \frac{1}{L} \left[ 1 - \frac{\sin^2 (\theta_{max})}{\theta_{max}^2} \right].
$$

In the prototype system, the phase drift range is $(-\pi/6, \pi/6)$. According to the above result, the SNR loss is approximately 0.3 dB, and the averaged SE loss is approximately 0.1 bps/Hz at high SNRs.

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