Distributed Coordinated Transmission with Forward-Backward Training for 5G Radio Access

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Abstract—Coordinated multipoint (CoMP) transmission and reception has been considered in cellular networks for enabling larger coverage, improved rates and interference mitigation. To harness the gains of coordinated beamforming, fast information exchange over a backhaul connecting the cooperating base stations (BSs) is required. In practice, the bandwidth and delay limitations of the backhaul may not be able to meet such stringent demands. Such impairments motivate the study of cooperative approaches based only on local channel state information (CSI) and which require minimal or no information exchange between the BSs. To this end, several distributed approaches are introduced for coordinated beamforming (CB) CoMP. The proposed methods rely on the channel reciprocity and iterative spatially precoded over-the-air pilot signaling. We elaborate how forward-backward (F-B) training facilitates distributed CB by allowing BSs and user equipments (UEs) to iteratively optimize their respective transmitters/receivers based on only locally measured CSI. The trade-off due to the overhead from the F-B iterations is discussed. We also consider the challenge of dynamic TDD where the UE-UE channel knowledge cannot be acquired at the BSs by exploiting channel reciprocity. Finally, standardization activities and practical requirements for enabling the proposed F-B training schemes in 5G radio access are discussed.

I. INTRODUCTION

The performance of mobile networks is significantly limited by inter-cell interference which is due to the reuse of radio resources in nearby cells. Consequently, designing advanced interference coordination techniques is of utmost importance for improving the performance of a cellular network. Different coordinated multipoint (CoMP) variants have been included for the downlink in the 3GPP LTE-Advanced standard such as coordinated beamforming (CB) and joint transmission (JT). For JT-CoMP, users in the cluster are served by all the cooperating BSs, which have access to the user data. To enable such cooperation, data and CSI for the users in the cluster have to be exchanged between the cooperating BSs and possibly a centralized processor. This imposes certain requirements on the capacity and delay of the backhaul, which may not be possible in practice. Furthermore, the deployment of small cells and ultra dense networks in future communication systems may further degrade the backhaul quality in a cooperating area.

In fact, the imperfect backhaul has been recognized as one of the key issues in fast multi-cell cooperation [1].

Enabling coordination or cooperation among network entities is always beneficial but the best coordination strategy depends on a variety of conditions including channel state information (CSI) and data availability, backhaul constraints, and network connectivity (level of interference). Two major considerations in the design of such schemes are to what extent the cooperation is managed centrally (requires CSI sharing) and whether each terminal should be served by multiple base stations (requires data sharing). The level of coordination can be divided into four basic categories based on the different combinations of local or global CSI, and local or global data available at the network nodes. In this paper we focus on distributed CB-CoMP schemes [2]–[6] with only local CSI and data available at each transmit node as depicted in Fig. 1. An extension to distributed JT-CoMP scenario with minimal central controller involvement was considered in [7], assuming the user data is shared by the cooperating BSs while the CSI is available only locally.
We present iterative distributed coordinated beamforming schemes that rely on uplink-downlink channel reciprocity and spatially precoded pilots [2]–[6]. To this end, we first elaborate on how forward-backward (F-B) training facilitates distributed CB by allowing the nodes (BSs and users) to iteratively optimize their respective transmitters/receivers based on local CSI only. We discuss the trade-off due to the overhead resulting from the F-B iterations as well as the effect of imperfect CSI on distributed iterative schemes.

Fully dynamic or flexible TDD is an essential 5G component, e.g., in 3GPP standardization [8], [9]. Consequently, there is a need for a new 5G air interface to meet the required low physical layer latencies without restrictions on assigning slots to uplink or downlink, or in addition, to serve a direct device-to-device link or provide self-backhauling [10], [11]. We also consider the required signaling to enable distributed coordination via F-B training in a challenging interference scenario with a fully dynamic/flexible TDD frame structure.

Practical requirements for enabling the proposed F-B training schemes in 5G radio access are discussed in Section IV. So far there has been good progress in the 3GPP new radio (NR) study item [8], [9] in this direction. The impact on frame structure, UE requirements, CSI uncertainty, etc. will be assessed. We emphasize that the centralized and decentralized approaches are not necessarily alternative but rather complementary techniques. As each centrally coordinated cluster of cells must have a limited size, decentralized coordination can be performed between neighboring coordination clusters as well using the proposed over-the-air training methods.

II. DISTRIBUTED COORDINATION VIA F-B TRAINING

Forward-Backward iterations are often also referred to as over-the-air (OTA) iterations, or bi-directional training/signaling. Let us now focus on the downlink, where each F-B signaling round (iteration) in the beamformer training consists of two phases: a DL (forward) phase and a UL (backward) phase. In the forward phase, the BSs transmit precoded pilots enabling the users to estimate their local CSI consisting of the effective channel, i.e. the cascade of channel and precoder, of its desired link as well as of the interfering links. The users proceed to optimize their receiver filters based on the acquired local CSI. The same process holds for the backward UL phase. A simplified TDD frame structure with two F-B iterations is depicted in Fig. 2(a).

F-B training allows a fully distributed coordinated computation of transmit/receive beamformers of the BSs/users in the cluster, without full CSI exchange over a backhaul. The filters can be computed based on different optimization criteria such as minimizing the interference leakage [5], maximizing SINR [4], minimizing the (weighted) sum MSE or maximizing the (weighted) sum rate [2], [3], [6], [7], [12]. Moreover, if every step of the global optimization problem can be decoupled among the nodes, the distributed iterative scheme incurs no loss in optimality (besides the overhead) compared to the centralized approaches [2].

The minimal number of orthogonal pilot resources in each forward/backward phase, increases with the number of transmit/receive antennas, and data streams. Thus, each F-B iteration has an associated overhead, namely, that of transmitting precoded uplink/downlink pilots. A coarse (optimistic) measure of communication overhead can thus be adopted (keeping in mind that the actual overhead will be dominated by this quantity), by counting the minimal number of orthogonal pilots symbols, needed for each F-B iteration. For a system with $L$ cells ($K$ users/cell), and $d$ data-streams per-user, $\Omega = T^2K L d$ pilot symbols are needed, where $T$ is the number of F-B iterations, and the factor 2 follows from the even split between the number of forward and backward pilots (due to channel reciprocity) [13]. In practice, assuming $\Omega$ exceeds the number of pilot resources, the limited pilot resources have to be reused across the network. This non-orthogonal pilot allocation causes $\text{pilot contamination}$ where the actual estimated channel is a superposition of all user channels reusing the same pilot resource [14].

The pilot overhead $\Omega$ may become excessive for a large $T$, even with relatively low mobility, thereby destroying any potential gains from coordination. In this paper, the rate of beamformer convergence is emphasized in practical environments with time-varying channels. Faster beamformer convergence rates allow smaller number of F-B iterations, which in turn lowers the beamformer training overhead. The purpose of this section is to review recent work [2]–[6], where fast-converging F-B training and signaling algorithms are proposed (e.g. $T < 10$), based on several design criteria. In all papers, the general downlink CB-CoMP problem with linear transmit-receive beamforming in MIMO interference broadcast channel (IBC) is considered. The proposed iterative methods naturally decouple the transmitter and receiver beamformer designs leading to fully distributed algorithms. Basic pilot signaling schemes for TX-RX beamformer training are introduced in [2]. An alternative approach to joint optimization of transmit and receive beamformers is proposed in [4] where the beamformers are estimated directly as adaptive filters. In order to speed up the convergence, both [2] and [5] allow internal optimization loop to run at the network nodes in between each OTA F-B signaling round. Further algorithmic convergence improvements are introduced in [3], [6] allowing each BS/UE to quickly discard the weak streams while focusing the power to streams with large gain.

A. Pilot Signalling Schemes for TX-RX Beamformer Training

In [2], the weighted sum rate (WSR) maximization is carried out via weighted sum mean-squared-error (WSMSE) minimization and alternating optimization of the transmit precoders and receivers. In decentralized optimization with local CSI and data, adaptation of the variables is distributed between the network elements. The focus in [2] is on the signaling of effective channel state information (CSI) that facilitates decentralized processing so that the network nodes can locally participate in the network adaptation. Three different signaling strategies are presented, as illustrated in Fig. 2(b). The figure depicts the pilot signals employed in a network of two cells. It is worth noting that in general, the pilot signals propagate over the whole network so that all the BSs are receiving all
forward phase. The process is then repeated until convergence.

The idea of the second signaling option, called Strategy C, is proposed. In this scheme, separate BB pilot signaling is not needed as the effective channels both at the serving and interfering BSs for each F-B signaling round can be constructed based on specifically designed whitening CS pilot responses and additional backhaul information [2, Alg. 5].

Fig. 3 illustrates the evolution of the sum rate over F-B adaptation steps, at 25 dB received SNR in a 2-BS cell-edge scenario [2]. Here, the convergence behavior of the algorithms is emphasized. The OTA signaling overhead per F-B round is considered in Section III. As can be seen, performing cell-specific iterations one BS at a time as in Strategy B, increases the convergence speed. The convergence is accelerated further by allowing parallel iterations as in Strategy C. Interestingly, even though this approach does not provide monotonic convergence per channel realization, but convergence on the average only, it induces no loss to the average converged sum rate performance. The results demonstrate that most of the objective improvement occurs during the first 4-10 F-B iterations. For example, if we set a limit for F-B iterations to be 4 in Fig. 3 the fast converging Strategy C would give a 55% throughput increase as compared to the baseline case. The non-cooperative strategy converges fast but results in a significantly lower sum rate.

B. Improved convergence rate of beamformer updates

The convergence of WSMSE based algorithms [2], [12] can be still fairly slow, especially at high SNR. In this subsection, a more thorough comparison in various operational settings can be found in [2]. The higher the cell edge SNR the larger are the relative gains from inter-cell coordination.
alternative WSR algorithms with significantly faster convergence are introduced [3], [9]. In addition to WSR, fast converging algorithms for interference leakage minimization are also considered [3]. The precoded pilot signaling strategies introduced in Section II-A can be straightforwardly incorporated into the fast converging beamformer design algorithms [3], [6].

A WSR maximization framework based on successive convex approximation (SCA) was proposed in [3], also with additional per user QoS/rate constraints. Similarly to [2], [12], the precoder design is based on MSE minimizing reformulation of the original WSR maximization problem, where the complexity is restricted to a set of non-convex MSE constraints. The weighted MSE minimization problem is solved iteratively, up to a locally optimal solution, by successively approximating the non-convex constraints. Instead of applying the conventional approximation of the non-convex objective function as in [2], [12], the SCA is performed over arbitrary MSE upper bounds. The SCA framework in [3] reveals a structure that enables the use of heuristic approximation methods that can be used to significantly improve the rate of convergence and lower the required number of over-the-air iterations as compared to the baseline case [12]. These approximation techniques are based on prediction of the stream specific rate progression and overestimating the next point of approximation.

The sum-rate maximization problem is also tackled in [6], where the sum-rate is lower bounded using a so-called Difference of Log and Trace (DLT) bound, and its relative tightness is established. Similarly to weighted MSE reformulation approaches used in [2], [3], [12], the DLT bound naturally decouples at the transmitters and receivers, thus leading to fully distributed algorithms. The proposed method has inherent ability to turn off streams exhibiting low-SINR, thereby greatly speeding up the convergence of the proposed algorithm. The DLT algorithm is benchmarked in [6] against several known schemes, e.g., distributed Interference Alignment (IA), max-SINR, weighted MMSE, in terms of performance and overhead, where the fast-converging nature of the proposed algorithms is made clear: more than 95% of the final performance is reached in just 2 iterations, allowing the 2-3 times faster convergence (and a same reduction in overhead). The reason for the massive performance gain is due to the non-homogeneous waterfilling solution, that allows each BS/UE to allocate zero power to streams with low SINR, and allocate the rest of the power to streams with better SINR. Moreover, the gap between the proposed schemes, and the benchmarks increases sharply, as the system dimensions grow (i.e., more antennas, cells, users). We refer the readers to [6] for extensive simulation results.

The interference leakage utility is tackled in [5], by relaxing the constraint on the well-known leakage minimization problem. A rank-reducing filter update structure is proposed, to solve the resulting non-convex problem, and gradually reduce the BS/UE filter rank, thus decreasing the dimension of the interference subspace, and greatly speeding up the convergence. The updates of the resulting algorithm, Iteratively Weighted Updates with Rank Reduction (IWU-RR), are shown to be monotonically decreasing in the leakage. Similarly to Strategy B/C introduced in Section II-A, a turbo-like structure is also proposed, where a separate internal optimization loop is run at each receiver, in addition to the main F-B iteration. The introduction of the turbo-iteration and the rank-reducing updates enable the algorithms to provide significantly lower values of the leakage, in just a few turbo iterations \( I \). The fast-converging nature of the IWU-RR is shown in Fig. 4 when benchmarked against distributed IA (DIA). The proposed algorithms are shown to converge to a locally optimal solutions with a drastically lower number of F-B iterations (compared to the hundreds of iterations required by conventional DIA algorithms). Moreover, the performance gap between proposed and conventional algorithms, increases with the system dimensions (e.g., antennas, users, cells). We refer interested readers to extensive numerical results in [5].
As with CSI-based estimation, orthogonalizing and jointly designing the pilot sequences can reduce the estimation error given a fixed training duration. The direct beamformer estimation approach potentially reduces the pilot overhead in dense systems, relative to estimating CSI. This is due to the large number of cross-channels causing significant inter-cell interference. All those channels must be estimated when computing the beamformers, requiring knowledge of all interfering pilot sequences. In contrast, the direct beamformer-estimation approach requires only local pilot sequence information and sufficient pilots to estimate the beamformer (not channel) coefficients.

### III. Dynamic/Flexible TDD

In small cell scenarios, the amount of instantaneous uplink (UL) and downlink (DL) traffic may vary significantly with time and among the adjacent cells. In such cases, Dynamic or Flexible TDD allows for resources to be dynamically adapted between the UL and DL by changing the amount of resources allocated to each direction at each time instant, providing vastly improved overall resource utilization. In addition to the normal UL-to-UL and DL-to-DL interference, UL-to-DL and DL-to-UL interference are also associated with Dynamic TDD in multi-cell operation. Allocating resources in such a system requires balancing the gains of flexible DL/UL allocation (e.g. in the form of reduced packet delivery delay) with the potential losses (in the form of excess interference).

In order to mitigate the user-to-user and BS-to-BS interference, the system may employ coordinated resource allocation and beamforming, where the transmissions within a coordinating set of cells are jointly designed. While the channel reciprocity can be utilized to acquire the CSI of the user-BS and BS-BS links, a specific challenge of the dynamic TDD approach is to acquire the CSI between the mutually interfering user terminals. Explicit feedback of the user-to-user channels in addition to a full CSI exchange between BSs would be required to enable optimal beamformer design which renders the centralized design impractical. However, such a centralized approach can be circumvented by employing F-B training to convey implicit information to the BSs about the interference and receivers at the users [15]. An adaptive frame structure with bi-directional control is however required as detailed in Section IV.

We now evaluate the performance of distributed CB with dynamic TDD in a 2-tier cellular system with wrap-around hexagonal grid consisting of 19 cells with 200m inter-site distance. Each cell is randomly allocated to operate either in UL or DL. Each BS has 8 antennas and serves four 2-antenna users in its cell. Two bi-directional F-B signaling strategies (A and B) introduced in Section II-A are investigated. The forward pilots are used to transmit precoded pilots from DL BSs and UL users while the backward pilots are used to transmit precoded pilots from DL users and UL BSs. In Dynamic TDD settings, where both BSs and users are involved in the iterative precoder optimization, wired backhaul is not available to exchange weight variables among the users and BSs. However, the user weights are embedded into additional precoded backward pilots as detailed in [15] Fig. 1. Therefore, both Strategies A and B require two backward pilots per F-B iteration. As a low overhead alternative solution, a heuristic scheme denoted as Strategy D is also proposed where the weight variables are assumed to be all ones for the other cell users while the MSE weights for the own cell users are calculated based on locally available information [15]. Thus, only a single backward pilot per stream is required in Strategy D.

The actual achievable sum rate from each training strategy versus the total overhead is demonstrated in Fig.5. The relative overhead per one signaling iteration is denoted as $\gamma$. Thus, the actual achievable sum rate of the system can be obtained as $(1 - T \gamma)R$, where $R$ is the achieved sum rate from the iterative algorithm after $T$ F-B iterations. In this particular example, we assume one signaling round consumes 1% of the available resources per scheduling interval for Strategies A and B. Note that for Strategy D, the overhead per iteration is just 2/3 of Strategies A and B. The numerical results demonstrate that there is a clear trade-off between the number of OTA iterations allowed and the improved throughput efficiency due to beamformer convergence. All F-B strategies achieve considerable gain (up to 110% at high SNR) as compared to the uncoordinated system where the transmit beamformers are designed locally ignoring the inter-cell interference altogether. In this particular example, about 4-8% of the resources, depending on the selected strategy, should be allocated to the F-B training in order to maximize the total throughput. Moreover, Strategy B provides a significant additional gain since it allows internal iterations at the BS in between the F-B iterations. Despite higher backward phase training overhead per iteration, both strategies A and B provide better peak
variable adjustments among coordinating cells.

throughput than Strategy D due to optimized MSE weight variable adjustments among coordinating cells.

IV. STANDARDIZATION ACTIVITIES AND PRACTICAL ASPECTS

3GPP new radio (NR) specification [9] will support multiple OFDM parameter sets and time-frequency scaling of LTE, leading to candidate subcarrier spacing options of 15 kHz, 30 kHz, 60 kHz, etc, and ensuring smooth implementation and good coexistence with LTE. Similarly to LTE, a new radio (NR) frame consists of ten subframes, each with length of 1 ms. According to 3GPP NR study item, a slot consisting of 14 OFDM symbols defines the basic scheduling interval. NR supports at least four slot types, illustrated in the upper part of Fig. 6 providing the basic support for both TDD and FDD modes: 1) bi-directional slot with DL data, 2) bi-directional slot with UL data, 3) DL only slot, 4) UL only slot. These different slot types can be concatenated in a flexible manner. Bi-directional slot types, including a bi-directional control signal part embedded in each slot and time separated from the data payload, are required in TDD mode to facilitate link direction switching between DL and UL. They also enable fully flexible traffic adaptation between the two link directions and with opportunity for low latency. Demodulation reference signal (DMRS) symbols are located e.g. in the first symbol of the data part and can be precoded with the data, enabling the receivers to estimate the equivalent channel of its desired and interfering links. Slot aggregation is also supported, enabling scheduling blocks consisting of multiple consecutive slots. Unlike LTE, 3GPP NR will support non-codebook based multi-stream uplink transmission. Furthermore, precoded uplink sounding reference signals are supported providing means for iterative Tx-Rx beamformer training. Since NR needs eventually to support carrier frequencies up-to 100 GHz and wireless relay / backhauling is an important scenario for deployments with high carrier frequencies, it is also agreed in the related RAN WG1 meetings that NR will further investigate frame structure design(s) to support backhaul relay links.

The aggregated scheduling block should be sufficiently long to allow for sufficient beamformer convergence and to avoid excessive overhead due to F-B training. Also, the user allocation in the adjacent cells should not change during the F-B training to allow fast adaptation to the interference scenario. Therefore, a scheduling block consisting of multiple aggregated slots would be useful in practice. However, there is a clear trade-off between the channel coherence time and the size of the scheduling interval, as well as traffic burstiness.

It can be noted that the basic NR bi-directional slot types defined in 3GPP and illustrated in the upper part of Fig. 6 can provide support for multiple Tx/Rx updates, i.e., multiple bi-directional F-B rounds within a slot. In principle, the related Tx/Rx switching could be distributed among consecutive slots within the scheduling block. However, in order to isolate the impact of sequential Tx/Rx switching operation and to minimize the involved latency it would make sense to concentrate Tx/Rx switching functionality into specific switching slots. As shown in the lower part of Fig. 6 an additional switching slot type used in the beginning of the scheduling block could consist of a plurality of Tx/Rx updates, i.e., multiple bi-directional F-B rounds within a 14-symbol slot. In such a case, the beamformer computation both at UEs and BSs must occur within each Tx/Rx update, which may pose challenges for practical implementation. This type of switching slot functionality may in practice be implemented via a mini-slot structure also already agreed in NR 3GPP [9]. A mini-slot is a shortened version of a slot with common DMRS and common control channel structures, enabling flexible HARQ/scheduling timing and physical downlink control channel monitoring. Utilization of mini-slot structure allows to have more than one Tx/Rx (DL/UL) switching points within a 14-symbol slot by using non-slot-based scheduling.

In order to support F-B training functionality the terminals should start performing similar functions as BSs have traditionally done, i.e., being more aware of the neighborhood and measuring the other nodes (both users and BSs) in the near vicinity. The UEs should be able to measure pilots, including the nearby users operating in reverse UL/DL mode in order to be able to compute their respective Tx/Rx beamformers to avoid excessive UE-UE interference. Moreover, F-B training
requires a dedicated PA/RF chain per antenna to allow for pilot precoding also at the UE side. Also, sufficient calibration of Tx/Rx RF chains both at BS and user side is required.

The concatenation of both analog and digital beamforming functions makes the mmWave communication scenario more challenging for the F-B training based distributed coordination. Ideally, with full antenna specific CSI, the pilot precoder would be just a concatenation of digital and analog beamformers and the F-B training procedure would be exactly the same as in the digital case. In practice, however, the antenna specific CSI is not available for hybrid implementation due to limited number of BB/RF chains requiring separate beam search mechanisms, thus complicating the implementation of additional OTA F-B training procedures. Note that the simulation studies in [6] assuming all-digital beamformer implementation demonstrate that simple inter-cell interference coordination mechanisms still provide significant gains in sub-28 GHz frequencies in dense deployments.

V. CONCLUSION

Distributed schemes for the multi-cell coordination were discussed in this paper. Motivated by the fact that several deployments in future wireless communication networks might have a backhaul with limited capabilities, approaches based solely on local CSI were considered. This assumption eases the burden on the backhaul by avoiding CSI exchange between the cooperating BSs, thus addressing core aspects for small cell integration. For this purpose, distributed coordination based on F-B training was proposed to gradually refine the transmit/receive beamformers of the nodes in a fully distributed manner. Several relevant issues of such iterative schemes were addressed like the training overhead, signaling and imperfect CSI. We have also shown how F-B training can be employed to manage interference in a dynamic TDD system. The numerical experiments demonstrated that the proposed F-B strategies achieve considerable gain as compared to the case without interference coordination. On the other hand, both UE and BS capabilities should be enhanced in order to support F-B training functionality. A new switching slot structure extension was introduced on top of the already agreed 3GPP NR slot types to support multiple bi-directional F-B rounds within a scheduling interval.

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