

Bi-directional Beamformer Training for Dynamic TDD Networks

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Abstract—In dynamic time-division-duplexing (TDD) networks, the available resources per cell can be freely allocated to either uplink (UL) or downlink (DL) depending on the instantaneous traffic demand. Hence, complicated UL-DL and DL-UL interference scenarios arise due to simultaneous UL and DL data transmission in adjacent cells. In this paper, decentralized iterative beamformer designs are obtained for several traffic aware network optimization objectives such that only minimal information exchange is required among the coordinated base-stations (BSs) and user-equipments (UEs). Bi-directional forward-backward training via spatially precoded over-the-air pilot signaling is used to facilitate coordinated beamforming. This allows BSs and UEs to iteratively optimize their respective transmitters/receivers based on only locally measured reverse link pilot measurements. Novel bi-directional beamformer training strategies and methods for direct estimation (DE) of the stream specific beamformers are developed for each intermediate beamformer update in a limited and noisy pilot environment. The proposed signaling and DE schemes allow for non-orthogonal and overlapping pilots, which considerably reduces the resource coordination effort. Also, the decontamination ability of the proposed strategies are analyzed with limited pilot resources. The numerical examples illustrate the superior system performance of the proposed training and estimation framework in comparison to both the traditional stream-specific channel estimation method and an uncoordinated system.

Index Terms—dynamic or flexible TDD, coordinated beamforming, pilot decontamination, direct estimation, weighted queue minimization, weighted sum rate maximization.

I. INTRODUCTION

Mobile data traffic is expected to grow exponentially in the coming years due to ever-increasing smartphone usage, and massive demand for online video and cloud services [1], [2]. Future wireless mobile networks should be able to satisfy the increasing traffic demand which is asymmetric and bursty in nature. Consequently, small-cell deployment has been identified as a key research direction to fulfill these requirements. A large number of small cells with very short coverage area can be used in addition to the traditional macro/micro cells to deliver mobile data in high mobile data traffic areas [3], [4]. Furthermore, asymmetric mobile data traffic can be efficiently handled with time division duplexing

(TDD) by allocating resources in uplink (UL) and downlink (DL) directions based on the instantaneous traffic demand. Hence, TDD based small-cell networks provide several benefits, such as reduced complexity channel state information (CSI) estimation using channel reciprocity, flexible handling of dynamic traffic and easy frequency re-use planning [5], [6].

In a small cell network, imposing the same fixed UL/DL configuration over the network would greatly limit the overall resource utilization as the adjacent cells potentially have different instantaneous UL/DL traffic demand. Dynamic TDD can be used to overcome this problem by adjusting the UL/DL mode asynchronously based on the traffic state of each individual cell [6], [7]. Moreover, 3rd generation partnership project (3GPP) new radio (NR) standard has given special attention to fully dynamic or flexible TDD, which is an essential 5th generation mobile networks (5G) component [8], [9]. Consequently, there is a need for the new 5G air interfaces to meet the physical layer latency requirements without restrictions on UL/DL slot assignment [10].

Interference management in dynamic TDD systems becomes more challenging as complicated interference scenarios arise due to simultaneous UL and DL data transmission in adjacent cells. Specifically, the DL base station (BS) transmission may be interfering with the UL reception (BS-BS interference) and the UL user equipment (UE) transmission may be interfering with DL reception (UE-UE interference). Previous studies on dynamic TDD have focused on complicated time slot allocation algorithms that mitigate this cross-link interference [11]–[16]. In addition to increased spectral efficiency and improved reliability, spatial processing via multiple-input-multiple-output (MIMO) systems provides additional degrees of freedom to mitigate the detrimental interference both at the transmitter and receiver. Hence, the interference management in dynamic TDD based small-cell deployments is more efficient when both BSs and UEs are equipped with multiple antennas.

While the channel reciprocity can be utilized to acquire the CSI of the UE-BS and BS-BS links, a specific challenge of the dynamic TDD approach is to acquire the CSI between the mutually interfering UEs. Explicit feedback of the UE-UE 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, the coordinated beamformer design for dynamic TDD systems can be carried out in a decentralized manner with the help of bi-directional forward-backward (F-B) training via spatially precoded over-the-air (OTA) pilot signaling [17], [18]. In this

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Parts of this work has been published in the IEEE ICC Workshop, London, U.K., 2015, the IEEE SPAWC, Stockholm, Sweden, 2015, the IEEE SPAWC, Sapporo, Japan, 2017, and the IEEE EuCNC, Oulu, Finland, 2017.

This research was supported by Finnish Funding Agency for Technology and Innovation (TEKES), Nokia Networks, Bittium, Keysight, Kytynel and MediaTek.

case, it is essential to have fast beamformer convergence to implement these systems in practice with fading channels and to minimize the training overhead [17], [18].

Accurate CSI estimation is essential for any beamformer design. Hence, we need to employ distinguishable pilot sequences to estimate corresponding channels at the relevant nodes. However, the number of orthogonal pilot sequences that can be used for CSI estimation is constrained due to limited coherence time and coherence bandwidth of the wireless channel [19], [20]. Consequently, in dense networks, the number of orthogonal pilots is not sufficient to distinguish all possible channels. Hence, we must reuse pilots sequences or employ non-orthogonal pilots to estimate the CSI. This, on the other hand, causes the so-called pilot contamination effect, where the desired channel is polluted by other channels. Therefore, beamformer or CSI estimation should be robust against pilot contamination effect.

A. Prior Work

Most of the dynamic TDD studies are directed towards distributed dynamic time slot allocation algorithms to alleviate the cross-slot interference. For example, in [11]–[16] various time slot allocation strategies have been proposed and compared with the existing methods. In [21], small cell dynamic TDD transmissions have been investigated for heterogeneous networks by employing cell clustering and power control based interference cancellation scheme. In [22], an energy efficiency (EE) beamformer design was proposed with the cloud radio access network assumption, which requires centralized processing.

In the context of synchronous UL/DL¹ TDD networks, numerous centralized and decentralized beamformer designs with different coordination assumptions have been considered to optimize network utilities such as weighted sum rate (WSR) maximization, EE, weighted queue minimization (WQM), and weighted sum mean square error (WSMSE) minimization, e.g., in [17], [23]–[31]. In [23], [24], the WSR maximization is carried out via WSMSE minimization and alternating optimization of the transmit precoders and receivers. Furthermore, the authors in [17] proposed a distributed CSI acquisition framework and novel fast converging strategies for iterative WSMSE based approach in a realistic multi-cell environment. Therein, bidirectional F-B training using spatially precoded pilots is employed to provide implicit exchange of intermediate beamformers between BSs and UEs, assuming that enough orthogonal pilots are available for stream specific precoded pilots. Further convergence improvements for WSR problem based on successive convex approximation (SCA) methods were proposed in [26], also with additional per user QoS/rate constraints. Recently, traffic aware transceiver design for weighted queue minimization has been investigated in [27]. Similarly to [17], [23], [24], [26], the decentralized solution in [27] was based on iterative evaluation of Karush-Kuhn-Tucker (KKT) conditions of the optimization problem. The resulting beamformer structures were shown to be very similar

to those corresponding to other optimization objectives such as WSR maximization, WSMSE minimization, etc. However, all the above studies assumed perfect channel estimation in their designs.

Practical implementation of coordinated precoding and CSI acquisition have been investigated in, e.g., [17], [32]–[35]. Moreover, the pilot contamination effect and possible ways to mitigate this impact have been studied, e.g., in [36]–[41]. An interesting approach to mitigate pilot contamination was proposed in [34], where direct least squares (LS) beamformer estimation from the contaminated UL/DL pilots was investigated. Moreover, there have been a few studies to mitigate pilot contamination by using pilot reuse algorithms with the use of channel statistics. For example, authors in [37] proposed a pilot reuse method utilizing spatial correlation properties. However, none of these studies consider dynamic TDD setting.

B. Contributions

Motivated by above concerns, we study several decentralized beamformer designs with different optimization objectives for multi-cell multi-user MIMO dynamic TDD systems. We consider WQM, and its special cases, queue weighted sum rate (QWSR) maximization and sum mean square error (SMSE) minimization objectives with power constraints at DL BSs and UL UEs. First, we improve the convergence properties of the WQM approach presented in [27] by reformulating it similarly to [26], and the problem is solved via iterative evaluation of KKT conditions leading to a distributed algorithm. Then, to facilitate practical implementation, we employ over-the-air (OTA) signaling architecture as in [17], [18], [34]. More specifically, we employ precoded pilots to exchange the intermediate beamformers in both backward and forward direction iteratively. Hence, we consider a TDD frame to carry out both OTA bi-directional signaling and data transmission. Moreover, several bi-directional training iterations can be embedded into a TDD frame before the data transmission. A methodology was proposed in [18], to implement this TDD frame structure by adapting standardization works on 3GPP NR [9]. As the number of OTA signaling rounds is increased, time remaining for the actual data transmission become shorter. Hence, the impact of OTA training overhead is investigated via numerical simulations. Then, we propose three different direct beamformer estimation methods to alleviate the pilot contamination effect. In these methods, we use the received precoded pilot information to estimate intermediate beamformers directly using LS based estimation without separately decorrelating individual pilot sequences. We refer these approaches as direct estimation (DE) methods. The DE approaches are compared with conventional stream-specific estimation (SSE) method, where the beamformers are constructed from the estimated equivalent (precoded) channel vectors. In both techniques, precoded pilot sequences are used to implicitly exchange information on beamformers and user-specific weights. However, when non-orthogonal pilots are used for the beamformer signaling, DE approach provides a better estimation due to the LS based estimation gain. Furthermore, the superiority of the DE method (versus SSE) is demonstrated analytically.

¹The term, Synchronous UL/DL is used refer UL/DL transmission synchronously over the multicell network

Finally, to enhance the decontamination further, we consider a traditional pilot reuse approach for alleviating pilot overlap. A simple (but centralized) pilot reuse approach is proposed for complicated dynamic TDD setup based on large-scale fading information of the BS-UE and UE-UE channels.

Major contributions of this paper are summarized as follows:

- Fast converging iterative decentralized beamformer design is proposed for dynamic TDD system with the WQM objective.
- The proposed design is adapted to QWSR maximization and SMSE minimization objectives as special cases of WQM design.
- OTA bi-directional signaling architecture is proposed to implement beamformer designs in practice.
- Three DE-based beamformer estimation strategies are proposed to mitigate the pilot contamination.
- The superiority of DE over SSE is proven analytically.
- A centralized pilot reuse algorithm is proposed to dynamic TDD setting.
- Performance of the proposed methods are studied with numerical examples.

This article is an extended version of our previously published conference papers [42]–[45]. In [42], [43] we investigated WSR maximization problem for dynamic TDD network by employing bi-directional signaling to facilitate iterative decentralized design. Then, in [44], we studied the above system by employing non-orthogonal pilots. In [45] we investigated pilot decontamination methods using pilot reuse algorithms with the queue minimization objective.

C. Organization and Notation

The rest of the paper is organized as follows. Section II presents the system model that used for the rest of the article. In Section III, the proposed decentralized beamformer design is presented for dynamic TDD. Training and signaling architecture that supports decentralized beamformer design is addressed in Section IV. Pilot decontamination using DE is introduced in Section IV.A and three different DE strategies are presented in Sections IV.B–D. The DE comparison with the SSE approach is shown in Section IV.E. Pilot decontamination using pilot reuse methods are discussed in Sections IV.F. Complexity and overhead study is presented in Section IV.G. Finally, Section V presents the numerical examples and Section VI concludes the paper.

Notations: $\mathbb{C}^{m \times n}$ denotes an $m \times n$ matrix with elements in the complex field. Capital bold letters represent matrices, simple bold letters represent vectors and simple letters represent scalar variables. $(\cdot)^{-1}$, $(\cdot)^T$, and $(\cdot)^H$ indicate inverse, transpose, and Hermitian of a matrix respectively. $\mathbb{E}\{\cdot\}$ is the expectation of a random variable. Cardinality of a discrete set \mathcal{A} is denoted as $|\mathcal{A}|$. $\mathcal{CN}(x, y)$ denotes a complex Gaussian random variable with mean x and variance y . A similar notation is valid when the variable is a vector or matrix.

II. SYSTEM MODEL

We consider a multi-cell multi-user MIMO system operating in dynamic TDD mode. The multi-cell network consists of

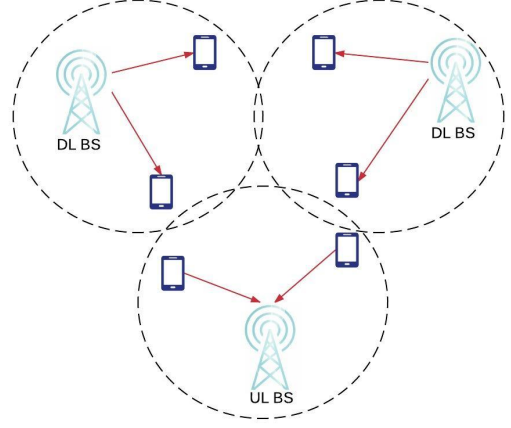


Fig. 1: Dynamic TDD system.

N BSs and K UEs. We denote the set of BS indices as $\mathcal{B} = \{1, \dots, N\}$ while the set of UEs served by each BS i is denoted by \mathcal{U}_i . The number of users served by each BS i is denoted by $K_i = |\mathcal{U}_i|$. Also, the serving BS of the user k is denoted as i_k . Each UE k employs N_k antenna elements, whereas each BS i employs M_i antenna elements. In a given time, a subset of base stations $\mathcal{B}_U \subseteq \mathcal{B}$ serves the uplink traffic and rest of the base stations $\mathcal{B}_D = \mathcal{B} \setminus \mathcal{B}_U$ are serving the DL traffic. The maximum number of spatial data streams allocated to UE $k \in \mathcal{U}_i$ is denoted by $L_k \leq \min(M_i, N_k)$. For notational simplicity, we define two sets $\mathcal{A}_{dl} = \{j, l | j \in \mathcal{U}_i, l = 1, \dots, L_j, i \in \mathcal{B}_D\}$ and $\mathcal{A}_{ul} = \{j, l | j \in \mathcal{U}_i, l = 1, \dots, L_j, i \in \mathcal{B}_U\}$. Here, \mathcal{A}_{ul} and \mathcal{A}_{dl} representing data stream indexing sets for the uplink and downlink transmissions, respectively. Furthermore, we assume the channels to be reciprocal in the UL and DL. The dynamic TDD model is illustrated in Fig. 1.

The received signal $\mathbf{x}_k^{(dl)} \in \mathbb{C}^{N_k}$ at the DL user k can be expressed as

$$\mathbf{x}_k^{(dl)} = \sum_{\{j, l\} \in \mathcal{A}_{dl}} \mathbf{H}_{i_j, k}^{(dl)} \mathbf{m}_{j, l}^{(dl)} d_{j, l}^{(dl)} + \sum_{\{j, l\} \in \mathcal{A}_{ul}} \mathbf{H}_{j, k}^{(ul-dl)} \mathbf{m}_{j, l}^{(ul)} d_{j, l}^{(ul)} + \mathbf{z}_k^{(dl)}, \quad (1)$$

where $\mathbf{H}_{i_j, k}^{(dl)} \in \mathbb{C}^{N_k \times M_{i_j}}$ is the channel matrix between the DL BS i_j and the UE k , $\mathbf{H}_{j, k}^{(ul-dl)} \in \mathbb{C}^{N_k \times N_j}$ is the interference channel matrix between the UL UE j and the DL UE k . The transmit precoder for l^{th} spatial data stream of the DL UE $j \in \mathcal{U}_i$ is denoted as $\mathbf{m}_{j, l}^{(dl)} \in \mathbb{C}^{M_i}$ and the transmit precoder for l^{th} spatial data stream of the UL UE $j \in \mathcal{U}_i$ is $\mathbf{m}_{j, l}^{(ul)} \in \mathbb{C}^{N_j}$. Transmitted data symbols to DL UE j in l^{th} spatial stream and transmitted data symbols from UL UE j in l^{th} spatial stream are denoted as $d_{j, l}^{(dl)}$ and $d_{j, l}^{(ul)}$, respectively. Here, the transmit data symbols are assumed to be independent and identically distributed with $\mathbb{E}\{|d_{j, l}^{(dl)}|^2\} = 1$ and $\mathbb{E}\{|d_{j, l}^{(ul)}|^2\} = 1$. We assume complex white Gaussian noise vector $\mathbf{z}_k^{(dl)} \in \mathbb{C}^{N_k}$ with variance \mathcal{N}_0 per element. Similarly, the received

signal $\mathbf{x}_i^{(\text{ul})} \in \mathbb{C}^{M_i}$ at the uplink BS i is given by

$$\mathbf{x}_i^{(\text{ul})} = \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \mathbf{H}_{i,j}^{(\text{ul})} \mathbf{m}_{j,l}^{(\text{ul})} d_{j,l}^{(\text{ul})} + \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{H}_{i,j}^{(\text{dl-ul})} \mathbf{m}_{j,l}^{(\text{dl})} d_{j,l}^{(\text{dl})} + \mathbf{z}_i^{(\text{ul})}, \quad (2)$$

where $\mathbf{H}_{i,j}^{(\text{ul})} \in \mathbb{C}^{M_i \times N_j}$ is the channel matrix between user j and UL BS i , $\mathbf{H}_{i,j}^{(\text{dl-ul})} \in \mathbb{C}^{M_i \times M_j}$ is the interference channel matrix between the DL BS i_j serving user j and the UL BS i . Also, we consider $\mathbf{z}_i^{(\text{ul})} \in \mathbb{C}^{M_i}$ to be complex white Gaussian noise vector with variance \mathcal{N}_0 per element. Note that, due to the channel reciprocity, $\mathbf{H}_{i,j}^{(\text{ul})} = \mathbf{H}_{i,j}^{(\text{dl})\text{T}}$.

To estimate the received data through l^{th} spatial stream, DL UE k employs a linear receiver $\mathbf{u}_{k,l}^{(\text{dl})} \in \mathbb{C}^{N_k}$. Similarly, the UL BS i_k employs a linear receiver $\mathbf{u}_{k,l}^{(\text{ul})} \in \mathbb{C}^{M_{i_k}}$ to decode the received data from UL user k through the spatial stream l . Then, the estimated data at a RX² node, corresponding to UL/DL data transmission can be written in a common form as $\hat{d}_{k,l}^{(a)}$. Here, for DL UE k , estimated data is given as $\hat{d}_{k,l}^{(\text{dl})} = \mathbf{u}_{k,l}^{(\text{dl})\text{H}} \mathbf{x}_k^{(\text{dl})}$ whereas for UL BS i_k , the estimated data transmitted by UE k is given as $\hat{d}_{k,l}^{(\text{ul})} = \mathbf{u}_{k,l}^{(\text{ul})\text{H}} \mathbf{x}_{i_k}^{(\text{ul})}$. From here on, for simplicity, a generic superscript ' a ' is introduced to represent both 'DL' and 'UL' directions.

The mean squared error (MSE) for l^{th} stream of for UE k corresponding to UL/DL data detection is defined as³

$$\begin{aligned} \epsilon_{k,l}^{(a)} &= \mathbb{E}_d[|d_{k,l}^{(a)} - \hat{d}_{k,l}^{(a)}|^2] \\ &= 1 - 2\Re(\mathbf{u}_{k,l}^{(a)\text{H}} \mathbf{H}_{i_k,k}^{(a)} \mathbf{m}_{k,l}^{(a)}) + \mathbf{u}_{k,l}^{(a)\text{H}} \mathbf{M}_k^{(a)} \mathbf{u}_{k,l}^{(a)}, \end{aligned} \quad (3)$$

where $\mathbf{M}_k^{(a)}$ is the received signal covariance matrix for UE k . This is given for DL UE k as

$$\begin{aligned} \mathbf{M}_k^{(\text{dl})} &= \mathbb{E}_d[\mathbf{x}_k^{(\text{dl})} \mathbf{x}_k^{(\text{dl})\text{H}}] = \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{H}_{i_j,k}^{(\text{dl})} \mathbf{m}_{j,l}^{(\text{dl})} (\mathbf{H}_{i_j,k}^{(\text{dl})} \mathbf{m}_{j,l}^{(\text{dl})})^{\text{H}} \\ &+ \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \mathbf{H}_{j,k}^{(\text{ul-dl})} \mathbf{m}_{j,l}^{(\text{ul})} (\mathbf{H}_{j,k}^{(\text{ul-dl})} \mathbf{m}_{j,l}^{(\text{ul})})^{\text{H}} + \mathcal{N}_0 \mathbf{I} \end{aligned} \quad (4)$$

and for UL UE k at BS i_k (note that in UL, the $\mathbf{M}_k^{(\text{ul})}$ is the same for all $k \in \mathcal{U}_{i_k}$) as

$$\begin{aligned} \mathbf{M}_k^{(\text{ul})} &= \mathbb{E}_d[\mathbf{x}_{i_k}^{(\text{ul})} \mathbf{x}_{i_k}^{(\text{ul})\text{H}}] = \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \mathbf{H}_{i_k,j}^{(\text{ul})} \mathbf{m}_{j,l}^{(\text{ul})} (\mathbf{H}_{i_k,j}^{(\text{ul})} \mathbf{m}_{j,l}^{(\text{ul})})^{\text{H}} \\ &+ \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{H}_{i_k,i_k}^{(\text{dl-ul})} \mathbf{m}_{j,l}^{(\text{dl})} (\mathbf{H}_{i_k,i_k}^{(\text{dl-ul})} \mathbf{m}_{j,l}^{(\text{dl})})^{\text{H}} + \mathcal{N}_0 \mathbf{I}. \end{aligned} \quad (5)$$

The linear minimum MSE (MMSE) receiver employed for data detection can be obtained from (3) as

$$\tilde{\mathbf{u}}_{k,l}^{(a)} = (\mathbf{M}_k^{(a)})^{-1} \mathbf{H}_{i_k,k}^{(a)} \mathbf{m}_{k,l}^{(a)}. \quad (6)$$

When the MMSE receiver is employed, the corresponding MSE can be obtain as

$$\tilde{\epsilon}_{k,l}^{(a)} = 1 - \tilde{\mathbf{u}}_{k,l}^{(a)\text{H}} \mathbf{H}_{i_k,k}^{(a)} \mathbf{m}_{k,l}^{(a)}, \quad (7)$$

²RX is used to refer DL UE for DL transmission or UL BS for UL transmission.

³ $\mathbb{E}_d\{\cdot\}$ is the expectation operation over transmit data symbols.

which is called the MMSE value of the estimated received data corresponding to the UL/DL data transmission of user k from spatial stream l . Finally, assuming independent detection of data streams, we can write the signal-to-interference-plus-noise ratio (SINR) $\gamma_{k,l}^{(a)}$ at RX node for DL/UL data transmission as in (8) and (9).

III. DECENTRALIZED BEAMFORMER DESIGN

The main problem in centralized dynamic TDD beamformer design is to acquire the CSI at the centralized node. That is, all the DL BS-UE channels, UL BS-UE channels, cross-UE channels and cross-BS channels should be available at the centralized unit. This is a tedious task as there are lots of cross-UE channels to be estimated and reported. Hence, decentralized beamformer design is more suited for dynamic TDD networks, where we can overcome the channel estimation problem by using bi-directional OTA signaling framework [18]. In this section, we study iterative decentralized beamformer design for dynamic TDD. First, we generalize the WQM solution from [27] to cover the dynamic TDD setting. Furthermore, we reformulate the problem for improved convergence using the ideas from [26] that were originally applied to WSR maximization. Second, we consider some special cases of WQM to obtain a beamformer design for QWSR maximization and SMSE minimization. In this Section, we consider only the algorithmic solution for the distributed framework. Practical implementation and related imperfections are presented in latter sections.

A. Weighted Queue Minimization

Here, weighted ℓ_q -norm queue minimization of the UL and DL users is considered with sum transmit power constraints at the transmitters. Let $Q_k^{(\text{dl})}$ denote the number of queued packets destined for DL user k and $Q_k^{(\text{ul})}$ denote the number of queued packets at UL user k at a given scheduling instant. Also, we model the traffic generation in the network using Poisson arrival process, where $\lambda_k^{(\text{dl})}(\tau) \sim \text{Pois}(A_k^{(\text{dl})})$ is the generated traffic for DL user k in time instance τ . Similarly, $\lambda_k^{(\text{ul})}(\tau) \sim \text{Pois}(A_k^{(\text{ul})})$ defines the generated traffic at UL user k at time instance τ . Here, $A_k^{(\text{dl})} = \mathbb{E}_\tau\{\lambda_k^{(\text{dl})}\}$ and $A_k^{(\text{ul})} = \mathbb{E}_\tau\{\lambda_k^{(\text{ul})}\}$ are the average number of packet arrivals in bits for the corresponding UL/DL users. Then, the total number of queued packets at $(\tau + 1)$ th time instant destined/available to user k is given by

$$Q_k^{(a)}(\tau + 1) = [Q_k^{(a)}(\tau) - R_k^{(a)}(\tau)]^+ + \lambda_k^{(a)}(\tau), \quad (10)$$

where $[x]^+ \triangleq \max\{x, 0\}$ and $R_k^{(a)}$ is the transmission rate to user k with $a = \{\text{UL}, \text{DL}\}$. Here, $R_k^{(a)} = \sum_{l=1}^{L_k} R_{k,l}^{(a)}$, where $R_{k,l}^{(a)}$ denotes the number of transmitted bits over the l th spatial stream to user k . For SINR $\gamma_{k,l}^{(a)}$, the maximum rate is bounded by $R_{k,l}^{(a)} \leq \log_2(1 + \gamma_{k,l}^{(a)})$. Now, we can define the queue deviation metric for the DL and UL as

$$\Psi_k^{(a)} = Q_k^{(a)} - R_k^{(a)} = Q_k^{(a)} - \sum_{l=1}^{L_k} \log_2(1 + \gamma_{k,l}^{(a)}). \quad (11)$$

$$\gamma_{k,l}^{(\text{dl})} = \frac{\left| \mathbf{u}_{k,l}^{(\text{dl})H} \mathbf{H}_{i_k,k}^{(\text{dl})} \mathbf{m}_{k,l}^{(\text{dl})} \right|^2}{\mathcal{N}_0 \|\mathbf{u}_{k,l}^{(\text{dl})}\|^2 + \sum_{\substack{\{j,n\} \in \mathcal{A}_{\text{dl}} \\ \{j,n\} \neq \{k,l\}}} |\mathbf{u}_{k,l}^{(\text{dl})H} \mathbf{H}_{i_j,k}^{(\text{dl})} \mathbf{m}_{j,n}^{(\text{dl})}|^2 + \sum_{\{j,n\} \in \mathcal{A}_{\text{ul}}} |\mathbf{u}_{k,l}^{(\text{dl})H} \mathbf{H}_{j,k}^{(\text{ul-dl})} \mathbf{m}_{j,n}^{(\text{ul})}|^2} \quad (8)$$

$$\gamma_{k,l}^{(\text{ul})} = \frac{\left| \mathbf{u}_{k,l}^{(\text{ul})H} \mathbf{H}_{i_k,k}^{(\text{ul})} \mathbf{m}_{k,l}^{(\text{ul})} \right|^2}{\mathcal{N}_0 \|\mathbf{u}_{k,l}^{(\text{ul})}\|^2 + \sum_{\substack{\{j,n\} \in \mathcal{A}_{\text{ul}} \\ \{j,n\} \neq \{k,l\}}} |\mathbf{u}_{k,l}^{(\text{ul})H} \mathbf{H}_{i_k,j}^{(\text{ul})} \mathbf{m}_{j,n}^{(\text{ul})}|^2 + \sum_{\{j,n\} \in \mathcal{A}_{\text{dl}}} |\mathbf{u}_{k,l}^{(\text{ul})H} \mathbf{H}_{i_j,i_k}^{(\text{dl-ul})} \mathbf{m}_{j,n}^{(\text{dl})}|^2} \quad (9)$$

In order to simplify the notation, let $\tilde{\Psi}^{(a)}$ denote a vector with elements $\tilde{\Psi}_k^{(a)} \triangleq \alpha_k^{1/q} \Psi_k^{(a)}$. Here, α_k is the weighting factor, used to prioritize users based on their corresponding QoS requirements. The WQM problem can be formulated as

$$\min_{\substack{\mathbf{m}_{k,l}^{(a)}, \mathbf{u}_{k,l}^{(a)}}} \|\tilde{\Psi}^{(\text{dl})}\|_q + \|\tilde{\Psi}^{(\text{ul})}\|_q \quad (12a)$$

$$\text{s. t.} \quad \sum_{k \in \mathcal{U}_i} \sum_{l=1}^{L_k} \|\mathbf{m}_{k,l}^{(\text{dl})}\|^2 \leq P_i^{(\text{dl})} \quad \forall i \quad (12b)$$

$$\sum_{l=1}^{L_k} \|\mathbf{m}_{k,l}^{(\text{ul})}\|^2 \leq P_k^{(\text{ul})} \quad \forall k, \quad (12c)$$

where optimization variables are transmit precoders $\mathbf{m}_{k,l}^{(a)}$ and receive combiners $\mathbf{u}_{k,l}^{(a)}$. Also, $P_i^{(\text{dl})}$ and $P_k^{(\text{ul})}$ are the maximum transmit powers available at the i -th DL BS and the k -th UL UE, respectively. Note that (12a) includes an implicit rate constraint $Q_k^{(a)} - \sum_{l=1}^{L_k} R_{k,l}^{(a)} \geq 0$ on the maximum number of transmitted bits for each user as governed by the number of backlogged packets [27]. The ℓ_q norm is used to provide a trade off between the fairness and sum queue minimization.

At RX, we employ MMSE receivers. Hence, we obtain the following relation between the MSE and the SINR [17]

$$\tilde{\epsilon}_{k,l}^{(a)} = (1 + \gamma_{k,l}^{(a)})^{-1}. \quad (13)$$

Therefore, we can write the user-specific rates using the user-specific MSE values as $R_k^{(a)} = \sum_{l=1}^{L_k} -\log_2(\tilde{\epsilon}_{k,l}^{(a)})$. Now, we introduce auxiliary MSE constraint as in [26] to (12) and rewrite the optimization problem as

$$\min_{\substack{\mathbf{m}_{k,l}^{(a)}, \mathbf{u}_{k,l}^{(a)} \\ t_{k,l}^{(a)}}} \sum_{a \in \{\text{UL, DL}\}} \sum_k \alpha_k \left(Q_k^{(a)} - \sum_{l=1}^{L_k} t_{k,l}^{(a)} \log_2(\beta) \right)^q \quad (14a)$$

$$\text{s. t.} \quad \epsilon_{k,l}^{(a)} \leq \beta^{-t_{k,l}^{(a)}} \quad (14b)$$

$$(12b), (12c), \quad (14c)$$

where β is a predefined constant to adjust the approximation function such that $\beta > 0$ [26]. By introducing these MSE constraints, our objective becomes a convex function of auxiliary variables $t_{k,l}^{(a)}$. However, the constraint (14b) is still in non-convex form. The non-convexity in (14b) can be handled

iteratively by using the first-order Taylor series approximation similarly to [26]

$$\beta^{-t_{k,l}^{(a)}} = -K_1 t_{k,l}^{(a)} + K_2, \quad (15)$$

where $K_1 = \beta^{-\bar{t}_{k,l}^{(a)}} \log(\beta)$ and $K_2 = \beta^{-\bar{t}_{k,l}^{(a)}} + \bar{t}_{k,l}^{(a)} K_1$. Here, $\bar{t}_{k,l}^{(a)}$ is the point of approximation. By employing the above approximation for the MSE constraints, we can re-write the equivalent optimization problem as

$$\min_{\substack{\mathbf{m}_{k,l}^{(a)}, \mathbf{u}_{k,l}^{(a)} \\ t_{k,l}^{(a)}}} \sum_{a \in \{\text{UL, DL}\}} \sum_k \alpha_k \left(Q_k^{(a)} - \sum_{l=1}^{L_k} t_{k,l}^{(a)} \log_2(\beta) \right)^q \quad (16a)$$

$$\text{s. t.} \quad 1 - 2\Re(\mathbf{u}_{k,l}^{(a)H} \mathbf{H}_{i_k,k}^{(a)} \mathbf{m}_{k,l}^{(a)}) + \mathbf{u}_{k,l}^{(a)H} \mathbf{M}_k^{(a)} \mathbf{u}_{k,l}^{(a)} \leq -K_1 t_{k,l}^{(a)} + K_2 \quad (16b)$$

(12b), (12c). (16c)

Finally, the optimization problem (16) can be solved using alternating optimization (AO) between the transmit and receive beamformers. We adopt an approach based on the KKT optimality conditions [26], [27]. Due to the independent nature of the optimization variables, the solution can be decoupled to calculate at RX and TX⁴ nodes iteratively. Therefore, we define tasks for each coordinated nodes to implement this distributed iterative solution. For example, the RX node performs the task '*Receiver update*' and the TX node performs the task '*Transmitter update*' as mentioned below.

Receiver update

Here, we present the beamformer design steps that the RX node should be performed. To do that, all the transmit precoders should be made available at the RX node. We begin by fixing, the transmit precoders and solving for the receive beamformers and the other variables (auxiliary and dual). First, we calculate MMSE receivers $\mathbf{u}_{k,l}^{(a)}$ using (6). Next, the corresponding MSE $\epsilon_{k,l}^{(a)}$ is obtained from (7). Then, the MSE bounds can be solved with respect to fixed MSE $\epsilon_{k,l}^{(a)}$ as

$$t_{k,l}^{(a)} = \bar{t}_{k,l}^{(a)} + \frac{1}{\log(\beta - \xi)} \left(1 - \epsilon_{k,l}^{(a)} \bar{t}_{k,l}^{(a)} \right), \quad (17)$$

⁴TX is used to refer DL BS for DL transmission or UL UE for UL transmission.

where $\bar{t}_{k,l}^{(a)}$ denotes $t_{k,l}^{(a)}$ from the previous iteration, $\xi = \frac{\beta-\theta}{n^\zeta}$, $\zeta \in \mathcal{R}$ is chosen to be an approximately small constant and $\theta > 1$. Here, the multiplier $\frac{1}{\log(\beta-\rho)}$ can be considered as a step size and ξ is used for more aggressive convergence as detailed in [26]. Then, dual variables $\omega_{k,l}^{(a)}$ corresponding to (15) are obtained as

$$\omega_{k,l}^{(a)} = (1 - \rho)\bar{\omega}_{k,l}^{(a)} + \rho \left[\frac{\alpha_k q \log_2(\beta)}{K_1} \left(Q_k^{(a)} - \sum_{l=1}^{L_k} t_{k,l}^{(a)} \log_2(\beta) \right)^{(q-1)} \right]^+, \quad (18)$$

where $\bar{\omega}_{k,l}^{(a)}$ denotes fixed $\omega_{k,l}^{(a)}$ from the previous iteration. Here, $\rho \in (0, 1)$ controls the convergence and is used to prevent overallocation. From here on, we refer to $\omega_{k,l}^{(a)}$ as user specific weight. The calculated MMSE receivers and user-specific weights information must be conveyed to /made available at coordinating TX nodes, in order to the perform 'Transmitter update' task.

Transmitter update

In the next step, we fix the MMSE receivers and solve for the transmit precoders. At this point, we assume all the MMSE receiver information and user-specific weights available at the TX node (to be detailed in Section IV). The transmit beamformers $\mathbf{m}_{k,l}^{(a)}$ can be derived from the first-order optimality conditions of (14) as

$$\mathbf{m}_{k,l}^{(a)} = \left(\Phi_k^{(a)} + \nu_k^{(a)} \mathbf{I} \right)^{-1} \omega_{k,l}^{(a)} \mathbf{H}_{i_k,k}^{(a)} \mathbf{u}_{k,l}^{(a)}, \quad (19)$$

where $\Phi_k^{(a)}$ and $\nu_k^{(a)}$ are the weighted transmit covariance matrix and the dual variable corresponding to power constraint at the transmitter (UL UE k or DL BS i_k). For DL BS i_k , $\Phi_k^{(dl)} \forall k \in \mathcal{U}_{i_k}$ is given by

$$\begin{aligned} \Phi_k^{(dl)} &= \sum_{\{j,l\} \in \mathcal{A}_{ul}} \omega_{j,l}^{(dl)} \mathbf{H}_{i_k,j}^{(dl)} \mathbf{u}_{j,l}^{(dl)} (\mathbf{H}_{i_k,j}^{(dl)} \mathbf{u}_{j,l}^{(dl)})^H \\ &+ \sum_{\{j,l\} \in \mathcal{A}_{ul}} \omega_{j,l}^{(ul)} \mathbf{H}_{i_j,i_k}^{(ul)} \mathbf{u}_{j,l}^{(ul)} (\mathbf{H}_{i_j,i_k}^{(ul)} \mathbf{u}_{j,l}^{(ul)})^H. \end{aligned} \quad (20)$$

Similarly, for UL user k , $\Phi_k^{(ul)}$ is given by

$$\begin{aligned} \Phi_k^{(ul)} &= \sum_{\{j,l\} \in \mathcal{A}_{ul}} \omega_{j,l}^{(ul)} \mathbf{H}_{i_j,k}^{(ul)} \mathbf{u}_{j,l}^{(ul)} (\mathbf{H}_{i_j,k}^{(ul)} \mathbf{u}_{j,l}^{(ul)})^H \\ &+ \sum_{\{j,l\} \in \mathcal{A}_{ul}} \omega_{j,l}^{(dl)} \mathbf{H}_{j,k}^{(ul-dl)} \mathbf{u}_{j,l}^{(dl)} (\mathbf{H}_{j,k}^{(ul-dl)} \mathbf{u}_{j,l}^{(dl)})^H. \end{aligned} \quad (21)$$

The transmit beamformers can efficiently solved from (19) by bisection search over the dual variables $\nu_k^{(dl)}$ and $\nu_k^{(ul)}$ to satisfy the power constraints $\sum_{k \in \mathcal{U}_i} \sum_{l=1}^{L_k} \|\mathbf{m}_{k,l}^{(dl)}\|^2 \leq P_i^{(dl)}$ and $\sum_{l=1}^{L_k} \|\mathbf{m}_{k,l}^{(ul)}\|^2 \leq P_k^{(ul)}$, respectively.

Here, we employed alternating optimization approach to calculate the precoders and decoders. Hence, beamformers are not optimal as they are optimized for their fixed counterparts. Thus, we need to repeat the precoder/decoder optimization until the estimated beamformers and/or the optimization objective have converged. This procedure is summarized in Algorithm 1. Note that the centralized unit can get the same

solution by considering this distributed implementation as independent subproblems, which can be solved in parallel. However, for dynamic TDD setting, we are more interested in the decentralized solution. Moreover, detailed signaling structure to facilitate the iterative algorithm is explained in Section IV.

Algorithm 1 Iterative Beamformer Design

- 1: Initializing feasible transmit beamformers $\mathbf{m}_{k,l}^{(a)}$. \triangleright TX
 - 2: Distribute initial transmit beamformers and prioritizing weights α_k to all RX. \triangleright TX
 - 3: **repeat**
 - 4: Estimate MMSE receivers $\mathbf{u}_{k,l}^{(a)}$ from (6). \triangleright RX
 - 5: Estimate auxiliary variables $t_{k,l}^{(a)}$, and user specific weights $\omega_{k,l}^{(a)}$ using (17) and (18). \triangleright RX
 - 6: Distribute all MMSE receivers and user specific weights to all TX. \triangleright RX
 - 7: Estimate transmit precoders $\mathbf{m}_{k,l}^{(a)}$ from (19). \triangleright TX
 - 8: Distribute all transmit precoders to all RX. \triangleright TX
 - 9: **until** convergence.
-

B. Queue Weighted Sum Rate Maximization

In this section, we consider a special case of WQM assuming $Q_k^{(a)}$ is large and $q = 2$. Consequently, (14) is reduced to the following equivalent QWSR maximization problem

$$\begin{aligned} \max_{\mathbf{m}_{k,l}^{(a)}, \mathbf{u}_{k,l}^{(a)}} \quad & \sum_{a \in \{\text{UL}, \text{DL}\}} \sum_k \sum_{l=1}^{L_k} \alpha_k Q_k^{(a)} R_{k,l}^{(a)} \\ \text{s.t} \quad & (12b), (12c). \end{aligned} \quad (22)$$

We can follow the same procedure as in WQM to obtain an iterative beamformer design for the QWSR maximization problem. Since we assume queue size to be large, we do not need to control the over allocation of assigned rates as in (18). Therefore, user-specific weights $\omega_{k,l}^{(a)}$ are given simply as

$$\omega_{k,l}^{(a)} = \frac{\alpha_k \log_2(\beta) Q_k^{(a)}}{K_1}. \quad (23)$$

The other beamformer and auxiliary variable updates are the same as in WQM. Note that when $Q_k^{(a)} = 1 \forall k$, QWSR objective is equivalent to WSR. Note that when $\beta = 2$, the beamformer estimation procedure is equivalent to our previously studied WSMSE based approach [42]–[44].

C. Sum MSE Minimization

The WQM problem can be approximated by a simple SMSE minimizing beamformer design provided that the system operates in high SNR regime with equal user priorities, the queue sizes are large with $q = 1$, and there are enough spatial degrees of freedom available such that all users can be served concurrently. The SMSE minimization problem can be formulated as

$$\begin{aligned} \min_{\mathbf{m}_{k,l}^{(a)}, \mathbf{u}_{k,l}^{(a)}} \quad & \sum_{a \in \{\text{UL}, \text{DL}\}} \sum_k \sum_{l=1}^{L_k} \epsilon_{k,l}^{(a)} \\ \text{s.t} \quad & (12b), (12c). \end{aligned} \quad (24)$$

In this special case, the weight updates are not needed and the optimal TX and RX beamformers (given fixed RX and TX beamformers) are solved directly from (19) and (6), respectively.

IV. TRAINING AND SIGNALING

In the previous section, we considered iterative beamformer designs for WQM, QWSR, and SMSE objectives. In this section, we introduced possible approaches to implement these algorithms in practice. In all of the proposed iterative beamformer algorithms, we need to iteratively exchange or make available the intermediate beamformers and user-specific weights between the coordinated nodes. However, in dynamic TDD setup, we do not have the luxury to use a backhaul based approach as UEs are also playing a role in beamformer estimation. Hence, we employ F-B OTA training for the implicit information exchange [17], [18].

In the considered F-B OTA training scheme, we employ precoded (and weighted) pilot sequences in the forward and backward directions. Here, the forward direction refers to transmitters sending their training sequences, and the backward direction is referring to receivers sending their training sequences. The bi-directional training allows a fully distributed coordinated computation of transmit/receive beamformers without full CSI exchange over a backhaul. Furthermore, bi-directional signaling is embedded into each TDD frame to facilitate fast iterative information exchange as shown in Fig. 2 [18], [43]. The nodes estimate their precoder/decoder based on the received forward/backward training sequences. Then, the estimated precoder/decoder is used for precoding the next iteration forward/backward training. Using this approach, we are able to practically implement the proposed beamformer designs.

It is possible to implement TDD frame structure in Fig. 2 (Scheduling block), with the approved 3GPP NR standard [9]. Beamformer signaling part can be implemented by concatenating multiple minislots together with the required guard period (GP) [18]. Then, multiple slots can be aggregated for data transmission. Moreover, each F-B iteration adds signaling overhead to the system. Hence, it is better to have a larger scheduling block to minimize the signaling overhead. However, it is constrained by coherence time and the traffic burstiness of the system. Note that, TDD frame should be synchronous over the UL/DL cells during the beamformer signaling. However, if the user scheduling remains the same for multiple TDD frames, and if the channel is slowly fading, the B-F training phase can use the beamformers from the previous frame as the starting point. Then, we can have less F-B iterations per TDD frame.

In a dense dynamic TDD network, a large number of orthogonal pilots would be required for ideal pilot estimation. In general, this is not possible due to the limited number of orthogonal resources. Therefore, we have to reuse the pilot sequences or employ non-orthogonal pilots during the training. Thus, the desired channel can be polluted by other user channels. This scenario is known as pilot contamination. Hence, it is essential to study the dynamic TDD system

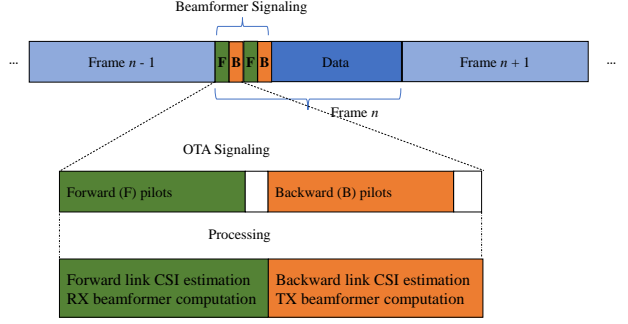


Fig. 2: TDD frame structure.

under imperfect OTA signaling conditions. Pilot contamination can be demoted in several ways, such as allocating pilots to minimize the pilot overlap and using clever channel estimation algorithms [36]–[40]. In the following subsections, we study various approaches to mitigate the pilot contamination while supporting the original beamformer design objectives. First, we consider three LS based strategies for direct beamformer estimation using only the precoded pilot information. Then, to further enhance the pilot decontamination, we propose pilot reuse method based on the large-scale fading information. Additionally, we analytically compare the proposed DE method with the SSE method to prove the superior decontamination capability of the DE approach.

A. Pilot decontamination by direct beamformer estimation

Here, we investigate the OTA signaling architecture under imperfect pilot conditions by assuming that the pilot training sequences used by each UE/BS are non-orthogonal, and only the pilot training sequences of the associated in-cell users are known to each UE/BS. As we employ non-orthogonal overlapping pilots, the effective channels are contaminated by interfering pilot training sequences. Therefore, they cannot be perfectly distinguished from each other. Without this information, we can not directly construct $\Phi_k^{(dl)}$ in (20) at the DL BS i_k or $\Phi_k^{(ul)}$ in (21) at the UL UE k in order to estimate their transmit precoders. To overcome this problem, we introduce three different strategies to facilitate the direct precoder/decoder estimation by using the received precoded training information directly without separately estimating all individual pilots (channels). In Table I, the signaling requirements for the forward/backward training are summarized for the proposed schemes. The proposed schemes are named as, Strategy A, Strategy B and Strategy C. Strategy A is proposed to implement exact beamformer design at both RX and TX with the minimum number OTA signaling (one forward and one backward training iteration per one beamformer signaling round). Hence, a separate (quantized) feedback link is required to transmit additional scalar weight information. Alternatively, we propose two designs; Strategy B and Strategy C. Both schemes use only the OTA signaling to exchange required information. In Strategy B, similar to Strategy A, we try to construct the beamformer design with the minimum number of OTA signaling. However, one backward training is not enough

TABLE I: Precoded pilots/Feedback used in each Strategy.

Strategy	Forward Training	Backward Training		Feedback
		1st	2nd	
Strategy A	$\mathbf{m}_{k,l}^{(a)}$	$\sqrt{\omega_{k,l}^{(a)}} \mathbf{u}_{k,l}^{(a)}$	NA	$\sqrt{\omega_{k,l}^{(a)}}$
Strategy B	$\mathbf{m}_{k,l}^{(a)}$	$\mathbf{u}_{k,l}^{(a)}$	NA	NA
Strategy C	$\mathbf{m}_{k,l}^{(a)}$	$\sqrt{\omega_{k,l}^{(a)}} \mathbf{u}_{k,l}^{(a)}$	$\omega_{k,l}^{(a)} \mathbf{u}_{k,l}^{(a)}$	NA

to fully reconstruct the required weighted covariance matrix at the TX node. Hence, Strategy B follows an approximated beamformer design. To overcome the limitation of Strategy B and for the fully construction of the beamformer design, we propose Strategy C with two backward training resources. Further details on each strategy are presented in below.

B. Strategy A

In this strategy, we employ two training signals and one feedback message for each precoder/decoder iteration. First, forward pilots are transmitted by precoding the training sequence with the transmit beamformers $\mathbf{m}_{k,l}^{(a)}$. Then, the RXs estimate their MMSE receivers $\mathbf{u}_{k,l}^{(a)}$ and the corresponding user-specific weights $\omega_{k,l}^{(a)}$ by using the received pilot training matrices. Next, the RX nodes use weighted MMSE receivers $\sqrt{\omega_{k,l}^{(a)}} \mathbf{u}_{k,l}^{(a)}$ as the precoders for backward training pilots. At the same time, the RXs transmit square root of user-specific weights $\sqrt{\omega_{k,l}^{(a)}}$ through the feedback channel. Both, the backward pilot information and feedback information are used to estimate the transmit precoder $\mathbf{m}_{k,l}^{(a)}$ at TX node. In the following, the direct beamformer estimation procedure for Strategy A is described in more detail.

Transmit Precoder Estimation

Let $\mathbf{b}_{k,l} \in \mathbb{C}^S$ denote the pilot training sequence for l^{th} data stream of DL/UL user k , where S is the length of the pilot sequence. For backward training, the pilots are precoded with $\sqrt{\omega_{k,l}^{(a)}} \mathbf{u}_{k,l}^{(a)}$. Then, the received precoded pilot training matrix of user k at DL BS i_k (note that the $\mathbf{R}_k^{(\text{dl})}$ is the same for all $k \in \mathcal{U}_{i_k}$) is given by

$$\mathbf{R}_k^{(\text{dl})} = \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \sqrt{\omega_{j,l}^{(\text{dl})}} \mathbf{H}_{i_k,j}^{(\text{dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})} \mathbf{b}_{j,l}^{\text{H}} + \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \sqrt{\omega_{j,l}^{(\text{ul})}} \mathbf{H}_{i_k,j}^{(\text{dl-ul})\text{H}} \mathbf{u}_{j,l}^{(\text{ul})} \mathbf{b}_{j,l}^{\text{H}} + \mathbf{N}_k^{(\text{dl})}, \quad (25)$$

where $\mathbf{N}_k^{(\text{dl})} \in \mathbb{C}^{M_{i_k} \times S}$ is the estimation noise matrix for all pilot symbols. Similarly, the received pilot training matrix at UL user k , during the first backward training, is given by

$$\mathbf{R}_k^{(\text{ul})} = \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \sqrt{\omega_{j,l}^{(\text{ul})}} \mathbf{H}_{i_k,j}^{(\text{ul})\text{H}} \mathbf{u}_{j,l}^{(\text{ul})} \mathbf{b}_{j,l}^{\text{H}} + \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \sqrt{\omega_{j,l}^{(\text{dl})}} \mathbf{H}_{i_k,j}^{(\text{ul-dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})} \mathbf{b}_{j,l}^{\text{H}} + \mathbf{N}_k^{(\text{ul})}, \quad (26)$$

where $\mathbf{N}_k^{(\text{ul})} \in \mathbb{C}^{N_k \times S}$ is the estimation noise matrix.

At DL BS i_k , we recover a noisy version of $\Phi_k^{(\text{dl})} \forall k \in \mathcal{U}_{i_k}$ in (20) directly using the received composite channel information $\mathbf{R}_k^{(\text{dl})}$ as,

$$\bar{\Phi}_k^{(\text{dl})} = \mathbf{R}_k^{(\text{dl})} \mathbf{R}_k^{(\text{dl})\text{H}} = \Phi_k^{(\text{dl})} + \Omega_{i_k}, \quad (27)$$

where Ω_{i_k} includes all the cross-terms in (25) due to non-orthogonal pilots as well as noise. With orthogonal pilots, Ω_{i_k} would contain only estimation noise. The structure and significance of Ω_{i_k} is examined in more detail in Section IV-E. Similarly, we can approximately construct $\Phi_k^{(\text{ul})}$ in (21) at UL user k directly using the received composite channel information $\mathbf{R}_k^{(\text{ul})}$ as

$$\bar{\Phi}_k^{(\text{ul})} = \mathbf{R}_k^{(\text{ul})} \mathbf{R}_k^{(\text{ul})\text{H}} = \Phi_k^{(\text{ul})} + \Omega_k, \quad (28)$$

where Ω_k indicates the cross pilot interference.

With the knowledge of the received training matrices $\mathbf{R}_k^{(a)}$, user-specific weights $\sqrt{\omega_{k,l}^{(a)}}$ (received via the feedback channel) and own training sequences $\mathbf{b}_{k,l}$, we can locally estimate the transmit beamformers in a closed form expressions as

$$\mathbf{m}_{k,l}^{(a)} = \left(\mathbf{R}_k^{(a)} \mathbf{R}_k^{(a)\text{H}} + \mathbf{I}_{\nu_k^{(a)}} \right)^{-1} \sqrt{\omega_{k,l}^{(a)}} \mathbf{R}_k^{(a)} \mathbf{b}_{k,l}, \quad (29)$$

where the optimal $\nu_k^{(\text{dl})}$ and $\nu_k^{(\text{ul})}$ are found by bisection search to satisfy the power constraints $\sum_{k \in \mathcal{U}_i} \sum_{l=1}^{L_k} \|\mathbf{m}_{k,l}^{(\text{dl})}\|^2 \leq P_i^{(\text{dl})}$ and $\sum_{l=1}^{L_k} \|\mathbf{m}_{k,l}^{(\text{ul})}\|^2 \leq P_k^{(\text{ul})}$, respectively. In the ideal conditions with orthogonal pilots and very high pilot SNR (or very large S), (29) would be equal to (19).

Receive Beamformer and Weights Estimation

In the forward training, the pilots are precoded with the transmit precoders $\mathbf{m}_{k,l}^{(a)}$. Then, the received precoded pilot training matrix at DL user k is given by,

$$\mathbf{T}_k^{(\text{dl})} = \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{H}_{i_k,j}^{(\text{dl})} \mathbf{m}_{j,l}^{(\text{dl})} \mathbf{b}_{j,l}^{\text{H}} + \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \mathbf{H}_{j,k}^{(\text{ul-dl})} \mathbf{m}_{j,l}^{(\text{ul})} \mathbf{b}_{j,l}^{\text{H}} + \mathbf{N}_k^{(\text{dl})}, \quad (30)$$

where $\mathbf{N}_k^{(\text{dl})} \in \mathbb{C}^{N_k \times S}$ is the estimation noise matrix for all pilot symbols. Similarly, the received precoded pilot training matrix at UL BS i_k is given by

$$\mathbf{T}_k^{(\text{ul})} = \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \mathbf{H}_{i_k,j}^{(\text{ul})} \mathbf{m}_{j,l}^{(\text{ul})} \mathbf{b}_{j,l}^{\text{H}} + \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{H}_{i_k,j}^{(\text{dl-ul})} \mathbf{m}_{j,l}^{(\text{dl})} \mathbf{b}_{j,l}^{\text{H}} + \mathbf{N}_k^{(\text{ul})}, \quad (31)$$

where $\mathbf{N}_k^{(\text{ul})} \in \mathbb{C}^{M_{i_k} \times S}$ is the estimation noise matrix. Then, by using the received composite channel information $\mathbf{T}_k^{(a)}$ and own pilot training sequence $\mathbf{b}_{k,l}$ we can directly estimate the MMSE receivers as

$$\mathbf{u}_{k,l}^{(a)} = \left(\mathbf{T}_k^{(a)} \mathbf{T}_k^{(a)\text{H}} + \mathcal{N}_k \mathbf{I} \right)^{-1} \mathbf{T}_k^{(a)} \mathbf{b}_{k,l}. \quad (32)$$

Also, the RX MSE can be estimated as

$$\epsilon_{k,l}^{(a)} = 1 - \mathbf{u}_{k,l}^{(a)\text{H}} \mathbf{T}_k^{(a)} \mathbf{b}_{k,l}. \quad (33)$$

Finally, we can estimate $\omega_{k,l}^{(a)}$ using (18) or (23) based on our optimization objective. Note that here we assume that, for any particular user, the forward and backward sequences are the same. However, the forward/backward pilots can also be designed separately.

C. Strategy B

In contrast to Strategy A, Strategy B does not require feed-back channel to exchange the user-specific weights. Similar to Strategy A, the forward training pilots are precoded with the transmit precoders $\mathbf{m}_{k,l}^{(a)}$. Then, the RX nodes estimate the MMSE receivers $\mathbf{u}_{k,l}^{(a)}$. Next, the estimated MMSE receivers are used to precode the backward training pilots. The information received from the backward training pilots is enough to reconstruct the $\bar{\Phi}_k^{(a)}$ at TX k/i_k . However, by using locally evaluated user-specific weights, we can only approximately estimate the transmit precoders.

Transmit Precoder Estimation

In the backward training, the pilots are precoded with the MMSE receivers $\mathbf{u}_{k,l}^{(a)}$ without weights $\omega_{k,l}^{(a)}$. The received pilot training matrix at DL BS $i_k, \forall k \in \mathcal{U}_{i_k}$ is, then, given by

$$\begin{aligned} \mathbf{R}_{k,1}^{(\text{dl})} &= \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{H}_{i_k,j}^{(\text{dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})} \mathbf{b}_{j,l}^{\text{H}} \\ &+ \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \mathbf{H}_{i_j,i_k}^{(\text{dl-ul})\text{H}} \mathbf{u}_{j,l}^{(\text{ul})} \mathbf{b}_{j,l}^{\text{H}} + \mathbf{N}_{i_k}^{(\text{dl})}. \end{aligned} \quad (34)$$

Similarly, the received pilot training matrix at UL user k , during the first backward training, is given by

$$\begin{aligned} \mathbf{R}_{k,1}^{(\text{ul})} &= \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \mathbf{H}_{i_j,k}^{(\text{ul})\text{H}} \mathbf{u}_{j,l}^{(\text{ul})} \mathbf{b}_{j,l}^{\text{H}} \\ &+ \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{H}_{j,k}^{(\text{ul-dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})} \mathbf{b}_{j,l}^{\text{H}} + \mathbf{N}_k^{(\text{ul})}. \end{aligned} \quad (35)$$

Then, we can estimate the user weights $\omega_{k,l}^{(a)}$ locally by using the first set of received composite channel $\mathbf{R}_{k,1}^{(a)}$ and training sequence $\mathbf{b}_{k,l}$ at TX k/i_k . To do that, first, we estimate MSE $\epsilon_{k,l}^{(a)}$ locally as

$$\epsilon_{k,l}^{(a)} = 1 - (\mathbf{R}_{k,1}^{(a)} \mathbf{b}_{k,l})^{\text{H}} \bar{\mathbf{m}}_{k,l}^{(a)}, \quad (36)$$

where $\bar{\mathbf{m}}_{k,l}^{(a)}$ is the transmit precoder estimated in the previous iteration or the initial condition. Then, we can estimate $\omega_{k,l}^{(a)}$

using (18) or (23). Finally, we construct $\bar{\Phi}_{k,1}^{(\text{dl})}$, at DL BS i_k , as

$$\begin{aligned} \bar{\Phi}_{k,1}^{(\text{dl})} &\triangleq \mathbf{R}_{k,1}^{(\text{dl})} (\mathbf{I} + \sum_{j \in \mathcal{U}_{i_k}} \sum_{l=1}^{L_j} \frac{(\omega_{j,l}^{(\text{dl})} - 1)}{S} \mathbf{b}_{j,l} \mathbf{b}_{j,l}^{\text{H}}) \mathbf{R}_{k,1}^{(\text{dl})\text{H}} \\ &= \sum_{j \in \mathcal{U}_{i_k}} \sum_{l=1}^{L_j} \omega_{j,l}^{(\text{dl})} \mathbf{H}_{i_k,j}^{(\text{dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})} (\mathbf{H}_{i_k,j}^{(\text{dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})})^{\text{H}} \\ &+ \sum_{\substack{\{j,l\} \in \mathcal{A}_{\text{dl}} \\ j \notin \mathcal{U}_{i_k}}} \mathbf{H}_{i_k,j}^{(\text{dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})} (\mathbf{H}_{i_k,j}^{(\text{dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})})^{\text{H}} \\ &+ \sum_{\{j,l\} \in \mathcal{A}_{\text{ul}}} \mathbf{H}_{i_j,i_k}^{(\text{dl-ul})\text{H}} \mathbf{u}_{j,l}^{(\text{ul})} (\mathbf{H}_{i_j,i_k}^{(\text{dl-ul})\text{H}} \mathbf{u}_{j,l}^{(\text{ul})})^{\text{H}} + \Omega_{i_k}. \end{aligned} \quad (37)$$

Similarly, at UL UE k , we construct $\bar{\Phi}_k^{(\text{ul})}$ as

$$\begin{aligned} \bar{\Phi}_{k,1}^{(\text{ul})} &\triangleq \mathbf{R}_{k,1}^{(\text{ul})} (\mathbf{I} + \sum_{l=1}^{L_k} \frac{(\omega_{k,l}^{(\text{dl})} - 1)}{S} \mathbf{b}_{k,l} \mathbf{b}_{k,l}^{\text{H}}) \mathbf{R}_{k,1}^{(\text{ul})\text{H}} \\ &= \sum_{l=1}^{L_k} \omega_{k,l}^{(\text{ul})} \mathbf{H}_{i_k,k}^{(\text{ul})\text{H}} \mathbf{u}_{k,l}^{(\text{ul})} (\mathbf{H}_{i_k,k}^{(\text{ul})\text{H}} \mathbf{u}_{k,l}^{(\text{ul})})^{\text{H}} \\ &+ \sum_{\substack{\{j,l\} \in \mathcal{A}_{\text{ul}} \\ j \neq k}} \mathbf{H}_{i_j,k}^{(\text{ul})\text{H}} \mathbf{u}_{j,l}^{(\text{ul})} (\mathbf{H}_{i_j,k}^{(\text{ul})\text{H}} \mathbf{u}_{j,l}^{(\text{ul})})^{\text{H}} \\ &+ \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{H}_{j,k}^{(\text{ul-dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})} (\mathbf{H}_{j,k}^{(\text{ul-dl})\text{H}} \mathbf{u}_{j,l}^{(\text{dl})})^{\text{H}} + \Omega_k. \end{aligned} \quad (38)$$

It is clear that in this estimation scheme, $\bar{\Phi}_{k,1}^{(\text{ul})}$ does not contain the ideal $\Phi_k^{(a)}$ from (20)-(21) unlike in (37)-(38). This is mainly due to unavailability of the user specific weights from the interfered users. This is equivalent to assuming $\omega_{k,l}^{(a)} = 1$ for all non-local data streams. As in Strategy A, with the knowledge of the received training matrices $\mathbf{R}_{k,1}^{(a)}$ and own training sequences $\mathbf{b}_{k,l}$, we can estimate the transmit beamformers directly in closed form as

$$\mathbf{m}_{k,l}^{(a)} = \left(\bar{\Phi}_{k,1}^{(a)} + \mathbf{I} \nu_k^{(a)} \right)^{-1} \omega_{k,l}^{(a)} \mathbf{R}_{k,1}^{(a)} \mathbf{b}_{k,l} \quad (39)$$

where the optimal $\nu_k^{(a)}$ is found by bisection search similarly to (29). The receive beamformer estimation procedure for Strategy B is same as in Strategy A.

D. Strategy C

In this strategy, we employ three training pilots per beamformer iteration, one in the forward direction and two consecutive training pilots in the backward direction. The forward training procedure is same as strategies A and B, where we use transmit precoders $\mathbf{m}_{k,l}^{(a)}$ as the pilot precoders. The RXs estimate their MMSE receivers $\mathbf{u}_{k,l}^{(a)}$ and the corresponding user weights $\omega_{k,l}^{(a)}$ from the received pilots. In the backward phase, the first training sequences are precoded with $\sqrt{\omega_{k,l}^{(a)}} \mathbf{u}_{k,l}^{(a)}$ and the second transmission pilot sequences are precoded with $\omega_{k,l}^{(a)} \mathbf{u}_{k,l}^{(a)}$. The estimated pilot training matrices for the first pilot sequence are the same as in Strategy A (25)-(26) denoted

by $\mathbf{R}_k^{(a)}$. The training matrix corresponding to the second pilot sequence denoted by $\mathbf{R}_{k,2}^{(a)}$ is the same except the weight difference ($\sqrt{\omega_{k,l}^{(a)}}$ replaced with $\omega_{k,l}^{(a)}$). The backward pilot information is used to estimate the transmit precoder $\mathbf{m}_{k,l}^{(a)}$ as

$$\mathbf{m}_{k,l}^{(a)} = \left(\mathbf{R}_k^{(a)} \mathbf{R}_k^{(a)\text{H}} + \mathbf{I}_{\nu_k^{(a)}} \right)^{-1} \mathbf{R}_{k,2}^{(a)} \mathbf{b}_{k,l}. \quad (40)$$

Other expressions are derived similarly to Strategies A and B and are omitted here to avoid repetition.

E. DE vs SSE

The signaling and training strategies proposed in previous subsections directly estimate the beamformers (DE approach) from the received pilot training matrices. As an alternative implementation, we consider the SSE technique. In the SSE method, we separately estimate each pilot, and the estimated information is used to calculate beamformers and user weights. Therefore, all the coordinating nodes need to know the pilot sequences used at each node. The SSE approach can be highly vulnerable to pilot contamination, if non-orthogonal pilot sequences are employed for OTA signaling. However, the DE is better suited for noisy environments and more resilient to pilot contamination. In this section, we analyze the DE and SSE estimation inaccuracies by considering the estimation of $\Phi_k^{(\text{dl})}$ in Strategy A. Also, without loss of generality, we examine *DL only* case ($\mathcal{A}_{\text{ul}} = \emptyset$) in order to ease the notational complexity.

In stream specific estimation, we assume that all pilots are first individually estimated. Then, the covariance matrices and beamformers are constructed from those individual parts. The signaling model remains the same, that is, the received training matrix is of form (25). Recall that $\mathbf{R}_k^{(\text{dl})}$ is the same for all $k \in \mathcal{U}_{i_k}$. From (25), each DL BS $i_k = 1, \dots, B, k \in \mathcal{U}_{i_k}$ estimate the UE (stream) specific pilots as

$$\begin{aligned} \mathbf{f}_{i_k,j,l}^{(\text{dl})} &= \mathbf{R}_k^{(\text{dl})} \mathbf{b}_{j,l}, \forall (j,l) \\ &= \sqrt{\omega_{j,l}^{(\text{dl})}} \mathbf{H}_{i_k,j}^{(\text{dl})\text{H}} \mathbf{u}_{j,l} + \delta_{i_k,j,l}, \end{aligned} \quad (41)$$

where $\delta_{i_k,j,l}$ denotes the estimation noise and pilot contamination corresponding to pilot sequence $\mathbf{b}_{j,l}$ at BS i_k . We can immediately observe a potential downside to this. In order to accomplish (41), BS i_k has to know all pilot sequences $\mathbf{b}_{j,l}$. Also, the amount of estimation noise and pilot contamination gradually increase with the number of pilot sequences. Then using all the collected stream specific estimates, the matrix $(\Phi_k^{(\text{dl})})_{\text{SSE}}$ for the SSE approach is given by

$$\begin{aligned} (\Phi_k^{(\text{dl})})_{\text{SSE}} &= \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{f}_{i_k,j,l}^{(\text{dl})} \mathbf{f}_{i_k,j,l}^{(\text{dl})\text{H}} = \Phi_k^{(\text{dl})} + \mathbf{K}_k \\ &\quad + \bar{\mathbf{K}}_k + \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{N}_{i_k}^{(\text{dl})} \mathbf{b}_{j,l} \mathbf{b}_{j,l}^{\text{H}} \mathbf{N}_{i_k}^{(\text{dl})\text{H}} \end{aligned} \quad (42)$$

where \mathbf{K}_k and $\bar{\mathbf{K}}_k$ are additional interference terms given in (43) and (44), respectively. On the other hand, the estimation expressions $(\Phi_k^{(\text{dl})})_{\text{DE}}$ for the DE approach are given by

$$(\Phi_k^{(\text{dl})})_{\text{DE}} = \mathbf{R}_k^{(\text{dl})} \mathbf{R}_k^{(\text{dl})\text{H}} = \Phi_k^{(\text{dl})} + \mathbf{K}_k + \mathbf{N}_{i_k}^{(\text{dl})} \mathbf{N}_{i_k}^{(\text{dl})\text{H}} \quad (45)$$

From the expressions in (45) and (42), we can observe that SSE expression differs from DE case due to additional estimation error term $\bar{\mathbf{K}}_k$ and estimated noise terms $\mathbf{N}_{i_k}^{(\text{dl})} \mathbf{N}_{i_k}^{(\text{dl})\text{H}}$ and $\sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{N}_{i_k}^{(\text{dl})} \mathbf{b}_{j,l} \mathbf{b}_{j,l}^{\text{H}} \mathbf{N}_{i_k}^{(\text{dl})\text{H}}$. In order to compare DE and SSE approaches, first, we can see that $\mathbb{E}[\mathbf{N}_{i_k}^{(\text{dl})} \mathbf{N}_{i_k}^{(\text{dl})\text{H}}]$ is a diagonal matrix of size $M_{i_k} \times M_{i_k}$ with each diagonal element equal to $\mathcal{N}_0 S$, i.e.,

$$\text{Tr}(\mathbb{E}[\mathbf{N}_{i_k}^{(\text{dl})} \mathbf{N}_{i_k}^{(\text{dl})\text{H}}]) = M_{i_k} \mathcal{N}_0 S. \quad (46)$$

For the SSE case, we can form a symmetric matrix $\mathbf{C}_{i_k} = \sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{b}_{j,l} \mathbf{b}_{j,l}^{\text{H}}$ with the size of $S \times S$, where the diagonal terms are equal to K/S . Since the matrix trace is invariant under cyclic permutations, the following holds

$$\text{Tr}(\mathbb{E}[\sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{N}_{i_k}^{(\text{dl})} \mathbf{b}_{j,l} \mathbf{b}_{j,l}^{\text{H}} \mathbf{N}_{i_k}^{(\text{dl})\text{H}}]) = M_{i_k} \mathcal{N}_0 K. \quad (47)$$

Assuming a practical scenario where the number of users served is larger than the available pilot resources (sequence length), $K > S$, then

$$\text{Tr}(\mathbb{E}[\sum_{\{j,l\} \in \mathcal{A}_{\text{dl}}} \mathbf{N}_{i_k}^{(\text{dl})} \mathbf{b}_{j,l} \mathbf{b}_{j,l}^{\text{H}} \mathbf{N}_{i_k}^{(\text{dl})\text{H}}]) > \text{Tr}(\mathbb{E}[\mathbf{N}_{i_k}^{(\text{dl})} \mathbf{N}_{i_k}^{(\text{dl})\text{H}}])). \quad (48)$$

Finally, by taking the MSE of estimates (45) and (42), we can obtain the following relationship

$$\mathbb{E}[|(\Phi_k^{(\text{dl})})_{\text{SSE}} - \Phi_k^{(\text{dl})}|^2] > \mathbb{E}[|(\Phi_k^{(\text{dl})})_{\text{DE}} - \Phi_k^{(\text{dl})}|^2] + \bar{\mathbf{K}}_k \bar{\mathbf{K}}_k^{\text{H}}, \quad (49)$$

where the inequality follows from (48) and from the fact that $\bar{\mathbf{K}}_k \bar{\mathbf{K}}_k^{\text{H}}$ is a positive definite matrix. Thus, DE provides better estimation performance than SSE in the MSE sense.

F. Decontamination via Pilot Reuse

In this section, we consider a traditional pilot reuse approach to enhance the pilot decontamination further. The main aim is to assess how much additional gain can be achieved by applying *centralized* pilot assignment as compared to the decentralized direct estimation methods proposed in Section IV. A simple pilot reuse approach is proposed for complicated dynamic TDD setup based only on large-scale fading information of the BS-UE and UE-UE channels. In dynamic TDD networks, finding a proper utility for the pilot assignment is challenging. For example, the received channel information at DL UE k in the forward training phase and received channel information at DL BS i_k in the backward training phase are contaminated with different set of BSs and UEs. In our previous work, we introduced logarithmically weighted interference-to-signal-ratio (ISR) based decontamination method for DL only case [45]. Here, we use the same approach but with slight modifications to cope with specific challenges due to the dynamic TDD scenario.

In the considered heuristic method, the pilot allocation is carried out utilizing the user specific path loss measurements and reports. The basic idea is to reuse the same pilot for two users when they are physically far from each other. In

$$\mathbf{K}_k = \sum_{\substack{\{j,l\} \in \mathcal{A}_{dl} \\ \{y,z\} \in \mathcal{A}_{dl} \\ (y \neq j \& z \neq l)}} \sqrt{\omega_{j,l}^{(dl)} \omega_{y,z}^{(dl)}} \mathbf{H}_{i_k,j}^{(dl)H} \mathbf{u}_{j,l}^{(dl)} \mathbf{b}_{j,l}^H \mathbf{b}_{y,z} (\mathbf{H}_{i_k,y}^{(dl)H} \mathbf{u}_{y,z}^{(dl)})^H + \sum_{\{j,l\} \in \mathcal{A}_{dl}} \sqrt{\omega_{j,l}^{(dl)}} \left(\mathbf{H}_{i_k,j}^{(dl)H} \mathbf{u}_{j,l}^{(dl)} \mathbf{b}_{j,l}^H \mathbf{N}_{i_k}^{(dl)H} + \mathbf{N}_{i_k}^{(dl)} \mathbf{b}_{j,l} (\mathbf{H}_{i_k,j}^{(dl)H} \mathbf{u}_{j,l}^{(dl)})^H \right) \quad (43)$$

$$\begin{aligned} \bar{\mathbf{K}}_k = & \sum_{\substack{\{\{j,l\}, \{y,z\}, \{s,t\}\} \in \mathcal{A}_{dl} \\ (s \neq j \& t \neq l)}} \sqrt{\omega_{s,t}^{(dl)} \omega_{y,z}^{(dl)}} \mathbf{H}_{i_k,s}^{(dl)H} \mathbf{u}_{s,t}^{(dl)} \mathbf{b}_{s,t}^H \mathbf{b}_{j,l} \mathbf{b}_{j,l}^H \mathbf{b}_{y,z} (\mathbf{H}_{i_k,y}^{(dl)H} \mathbf{u}_{y,z}^{(dl)})^H \\ & + \sum_{\substack{\{\{j,l\}, \{y,z\}\} \in \mathcal{A}_{dl} \\ (y \neq j \& z \neq l)}} \sqrt{\omega_{y,z}^{(dl)}} \left(\mathbf{H}_{i_k,y}^{(dl)H} \mathbf{u}_{y,z}^{(dl)} \mathbf{b}_{y,z} \mathbf{b}_{j,l} \mathbf{b}_{j,l}^H \mathbf{N}_{i_k}^{(dl)H} + \mathbf{N}_{i_k}^{(dl)} \mathbf{b}_{j,l} \mathbf{b}_{j,l}^H \mathbf{b}_{y,z} (\mathbf{H}_{i_k,y}^{(dl)H} \mathbf{u}_{y,z}^{(dl)})^H \right) \quad (44) \end{aligned}$$

addition to BS-UE path loss measurements, we assume UE-UE received signal strength indicator (RSSI) based measurements are made available at BSs to avoid allocating same pilots to severely interfering DL and UL users. In order to do that, UE should be able to listen to received signals from both BSs and nearby UEs. Based on the RSSI measurements, UE reports a set of strongest measured RSSI values, both from BSs and UEs to serving BS via a separate control channel.

To assign the pilots, we define a cost function $R_{\mathcal{G}_p}$ for every orthogonal pilot $p \in \{1, \dots, S\}$ that is shared with a set of users $\mathcal{G}_p \subset \mathcal{U}$ as

$$R_{\mathcal{G}_p} = \sum_{k \in \mathcal{G}_p} \log(1 + \sum_{j \in \mathcal{G}_p / \{k\}} I_j / S_k) \quad (50)$$

where S_k is the path gain between user k serving BS i_k , and I_j is the path gain between interfering user j and BS i_k . Logarithmic ISR weighting is used to provide fairness such that weak users (far from BS) are not severely penalized. Every time a pilot is reused the cost function is increased correspondingly. The resulting ISR value is scaled by 1 to make the utility function always positive. Finally, the minimization problem used for the pilot allocation is formulated as

$$\begin{aligned} & \underset{\mathcal{G}_p \forall p}{\text{minimize}} \quad \sum_{p=1}^S R_{\mathcal{G}_p} \\ & \text{s.t.} \quad \mathcal{Y}_k \cap \mathcal{G}_p = \emptyset \quad \forall k, p, \end{aligned} \quad (51)$$

where \mathcal{Y}_k is the set of users with shortest UE-UE distance to user k . Finding optimal solution for above integer problem is highly complex for large S and K . Hence, a sub-optimal greedy method is used to solve the problem and the entire process is summarized in Algorithm 2. First, potential cost values for each pair are computed assuming they share the same pilot. Then, the user pair with minimum cost is assigned with the same pilot. Consequently, next pilot resources are assigned to the unassigned user pairs with the minimum utility value. Continuing this, up to $2S$ users are assigned. Then, the rest of the unassigned users are allocated to pilots using the same greedy method on the per pilot basis such a way that corresponding pilot will not be used more than $K/S + 1$ times. Here, the main target is to minimize the total log weighted pilot interference in the system. This may not accurately match with the original traffic aware optimization objective

in Section III. However, the results show significant sum rate improvement as compared to random pilot assignment.

Algorithm 2 Pilot Reuse Algorithm

1: **Initialize :**

- Define $k_{\max} = \lceil \frac{K}{S} \rceil$ - maximum number of users that are assigned to the same pilot.
- Find \mathcal{Y}_k for each user k and set $\mathcal{G} = \emptyset$.

2: **First phase:** Assign pilots up to $2S$ users

3: For $a = 1 : K$, For $b = 1 : K$, If $b \notin \mathcal{Y}_a$ do:

4: Calculate $R_{\{a,b\}}$ for $\{a,b\}$ UE pair from (50).

5: End, End, End

6: For $p = 1 : S$ do:

7: Define set $\mathcal{X} = \{\{a,b\} \mid \{a,b\} \subset \mathcal{U} \text{ and } \{a,b\} \notin \mathcal{G}\}$

8: $\underset{\forall \{a,b\} \subset \mathcal{X}}{\text{argmin}} \quad R_{\{a,b\}} \rightarrow \mathcal{G}_p = \{a,b\}$

9: Update user assignment $\mathcal{G} = \mathcal{G}_1 \cup \dots \cup \mathcal{G}_S$

10: End

11: **Last phase:** Assign pilots to unassigned users

12: For $c = 1 : k_{\max} - 2$, For $p = 1 : S$, do:

13: Define set $\mathcal{Z} = \{x \mid \mathcal{Y}_x \cap \mathcal{G}_p = \emptyset \text{ and } x \notin \mathcal{G}\}$

14: $\underset{x \in \mathcal{Z}}{\text{argmin}} \quad R_{\mathcal{G}_p \cup \{x\}} \rightarrow \mathcal{G}_p = \mathcal{G}_p \cup \{x\}$

15: Update pilot assignment $\mathcal{G} = \mathcal{G}_1 \cup \dots \cup \mathcal{G}_S$

16: End End

G. Complexity and Overhead

It is important to study the complexity and associated overhead of the proposed DE-based strategies. Therefore, in this subsection, we look into those two concerns.

Complexity Study

Here, we study the computational complexity of the proposed direct beamformer estimation methods. All strategies have similar computational complexities. Hence, we consider Strategy A in this study. In proposed iterative strategies, the complexity is linearly proportional to the number of OTA signaling rounds. Hence, we focus on one iteration only. There are 4 types of nodes involved in computing beamformers. The corresponding complexity at each node is as follows,

- DL BS - The dominant operation is the matrix inversion in (29). Also, there is a dual variable which we found by

bisection search to satisfy the power constraint. Hence, the complexity is $\mathcal{O}(M_i^3 \times \Delta \times K_i \times L_k)$, where Δ is the number bisection iterations required to satisfy the power constraint.

- DL UE - Here, the dominant operation is the matrix product operation within the inverse matrix in (32). Hence the complexity is $\mathcal{O}(N_k^2 \times S)$.
- UL BS - The complexity due to operations in (32) is roughly $\mathcal{O}(M_i^2 \times (M_i + S + L_k \times K_i))$.
- UL UE - The dominant complexity is coming from the bisection iterations and the matrix inversion in (29). Therefore, the complexity is $\mathcal{O}(N_k^3 \times \Delta \times L_k)$.

It is obvious that BS should have a higher computational capability compared to UEs. For the proposed strategies, for BSs, maximum complexity requirement arise when it is in DL mode. Which is $\mathcal{O}(M_i^3 \times \Delta \times K \times L_k)$ per one beamformer signaling round. Also, for UEs, maximum complexity requirement is $\mathcal{O}(N_k^3 \times \Delta \times L_k)$, which arises when it is in UL mode.

Overhead Model

As in Fig.2, the TDD frame is divided into two portions; 1. beamformer signalling, 2. data transmission. Therefore, the actual achievable rate of the system pretty much depends on the beamformer training duration. Here, we can model it as,

$$R_{ac} = (1 - \frac{\tau_0}{T} \text{BIT}) R_{sum}, \quad (52)$$

where, R_{ac} is the actual achievable sum rate and R_{sum} is the achieved sum rate from the iterative algorithm after BIT bi-directional precoder/decoder training rounds. The signaling overhead per one signaling round is $\frac{\tau_0}{T}$, where τ_0 and T are the duration for a one precoder/decoder iteration and the duration of the TDD frame, respectively. Here, we refer τ_0 as the 'effective overhead duration per F-B training round'. Following tasks are performed during the τ_0 ,

- Tx nodes transmit precoded pilots, which are precoded with transmit beamformers (F-training).
- Rx nodes estimate receiver beamformers and user-specific weights.
- Rx nodes transmit pilots using the estimated receive beamformers as pilot precoders possibly weighted by the user-specific weights as described in Section IV.B-D (B-training). Moreover, in Strategy A, we utilize a separate (quantized) feedback mechanism to exchange the scalar weights.
- Tx nodes estimate transmit precoders.

In addition to the above tasks, a guard period is required when the communication direction changes forward to backward and vice-versa. However, the overhead related for exchanging control messages such as measured RSSI values, explicit information about the queue sizes and prioritize coefficients is not included in this formula as the reporting period for such messages is much longer. In numerical examples, we investigate optimal number of bi-directional signaling rounds required for a TDD frame with this overhead model.

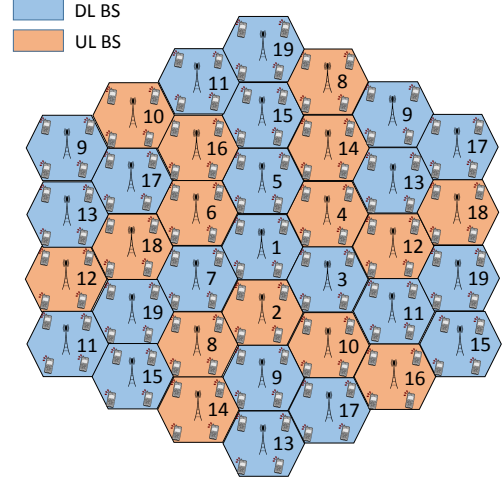


Fig. 3: 19-cell wrap-up model.

V. NUMERICAL EXAMPLES

The simulations are carried out for nineteen cell (= 19) wrap-around model as illustrated in Fig. 3. The distances between the BSs are considered to be 200 m and the UEs are randomly placed at the cell edge. For all the simulations, the path loss exponent is fixed to 3.67. The power constraint for DL BSs and UL UEs are normalized such that $P_k^{(ul)} = P_i^{(dl)} / K_i$, i.e., the total cell-specific UL power is equal to the DL power. However, we consider different power allocation in Fig. 7. Moreover, SNR is defined with respect to the DL cell edge user ($\text{SNR} = S_k P_{i_k}^{(dl)} / N_0$). To simplifying the study, all the user priority weights are assumed to be $\alpha_k = 1$. In Fig. 8, we examine time-correlated block fading, which is generated using Jake's Doppler spectrum model with the normalized user terminal velocity $t_s f_D = 0.01$, where t_s and f_D are the signaling rate and the maximum Doppler shift, respectively. For the rest of the figures, we have used uncorrelated block fading model. We have randomly assigned UL/DL BSs with DL cell probability = 0.5, for all the results except in Fig. 6. User weights $\alpha_k Q_k^{(a)} = 1 \forall k$ are used for all results with WSR maximization. Perfect CSIT is assumed to be available in simulation results shown in Figs. 4–8. For the practical channel/beamformer estimation results shown in Figs. 9–11 the pilot gain is considered to be 10dB.

The actual achievable sum rate obtained from the WSR maximization objective versus the total overhead due to OTA signaling is shown in top of the Fig. 4. The second figure illustrates the convergence of the beamformer algorithm with respect to the number of beamformer iterations. In this particular example, we assume that a single precoder/decoder iteration consumes 1% ($\frac{\tau_0}{T} = 0.01$) of the frame length. Note that, it is possible to have τ_0 smaller than 0.1ms with the proposed TDD frame structure [18]. Hence, we can obtain $\frac{\tau_0}{T} = 0.01$ even with relatively short coherence time (if the coherence time is 10 ms, we can have a TDD frame with $T = 10$ ms). We can observe that the scenario with $\beta = 30$, $\zeta = 0.05$ and $\theta = e$ has a better converging behaviour in comparison

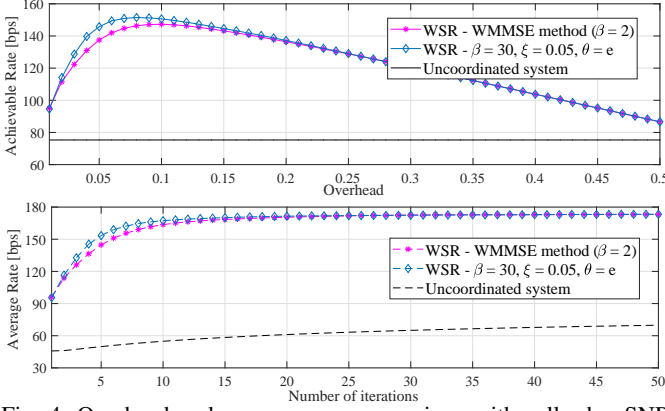


Fig. 4: Overhead and convergence comparison with cell edge SNR = 20 dB, $K = 152$, $K_i = 8$ & $M_i = 8 \forall i \in \mathcal{B}$, $N_k = 2 \forall k$.

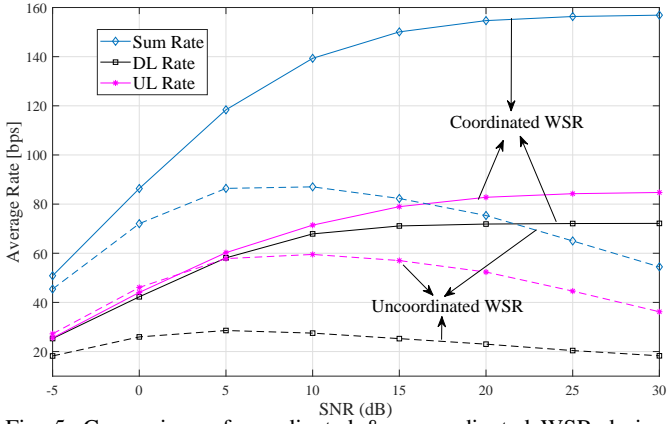


Fig. 5: Comparison of coordinated & uncoordinated WSR designs with $K = 152$, $K_i = 8$ & $M_i = 8 \forall i \in \mathcal{B}$, $N_k = 2 \forall k$.

to WMMSE [24] approach. Also, the coordinated system provides considerable gain as compared to the uncoordinated system. The uncoordinated beamformer design is introduced as a reference, where the beamformers are calculated locally without considering the inter-cell interference. It shows that the achievable rate peaks, when the overhead is between 0.05 – 0.10, i.e., BIT = 5 – 10 rounds. The achieved gain over the uncoordinated scheme is almost 100% due to the greatly improved interference coordination. For the rest of the figures, we will use parameters $\beta = 30$, $\zeta = 0.05$, $\theta = e$ and BIT = 5.

Fig. 5 illustrates the average rate of the dynamic TDD system versus the transmit SNR considering the DL, UL and UL/DL sum rates. Note that the results are shown after 5 precoder/decoder iterations. We can observe that the sum rate improves for both coordinated and uncoordinated systems with SNR up to 5 dB. After that the uncoordinated system performance degrades due to the strong interference from the other-cell users. However, the proposed coordinated scheme performs well even at high SNR region. Due to user specific power constraints, the each UL user uses all the power for transmit beamforming. This leads to high UL-to-DL interference, which degrades the DL user SINR and rate. Thus, the UL users have somewhat higher rate at high SNR. Fig. 6,

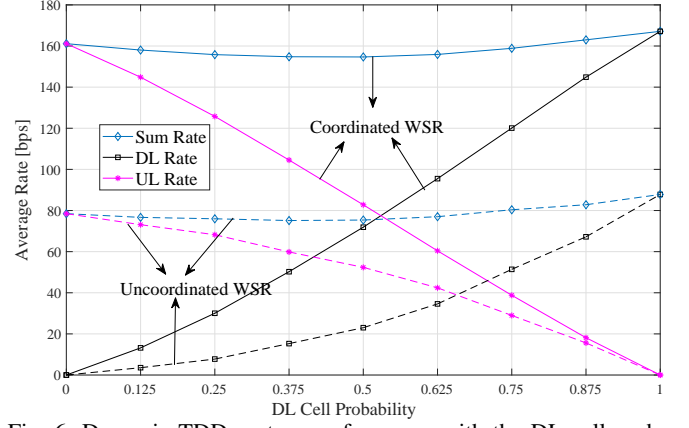


Fig. 6: Dynamic TDD system performance with the DL cell probability at cell edge SNR = 20 dB, $K = 152$, $K_i = 8$ & $M_i = 8 \forall i \in \mathcal{B}$, $N_k = 2 \forall k$.

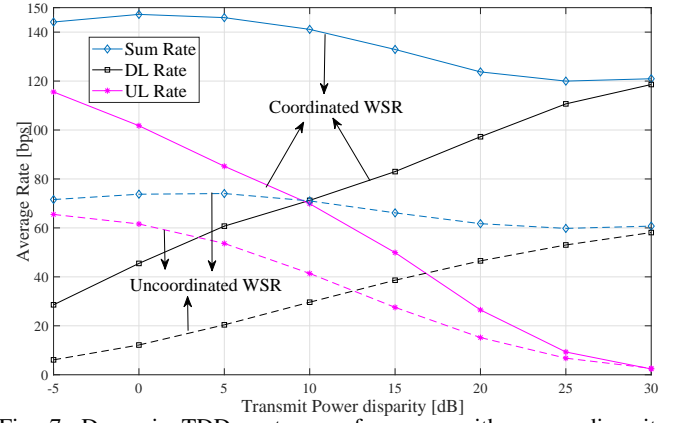


Fig. 7: Dynamic TDD system performance with power disparity between DL and UL transmissions at cell edge SNR = 20 dB, $K_i = 4$, $M_i = 8 \forall i \in \mathcal{B}$, $N_k = 2 \forall k$.

represents average rate performance of the dynamic TDD system with given DL cell probability. Despite difficult UL-DL interference scenarios, the sum rate is only slightly decreased (around 5 – 6%) with 0.5 DL cell probability as compared to the DL or UL only cases.

The average rate of the dynamic TDD system against the power disparity between DL and UL transmissions is shown in Fig. 7. Power disparity is defined as $10 \log_{10}(P_i^{(dl)}/P_k^{(ul)})$ dB. We change the UL power while keeping DL power fixed to obtain different disparity levels. We can observe that the UL rate degrades and DL rate increases linearly with the power disparity. Also, UL and DL rates show similar performance, when the power disparity is 10dB. Similar to previous cases, the coordinated design show 100% gain in comparison to the uncoordinated case in all disparity levels.

In Fig. 8, we compare the proposed beamformer objectives with respect to total backlogged packets in the system queues for a given traffic arrival rate. As we study the system for time-correlated fading, we can use beamformers estimated in the previous time slot to initialize the beamformers for the current time slot (with memory). Thus, we can improve the beamformer convergence. Note that, this is only useful when our objectives are WQM or QWSR maximization. In

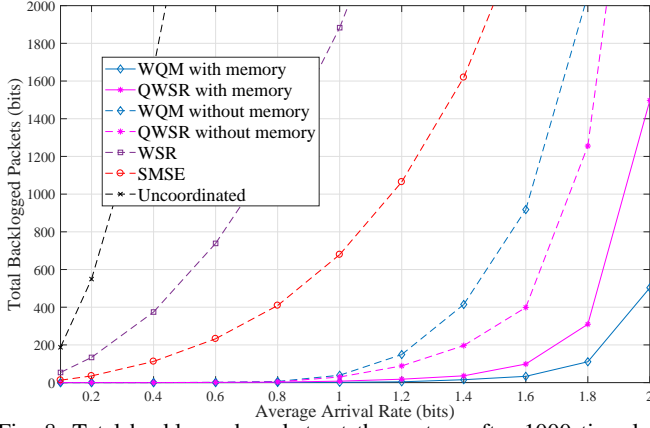


Fig. 8: Total backlogged packets at the system after 1000 timeslots for each optimization objective with cell edge SNR = 20 dB, $K = 38$, $K_i = 2$ & $M_i = 4 \forall i \in \mathcal{B}$, $N_k = 2 \forall k$.

other objectives 'with memory' approach works only when every user has a large queue. Here, WQM provides better performance with memory compared to other methods, due to the improved convergence properties. However, QWSR provides good performance in both 'with memory' and 'without memory' approaches due to its fast rate of convergence. Interestingly, (W)SR has very poor performance, since it ignores the backlog status in the user queues altogether and tends to assign non-zero weights $\omega_{k,l}^{(a)}$ only to a subset of users with good channel (and interference) conditions. On the other hand, using SMSE criterion results in somewhat more fair resource allocation as $\omega_{k,l}^{(a)} = 1 \forall k, l$. As a result, the traffic aware (WQM, QWSR) beamformer design can handle up to 2 – 3 or 10 times larger traffic loads than traditional (W)SR and SMSE criteria or uncoordinated design, respectively.

In Fig. 9, the performance of the proposed bi-directional direct beamformer estimation strategies are illustrated with the SSE approach. In general, we do not assume any pilot coordination between cells. Therefore, the user specific training sequences in both forward and backward directions are non-orthogonal (overlapping). However, the pilots for same cell users can be still made orthogonal. Thus, in Fig. 9 each pilot sequence is interfered by up to 72 partially overlapping pilot sequences. For short sequence lengths, the received precoded pilot matrix is heavily contaminated by pilot interference. Especially, Strategy C does not perform well in these conditions due to significant mismatch between the received pilot matrices $\mathbf{R}_k^{(a)}$ and $\mathbf{R}_{k,2}^{(a)}$ required to compute the beamformers in (40). Strategy B is less prone to errors in updating the weights $\omega_{k,l}^{(a)}$ as they are estimated only for intra-cell users. Therefore, it performs somewhat better than Strategy A with short sequence lengths. However, its performance saturates with less overlapping pilots as the user weights from other cell users are not available. The proposed strategies A and B start to perform reasonably well when the sequence length is longer than 24. In general, the DE approach provides significantly better performance than the SSE method. Moreover, due to the improved decontamination ability discussed in Section IV-E, it is able to provide the same sum rate as the SSE method with much shorter ($\leq 1/2$) pilot sequence lengths.

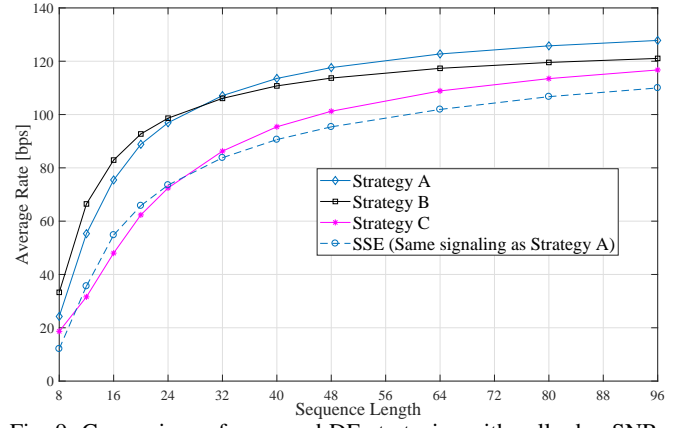


Fig. 9: Comparison of proposed DE strategies with cell edge SNR = 20 dB, $N = 19$, $K = 76$, $K_i = 4$ & $M_i = 8 \forall i \in \mathcal{B}$, $N_k = 2 \forall k$.

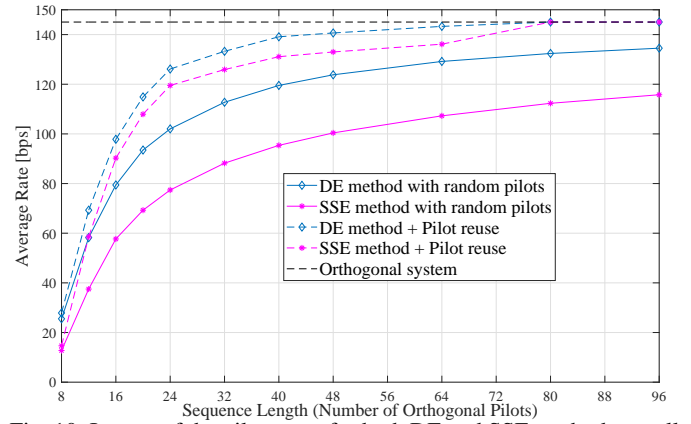


Fig. 10: Impact of the pilot reuse for both DE and SSE methods at cell edge SNR = 20 dB, $K = 76$, $K_i = 4$ & $M_i = 8 \forall i \in \mathcal{B}$, $N_k = 2 \forall k$.

Fig. 10 illustrates the added value of centralized pilot allocation given in Algorithm 2 for both DE and SSE methods (both with Strategy A signaling). As expected, the centralized pilot allocation, requiring tight resource coordination (via backhaul) among adjacent cells, further improves the performance of both beamformer estimation schemes. Especially, the performance of the SSE method is greatly improved due to minimized pilot overlap. However, an uncoordinated random pilot allocation combined with the proposed direct beamformer estimation framework can provide most of these gains while requiring minimum or no coordination. Note that, in this example, the number of data streams per user is restricted to 1. Therefore, every stream can be allocated with an orthogonal pilot for the bi-directional training when the pilot length is greater than 76. Finally, In Fig 11, the performance of the Dynamic TDD system by employing both Strategy A and pilot reuse is illustrated for different UE/BS densities (K_i). There is a significant rate loss for the $K_i = 8$ case, when the number of pilots is less than 20. There, for number of pilots 8 - 20, sum rate of the system is in the range of 10% - 60% in comparison to the orthogonal system. However, note that this is due to the severe pilot contamination of the system, where same pilot will be shared with more than 8 users. For all the UE/BS densities, system performance is quite satisfactory when the pilots/user

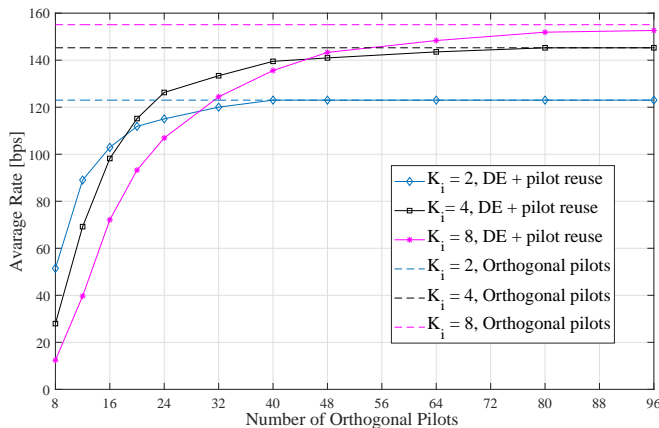


Fig. 11: Pilot decontamination using both DE and pilot reuse at cell edge SNR = 20 dB, $M_i = 8 \forall i \in \mathcal{B}$, $N_k = 2 \forall k$

ratio is greater than 25%.

VI. CONCLUSIONS

Multiantenna interference management for dynamic TDD systems was investigated with several network optimization objectives. Bi-directional OTA signaling and training framework was developed to iteratively optimize the transmit and receive beamformers both in UL and DL. Distributed fast converging beamformer design based on the WQM criterion was shown to be the best approach for handling both dynamic traffic variation and difficult interference scenarios. Three DE strategies were proposed to alleviate the contamination due to non-orthogonal and overlapping pilot allocation. The Strategies A and B were shown to perform reasonably well even with relatively short pilot sequence lengths. Finally, a centralized pilot allocation scheme was introduced to further enhance the pilot decontamination. The numerical results demonstrate that the proposed training and estimation framework provides superior system performance over the uncoordinated scheme for different dynamic TDD network parameters and optimization objectives.

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