Scheduling for Backhaul Load Reduction in CoMP

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Abstract—Coordinated multi-point (CoMP) transmission has received a lot of attention, as a way to improve the system throughput in an interference limited cellular system. For joint processing in CoMP, the user equipments (UEs) need to feed back the channel state information (CSI), typically to their serving base stations (BSs). The BS forwards the CSI to a central coordination node (CCN) for precoding. These precoding weights need to be forwarded from the CCN to the corresponding BSs to serve the UEs. In this work, a feedback load reduction technique is employed via partial joint processing to alleviate the CSI feedback overhead. Similarly, to achieve backhaul load reduction due to the precoding weights, scheduling approaches are proposed. The state of the art block diagonalization solution is compared with our proposed constrained and unconstrained scheduling. Our main contribution is the method of choosing the best subset of the BSs and UEs at the CCN that yields the best sum rate under the constraint of efficient backhaul use. In particular, with constrained scheduling, the choice of a smaller subset proportionally reduces the backhaul load. Simulation results based on a frequency selective WINNER II channel model, show that our proposed constrained scheduling outperforms the block diagonalization approach in terms of the average sum rate per backhaul use.

Index Terms—Backhaul Load Reduction, Scheduling, CoMP, Partial Joint Processing, Zero Forcing

I. INTRODUCTION

In future cellular communication systems, coordinated multi-point (CoMP) transmission is a promising technique proposed to improve the throughput of the user equipments (UEs) at the cell edge, being limited by interference [1]-[2]. To realize these gains, the UEs need to feed back the channel state information (CSI) typically to their serving base station (BS). The CSI is forwarded to the central coordination node (CCN) to form the aggregated channel matrix that is used to create the precoding matrix to jointly mitigate interference. To reduce the overhead of feedback the CSI, clusters of BSs are formed [2]. In particular, partial joint processing (PJP) was proposed in [3] for feedback load reduction, in which dynamically overlapping clusters of BSs are formed.

PJP can be seen as a framework that attempts to categorize the trade off between how much load can be reduced for a given perceivable loss in the system performance. In this regard, the CSI feedback load reduction can be achieved by limiting the quantity of feedback by the UEs. To this end, a relative thresholding is proposed in [3], where the UE only feeds back the CSI for a set of BSs links that fall within a threshold relative to its strongest BS. The CSI of the BSs that fall outside this threshold are modeled as zeros in the aggregated channel matrix. Likewise, in this context, the signaling in the backhaul (BSs-CCN) is primarily due to the distribution of the precoding weights from the CCN to the cooperating BSs. Limiting the feedback causes the aggregated channel matrix to be sparse and poses problems in the case of precoders such as zero forcing (ZF). Under these circumstances, achieving an efficient use of the backhaul is difficult. Hence, the structure in the aggregated channel matrix formed at the CCN needs to be exploited, such that the zeros are correspondingly preserved in the precoder matrix for reducing the backhaul load. To achieve this, backhaul load reduction can be carried out at the medium access control (MAC) layer or physical (PHY) layer, as proposed in [4].

The MAC layer approach is a scheduling based scheme, where disjoint BS subgroups are formed, such that the aggregated channel matrix is block diagonal. The main benefit of this approach is that the inverse of a block diagonal matrix is still block diagonal and that the zeros are preserved. The PHY layer approach is a ZF precoding approach, where the aggregated channel matrix is repeated such that a block diagonal structure is created, and the precoding matrix is created with zeros where needed. The limitations of the PHY layer approach are discussed in [5].

In this paper, we propose a constrained scheduling (CS) and an unconstrained scheduling (US) for backhaul load reduction. In the CS approach, an exhaustive search is carried out to find the best subset of the aggregated channel matrix, such that zeros are avoided in the aggregated channel matrix. This approach directly aims at reducing the backhaul load as the zeros are disallowed. The US approach is similar to the CS approach except that the zeros are allowed to be present in the aggregated channel matrix, and the backhaul load reduction is achieved by explicit nulling of the precoding weights corresponding to the zeros in the aggregated channel matrix. We compare our techniques with the MAC layer scheduling based block diagonalization (BD) technique proposed in [4]. The BD approach achieves the backhaul load reduction by forming a block diagonal structure of the aggregated channel matrix. All the above techniques are evaluated with the PJP based CSI feedback load reduction as proposed in [3]. To summarize our contribution, our proposed CS and US algorithms (i) reduce the backhaul load, (ii) significantly increase the performance, as a larger feasible subset is considered compared to the BD approach, which poses a stricter constraint of being block
diagonal, and (iii) the best subset of BSs and UEs are clustered.

The paper is organized as follows, in Section II the system model is introduced with the focus on how the feedback and backhaul load reduction are achieved in a frequency selective channel. Discussions on the scheduling strategies for backhaul load reduction are presented in Section III. The performance of these scheduling strategies are discussed in Section IV and finally the main results are concluded in Section V. The notation used in this paper is summarized in the footnote.

II. SYSTEM MODEL

Consider the cluster layout as shown in Fig. 1, where $K = |\mathcal{K}|$ single antenna BSs need to serve $M = |\mathcal{M}|$ single antenna UEs. $h_m = [h_{m,1}, h_{m,2}, \ldots, h_{m,K}]$ is the CSI of the links from the $K$ BSs to the $m$th UE. In this work, we study block-fading channels where the CSI available at the CCN is considered to be error free, i.e., the quantization loss and the backhaul delays are assumed to be negligible [6]. In a wideband system, consisting of a number of subcarriers, each UE feeds back the CSI for a given frequency resource. The CSI being fed back can be applied to a group of subcarriers. The CSI feedback process is performed under the PJP framework proposed in [3], using a relative active set thresholding as summarized in [5, Algo.1]. The CSI feedback from the $m$th UE based on the channel from $K$ BSs can be represented as

$$h_m = \mathbf{t}_{x,m},$$

where $\mathbf{t}_{x,m} (k) \in \{0, 1\}, \forall k = 1, \ldots, K$. The operation is independently performed over a collection of subcarriers (frequency adaptive thresholding) [7], where all the $M$ UEs report the CSI for all the subcarriers. When the $m$th UE feeds back the CSI of $k$th BS, it is denoted “1” while a “0” denotes that the CSI was not fed back. The feedback load reduction can be seen as a masking operation by a binary threshold vector $\mathbf{t}_{x,m}$ via element wise multiplication with the CSI measured by the $m$th UE. The subscript $x$ denotes the threshold value in dB. When $x = 0$ dB, it represents a scenario where only the strongest BS is serving the UE, while the threshold of $x = \infty$ dB represents that all the links are fed back. If $K = 3$ then the $m$th UE will feed back in one of the following ways: $\mathbf{t}_{x,m} = \{\{0, 0, 0\}, \{0, 1, 0\}, \{0, 0, 1\}, \{1, 1, 0\}, \{0, 1, 1\}, \{1, 0, 1\}, \{1, 1, 1\}\}$. However, with relative thresholding [3], $\mathbf{t}_{x,m} = \{0, 0, 0\}$ will never occur, as it enables the UE to feedback at least its strongest BS.

For backhaul load reduction, consider a subset of the cluster formed at the CCN, with $N = |\mathcal{N}|$ UEs and $L = |\mathcal{L}|$ BSs, where $N \subseteq M$ and $L \subseteq K$. The maximum number of BSs that can be chosen is $L_{\text{max}} = K$ and the maximum number of UEs that can be scheduled in a given subcarrier group/resource is $N_{\text{max}} = L_{\text{max}}$. The discrete time signal received at the $N$ selected UEs, $\mathbf{y} \in \mathbb{C}^{N \times 1}$ is

$$\mathbf{y} = \mathbf{H}\mathbf{Wx} + \mathbf{n},$$

where $\mathbf{H} \in \mathbb{C}^{N \times L}$ is the channel matrix for the subset of the cluster. $\mathbf{W} \in \mathbb{C}^{L \times N}$ is the precoding matrix and $\mathbf{n}$ is the receiver noise at the UEs, which are spatially and temporally white with variance $\sigma^2$. A linear ZF precoding is considered in this work. The precoding matrix is firstly calculated as the Moore-Penrose pseudoinverse of the aggregated channel matrix $\tilde{\mathbf{H}}$

$$\mathbf{W} = \tilde{\mathbf{H}}^H (\tilde{\mathbf{H}}\tilde{\mathbf{H}}^H)^{-1},$$

where $\tilde{\mathbf{H}} = \mathbf{H} \circ \mathbf{T}_x$ and $\mathbf{T}_x = [\mathbf{t}_{x,1}^T, \mathbf{t}_{x,2}^T, \ldots, \mathbf{t}_{x,N}^T]^T$. Then, the columns of $\mathbf{W}$ are normalized to have a unit norm [4]. Finally, based on equal user rate power allocation [8], the precoding matrix can be obtained as

$$\tilde{\mathbf{W}} = \left( \frac{\max_{l=1,\ldots,L} ||\mathbf{W}(l,:)||_2^2}{P_{\text{max}}} \right)^{\frac{1}{2}} \mathbf{W},$$

where $P_{\text{max}}$ is the maximum power at which a BS can transmit on a given resource, i.e., we are not considering optimal power allocation over the parallel resources. The signal to interference plus noise ratio (SINR) for the $m$th UE is given as

$$\text{SINR}_m = \frac{||\mathbf{h}_m \tilde{\mathbf{W}} (:) ||^2}{\sum_{j \in \mathcal{N}, j \neq m} ||\mathbf{h}_m \tilde{\mathbf{W}} (:) ||^2 + \sigma^2}.$$  

The sum rate in bps/Hz for scheduling the $N$ different UEs on the same frequency/time resource is

$$R_{\text{tot}} = \sum_{n=1}^{N} \log_2 (1 + \text{SINR}_n).$$

Due to feedback load reduction, the channel matrix $\tilde{\mathbf{H}}$ might have zero elements depending on the threshold $x$ dB. Hence, a sparse channel matrix is used to obtain the precoding matrix, $\mathbf{W}$. The zeros in $\mathbf{H}$ pose problems for the ZF precoder for backhaul load reduction. For example, if the $m$th UE does not

![Fig. 1. The cluster layout](Image 321x610 to 530x748)
feed back the CSI for the $l$th BS, then $\tilde{H}(n,l) = 0$. Applying
the pseudoinverse in (3), the sparse aggregated channel matrix
$\tilde{H}$ of size $N \times L$, will create $\tilde{W}$ of size $L \times N$, however, it
could lead to $\tilde{W}(l,n) \neq 0$. This will lead to unnecessary
backhaul, given that the UE has not fed back the CSI while
the uplink resources are already being spent for the $n$th UE to feed
back the CSI. Hence, suitable scheduling strategies need to be
developed in achieving an efficient use of the backhaul. These are
load reduction which conserves an equivalent feedback load
increase the threshold towards infinity. However, this increases
the cluster center, via small relative thresholds [7].

A. Block Diagonalization (BD)

In [4], a MAC-layer approach is proposed where disjoint
subgroups of BSs are formed to preserve the block diagonal
structure of the aggregated channel matrix. An important
property of a block diagonal structure is that it is preserved
even under matrix inversion. This property is key to backhaul
load reduction which conserves an equivalent feedback load
reduction for the scheduled UEs belonging to the set $N$, i.e.,
if $\tilde{H}(n,l) = 0$ then $\tilde{W}(l,n) = 0$. However, it should be noted
that this BD approach based on [4] always requires $N_{\max}$ UEs
to be scheduled. Therefore, with feedback load reduction, $M$
UEs feeding back the CSI results in $N_{\max} = L_{\max} = K$
UEs being scheduled. The choice of $N_{\max}$ corresponds to
an exhaustive search for the best combination of UEs that
maximizes the sum rate given that the aggregated channel
matrix is block diagonal. The BD approach can be summarized
as choosing the combination of the UEs as in Algorithm 1.

B. Unconstrained Scheduling (US)

With feedback load reduction, the aggregated channel matrix
is sparse depending on the threshold. The choice of a feasible
subset of BSs and UEs, $\{L^*, N^*\}$, that produces the
best sum rate is summarized in Algorithm 2.
nulling of the precoded weights as \( \hat{W}_{\text{US}} = \bar{W} \odot (T_x)^T \), to achieve backhaul load reduction based on the nulls due to feedback load reduction. However, explicit nulling gives rise to multi-user interference to remain in the system. It should be noted that the explicit nulling is automatically taken care of in the BD approach in Section III-A. Explicit nulling seems like an intuitive approach but the ZF precoder has its own limitations when there are zeros in the aggregated channel matrix (see Section II).

C. Constrained Scheduling (CS)

The CS approach is similar to the US approach with an important constraint that the aggregated channel matrix \( \tilde{H}_{\text{CS}} \) is full due to the proper selection of UEs and BSs, i.e., \( \tilde{H}_{\text{CS}} = H \odot T_x \), where \( H_{\text{CS}} \in \mathbb{C}^{N \times L} \) and \( H_{\text{CS}}(i,j) \neq 0, \forall i,j \) as \( T_x(n,l) \in \{1\}, \forall n = 1, \ldots, N \) and \( \forall l = 1, \ldots, L \). This simplifies the ZF in (3). The CS approach is summarized in Algorithm 3. The main advantage of this approach is that the backhaul load reduction is automatically achieved by this constrained scheduling approach as smaller subset of a matrix, \( H_{\text{CS}} \), is formed from \( H \). Also, multi-user interference is removed from the system.

Algorithm 3: CS approach

1. \( M \) UEs feed back the CSI as defined in Section II
2. Assign \( L = k \)
3. while \( L > 1 \) do
4.    for \( L : L \subseteq K : |L| = L \) do
5.       for every \( N \) from \( M \) such that \( N = |N| \leq L \) do
6.          Form \( T_x(n,l) \in \{1\}, \forall n = 1, \ldots, N; \forall l = 1, \ldots, L \)
7.          Evaluate (7)
8.    end for
9. end for
10. \( L = L - 1 \)
11. end while
12. return Schedule the subset formed with \( \{L^*,N^*\} \) using \( T_x \)

Illustrative Example: To illustrate the above algorithms with an example, consider \( T_x = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \). This subset is feasible with the BD approach, while the CS approach requires the zeros to be removed. Hence, a feasible subset \( T_x \) after removing the zeros can be any of these \( \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix} \) \( \Rightarrow S_{\text{CS}} = \{2 \times 2, 1 \times 2, 1 \times 1 \} \) while \( \{3 \times 3, 2 \times 3, 1 \times 3 \} \notin S_{\text{CS}} \) for this particular case of \( T_x \). As for the US approach, all possible combinations are feasible. From our proposed algorithms, what clearly falls out is that they offer an inherent seamless mode switching capability between CoMP and single cell 1 x 1 scenario. When \( N \) users are selected to be served from \( L \) BSs, they are expressed as \( N \times L \). Table I summarizes the possible combinations of the various user scheduling strategies described above. In all the scheduling strategies, it should be noted that the UEs that are not currently being served can be expected to be served in another resource, thereby achieving user fairness.

<table>
<thead>
<tr>
<th>Interference</th>
<th>Feasible</th>
<th>Partially Removed</th>
</tr>
</thead>
<tbody>
<tr>
<td>BD</td>
<td>{3 \times 3}</td>
<td>{3 \times 3, 2 \times 3}</td>
</tr>
<tr>
<td>US</td>
<td>{2 \times 2, 1 \times 3}</td>
<td>{2 \times 2, 1 \times 1}</td>
</tr>
<tr>
<td>CS</td>
<td>{1 \times 2}</td>
<td>{1 \times 1}</td>
</tr>
</tbody>
</table>

† The subscript “algo” refers to BD or US or CS.
‡ The zeros in the aggregated channel matrix, \( \tilde{H} \), formed at the CCN.

IV. PERFORMANCE EVALUATION

Consider the cluster center where \( M \) single antenna UEs moving at 3 kmph are dropped as shown in Fig. 1. The radius of the cell is \( R = 500 \) m. These UEs are uniformly dropped in an ellipsoid in \( \mathbb{R}^2 \), whose center is the cluster center. The major and minor axis of the ellipsoid are \((2\Delta x, 2\Delta y)\) where \( 0 \leq \Delta x \leq \frac{R}{\sqrt{2}}, 0 \leq \Delta y \leq \frac{b}{\sqrt{2}} \) and \( b \) is the height of the hexagon or cluster. \( K = 3 \) single antenna BSs are positioned as shown in Fig. 1. A realistic WINNER II channel model [9] corresponding to scenario B1: urban micro-cell, non-line of sight with pathloss and shadow fading is considered with 500 independent channel realizations at 2 GHz center frequency. The signal to noise ratio at the cell-edge (reference value for one user located at the cell-edge) is fixed at 15 dB. For the B1 scenario, the channel provided by the WINNER II model is converted to the frequency domain with a 256-fast Fourier transform, where 32 consecutive subcarriers correspond to one resource for simplicity. The feedback load reduction is performed for one such resource, \( T_x \), where \( x \) takes the values 0, 5 and 10 dB. The results presented are averaged over the Monte Carlo simulations over all the resources.

Figure 2 shows the average sum rate of the various scheduling algorithms considered in this work. As expected for lower thresholds, the unconstrained scheduler, US, performs better than the constrained scheduler, CS. However, this is achieved at the expense of the backhaul. This is due to the smaller sets of \( L \) and \( N \) being formed with \( CS \) unlike US. For CS and US, the sum rate increases with the increase in the feedback threshold. However in the case of BD, for lower number of UEs, the 0 dB threshold outperforms the 5 dB. This is related to Fig. 3 where the original BD algorithm is unable to find a block diagonal structure. The BD 0 dB case has a better chance of finding an identity matrix that results in block diagonal structure than the BD 5 dB, as the 0 dB thresholding maps to 0, 5 and 10 dB. The results presented are averaged over the Monte Carlo simulations over all the resources.

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The BD algorithm performs reasonably well in terms of sum rate, however, it is not feasible when the number of UEs are small with lower threshold. Figure 3 captures this in terms of the probability of failure to find a block diagonal structure.
that the subsets can be avoided if the BD approach in [4] is generalized, such
than not. Hence, the BD procedure can easily be applied to a
fact that a bigger threshold allows the UE to feed back the
block diagonal structure is as low as
40 dB, and
0.6% for 0 dB, 5 dB, and 40 dB, respectively. These values do not change with the increase
in the number of UEs. Let us consider the number of UEs to
be 30. This translates to the total number of attempts being
\( \binom{30}{j} = \frac{30!}{j! (30-j)!} \approx 4060 \). With a feedback load reduction threshold of
5 dB, corresponding to the cluster center [10, Fig. 4.19],
the BD approach cannot be evaluated for potentially 94.9%
of the time. With a threshold of 40 dB, the failure to find a
block diagonal structure is as low as 0.6\%, this is due to the
fact that a bigger threshold allows the UE to feed back the
CSI from more BSs, causing \( \mathbf{H} \) to be a full matrix more often
than not. Hence, the BD procedure can easily be applied to a
40 dB threshold. However, it should be noted that this failure
can be avoided if the BD approach in [4] is generalized, such
that the subsets \( \{2 \times 2, 1 \times 1\} \) are also included. This is treated
as part of our future work.

We define the average feedback load reduction, \( \bar{J}_{LR} \), as the average of the number of zeros in a sparse aggregated
channel matrix \( \mathbf{H} \in \mathbb{C}^{M \times K} \), i.e., the cardinality of set
\( S_{FB} = \{ \mathbf{H}(i,j) = 0, \forall i,j \in \mathbb{N}^+, i \leq M, j \leq K \} \). The average
feedback load reduction is calculated as
\[
\bar{J}_{LR} = \mathbb{E}_{\mathbf{H}} \{ |S_{FB}| \}. \tag{9}
\]
Figure 4 shows the \( \bar{J}_{LR} \) due to various thresholds that were applied to all the scheduling algorithms considered in this
work. As more number of UEs feed back the CSI, the same
needs to be available at the CCN. The savings in the feedback load
is linear whose slope decreases with increasing threshold.
As expected, the feedback load reduction with threshold of 40
\( dB \) and \( \infty \ dB \) has poor savings.

Now we discuss the impact on the backhaul due to the
preceding weights. We define the normalized average backhaul
load reduction as the relative difference in the total number
of UEs and BSs to the cardinality of the set, \( S_{BH} \) consisting of
non-zeros in the precoded matrix, \( \mathbf{W}_{\text{algo}} \in \mathbb{C}^{L \times N} \), i.e.,
\( S_{BH} = \{ \mathbf{W}_{\text{algo}}(j,i) \neq 0, \forall i,j \in \mathbb{N}^+, i \leq N, j \leq L \} \). The
normalized average backhaul load reduction is calculated as
\[
\bar{J}_{BLR} = \frac{(L_{max}N_{max}) - \mathbb{E}_{\mathbf{H}} \{ |S_{BH}| \}}{L_{max}N_{max}} \tag{10},
\]
where \( L_{max} = K = 3 \) and \( N_{max} = L_{max} \) as the maximum
number of UEs served is limited by the maximum number of
BSs selected. This is captured in Fig. 5 for the various scheduling
algorithms considered in this work. The CS approach has
nearly 90% backhaul savings with the smallest feedback load
reduction threshold, and the savings diminish as the threshold
increases. As the number of UEs grows, it is interesting to note
that with CS 40 dB and US 40 dB, the savings are nearly
similar, with both undergoing an exponential decay. An \( \infty \ dB \) threshold also shows this decay, resulting in savings in the
backhaul. This is due to the fact that the scheduler is capable of
sum rate per backhaul use is calculated as compared to the CSI feedback [5, Fig. 1]. Hence, the average non-zero precoding weight. This will dominate the backhaul as the user data will be routed at the CCN based on the structure that results in the savings in the backhaul as observed has better savings in the backhaul compared to BD 0 dB when BD, as the aggregated channel matrix is full. The BD 5 dB has better savings in the backhaul compared to BD 0 dB when \( M \) is small. This is due to the failure to find a block diagonal structure that results in the savings in the backhaul as observed in Fig. 3.

The metric average sum rate per backhaul use is considered, as the user data will be routed at the CCN based on the non-zero precoding weight. This will dominate the backhaul compared to the CSI feedback [5, Fig. 1]. Hence, the average sum rate per backhaul use is calculated as

\[
\bar{R}_{\text{tot}}^{\text{per backhaul use}} = \frac{\tilde{\bar{R}}_{\text{tot}}^{\text{per backhaul use}}}{1 - \tilde{b}_{\text{LR}}} \leq \frac{\bar{R}_{\text{tot}}^{\text{per backhaul use}}}{L_{\max} N_{\max}} = \frac{\bar{R}_{\text{tot}}^{\text{per backhaul use}}}{E_{\text{H}}(|S_{\text{int}}|)},
\]

(11)

and Fig. 6 captures this metric. It can be observed that our proposed CS algorithm performs the best compared to all the other algorithms, providing the best sum rate per backhaul use.

The limitation of the proposed approaches is that they need to perform an exhaustive search to find the best possible set of BSs and UEs that gives the best sum rate. However, a greedy based user selection can be easily implemented based on the proposed algorithm in order to reduce the complexity [11]. It should be noted that the algorithms presented in this paper are independent of the scheduling criteria (7).

V. CONCLUSION

In this work, we explore scheduling techniques that can efficiently use the backhaul for distributing the precoding weights (from CCN to corresponding BSs) under feedback load reduction achieved via partial joint processing for coordinated multipoint transmission. We proposed the constrained and unconstrained scheduling schemes, comparing them to the state of the art MAC layer block diagonalization technique for backhaul load reduction. The constrained scheduling achieves the best tradeoff in terms of the sum rate per backhaul use. The block diagonalization technique performs well in terms of the sum rate when the number of users is large, however, they fail to find a block diagonal structure when the number of users are small.

As part of our future work, combining the constrained scheduling and the block diagonalization technique can harness the gains of both these approaches and overcome their limitations simultaneously. This combined technique can achieve a better tradeoff between the sum rate and backhaul use. Also, generalizing the block diagonalization technique, such that \( N = L < K \) can improve these preliminary results.

REFERENCES


