Centralized Scheduling for Joint Decoding
Cooperative Networks Subject to Signalling Delays

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Abstract—Joint detection in the uplink of a cellular network involving several non-colocated base stations is a promising means to turn inter-cell interference into useful signal energy and hence dramatically increase spectral efficiency of reuse one networks. To maximize the benefits of the new degrees of freedom that come with base station cooperation, cluster centric schedulers need to be aware of the interference situation in all participating cells. Since the required exchange of information on the backhaul infrastructure can be subject to significant delays, scheduling decisions are potentially based on outdated channel state information and will thus lead to suboptimal system performance. In this contribution we extend our framework for studying the impact of these signaling delays on the system performance by allowing bigger cooperation clusters. By comparing new algorithms and introducing the possibility of channel prediction, we provide further insight into the system behavior.

Index Terms—Joint Scheduling, Cooperative Detection, UL CoMP, Backhaul Latency

I. INTRODUCTION

Due to its high utilization, radio spectrum is a scarce resource that requires more efficient usage in order to significantly increase the performance of wireless communication systems. Currently, inter-cell interference puts a tight cap on the achievable system performance in dense networks. To overcome this limitation, cooperative signal processing is seen as a promising technology for upcoming standards. In cooperative networks, signals transmitted or received by spatially separated antenna sites are jointly processed, enabling so called Coordinated Multi-Point (CoMP) techniques.

In this contribution we focus on cellular systems that cooperate in the uplink direction by exchanging received signals to perform joint detection of the users’ transmit signals. In effect, the system can utilize greater spatial degrees of freedom as the transmitt signals of the terminals are observed by more uncorrelated antennas. By doing so, inter-cell interference is transformed into useful signal energy and adds to the detection performance. However, to utilize the new degrees of freedom to their full potential, a centralized scheduler that is aware of the interference situation in all participating cells is required. The scheduler performs two main tasks: it allocates common radio resources to a set of users (user grouping) and assigns transmission rates to the users (modulation and coding schemes in practical systems).

It is well understood that the above described approach can achieve significant performance gains and as the scheduling problem is in general equal to that of scheduling for the multi-user uplink of a single base station equipped with multiple antennas, many algorithms for user grouping have been proposed (e.g. [2] - [5]). An overview of SDMA resource allocation is given in [1]. Unlike the systems considered in these references, practical systems that employ joint detection can suffer from constraints that are imposed by the backhaul infrastructure, which is required to communicate with the central scheduler and exchange receive signals for joint detection. Depending on the deployment, different technologies are used for backhauling, e.g. DSL, micro-wave links, optical fibers. These technologies often introduce latency (especially because there are commonly no direct links between neighboring base stations and signals have to travel to their destination via multiple routers).

In this contribution, we investigate the effects of backhaul latency on the performance of joint (i.e. centralized) scheduling. As the central scheduler requires channel state information (CSI) from all involved base stations, CSI has to be exchanged on the backhaul. Latency will therefore lead to outdated CSI.

In [6], we first introduced our framework for analyzing delay effects and compared centralized and decentralized scheduling strategies for cooperation clusters with two base stations. In this contribution, we focus on centralized scheduling and extend our framework for the analysis of bigger clusters with three base stations. Accordingly, we extend our pathloss based scheduling approach to the new cluster size. Through analysis of rate distributions and outage probabilities, we provide more insight into the system behavior. Furthermore, we apply greedy user grouping and channel prediction and compare the performance to the previously investigated joint scheduling.

The paper is structured as follows, in Section II we define our system model, before we introduce different scheduling strategies in Section III. Finally, we present simulation results in Section IV and conclude the paper in Section V.

Notation: We use bold lower case letters to denote vectors and bold upper case letters to denote matrices. $(\cdot)^T$ and $(\cdot)^H$ express transpose and conjugate transpose. With $\text{diag}(x, y, z)$

1Unlike this work, some of the cited works consider the downlink direction. However, as spatial compatibility is equal to the uplink case, many findings can still be applied.
we denote a $3 \times 3$ diagonal matrix with $x$, $y$ and $z$ on the diagonal.

II. SYSTEM MODEL

We investigate a small scenario with three cooperating base stations that are connected to a central scheduler via an error free backhaul without capacity constraints. After data transmission, the received signals of the base stations are forwarded to a joint decoder. In the scenario considered, the three base stations serve a total of $K$ users, who are located in the triangle between the sites. Users and base stations each possess a single omnidirectional, transmit and receive antenna, respectively. Thus, there are, in total, $N_R = 3$ receive antennas available for joint decoding. As this allows for spatial multiplexing of three users, the central scheduler assigns groups of three users to common radio resources. Thus, for spatial multiplexing of three users, the central scheduler assigns groups of three users to common radio resources. Thus, for ease of notation.

Schedulers can be designed for various optimization criteria. In this contribution we focus on schedulers that try to maximize the overall system throughput (i.e. sum rate). As this scheduling target requires the same maximization of the sum rate on all $L$ RBs, we do not distinguish between RBs for ease of notation.

Channel state information (CSI) is obtained at the individual base stations. In order to facilitate central scheduling decisions, CSI is forwarded to the central scheduler. As stated before, a scheduling decision is composed of the allocation of users to RBs and the assignment of transmission rates to each granted user. As we assume full-buffer traffic, every scheduled user has data to transmit. Once the scheduling decision is made, it is communicated to the base stations, which then inform the users of their allocations (transmission grants). The actual uplink transmission occurs thereafter. This process is depicted in Figure 2. It is obvious that a considerable delay can occur between the time the CSI is obtained and the actual transmission is carried out. With current infrastructure, the biggest cause of latency will be the backhaul usage. Realistic backhaul delays for current systems can be in the order of 10ms [7]. Thus, scheduling decisions are based on outdated information ($h \neq \hat{h}$) which will lead to performance degradation depending on the coherence time of the channel.

A joint scheduler will base its decision to select the best user group $(a^*, b^*, c^*)$ on an optimization problem that can be written as

$$ (a^*, b^*, c^*) = \arg \max_{a,b,c \in \{1, \ldots, K\}} O(\hat{H}_{abc}), \text{ s.t. } a \neq b, b \neq c, a \neq c $$

where $O(\hat{H}_{abc})$ is an objective function that is evaluated based on the CSI available. Once a user group has been selected, the rate assignment can be performed. We assume that the

$$ y = [h_a h_b h_c] \mathbf{P} x + n = \mathbf{H}_{abc} \mathbf{P} x + n, $$

where $y \in \mathbb{C}^{N_R}$ is the compound vector of received symbols at the three base stations. The vector $\mathbf{x} \in \mathbb{C}^{N_R}$ denotes the vector of transmit symbols of the three users $a, b, c \in \{1, \ldots, K\}$, $a \neq b, b \neq c, a \neq c$ that are scheduled for transmission on the RB. The users transmit with powers $p_a$, $p_b$ and $p_c$ that constitute matrix $\mathbf{P} = \text{diag}(p_a, p_b, p_c)$. As their transmit symbols are uncorrelated, $E[\mathbf{x}\mathbf{x}^H] = \mathbf{I}$. The vector $n \in \mathbb{C}^{N_R}$ denotes white Gaussian noise at the receivers with covariance $E[nn^H] = \sigma_n^2 \mathbf{I}$. The compound channel matrix that describes the channels from the selected users to the base stations is denoted as $\mathbf{H}_{abc} = [h_a h_b h_c] \in \mathbb{C}^{N_R \times N_T}$. We assume the transmit power of the users to be fixed so that they achieve a given average SNR $\gamma$, at the nearest base station. Thus, if $h_{mk}^n$ is the channel coefficient that describes the channel from user $k$ to the nearest base station, the user’s transmit power is set to

$$ p_k = \frac{\gamma \sigma_n^2}{E[|h_{k1}|^2]}. $$

![Fig. 1. Considered scenario](image-url)
modulation and coding of the users can achieve the capacity of the wireless channel (i.e. Gaussian codebooks are used). We define the assigned data rate of user \( k \in \{a^*, b^*, c^*\} \) as

\[
R_k = \alpha C_k(\hat{H}_{a^*b^*c^*}),
\]

where \( C_k(\cdot) \) is the maximum achievable rate of user \( k \) and \( \alpha \) can be chosen from the interval \([0, 1]\). The rate that is achieved during transmission is then defined as

\[
R_k = \begin{cases} 
\hat{R}_k & \text{if } \hat{R}_k \leq C_k(\hat{H}_{a^*b^*c^*}) \\
0 & \text{otherwise.}
\end{cases}
\]  

Thus, the transmission is successful if the transmission channel supports the rate that was assigned to the user. Otherwise the transmission fails (outage). The achieved sumrate \( R \) on the RB is then defined as

\[
R = R_{a^*} + R_{b^*} + R_{c^*}.
\]  

The parameter \( \alpha \) in (5) is chosen to maximize the expected sum rate over many scheduling decisions. Thus,

\[
\alpha^* = \arg \max_{\alpha \in [0,1]} E[R].
\]  

In the numerical examples presented in section IV this optimization is solved through an exhaustive search.

Besides the outage rates defined above, we also consider the case where we do not allocate rates. Instead, we assume that the mobile terminals can always transmit at the maximum achievable rate of the current channel. In [6], we referred to this case as optimal HARQ. Here, we change the nomenclature to \( w/o \) rate allocation (RA) to ease understanding. Hence,

\[
R_{k/w/o \ RA} = C_k(\hat{H}_{a^*b^*c^*}).
\]  

A. Channel Prediction

In this contribution we also consider channel prediction as a possibility to reduce the degradation due to outdated CSI. We employ a linear MMSE predictor \( w \in \mathbb{C}^N \). From the solution of the Wiener-Hopf equations we know that a channel coefficient at time \( \Delta \) can be estimated by

\[
h'_{\Delta} = w \hat{h} = R_{hh}^{-1} r_{hh'}^T \hat{h},
\]

where \( \hat{h} = [h_{-N+1}, \ldots, h_0] \) is a series of \( N \) channel observations corresponding to the time instants \( -N + 1 \) till \( 0 \). \( R_{hh} = E[\hat{H}H]\) and \( r_{hh'} = E[[h_{-N+1}, \ldots, h_0] h_{\Delta}]. \) Thus, the autocorrelation function of the statistical process is sufficient to obtain \( w \).

For perfect knowledge of the autocorrelation function, we calculate \( w \) as given above. With estimated time correlation the above equation with the matrix inversion often leads to unstable results. Thus, as an integrated approach which directly estimates \( w \) from observed channel realizations, we employ burg’s algorithm which is numerically stable [8].

A. Instantaneous Capacity based Joint Scheduling

The most straightforward scheduling strategy to maximize the sum rate is to use the capacity of the MAC channel as the objective function for user grouping:

\[
O(\hat{H}_{abc}) = C(\hat{H}_{abc}) = \log_2 \left| \frac{1}{\sigma_n^2} \hat{H}_{abc}^H P \hat{H}_{abc} \right|. \quad (11)
\]

Hence, to solve the optimization defined in (4) this grouping strategy requires the calculation of the sum rate for all \( \binom{K}{3} \) possible user groups. Assuming the capacity achieving MMSE-SIC decoder and the fixed decoding order \( a, b, c \), we label \( a, b, c \) as 1,2,3 and give the user rates as follows

\[
C_k(\hat{H}_{abc}) = \log_2 \left| \frac{1}{\sigma_n^2} \sum_{j=k+1}^3 p_j \hat{h}_j \hat{h}_j^H + I_{n} \right|^{-1} \left( \sum_{j=k+1}^3 p_j \hat{h}_j \hat{h}_j^H \right) \right|^H \hat{h}_k.
\]  

At the decoder side, all decoding orders are tested to obtain the actual transmission rates \( R_k \) and we take error propagation in the SIC process into account.

B. Greedy Grouping

Instead of trying all possible user combinations as suggested above, we also employ a greedy grouping approach as described in [9] that first picks the user with the highest instantaneous received power for transmission on a RB. In the following steps, each remaining user is tested for compatibility with the already selected users by evaluating the MAC Capacity and the best is added until the group size \( G = 3 \) is reached. In this way, the greedy algorithm significantly reduces the complexity of user grouping.

C. Joint Scheduling based on Channel Statistics

Another considered option is scheduling based on long term channel statistics rather than instantaneous CSI. Since there is no analytical formulation for the ergodic MAC capacity, we
\[
C_{\text{stat}}(\hat{H}_{123}) = \log_2 \left( \prod_{i=1}^{3} \left( 1 + \frac{p_i E[|\hat{h}_i|^2]}{\sigma_n^2} \right) + \frac{2}{\sigma_n^2} \prod_{i=1}^{3} \sum_{j=1}^{3} p_j E[|\hat{h}_{ij}|^2] - \sum_{j,k \in \{1,2,3\} \backslash i}^{3} p_j p_k E[|\hat{h}_i|^2 | \sigma_n^4] \right)
\]

(13)

introduced a metric based on the sum rate of the expected SINR in [6], which we now extend to the three user case.

We refer to the selected users \(a, b, c\) as 1, 2, 3 so that we can denote the sum rate as given in (13), which represents \(\log_2(1 + E[\text{SINR}])\) and which is used as the objective function.

The grouping metric is thus solely based on long term statistics (i.e. pathloss). The advantage of only using pathloss information is that frequent CSI signalling is not required any longer. However, by this method, rate allocation at the central scheduler also needs to be based on pathloss. Assuming the fixed decoding order \(a, b, c\) and using the two-user formulation \(C_{\text{stat}}(\hat{H}_{ab})\) from [6] we assign rates by

\[
C_{\text{stat}}(\hat{H}_{abc}) = \log_2 \left( 1 + \frac{p\cdot E[|\hat{h}_a|^2]}{\sigma_n^2} \right)
\]

(14)

\[
C_{\text{stat}}(\hat{H}_{abc}) = \frac{C_{\text{stat}}(\hat{H}_{bc}) - C_{\text{stat}}(\hat{H}_{abc})}{C_{\text{stat}}(\hat{H}_{ab}) - C_{\text{stat}}(\hat{H}_{abc})}
\]

(15)

\[
C_{\text{stat}}(\hat{H}_{abc}) = \frac{C_{\text{stat}}(\hat{H}_{abc}) - C_{\text{stat}}(\hat{H}_{abc}) - C_{\text{stat}}(\hat{H}_{abc})}{C_{\text{stat}}(\hat{H}_{abc})}
\]

(16)

IV. SIMULATION RESULTS

In the following, we discuss simulation results for the scheduling strategies introduced above. We employ the 3GPP-SCME channel model [10] and parameterize it with 20 MHz 3GPP-LTE in mind. Key parameters are given in Table I. The orthogonal RBs correspond to consecutive LTE physical resource blocks, which are obtained by transforming SCME channel impulse responses to the frequency domain with a 2048 FFT and selecting subcarrier coefficients with a spacing of 12. The correlation of channel realizations over time is influenced by the user velocity, which we assume to be equal for all users. The autocorrelation over time for the SCME model corresponds to the well-known Jakes model:

\[
a_{h}(\tau) = E[\hat{h}(t)\hat{h}^*(t+\tau)] = J_0 \left( \tau \cdot v \frac{2\pi f_c}{c} \right),
\]

(17)

where \(J_0(.)\) is the zeroth order Bessel-function of the first kind, \(v\) the velocity, \(f_c\) the carrier frequency and \(c\) the speed of light.

For numerical evaluation, we simulate 1000 user drops. In each drop, \(K = 30\) users are randomly placed in the triangle between the base stations, with a uniform distribution. The user positions effect the expected channel gains and the transmit power of the users as specified in (3). We then obtain time varying channel realizations and evaluate the performance of each scheduling strategy for 10 consecutive TTIs.

Figures 3 and 4 depict the average sum rate per RB achieved for different user velocities, different algorithms, with and without rate allocation (RA) and for different delays. For CSI based scheduling, we can first observe, that the performance of greedy user grouping is extremely close to the optimal performance through exhaustive search. For the cases without prediction, we observe that the system performance significantly degrades with increasing user speed. The sensitivity depends on the assumed signalling delays. The greater the delay, the sooner the degradation due to increasing speeds (i.e. decreasing coherence times). Comparing the two figures, we see that suboptimal rate allocation has a significant impact in the degradation. In fact, degradation nearly doubles when rate allocation is considered.

If MMSE prediction is used with optimal knowledge of the autocorrelation function, the system is extremely robust against user velocity (for delays smaller than 5ms even up to 100 km/h). However, if we employ practical prediction (we use burg’s algorithm to estimate the predictor with the help of 5000 channel realizations), we can make the following observations: the gains of practical prediction are very low and decrease with increasing signaling delay.

For all depicted cases, the performance of scheduling based on CSI goes below the performance of pathloss based scheduling at some point as also observed in [6]. Thus, past a certain user speed the exchange of instantaneous CSI is not beneficial anymore.

Figure 5 depicts the distribution of user rates (averaged over the 10 TTIs of each drop and the \(L = 3\) RBs). For static channels (0 km/h) and pathloss based grouping, the same three users are granted transmission on each RB for each drop. Due to the fixed decoding order, we can clearly distinguish three different throughput groups. The high overall percentage of users with zero transmission rate is due to the small number of available RBs, when compared to the number of users (\(K=30\)). As the user speed increases, more fading peaks are experienced during the observed TTIs leading to more users being granted transmission. Naturally, the rate distribution thus becomes fairer with increasing channel variability. Observing the spatial distribution of the user traffic, we can state that CSI based scheduling also provides a more uniform service over

### Table I. Simulation Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier frequency</td>
<td>(f_c = 2)GHz</td>
</tr>
<tr>
<td>Channel taps</td>
<td>6</td>
</tr>
<tr>
<td>Inter-site distance</td>
<td>(d = 500)m</td>
</tr>
<tr>
<td>Prediction window</td>
<td>(N = 20)</td>
</tr>
<tr>
<td>Resources (RBs)</td>
<td>(L = 3)</td>
</tr>
<tr>
<td>Sampling frequency(^1)</td>
<td>30.72 MHz</td>
</tr>
<tr>
<td>SCME Scenario</td>
<td>Dense Urban</td>
</tr>
<tr>
<td>Target SNR</td>
<td>(\gamma = 20)dB</td>
</tr>
<tr>
<td>TTI</td>
<td>1ms</td>
</tr>
<tr>
<td>Users</td>
<td>(K = 30)</td>
</tr>
</tbody>
</table>

\(^1\) effects the resolution with which incoming channel taps can be separated in time.
the area. The distribution of the pathloss based scheduling is however mainly due to the assumed power control.

Finally, we provide some insight on the optimization of the backoff factor $\alpha$ and the achieved outage probabilities in Figure 6. As we can see, $\alpha$ decreases with increasing user speed until it stabilizes around a fixed value, leading to a fixed outage probability. While the pathloss based method leads to a similar optimal $\alpha$ than the CSI method at high speeds, its different way of rate allocation leads to a smaller outage probability.

V. CONCLUSIONS

In this contribution we analyzed the impact of outdated CSI on the performance of joint scheduling for cooperative detection clusters. We extended our framework to consider clusters of three base stations. New insight into the system behavior was presented and greedy grouping and channel prediction were applied. While prediction using perfect knowledge of the autocorrelation makes the system very robust against high user speeds, realistic prediction methods fail to provide increased robustness as the delays increase. As greedy user grouping achieves close to optimal performance with much less complexity, it is the preferred method for user grouping. To reduce the system overhead, the pathloss based scheduling that we introduced is an interesting alternative for high speed users, even though it provides less fairness.

REFERENCES