Cooperative Interference Prediction for Enhanced Uplink Link Adaptation Under Backhaul Delays

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Abstract—Inter-cell Interference (ICI) in the uplink of modern cellular communication systems with high frequency reuse is hard to predict, as fast scheduling and link adaptation lead to a high interference fluctuation. This fluctuation poses a big challenge for link adaptation algorithms that need an accurate SINR estimate to assign suitable modulation and coding schemes for transmission. To enable ICI prediction it has been proposed to exchange scheduling decisions amongst base stations. However, if this exchange is subject to delays, the system performance decreases as scheduling decisions become suboptimal. In this paper we propose a new scheme that maintains scheduling optimality at the cost of reduced link adaptation accuracy when faced with backhaul delays. We compare both schemes and provide insights into the multi-user diversity / link adaptation accuracy trade-off that arises for non-stationary users if information exchange on the backhaul is subject to delays.

Index Terms—Inter-Cell Interference Prediction, Backhaul Latency, Scheduling, Link Adaptation

I. INTRODUCTION

A high reuse of spectrum is desirable in cellular wireless communication systems leading to substantial inter-cell interference (ICI) in dense deployments. It is well known that this type of interference leads to significant performance degradation for users that are located close to cell edges.

The TDMA/FDMA characteristic of access schemes in current and upcoming wireless standards (e.g., SC-FDMA in the uplink of 3GPP LTE) along with fast scheduling and link adaptation allow systems to quickly adapt to varying channel conditions and thus exploit the fading variations in time and frequency. In this way, users can be allocated to favorable transmission resources with a fine granularity leading to high potential spectral efficiency gains. As different users experience uncorrelated channels, multi-user diversity gains can be extracted. Once users have been assigned to transmission resources, adaptive modulation and coding (AMC) allows the system to adapt to a large variety of potential SINRs, thus making the best use of the propagation conditions.

In the cellular uplink, this fast adaptivity leads to a high fluctuation of ICI. As every time/frequency resource is only occupied by one user per cell, the interference depends on the resource allocation decision of the base stations (BSs), which can change in the order of a millisecond. Thus, it is very difficult for AMC algorithms to select suitable modulation and coding schemes (MCS). In 3G systems this was less of a problem as the usage of WCDMA yields predictable ICI with characteristics close to that of additive white Gaussian noise [1]. The characteristics of ICI for current access schemes are investigated in [2] and found to be unpredictable. While the authors of [3] show the performance degradation for fast AMC due to ICI fluctuation, [4] still reports a 20-25% gain when compared to slow AMC.

A promising way to cope with ICI is inter-cell interference coordination (ICIC). A prominent static ICIC strategy is fractional frequency reuse, where neighboring cells do not reuse the whole spectrum for cell-edge users in order to avoid high ICI. Dynamic approaches that involve signaling between neighboring BSs are for example presented in [6]–[8]. Another option is interference randomization that ensures predictable interference properties. [9] compares ICIC with randomization and comes to the conclusion that ICIC is preferable for low load situations and randomization for high load situations. Other interesting ways to make ICI more predictable are presented in [10] and [11]. Here, resource allocation is performed in a way to minimize ICI fluctuation. One downside of all these approaches to cope with ICI is that they reduce achievable diversity gains (e.g., by refraining from utilizing a certain part of the available spectrum).

This is different for the solution proposed in [12]. Here, the authors propose that neighboring BSs exchange their resource allocation decisions via a high-speed backhaul infrastructure. Assuming multi-cell channel estimation, this makes the interference situation predictable for each BS and thus AMC algorithms can choose the best MCSs. However, in practice, the backhaul often introduces considerable delays. Realistic backhaul delays for current systems are reported to be in the order of 10 ms [13]. Considering such delays, the methodology proposed in [12] still leads to predictable ICI if the scheduling decisions are made in advance, but scheduling decisions are suboptimal as the CSI used for scheduling is outdated at the time of transmission. Thus, multi-user diversity is reduced.

In this paper we investigate a new approach motivated by [12] that is based on the exchange of scheduling probabilities. In the face of backhaul delays, it maintains the full degree of multi-user diversity, but reduces the AMC accuracy. Comparing it to [12] we want to answer the question, whether multi-user diversity is worth loosing ICI prediction accuracy.

The paper is structured as follows: In Section II we describe our system model. In Section III we describe the two ICI prediction schemes, before we present numerical results in Section IV. Finally, the paper is concluded in Section V.
II. System Model

We consider a small toy-senario with two neighboring BSs as depicted in Figure 1. The user terminals are placed on a straight line between the two access points. All user terminals on the line segment \([d_0, d/2]\) belong to the set \(\mathcal{K}_1\) with cardinality \(|\mathcal{K}_1| = K_1\), which constitutes cell 1. Analogously, the user terminals on the line segment \([d/2, d-d_0]\) belong to the set \(\mathcal{K}_2\), with cardinality \(|\mathcal{K}_2| = K_2\), constituting cell 2. Both, BSs and user terminals are equipped with a single receive and transmit antenna, respectively.

Each BS schedules the user transmissions in its cell. For simplicity, we focus on a single flat transmission resource that is reused by both cells and that can be assigned to one user for transmission in each cell for every transmission time interval (TTI). If BS1 assigns user \(i \in \mathcal{K}_1\) for transmission in cell 1 and BS2 assigns user \(j \in \mathcal{K}_2\) for transmission in the same TTI, the received signal at BS1 is

\[
y = h_{i,1} \sqrt{p_i} x_i + h_{j,1} \sqrt{p_j} x_j + n,
\]

where \(x_i\) and \(p_i\) are the transmit signal and transmit power of user \(k\), respectively and \(n \sim \mathcal{CN}(0, \sigma_n^2)\) models thermal noise at the receiver. We assume that the transmit symbols of the users are drawn from a Gaussian distribution with unit variance. Finally, \(h_{k,m}\) denotes the channel coefficient of user \(k\) to BS \(m\). We model the channel gains as complex Gaussian random variables with zero mean and a distance dependent variance

\[
\sigma_h^2(k,m) = \left(\frac{1}{\varepsilon_{k,m}}\right)^r,
\]

where \(\varepsilon_{k,m}\) is the distance between transmitter and receiver and \(r\) is the pathloss exponent. The temporal correlation of each channel coefficient \(h\) depends on the user speed and is modeled after the well known Jakes Model with the autocorrelation

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

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

We assume that the user power is adjusted to achieve an average target SNR \(\gamma_s\) at the nearest BS. If user \(k\) belongs to cell \(m\), the transmit power is given by \(p_k = \gamma_s \sigma_h^2 / \sigma_n^2(k,m)\).

Given the above described transmission scenario, the achievable transmission rate of user \(i\) is

\[
C_{i,j} = \log_2(1 + \text{SINR}_{i,j}) = \log_2 \left(1 + \frac{p_i|h_{i,1}|^2}{p_j|h_{j,1}|^2 + \sigma_n^2}\right).
\]

After the allocation of transmission resources to users, the BSs also assign transmission rates to the terminals. We denote the rate allocation of user \(i\) as \(R_i\). We model the actual achieved rate \(\hat{R}_i\) during transmission as

\[
R_i = \begin{cases} 
\hat{R}_i & \text{if } C_{i,j} \geq \hat{R}_i \\
\beta C_{i,j} & \text{otherwise}
\end{cases}
\]

where \(\beta \in [0, 1]\) is used to model the degree to which the system can make use of the transinformation conveyed in the transmission attempt (when decoding is not successful). This can be justified by hybrid automatic repeat request (HARQ) methods that, e.g., use incremental redundancy to allow decoding of an earlier transmission. If \(\beta = 0\), outage occurs and all transinformation is lost. For ease of description, we refer to every case where the allocated transmission rate is not supported as \(\text{outage}\) in the following (independent of the value of \(\beta\)). In theory, HARQ schemes can make use of all transinformation supported by the channel at the time of transmission (i.e., \(\beta = 1\)) [14]. We refrain from modeling a specific retransmission protocol. Instead, we assume that the missing transinformation needed for decoding the failed transmission is transmitted at the next occasion the user is scheduled (along with new information, if supported by the channel). Hence, we do not assume a time limit for retransmissions.

Each BS employs a max rate scheduler that selects the users with the best received signal strength for transmission and thus makes best use of multi-user diversity. Each BS \(m\) selects the user \(k^*\), where

\[
k^* = \arg \max_{k \in \mathcal{K}_m} p_k |h_{k,m}|^2.
\]

We assume that every BS \(m\) has perfect knowledge of the channel coefficients \(h_{k,m}\) for each user \(k \in \mathcal{K}_1, \mathcal{K}_2\), requiring perfect multi-cell channel estimation to be available.

As mentioned in the introduction, the two BSs can exchange information. However, this exchange is subject to a delay \(\Delta\). Thus, information that is based on instantaneous channel conditions is potentially outdated once the messages are received by the neighboring BS. To minimize the error, the BSs can predict the expected future channel coefficient \(h\) of a certain user, based on the previous \(L\) channel observations. This MMSE estimate is given as

\[
\hat{h}[t+\Delta] = E[h[t+\Delta]|h[t], \ldots, h[t-L+1]] = r_{h^\Delta h} R_{h^\Delta}^{-1} h,
\]

where \(h = [h[t], \ldots, h[t-L+1]]^T\) is the vector of channel observations, \(R_{h} = E[h h^H]\) is the covariance matrix of the observations, and \(r_{h^\Delta h} = E[h[t+\Delta] \cdot h^\Delta]\) expresses the covariance between the channel at time \(t + \Delta\) and the \(L\) previous channel observations. Both, \(r_{h^\Delta h}\) and \(R_{h}^{-1}\) can be obtained using the autocorrelation (3).

For ease of notation, we will denote the estimated channel coefficients (\(\Delta\) time steps ahead) as \(h^\Delta\) and the actual channel during transmission as \(h^0\). As \(h^\Delta\) is not yet known at the time
of prediction, it remains a random variable that is conditionally distributed on $h$ as $\mathcal{CN}(h^\Delta, \sigma_{\text{MSE}}^2)$, where

$$\sigma_{\text{MSE}}^2 = \sigma_h^2 - \mathbf{r}_{h^\Delta h} \mathbf{R}_{h^\Delta h} \mathbf{r}_{h^\Delta h}^H.$$  

\section{ICI Prediction Methods}

In this section we present the two cooperative ICI prediction methods that allow for a better assignment of transmission rates $\hat{R}_k$. Both methods are based on the exchange of information among the two base stations. However, scheduling decisions are made at different time instances. An overview of both methods is given in Figure 2.

A. Hard Decision Exchange

Assuming perfect multi-cell channel state estimation, BSs can perfectly predict ICI if they know the scheduling decisions in the neighboring cells. This allows them to assign the best transmission rates (i.e., $\hat{R}_k = C_{k,j}$, if user $j$ is scheduled in the neighboring cell). Thus, it was proposed in [12] to exchange scheduling decisions between the BSs. In this paper, we slightly extend this scheme to incorporate the delay $\Delta$ that occurs for the information exchange.

Each BS predicts the channels of its users for the time $t + \Delta$. Then, the user with the expected best transmission conditions (based on (6)) is selected to be scheduled in $\Delta$ time instances. This decision is then sent to the other base station, where it arrives $\Delta$ time instances later. As the base stations now have updated local channel state information, AMC is able to select the best rate allocation. Finally, the transmission occurs. For simplicity, we do not assume a delay between the reception of the scheduling information and the transmission of the terminals thereafter.

While this scheme allows to perfectly predict ICI and assign transmission rates accordingly, the scheduling decisions are outdated once the terminals transmit. Thus, the opportunistic scheduler is potentially not able to extract the full degree of multi-user diversity.

B. Soft Decision Exchange

Motivated by the scheme described above, we introduce a second scheme that allows to keep the full degree of multi-user diversity. However, this comes at the price of reduced ICI predictability and thus less accurate AMC. Instead of fixing the scheduling decisions $\Delta$ time slots before the actual transmission, we propose exchanging only the probabilities of the users to be selected for transmission at time $t + \Delta$. In this way, scheduling decisions are not fixed and the BSs can still select the best users shortly before transmission.

In the following we first describe how we can obtain the scheduling probabilities, before we describe the optimal way to allocate transmission rates given the scheduling probabilities of the users in the neighboring cell.

\section{Calculating Scheduling Probabilities}

As we assume max rate scheduling and do not consider a retransmission protocol, the scheduling decisions for one time slot are independent of earlier decisions and are solely based on the predicted channels. The probability $P_k$ that a user $k \in \mathcal{K}_m$ will be scheduled in cell $m$ equals the probability that $\sqrt{p_k}|h_{k,m}^\Delta| \geq \sqrt{\tau}|h_{j,m}^\Delta|$, $\forall j \in \mathcal{K}_m \setminus k$.

Since all coefficients $h^\Delta$ are non-zero Gaussian random variables at the time of the prediction, $z = \sqrt{\tau}|h^\Delta|$ follows the Ricean distribution

$$f_z(z) = \frac{\sqrt{2\tau}}{\sqrt{p} \sigma_{\text{MSE}}} I_0 \left( \frac{\hat{z}z}{p \sigma_{\text{MSE}}^2} \right) \exp \left(-\frac{z^2 + \hat{z}^2}{p \sigma_{\text{MSE}}^2} \right),$$

where $I_0$ is the modified Bessel function of first kind and order zero, and $\hat{z} = \sqrt{\tau}|h^\Delta|$ is the scaled magnitude of the channel prediction obtained by (7).

The probability that user $k \in \mathcal{K}_m$ will be scheduled can be calculated by

$$P_k = \mathbb{E}_{z_k} \left[ P\left( (z_1 < z_k) \land \ldots \land (z_{k-1} < z_k) \land (z_{k+1} < z_k) \land \ldots \land (z_{K_2} < z_k) \right) \right] = \int_0^{\infty} f_{z_k}(z_k) \prod_{j \in \mathcal{K}_m \setminus k} P(z_j < z_k) \, dz_k. \quad (10)$$

The probability $P(z_j < z_k)$ is equivalent to the evaluation of the cumulative distribution function (CDF) of $z_j$ at the value $z_k$. For the Ricean random variables observed here, the CDF is given as [15, chapter 2]

$$F_z(z) = \begin{cases} 1 - Q_1 \left( \sqrt{\frac{\tau z}{\sqrt{p} \sigma_{\text{MSE}}^2}} \right) & z \geq 0, \quad (11) \\ 0 & \text{otherwise} \end{cases}$$

where $Q_1$ is the Marcum Q function. Thus, $P(z_j < z_k) = F_{z_j}(z_k)$. The integration limits in (10) can be upper bounded with a small error, as the Ricean PDF quickly approaches zero. The numerical evaluation of (10) involves evaluating the Marcum Q function at many different values which is computationally expensive. To speed up the computation, the Marcum Q function can be approximated as proposed in [16]. In our simulations, we solve the integral by means of numerical integration within the bounds $\max\{0, z - 6\sigma \} \leq z \leq z + 6\sigma$, where $\sigma = \sqrt{p \cdot \sigma_{\text{MSE}}^2}/\sqrt{2}$. The results show very good accuracy when compared to Monte-Carlo evaluation of
the probabilities of Rician distributed random variables.

2) Rate Allocation: Given that each BS knows the scheduling probabilities of all users in the neighboring cells, we can now derive a rate allocation that maximizes the expected cell throughput. Without loss of generality we focus on cell 1. BS 1 selects its user \( i \in K_1 \) with the strongest instantaneous received signal for transmission. Depending on the scheduling decision in cell 2, there are \( K_2 \) different maximum achievable rates \( C_{i,k} \) for \( k \in K_2 \) as specified in (4). For ease of notation let us now refer to these different maximum achievable rates as \( C_1, \ldots, C_{K_2} \), constituting the set \( \mathcal{T} \) and occurring with probabilities \( P_1, \ldots, P_{K_2} \). Without loss of generality, let us assume that \( C_1 < \ldots < C_{K_2} \). Thus, given a rate allocation \( \hat{R}_i = C_k \), the outage probability is the probability that one of the \( k-1 \) interference situations occur which lead to lower achievable rates. Thus, the outage probability is given as

\[
P(R_i < \hat{R}_i | \hat{R}_i = C_k) = \sum_{l=1}^{k-1} P_l
\]

(12)

Analogously, the probability that the allocated rate can be achieved is \( 1 - P(R_i < \hat{R}_i | \hat{R}_i = C_k) = \sum_{l=k}^{K_2} P_l \). Using the model in (5), we can thus calculate the expected transmission performance for a specific rate allocation \( \hat{R}_i = C_k \), which is

\[
E[R_i | \hat{R}_i = C_k] = C_k \sum_{l=k}^{K_2} P_l + \sum_{l=1}^{k-1} \beta C_l \cdot P_l.
\]

(13)

The first part of the above equation accounts for the case that the transmission is successful. The second part weighs the transmission performance for each interference case in which the channel does not support the assigned rates with the probability of its occurrence. To maximize the expected throughput performance we choose \( \hat{R}_i = C^* \), where

\[
C^* = \arg \max_{C_k \in \mathcal{T}} E[R_i | \hat{R}_i = C_k].
\]

(14)

IV. SIMULATION RESULTS

In this section we present simulation results to compare the two cooperative ICI prediction methods considered. The simulation parameters are given in Table I. We assume full buffer traffic (each user has data to transmit) and set \( K_1 = K_2 = K \). Furthermore, we assume that all users are moving at the same speed.

Figure 3 depicts the average achieved rates of the different schemes for varying user speeds under an assumed delay of \( \Delta = 10 \text{ms} \). For comparison, we also depict the results for random scheduling with perfect rate allocation (rand) and a scheme that is based on the proposed soft decision exchange (SDE), but does not require exchanging information (no-xc). The latter method uses the rate allocation defined in (14). Since no additional information is available, all users are equally likely to be scheduled, i.e., \( P_k = 1/K \) for the considered power control scheme. It is thus the lower bound of SDE.

For the schemes that are based on information exchange, the prediction quality of the expected channel states degrades with increased user speed. This leads to suboptimal resource and/or rate allocation and thus degraded system performance. For slow moving users, hard decision exchange (HDE) is clearly preferable. In this regime very little multi-user diversity is lost as the channels only change slightly and the perfect rate allocation pays off. The scheme is lower bounded by random scheduling. SDE can only outperform HDE for faster moving users and high enough \( \beta \). For small \( \beta \), multi-user diversity cannot outweigh accurate link adaptation. SDE reaches its lower performance bound (no-xc) sooner, the closer \( \beta \) is to one. Thus, with increasing \( \beta \) the accuracy of the exchanged probability information becomes less important. This is intuitive: the price for inaccurate rate allocation decreases for increasing \( \beta \). In realistic systems, a rather high value of \( \beta \) can be expected. In this case, an ideal system would switch between HDE and SDE based on user speed. As accurate probability information is not so important in this regime, it is questionable whether the exchange is desirable at all for SDE.

Figure 4 depicts the performance behavior for different signaling delays \( \Delta \). As expected, the schemes become more sensitive to user speed with increasing delays. Furthermore, we also depict the Jain’s index of the exchanged probabilities for SDE. The Jain’s index is calculated as \( (\sum P_k)^2 / (K \sum P_k^2) \) and serves us as an indication of the ICI uncertainty. If all but one scheduling probability is zero, the index has the value 1/K. On the other hand, if all users are scheduled with the same probability (i.e., \( P_k = 1/K \)), the index is 1. As we can see, the ICI uncertainty increases with user speed. Clearly, SDE performance saturates, before the uncertainty reaches its maximum. Despite high uncertainty, SDE is able to achieve a good performance/outage trade-off.

Figure 5 depicts the average outage probabilities (measured and calculated with (12)) that occur for SDE. Be reminded that by outage we here refer to every case where the allocated rate is not supported by the channel (i.e., including cases where transinformation is preserved as \( \beta > 0 \)). The scheme automatically adjusts the outage probability to optimize the average throughput. As the value of \( \beta \) increases, outage becomes less harmful and the system tends towards higher rate allocations. As we can see, the calculated average outage probabilities match the ones measured very well.

Figure 6 depicts the throughput performance in relation to the number of users per cell \( K \). As expected, multi-user diversity is completely lost for HDE for high user speeds. While the performance of SDE also degrades, performance scaling with the number of users persists.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inter-site distance</td>
<td>( d = 500 \text{m} )</td>
</tr>
<tr>
<td>Minimum distance</td>
<td>( d_0 = 50 \text{m} )</td>
</tr>
<tr>
<td>Pathloss exponent</td>
<td>( r = 4 )</td>
</tr>
<tr>
<td>User distribution</td>
<td>uniform</td>
</tr>
<tr>
<td>User drops</td>
<td>1000</td>
</tr>
<tr>
<td>Channel realizations per drop</td>
<td>250</td>
</tr>
<tr>
<td>Target SNR</td>
<td>( \gamma = 20 \text{dB} )</td>
</tr>
<tr>
<td>Carrier frequency</td>
<td>( f_c = 2 \text{GHz} )</td>
</tr>
<tr>
<td>Prediction window</td>
<td>( L = 10 )</td>
</tr>
<tr>
<td>Transmission time length (TTI)</td>
<td>1ms</td>
</tr>
</tbody>
</table>
V. CONCLUSIONS

In this paper, we have proposed a new scheme for cooperative ICI prediction and enhanced link adaptation and have compared it to an existing scheme under the assumption of backhaul delays. While the latter scheme maintains accurate link adaptation (hard decision exchange), the new scheme maintains full multi-user diversity (soft decision exchange) for non-stationary users. For low-speed users, or if transmission from failed transmission attempts cannot be used, it is always desirable to maintain accurate link adaptation at the cost of reduced multi-user diversity. This changes, for faster moving users, if transmission from failed transmissions can be utilized. In this regime, the newly proposed soft decision method achieves a good trade-off between outage and throughput.

REFERENCES