Uplink Multicell Processing with Limited Backhaul via Successive Interference Cancellation

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***Abstract*—This paper studies an uplink multicell joint processing model in which the base-stations are connected to a centralized processing server via rate-limited digital backhaul links. Unlike previous studies where the centralized processor jointly decodes all the source messages from all base-stations, this paper proposes a suboptimal achievability scheme in which the Wyner-Ziv compress-and-forward relaying technique is employed on a per-base-station basis, but successive interference cancellation (SIC) is used at the central processor to mitigate multicell interference. This results in an achievable rate region that is easily computable, in contrast to the joint processing schemes in which the rate regions can only be characterized by exponential number of rate constraints. Under the per-base-station SIC framework, this paper further studies the impact of the limited-capacity backhaul links on the achievable rates and establishes that in order to achieve to within constant number of bits to the maximal SIC rate with infinite-capacity backhaul, the backhaul capacity must scale logarithmically with the signal-to-interference-and-noise ratio (SINR) at each base-station. Finally, this paper studies the optimal backhaul rate allocation problem for an uplink multicell joint processing model with a total backhaul capacity constraint. The analysis reveals that the optimal strategy that maximizes the overall sum rate should also scale with the log of the SINR at each base-station.**

I. Introduction

In traditional cellular topologies, out-of-cell interference is treated as part of the noise. When base-stations are densely deployed, the cellular network becomes interference limited. Because of this, in current cellular deployment, the per-cell achievable rate is typically much smaller than that of a single isolated cell. To address this issue, joint multicell processing has been proposed as a viable approach for inter-cell interference mitigation in future cellular systems. When base-stations share the transmitted and received signals, the codebooks, and the channel state information with each other, it is theoretically possible to perform joint transmission in the downlink and joint reception in the uplink to eliminate out-of-cell interference entirely.

One way to implement multicell joint processing is to deploy a centralized processing server that connects to all the base-stations via backhaul links. When the capacity of the backhaul links are infinite (or sufficiently large), the uplink joint processing problem becomes that of a multiple-access channel, and the downlink becomes a broadcast channel for which the capacity regions can be easily computed. In the uplink, for example, the centralized processor can jointly decode the source messages for all users in different cells, thus eliminating intercell interference completely. This gives rise to the concept of network MIMO [1], [2].

The practical implementation of a network MIMO system, however, must also consider the effect of finite capacity in the backhaul. In this realm, the information theoretical capacity analysis of the multicell cooperation model becomes more involved. This paper focuses on the uplink of a network MIMO model with limited backhaul. This uplink model, shown in Fig. 1, can be thought of as a combination of a multiple-access channel (with remote terminals acting as the transmitters and the centralized processor as the receiver) and a relay channel (with the base-stations acting as the relay).

Although the information theoretical capacity of this uplink model with limited backhaul is still an open problem, considerable progress has been made for the case of the circular Wyner model, in which all the base-stations are placed along a circular array and each mobile terminal transmits only to two neighbouring base-stations. This channel model is comprehensively studied in [3]–[5]. In [3], two different types of base-station operation are considered. When the base-stations are not capable of decoding, they quantize the received signals and forward to the centralized processor, which then performs *joint decoding* of both the source messages and quantized codewords. Alternatively, to reduce the burden on the centralized processor and to more efficiently utilize the backhaul links, base-stations can also decode part of the messages of users of their own cell, then forward the decoded data along with the remaining part to the centralized processor, thus shifting the computational burden using decentralized processing [4]. A comprehensive review of these results is available in [2].

The application of the above results to practical systems, however, poses additional challenges. In particular, the achievability rate region of [3, Proposition IV.1], involves $2^L - 1$ rate constraints, each requiring a minimization of 2^L terms, where L is the number of users in the uplink multicell model. This complexity makes the evaluation of the achievable rate region computationally prohibitive, when the number of users is large. We remark that the same achievable rate region can also be derived using the technique of noisy network coding [6]. Further, [6] shows that the rate derived in [3] is in fact within constant gap to the outer bound for this channel model if the quantization levels at the base-stations are chosen appropriately. Nevertheless, the same exponential complexity

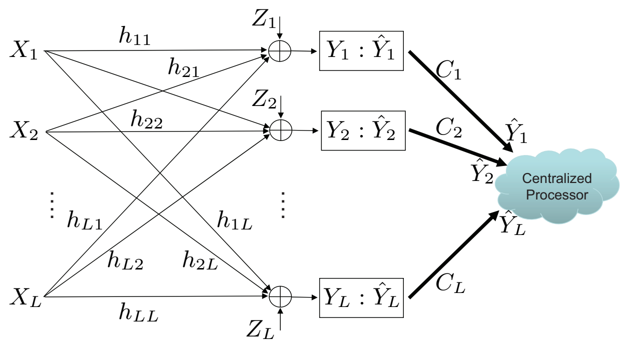

Fig. 1. Uplink multicell joint processing via a centralized processor

in the evaluation of the achievable rate region remains.

This paper aims to derive a computationally feasible achievable rate region for the uplink multicell joint processing problem. Toward this end, this paper focuses on the fully connected multicell model with finite backhaul to the centralized server, and proposes a suboptimal achievability scheme based on *successive decoding*. In particular, instead of performing joint decoding of the source messages and quantized messages, this paper applies the Wyner-Ziv compress-and-forward relaying scheme on a per-base-station basis and performs single-user decoding with successive interference cancellation (SIC) at the centralized server. Although the resulting rate regions are no longer the best achievable, they are more easily computed, and they lead to receiver architectures that are more amenable to implementation.

Under the proposed per-base-station SIC framework, we also ask the following question: How much backhaul capacity is needed to approximately achieve the theoretical successive-decoding rate with infinite backhaul? As the result of this paper shows, the backhaul rates need to scale logarithmically with the received signal-to-interference-and-noise ratio in order to achieve to within $\frac{1}{2}$ bit of the successive decoding rates attainable with unlimited backhaul capacity.

Further, this paper addresses the question of how should the backhaul rates be allocated across the different backhaul links. Under the proposed SIC framework, in order to maximize the sum rate over the entire network under a sum rate constraint on the backhaul capacity, the individual backhaul links should again have rates allocated according to the log of the SINR.

II. Channel Model

Consider the uplink of a multicell network with joint processing. Assuming that there is only one user operating in each time-frequency resource block in each cell, the multicell network can be modelled by L users each sending a message to their corresponding base-station. Base-stations essentially serve as intermediate relays for the centralized server, which eventually decodes all the transmit messages. Equivalently, the uplink multicell joint processing model can be thought of as a multiple access channel with L users sending messages to the destination, i.e., the centralized processor.

As depicted in Fig. 1, the uplink joint processing model consists of two parts. The left half is an L-user interference channel with X_i as the input signal from the i^{th} user, Y_i as the output signal, Z_i as the additive white Gaussian noise (AWGN), and h_{ij} as the channel gain from user i to user j, where $i, j = 1, 2, \cdots, L$. The right half can be seen as a *digital* multiple-access channel, where the received signal Y_i is quantized to $\hat{Y}_i$ which is then sent to the centralized processor through the digital link of capacity C_i, $i = 1, 2, \cdots, L$. Without loss of generality, it is assumed that the power of the input signal X_i is limited by P_i and that the variances of the receiver noises are identical, i.e., $E[|X_i|^2] \le P_i$ and $Z_i \sim \mathcal{N}(0, N_0)$, $i = 1, 2, \cdots, L$.

III. Wyner-Ziv Compress-and-Forward with Successive Interference Cancellation

This paper focuses on a compress-and-forward strategy for the uplink joint processing model, i.e., each of the transmitted signal at the input of the digital backhaul links represents a compression index of Y_i. We are motivated to adopt this the same scheme as in [3], [6], because it can be proved that with joint decoding at the centralized server, this compress-and-forward scheme can achieve the capacity region of a Gaussian relay network to within a constant gap (which is dependent on the size of the network).

Unfortunately, the evaluation of the achievable rate for joint decoding can be hard. For example, for the uplink joint processing model studied in this paper, the achievable rate region using noisy network coding [6] or joint decoding [3] requires a minimization of 2^L terms for each rate constraint, and there are $2^L - 1$ different rate constraints describing the rate region. Even when the size of the network is in a reasonable range, for example as in a 19-cell topology, it is computationally prohibitive to minimize over 2^{19} terms for $2^{19} - 1$ different rate constraints.

In order to render the study of the performance of multicell joint processing more tractable, in [3] the fully connected uplink channel is simplified to a modified Wyner model (see [7]), where each transmitter-receiver pair only interferes with one neighbouring transmitter-receiver pair, and is subject to interference from only one neighbouring transmitter-receiver pair. Further, certain symmetry is introduced so that all the direct channels are identical, and so are all interfering channels. With this symmetric and less complex cyclic structure, the computation of the sum rate becomes tractable [3].

In this paper, instead of studying the symmetric Wyner model with joint decoding, we focus on the general multicell model and propose a suboptimal achievability scheme based on the successive decoding of source messages. Based on the observation that the exponential complexity of noisy network coding is introduced by the joint decoding step at the destination, this paper proposes to apply the Wyner-Ziv compress-and-forward relaying technique [8] at each base-station independently, but use a SIC decoding scheme at the centralized processor, resulting in much simpler rate expressions.

Specifically, assuming a *fixed* decoding order of decoding first X_1, then $X_2, X_3, \cdots, X_L$. The kth decoding stage for decoding X_k at the centralized processor works as follows:

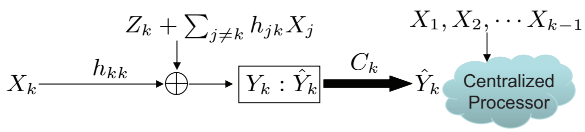

Fig. 2. Equivalent channel of user k in the k^{th} decoding stage

Upon receiving Y_k, the base-station k quantizes Y_k into $\hat{Y}_k$ using the Wyner-Ziv compress-and-forward technique and sends the description to the destination via digital link C_k. Note that the quantization process at the base-station k treats interference from all other users as noise. To decode user k's message X_k, the centralized processor first decodes the quantization message $\hat{Y}_k$ upon receiving its description from the digital link C_k, and then decodes the message of user k using joint typicality between the quantized message $\hat{Y}_k$ and X_k. Both the decoding of $\hat{Y}_k$ and X_k assume the knowledge of previously decoded messages $X_1, X_2, \cdots, X_{k-1}$ at the centralized processor. In this way, the impact of interference from $X_1, \cdots X_{k-1}$ eventually disappears and the effective interference is only due to users not yet decoded, i.e., X_j, for $j > k$. After decoding X_k, the central processor moves to the next decoding stage treating X_k as known side information. The following theorem gives the achievable rate using the proposed per-base-station Wyner-Ziv compress-and-forward relaying scheme and SIC decoding scheme.

Theorem 1. *For the uplink multicell joint processing channel depicted in Fig. 1, the following rate is achievable using Wyner-Ziv compress-and-forward relaying at the base-stations followed by successive interference cancellation at the centralized processor with a fixed decoding order:*

$$R_k = \frac{1}{2}\log\frac{1+\mathsf{SINR}_k}{1+2^{-2C_k}\mathsf{SINR}_k}, \tag{1}$$

where

$$\mathsf{SINR}_k = \frac{h_{kk}^2 P_k}{N_0 + \sum_{j>k} h_{jk}^2 P_j} \tag{2}$$

Proof: In the kth stage of the successive-interference-cancellation decoder, $X_1, \cdots, X_{k-1}$ decoded in the previous decoding stages serve as side information for stage k. The equivalent channel of user k is depicted in Fig. 2. This is a three-node relay channel without the direct source-destination link. Specifically, source signal X_k is sent from the transmitter to the relay, which receives Y_k, quantizes into $\hat{Y}_k$ and forwards its description to the centralized processor via the noiseless digital link of capacity C_k. At the centralized processor, $X_1, \cdots, X_{k-1}$ serve as side information and facilitate the decoding of $\hat{Y}_k$ and X_k. According to [8, Theorem 6], the achievable rate of user k using Wyner-Ziv compress-and-forward can be written as

$$R_k = I(X_k; \hat{Y}_k | X_1, \cdots, X_{k-1}) \tag{3}$$

subject to the constraint

$$I(Y_k; \hat{Y}_k | X_1, \cdots, X_{k-1}) \leq C_k \tag{4}$$

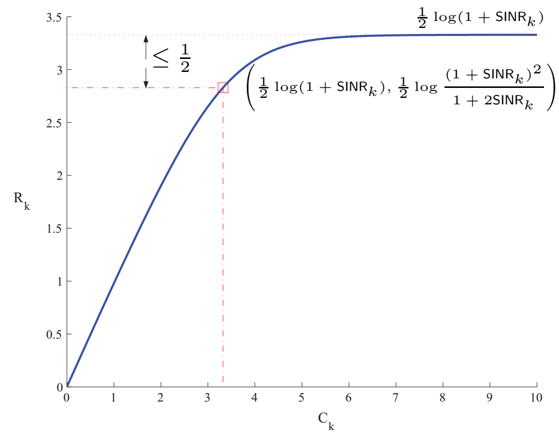

Fig. 3. Achievable rate of user k versus the backhaul capacity C_k

We constrain ourselves to Gaussian input signals and the Gaussian quantization scheme, i.e., $X_k \sim \mathcal{N}(0, P_k)$ and

$$\hat{Y}_k = Y_k + e_k, \tag{5}$$

where e_k is the Gaussian quantization noise following $\mathcal{N}(0, \mathsf{q}_k)$, and is independent of everything else. To fully utilize the digital link, it is natural to set

$$I(Y_k; \hat{Y}_k | X_1, \cdots, X_{k-1}) = C_k. \tag{6}$$

Now, substituting $Y_k = \sum_{j=1}^{L} h_{jk}X_j + Z_k$ and $\hat{Y}_k = Y_k + e_k$ into (6), we have

$$\begin{aligned} C_k &= I(Y_k; \hat{Y}_k | X_1, \cdots, X_{k-1}) \\ &= h(\hat{Y}_k | X_1, \cdots, X_{k-1}) - h(e_k) \\ &= \frac{1}{2}\log\left(1 + \frac{N_0 + \sum_{j\geq k} h_{jk}^2 P_j}{\mathsf{q}_k}\right), \end{aligned} \tag{7}$$

which results in the following quantization level that fully utilizes the digital links C_k:

$$\mathsf{q}_k^* = \frac{N_0 + \sum_{j\geq k} h_{jk}^2 P_j}{2^{2C_k} - 1}. \tag{8}$$

With the above q_k^*, the achievable rate of user k can be calculated as

$$\begin{aligned} R_k &= I(X_k; \hat{Y}_k | X_1, \cdots, X_{k-1}) \\ &= h(\hat{Y}_k | X_1, \cdots, X_{k-1}) - h(\hat{Y}_k | X_1, \cdots, X_k) \\ &= \frac{1}{2}\log\frac{\mathsf{q}_k^* + N_0 + \sum_{j\geq k} h_{jk}^2 P_j}{\mathsf{q}_k^* + N_0 + \sum_{j>k} h_{jk}^2 P_j} \\ &= \frac{1}{2}\log\frac{N_0 + \sum_{j>k} h_{jk}^2 P_j + h_{kk}^2 P_k}{N_0 + \sum_{j>k} h_{jk}^2 P_j + 2^{-2C_k} h_{kk}^2 P_k} \\ &= \frac{1}{2}\log\frac{1+\mathsf{SINR}_k}{1+2^{-2C_k}\mathsf{SINR}_k}, \end{aligned} \tag{9}$$

which completes the proof. ■

Note that the above proposed SIC scheme is not the only possibility for simplifying the joint decoding of $\{X_k, \hat{Y}_k\}_{k=1}^{L}$. The above SIC scheme essentially imposes a decoding order of $\hat{Y}_1$, then X_1, then $\hat{Y}_2$, then X_2, etc, with previously decoded X_k serving as side information. Alternatively, one may proceed in a two-stage process of decoding all of $\{\hat{Y}_k\}_{k=1}^L$ first, then $\{X_k\}_{k=1}^L$. Each of these two stages can be accomplished in an SIC fashion. The resulting rate can be obtained from expressions in [4], [9], [10] as

$$I(Y_k; \hat{Y}_k | \hat{Y}_1, \cdots, \hat{Y}_{k-1}) \leq C_k, \quad k = 1, \cdots, L \tag{10}$$

and

$$R_k = I(X_k; \hat{Y}_1, \cdots, \hat{Y}_L | X_1, \cdots, X_{k-1}), \quad k = 1, \cdots, L \tag{11}$$

The above rate expression can potentially outperform the achievable rate (1), because in the above expression each X_k is decoded based on the quantized observations of *a*ll base-stations, rather than just the kth base-station. For the same reason, the implementation of the above scheme is also expected to be more involved. For the rest of this paper, we will only focus on the per-base-station SIC decoding of (1).

Now back to Theorem 1, the rate expression (1) shows how the achievable rates are affected by the limited capacities of the digital backhaul links under the proposed per-base-station SIC decoding framework. Fig. 3 plots the achievable rate of R_k as a function of the backhaul link capacity C_k with SINR_k equal to 20dB. When C_k is small, R_k grows almost linearly with C_k, which means that each bit of the backhaul link provides approximately one bit increase in the achievable rate for user k. The digital backhaul is efficiently exploited in this regime. However, as C_k grows larger, each bit of the backhaul link returns increasingly less achievable rate. On the extreme scenario where the capacity of the digital link is unlimited, i.e. $C_k = \infty$, R_k is saturated and approaches $\frac{1}{2}\log(1+\mathsf{SINR}_k) \stackrel{\triangle}{=} \bar{R}_k$, which can be thought of as the upper limit for the rate of user k when the SIC decoder is employed.

Since backhaul links do not come for free, it is natural to ask how large does C_k need to be to achieve a rate R_k that is close to the maximal SIC rate with unlimited backhaul? It is easy to see that when $C_k = \frac{1}{2}\log(1+\mathsf{SINR}_k)$, $\bar{R}_k - R_k$ is upper bounded by one half, i.e.,

$$\begin{aligned} \bar{R}_k - R_k &= \frac{1}{2}\log(1+\mathsf{SINR}_k) \\ &\quad - \frac{1}{2}\log \frac{1+\mathsf{SINR}_k}{1+2^{-2C_k}\mathsf{SINR}_k}\bigg|_{C_k=\frac{1}{2}\log(1+\mathsf{SINR}_k)} \\ &= \frac{1}{2}\log\left(1+\frac{\mathsf{SINR}_k}{1+\mathsf{SINR}_k}\right) \\ &\leq \frac{1}{2}. \end{aligned} \tag{12}$$

Therefore, when the digital link $C_k = \frac{1}{2}\log(1+\mathsf{SINR}_k)$, the achievable rate is half a bit away from the SIC upper limit. This is also the point under which the utilization of C_k is most efficient, as shown in Fig. 3.

IV. Optimal Rate Allocation with a Total Backhaul Capacity Constraint

A practical system may have a constraint on the sum capacity of all digital backhaul links. So, it may be of interest to optimize the allocation of backhaul capabilities among the base-stations in order to achieve an overall maximum sum rate under a total backhaul capacity constraint. This optimization problem can be formulated as the following:

$$\begin{aligned} \text{maximize} \quad & \sum_{k=1}^L R_k \\ \text{subject to} \quad & C_k \geq 0, \;\; k = 1, 2, \cdots, L. \\ & \sum_{k=1}^L C_k \leq C \end{aligned} \tag{P1}$$

where $R_k, k = 1, 2, \cdots, L$ are functions of C_k as derived in Theorem 1, and $C > 0$ is the total available backhaul capacity. The following theorem provides an optimal solution to the above optimization problem.

Theorem 2. *For the uplink multicell joint processing model shown in Fig. 1, with Wyner-Ziv compress-and-forward relaying and successive interference cancellation at the centralized processor, the optimal allocation of backhaul link capacities subject to a total backhaul capacity constraint C is given by*

$$C_k^* = \max\left\{\frac{1}{2}\log(\mathsf{SINR}_k) - \alpha, 0\right\}, \tag{13}$$

where α is chosen such that $\sum_{k=1}^L C_k^* = C$.

Proof: Substituting the rate expression (1) for R_k into the optimization problem (P1), we obtain the following equivalent minimization problem:

$$\begin{aligned} \text{minimize} \quad & \sum_{k=1}^L \frac{1}{2}\log\left(1+2^{-2C_k}\mathsf{SINR}_k\right) \\ \text{subject to} \quad & C_k \geq 0, \;\; k = 1, 2, \cdots, L. \\ & \sum_{k=1}^L C_k \leq C \end{aligned} \tag{P2}$$

It can be easily seen that (P2) is a convex optimization problem, as the constraints are linear and the objective function is the sum of convex functions, as can be verified by taking their second derivatives.

Now introducing Lagrange multipliers $\boldsymbol{\nu} \in \mathbb{R}_+^L$ for the positivity constraints $C_k \geq 0, k = 1, 2, \cdots, L$, and $\lambda \in \mathbb{R}_+$ for the backhaul sum-capacity constraint $\sum_{k=1}^L C_k \leq C$, we form the Lagrangian

$$\begin{aligned} L(C_k, \boldsymbol{\nu}, \lambda) = \sum_{k=1}^L \frac{1}{2}\log\left(1+2^{-2C_k}\mathsf{SINR}_k\right) - \sum_{k=1}^L \nu_k C_k \\ + \lambda\left(\sum_{k=1}^L C_k - C\right) \end{aligned} \tag{14}$$

Taking the derivative of the above with respect to C_k, we obtain the following Karush-Kuhn-Tucker (KKT) condition

$$-\frac{2^{-2C_k^*}\mathsf{SINR}_k}{1+2^{-2C_k^*}\mathsf{SINR}_k} - \nu_k + \lambda = 0, \tag{15}$$

for the optimal C_k^*, where $k = 1, 2, \cdots, L$. Note that $\nu_k = 0$ whenever $C_k > 0$. Now, the optimal C_k^* must satisfy the backhaul sum-capacity constraint $\sum_{k=1}^{L} C_k^* \leq C$ with equality, because the objective of the minimization R_k monotonically increases with C_k. Solving the condition (15) together with the fact that $\sum_{k=1}^{L} C_k^* = C$ gives the following optimal C_k^*:

$$C_k^* = \max\left\{\frac{1}{2}\log\frac{\mathsf{SINR}_k}{\beta}, 0\right\}, \tag{16}$$

where β is chosen such that $\sum_{k=1}^{L} C_k^* = C$. This is equivalent to (13). ■

An interpretation of (16) is that whenever the SINR of user k is above a threshold β, $\frac{1}{2}\log\frac{\mathsf{SINR}_k}{\beta}$ bits of the backhaul link should be allocated to user k. Otherwise, this user is not being used in the uplink transmission. This optimal rate allocation is in fact quite similar to the classic water-filling solution for the sum-capacity maximization problem for a parallel set of Gaussian channels, in which more power (backhaul capacity in this case) is assigned to users with a better channel.

When written as (13), the optimal backhaul capacity allocation can be interpreted as follows: $C_k = \frac{1}{2}\log(\mathsf{SINR}_k)$ can be thought of as the nominal optimal backhaul link capacity. If the total backhaul rate is above (or below) the nominal $\sum_k \frac{1}{2}\log(\mathsf{SINR}_k)$, then the extra capacity must be distributed (or taken away) from each base-station equally. In other words, all base-station should nominally operate at the point 1/2 bits away from the SIC limit (as shown in Fig. 3). If more (or less) backhaul capacity is available than the nominal value, all base-stations should move above (or below) that operating point in the same manner.

Finally, we remark that the decoding order at the centralized processor plays an important role in the optimal rate allocation. Different decoding orders result in different rate expressions in Theorem 1 and thus different rate allocations in Theorem 2, and as a consequence different achievable sum rates. In order to determine the best decoding order that results in the largest sum rate, we need to exhaustively search over $K!$ different decoding orders. This is a fairly complex and nontrivial problem that is also encountered in other contexts involving successive decoding.

V. Numerical Results

To obtain further insights on the SIC-based scheme proposed in this paper, the achievable rate region of Theorem 1 is now compared with that obtained by three other schemes: 1) single-user decoding without joint processing, 2) noisy network coding, 3) joint base-station processing SIC, for a two-user symmetric scenario where $L = 2$, $P_1 = P_2 = N_0 = 1$, $h_{11}^2 = h_{22}^2$, $h_{12}^2 = h_{21}^2$, and $C_1 = C_2$. Under the symmetric setting, Theorem 1 gives two symmetric achievable rate pairs depending on the decoding order. Time-sharing of the two achievable rate pairs gives a pentagon shaped achievable rate region.

In single-user decoding without joint processing, each receiver decodes its own signal while treating the other user's signal as noise. This gives the following achievable rate pair

$$\begin{cases} R_1 = \min\left\{\frac{1}{2}\log\left(1 + \frac{h_{11}^2}{1+h_{21}^2}\right), C_1\right\} \\ R_2 = \min\left\{\frac{1}{2}\log\left(1 + \frac{h_{22}^2}{1+h_{12}^2}\right), C_2\right\} \end{cases} \tag{17}$$

which in the symmetric setting results in a square shaped achievable rate region with (R_1, R_2) as the top-right corner.

This paper also plots the noisy-network-coding rate with the quantization levels at the two base-stations set to the noise variance level N_0, resulting in an achievable rate region which is within a constant gap to capacity. This quantization level can be further optimized, for example, as in the two-stage process (10)-(11). We restrict ourselves to symmetric quantization levels here, and refer this as the *joint base-station processing SIC region* in the plots.

The achievable rate regions obtained above are compared for the following channel settings:

- $h_{ii}^2 = 30$dB, $h_{ij}^2 = 20$dB, $C_i = 5$ bits;
- $h_{ii}^2 = 30$dB, $h_{ij}^2 = 5$dB, $C_i = 5$ bits;
- $h_{ii}^2 = 30$dB, $h_{ij}^2 = 20$dB, $C_i = 10$ bits;
- $h_{ii}^2 = 30$dB, $h_{ij}^2 = 20$dB, $C_i = 2$ bits.

Fig. 4 shows the achievable rate regions in the setting where the direct links are 30dB, the cross links are 20dB, and the backhaul links are 5 bits per channel use. As can be seen from the figure, our proposed SIC scheme expands the baseline achievable rate region by about 2.8 bits on both the individual rates and the sum rate. The noisy-network-coding and the joint base-station processing regions further outperform the proposed scheme in sum rate by about 2.5 bits due to the benefits of joint decoding.

However, when the interfering links are weak, as shown in Fig. 5 where $h_{12}^2 = 5$dB, all four achievable rate regions are close to each other. This is the regime where treating interference as noise is close to optimal, so multicell processing does not provide significant benefits.

In the above two examples, the capacities of the backhaul links are already quite abundant, since they are set to be the rate supported by the direct links: $\frac{1}{2}\log(h_{11}^2) \approx 5$. In Fig. 6, we further increase the backhaul capacity to 10 bits, and show that doing so does not significantly improve the achievable rate region for either SIC or noisy network coding. Note that in this case, SIC may have higher individual rate than noisy network coding. But, this is because the noisy network coding scheme sets the quantization level to be N_0. The joint base-station processing scheme with appropriate quantization setting ultimately outperforms both the noisy network coding and the per-base-station SIC schemes in these examples.

Finally, we decrease the backhaul capacity from 5 bits to 2 bits in Fig. 7. Interestingly, this is a situation in which the base-line scheme can outperform per-base-station SIC. But the largest sum rate is still obtained with joint base-station processing SIC.

VI. Conclusion

This paper proposes a novel achievability scheme employing the Wyner-Ziv compress-and-forward and the SIC receiver

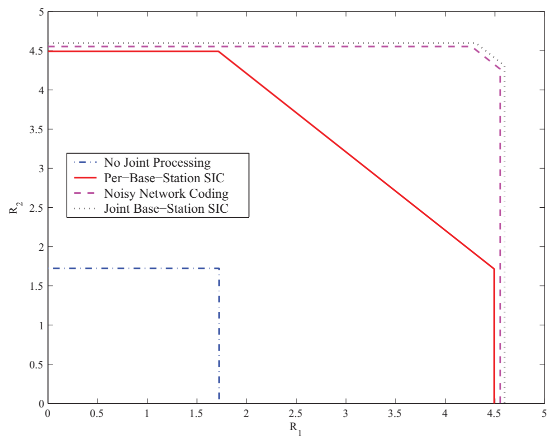

Fig. 4. Comparison of the proposed achievability scheme and another two schemes, $h_{11}^2 = h_{22}^2 = 30$dB, $h_{12}^2 = h_{21}^2 = 20$dB, $C_1 = C_2 = 5$ bits

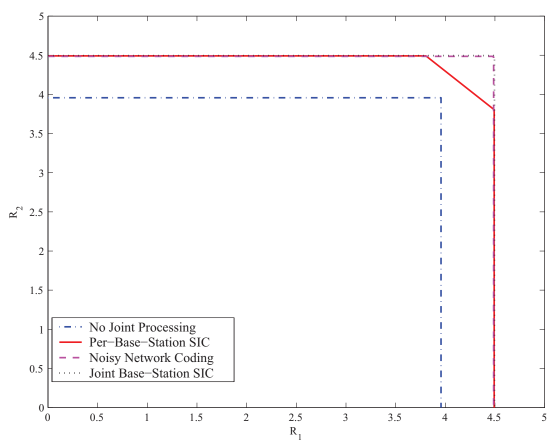

Fig. 5. Comparison of the proposed achievability scheme and another two schemes, $h_{11}^2 = h_{22}^2 = 30$dB, $h_{12}^2 = h_{21}^2 = 5$dB, $C_1 = C_2 = 5$ bits

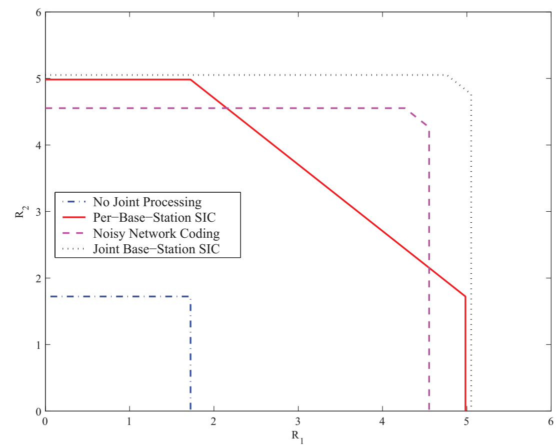

Fig. 6. Comparison of the proposed achievability scheme and another two schemes, $h_{11}^2 = h_{22}^2 = 30$dB, $h_{12}^2 = h_{21}^2 = 20$dB, $C_1 = C_2 = 10$ bits

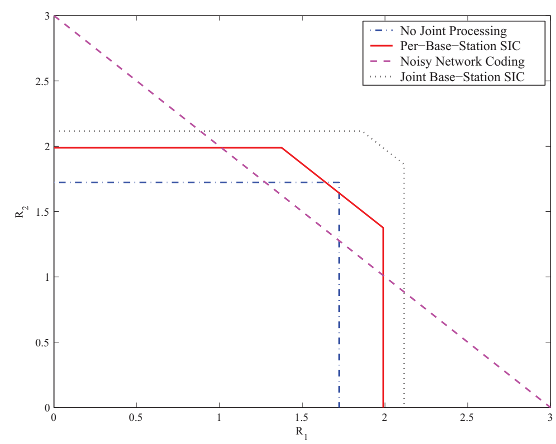

Fig. 7. Comparison of the proposed achievability scheme and another two schemes, $h_{11}^2 = h_{22}^2 = 30$dB, $h_{12}^2 = h_{21}^2 = 20$dB, $C_1 = C_2 = 2$ bits

structure on a per-base-station basis for the uplink of the multicell processing system in which the base-stations are connected to a centralized processor with finite capacity backhaul links. The main advantage of the proposed scheme is that the resulting achievable rate region is easily computable, and it leads to an architecture that is more amendable to practical implementation. Under the per-base-station SIC framework, this paper shows that the capacities of the backhaul links should scale with the logarithm of the SINR in each base-station, both from a point of view of approaching the theoretical maximal SIC rate with unlimited backhaul, as well as for maximizing the overall sum rate subject to a total backhaul rate constraint.

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