Efficient Zero-Forcing Based Interference Coordination for MISO Networks

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***Abstract*—We consider coordination of transmission strategies in interference networks, where multiple antennas at the transmitters can be used to adjust the spatial signature of the transmitted signal. For single antenna receivers the interference power received can be constraint by so-called interference temperatures, which can be used to coordinate the amount of interference in the network. We recapitulate recent research results on this topic and discuss methods to select interference temperatures that lead to performance gains compared to uncoordinated transmission. A special configuration is to demand interference to be completely eliminated, so-called zero-forcing. Methods based on zero-forcing allow for simple computation of the transmit strategies, while for general temperatures iterative algorithms are required. Strictly enforcing completely orthogonalized transmission drastically reduces the number of active users in the network and is therefore too restrictive for larger networks. We suggest an efficient algorithm that enforces orthogonal transmission only in part, which leads to an increased number of users and significant performance gains, while maintaining the low complex computation of the transmit strategies. The method is based on successive user allocation, that avoids an exhaustive search for the active user set and the user transmitter pairs for which interference should be eliminated.**

I. Introduction

In the downlink of a cellular network inter-cell interference (ICI) can be a severely limiting factor, especially users at the cell edge are affected and might be excluded from network service. A possible solution to completely eliminate ICI is the joint encoding of information over multiple transmitters [1], [2], so-called network MIMO. In case full channel state information and all data is available at a central controller, joint encoding over geographically distributed antennas renders the network into a super-cell, and network MIMO can efficiently exploit all spatial degrees of freedom to eliminate ICI. Network MIMO requires a huge amount of additional complexity and signaling compared to single cell signal processing and might be difficult to implement in practice. Therefore, methods aiming at elimination of interference by cooperation of the transmitters, while every user is served by a single transmitter, are attractive for deployable networks. In order to cancel interference, user signals are orthogonalized in the signal space constituted by the available resources, for example time, frequency, and space. The availability of multiple antennas at transmitter (and receiver) allows to serve multiple users interference free at the same time on the same frequency by spatial multiplexing. Interference coordination by adjusting the transmission space of each user is well understood and can be solved optimally for a single cell [3], [4]. In conventional cellular network design, signal processing in the spatial domain is only performed per cell, but interesting research towards extending spatial multiplexing over multiple transmitters is emerging. For networks where the transmitters have multiple antennas and the receivers are equipped with a single antenna (MISO), the optimal solution is known [5], however the presented algorithm has prohibitive complexity for larger networks. In [6] a local optimization on the transmit covariance matrices is used, a similar approach for beamforming can be found in [7].

Other less complex approaches for coordinating the transmission spaces of each transmitter are proposals that perform a joint decision on the users to schedule [8], [9], where at each time slot only a single user per cell is active. Each user is served using a transmit filter matched to the MISO channel and by the joint scheduling decision transmit filters are combined such that interference is reduced. Clearly, it is advantageous to select transmit filters that are not optimal for the user, but reduce the interference caused to other users. Methods based on pricing for the interference caused [10], thresholds for a forbidden interference direction [11], or so-called interference temperatures [12], [13] have potential for implementation with reasonable complexity. Methods based on zero-forcing [14], [15] allow for simple computation of the transmit strategies and are therefore especially attractive.

After introducing the system model, stating the problem formulation, and discussing solution strategies in Section II, we investigate some resent research results on interference temperatures in Section III. In Section IV, we illustrate how zero-forcing constraints can be established as a special class of binary interference temperatures. Based on successive user allocation and binary temperatures, we present a low complexity algorithm for interference coordination in Section V, and show significant gains compared to uncoordinated approaches by numerical results in Section VI. Finally we draw some conclusions and make suggestions for future research directions in Section VII.

II. System Model and Problem Formulation

The cellular system is given by a set of transmit arrays $\mathcal{T}, T = |\mathcal{T}|$, and a set of users $\mathcal{K}, K = |\mathcal{K}|$ distributed throughout the covered area. User assignment to a transmitter is done by a cell selection scheme formally described by a mapping $f : \mathcal{K} \to \mathcal{T}$. The assignment to a transmitter is fixed for each user and therefore f partitions the users such that

$$\mathcal{K} = \mathcal{K}_1 \cup \mathcal{K}_2 \cup \ldots \cup \mathcal{K}_T \text{ and } \mathcal{K}_i \cap \mathcal{K}_j = \varnothing \text{ if } i \neq j.$$

The receivers are equipped with a single antenna and N is the number of transmit antennas. The channel matrices are

$$\{\boldsymbol{h}_{kt}^{\mathrm{H}}\}^{k\in\mathcal{K}, t\in\mathcal{T}} \in \mathbb{C}^{1\times N},$$

where $\boldsymbol{h}_{kt}^{\mathrm{H}}$ is the channel matrix between transmitter t and user k. To have a more pleasant notation, we write $\boldsymbol{h}_{kj}^{\mathrm{H}}$ as a short cut for $\boldsymbol{h}_{kf(j)}^{\mathrm{H}}$, the channel between user k and the transmitter user j is assigned to. The received signal of user k consists of the desired signal, intra-cell, and inter-cell interference and can be expressed as

$$y_k = \boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{x}_k + \underbrace{\sum_{i\in\mathcal{K}_{f(k)}\setminus k} \boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{x}_i}_{\text{intra-cell interference}} + \underbrace{\sum_{i\in\mathcal{K}\setminus\mathcal{K}_{f(k)}} \boldsymbol{h}_{ki}^{\mathrm{H}}\boldsymbol{x}_i}_{\text{inter-cell interference}} + \eta,$$

where $\boldsymbol{x}_i \in \mathbb{C}^{N\times 1}$ is the transmit signal for user i, $\eta \sim \mathcal{CN}(0, \sigma^2)$ represents white Gaussian noise and σ^2 is the noise power. Assuming Gaussian modulation, the covariance matrix of the transmit symbol $\boldsymbol{x}_i$ is $\mathrm{E}\{\boldsymbol{x}_i\boldsymbol{x}_i^{\mathrm{H}}\} = \boldsymbol{Q}_i \in \mathbb{C}^{N\times N}$, a Hermitian and positive semi-definite matrix, denoted as $\boldsymbol{Q} \succeq 0$. Considering linear precoding, the information theoretic rate for user k is given by

$$r_k = \log_2\left(1 + \frac{\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{Q}_k\boldsymbol{h}_{kk}}{\sigma^2 + \sum_{j\in\mathcal{K}\setminus k}\boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{Q}_j\boldsymbol{h}_{kj}}\right).$$

Coordination of transmission strategies $\boldsymbol{Q}_1, \ldots, \boldsymbol{Q}_K$, subject to a per transmitter power constraint P, in order to maximize performance of the network, here the sum-rate of all users, is captured by the following optimization problem:

$$\begin{aligned}
\mathscr{Q} : \underset{\boldsymbol{Q}_1,\ldots,\boldsymbol{Q}_K}{\text{maximize}} \quad & \sum_{k\in\mathcal{K}} \log_2\left(1 + \frac{\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{Q}_k\boldsymbol{h}_{kk}}{\sigma^2 + \sum_{j\in\mathcal{K}\setminus k}\boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{Q}_j\boldsymbol{h}_{kj}}\right) \\
\text{subject to} \quad & \sum_{k\in\mathcal{K}_t} \mathrm{tr}\{\boldsymbol{Q}_k\} \leq P \ \forall\ t \in \mathcal{T}, \\
& \boldsymbol{Q}_k \succeq 0 \ \forall\ k \in \mathcal{K}.
\end{aligned}$$

In [16] the optimality of beamforming for MISO systems is proven, meaning a solution to Problem ($\mathscr{Q}$) can be found where all transmit covariances are rank 1, i.e. $\boldsymbol{Q}_k = \boldsymbol{w}_k\boldsymbol{w}_k^{\mathrm{H}}$, which implies an equivalent formulation in the precoders $\boldsymbol{w}_1, \ldots, \boldsymbol{w}_K \in \mathbb{C}^{N\times 1}$,

$$\begin{aligned}
\mathscr{W} : \underset{\boldsymbol{w}_1,\ldots,\boldsymbol{w}_K}{\text{maximize}} \quad & \sum_{k\in\mathcal{K}} \log_2\left(1 + \frac{\left|\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{w}_k\right|^2}{\sigma^2 + \sum_{j\in\mathcal{K}\setminus k}\left|\boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{w}_j\right|^2}\right) \\
\text{subject to} \quad & \sum_{k\in\mathcal{K}_t} \boldsymbol{w}_k^{\mathrm{H}}\boldsymbol{w}_k \leq P \ \forall\ t \in \mathcal{T}.
\end{aligned}$$

The transmission coordination Problems ($\mathscr{Q}$) and ($\mathscr{W}$) can be solved by changing the optimization domain to a rate space problem, which results in a monotonic optimization problem, see [5]. The complexity of solving monotone program prohibits to compute the solution for larger networks, which demands methods that have potential for implementation with reasonable complexity while accomplishing good performance. In [6] a gradient projection method on the covariance matrices is used to compute a local maximum of Problem ($\mathscr{Q}$), a similar approach for beamforming, Problem ($\mathscr{W}$), can be found in [7].

III. Interference Temperatures

From the area of cognitive radio stems the concept to constrain the interference power on other users, called interference temperatures [12], [11], [13]. These approaches essentially exploit the fact that the interference power a user exhibits can be described by a scalar, which allows for a new parametrization of the coordination problem. In [11] the interference temperature constraint for user k is given by

$$\sum_{j\in\mathcal{K}\setminus k} \boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{Q}_j\boldsymbol{h}_{kj} \leq \gamma_k.$$

Adding the temperature constraints to Problem ($\mathscr{Q}$) implies that the interference power a user receives is certainly smaller than the users temperature. Using a worst case rate allocation, assuming the temperature constraints are fully utilized, the new coordination problem is

$$\begin{aligned}
\mathscr{C} : \underset{\boldsymbol{Q}_1,\ldots,\boldsymbol{Q}_K}{\text{maximize}} \quad & \sum_{k\in\mathcal{K}} \log_2\left(1 + \frac{\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{Q}_k\boldsymbol{h}_{kk}}{\sigma^2 + \gamma_k}\right) \\
\text{subject to} \quad & \sum_{k\in\mathcal{K}_t} \mathrm{tr}\{\boldsymbol{Q}_k\} \leq P \ \forall\ t \in \mathcal{T}, \\
& \boldsymbol{Q}_k \succeq 0 \ \forall\ k \in \mathcal{K} \\
& \sum_{j\in\mathcal{K}\setminus k} \boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{Q}_j\boldsymbol{h}_{kj} \leq \gamma_k \ \forall\ k \in \mathcal{K},
\end{aligned}$$

which is a convex optimization problem and can be solved efficiently. In [13] interfering MISO point-to-point links are regarded and the interference temperatures constrain the amount of interference from an individual transmitter to a user. Adopting the same principle for multi-user scenario, we can constrain the interference users generate among each other. The interference power at user k from user j is constraint by

$$\boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{Q}_j\boldsymbol{h}_{kj} \leq \delta_{kj}.$$

Adding these constraints to Problem ($\mathscr{Q}$), the problem decouples into T individual problems per transmitter. The problem for transmitter t and its users $\mathcal{K}_t$ is:

$$\begin{aligned}
\mathscr{D} : \text{maximize} \quad & \sum_{k\in\mathcal{K}_t} \log_2\left(1 + \frac{\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{Q}_k\boldsymbol{h}_{kk}}{\sigma^2 + \sum_{j\in\mathcal{K}\setminus k}\delta_{kj}}\right) \\
\text{subject to} \quad & \sum_{k\in\mathcal{K}_t} \mathrm{tr}\{\boldsymbol{Q}_k\} \leq P, \\
& \boldsymbol{Q}_k \succeq 0 \ \forall\ k \in \mathcal{K}_t \\
& \boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{Q}_j\boldsymbol{h}_{kj} \leq \delta_{kj} \ \forall\ kj \in \mathcal{K} \times \mathcal{K}_t.
\end{aligned}$$

By adjusting the values of the interference temperatures both approaches have the potential to achieve the same objective as the original problem, as one can simply measure the interference powers of a solution to Problem $(\mathscr{Q})$ and set the temperatures to these values. Having observed the potential of the interference temperature approaches, the important question is on how to choose temperatures that achieve optimal or close to optimal performance with reasonable complexity. For the one user per transmitter case, it has been shown that all pareto optimal user rate points can be parametrized by interference temperatures and a distributed scheme, where transmitters update the temperatures pairwise, which guarantees to converge to a pareto efficient rate point is suggested, see [13] for details. The resulting rate configuration depends on the initialization, however a mechanism to steer the rate configuration to specific points, in order to maximize a utility of the user rates, is missing. We briefly discuss a method on how to find the optimal temperatures and compare it to the approach in [5]. By relating the actual interference temperature to the maximal possible interference power,

$$\hat{\gamma}_k = \sum_{j\in\mathcal{K}\setminus k} \boldsymbol{h}_{kj}^{\mathrm{H}} \boldsymbol{h}_{kj} P,$$

we are able to use normalized temperatures $\{\kappa_k\}^{k\in\mathcal{K}} \in [0,1]$ and restate Problem $(\mathscr{C})$ as

$$\begin{aligned}
\mathscr{K} : \underset{\boldsymbol{Q}_1,\ldots,\boldsymbol{Q}_K}{\text{maximize}} \quad & \sum_{k\in\mathcal{K}} \log_2\left(1+\frac{\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{Q}_k\boldsymbol{h}_{kk}}{\sigma^2+\hat{\gamma}_k\left(1-\bar{\kappa}_k\right)}\right)\\
\text{subject to} \quad & \sum_{k\in\mathcal{K}_t} \mathrm{tr}\{\boldsymbol{Q}_k\} \le P \;\forall\; t\in\mathcal{T},\\
& \boldsymbol{Q}_k \succeq 0 \;\forall\; k\in\mathcal{K}\\
& \sum_{j\in\mathcal{K}\setminus k} \boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{Q}_j\boldsymbol{h}_{kj} \le \hat{\gamma}_k\kappa_k \;\forall\; k\in\mathcal{K},
\end{aligned}$$

where $\bar{\kappa}_k = 1-\kappa_k$. The function $\mathscr{K}(\kappa_1,\ldots,\kappa_K,\bar{\kappa}_k,\ldots,\bar{\kappa}_K)$ computes the objective of Problem $(\mathscr{K})$ and is obviously non-decreasing in all its parameters. Therefore finding the optimal temperatures is expressed by the following monotone program

$$\begin{aligned}
\mathscr{M} : \underset{\substack{\kappa_1,\ldots,\kappa_K\\ \bar{\kappa}_k,\ldots,\bar{\kappa}_K}}{\text{maximize}} \quad & \mathscr{K}(\kappa_1,\ldots,\kappa_K,\bar{\kappa}_k,\ldots,\bar{\kappa}_K)\\
\text{subject to} \quad & \bar{\kappa}_k = 1-\kappa_k \;\forall\; k\in\mathcal{K}.
\end{aligned}$$

As the feasible set is a normal set we can employ the polyblock algorithm, as in [5]. The polyblock algorithm outer approximates the constraint set by polyblocks, whose vertices correspond to upper bounds on the utility. The algorithm needs a membership test for the feasible set, which is a costly optimization in [5] however is trivial for Problem $(\mathscr{M})$. Contrary, calculating the values of the vertices is cheap in [5] and requires to solve Problem $(\mathscr{K})$ for the temperature formulation. As in general for the polyblock algorithm, the number of vertices is much higher than the number of feasibility tests, one should alternatively consider a branch-and-bound method for the temperature formulation, as they require only two upper bounds per update, usually at the price of more iterations. However, both approaches have a non-polynomial worst-case complexity and are therefore not suitable for practical implementation and sub-optimal choices must be considered.

In [11] the authors refer use rule of thumb for choosing the global temperatures by setting all temperatures to the thermal noise power, a rule that did not perform well in the scenarios we regarded in Section VI. However, having a single scalar to adjust the amount of interference in the network is an appealing approach. By setting all temperatures to the same value γ and performing a search for the best value $\gamma \in [0, \max_{k\in\mathcal{K}}\{\hat{\gamma}_k\}]$ we achieved surprisingly good performance. The draw back however is that Problem $(\mathscr{C})$ has to solved for every value γ we check, which is costly and motivates to search for less complex methods.

IV. Zero-Forcing

Zero-forcing methods are especially attractive as they allow low complex solutions. An example can be found in [14], where the interference of an uncoordinated approach is first measured and the strategy of each transmitter is then updated such that the worst interference caused is zero-forced. Depending on the network regarded, complete cancellation of interference is not desired, as it drastically reduces the number of data streams transmitted. While the interference temperature approach inherently considers the gains of the cross channels, and therefore implements a spatial reuse, the zero-forcing based approaches will avoid interference to all other users regardless of the cross channel gain. In [15] higher layer decisions are used to apply a zero-forcing algorithm only to the cell-edge users, while the other users are served by an uncoordinated approach. Here, we follow a different approach and suggest that zero-forcing constraints are only established in part and therefore the number of active users can be increased. We will see that this partial zero-forcing can be interpreted as special choice of the interference temperatures, an observation which will guide us to efficient coordination algorithm in Section V. Corresponding to the definition of the normalized per user temperatures $\kappa_1,\ldots,\kappa_K$ in Section III, we define the normalized individual temperatures

$$\eta_{kj} = \frac{\delta_{kj}}{\hat{\delta}_{kj}}, \tag{1}$$

where $\hat{\delta}_{kj} = \boldsymbol{h}_{kj}^{\mathrm{H}}\boldsymbol{h}_{kj}P$ and $\bar{\eta}_{kj} = 1-\eta_{kj}$. Zero-forcing refers to a special binary selection of the normalized temperatures and has a simple solution for the transmission strategies. Clearly, for all users $k\in\mathcal{K}$ where $\sum_{j\in\mathcal{K}\setminus k}\bar{\eta}_{jk} \ge N$ are shut down and we can use binary temperatures to perform a user selection. The solution for the other users can be calculated as follows: $\mathcal{J}_k = \{j\in\mathcal{K} : \eta_{jk} = 0\}$ is the set of users that need to be zero-forced by user k. The stacked cross-channels to the interfering users are

$$\boldsymbol{H}_k = \left[\boldsymbol{h}_{k1},\ldots,\boldsymbol{h}_{k|\mathcal{J}_k|}\right].$$

The $N\times N$ identity matrix is denoted by $\boldsymbol{I}$ and by using the projection matrix

$$\boldsymbol{U}_k = \left(\boldsymbol{I} - \boldsymbol{H}_k\left(\boldsymbol{H}_k^{\mathrm{H}}\boldsymbol{H}_k\right)^{-1}\boldsymbol{H}_k^{\mathrm{H}}\right),$$

the solution for user k is expressed as

$$\boldsymbol{Q}_k = \boldsymbol{U}\boldsymbol{h}_{kk}\frac{P_k}{\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{U}\boldsymbol{h}_{kk}}\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{U}, \tag{2}$$

where P_k is the transmit power used for user k. The power allocation is found by waterfilling.

As soon as the normalized temperatures are fixed to binary values, computation of the transmission strategies is cheap. However an exhaustive search among all binary allocations is prohibitive and in Section V we therefore propose an efficient coordination algorithm avoiding an exhaustive search.

V. Successive User Allocation and Binary Temperatures

The cross-channel gains play an important role when deciding if to avoid interference by zero-forcing to some user or to allow interference and thereby implement spatial reuse. A simple attempt would be to set η_{kj} to zero in case $\hat{\hat{\delta}}_{kj}$ exceeds a certain threshold, to one otherwise. However, this attempt fails as the resulting binary temperatures rarely provide useful solutions as they miss an efficient user selection. Next, we present an efficient and low complexity algorithm based on a successive user allocation and binary temperatures.

Given a set of active users $\mathcal{D} = \{1, \ldots, D\}$ and binary temperatures $\{\eta_{kj}\}^{k\in\mathcal{D}, j\in\mathcal{D}}$, as defined in Equation (1), a worst case rate allocation for user d is

$$r_d = \log_2\left(1 + \frac{\boldsymbol{h}_{dd}^{\mathrm{H}}\boldsymbol{Q}_d\boldsymbol{h}_{dd}}{\sigma^2 + \sum\limits_{i\in\mathcal{D}\setminus d}\eta_{di}\hat{\hat{\delta}}_{di}}.\right), \tag{3}$$

As the constraints on the interference are either zero-forcing constraints or can be dropped, the transmit covariance matrices are chosen according to Equation (2). We now develop a scheme that selects the user set $\mathcal{D}$, aiming at the maximization of the sum-rate utility, where interference is controlled according to the choice of binary temperatures, meaning that

$$\boldsymbol{h}_{di}^{\mathrm{H}}\boldsymbol{Q}_i\boldsymbol{h}_{di} \leq \eta_{di}\hat{\hat{\delta}}_{di}\ \forall\ i \in \mathcal{D}\setminus d,$$

for all $d \in \mathcal{D}$. In each step the set of selected users served by transmitter t is $\mathcal{D}_t = \{k \in \mathcal{D} : f(k) = t\}$ and the user set

$$\mathcal{K}_+ = \left\{k \in \mathcal{K} : \sum_{j\in\mathcal{D}_t}\hat{\eta}_{kj} < N\ \forall\ t \in \mathcal{T}\right\}$$

are the users which can be added, such that the transmitters of the already active users can still fulfill all required zero-forcing constraints. Out of this set we select the user that promises the most gain in sum-rate

$$e = \underset{k\in\mathcal{K}_+}{\operatorname{argmax}} \quad \frac{\boldsymbol{h}_{kk}^{\mathrm{H}}\boldsymbol{U}_k^{(m)}\boldsymbol{h}_{kk}\frac{P}{1+|\mathcal{D}_{f(k)}|}}{\sigma^2 + \sum_{d\in\mathcal{D}}\eta_{kd}\hat{\hat{\delta}}_{kd}}.$$

Explanation: the factor $\frac{P}{1+|\mathcal{D}_{f(k)}|}$ accounts for the number of users that have to share a power budget of a transmitter. Additionally the projection matrices $\boldsymbol{U}_1^{(m)}, \ldots, \boldsymbol{U}_K^{(m)}$ account for the zero-forcing constraints to the already active users. The projector matrices are initialized by identity matrices and updated after each step of the stream allocation. Assuming the m-th stream is allocated to user e the projection matrices are updated as follows:

$$\boldsymbol{U}_K^{(m+1)} = \boldsymbol{U}_k^{(m)} - \hat{\eta}_{ek}\frac{\boldsymbol{U}_k^{(m)}\boldsymbol{h}_{ek}\boldsymbol{h}_{ek}^{\mathrm{H}}\boldsymbol{U}_k^{(m)}}{\boldsymbol{h}_{ek}^{\mathrm{H}}\boldsymbol{U}_k^{(m)}\boldsymbol{h}_{ek}}\ \forall\ k \in \mathcal{K}_+$$

When a new user is added, all users that are already in $\mathcal{D}$ have to update their transmission strategy in case they have a zero-forcing constraint on the new user. Further, the new user might cause interference to some users in $\mathcal{D}$ for which he is allowed to interfere with. Therefore before we add the user e to $\mathcal{D}$ we check if the user actually improves the sum-rate, otherwise he is dropped. The algorithm ends as soon as the set $\mathcal{K}_+$ is empty.

For a more consistent notation we formulated our new coordination algorithm in the covariance matrices, which have rank 1 due to the way they are selected. Therefore we directly do provide a beamforming solution, which has to be calculated by an iterative algorithm on the interference temperature solutions of Problem $(\mathscr{C})$ and Problem $(\mathscr{D})$.

VI. Simulation Results

For the numerical simulations, we regard a very simple model where the transmitters are placed on a line with a distance of 500m. The line is connected at the two ends such that the distance between the first and the last transmitter is again 500m. Each transmitter serves one user, that is located half way between the serving cell and the next transmitter. This means increasing the number of transmitters also increases the area covered by the network. We assume $N = 4$ antennas at each transmitter and the channels are drawn from a complex Gaussian distribution, where the attenuation due to distance is accounted by a pathloss factor of 3. As the scenario is completely symmetric, every users has the same channel statistics and when preforming Monte Carlo simulations we can plot over the average receive SNR, which is the same for every user. First we investigate a scenario with 4 transmitters. We compute a solution of Problem $(\mathscr{Q})$ and compare it to the temperature approach where we set all temperatures to the same value. We used an exhaustive search for the best common temperatures for each realization and SNR value. For fixed temperatures the resulting Problem $(\mathscr{C})$ is directly supported by SDPT3 [17], which we used to compute the solution. Additionally, we include an uncoordinated approach and a strict zero-forcing solution where all temperatures are zero and up to N active users; the best performing set is found by trying all combinations. For our low complexity coordination algorithm the binary temperatures ares selected by a simple threshold on the maximal interference power. Figure 1 shows the performance in terms of average spectral efficiency per user. The interference temperature approach performs close to optimal. The zero-forcing approach clearly does outperform the uncoordinated approach in the high SNR regime, while having a performance penalty in the low SNR regime. Our

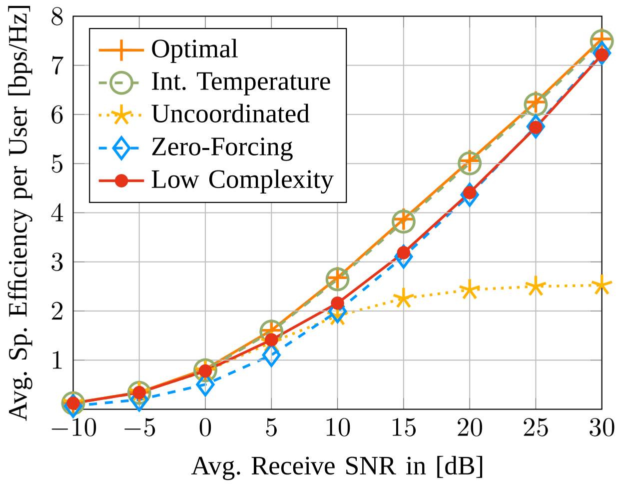

Fig. 1. Simulation Results – 4 Users

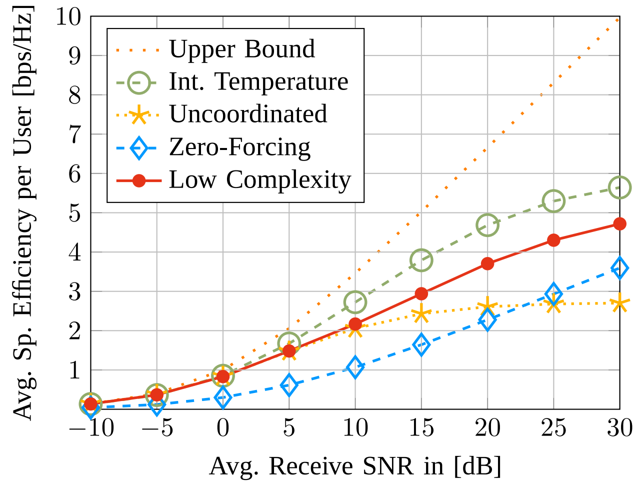

Fig. 2. Simulation Results – 10 Users

low complexity algorithm performs at least as good as the uncoordinated approach in the low SNR and matches the zero-forcing in the high SNR regions. The situation changes drastically when we investigate a scenario with ten users, where computing the optimum is intractable due to the high complexity of the monotone programming, so we include the interference free the single user rates as an upper bound. Regarding Figure 2, we can see that the zero-forcing approach is not competitive with the uncoordinated transmission, as it is to restrictive. The interference temperature approach provides the best performance however saturates as the single temperature approach does not allow to shut down some of the users and violate their temperature constraints, which would be beneficial in the high SNR. Our low complexity algorithm provides significant gains to the uncoordinated approach in the mid and high SNR regions, and the approach is no more limited by interference. Our algorithm performs within one bit to the temperature approach that has drastically higher complexity. We therefore consider our approach as a reasonable trade-off between performance and complexity, that might be suitable for practical implementation.

VII. Conclusions

Our main contribution is a low complexity algorithm for interference coordination in MISO interfering networks. It is based on a successive user selection and transmission strategies based on zero-forcing, which allow for efficient computation. Numerical simulations show significant gains compared to uncoordinated approach and reasonable performance compared to interference temperature approach that requires to run a sequence of costly iterative optimizations.

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