Weighted Sum Rate Maximization in the Underlay Cognitive MISO Interference Channel

Laurent Gallo*, Francesco Negro†, Irfan Ghauri‡, Dirk T.M. Slock†
*Politecnico di Torino, 24 Corso Duca degli Abruzzi, 10129 Torino, Italy
Email: laurent.gallo@studenti.polito.it
‡Intel Mobile Communications, GAIA, 2600 Route des Crêtes, 06560 Sophia Antipolis Cedex, France
Email: irfan.ghauri@intel.com
†Mobile Communications Department, EURECOM, 2229 Route des Crêtes, BP 193, 06904 Sophia Antipolis Cedex, France
Email: francesco.negro@eurecom.fr, dirk.slock@eurecom.fr

Abstract— **In this paper we address the problem of Weighted Sum Rate (WSR) maximization for a K-user Multiple-Input Single-Output (MISO) cognitive Interference Channel (IFC) with linear transmit beamforming (BF) vectors in an *underlay* cognitive radio setting. We consider a set of L single-antenna Primary receivers to which the cognitive system can causes a limited amount of interference. We thus propose an iterative algorithm to determine the BF vectors for the secondary transmission. The optimization of the Lagrange multipliers involved in the optimization problem is based on the subgradient method. The expression of the BF vector can be interpreted as dual Uplink (UL) MMSE receiver that takes into account the interference caused by a fictitious link between the primary user and secondary base station. Finally *Deterministic Annealing* is applied to make the convergence of the algorithm easier.**

I. Introduction

In the last decades wireless communications have experienced an outstanding success worldwide, consequently, devices that exploit the radio channel to communicate are always more widespread. Since the 1920s, national regulatory entities allocate spectrum portions to licensed users, with the purpose of preventing mutual interference. This rigid frequency allocation has not changed significantly since then, as a result, some licensed band are underutilized, while others, like the cellular telephony ones, are getting more and more crowded. Cognitive Radio (CR) is a set of techniques that is being developed in order to allow an opportunistic access to the radio spectrum and a smarter utilization of the transmission resources.

There are three CR paradigms: *Interweave*, *Overlay* and *Underlay* [1]. Interweave exploits the *white spaces* in time, frequency or space [2] of the concurrent transmissions; Overlay is a cooperative technique, in which the secondary transmitted signals are generated to improve the primary communication, requiring thus a shared knowledge of the codebooks and modulation schemes. The Underlay CR allows the coexistence of a Primary (usually licensed) network and a Secondary (cognitive) one, constraining the interference caused by secondary transmitters on primary receivers under a certain threshold: this is the paradigm we are focusing on in this paper.

Beamforming techniques for the WSR maximization have been studied in a non-cognitive scenario for the MISO interference channel (IFC) in [3], where a distributed algorithm is presented. In [4] the authors propose optimal solutions for beamforming design for weighted sum rate (WSR) maximization for the Multiple-Input Multiple-Output (MIMO) Broadcast channel (BC) and in [5] and [6] for the MIMO IFC. The underlay CR MIMO BC is then considered in [7], where a solution is derived in case of one single-antenna Primary Receiver.

In this paper we study the WSR maximization problem in an underlay CR scenario, where a secondary system is represented by a MISO IFC that coexists with a set of single antenna primary receivers. In addition the interference that each secondary users receives is treated as additional Gaussian noise contribution. The optimization problem is known to be non convex. To overcome this difficulty we propose an iterative algorithm based on alternating minimization where the BF vectors can be interpreted as virtual dual MMSE receiver filters. The Lagrange multipliers are updated at every step according to the subgradient method.

During the preparation of the camera ready version of this paper the authors came across [8] where a similar problem has been studied. In our paper a different approach has been used to determine the beamformers and in addition we introduce *Deterministic Annealing* to make the convergence easier.

II. Channel and Signal Model

We study a CR MISO IFC as in figure 1, with K pairs BS-receiver (Secondary Users - SUs) and an additional set of L single-antenna Primary Users (PUs). This setting is relevant in the case of a network of two or more cognitive femtocells base stations (BS), that represent the secondary system, where each femtocell BS is serving a single user in the time-frequency unit of interest. The femto cells are deployed in the same area of a macro cell and they want to coexist with L mobile users that belong to the macro cell. The k-th secondary base station BS_k is equipped with a N_k- antennas, onto which the information symbol s_k, drawn from a Gaussian distribution with zero mean and unit variance, is mapped by the BF vector $\mathbf{g}_k \in \mathbb{C}^{N_k \times 1}$, where $\|\mathbf{g}_k\|_2^2$ is equal to the transmission power. In real systems symbols are transmitted using more practical constellations. This causes a shaping loss, compare to the Gaussian signaling, for the useful signal part that determines an effect similar to a modest SNR offset in the sum rate curve. On the other hand the Gaussian interference is the

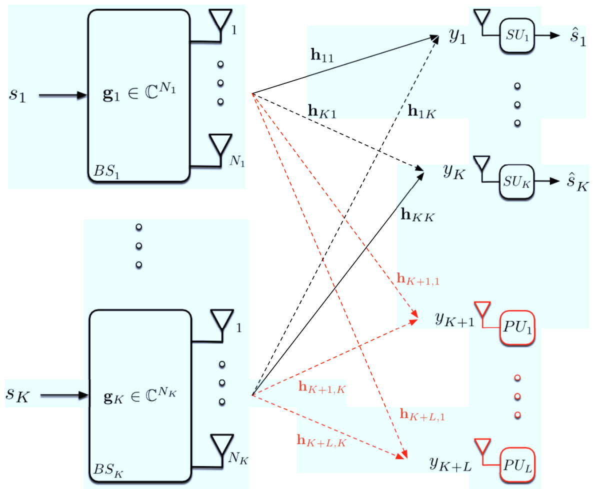

Fig. 1: System Model (dashed lines are interference links)

worst interference contribution for a given power. In addition this assumption matches with the assumption of treating the interference at each receiver as an additional Gaussian noise contribution. We denote with $\mathbf{h}_{jk} \in \mathbb{C}^{1\times N_k}$ the channel vector between BS$_k$ and SU$_j$ and, without loss of generality, with $\mathbf{h}_{K+l,k} \in \mathbb{C}^{1\times N_k}$ the channel vector between BS$_k$ and PU$_l$. In the latter case, a comma is inserted between the indexes to make the notation clearer. Channel entries are circular symmetric Gaussian distributed, according to the Rayleigh flat fading model. Moreover, we assume that all the secondary BSs have full CSIT about the channels of the secondary network. In addition for the BF design, as will be clear later on, they only need the knowledge of the cross channels that link the secondary BSs to the primary receiver. This information can be acquired without cooperation or additional overhead in TDD transmission strategies.

The scalar signal received by SU$_k$, indicated as y_k, is given by:

$$y_k = \underbrace{\mathbf{h}_{kk}\mathbf{g}_k s_k}_{\text{desired signal}} + \underbrace{\sum_{j\neq k}^{K} \mathbf{h}_{kj}\mathbf{g}_j s_j}_{\text{interference term}} + \underbrace{n_k}_{\text{noise term}} \tag{1}$$

where n_k is a temporarily white noise term, complex Gaussian distributed with zero mean and variance equal to σ_k^2.

Similarly, the signal received by PU$_l$, indicated with y_{K+l}, is given by the following expression:

$$y_{K+l} = \sum_{k=1}^{K} \mathbf{h}_{K+l,k}\mathbf{g}_k s_k \tag{2}$$

where all the power transmitted by the K base stations received by a primary receiver is accounted as interference.

III. Weighted Sum Rate Maximization

A. Problem statement

Our objective is to find the set of BF vectors $\{\mathbf{g}_i\}$ that maximizes the WSR of the Secondary Network (SN) imposing the following two sets of constraints. Each base station BS$_k$ has a limited maximum transmission power equal to $\mathcal{P}^{tx}_{max,k}$ and the total maximum interference power at each PU$_l$ from the SN BSs is constrained to be at maximum equal to $\mathcal{P}^{int}_{max,l}$. In mathematical terms:

$$\begin{aligned}
&\max_{\mathbf{g}_1,\dots,\mathbf{g}_K} \sum_{k=1}^{K} u_k \log_2\left(1+\frac{\mathbf{h}_{kk}\mathbf{g}_k\mathbf{g}_k^H\mathbf{h}_{kk}^H}{\sum_{j\neq k}^{K}\mathbf{h}_{kj}\mathbf{g}_j\mathbf{g}_j^H\mathbf{h}_{kj}^H+\sigma_k^2}\right)\\
&\quad \text{s.t:}\quad \mathbf{g}_k^H\mathbf{g}_k \le \mathcal{P}^{tx}_{max,k}; \quad \forall k\\
&\qquad \sum_{k=1}^{K}\mathbf{h}_{K+l,k}\mathbf{g}_k\mathbf{g}_k^H\mathbf{h}_{K+l,k}^H \le \mathcal{P}^{int}_{max,l}; \quad \forall l
\end{aligned} \tag{3}$$

where u_k is the weight factor associated to the rate of k-th secondary link.

Unfortunately, problem (3) is non-convex, so it is not possible to find the global maximum in a direct way by using the common convex optimization tools. By the way, we can study the KKT optimality conditions (for more details refer to [9]). The *Lagrangian* of the optimization problem is:

$$\begin{aligned}
\mathcal{L}(\mathbf{g}_k,\lambda_k,\mu_k) = &\sum_{k=1}^{K} u_k \log_2\left(1+\frac{\mathbf{h}_{kk}\mathbf{g}_k\mathbf{g}_k^H\mathbf{h}_{kk}^H}{\sum_{j\neq k}^{K}\mathbf{h}_{kj}\mathbf{g}_j\mathbf{g}_j^H\mathbf{h}_{kj}^H+\sigma_k^2}\right)\\
&-\sum_{k=1}^{K}\lambda_k\left(\frac{\mathbf{g}_k^H\mathbf{g}_k}{\mathcal{P}^{tx}_{max,k}}-1\right)\\
&-\sum_{l=1}^{L}\frac{\mu_l}{\mathcal{P}^{int}_{max,l}}\left(\sum_{k=1}^{K}\mathbf{h}_{K+l,k}\mathbf{g}_k\mathbf{g}_k^H\mathbf{h}_{K+l,k}^H-1\right)
\end{aligned} \tag{4}$$

where λ_k is the Lagrange multiplier associated to the k-th BS transmission power, and μ_l is the Lagrange multiplier of the l-th PU received interference.

To find the optimal BF vector $\mathbf{g}_k$ we compute the derivative of the Lagrangian (4) w.r.t. the k-th BF and equating it to zero. After some calculations we obtain

$$\begin{aligned}
\frac{\partial\mathcal{L}(\mathbf{g}_k,\lambda_k,\mu_l)}{\partial\mathbf{g}_k^*} = &\, u_k\frac{f_k^*\mathbf{h}_{kk}^H}{\log_e 2} - \sum_{j\neq k}^{K} u_j\frac{f_j w_j f_j^*\mathbf{h}_{jk}^H\mathbf{h}_{jk}\mathbf{g}_k}{\log_e 2}\\
&-\frac{\lambda_k\mathbf{g}_k}{\mathcal{P}^{tx}_{max,k}}-\sum_{l=1}^{L}\frac{\mu_l}{\mathcal{P}^{int}_{max,l}}\mathbf{h}_{K+l,k}^H\mathbf{h}_{K+l,k}\mathbf{g}_k=\mathbf{0}_{N_k}
\end{aligned} \tag{5}$$

where the following quantities are defined as:

$$f_k = e_k d_k^{-1}\mathbf{g}_k^H\mathbf{h}_{kk}^H; \tag{6}$$

$$e_k = \left(1+\mathbf{h}_{kk}\mathbf{g}_k\mathbf{g}_k^H\mathbf{h}_{kk}^H d_k^{-1}\right)^{-1}; \tag{7}$$

$$w_k = e_k^{-1}; \tag{8}$$

$$d_k = \textstyle\sum_{j\neq k}^{K}\mathbf{h}_{kj}\mathbf{g}_j\mathbf{g}_j^H\mathbf{h}_{kj}^H+\sigma_k^2. \tag{9}$$

Looking at the the definitions (6)-(9) it is possible to observe how every single term of (5) depends on the optimization variables $\mathbf{g}_k \forall k$. Hence it is not possible to find an explicit solution for $\mathbf{g}_k$ directly using that formula. To solve the given optimization problem, as will be explained in the next section, we use alternating minimization. We consider all the scalar quantities in (6)-(9) to be fixed when we optimize w.r.t. the BF vector $\mathbf{g}_k$, with this assumption it is possible to solve

(5) w.r.t the BF vector obtaining expression (10). We can observe that the scalar f_k in (6) has an expression of a scalar MMSE receiver that is applied at the k-th SU receiver while (7) represents the minimum mean squared error of the Rx signal at the k-th SU Rx after the MMSE receiver.

B. Iterative Algorithm

To obtain the solution of the optimization problem (3) we propose an iterative algorithm based on alternating optimization. In this optimization framework the complete set of optimization variables is split in two or more sets. In the optimization procedure a set of variables is determined assuming fixed the others. In our optimization procedure we consider the values of $\mathbf{g}_k$ which are explicit in (5) to be those at *current step*, while the values of $\{\mathbf{g}_i\}$ within the definitions of w_k and $f_k \forall k$ are assumed to be those at the *previous iteration* step.

The strategy we propose to update the Lagrange multipliers λ_k and μ_l is based on *subgradient method*, as described in [10] and [11]:

$$\lambda_k^{(n+1)} = \left[\lambda_k^{(n)} + t_{\lambda,k}\left(\|\mathbf{g}_k^{(n+1)}\|_2^2 - \mathcal{P}_{max,k}^{tx}\right)\right]^+ \quad (13)$$

$$\mu_l^{(n+1)} = \left[\mu_l^{(n)} + t_{\mu,l}\left(\textstyle\sum_k |\mathbf{h}_{K+l,k}\mathbf{g}_k^{(n+1)}|^2 - \mathcal{P}_{max,l}^{int}\right)\right]^+ \quad (14)$$

where the notation $[\cdot]^+$ denotes $\max\{\cdot, 0\}$. The parameters $t_{\lambda,k}$ and $t_{\mu,l}$ are the subgradients' *stepsizes*, whose values are to be chosen: the convergence of the algorithm is ensured as long as they are set sufficiently small [11].

The final algorithm proposed for WSR maximization is summarized in Table **Algorithm 1**.

Algorithm 1 CR-MWSR

Initialize $\mathbf{g}_k^{(0)}$, $\lambda_k^{(0)}$, $t_{\lambda,k}^{(0)}$ $\quad \forall k \in 1,\ldots,K$
$\mu_l^{(0)}$, $t_{\mu,l}^{(0)}$ $\quad \forall l \in 1,\ldots,L$
$n = 0$
repeat
  $n \leftarrow n+1$
  compute the BF vectors $\mathbf{g}_k^{(n)} \forall k \in 1,\ldots,K$ as in (11)
  update $\lambda_k^{(n)} \forall k \in 1,\ldots,K$ as in (13)
  update $\mu_l^{(n)} \forall l \in 1,\ldots,L$ as in (14)
until convergence

Please note that no specific initial values are suggested for any of the optimization parameters, as there is not a binding rule: the initial BF vectors, could be drawn randomly with norm equal to $\sqrt{\mathcal{P}_{max,k}^{tx}}$. The stepsizes values must be chosen possibly small, as a compromise between ensuring convergence and reducing the time needed to converge: a larger value will require less iterations, but may lead to oscillating behaviors. To best of our knowledge, there is no rule to decide a proper value for $t_{\lambda,k}$ and $t_{\mu,l}$: moreover, these values appear depending on the noise powers and maximum interference constraints, so choosing a proper set of initializers might be a difficult task.

C. Duality in the MISO CR channel

From the optimal expression of the BF vector in (10) we can see that it has an MMSE like expression and, in addition, it can be interpreted as receiver filter of a virtual dual uplink (UL) Single-Input Multi-Output (SIMO) cognitive IFC where the DL and UL channel are the reciprocal of each other. In this dual system the scalar Rx filter f_k terms act like virtual scalar complex precoding filters. The first sum, in the squared brackets in (10) can be seen as the *virtual dual SU cross-talk term*, that accounts for the interference caused by SU_j to secondary BS_k, with $j \neq k$. The second sum can be interpreted as the *virtual dual PU interference*, *i.e.* it depends on the amount of interference power received by the secondary BS_k generated from a virtual PU transmission. The Lagrange multiplier associated to the interference power constraint plays the role of the virtual power transmitted by the PU. Finally the Lagrange multiplier associated to the per-user power constraint represents the *virtual dual noise*. The value of the virtual PU transmitted power and dual noise should be optimized. For further considerations on duality for IFC in CR setting refer to [12].

IV. Convergence analysis and Deterministic Annealing

A. Observations on convergence

The subgradient method is commonly considered an attractive technique in optimization thanks to the low computational effort required for a single step. However, to achieve convergence, relatively small values of the stepsizes must be chosen furthermore, to solve our objective problem this technique is jointly applied to a set of $K+L$ Lagrange multipliers, for these reasons the number of iterations required to get to convergence is large, even for small values of K and L. The beamforming design is based on WSR maximization, this cost function defines a very non convex optimization problem. This means that the optimality conditions (5), that we used to derive the optimal expression of the BF, can represent only a local extrema. Hence convergence to global optimum can not be shown. In addition converging to a local optimum in High SNR regime seems to be more probable than the Low SNR.

B. Deterministic Annealing

To overcome the convergence difficulties in non-convex optimization problem several heuristic approaches have been proposed. Among them we have *Simulated Annealing* (SA) [13]. This method takes its name from the physical annealing process in which a system is first "melted" and then slowly cooled down in order to allow the atoms in the system to find a state with lower energy until the system is "frozen" in a globally optimum state. In our objective problem, the role of temperature is played by the *noise power* σ_k^2, which starting from now we assume, without losing generality, equal to $\sigma^2 \forall k$. Starting from the same principle of SA *Deterministic Annealing* (DA) has been proposed (refer to [6] for the application of DA to MIMO IFC). The main difference between the two methods is that in DA does not involve any randomness. The

$$\mathbf{g}_k = \left[\sum_{j \neq k}^{K} u_j \frac{f_j w_j f_j^{\,*}}{\log_e 2} \mathbf{h}_{jk}^H \mathbf{h}_{jk} + \sum_{l=1}^{L} \frac{\mu_l}{\mathcal{P}_{max,l}^{int}} \mathbf{h}_{K+l,k}^H \mathbf{h}_{K+l,k} + \frac{\lambda_k}{\mathcal{P}_{max,k}^{tx}} \mathbf{I} \right]^{-1} \frac{\mathbf{h}_{kk}^H f_k^{\,*}}{\log_e 2} u_k \tag{10}$$

basic principle behind these techniques is that the optimum of the problem in the next value of temperature is in the region of attraction of the solution of the problem in the previous temperature.

The convexity properties of the optimization problem make the convergence to the optimum BF values more probable and in high temperature case (Low SNR), *i.e.* with larger values of σ^2. To increase even more the probability of converging to the global optimum, it is possible to initialize the algorithm in **Algorithm 1** with different random BF vectors $\mathbf{g}_k^{(0)}$ and finally select the one that ensures the best WSR in low SNR. Once the optimal BF vector has been found reduce the noise power σ^2 by a relatively small quantity $\Delta\sigma^2$ and run again **Algorithm 1** using as initial BF vectors the optimal ones found at the previous SNR point. Iterating this process until the desired noise power level is reached, it is possible to reliably approach the optimal BF values in high-SNR.

If we denote with the superscript $(\cdot)^{opt,\sigma^2}$ the optimum value obtained after performing **Algorithm 1** with noise power equal to σ^2, the resulting algorithm is as in **Algorithm 2**.

Algorithm 2 Deterministic Annealing

Initialize σ^2
for $n = 1$ to N **do**
  Initialize $\mathbf{g}_k^{(0)}$ randomly, with $\|\mathbf{g}_k^{(0)}\|_2^2 = \mathcal{P}_{max,k}^{tx}$
  Perform Algorithm 1 $\rightarrow$ obtain $\mathbf{g}_k^{opt,\sigma^2} \forall k$
  $n \leftarrow n + 1$
end for
Choose the new set of $\mathbf{g}_k^{(0)}$ as the set of BF vectors that brings to the maximum WSR, among the previously obtained $\mathbf{g}_k^{opt,\sigma^2}$
repeat
  $\sigma^2 \leftarrow \sigma^2 - \Delta\sigma^2$
  Perform Algorithm 1 $\rightarrow$ obtain $\mathbf{g}_k^{opt,\sigma^2} \forall k$
  $\mathbf{g}_k^{(0)} \leftarrow \mathbf{g}_k^{opt,\sigma^2}$
  Decrease the values of $t_{\lambda,k} \forall k$ and $t_{\mu,l} \forall l$
until σ^2 is the desired noise power value

V. Simulation Results

In this section we show the average performances achieved by the proposed algorithm, via Montecarlo simulations. All the results shown in this section have been obtained imposing $u_k = 1 \forall k$, *i.e.* Sum Rate (SR) Maximization.

A. Sum Rate Performances varying $\mathcal{P}_{max,l}^{int}$

We compare the SR achieved by the presented algorithm, in a CR MISO IFC, with the maximum SR that can be obtained by the same channel, described in section II, *excluding the PUs* (traditional MISO IFC). Unfortunately, the capacity region of a general IFC is still an open problem: the only case in which it is possible to analytically find the maximum SR is in fact the $K = 2$ users MISO IFC. In this scenario, we know by the theory in [14] and references therein that the maximum SR point belongs to the *Pareto Boundary* and can be obtained using BF vectors computed as a weighted sum of a matched transmission filter and a zero forcing BF. We will then refer to this specific maximum SR as *MISO IFC SR*.

In figure 2 is plotted the average ratio between the MISO IFC SR and the SR obtained with the proposed algorithm, in table **Algorithm 1** in the CR setting, expressed in percentage, for different values of the maximum interference power constraint $\mathcal{P}_{max,1}^{int}$. The simulation parameters are the following: $K = 2$, $L = 1$ PU, $N_k = 2$ antennas per BS $\forall k$, $\sigma^2 = -10$ dB$_W$, $\mathcal{P}_{max,k}^{tx} = 0$ dB$_W \forall k$, $t_{\lambda,k} = 5 \cdot 10^{-4} \forall k$ and $t_{\lambda,l} = 5 \cdot 10^{-4} \forall l$ kept fixed all along the iterations. 125 Montecarlo repetition were performed, each time drawing the channel signatures' entries from a complex Gaussian distribution. For each Montecarlo repetition, **Algorithm 1** has

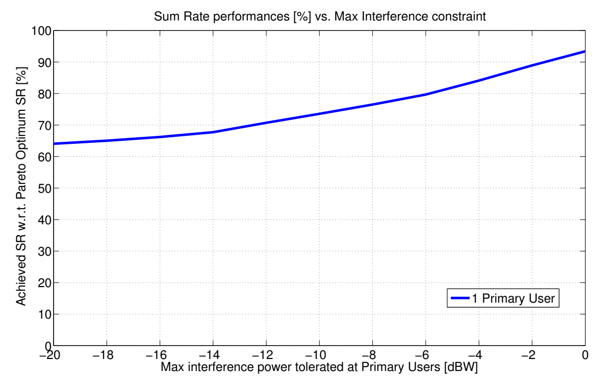

Fig. 2: Sum Rate Performances varying $\mathcal{P}_{max,l}^{int}$

been initialized with different random BF vectors, then only the one that provides the best result in terms on SR has been chosen.

In the case of $N_k = 2$ antennas for every BS, figure 2, the SR value is shown tending to a fixed value as long as the value of the maximum interference power tolerated at the PU decreases. For very weak interference power constraint to the PU the SR obtained for the CR system seems to approach the SR of a traditional MISO IFC. For stronger interference power constraint , on the other hand, the algorithm tends to maximize the rate of only one of the two links, shutting down the other one.

B. Sum Rate Performances varying σ^2

We consider now a scenario in which the interference power constraint, $\mathcal{P}_{max,l}^{int}$, is fixed, and we study the behavior of the proposed algorithm in table **Algorithm 2** for decreasing values of σ^2. In figure 3, we compare the SR obtained using our algorithm for the sum-rate maximization in a CR setting against the performance of an equivalent traditional MISO interference channel. In particular we consider a CR MISO IFC with $N_k = 3$ transmitting antennas at each BS and we impose two different interference power constraints to the PU: $\mathcal{P}^{int}_{max,l} = -10$ dB$_W$ and $\mathcal{P}^{int}_{max,l} = -20$ dB$_W$. The noise power, σ^2, ranges from 5 dB$_W$ to -30 dB$_W$, with $\Delta\sigma^2 = 2$ dB$_W$. As we can see imposing a stronger interference power constraint determines a reduction in term of SR. In high SNR the SR obtained with our algorithm has a loss in term of slope in comparison to the traditional MISO IFC without interference constraint. This is due to the fact that for some channel realizations the algorithm converges to a solution in which only one user transmits switching off the remaining user. This has an effect on the average SR curve determining the loss in slope. The reason of this behaviour is related to the non convexity of the cost function, weighted sun rate, so for some channel realizations the proposed algorithm converges to a local optimum where only one user is transmitting. In addition in DA the solution at a given temperature value is used as initialization of the following noise power level. This implies that if the optimal solution in one SNR point requires only one user transmitting then this solution is used as initialization for the following SNR point. This can be a bad initialization for that SNR because probably a second transmitter must be activated . The algorithm proposed here should be modified to account that possibility similarly to what has been proposed in [6] for a multistream MIMO IFC.

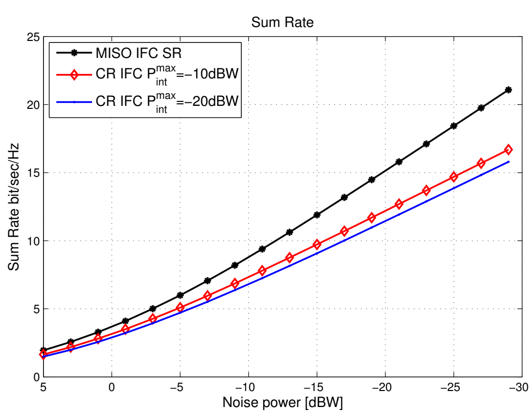

Fig. 3: SR Performances varying σ^2

VI. Conclusion

In this paper we addressed the problem of WSR maximization for a K-users MISO IFC in presence of L Underlay CR PUs. We showed that the KKT conditions of our optimization problem cannot be solved via direct analytical computation and thus we proposed an iterative algorithm for the BF optimization. The optimal expression of the BF vector is similar to MMSE BF vectors and subgradient method is used to update the values of the Lagrange multipliers involved in the optimization problem. In addition the optimization problem is studied as a dual UL problem where the BF vector can be interpreted as MMSE receiver. The Lagrange multipliers associated to the interference constraint play the role of virtual Tx power in a fictitious link between the PU and the secondary BS. At the same time the Lagrange multipliers associated to the per-user power constraints represent the dual noise powers that still need to be optimized. Finally Deterministic Annealing is applied to ease the convergence of the proposed iterative algorithm.

VII. Acknowledgment

EURECOM's research is partially supported by its industrial members: BMW Group, Swisscom, Cisco, ORANGE, SFR, ST Ericsson, Thales, Symantec, SAP, Monaco Telecom. The research of EURECOM and Intel Mobile Communications France is also supported in part by the EU FP7 projects CROWN, SACRA and WHERE2.

References

[1] A. Goldsmith, S. Jafar, I. Maric, and S. Srinivasa, "Breaking Spectrum Gridlock With Cognitive Radios: An Information Theoretic Perspective," *Proceedings of the IEEE*, vol. 97, no. 5, pp. 894 –914, May 2009.
[2] F. Negro, I. Ghauri, and D. T. M. Slock, "Transmission techniques and channel estimation for spatial interweave tdd cognitive radio systems," in *Proceedings of the 43rd Asilomar conference on Signals, systems and computers*, ser. Asilomar'09, 2009, pp. 523–527.
[3] S.-H. Park, H. Park, and I. Lee, "Distributed Beamforming Techniques for Weighted Sum-Rate Maximization in MISO Interference Channels," *Communications Letters, IEEE*, vol. 14, no. 12, pp. 1131–1133, December 2010.
[4] S. Christensen, R. Agarwal, E. Carvalho, and J. Cioffi, "Weighted Sum-Rate Maximization Using Weighted MMSE for MIMO-BC Beamforming Design," *Wireless Communications, IEEE Transactions on*, vol. 7, no. 12, pp. 4792–4799, December 2008.
[5] F. Negro, S. P. Shenoy, I. Ghauri, and D. T. M. Slock, "On the MIMO Interference Channel," in *ITA 2010, IEEE Information Theory and Applications Workshop, San Diego, January 31-February 5, 2010*, 01 2010.
[6] F. Negro, I. Ghauri, and D. T. M. Slock, "Deterministic Annealing Design and Analysis of the Noisy MIMO Interference Channel," in *ITA 2011, IEEE Information Theory and Applications Workshop, San Diego, February 6-February 11, 2011*, 2011.
[7] L. Zhang, Y. Xin, and Y.-C. Liang, "Weighted Sum Rate Optimization for Cognitive Radio MIMO Broadcast Channels," in *Communications, 2008. ICC '08. IEEE International Conference on*, May 2008, pp. 3679–3683.
[8] F. Wang and W. Wang, "Sum rate optimization in interference channel of cognitive radio network," in *Communications (ICC), 2010 IEEE International Conference on*, may 2010, pp. 1 –5.
[9] S. P. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.
[10] E. Mijangos, "Approximate Subgradient Methods for Lagrangian Relaxation on Networks," in *System Modeling and Optimization*, vol. 312. IFIP International Federation for Information Processing, 2007, pp. 370–381.
[11] S. Boyd and A. Mutapcic, "Subgradient Methods," April 2008. [Online]. Available: http://www.stanford.edu/class/ee364b/lectures/subgrad_method_notes.pdf
[12] F. Negro, I. Ghauri, and D. T. M. Slock, "Beamforming for the underlay MISO interference channel via UL-DL duality," in *Cognitive Radio Oriented Wireless Network Communications (CROWNCOM), 2010 Proceedings of the Fifth International Conference on*, June 2010.
[13] S. Kirkpatrick, C. D. Jr. Gelatt, and M. P. Vecchi, "Optimization by Simulated Annealing," *Science*, vol. 13, pp. 671–680, May 1983.
[14] E. A. Jorswieck, E. G. Larsson, and D. Danev, "Complete Characterization of the Pareto Boundary for the MISO Interference Channel," *IEEE Transaction on Signal Processing*, vol. 56, no. 10-2, pp. 5292–5296, 2008.