Channel Capacity Maximization in Multiuser Large Scale MIMO-Based Cognitive Networks

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Abstract—This paper proposes an adaptive multiuser Multiple Input Multiple Output-Space Division Multiplexing Access (MU-MIMO-SDMA) technique for uplink access in broadband wireless cognitive networks with multiple primary users (PUs) and secondary users (SUs) sharing the same spectrum. The proposed algorithm uses gradient search of the channel capacity to seek, iteratively, the optimal transmit weight vectors that maximize the MIMO channel capacity for each cognitive user, while controlling the interference levels to the PUs. Simulation results show that the symbol error rate (SER) performance and the capacity of cognitive MIMO systems using the proposed adaptive MIMO-SDMA algorithm is substantially higher than the one based on conventional approaches such as eigen-beamforming. The paper also investigates the performance of large scale MIMO-SDMA system and shows that as the number of base station antennas becomes larger, the constraints imposed by the primary network could be relaxed and the performance of SUs are improved without harming the PUs performance.

Index Terms—Cognitive radio, adaptive beamforming, MIMO-SDMA, channel capacity, large scale MIMO.

I. INTRODUCTION

Multi-user Multiple Input Multiple Output (MIMO)-Space Division Multiplexing Access (SDMA) has attracted significant interests among researchers and developers of new generation wireless systems because of its potentials of achieving high spectral efficiency, by multiplexing multiple users on the same time-frequency resources [1-3]. On the other hand, we are observing recently a huge interest in cognitive radio networks (CRNs) from both the research and policy/regulation communities [4-10]. These CRNs can intelligently share spectrum and extract more bandwidth via “opportunistic use” of shared spectrum resources. They will be the essential technology needed to make significantly better use of available spectrum, and to address the real issue with the fixed assigned spectrum. However, for CRs to discover under-utilized spectrum and adapt its transmission settings accordingly without causing interference to licensed users its physical layer needs to be highly flexible and adaptable. Among many possible technologies, MIMO-SDMA has been widely recognized as a versatile multiple access scheme for cognitive radios that may increase the CR network capacity. MIMO-SDMA techniques has been successfully deployed in 3G/4G cellular systems based on traditional static spectrum access approach and a vast number of multi-user detection algorithms, such as maximum ratio combining (MRC) and minimum mean-squared error (MMSE), are presently being tailored towards solving the SDMA processing in MIMO cognitive networks [6-10], where additional constraints to protect PUs’ QoS are imposed. Within this context, we are developing a new MIMO-SDMA technique for dynamic communications environments such as cognitive radios. More specifically, we propose a new adaptive beamforming algorithm that targets the maximization of the channel capacity for each SU, while controlling the interference levels to the PUs, and thus enhance the overall system capacity. Due to the nonconvexity of the constrained channel capacity, solving the channel capacity maximization problem is a challenging task. To efficiently deal with this problem, we propose using the steepest ascent gradient of the MIMO-SDMA channel capacity to iteratively seek the transmitting weight [11]. It is shown that
the capacity of the MIMO-SDMA system whose transmitting weights have been computed using the proposed algorithm is significantly higher than that of conventional systems such as constrained eigen-beamforming (CEigBF). Moreover, this paper also consider the deployment of a large number of base station (BS) antennas in comparison to the served users’ antennas in order to relax the power and interference constraints imposed on SUs without affecting the performance of PUs. This concept was initially investigated for cellular networks [12-14], and there is a clear potential in the area of cognitive radio where interference between PN and SN is even more problematic. With this large number of antennas, the central limit theorem and the law of large numbers can be applied and close to optimal performances can be achieved with the simplest forms of user detection and beamforming, i.e., MRC, and eigenbeamforming (EigBF). Using simulation, the symbol error rate (SER) performance and system capacity of PUs and SUs are evaluated as a function of the interference power constraints imposed to SUs and the number of antennas used at the base stations, when both constrained and conventional MIMO-MRC are used.

II. SYSTEM MODEL

We consider the uplink scenario shown in Fig. 1 where \( L_s \) secondary users (SUs) and one secondary base station (SBS) coexist with \( L_p \) primary users (PUs) and one primary base station (PBS) via concurrent spectrum access. In both networks, the users and the base stations are equipped with multiple antennas. Let \( \mathbf{x^s} = \{ x_1^s, x_2^s, \ldots, x_{L_s}^s \} \) denote the set of \( L_s \) SUs signals and \( \mathbf{x^p} = \{ x_1^p, x_2^p, \ldots, x_{L_p}^p \} \) the set of \( L_p \) PUs signals, where \( x_i^s \) and \( x_i^p \) are complex-valued random variables with unit power, i.e.,

\[
E[\|x_i^s\|^2] = E[\|x_i^p\|^2] = 1
\]

The expression for the array output of the SBS in Fig. 1 can be written as

\[
\mathbf{y}_{SBS} = \sum_{i=1}^{L_s} \mathbf{H}_{sp,i} \mathbf{w}_i^s \mathbf{x}_i^s + \mathbf{n} + \mathbf{I}_{PU} \tag{1}
\]

where \( \mathbf{y}_{SBS} = [y_1^s, y_2^s, \ldots, y_{N_s}^s]^T \) is the \( N_S \times 1 \) containing the outputs of the primary base station’s element array to the SBS’s channel fading matrix from secondary user \( i \)'s \( N_S \) element antenna array to the SBS’s element antenna array. \( \mathbf{w}_i^s = [w_{i1}^s, w_{i2}^s, \ldots, w_{iN_S}^s]^T \) is the complex transmit weight vector at the transmitter for SU \( i \), \( i = 1, \ldots, s \). \( \mathbf{n} = [n_1, n_2, \ldots, n_{N_S}]^T \) is the \( N_S \times 1 \) complex additive white Gaussian noise (AWGN) vector, and \( \mathbf{I}_{PU} \) represents the interference introduced by PUs at the SBS and is given by

\[
\mathbf{I}_{PU} = \sum_{p=1}^{L_p} \mathbf{H}_{ps,p} \mathbf{w}_p^s \mathbf{x}_p^s \tag{2}
\]

where \( \mathbf{H}_{ps} \) is the \( N_S \times N_P^p \) channel matrix representing the fading coefficients from PUs to

![System Model: Primary and secondary networks](image-url)
the SBS’s $N_F^s$-element antenna array. On the other hand, the interference seen by the primary base station due to secondary transmission is given by

$$y_{s,l}^p = \sum_{i=1}^{L_s} H_{s,p,l} w_i^s x_i^l$$

(3)

and its corresponding power level can be expressed as

$$J_{s,l} = \sum_{i=1}^{L_s} H_{s,p,l} w_i^s w_i^s H_{s,p,l}$$

(4)

where $^H$ denotes the hermitian transpose and $H_{s,p}$ is the $N_F^s \times N_F^p$ channel matrix representing the fading coefficients from SUs to the PBS’s $N_F^p$-element antenna array.

In the case of a wide-band, frequency-selective channel, one may conceptually decompose the channel into parallel independent narrow-band channels (flat-fading channel), each of which is described in the manner of (1). Indeed, Orthogonal Frequency-Division Multiplexing (OFDM) rigorously performs this decomposition. Notice that SDMA is subcarrier parallel and that the update is done separately on each subcarrier. For brevity therefore, we concentrate on the per subcarrier analysis.

Assuming the well-known Kronecker correlation structure [15-17], $H_{ss,l_s}$, $H_{sp,l_s}$, $H_{ps,l_p}$, and $H_{pp,l_p}$ can be modeled as

$$H_{ss,l_s} = R_{rs}^{1/2} H_{ss,l_s}^\omega R_{ts}^{1/2},$$

$$H_{sp,l_s} = R_{rs}^{1/2} H_{sp,l_s}^\omega R_{ts},$$

$$H_{ps,l_p} = R_{rs}^{1/2} H_{ps,l_p}^\omega R_{tp}^{1/2},$$

$$H_{pp,l_p} = R_{rs}^{1/2} H_{pp,l_p}^\omega R_{tp}^{1/2},$$

respectively,

where $R_{rs} \in \mathbb{C}^{N_F^s \times N_F^s}$, $R_{rs} \in \mathbb{C}^{N_F^p \times N_F^p}$,

$$R_{ts} \in \mathbb{C}^{N_F^s \times N_F^s},$$

and $R_{tp} \in \mathbb{C}^{N_F^p \times N_F^p}$ are positive definite Hermitian matrices specifying the receive and transmit fading correlations.

$H_{ss,l_s} \in \mathbb{C}^{N_F^s \times N_F^s}$, $H_{sp,l_s} \in \mathbb{C}^{N_F^s \times N_F^p}$,

$H_{ps,l_p} \in \mathbb{C}^{N_F^p \times N_F^s}$, and $H_{pp,l_p} \in \mathbb{C}^{N_F^p \times N_F^p}$ consist of iid (independent and identically distributed) complex Gaussian entries, with zero mean and unit variance. In fact when using, precoding methods such as eigen-beamforming, zero-forcing, minimum mean-square error or capacity-aware as proposed in this paper, the convergence to the i.i.d. channel performance is faster as the number of base station antennas is increased. In this paper we assume that the mobile transmit antennas and the base station antennas have sufficient inter-element spacing such that spatial de-correlation between simultaneously transmitted data streams on different transmit channels is feasible. For mobile devices, MIMO-beamforming can usually be accommodated for frequency bands higher than 2.5 GHz. However a new approach is needed to support multiple antennas in the lower frequency ranges due to the highly correlated channels. The transfer functions from the $l_s$th SU device to the SBS large scale antenna array (the cascade of $H_{ss,l_s}$ and $w_i^s$), result in a unique spatial signature for each SU, which can be exploited to effect the separation of the user data at the BS using appropriate multiuser detection techniques. The SBS detects all $L_s$ SUs simultaneously at the multiuser detection module of the SDMA system, by multiplying the output of the array with $w_i^s = [w_{i1}^s, w_{i2}^s, \ldots, w_{iN_F^p}^s]^T$, the receiving weight vectors for each SU $l_s$, $l_s = 1, \ldots, L_s$. The detection of secondary user $l_s$ out of $L = L_s + L_p$ users (with $L-1$ interfering users) can thus be depicted as

$$\hat{x}_{l_s} = w_i^H y_{SBS} = S_d + S_{l_s} + S_{p} + N$$

(5)

where $N = w_i^H n$ is the noise signal at the array output of the SBS, $S_d$ is the desired signal for the detection of user $l_s$’s signal, $S_{l_s}$ is the multiple-access interference (MAI) contributed by the $L_s-1$ other SUs and $S_{p}$ is the MAI from $L_p$ PUs. $S_d$, $l_s$, and $S_{p}$ are given by

$$S_d = w_i^H H_{s,i} w_i^s x_i^l$$

(6)

and

$$S_{l_s} = w_i^H \sum_{i=1, i\neq l_s}^{L_s} H_{s,i} w_i^s x_i^l$$

(7)
In mathematical terms, is the signal \( S \), subject to
\[
\max_{\lambda_i} \quad \frac{1}{N_i} B_i^T \mathbf{H}_{n_i} w_i^t \cdot^T \left( \sum_{n_i=1}^{I_i} \bar{H}_{n_i}^T \mathbf{x}_n \right)
\]

where
\[
\bar{H}_{ss,i}^t = H_{ss,i} w_i^t \quad \text{and} \quad \bar{H}_{ps,l_p}^t = H_{ps,l_p} w_i^t
\]

During the analysis and simulation, perfect channel estimation is assumed. This assumption is justified by the fact that when the number of antennas grows towards infinity, effects of noise, interference and imperfect channel state information (CSI) disappear [12-14]. However, when pilot-based CSI is used with time-division duplex (TDD) MIMO systems, pilot contamination (PC) remains a limiting factor [18-20]. PC is a well-known problem in pilot-aided channel estimation (PACE) and it happens when other users in the system are reusing the same set of pilot signals due to the limitation imposed by the number of available orthogonal pilots. This PC problem is accentuated even more with massive MIMO since it causes the interference rejection performance to quickly saturate with the number of antennas. Within the context of cognitive radio, if there is no cooperation between the SN and the PN, it is likely that the pilots used in both networks do not satisfy orthogonality, which may lead to pilot contamination. Another alternative to PACE is to use blind channel estimation (BCE) techniques that require no or a minimal number of pilot symbols. One particular class of BCE methods that works well with massive MIMO is the one based on subspace estimation techniques [21-23] that estimate the channel from the eigenvector of the covariance matrix of the received signal. This class requires unused degrees of freedom, which is the case of massive MIMO where the number of users is much less than the number of antennas at the base station.

III. CHANNEL CAPACITY MAXIMIZATION

Based on the system model described in Section II, the Ergodic channel capacity of the secondary network is given by [18-20]

\[
C = E \left\{ \log_2 \left[ 1 + \frac{1}{N_i} B_i^T \mathbf{H}_{n_i} w_i^t \cdot^T \left( \sum_{n_i=1}^{I_i} \bar{H}_{n_i}^T \mathbf{x}_n \right) \right] \right\}
\]

Our objective is to find the optimal beamforming vector, \( \mathbf{w}_i^t \), that maximizes the Ergodic channel capacity for each SU \( l_i \), of the SN imposing the following two sets of constraints: 1) each secondary user \( l_i \) has a limited maximum transmission power equal to \( P_{\text{max},l}^i \) and 2) the total maximum interference power at each PBS from the SN’s SUs is constrained to be at maximum equal to \( J_{l_p}^\text{max} \). In mathematical terms, these two constraints are expressed as follows:

\[
\max_{\mathbf{w}_i} \quad E \left\{ \log_2 \left[ 1 + \frac{1}{N_i} B_i^T \mathbf{H}_{n_i} w_i^t \cdot^T \left( \sum_{n_i=1}^{I_i} \bar{H}_{n_i}^T \mathbf{x}_n \right) \right] \right\}
\]

Subject to:

\[
\mathbf{w}_i^t \cdot^T \mathbf{w}_i^t \leq P_{\text{max},l_i}^i
\]

where \( \rho_i \) is the signal-to-noise ratio (SNR) of SU \( i \), \( \bar{H}_{ss,ls}^t = H_{ss,ls} w_s^l \cdot^T \) and \( \bar{H}_{sp,ls}^t = H_{sp,ls} w_s^l \cdot^T \),

\[
\mathbf{B}_i = \mathbf{B}_{ss} + \mathbf{B}_{ps} + \sigma_i^2 \mathbf{I}_{N_i^t}
\]

\[
\mathbf{B}_{ss} = \sum_{l=1,l \neq l_i}^{L} \bar{H}_{ss,ls}^t \cdot^T \bar{H}_{ss,ls}^t \quad \text{and} \quad \mathbf{B}_{ps} = \sum_{l_p=1}^{L_p} \bar{H}_{sp,ls}^t \cdot^T \bar{H}_{sp,ls}^t
\]

This problem is a constrained optimization problem which is highly non-convex and complicated to solve. However, a sub-optimal solution can be obtained by exploiting the method of Lagrange multipliers as follows:

\[
\mathcal{L}(\mathbf{w}_i^t, \nu_i, \lambda_i) = E \left\{ \log_2 \left[ 1 + \frac{1}{N_i} B_i^T \mathbf{H}_{n_i} w_i^t \cdot^T \left( \sum_{n_i=1}^{I_i} \bar{H}_{n_i}^T \mathbf{x}_n \right) \right] \right\} - \nu_i \sum_{l_i=1}^{I_i} \bar{H}_{n_i}^T \mathbf{w}_i^t \cdot^T \mathbf{w}_i^t \cdot^T \mathbf{w}_i^t \frac{P_{\text{max},l_i}^i}{J_{l_i}^{\text{max}}}
\]

where \( \nu_i \) and \( \lambda_i \) are the Lagrange multipliers associated with the \( l_i \)-th SU transmission power and the PBS received interference, respectively.
In the proposed algorithm, the weight vector for user $i$, is updated at each iteration $n$, according to

$$w^t_{s,l}(n+1) = w^t_{s,l}(n) + \mu \nabla_{w^t_{s,l}} \mathcal{L}(w^t_{s,l}, \lambda^t_{l})$$

(12)

where $\nabla_{w^t_{s,l}}$ is the gradient of $\mathcal{L}(w^t_{s,l}, \lambda^t_{l})$ w.r.t. to $w^t_{s,l}$ and $\mu$ is an adaptation constant.

$$\nabla_{w^t_{s,l}} \mathcal{L}(w^t_{l}, \eta^t_{l}, \lambda^t_{l}) =$$

$$\frac{1}{\ln(2)} \left( \rho_{l} \B(n)_{l}^{-1} \mathbf{w}(n) + \frac{V_{l}}{\max_{p}} \mathbf{H}^{H}_{s,l} \mathbf{H}^{H} \mathbf{w}(n) - \frac{\lambda_{l}}{P_{\max}} \mathbf{w}(n) \right)$$

(13)

The gradient of the Lagrangian can be expressed asymptotically as in (12). Our proposed constrained capacity-aware algorithm (CCA) will be compared to the constrained transmit eigenbeamforming (CEigBF), employing MRC at the receiver. In such a case, the transmit weight are updated according to

$$w^{t,CEigBF}_{s,l}(n+1) = w^{t,CEigBF}_{s,l}(n)$$

$$+ \mu \nabla_{w^{t,CEigBF}_{s,l}} \mathcal{L}_{CEigBF}(w^{t,CEigBF}_{s,l}, \eta^t_{l}, V_{l}, \lambda^t_{l})$$

(14)

where $\nabla_{w^{t,CEigBF}_{s,l}}$ is the gradient of $\mathcal{L}_{EBF}(w^{t}_{s,l}, \eta^t_{l}, V_{l}, \lambda^t_{l})$ w.r.t. to $w^{t,CEigBF}_{s,l}$ that can be expressed as

$$\nabla_{w^{t,CEigBF}_{s,l}} \mathcal{L}_{EBF}(w^{t,CEigBF}_{s,l}, \eta^t_{l}, V_{l}, \lambda^t_{l}) =$$

$$-\eta_{l} \left( \mathbf{H}_{s,l}^{H} \mathbf{B}^{-1}_{l}(n) \mathbf{H}_{s,l} \right) \mathbf{w}^{t,CEigBF}_{s,l}(n)$$

$$+ \frac{V_{l}}{\max_{p}} \mathbf{H}^{H}_{s,l} \mathbf{w}^{t,CEigBF}_{s,l}(n)$$

$$+ \frac{\lambda_{l}}{P_{\max,l}} \mathbf{w}^{t,CEigBF}_{s,l}(n)$$

(15)

where $\eta^t_{l}$ is the Lagrange multipliers associated with the gain constraint of the EBF algorithm.

In our optimization procedure we consider that the initial value of $w^{t}_{s,l}(n)$ at iteration index $n = 0$ is given by the EBF weight, i.e.

$$w^{t}_{s,l}(0) = \sqrt{P_{\max,l}} \mathbf{u}_{\max,l}$$

where $\mathbf{u}_{\max,l}$ denotes the eigenvector corresponding to $\lambda_{\max,l}$, the maximum eigenvalue of $(\mathbf{H}_{s,l})^{H} \mathbf{H}_{s,l}$. This value is then used to compute the initial value of the received beamforming vector at iteration index $n = 0$. In our case we assume MRC at the receiving SBS:

$$w^{t}_{s,l}(0) = (\mathbf{B}_{l})^{-1}(0) (\mathbf{H}^{t}_{s,l}) (0)$$

(16)

IV. SYMBOL ERROR RATE (SER) PERFORMANCE OF COGNITIVE MIMO-SDMA SYSTEMS

The probability of error, $P_r(E_i)$, associated with the $l^th$ user ($i = s$ or $p$), can be expressed as [24]

$$P_r(E_i) = E_{\gamma_i} \left[ a \sqrt{2 \gamma_i} \right]$$

(17)

where $E[.]$ denotes the expectation operator, $Q(.)$ denotes the Gaussian Q-function, $\gamma_i$ is the signal-to-interference-plus-noise ratio (SINR) for user $l_i$, and $a$ and $b$ are modulation-specific constants. For binary phase shift keying (BPSK), $a = 1$ $b = 1$, for binary frequency shift keying (BFSK) with orthogonal signaling $a = 1$ $b = 0.5$, while for M-ary phase shift keying (M-PSK) $a = 2$ $b = \sin^{2}(\pi/M)$. The SINR for SU $l_s$, $\gamma_s(n)$, is given by

$$\gamma_s(n) = \frac{w^{t}_{s}(n) \mathbf{H}^{t}_{s,l}(n) \mathbf{B}^{t}_{l}(n) \mathbf{w}^{t}_{s}(n)}{w^{t}_{s}(n) \mathbf{B}^{t}_{l}(n) \mathbf{w}^{t}_{s}(n)}$$

(18)

and the SINR of PU $l_p$, $\gamma_p$, is given by

$$\gamma_p = \frac{w^{t}_{p} \mathbf{H}^{t}_{p,l}(n) \mathbf{H}^{t}_{p,l}(n) \mathbf{w}^{t}_{p}}{w^{t}_{p} \mathbf{H}^{t}_{p,l}(n) \mathbf{w}^{t}_{p}}$$

(19)

We observe that in general, the off diagonal elements of $\mathbf{B}_l$ and $\mathbf{B}_p$ are non-zero, reflecting the colour of the interference. However in the asymptotic case of large $N^f_l$ and $N^f_p$ (massive
antenna array at SBS and PBS), and given equal power transmitted by all users \( P_s = P_p \), the central limit theorem (CLT) can be invoked to show that \[ (20) \]

Thus assuming MRC at the receiving SBS and PBS, we can express \( s_l n \gamma \) and \( p_l \gamma \) as

\[ (22) \]

\[ (23) \]

where \( \tilde{H}_{ss,l}(n) = H_{ss,l} w_{s,l}(n) \) and \( \tilde{H}_{pp,l} = H_{pp,l} w_{p,l} \)

V. SIMULATION RESULTS

The steps for our simulation of the system given in Fig. 1 are summarized in Table 1. In our simulation setups we consider a CR-based MIMO-SDMA system with \( T_f = T_p = 2 \) transmit antennas. The number of antennas at the PBS and at the SBS is the same, \( N_f = N_p \), and varies from 16 up to 64. \( L_s = 4 SUs \) and \( L_p = 4 PUs \). We assume BPSK modulation. We impose \( P_{t,x} = 0 dB \) and \( J_{sp,max} = -5, -10, -15, and -20 db \) on the SUs. For the PN we assume a MIMO-SDMA system with non-constrained MIMO-MRC, i.e., EigBF at the transmitter and MRC at the receiving PBS. Fig. 2 shows the impact of \( J_{sp,max} \) on the SER performance of SUs when using the CCA and the CEigBF schemes in cognitive MIMO-SDMA system with \( N_f = 32 \). As we can see, imposing a stronger \( J_{sp,max} \) degrades significantly the SER of both schemes. It is also noted that CCA is slightly outperforming CEigBF.

Fig. 3, on the other hand, shows the impact of the interference power constraints, \( J_{sp,max} \), on the SER of SUs, SUs using CCA and CEigBF schemes with \( N_f = 32 \).

<table>
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<th>Table 1: Steps for system simulation.</th>
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CEigBF schemes in cognitive MIMO-SDMA system with \( N_f = 32 \). As we can see, imposing a stronger \( J_{sp,max} \) degrades significantly the SER of both schemes. It is also noted that CCA is slightly outperforming CEigBF.

Fig. 2. Impact of interference power constraint, \( J_{sp,max} \), on the SER of SUs, SUs using CCA and CEigBF schemes with \( N_f = 32 \).
that as we increase $N_P^r$ and $N_S^r$, the SER performance of PUs varies slightly with $J_{sp}^{max}$ variations. This means that when the number of base station antennas becomes large, the interference constrained imposed on SUs could be relaxed without impacting the SER performance of PUs.

![Impact of interference power constraint, $J_{sp}^{max}$, on the SER of PUs.](image)

Fig. 4 shows the capacity of SN using CEigBF and CCA with various antenna configurations. For all cases it is noted that increasing the number of base station antennas results in an increase of system capacity. It is also seen that for the $2 \times 64$ and $2 \times 32$ cases, the CCA and CEigBF capacity curves are almost identical, however for the lower number of base station antennas ($2 \times 24$) CCA is outperforming CEigBF.

![Capacity of SN for different numbers of base station antennas](image)

Fig. 5 shows the impact of the interference power constraints, $J_{sp}^{max}$, on the capacity of SN. It is noted that, for both schemes, as $J_{sp}^{max}$ becomes larger, the capacity of SUs is significantly reduced. On the other hand, it is noted that for the strongest interference constraint of $J_{sp}^{max} = -20$ dB the CCA is outperforming the CEigBF.

![Impact of interference power constraint, $J_{sp}^{max}$, on the capacity of SN when SUs using CCA and CEigBF](image)

Fig. 6 shows the impact of the interference power constraints, $J_{sp}^{max}$, on the capacity of PN. For all cases of number of antennas at base stations, it is noted that as $J_{sp}^{max}$ becomes larger, the capacity of PUs is improved due to the decreased and limited interferences from SUs.

![Impact of interference power constraint, $J_{sp}^{max}$, on the capacity of PN.](image)

VI. CONCLUSION

This paper presents a new adaptive beamforming algorithm for multiuser access in cognitive MIMO-SDMA systems. The proposed algorithm iteratively seeks the optimal transmit weight vectors that maximize the channel capacity of each secondary user in the secondary network while protecting PUs from SUs’ interferences. It is shown that in all cases the MIMO-SDMA systems with the transmit weights obtained using...
the proposed algorithm (CCA) is outperforming the well-known constrained eigenbeamforming approach (CEigBF). It is also shown that the use of a large number of antennas at the SBS could efficiently control the interference to PBS and could relax the constraints imposed on SUs. Thus, to achieve the QoS needs of the SN without negatively affecting the PN one should use a large scale MIMO-SDMA system.

REFERENCES


