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Multiple-input multiple-output cross-layer antenna selection and beamforming for cognitive networks

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Abstract: Beamforming techniques can be used to suppress co-channel interference in radio devices. In a cognitive setting, beamforming can be beneficial as it can be applied to cancel interference among co-located primary users and cognitive users. In this study, the authors propose an antenna selection algorithm combined with zero-forcing beamforming to improve the throughput of cognitive multiple-input multiple-output (MIMO) radios. The algorithm consists of two phases. First, cognitive nodes apply antenna selection approach to achieve high transmission efficiency among communicating pairs. Cognitive nodes then exploit the spatial opportunities of MIMO systems and employ beamforming to cancel interference between cognitive and primary users. In that, the authors maximise an objective function for the system throughput where precoding is applied on the transmitted spatial multiplexed signals. Numerical results show the advantages offered by the proposed algorithm under different system scenarios.

1 Introduction

During the last decade extensive research has been conducted to improve the spectrum utilisation in wireless applications. Among these activities multiple-input multiple-output (MIMO) technology has shown to improve the spectrum efficiency and the reliability of the channel. Despite these efforts, spectrum crisis situations still exist because of the fixed spectrum allocation policy where users are assigned portions of the spectrum permanently. Owing to the unprecedent growth of wireless users, some portions of the assigned spectrum become heavily congested, while leaving other parts unutilised. To solve this problem, and to efficiently utilise the available spectrum, cognitive radios (CR) have been proposed. It is envisioned that CR will share the spectrum along with existing primary users in a dynamic and an opportunistic manner [1].

Opportunity detection is one of the key challenges for CR. CR may apply sensing and learning algorithms for this purpose [2]. A good discussion on spectrum sensing techniques and challenges are presented in [3]. Cognitive nodes can also use node cooperation to further improve the sensing capability [3, 4]. By sensing the environment, CR may determine opportunity in time, frequency or space domain. For instance, inside a time-division multiple-access based primary network cognitive nodes can use the unused time slots as an opportunity [5, 6]. Also, CR can use the unused frequency spaces of the primary network [7]. However, in addition to time, frequency and space domain, MIMO systems add another degree of freedom to the CR. For instance, cognitive users equipped with MIMO can use beamforming to reduce interference on primary users and thus operate concurrently. In some recent works [8–10], this type of interference reduction technique is formulated as non-convex optimisation problem. Although, theoretically achievable information rate is determined in [8–10], it is very difficult to determine the wight vector as the problem is non-convex. Another approach is presented in [11], to completely cancel interference between primary and cognitive nodes using pre-coding and post-coding techniques. In addition, a closed-form expression for achievable capacity limit is also presented by the authors.

Apart from the opportunity detection phase, utilising the detected spectrum is one of the key challenges for cognitive networks. One of the prominent techniques to improve spectrum utilisation is through MIMO techniques. As CR are able to access very small amount of wireless resources, this high spectrum efficiency renders MIMO systems extremely valuable for cognitive devices. However, spectrum efficiency of the MIMO system can be further improved by using antenna selection schemes [12]. Moreover, it is also shown that a cross-layer antenna selection scheme can reap a very high transmission efficiency in a 'point-to-point' MIMO system [13]. On the other hand, in [14] the authors exploit the spatial and temporal domains of MIMO cooperative cognitive networks to achieve high transmission efficiency.

Motivated by the works in [11, 13, 15], we propose a cross-layer MIMO transmit antenna selection algorithm and beamforming to reach high transmission efficiency as well as concurrent operation with the primary user for cognitive MIMO systems. Cross-layer antenna selection is beneficial as packet error rate (PER) is considered at the link-layer that identifies usable channels. Thus, with low number of radiofrequency (RF) chains, high efficiency is achievable with low decoding complexity. On the other hand, when

beamforming is employed with cross-layer antenna selection, interference imposed on the primary user can be mitigate. As a result, cognitive users are able to communicate below the primary user interference level. Different from [14], we use a cross-layer design where efficiency is considered for selecting less number of antennas per user.

The rest of the paper is organised as follows. Section 2 introduces the proposed system model where we consider both perfect and imperfect channel-state information (CSI). Performance evaluations and discussions are provided in Section 3. Finally, conclusions are presented in Section 4.

2 Proposed cross-layer design

We consider a scenario similar to [11], where cognitive users opportunistically use the wireless resources of a licensed primary user. In addition, we assume cognitive nodes use Go-Back-N (GBN) protocol for the logical link control (LLC) sub-layers. At the physical layer cognitive nodes use data multiplexer to divide the incoming data into M parallel streams (Fig. 1). These data streams (layers) are fed to M RF chains. Assuming that CSI is available at the transmitter through a feedback channel, cognitive nodes perform antenna selection and precoding. For the antenna selection, cognitive nodes search for M antennas from N_t available transmit antennas for maximum LLC layer throughput. That is given an antenna set P, the optimal subset $p \in P$ of size $M \leq N_t$ is selected for maximum throughput.

Having selected the optimal antennas, in the precoding stage, cognitive nodes use the CSI of 'cognitive-to-primary' link to determine the beamforming vector. That is, the proposed cross-layer antenna selection and beamforming (CLBF) algorithm works as precoded symbols are transmitted using the selected antennas. On the other hand, cognitive receivers are equipped with $N_r(N_t \leq N_r)$ receive antennas, and decision-feedback detector to extract the transmitted data streams.

In the following analysis, we choose boldface letters to represent vectors and matrices, $(.)^H$ represents conjugate transpose, $E(.)$ denotes the expectation, $\|.\|$ stands for 2-norm.

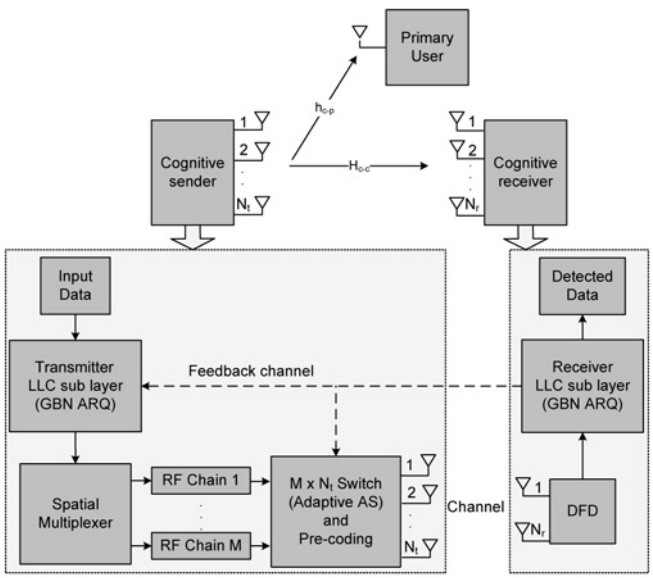

Fig. 1 *Communication system model for cross-layer antenna selection and beamforming algorithm*

2.1 Performance analysis for perfect channel estimation

In this subsection, we consider perfect CSI is available at the cognitive receiver. Thus, for the above-mentioned system the received signal $\boldsymbol{y}_c \in C^{N_r \times 1}$ at cognitive receivers can be expressed as

$$\boldsymbol{y}_c = \boldsymbol{H}_p \boldsymbol{x} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{H}_p$ represents $N_r \times M$ channel sub-matrix of 'cognitive-to-cognitive' $N_r \times N_t$ channel matrix $\boldsymbol{H}$ where we model the channels between users as quasi-static Rayleigh fading ones, $\boldsymbol{x}$ denotes $M \times 1$ cognitive user transmit symbol vector, and $\boldsymbol{n} \in CN(0, N_o I_{N_r})$ is a complex Gaussian noise vector with elements of zero mean and variance N_o, where $\boldsymbol{I}_{N_r}$ is an identity matrix of size N_r.

The interference signal $\boldsymbol{y}_p$ at the primary user because of cognitive user communications can be written as

$$y_p = \boldsymbol{h}_{c-p} \boldsymbol{x} \tag{2}$$

where $\boldsymbol{h}_{c-p}$ denotes the 'cognitive-to-primary' channel matrix. Using (2) we write the instantaneous interference power at the primary user as

$$I = y_p^H y_p = \sigma \boldsymbol{h}_{c-p} \boldsymbol{h}_{c-p}^H \tag{3}$$

where $\sigma = x^H x$ represents the transmitted signal energy. For zero forcing beamforming cognitive nodes determine a precoding matrix $\boldsymbol{A} \in C^{M \times M}$, such that the primary user experiences zero interference because of 'cognitive-to-cognitive' communication, that is

$$\boldsymbol{h}_{c-p} \boldsymbol{A} = 0 \quad \text{s.t. } \|\boldsymbol{A}\|_2 = 1 \tag{4}$$

Using (4) and introducing $\boldsymbol{x}_c = \boldsymbol{A}\boldsymbol{x}$, from (1) to (3) we obtain

$$\boldsymbol{y}_c = \boldsymbol{H}_p \boldsymbol{x}_c + \boldsymbol{n} = \boldsymbol{H}_p \boldsymbol{A} \boldsymbol{x} + \boldsymbol{n} \tag{5}$$

$$y_p = \boldsymbol{h}_{c-p} \boldsymbol{x}_c = \boldsymbol{h}_{c-p} \boldsymbol{A} \boldsymbol{x} = 0, \; I = y_p^H y_p = 0 \tag{6}$$

By introducing $\boldsymbol{H}_p \boldsymbol{A} = \widetilde{\boldsymbol{H}}$, (5) can be transformed as

$$\boldsymbol{y}_c = \widetilde{\boldsymbol{H}} \boldsymbol{x} + \boldsymbol{n} \tag{7}$$

The received signal-to-noise ratio (SNR), ρ, for the selected antenna combinations can be written as [11]

$$\rho = \frac{\psi}{\lambda} \tag{8}$$

where $\psi = d_{11}\sigma$, λ denotes the first element of the covariance of the noise $\boldsymbol{n}$, σ is the cognitive transmit power, and d_{11} is the non-trivial diagonal element of the matrix $\boldsymbol{D}$ with $\boldsymbol{D}$ being calculated using singular value decomposition as, $\widetilde{\boldsymbol{H}} = \boldsymbol{U}\boldsymbol{D}\boldsymbol{V}^H$ (where $\boldsymbol{U}$ and $\boldsymbol{V}$ are unitary matrices).

If binary phase-shift-keying (BPSK) modulation is considered, bit-error rate (BER) of the data stream for selected antenna combinations can be written as

$$\text{BER} = Q\left(\sqrt{2\rho}\right) \tag{9}$$

where $Q(.)$ represents the Gaussian Q-function. Since each L-bit data packet is divided into M parallel streams before transmission, PER is given by

$$\mathrm{PER}(\boldsymbol{H}_{\mathrm{p}}, \rho) = 1 - (1 - \mathrm{SER})^{L/M} \tag{10}$$

Using the obtained PER, the transmission efficiency (i.e. normalised throughput) for GBN protocol for window size W can be written as

$$\eta(\boldsymbol{H}_{\mathrm{p}}, \rho) = \frac{1 - \mathrm{PER}(\boldsymbol{H}_{\mathrm{p}}, \rho)}{1 + (W - 1)\mathrm{PER}(\boldsymbol{H}_{\mathrm{p}}, \rho)} \tag{11}$$

Algorithm 1 Cross-layer antenna selection and beamforming

1. Session Initiation
2. Determine $\boldsymbol{h}_{\mathrm{c-p}}$ using primary users' pilot signals.
3. Measure I_{total} using $\boldsymbol{h}_{\mathrm{c-p}}$.
4. Determine $\boldsymbol{H}_{\mathrm{p}}$ using (19).
5. Use step 2 measurement to determine the matrix $\boldsymbol{A}$.
6. Determine the beamforming symbol vector $\boldsymbol{x}_{\mathrm{c}} = A\boldsymbol{x}$.
7. Transmit $\boldsymbol{x}_{\mathrm{c}}$.
8. End of session.

2.2 Performance analysis for delayed and imperfect CSI

Here, we derive an expression of the instantaneous transmission efficiency for imperfect CSI. In the following analysis, we have considered two cases: (a) delayed CSI and (b) erroneous or imperfect CSI. First, we present the case of delayed CSI. Given the channel $\boldsymbol{H}_{\mathrm{p}}$, we denote the delayed channel estimate at the receiver by $\hat{\boldsymbol{H}}_{\mathrm{p}}$. For this purpose, we use the channel estimation analysis presented in [16] to relate the delayed CSI and the actual CSI at the cognitive receiver by

$$\hat{\boldsymbol{H}}_{\mathrm{p}} = \beta \boldsymbol{H}_{\mathrm{p}} + \sqrt{1 - \beta^2}\boldsymbol{Z} \tag{12}$$

where $\beta = J_o(2\pi f_{\mathrm{d}} T\Delta)$, $J_o(.)$ represents zero-order Bessel function, f_{d} is the Doppler frequency, T is frame duration, Δ is the feedback delay in frames and the elements of $\boldsymbol{Z} \in C^{N_{\mathrm{r}} \times M}$ represent zero-mean unit-variance Gaussian random variables. Hence, one can rewrite the received signal vector at the cognitive user in (5) as

$$\boldsymbol{y}_{\mathrm{c}} = \boldsymbol{H}_{\mathrm{p}}\boldsymbol{x}_{\mathrm{c}} + \boldsymbol{n} = \left[\frac{1}{\beta}\hat{\boldsymbol{H}} - \frac{\sqrt{1 - \beta^2}}{\beta}\boldsymbol{Z}\right]\boldsymbol{x}_{\mathrm{c}} + \boldsymbol{n} \tag{13}$$

Using the singular-value-decomposition of $\hat{\boldsymbol{H}} = \boldsymbol{U}\hat{\boldsymbol{D}}\boldsymbol{V}^{\mathrm{H}}$, (13) can be written as

$$\begin{aligned}\tilde{\boldsymbol{y}}_{\mathrm{c}} &= \frac{1}{\beta}\boldsymbol{D}\hat{\boldsymbol{V}}^{\mathrm{H}}\boldsymbol{x}_{\mathrm{c}} - \frac{\sqrt{1 - \beta^2}}{\beta}\boldsymbol{U}^{\mathrm{H}}\boldsymbol{Z}\boldsymbol{x}_{\mathrm{c}} + \boldsymbol{U}^{\mathrm{H}}\boldsymbol{n} \\ &= \frac{1}{\beta}\hat{\boldsymbol{D}}\hat{\boldsymbol{x}}_{\mathrm{c}} - \frac{\sqrt{1 - \beta^2}}{\beta}\Omega\boldsymbol{x}_{\mathrm{c}} + \tilde{\boldsymbol{n}}\end{aligned} \tag{14}$$

where $\Omega = \boldsymbol{U}^{\mathrm{H}}\boldsymbol{Z}$. Since $E[\hat{\boldsymbol{x}}_{\mathrm{c}}^{\mathrm{H}}\hat{\boldsymbol{x}}_{\mathrm{c}}] = E[\boldsymbol{x}_{\mathrm{c}}^{\mathrm{H}}\boldsymbol{V}\boldsymbol{V}^{\mathrm{H}}\boldsymbol{x}_{\mathrm{c}}] = E[\boldsymbol{x}_{\mathrm{c}}^{\mathrm{H}}\boldsymbol{x}_{\mathrm{c}}] = E[\boldsymbol{x}^{\mathrm{H}}\boldsymbol{A}^{\mathrm{H}}\boldsymbol{A}\boldsymbol{x}] = \sigma$ and $E[\tilde{\boldsymbol{n}}^{\mathrm{H}}\tilde{\boldsymbol{n}}] = E[\boldsymbol{n}^{\mathrm{H}}\boldsymbol{U}\boldsymbol{U}^{\mathrm{H}}\boldsymbol{n}] = E[\boldsymbol{n}^{\mathrm{H}}\boldsymbol{n}] = N_{\mathrm{o}}$, the received SNR can defined as

$$\rho = \frac{\frac{1}{\beta^2}d_{11}^2\sigma}{\sigma\frac{1 - \beta^2}{\beta^2}\sum_{j=1}^{2}|\Omega_{1j}|^2 + \lambda} \tag{15}$$

Similar to the perfect CSI case and considering BPSK modulation, using (9)–(11) and (15), the instantaneous transmission efficiency is given by

$$\eta(\boldsymbol{H}_{\mathrm{p}}, \rho) = \frac{\left[1 - Q(\sqrt{2\rho})\right]^{L/M}}{1 + (W - 1)\left(1 - \left[1 - Q(\sqrt{2\rho})\right]^{L/M}\right)} \tag{16}$$

Now, we investigate the effect of imperfect CSI. For this purpose, we assume a timeframe consisting of L_{t} training or pilot symbols and L_{d} data symbols. Radio devices can estimate the channel $\boldsymbol{H}_{\mathrm{p}}$ using *a priori* knowledge of these training symbols in maximum-likelihood estimation method to yield

$$\hat{\boldsymbol{H}} = \boldsymbol{H}_{\mathrm{p}} + \Delta\boldsymbol{H}_{\mathrm{p}} \tag{17}$$

where $\Delta\boldsymbol{H}_{\mathrm{p}}$ represents the error matrix for channel estimation. Given the channel estimation technique, one can evaluate the received SNR as

$$\rho = \frac{d_{11}^2\sigma}{\sigma\sum_{j=1}^{2}|\Omega_{1j}|^2 + \lambda} \tag{18}$$

where $\Omega = U^{\mathrm{H}}\Delta\boldsymbol{H}_{\mathrm{p}}$ and d_{11} is the non-trivial diagonal element of the matrix $\boldsymbol{D}$ with $\boldsymbol{D}$ being calculated using singular-value-decomposition, $\hat{\boldsymbol{H}}_{\mathrm{p}} = \boldsymbol{U}\boldsymbol{D}\boldsymbol{V}^{\mathrm{H}}$. Using the SNR, one can evaluate the instantaneous transmission efficiency for imperfect channel estimation.

Finally, the cross-layer based antenna-selection and beamforming algorithm works as cognitive source node first selects the antenna combination to achieve maximum throughput at the LLC sub-layer. Then precoding is applied to the transmitted symbols for zero-forcing the interference at the primary user, as presented in (19)

$$\boldsymbol{H}_{\mathrm{p}} = \arg\max_{\boldsymbol{H}_{\mathrm{p}}} \eta(\boldsymbol{H}_{\mathrm{p}}, \rho) \tag{19}$$

It is important to mention that in the cross-layer antenna selection algorithm, antenna combination is selected from the available antennas that achieve maximum transmission efficiency at the LLC sub-layer. For this purpose, a search process considers all possible antenna combinations. Conversely, in the cross-layer antenna selection and beamforming, the search process considers only the combinations that can be applied to beamform the transmitted symbols. That is beamforming is sed here to cancel interference between cognitive and primary users.

2.3 Complexity analysis

It is worth noting that the complexity of the proposed algorithm grows with the number of transmit antennas. We calculate the complexity of the algorithm by the required number of floating point operations (flops). One can note

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that determining the beamforming matrix [11] requires only six flops, and the antenna search algorithm requires $\binom{N_t}{M}$ operations for the combined algorithm. Thus, the total complexity of the cross-layer antenna selection and beamforming algorithm is equivalent to $O(\binom{N_t}{M}6)$.

3 Performance evaluation

We carry out numerical analysis for performance evaluation of the above-mentioned algorithm. For this purpose, we consider cognitive users operate in the adjacent frequency band of the primary user. We assume cognitive nodes have perfect CSI of 'cognitive-to-cognitive' link. In addition, cognitive nodes either use primary users pilot symbols [12] or blind channel estimation methods [17] to estimate the CSI of 'primary-to-cognitive' channel. We also assume, channel remains static for the entire period of a packet transmission. Let us choose the elements of 'cognitive-to-cognitive' channel matrix $\boldsymbol{H}$ as Rayleigh variable with zero mean and unit variance. However, to model the elements of the 'cognitive-to-primary' channel matrix we choose Rayleigh variable with zero mean and 10^{-3} variance. Here, a different variance is considered to model the spill over energy of adjacent frequency bands. This type of channel models are also used in [15]. Although, we do not consider the 'primary-to-cognitive' channel for the sake of simplicity, our study can be easily extended to this case. Other simulation parameters are listed in Table 1. Before going through the simulation results, it is worth mentioning that we considered 10 000 channel realisations in the event driven simulation to generate each data point of the reported results.

We plot the normalised throughput curves in Fig. 2 where we consider five scenarios: (i) no antenna selection, (ii) beamforming in a 2×2 MIMO system (BF), (iii) cross layer antenna selection (CLAS), (iv) proposed CLBF in 2×2 system ($M = 2$ antennas selected from $N_t = 4$ antennas) and (v) proposed CLBF in 2×2 system ($M = 2$ antennas selected from $N_t = 6$). The performance of these algorithms are evaluated under the condition that cognitive communication limited by the primary user interference constraint ≤ -20 dBm. For the no antenna selection case, cognitive nodes are able to communicate, if the resultant primary user interference is lower than the specified interference threshold. In CLBF, cognitive nodes first select the antenna combinations for maximum LLC layer normalised throughput, then apply beamforming over the selected antennas.

In Fig. 2, one can note that the CLBF algorithm outperforms CLAS, BF and no antenna selection algorithms. As one can see, the use of antenna selection combined with beamforming offers larger throughput gains as the number of available antennas increases. The extra throughput gain achieved is owing to the ability of the proposed algorithm to remedy the interference effects at the primary users while maximising the throughput of the cognitive network. Different from the CLBF and BF algorithms, the performance with CLAS and no antenna selection is shown to deteriorate as the SNR goes high because of the interference constraint set at the primary user.

Table 1 Simulation settings

Parameter	Value
packet payload	1024 bytes
frame duration	2 ms
automatic repeat-request (ARQ) protocol	GBN
ARQ window size	4 packets
PER threshold	10^{-6}
no. of RF chain, M	2

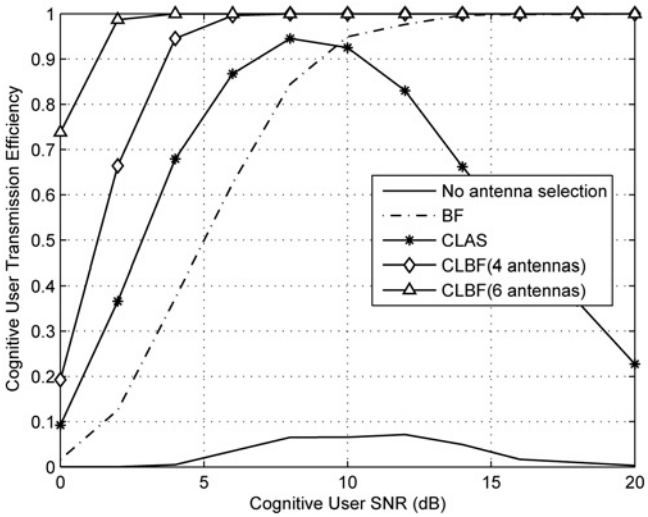

Fig. 2 *Throughput performance of cognitive users with a primary user interference constraint ≤ -20 dBm and ARQ window size = 4*

In Fig. 3, we examine the effect of delayed CSI on the throughput performance. From these results, one can note that performance degradation occurs because of delayed CSI where degradation is more evident in the BF case than the CLBF case. Also as seen, in all cases, the proposed cross-layer design is shown to outperform the beamforming scheme.

In Fig. 4, we examine the effect of imperfect (CSI) on the transmission efficiency. One can note that similar to the delayed CSI case, imperfect CSI causes small degradation in the transmission efficiency using small number of training symbols. Furthermore, in all cases, the proposed cross-layer design is shown to outperform the beamforming scheme.

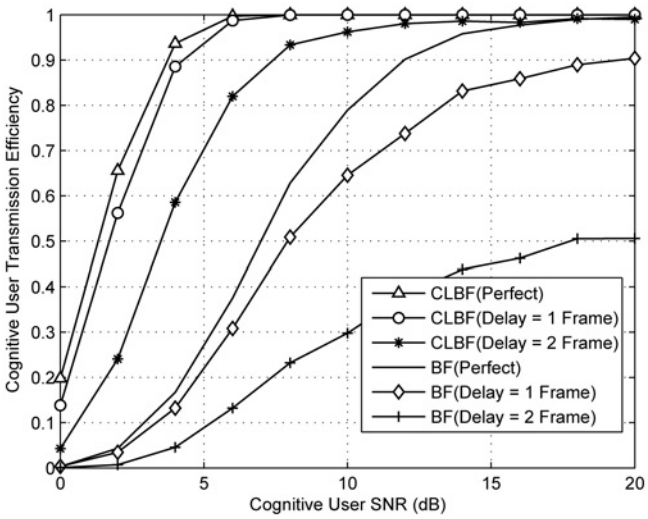

Fig. 3 *Effect of channel estimation delay on the throughput performance of cognitive users with primary user interference constraint ≤ -20 dBm and ARQ window size = 4*

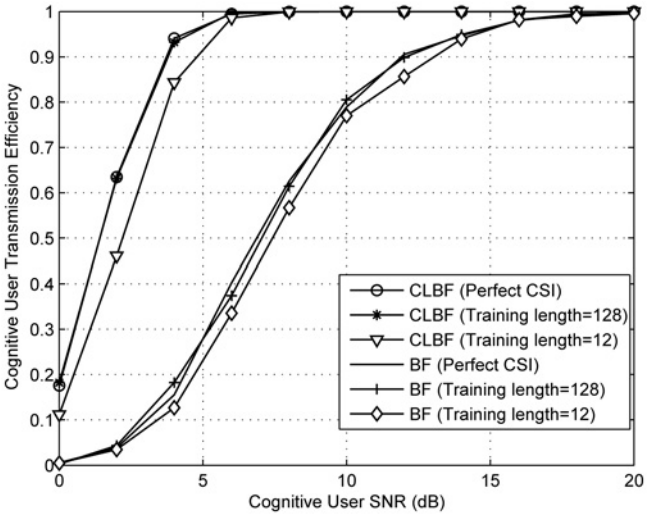

Fig. 4 *Effect of imperfect channel estimation errors on the throughput performance of cognitive users with primary user interference constraint* ≤ -20 *dBm and ARQ window size* $= 4$

To further explore the effect of number of antenna combination, we examine the throughput performance as a function of available antennas N_t resulting a 2×2 MIMO system. The results are shown in Fig. 5 where we compare the performance of the CLAS without beamforming with the proposed CLBF. Note that the CLAS, similar to the no antenna selection case, is limited by the interference threshold at the primary user. As shown, one can leverage large throughput gains by increasing the number of available antennas in the CLBF algorithm. On the contrary, the CLAS achievable throughput is limited by the primary user interference constraint.

In Fig. 6, we plot the achievable efficiency curves of cognitive users as a function of the interference constraint at the primary user for a cognitive SNR = 8 dB. The results reveal the differences between three scenarios; no antenna selection, BF and proposed CLBF where the CLBF and BF are shown to be interference resistant with the former offering larger throughput gain.

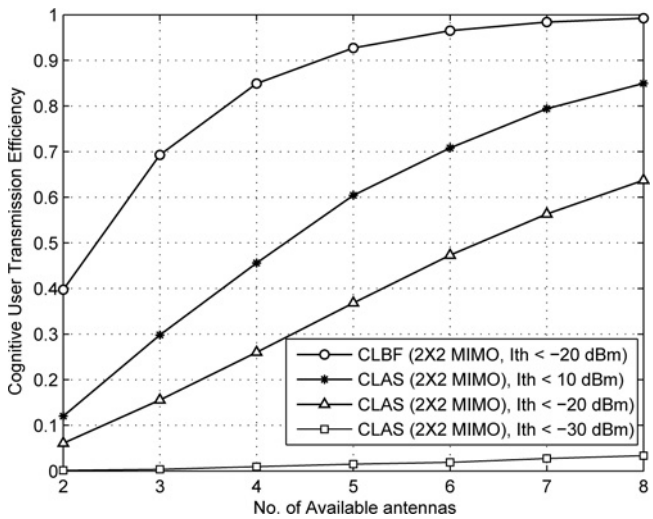

Fig. 5 *Throughput as a function of number of antenna combinations for a* 2×2 *MIMO system at SNR* $= 8$ *dB and ARQ window size* $= 4$

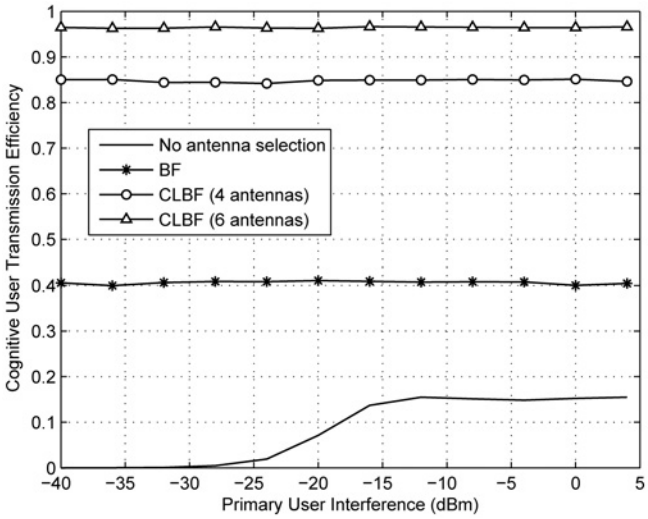

Fig. 6 *Effect of primary user interference threshold for cognitive user SNR* $= 8$ *dB and ARQ window size* $= 4$

We have simulated the system to investigate the effect of window size. The results are shown in Fig. 7. We simulate the system for three window sizes, $w = 4$, 16 and 64. From (11), one can note that efficiency is inversely proportional to the window size. This phenomenon is also revealed in the simulation results. In the figure, simulation results indicate that for low SNRs the efficiency decreases with the increase in window size. Conversely at high SNRs as the packet-error rate becomes zero, the window size has no effect on the efficiency.

Finally, we show the data rate curves against cognitive user SNR in Fig. 8. A performance similar to the throughput curves (Figs. 2–6) is also noted here. At low SNRs ([0 6] dB) all algorithms result in very low data rates, as the PER is very high. However, among the algorithms, the WAS algorithm results in the lowest data rate as interference on the primary user is the limiting force. Although the throughput curves in Fig. 2 indicate a bell-shape curve with peak around 10 dB for the WAS algorithm, the data rate curve saturates after 10 dB. This

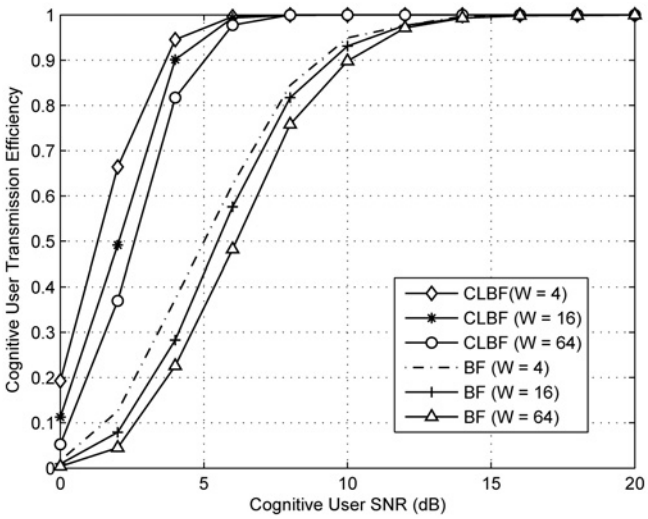

Fig. 7 *Effect of the window size on the throughput performance of cognitive users at a primary user interference constraint* ≤ -20 *dBm*

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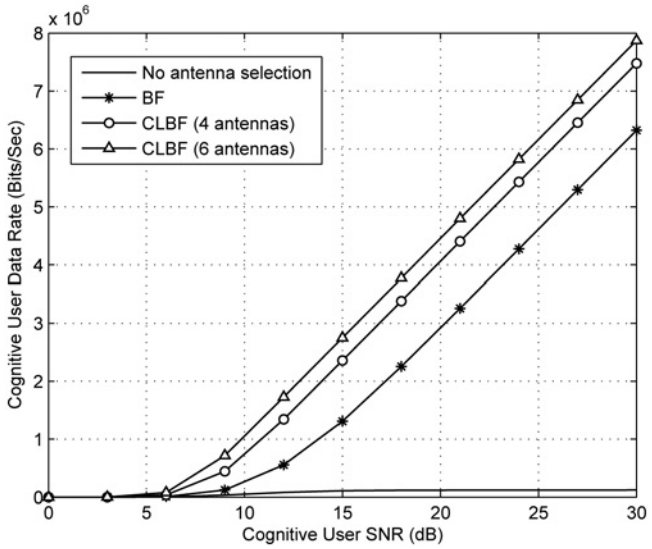

Fig. 8 *Data rate curves of cognitive user a primary user interference constraint* ≤ -20 *dBm*

occurs as the PER decreases with the increase in SNR. On the contrary in BF and CLBF algorithms, primary user interference is mitigated using precoding which results in data rate increase with the increase in SNR. However, the CLBF algorithm reveals further increase in data rate, as better channels are selected.

4 Conclusions

We proposed an antenna selection algorithm applied with beamforming to gain high throughput in CR networks. The proposed algorithm allows cognitive users to access the channel with no interference effect on primary users using beamforming. Our proposed cross-layer algorithm is shown to be offer high throughput using low number of RF chains. Our simulation results also show that the effect of imperfect (CSI) and delayed estimates is not significant where the system still able to outperform other schemes.

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