Cross-Layer Antenna Selection and Channel Allocation for MIMO Cognitive Radios

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***Abstract*—We propose algorithms to address the spectrum efficiency and fairness issues of multi band multiuser Multiple-Input and Multiple-Output (MIMO) cognitive ad-hoc networks. To improve the transmission efficiency of the MIMO system, a cross layer antenna selection algorithm is proposed. Using the transmission efficiency results, user data rate of the cognitive ad-hoc network is determined. Objective function for the average data rate of the multi band multiuser cognitive MIMO ad-hoc network is also defined. For the average data rate objective function, primary users interference is considered as performance constraint. Furthermore, using the user data rate results, a learning-based channel allocation algorithm is proposed. Finally, numerical results are presented for performance evaluation of the proposed antenna selection and channel allocation algorithms.**

***Index Terms*—Ad-hoc networks, cognitive networks, cross-layer design, game theory, MIMO systems.**

I. Introduction

THE rigid structure of current spectrum allocation policies creates a bottleneck for rapidly growing wireless users. On the other hand, the Federal Communication Commission (FCC) measurements reveal that most of the licensed frequency bands are either unused or utilized less than 10% of the time [1]. To address the limitations on spectrum usage, the FCC has motivated the use of opportunistic spectrum sharing to make the licensed frequency bands accessible for unlicensed wireless users. The intention behind this is to create cognitive capability of wireless devices for concurrent spectrum usage.

Cognitive radios apply two distinct approaches for concurrent spectrum access, viz., spectrum overlay and spectrum underlay [2]. In the underlay scheme, secondary users occupy the whole bandwidth and transmit at power lower than the noise floor of the primary user. As power is very low in these schemes, secondary users communication appears as white noise at the primary user. On the other hand, in the overlay scheme, secondary users use opportunistic or adaptive techniques to determine when and where to transmit. In this study, we will only focus on overlay communications of cognitive users.

Determining spectrum opportunity is one of the key challenges for the overlay scheme. Cognitive radios are envisioned to have sensing and learning capability for this purpose [3],[4]. It is worthwhile to mention that cooperation among cognitive nodes can further improve spectrum sensing capability of cognitive radios [5]. However, for this study, we assume cognitive nodes have perfect knowledge of available frequency channels and respective bandwidths.

After successful detection of opportunity, unutilized frequency channels are assigned to cognitive radios. It is known that spectrum assignment has two primary goals: fairness and utilization. One of the prominent techniques to improve spectrum utilization is through Multiple-Input and Multiple-Output (MIMO) techniques. As the cognitive radios are able to access very small amount of wireless resources, this high spectrum efficiency makes MIMO systems extremely valuable for cognitive devices. However, spectrum efficiency of the MIMO system can be further improved by using antenna selection schemes [6]. Moreover, it is also shown that a cross layer based antenna selection scheme can reap a very high transmission efficiency in a 'point-to-point' MIMO system [7].

Apart from the above mentioned considerations, cognitive radios in ad-hoc networks encounter few more challenges: such as, lack of cooperation between nodes, unstable user statistics, resource management, etc. In that sense, game theory can mathematically model the ad-hoc network [8] to address these challenges. In some recent works, game theory is used to determine the achievable capacity or transmit power of cognitive networks. In [9], game theory is used to reduce the interference on primary users due to concurrent communication of cognitive and primary users in the same frequency band. Game theory is also used in [10] to determine the maximum achievable capacity problem for Multi Band Multiuser MIMO Cognitive Ad-hoc Networks (MBMMCAN). On the other hand, in [11] the authors used optimization techniques to address the maximum achievable capacity problem of MBMMCAN. Optimization techniques are also used in [12], for power loading and channel selection for a multi-carrier MIMO orthogonal-frequency-division multiplexing (OFDM) cognitive radios to maximize the transmit power and capacity, given primary users' interference constraint. In [13], the authors used 'user satisfaction' to address the joint power and channel allocation problem for cognitive ad-hoc networks. In [14], machine learning is used to address the channel selection problem for cognitive ad-hoc Single-Input and Single-Output (SISO) networks. Machine learning is also used in [15] to address the channel allocation problem for heterogenous (unequal and available frequency slots or interference limit on primary users) cognitive networks. It is worth noting that, the channel allocation problem for heterogeneous cognitive networks was first studied in [16] and to our best knowl-

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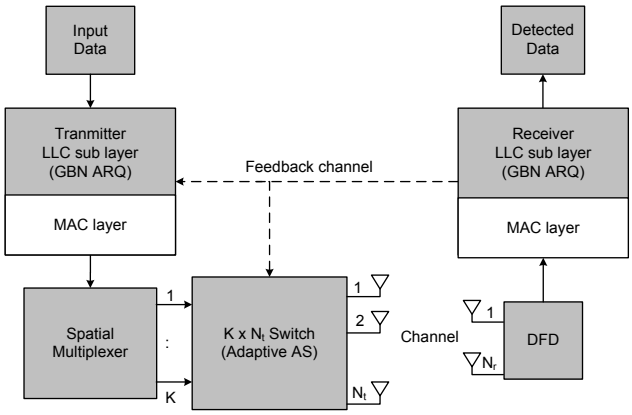


Fig. 1: Communication system model for cognitive nodes.

edge, fairness issues for channel allocation in heterogeneous cognitive networks are not considered to date. Also, other previously mentioned works in [10], [11], [13], and [14], have not considered the effect of interference on primary users for channel allocation and performance improvement. Other approaches are presented in [17] and [18] for performance improvement in cognitive networks. For instance, the authors in [17] proposed an antenna selection approach to select nodes with frequency channels orthogonal to the primary users in an infrastructure-based cognitive network. The proposed technique is shown to minimize the interference at the primary user side and maximize the sum rate. Also, in [18] a cross layer technique is used to select possible modulation schemes for performance improvements.

Motivated by the works in [7], [12], [14], and [16], we propose a MIMO cross-layer transmit-antenna selection algorithm to improve the spectrum utilization in a cognitive setting. We also propose a learning-based channel allocation strategy to reduce the number of channel switching as well as data rate variations among cognitive nodes i.e., address fairness issues of the MBMMCAN. The proposed algorithms can also be applied to wireless systems with similar heterogeneity and/or interference problem. The rest of the paper is organized is as follows. The system model is presented in Section II. The proposed antenna selection and channel allocation algorithms are presented in Section III. Performance evaluations of the proposed cross layer design are discussed in Section IV. Finally, conclusions are drawn in Section V.

II. System model

We consider a cognitive ad-hoc network coexists with licensed primary users (PU) in the same geographical area. To facilitate the cognitive network design, we make the following assumptions. The ad-hoc network contains M pairs of cognitive users (CU) and any node can listen to all other nodes in the network. For wireless resource allocation purposes, we consider cognitive nodes that can make use of C unused frequency bands of the primary users. Also, the number of available channels for cognitive radios are less than the number of cognitive user, i.e., $C < M$. As a result, a channel may be shared by more than one cognitive user using multiple access techniques. If a channel is selected by many users, the overall data rate per node will reduce due to collisions and users will then be forced to search for a different channel. To reduce the number of channel switchings, nodes employ a learning-based channel selection algorithm. On the other hand to improve the wireless resource utilization, cognitive source-destination pairs use N_t transmit and N_r receive antennas. Nodes also use Decision Feedback Detection (DFD) to cancel interference and improve detection. In the Logical Link Control (LLC) sub-layer, nodes use Go-Back-N (GBN) protocol, and Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) protocol in the Media Access (MAC) sub-layer of the data link layer as shown in Fig. 1. Nodes exchange information between physical layer and data link layer for cross layer antenna selection and channel allocation purposes. In the following subsections we address these algorithms in detail.

TABLE I: List of Symbols

M	No. of cognitive pairs
C	No. of unused frequency bands of primary users
N_t	No. of transmit antennas
N_r	No. of receive antennas
K	No. of selected transmit antennas
$\boldsymbol{H}$	$N_r \times N_t$ 'cognitive-to-cognitive' channel matrix
$\mathbf{x}$	$N_t \times 1$ cognitive user transmit symbol vector
$\mathbf{y}_c$	$C^{N_r \times 1}$ received signal at cognitive user
$\mathbf{y}_{pl}^i$	interference signal at primary user l from cognitive user $i \in M$
I_i^l	interference at the lth primary user due to cognitive user $i \in M$
I_{total}	total interference at the primary user
τ_i	transmission probability of the ith cognitive user
ρ_o	average received SNR per receive antenna
η	transmission efficiency (normalized throughput)
χ	LLC sub-layer achievable data rate
U_i	utility of channel i
$\beta, \gamma, \& \delta$	user defined parameters for the utility function
S_i	set of strategies for node $i \in M$
s_a	strategy to select channel $a \in C$
$p_i^{t+1}(s_a)$	probability to select strategy s_a
α	learning rate

Throughout the paper, we use boldface letters to represent vectors and matrices. Table I lists all symbols and notation used in the paper.

III. Antenna Selection and Channel Allocation

In this section, we first present the antenna selection algorithm followed by the cognitive channel allocation algorithm. Finally, we examine the case where both antenna and channel selection techniques are combined to leverage large throughput gains in the cognitive network.

A. Antenna Selection Algorithm

In this subsection, we introduce a cross layer transmit-antenna selection algorithm taking into account primary users' interference constraints. The proposed algorithm works as follows. At first, a cognitive source node determines the combination of maximum possible usable antennas for a given transmit power and primary users' interference constraint.

Then, source nodes consult with respective receivers on the optimum combination of $K \leq N_t$ transmit antennas. During this phase, a cognitive receiver searches for the subset p, from all possible combination set $P = \{\binom{N_t}{K},\ for\ K = 1, 2...N_t\}$, that achieves the maximum transmission efficiency at the LLC sub layer. This information of the optimum subset p of transmit antennas is relayed back to the cognitive transmitter through a feedback channel. At the transmitter side, cognitive nodes use this subset p to divide the incoming data into K parallel streams for spatial multiplexing and subsequent transmission from the K-selected antennas.

To develop the mathematical model for the transmission efficiency, we express the received signal $\mathbf{y}_c \in C^{N_r \times 1}$ at cognitive receivers as

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

where $\boldsymbol{H}_p$ is an $N_r \times K$ channel sub-matrix, $\boldsymbol{\Pi} \in \mathbb{R}^{K \times K}$ represents channel dependent permutation matrix for greedy QR detection ordering [19], $\boldsymbol{x}$ denotes $N_t \times 1$ cognitive user transmit symbol vector, and $\boldsymbol{n} \in CN(0, N_o I_{N_r})$ is the complex Gaussian noise vector with zero mean and variance N_o, where $\boldsymbol{I}_{N_r}$ is an identity matrix of size N_r

We also define the interference signal $\boldsymbol{y}_{pl}^i$ due to spill over energy at any primary user l for using adjacent channels [1], [12] by the cognitive user $i \in M$ as,

$$y_{pl}^i = \boldsymbol{G}_i \boldsymbol{x} \tag{2}$$

where $\boldsymbol{G}_i$ stands for an $1 \times N_t$ channel vector representing the corresponding channels between a primary user and cognitive node $i \in M$.

From (2), one can express the instantaneous interference power at the lth primary user as

$$I_i^l = (y_p^i)^H y_p^i = \sigma \boldsymbol{G}_i.(\boldsymbol{G}_i)^H, \tag{3}$$

where $\sigma = E[x^H x]$. Since many cognitive and primary users coexist in the same geographical area, we assume the received noise power at the cognitive user to be zero mean and unit variance Gaussian. We also consider all cognitive users have uniform interference effect on primary users. For this reason we drop the subscript l for our further analysis. If cognitive node transmission probability is τ_i, then the total interference level at the primary user for M cognitive users can be written as,

$$I_{total} = \sum_{i=1}^{M} \tau_i I_i. \tag{4}$$

We assume channel state information (CSI) between cognitive source and destination pairs is available at the cognitive receiver. Also, cognitive receivers use Zero-Forcing (ZF) algorithm to suppress the interference between the K spatially-multiplexed layers [6]. If no error propagation occurs among the detected layers at the DFD, the MIMO channel between cognitive nodes decouple into K parallel SISO virtual sub-channels [20]. Given this, the output signal-to-noise ratio (SNR) for the jth sub-channel can be written as,

$$\rho_j = r_{jj}^2 \rho_o, \tag{5}$$

TABLE II: Cross Layer Antenna Selection Algorithm

Packet Transmission Initiation	
1	Measure I_{total} using primary users' pilot signals.
2	Use step 1 measurement results to calculate the maximum number of usable antennas during DIFS period of the IEEE 802.11 standard.
3	Send RTS signal using antennas identified in step 2.
4	Calculate H_p at the receiver side using (9).
5	Add the sub-matrix p with the CTS signal of the receiver.
6	Transmit CTS.
7	Use the sub-matrix p to divide and transmit data.
End of packet transmission	

where $\rho_o = E[\boldsymbol{x}^H \boldsymbol{x}]/KN_o$ is the average received SNR per receive antenna, and r_{jj}^2 is the diagonal elements of the matrix $\boldsymbol{R}_p$ calculated using $\boldsymbol{H}_p \boldsymbol{\Pi} = \boldsymbol{Q}_p \boldsymbol{R}_p$.

Considering binary-phase-shift-keying (BPSK) transmission, the bit-error rate (BER) of the jth layer provided that all previous layers are correctly detected, can be written as

$$BER_j = Q(\sqrt{2r_{jj}^2 \rho_o}),\ for\ j = 1, 2, ..., K, \tag{6}$$

where $Q(.)$ is the Gaussian Q-function. Since each L-symbol data packet is divided into K-parallel streams before transmission, the packet error rate is given by

$$PER(\boldsymbol{H}_p, \rho) = 1 - \left[\prod_{j=1}^{K} (1 - BER_j)\right]^{L/K}. \tag{7}$$

Having obtained the PER in (7), one can evaluate the transmission efficiency (i.e., normalized throughput), defined as the ratio of effective information transfer rate to the information or bit rate of the channel. For GBN protocol with window size W, the instantaneous transmission efficiency [21] at the receiver side of node i can be expressed as,

$$\eta_i(\boldsymbol{H}_p, \rho) = \frac{K}{N_t} \frac{1 - PER(\boldsymbol{H}_p)}{1 + (W-1)PER(\boldsymbol{H}_p)}. \tag{8}$$

Table II summarizes this antenna selection algorithm. For the cross layer antenna selection algorithm, cognitive source nodes select the antenna combination that provides maximum transmission efficiency at the LLC sub-layer for a given interference threshold at the primary user, that is

$$H_p = \arg\max_{H_p} \eta_i(\boldsymbol{H}_p, \rho), \quad s.t.\ I_{total} \leq I_{th}. \tag{9}$$

Note that for the optimization criteria we consider the transmission efficiency over throughput, as it clearly indicates the sources of inefficiency while it can also be used to evaluate the achievable throughput of the network.

B. Channel Assignment Algorithm

In cognitive networks, users share unutilized frequency slots of primary users on opportunistic basis. These frequency slots are, in general, distributed across the primary users' frequency band and of unequal bandwidth. Here, we propose a learning-based channel assignment algorithm for cognitive users competing for available frequency slots. The proposed channel assignment, through a learning process, takes in consideration the interference threshold at the primary users and

the bandwidth of the available frequency slots when assigning channels to cognitive users.

We use the transmission efficiency results of the previous subsection to determine the achievable data rate for cognitive nodes. To determine the achievable data rate, we first determine the LLC layer transmission efficiency $\eta_i(\boldsymbol{H}_p, \rho)$. Then, we multiply the transmission efficiency by the bit rate KR_{tr}. Note that R_{tr} is the bit rate per transmit antenna and K is the number of applied transmit antennas. We express the achievable data rate, χ_i, at the LLC sub layer of any cognitive node $i \in M$ as

$$\chi_i = KR_{tr}\eta_i(\boldsymbol{H}_p, \rho). \tag{10}$$

From (6)-(8), we notice that, in order to maximize the transmission efficiency, the SNR needs to be increased. However, the interference at the primary users also increases with the increase in SNR. For this reason, we express the average data rate of cognitive nodes (limited by the interference threshold I_{th} of primary users) as

$$f(\rho) = \frac{\sum_{i=1}^{M} \chi_i}{M} \quad s.t.\ I_{total} \leq I_{th}. \tag{11}$$

At this point, we investigate the effect of the channel transmission rate (R_{tr}^a) on the performance of the network. This happens as available frequency slots can offer different bandwidths. It is noted that random channel assignment results in large difference in data rates among cognitive nodes, which as will be shown later results in some throughput degradation. To overcome this problem, we propose a learning-based channel selection algorithm for cognitive nodes. In that, cognitive nodes apply the proposed channel selection strategy in the noncooperative game model of the ad-hoc network. We mathematically define the noncooperative game as $\{M, \{S_i\}_{i\in M}, \{U_i\}_{i\in M}\}$, where M is the set of cognitive nodes (decision makers), S_i is the set of strategies $\{s_a, s_b ... s_C\}$ for node i for C available channels. Player i uses the utility function $U_i : S_i \rightarrow \mathbb{R}$ to select the strategy s_a from the set S_i for the current strategy profile of its opponents: S_{-i}. At some point of the game, nodes may select a strategy profile $S = [s_1, s_2 .... s_M]$ such that no players would deviate anymore. This point is known as the Nash equilibrium point and this only happens iff

$$U_i(S) \geq U_i(\acute{s}_a, s_{-a}), \forall i \in M, \acute{s}_a \in S_i. \tag{12}$$

To calculate the utility of strategies, we use the function in (13) [22] that accounts for the data rate, χ_i, at a particular SNR of selfish cognitive nodes in the noncooperative game,

$$U_i(\acute{s}_a, s_{-a}) = \beta + \gamma \log(\chi_i - \delta), \tag{13}$$

where $\log(.)$ stands for natural logarithm function. The numerical constants β, γ, and δ in the utility function are user defined. If cognitive nodes use only the utility to select channels, it will cause large number of channel switching events i.e., operation overhead. To minimize the number of channel switching, we apply no-external-regret learning algorithm [23], and use the exponential updating scheme. In the learning algorithm, cognitive nodes compute the probability to select a channel. Cognitive nodes then record the utility of the channels for a certain amount of time and use these utilities to compute the future channel selection probability given by

$$p_i^{t+1}(s_a) = \frac{(1+\alpha)^{U_i^t(s_a)}}{\sum_{\acute{s}_a \in S_i}(1+\alpha)^{U_i^t(\acute{s}_a)}}, \tag{14}$$

where $U_i^t(s_a) = \sum_{j=1}^{t} U_i^j(s_a)$ and $U_i^t(\acute{s}_a) = \sum_{j=1}^{t} U_i^j(\acute{s}_a)$ denote the cumulative utilities over time t for strategies s_a and $\acute{s}_a$ respectively, $p_i^{t+1}(s_a) \in \Phi$ represents the probability assigned to strategy s_a at time $t+1$ for $\alpha > 0$ with Φ being the set of all transformation probabilities and α represents the learning rate. Table III summarizes our learning-based algorithm. At this point it is worthwhile to mention that this learning algorithm reaches the Nash equilibrium point [23]. It is known that at the Nash equilibrium all nodes have equal utilities, otherwise nodes have to switch channels to reach the channel with best utility as indicated by (12). This indicates that our algorithm ensures equal utility i.e., fairness among nodes.

TABLE III: Channel Selection/Allocation Algorithm

1. Begin with random channel allocation.
2. while channel < available frequency channels, C
   Calculate channel utility from the received packet date rate.
   Compute $U_i^t(s_a) = \sum_{j=1}^{t} U_i^j(s_a)$.
   channel=channel+1
   end
3. Compute probability using (14).
4. Choose the channel $\max_{(s_a)}(p_i^{t+1}), \forall a \in C$ and set the channel to transmit packet.
5. Repeat step 2-4 for every packet.

It is to be noted that in the proposed channel selection algorithm, nodes do not need to know the utility of other nodes. In the process nodes use past experience of using channels. That is, in (14) nodes calculate the utility of all previously visited channels to determine the channel selection probability. In a network, the number of active nodes in a channel affects the overall data rate. As a result, in the multiband cognitive network, channels have different utilities depending on the number of nodes in the channel. In the proposed algorithm, the strategy of a node is to select the best channel using the utilities of all available channels, and not the utilities of the nodes. Thus nodes do not need any feedback link for channel selection. One should also notice that τ_i in (4) represents the probability of packet availability in the buffer of cognitive nodes for transmission. In our work, we consider that packets are always available in the buffer of cognitive nodes i.e., τ_i = 1. That is all cognitive nodes are contending for available channels. As a result, τ_i does not have any effect on the channel selection process.

C. Combined Antenna/Channel Selection

Nodes in a Multi Band Multiuser MIMO Cognitive Ad-hoc Networks (MBMMCAN) may deploy antenna selection along with channel selection scheme for throughput improvement. For the combined cross layer antenna/channel selection scheme, nodes apply the algorithms in steps. During the session initiation period, nodes transmit using antenna

selection algorithm in a randomly selected channel and record channel performance parameters. Over the course of time, nodes switch the operating channel to learn about all available channels. In particular, nodes apply the learning algorithm to calculate the channel switching probability in (14). Given this, nodes apply the antenna selection algorithm for the chosen frequency slot (channel). When a session ends, nodes erase all learned data and repeat the whole process for the next session.

D. Complexity Analysis

Each iteration of the channel selection algorithm at any node $i \in M$ has a time complexity $O(max\{|U_i||C|^2, |C|^3\})$, and the antenna selection algorithm through exhaustive search method has complexity $O(2^{N_t})$. This complexity arises as step 2 of the channel selection algorithm in Table III has time complexity $O(|U_i||C|)$ and step 4 has complexity $O(|U_i||C|^2)$. However, the optimization at step 4 can take a maximum of $O(|C|^3)$ using Gaussian elimination. On the other hand, the exhaustive search of the antenna selection algorithm runs over all combination of $\{\binom{N_t}{K},\ for\ K = 1, 2...N_t\}$ that results in time complexity $O(2^{N_t})$. Therefore, the time complexity of the combined antenna selection and channel selection algorithm can be expressed as $O(max\{|U_i||C|^2 + 2^{N_t}, |C|^3 + 2^{N_t}\})$.

Examining the channel selection algorithm, one can see that the memory space complexity of $O(|U_i||C|^2)$, as it is necessary to store $|C| \times |C|$ dimension Φ matrices at step 4 of Table III. Also the antenna selection algorithm has to store $O(2^{N_t})$ elements, resulting in memory space complexity $O(2^{N_t})$. Therefore, the memory space complexity of the combined algorithm can be expressed as $O(|U_i||C|^2 + 2^{N_t})$.

IV. Simulation Results

In this section, we evaluate the performance of the above mentioned algorithms. For this purpose, we build an IEEE 802.11 [24] compliable ad-hoc network. All nodes are equipped with four antennas (4×4 MIMO). The ad-hoc network contains 40 cognitive source-destination pairs. We consider cognitive nodes with perfect channel state information (CSI). We also assume nodes use primary users pilot symbols [6] or blind channel estimation methods [25] to estimate the CSI of 'primary-to-cognitive' channels. We assume there exists a line-of-sight (LOS) component in the wireless link between the cognitive source and destination pairs. At this point, we consider nodes experience flat fading in all frequency channels and choose the elements of 'Cognitive-to-Cognitive' channel matrix H_p as Ricean variable. To generate the matrix, we use the model [6],

$$H_p = \sqrt{\frac{\kappa}{\kappa+1}}\Psi + \sqrt{\frac{1}{\kappa+1}}H_w, \tag{15}$$

where κ represents the Ricean factor, Ψ is an $N_r \times K$ LOS matrix of all ones, H_w is the $N_r \times K$ matrix, with elements being zero mean and unit variance independent and identically distributed (i.i.d.) circularly symmetric Gaussian variables. In the system model, cognitive and primary users use side by side bands, resulting in spill over energy among adjacent frequency bands. To model this spill over energy, we consider the elements of 'Cognitive-to-Primary' channel matrix G, as zero mean and 10^{-3} variance complex Gaussian variables [12]. The remaining simulation parameters are listed above. We use these parameters to build a MATLAB simulation program for the cognitive network introduced in section II. It is to be noted that in the following performance results each data point represents an average over 10,000 events or channel realizations.

TABLE IV: Simulation setting

Parameter	Value
No. of cognitive nodes	40
No. of channels	3
Bandwidth, Channel 1, 2 & 3	0.5 MHz, 1 MHz & 1.5 MHz
Data type	Best effort
Packet arrival rate	2 Packets/s
Packet Payload	8184 bits
ARQ protocol	GBN
ARQ window size	4 Packets
MAC header	272 bits
MAC protocol	CSMA/CA
$\beta, \gamma, \& \delta$ of utility function	0.16, 0.8 & 400
α	0.02
PHY header	127 bits
ACK	112 bits+PHY header
RTS	160 bits+PHY header
CTS	112 bits+PHY header
Slot time	50 μs
DIFS	128 μs
SIFS	28 μs
No. of transmit antennas	4
No. of receive antennas	4
κ	3 dB
Bit rate, channel 1, 2 & 3	0.5 Mb/s, 1 Mb/s, 1.5 Mb/s
Channel switching time	100 μs

First we present the performance results for the antenna selection algorithm. For performance comparison purposes, we consider three cases, viz., Without Antenna Selection (WAS), Maximum Antenna Selection (MAS) and Cross Layer Antenna Selection (CLAS). In the WAS strategy, cognitive nodes transmit using all the available antennas, provided that the interference imposed by primary users is below the prespecified threshold. If the interference constraint is not satisfied, cognitive users turn off all their antennas. On the contrary, cognitive users in the MAS algorithm use physical layer measurements to determine the maximum possible usable antennas given the interference threshold on the primary user is satisfied. In our CLAS algorithm, nodes select the antennas that maximize the LLC transmission efficiency defined by (9).

We plot the transmission efficiency results and percentage of antenna usage in Figs. 2 and 3, respectively. In Fig. 2 one can notice that, at relatively low SNRs ([0-12] dB), the CLAS algorithm offers the largest transmission efficiency where both MAS and WAS have lower but similar transmission efficiency. This is due to the fact that, at low SNRs, the channel between cognitive users has more dominant effect on the BER performance than the imposed interference threshold at the primary user. In the CLAS algorithm, since the performance of the wireless links differ widely at low SNRs, the antenna selection algorithm shows significant transmission efficiency gains. On the other hand, as MAS and WAS algorithms do not consider channel reliability for antenna selection, data packets

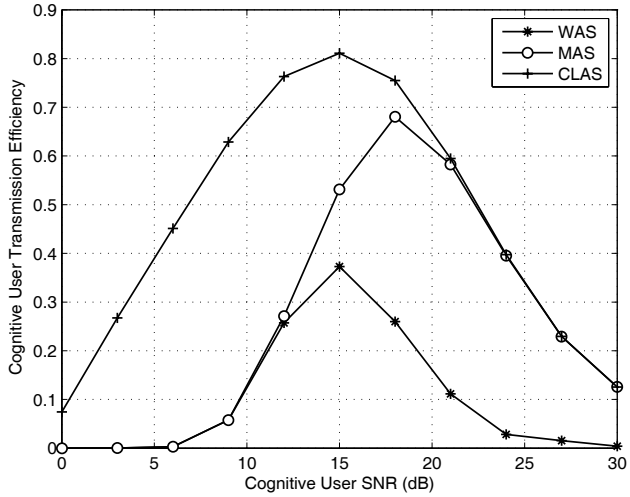


Fig. 2: Transmission efficiency for cognitive nodes with different antenna selection algorithms, primary user interference constraint $\leq$ -10 dBm.

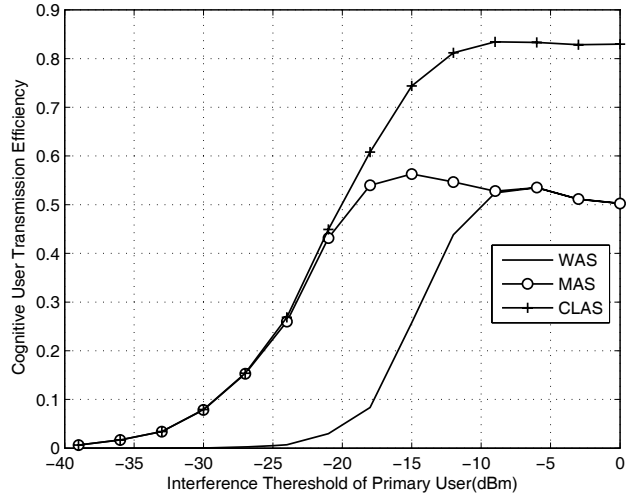


Fig. 4: Achievable cognitive user transmission efficiency for different interference constraints and 12 dB cognitive user transmit power.

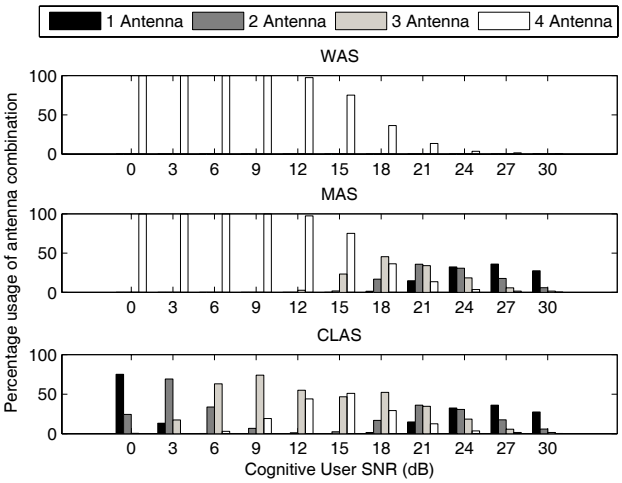


Fig. 3: Percentage of antenna usage for primary user interference constraint $\leq$ -10 dBm.

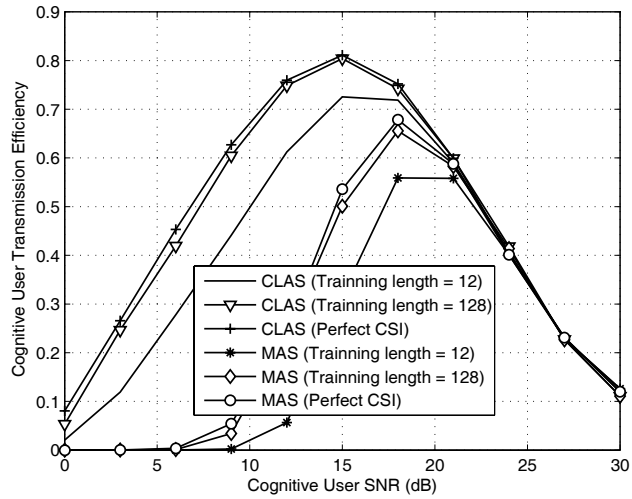


Fig. 5: Transmission efficiency for cognitive nodes with different antenna selection algorithms, primary user interference constraint $\leq$ -10 dBm at imperfect CSI .

need to be retransmitted until it is successfully received. This argument ties well with the percentage of antenna usage results in Fig. 3. As seen, one antenna usage is dominant at very low SNRs ([0-3] dB) while multiple antennas (2 and 3 antennas) combination usage becomes dominant at moderate SNRs ([3-12] dB) for the CLAS. On the contrary, at low SNRs, both WAS and MAS select four antenna combination most of the time.

At high SNRs ([12-30] dB), the results in Fig. 2 indicate that the transmission efficiency of the MAS algorithm improves and converges with the CLAS. Also, all three algorithms reach a maximum value after which, the performance is controlled by the more dominant interference threshold where any increase in SNR results in lower transmission efficiency. This agrees with the results in Fig. 3 where one can notice that when the SNR increases, nodes increasingly become unable to use more antennas due to the interference constraint. One can also see as the channel has less effect at high SNRs, both CLAS and MAS perform equally.

We plot the achievable transmission efficiency curves in Fig. 4 as a function of the primary users' interference threshold, where the transmit power is set to 12 dB. At low values of interference thresholds ([-40 to -20] dBm), the number of usable/selected antennas is very small to limit the effect of interference on primary users. As a result, the CLAS algorithm has fewer choices for antenna selection and hence similar transmission efficiency for both CLAS and MAS algorithms. For the same reasons, the performance of the WAS is very poor in this case. At high interference thresholds, the CLAS has higher degrees of freedom to leverage large transmission efficiency gains.

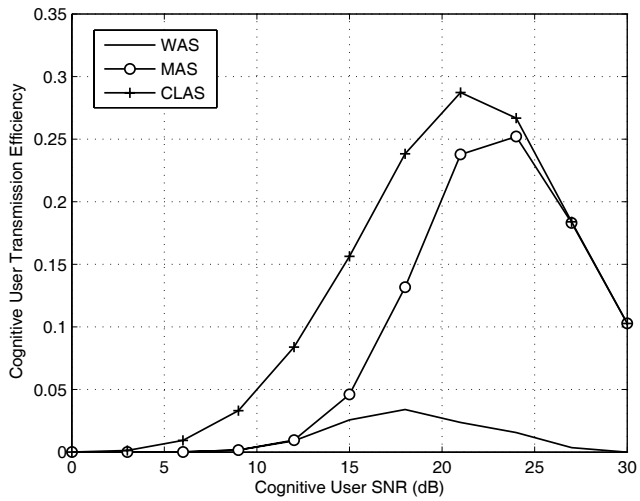


Fig. 6: Transmission efficiency for cognitive nodes with different antenna selection algorithms, primary user interference constraint $\leq$ -10 dBm for error propagation between sub-streams.

At this point we evaluate the effect of CSI and error propagation among sub-streams of the zero forcing algorithm on the system throughput. First, we present results for imperfect CSI. To generate the results we use analysis similar to [7] where training-based channel estimation is employed. From the throughput curves in Fig. 5, one can notice that some performance degradation occurs due to imperfect CSI. With the increase of number of training symbols, the performance of the proposed algorithm show results close to the perfect CSI case. Another important remark is that, in all cases, the proposed cross-layer design is shown to outperform other conventional schemes.

To evaluate the effect of error propagation of the spatially-layered system on the throughput performance, we consider the error propagation model and analytical results presented in [26] and [27]. The corresponding throughput results are shown in Fig. 6. Similar to the imperfect CSI case, one can notice that all systems are affected equally by the error propagation in the detected layers. In all systems, we have noticed throughput degradation relative to the ideal of no error propagation. However, as can be seen, the proposed CLAS still outperforms both the MAS and the case of no antenna selection.

Now we evaluate the performance of the learning-based channel assignment algorithm introduced in Table III. First, we consider the effect of cognitive nodes' data rate variance as a performance matric defined as,

$$var(\chi) = E(\chi_i - \overline{\chi})^2, \tag{16}$$

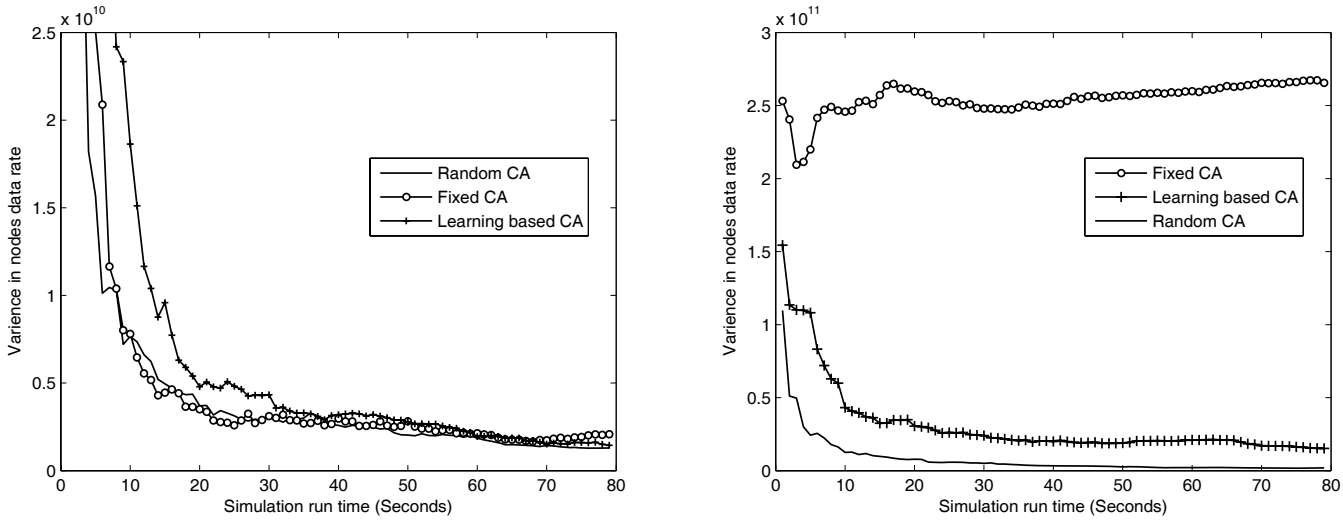
where χ_i is the transmission data rate of node $i \epsilon M$ and $\overline{\chi}$ represents the average data rate over all cognitive nodes i.e., $\overline{\chi} = E(\chi_i), \forall i \epsilon M$. These results are presented in Fig. 7 where we compare the performance of random and fixed channel assignments with the proposed learning-based channel assignment. We consider two scenarios; equal (1 MHz each frequency slot) and unequal channel bandwidth.

In the fixed channel assignment policy, channels are assigned to the cognitive nodes at the beginning of the session for the entire period. However, in random assignment strategy, nodes choose channels randomly before each channel use i.e., packet transmission. The results show that fixed channel assignment strategy, in unequal bandwidth case, results in very high data rate variance among cognitive nodes whereas both learning-based and random algorithms offer lower variance. This happens as channels offer different data rates, and in the fixed channel assignment only few nodes enjoy high data rates while others suffer from congestion. This is different in the learning-based and random channel assignments, as nodes switch channels for better performance. This argument also confirms the similar performance gain of these algorithms when applied to the case of equal bandwidth.

In Fig. 8 we plot the average number of channel switching for the more realistic case of unequal bandwidths. To generate these results, we record the total number of channel switching events that take place during one second interval against the simulation run time. This is true as nodes learn channel behavior over time and start switching channels only for better performance. It is needless to say that low number of switching events indicates lower operation overhead for the learning-based algorithm.

From the previous results, it becomes clear that combining the cross layer antenna selection with the learning-based channel selection can further improve the transmission efficiency of the cognitive network. To demonstrate this, we employ the combined channel and antenna selection algorithm in the multi-band multiuser MIMO cognitive ad-hoc network. We apply four different combinations of strategies for performance evaluation, namely, (1) learning-based channel allocation and CLAS, (2) random channel allocation and CLAS, (3) learning-based channel allocation and WAS, and (4) random channel allocation and WAS. The reported average data rate results in Fig. 9 show that the CLAS algorithm along with learning-based channel selection policy achieves the highest average network data rate. This is simply due to the fact that in learning-based algorithm, nodes have less channel switching events (i.e., less overhead) and hence better throughput.

Apart from the equal interference case presented before, we also study the effect of random interference on the network performance. To generate these results we consider σ in (3) to be uniformly distributed over the range 0 to 12 dB. Given this, we apply the combined channel and antenna selection algorithm in the multi-band multiuser MIMO cognitive ad-hoc network. For performance comparison, we consider the four combinations of antenna selection and channel selection algorithms introduced in Fig. 9. As seen from Fig. 10, the reported average data rate results for the random interference case show that the CLAS algorithm along with learning-based channel selection policy achieves the highest average network data rate. This is simply due to the fact that in learning-based algorithm, nodes have less channel switching events (i.e., less overhead) and hence better throughput. However, it is worthwhile to notice that the performance comparison of the antenna selection and the channel selection algorithms show similar trend for both equal (Fig. 9) and random interference (Fig. 10) cases.



(a) (b)

Fig. 7: Variance in nodes data rate for channel assignment algorithms for (a) Equal bandwidth and (b) Unequal bandwidth, at 12 dB cognitive user transmit power and interference threshold $\leq$ -10dBm.

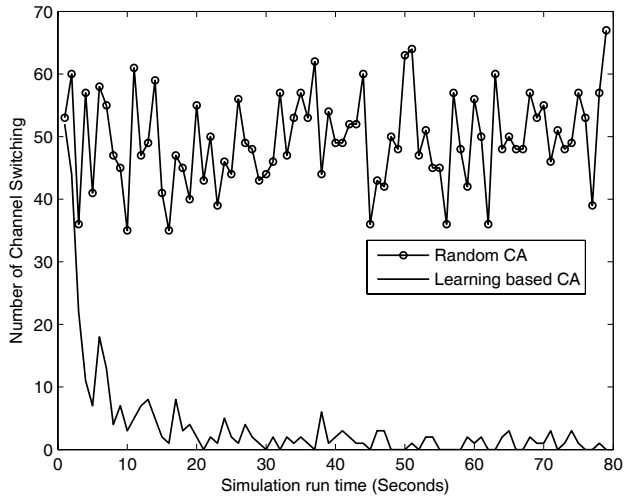


Fig. 8: Total number of channel switching events in the cognitive network at 12 dB cognitive user transmit power and interference threshold $\leq$ -10dBm with unequal frequency slots.

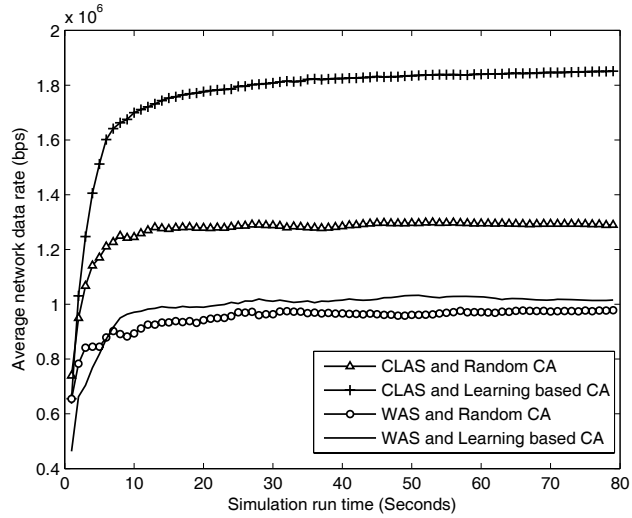


Fig. 9: Average data rate of the cognitive nodes for different antenna selection algorithms at 12 dB transmit power and interference threshold $\leq$ -10dBm with unequal frequency slots.

V. Conclusions

We investigated the performance of cross layer antenna allocation and channel selection approaches for cognitive ad-hoc networks. We presented the average data rate objective function for multi band cognitive ad-hod network that accounts for interference constraints at the primary users. It was shown that the cross layer antenna selection algorithm can improve the transmission efficiency, and the learning based algorithm can reduce the data rate variance among cognitive nodes as well as number of channel switching events. Our results also indicate that when the cross layer antenna selection algorithm is combined with the learning-based channel selection, the average data rate of the cognitive network improves significantly.

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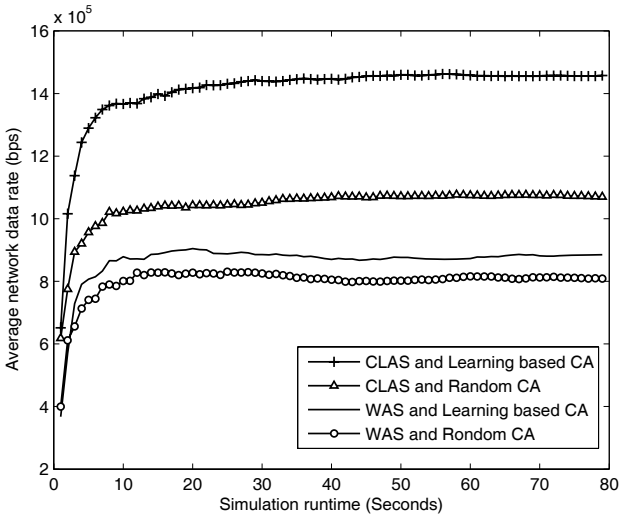

Fig. 10: Average data rate of the cognitive nodes for different antenna selection and channel selection algorithms for interference threshold $\leq$ -20dBm with unequal frequency slots and random interference at primary users.

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