A Game-Theoretic Spectrum Allocation Framework for Mixed Unicast and Broadcast Traffic Profile in Cognitive Radio Networks

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***Abstract*—In this paper, we present a game theoretic framework for spectrum allocation in distributed cognitive radio networks containing both unicast and broadcast traffic. Our proposed scheme aims to minimize broadcast latency for broadcast traffic and minimize interference and access contention for both types of traffic. We develop a utility function that ensures that both objectives are met yielding a higher network throughput. Our proposed spectrum allocation game is also formulated as a potential game and is guaranteed to converge to a Nash equilibrium if the sequential best response dynamics is followed. A proof of concept of the proposed algorithm has been implemented on the Orbit radio testbed and the results verify the convergence of the potential game. Our simulation and experimental results also reveal that the choice of utility function improves the average network throughput for a mixed traffic profile.**

***Index Terms*—Broadcast Traffic, Spectrum Assignment, Cognitive Radio Networks, Unicast Traffic, Game Theory, Nash Equilibrium (NE)**

I. Introduction

Cognitive Radios (CRs) have recently emerged as an effective solution for efficient utilization of the wireless spectrum. They can sense the RF environment and make decisions to improve their performance by dynamically adjusting the transmission parameters. Cognitive Radio Networks (CRNs) essentially comprise of licensed spectrum users called the Primary Users (PUs), and Secondary Users (SUs) that opportunistically use the spectrum while the PUs are idle. SUs periodically search the spectrum to identify white spaces that can be used for their communication, avoiding harmful interference to the PUs. In this work we assume a *spectrum sensing cognitive radio* [1] that only uses dynamic spectrum access, instead of the *full cognitive radio* envisioned by Mitola in [2].

Channel Assignment (CA) or Spectrum Allocation (SA) is the basic mechanism that aims to reduce the performance degradation in wireless networks particularly due to interference or access contention. In networks where the dominant traffic type is either unicast or broadcast or a combination of the two, spectrum allocation becomes crucial since both the traffic types have fundamentally conflicting preferences. This problem is particularly relevant for cognitive wireless sensor networks, which may have to deal with both unicast and broadcast traffic. In this paper, we consider one-hop broadcast and unicast traffic since they form the basis for multi-hop communication.

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Unicast traffic would prefer to have minimum interference as well as access contention from neighboring nodes thus requiring different channels being used in the neighborhood of a node. On the contrary, broadcast traffic would prefer to have all its neighbors on the same channel, thereby reaching all the neighbors in a single transmission, thus exploiting the Wireless Broadcast Advantage (WBA) [3]. If broadcast takes place in a network having many diverse channels, it will have to repeat its transmissions for every neighbor each time changing its transmission frequency, thus increasing the broadcast latency. Similarly, if unicast takes place in a network using a common channel, nodes would suffer from access contention as well as interference which significantly degrades its performance.

In such a scenario, an efficient SA algorithm should intelligently assign similar channels to nodes in the transmission range of the broadcast sources and distribute the rest of the channels in the network so as to simultaneously satisfy the conflicting requirements of minimizing interference and maximizing connectivity.

In this paper, we propose a dynamic and distributed spectrum allocation framework that takes into account the preferences of both unicast and broadcast traffic and also adapts according to the changing patterns of these traffics to provide a high network throughput. We use a game theoretic framework to solve this SA problem since the CR nodes can be seen as autonomous agents and it is appropriate to model their interactions using a spectrum game in which the nodes are the players while their actions are the choice of channels selected for communication, which affect their performance as well as the performance of other nodes.

For the purpose of performance evaluation, we implement our algorithm on the GNU Radio platform. GNU Radio is one of the open source Software Defined Radio (SDR) [4] platforms which enables us to dynamically change physical radio parameters. The Universal Software Radio Peripheral (USRP) provides a reconfigurable RF front end while the signal processing and other functions are implemented using GNU Radio and standard computers. The experiments are performed at the Orbit [5] radio grid testbed located at Rutgers University [6] which comprises of a grid of wireless nodes

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some of which are equipped with the USRP hardware.

We compare our algorithm with an adaptive minimum interference channel allocation algorithm proposed in literature [7], which we refer to as the *baseline* algorithm. We also compare our work with the *Common Channel Assignment (CCA)* [8] algorithm which is suited to broadcast traffic since it uses a common channel on all nodes and maximizes connectivity. Therefore we use these algorithms as a reference to measure the effectiveness of our proposed scheme.

The main contributions of this paper are as follows:

- A distributed and dynamic channel assignment algorithm based on a game theoretic framework, which adapts according to the type of traffic in the network.
- Formulation of a utility function that incorporates the preferences of both unicast and broadcast traffic.
- A comprehensive performance evaluation of the proposed algorithm on the Orbit testbed that shows significant improvements in the overall network throughput.

The remaining sections are organized as follows: in section II we review some of the existing work related to dynamic channel assignment in CRNs. Section III states the system model and assumptions, section IV discusses our proposed game theoretic framework, section V evaluates the performance of our algorithm, and finally we conclude the paper in section VI.

II. Related Work

Spectrum Assignment has been thoroughly examined in literature particularly for cognitive radio networks. Both centralized [9] [10] and distributed [11] approaches have been proposed to solve these problems in CRNs. Different criteria for channel assignment have been employed including minimizing interference [12] and delay [13] or increasing throughput [9], connectivity [14] and energy efficiency [15] [16]. In [10], a centralized solution for receiver based channel assignment is provided. A Tunable Transmitter - Fixed Receiver (TT-FR) communication mode is used which ensures network connectivity and avoids the need of a Common Control Channel (CCC).

In [11], the ZAP algorithm is proposed, which uses local knowledge to provide efficient channel allocation in distributed cognitive networks. It uses graph theory to construct a conflict graph and then uses it in the channel selection framework according to the 2 hop binary interference model. Although, the ZAP algorithm is suitable for localized unicast traffic due to its minimum interference characteristics, it is not efficient for broadcast traffic and will thus incur broadcast latency.

On the other hand, several works including [17], [18] and [19] present algorithms developed for minimum latency broadcasting using broadcast scheduling. A channel assignment algorithm for effective data dissemination, SURF has been proposed in [20], however it suffers from access contention and interference if used for unicast traffic. Although the SURF approach is effective for broadcast, we aim to achieve the same objective using efficient spectrum allocation that also caters for unicast traffic in the network.

Recently game theory has found widespread application in distributed spectrum assignment problems since it aptly models the interactive decision making process among autonomous cognitive radio nodes. A stable spectrum decision is sought using the concept of the Nash equilibrium. A game-theoretic interference minimization scheme has been proposed in [7], in which the author provides a utility function, which captures the interference perceived by a node as well as the interference created by that node for other nodes. The author also formulates a potential game for cooperative users and shows that the scheme converges to the Nash equilibrium. Furthermore, a framework based on Φ-no regret learning, has also been developed for a non-cooperative game. A potential game approach similar to the one in [7] is used in [21] to manage the interference in the network considering the interference to the primary users. The utility function also incorporates a power efficiency objective.

Although the game theoretic and learning algorithms mentioned above are adaptive schemes, they do not consider the type of traffic in the network. Therefore such schemes, although better than static allocation algorithms, do not solve the problem in networks containing significant broadcast and thus incur a cost in terms of broadcast latency. Moreover, such schemes also do not adapt in dynamic traffic environments and thus offer a reduced throughput performance.

Spectrum allocation for mixed unicast and broadcast traffic profile has been investigated previously by the UCA [22], in which a weighted average based channel weight function is formulated. The weight function includes both the interference and connectivity parameters, which are weighted according to the relative proportions of broadcast and unicast traffic. Although the UCA provides a higher network throughput than traditional schemes in a mixed traffic scenario, the proposed weight function is not guaranteed to converge to a stable solution. The UCA also suffers from connectivity problems due to the absence of a channel coordination mechanism.

Therefore, we develop a dynamic and distributed framework that can fit into a variety of mixed traffic networks and provides a high network throughput due to its adaptive behavior.

III. System Model

We consider a Cognitive Radio Ad-Hoc Network (CRAHN) [23] of N stationary nodes uniformly distributed in a square region. Each node has a homogeneous set of available channels, C to be used for communication. Additionally we assume that the transceivers are full duplex and follow the Tunable Transmitter - Fixed Receiver (TT-FR) communication paradigm used in [10], whereby SU nodes can receive on a fixed frequency but can transmit on different frequencies. Our proposed algorithm, therefore, assigns channels to nodes as opposed to links in the network. The advantages of using such an architecture are: (1) it ensures full network connectivity if neighbors have at least one common channel; (2) it does not require a channel coordination between the nodes for communication. Further validation on the use of the TT-FR architecture can be found in [10].

In this paper, we assume that the nodes have information about the available channels to use for communication and thus spectrum sensing in not part of our algorithm.

IV. Game Theoretic Framework

Game theory provides a mathematical framework for interactive decision making between autonomous agents. It helps in predicting the outcomes of these interactions and in identifying optimal strategies for the players. Typically, a game consists of a set of players, a set of strategies available to those players and the utility associated with each combination of strategies.

In this work, we model our spectrum assignment problem with a normal form game in which, the players are all the SU nodes, the strategies are the channels available to each node and the utility is their preference associated with the choice of a particular channel. Mathematically, the normal form game can be expressed as $\Gamma = \{\mathcal{N}, \mathcal{S}_i, \mathcal{U}_i\}_{i\in\mathcal{N}}$, where $\mathcal{N} = \{0, 1, 2, ..., N\}$ is the finite set of players and $\mathcal{S}_i$ is the set of strategies (channels) associated with player i.

The strategy space is defined as $\mathbb{S} = \times\mathcal{S}_i, i \in \mathcal{N}$ and the set of utility functions that the players associate with the strategies is defined as $\mathcal{U}_i : \mathbb{S} \rightarrow \mathbb{R}$. The strategy selected by player i is denoted by s_i while $s_{-i} = \{s_1, ..., s_{i-1}, s_{i+1}, ..., s_N\}$ collectively represents the strategies of all other players except player i. $\mathcal{U}_i$ represents the payoff received by player i as a function of the action it chooses, s_i and the action of other players, s_{-i}.

A Nash equilibrium is used to predict the outcome of the game and is defined as a strategy profile for which a unilateral deviation does not result in any gain for the deviating player. A strategy profile, $\mathcal{S} = \{s_1, s_2, ..., s_N\}$ for the players is a Nash equilibrium if and only if

$$\mathcal{U}_i(\mathcal{S}) \geq \mathcal{U}_i(s_i', s_{-i}), \forall i \in \mathcal{N}, s_i' \in S_i. \quad (1)$$

where s_i' is a strategy other than s_i.

A. Interference Model

In our work, we use a generic n-hop binary interference model for the network where nodes either interfere or do not interfere. We assume a worst case scenario where all the nodes are receiving traffic and hence nodes selecting the same channel are deemed to cause interference. The interference function, $f(i, j)$ characterizes the interference as well as access contention perceived by node i due to node j and is defined as:

$$f(s_i, s_j) = \begin{cases} 1 & \text{if } s_i = s_j, i \neq j \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

The interference perceived by node i due to all the other nodes in the network can then be summarized by the function:

$$I_i(s_i, s_j) = \sum_{\substack{j=1 \\ j\neq i}}^{N} n_{i,j}^{-\gamma} f(s_i, s_j), \quad (3)$$

where $n_{i,j}$ is the number of hops between node i and node j and γ is the path loss exponent. In this work, we assume that $\gamma = 4$ and the hop distance is identical for all the links, which is consistent with our experiments on the Orbit testbed.

B. Utility Function

The utility function that we propose ensures that the nodes in one-hop neighborhood of a broadcast source have a higher incentive to switch to a common channel whereas nodes more than one-hop away from the broadcast source strive to minimize the interference with nearby nodes. Such a channel allocation is desired because the broadcast transmitter would be able to reach all its neighbors in a single transmission whereas the unicast transmissions can take place with minimum access contention.

The utility of node i given it selects strategy s_i and other players select s_{-i}, is defined by the following function:

$$\mathcal{U}_i(s_i, s_{-i}) = -w_{a,i} I_i(s_i, s_{-i}) - w_{b,i} T_i(s_i, s_{-i}) \quad (4)$$

$$\forall i \in \mathcal{N}.$$

$$T_i(s_i, s_{-i}) = \sum_{\substack{k=1 \\ k\neq i}}^{N} \sum_{\substack{j=1 \\ j\neq i \\ j\neq k}}^{N} \alpha_k \beta_{i,k} \beta_{k,j} g(s_i, s_j), \quad (5)$$

where

$$\alpha_k = \begin{cases} 1 & \text{if } k \text{ is broadcast source} \\ 0 & \text{otherwise,} \end{cases} \quad (6)$$

$$\beta_{i,k} = \begin{cases} 1 & \text{if } i \text{ and } k \text{ are one-hop neighbors} \\ 0 & \text{otherwise,} \end{cases} \quad (7)$$

and

$$g(s_i, s_j) = 1 - f(s_i, s_j). \quad (8)$$

$I_i(s_i, s_{-i})$ is the interference function as defined in eq(3). This makes sure that the same channel is assigned to nodes separated by a maximum number of hops depending on the number of available channels. $T_i(s_i, s_{-i})$ estimates the broadcast latency incurred against a particular strategy profile. Due to these functions, two neighboring nodes can only be assigned a same RX channel if they are in the transmission range of a broadcast transmitter. $w_{a,i}$ and $w_{b,i}$ are the weights associated with the interference and broadcast latency objectives on i^{th} node respectively and signify the relative importance of both the traffics in the network. Adjusting these two coefficients in the utility function, we can set the preference of achieving the objectives of the utility function. This would create an impact when the unicast and broadcast traffic overlap and nodes need to decide which type of traffic to prefer over the other. In this paper, we use $w_{a,i} = 1$ whereas $w_{b,i} = 2$, when broadcast traffic received by a node is greater than the unicast traffic and $w_{b,i} = 1$ otherwise.

C. Potential Game Formulation

A potential game is a class of games for which there exists a potential function representing the network utility. The potential function summarizes the incentive of all the players in the game to change their strategies. If the players take action sequentially in a potential game, then the game converges to a pure strategy Nash equilibrium which maximizes the potential function [24].

Mathematically, a game is a potential game if there exists a potential function $P : \mathbb{S} \rightarrow \mathbb{R}$, that satisfies the property:

$$\mathcal{U}_i(s_i, s_{-i}) - \mathcal{U}_i(s'_i, s_{-i}) = P_i(s_i, s_{-i}) - P_i(s'_i, s_{-i}). \tag{9}$$

For our proposed spectrum assignment game with a utility function $\mathcal{U}_i(s_i, s_{-i})$, we define an exact potential function to be:

$$P(s_i, s_{-i}) = -\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N} \frac{w_{a,i}^2}{w_{a,i}+w_{a,j}} n_{i,j}^{-\gamma} f(s_i, s_j) - \sum_{i=1}^{N}\sum_{\substack{k=1\\ k\neq i\\ k\neq j}}^{N}\sum_{\substack{j=1\\ j\neq i\\ j\neq k}}^{N} \frac{w_{b,i}^2}{w_{b,i}+w_{b,j}} \alpha_k \beta_{i,k}\beta_{k,j} g(s_i, s_j). \tag{10}$$

A proof of the exact potential function is provided in the Appendix[1] for interested readers. In order to converge to a Nash equilibrium, the potential game must be played in a way that players take decisions sequentially. However such scheduling of the decision process is not feasible in a CRAHN. Therefore we use the random access decision making described in [7], in which each node executes a Bernoulli trial at the beginning of each time slot and if successful, plays the best response strategy. The probability of success in the trial, $p = 1/N$ where N is the number of players in the game. This method ensures that on average, at least one player makes a decision in a time slot. However, two or more nodes may also be successful at the same time and may take a decision simultaneously. We show experimentally that our framework ultimately converges to the Nash equilibrium despite multiple simultaneous decisions.

To provide information required for the calculation of utilities on a node, we assume that a common control channel is available to all SU nodes on a dedicated interface [25]. The information required for the execution of our algorithm is:

- A list of players of the spectrum allocation game
- A list of one hop neighbors of all the network nodes
- Knowledge of broadcasting node(s) in the network
- Channel selected by other players

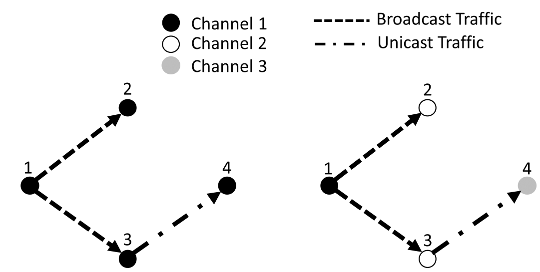
The steps mentioned in *Algorithm 1* are executed on all the nodes. Initially, each node selects a common channel and tunes it for receiving traffic. A Bernoulli trial is then played by the nodes with a success probability of $1/N$. If a node is successful, it calculates the interference as well as the broadcast latency parameter to evaluate the utility for all the possible strategies. The strategy with the highest utility, considering the decisions of other nodes is selected by the node as its RX channel. In case of multiple strategies having the same utility, a channel is selected at random. This is called the best response play in which each node plays its best strategy taking into account the decisions of other players. This decision made by the node is then announced to other nodes to assist them in making their channel decisions.

If the Bernoulli trial is unsuccessful, the node sits idle and listens to the control interface for decisions made by other nodes. The entire process is then repeated continuously in order to adapt to the changing traffic and dynamic network conditions. We further elaborate the execution of our algorithm with an example.

[1] Appendix can be found at http://goo.gl/U4lVv

Algorithm 1 *Dynamic Spectrum Assignment for Unicast & Broadcast Traffic*

1: Common channel assignment
2: Bernoulli trial with $p = 1/N$
3: **if** trial is successful **then**
4: Compute interference perceived using eq (3)
5: Calculate broadcast latency parameter using eq (5)
6: Determine utility for all set of strategies using eq (4)
7: Select channel with highest utility considering the decisions of other players (select randomly if several channels have the same utility)
8: Announce channel decision using the control interface
9: **else**
10: Listen on the control interface for decisions made by other players
11: **end if**
12: Repeat step 1 to 9



(a) Before channel assignment (b) After channel assignment

Fig. 1: Example Channel Assignment

Example: We will now explain this algorithm through an example. Let's consider a network of 4 nodes arranged in the topology in Figure 1(a). We have chosen a simple example limited to 4 nodes for ease of exposition. However the insights gained also scale to larger networks. Each node has 3 available channels to select for receiving traffic. The network contains one unicast source (node 3) and one broadcast source (node 1) and the traffic flows are identified in the figure. Initially, all the nodes are assigned a common channel (in this case, channel 1), as illustrated in Figure 1(a). Each node has a strategy space of all the possible strategy profiles. In this example the strategy space contains 81 entries since the possible combinations of strategy profiles for 4 nodes with 3 available channels are 3^4. The nodes, play a Bernoulli trial with a success probability of $1/N$ i.e. $1/4$. If a node is successful, it computes the interference and broadcast latency parameter defined in eq. (3) and eq. (5) respectively to calculate the utility from eq. (4), against all the strategy profiles. A strategy profile that has the highest utility for that particular node is then selected. In

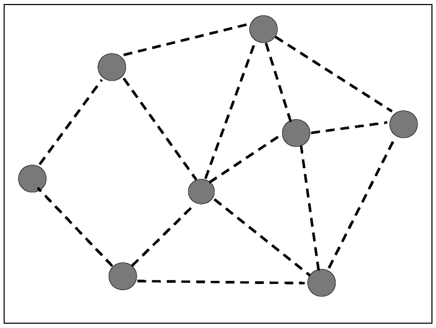


Fig. 2: Topology of nodes used at Orbit testbed

TABLE I: GNU Radio Configurations

Parameter	Value
Modulation	DBPSK
Frequency	400 MHz
Bit Rate	100 kbps
MAC Protocol	CSMA
Transport Protocol	UDP

case of multiple profiles having the same utility, a decision is made at random with all the profiles being equally likely. Finally, the channel decision is announced to all the players. If the Bernoulli trial is unsuccessful, the node waits and listens for channels selected by other nodes to use them in its decision making. When all the nodes have reached to a stable state, the Nash equilibrium is achieved since our game is formulated as a potential game.

The final channel assignment is illustrated in Figure 1(b). For the selected strategy profile i.e. $\mathcal{S} = \{1, 2, 2, 3\}$, the utilities of individual nodes are evaluated to be $\mathcal{U} = \{0, -2^{-4}, -2^{-4}, 0\}$ and the sum of these utilities is the highest among all other strategy profiles. It can be observed that for the given topology and traffic profile in our example, the broadcast transmitter is able to reach its neighbors in a single transmission since both the receivers have selected a common channel i.e. channel 2, as their RX channel. The other nodes, select different RX channels so as to cause minimum interference and access contention to the other transmissions.

In this way, our spectrum allocation framework is able to satisfy the needs of both the traffics simultaneously. For simplicity, we did not consider overlapping unicast and broadcast traffic in this example, but our algorithm has the provision to accommodate such scenarios by selecting appropriate coefficients in the utility function according to the priority of the traffic objectives.

V. Performance Evaluation

We perform a comprehensive evaluation of our algorithm using both the Orbit testbed and simulations. The methodology used and results obtained are detailed in the subsequent subsections.

A. Experiment Setup

The performance of our proposed algorithm is evaluated using the GNU Radio / USRP platform available at the Orbit radio grid testbed. The Orbit testbed consists of a grid of 400 (20x20) wireless nodes with an inter-node spacing of ~1m. For our experiments, we use 8 nodes on locations shown in the map in Figure 2, due to limited availability. We run our experiments on USRP N210 nodes equipped with SBX Wide Band Transceiver daughterboards. The SBX provides a 40 MHz of bandwidth capability and can be used to access a number of different bands within the frequency range 400 MHz to 4400 MHz. Since the USRP devices have a single radio interface, we utilize the wifi interface of each node as the control interface.

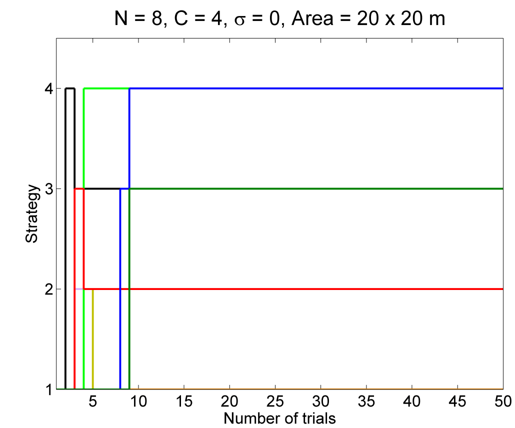
For the implementation of our algorithm, we have used the functionality of the *tunnel.py* program available in GNU Radio examples for communication between the nodes. This program creates a virtual tun-tap interface on the node which enables us to use the GNU Radio at the PHY layer while using the higher layers from the TCP/IP protocol stack implemented in linux kernel. Table I lists the configurations and protocols that were used for the data transmission in the experiment.

B. Metrics

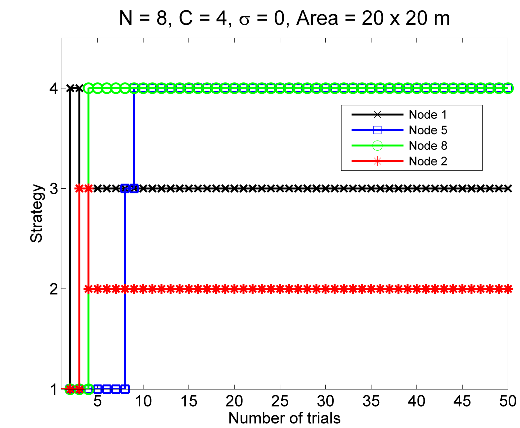
The following metrics have been used to evaluate the performance of our algorithm:

- *Average Network Throughput*:
  It is the average rate of successful message delivery in the network and is defined as:
  $$Throughput = \frac{1}{N}\sum_{i=1}^{N}\frac{R_i}{\Delta t}. \quad (11)$$
  where R_i is the number of packets received by i^{th} node and Δt is the experiment time.
- *Removed Interference*:
  It measures the percentage of Interference (as defined in eq. (3)) that has been removed by the channel assignment as compared to the CCA. It is defined as:
  $$Removed\,Interference = \frac{I_{max} - I_{calculated}}{I_{max}}. \quad (12)$$
  where I_{max} is the sum of interference perceived by all the nodes when only one channel is available while $I_{calcualted}$ is the total interference calculated after our proposed algorithm has converged to an equilibrium point.

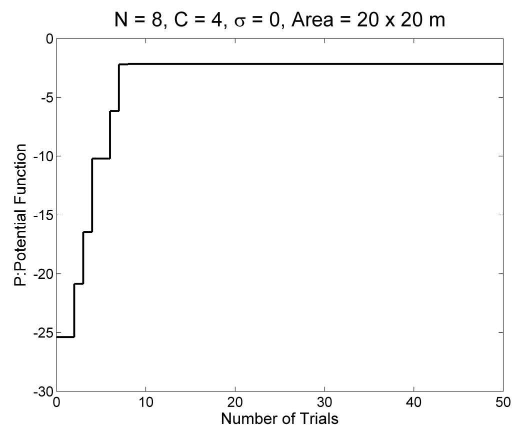
We also evaluate the performance of our algorithm against the broadcast traffic proportion parameter referred to as ζ. This is a measure of the relative proportion of broadcast and unicast traffic in the network and is calculated according to the number of flows of both the traffics. Furthermore, we define the traffic variability parameter, σ which refers to the probability that the traffic changes from broadcast to unicast or vice versa in the next time slot. It is essentially a value between 0 and 1 where 0 represents that the traffic profile is static and does not change in the next slot while 1 represents a very dynamic traffic where the traffic type changes in every slot. These parameters are



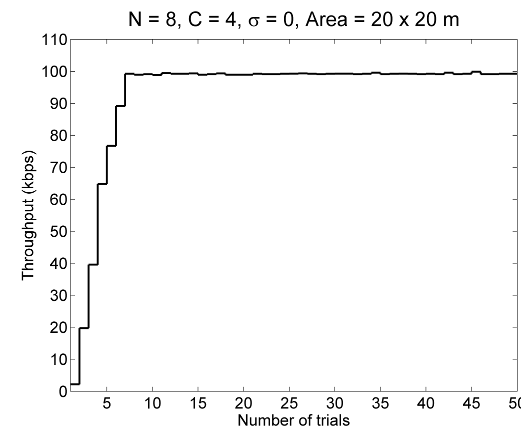
(a) Strategy evolution of all the players in the potential game



(b) Strategy evolution of selected players



(c) Potential function evolution



(d) Throughput evolution

Fig. 3: Convergence properties of Game Theoretic framework.

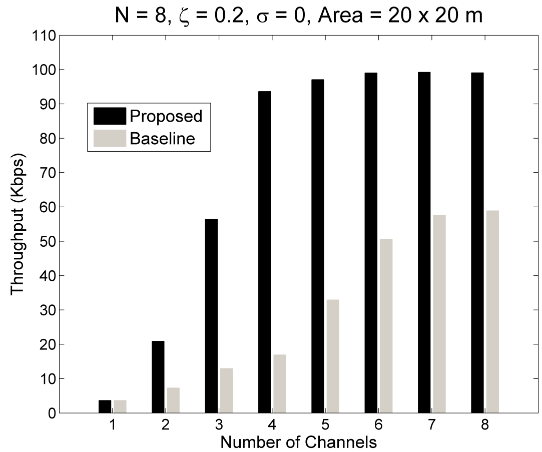
used to study the results of our proposed algorithm under dynamic traffic conditions.

C. Results

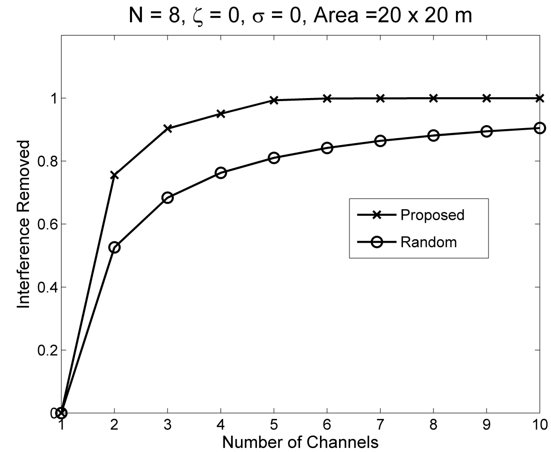
Convergence properties: We will first show the convergence properties of our algorithm. Since we have formulated a potential game, we expect our algorithm to certainly converge to a pure strategy nash equilibrium. Figure 3(a) and 3(b) confirm that for a constant traffic, the strategies adopted by the nodes ultimately converge to a stable solution after which there is no further incentive for any node to deviate from its selected strategy. The convergence is also evident from Figure 3(c), which shows that the value of the potential function increases monotonically to reach a maximum value. Thus by adopting a best response strategy, the overall network utility is maximized. Similarly, Figure 3(d) shows that for a non-varying traffic, the average network throughput progressively increases as the game converges to the equilibrium point.

Efficiency and interference minimization: The average network throughput for our proposed scheme increases as the number of channels available to the nodes increase for a given broadcast/unicast traffic mixture ($\zeta = 0.2$). As compared to the baseline algorithm, optimized for unicast traffic, our algorithm provides significant throughput improvements due to a traffic centric approach. Also, the rate of throughput increase against the number of channels is higher than the baseline algorithm signifying a higher spectrum assignment efficiency, evident from Figure 4(a). Figure 4(b) shows that for a unicast-only network (i.e. $\zeta = 0$), our algorithm is able to minimize the interference, if sufficient number of channels are available. In our experiment of 8 nodes, the algorithm can successfully remove 90% interference with only 3 available channels. This characteristic is similar to the baseline algorithm so we can conclude that our algorithm exactly reflects the properties of the baseline algorithm for a network with unicast traffic only. A random channel selection on nodes is unable to completely remove the interference even with a large number of channels.

Effect of traffic proportion on throughput: The advantage of our proposed algorithm is illustrated in Figure 5(a). Our algorithm provides a consistently higher average network throughput for different values of the broadcast traffic proportion, ζ given that the coefficients in the utility function are tuned appropriately. This is because our algorithm leads to a higher throughput for both unicast and broadcast traffic. On the other hand, both the baseline and the CCA are significantly affected

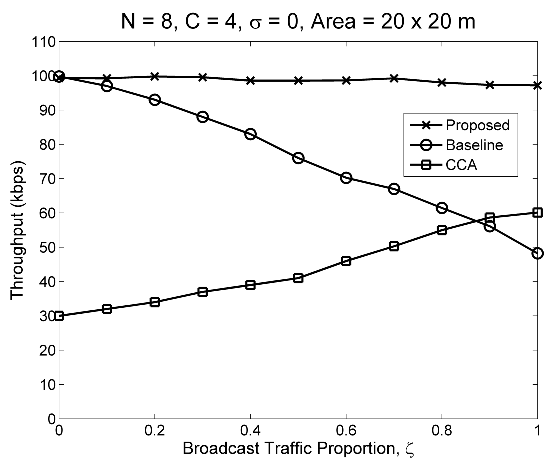


(a) Average network throughput against number of channels

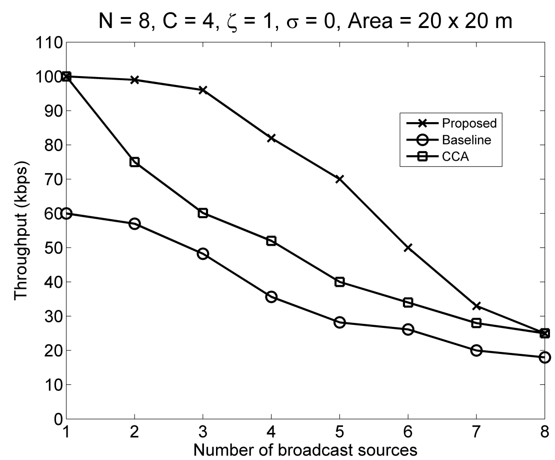


(b) Percentage of removed interference against number of channels

Fig. 4: Experimental results of throughput and removed interference.



(a) Average network throughput against broadcast traffic proportion



(b) Average network throughput against number of broadcast sources

Fig. 5: Simulation results of throughput against broadcast traffic proportion and number of broadcast sources.

by the proportion of broadcast traffic in the network because they favor one type of traffic. The performance of the baseline deteriorates significantly when the proportion of broadcast flows increases mainly because of the broadcast latency associated with a minimized interference channel allocation. On the contrary, CCA has a worse throughput performance when the network has all unicast flows since several transmitters would fight for access to the same channel. When the network contains only broadcast traffic, the performance of the CCA although improves but not as much because multiple broadcast transmitters would also interfere and contend for access on the same channel ,thus degrading the performance. Our proposed algorithm can be made to provide a higher network throughput under different mixtures of broadcast/unicast traffic.

Effect of number of broadcast sources on throughput: We observe that the number of broadcast sources in the network also significantly impacts the throughput of the network. If multiple nodes start transmitting broadcast traffic, it is difficult to assign channels in a way that all the nodes receiving broadcast traffic from a source select the same channel. This problem grows as the number of broadcast sources increase as illustrated in Figure 5(b). Our proposed strategy clearly outperforms the reference algorithms. The baseline performs badly in a broadcast-only network and becomes worst as the number of broadcast sources increase. The CCA and our proposed algorithm perform identically in a broadcast only network with one broadcast source. Similarly, when all the network nodes become sources of broadcast traffic, our algorithm converges to the CCA. However, CCA shows an exponential decrease in throughput as the number of broadcast sources increase.

Adaptive properties: We have also evaluated the throughput of our proposed algorithm in the presence of a varying traffic profile. The traffic variability factor, σ captures the probability

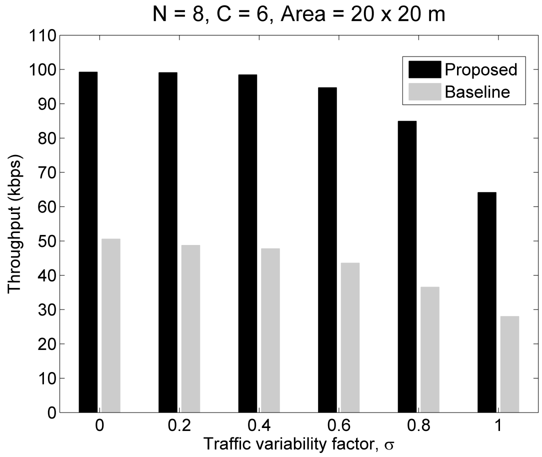


Fig. 6: Average network throughput against traffic variability factor, σ

that the traffic profile changes in every next time slot in the execution of the game. $\sigma = 0$ indicates that the traffic is monotonous, while $\sigma = 1$ represents a highly dynamic traffic profile. Figure 6 shows that our proposed algorithm demonstrates an adaptive behavior similar to the baseline algorithm but maintains its higher throughput characteristics.

VI. Conclusion

In cognitive radio networks having a mixed unicast and broadcast traffic profile, resource allocation to individual radios becomes challenging due to the conflicting preferences of both the traffics. This paper provides a dynamic and distributed spectrum sharing framework using game theory, which serves the preferences of both the unicast and broadcast traffic. We formulate the spectrum allocation problem as a potential game that is guaranteed to converge to a pure strategy Nash equilibrium if the sequential best response dynamics is used. Our main contribution is the development of a utility function that incorporates both the minimum interference and minimum broadcast latency objectives. Through coefficient adjustment in the utility function, we can set the priorities of these objectives and thus our proposed scheme can be used in a variety of different networks as well as mixtures of traffic profiles.

A proof of concept of the algorithm has been performed at the Orbit testbed using the GNU Radio/USRP platform. Experimental results show that our algorithm indeed converges to a stable solution even when the best response dynamics based on a Bernoulli trial are used. Simulation and testbed results also confirm that our proposed framework provides a higher network throughput under different proportions of broadcast and unicast traffic in the network. The algorithm shows an adaptive behavior under a dynamic traffic profile as opposed to traditional static allocation schemes, thus avoiding the performance degradation under dynamic traffic conditions.

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