COST DOMINATED CONGESTION CONTROL IN SPECTRUM SHARING COGNITIVE RADIO NETWORKS

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Abstract - The increased demand of scarce bandwidth resources in wireless networks may result in poor communication and congestion. In Cognitive Radio networks, an efficient resource sharing approach is a pivotal issue for cognitive radio users (secondary users). The users compete to avail best suitable channel in a selfish manner that may result in excessive interference causing degradation in Quality of Service within the network. This paper addresses the selfish behavior of Cognitive Radios as well as the congestion on the available spectrum using game theoretic approach. In order to mitigate the effects of selfish behavior, it is interesting to apply cooperative game and improve spectrum sharing. The equilibrium of cooperative congestion game is considered socially optimal if and only if the cost of players can be interpreted as a negative function. This leads to the ultimate minimization of aggregate cost shown as the maximization of a global function of the network. The cost dominance is considered as an influencing factor for CRs to cooperate.The simulation results show the convergence of utility and achieving Nash equilibrium at a desirable point.

Keywords - Cognitive Radio, Cooperative Congestion Game, Spectrum Sharing, Waveform Adaptation, Nash Equilibrium

I. INTRODUCTION

In this modern era of high speed communications, the users and designers face the issue of efficient spectrum utilization primarily due to its scarcity. In general, sometimes the wireless systems have licensed spectrum bands allocated to primary users (PU) that are often underutilized. However, the cognitive radio paradigm has eased the problem of spectrum utilization. In cognitive radio networks, the licensed PU can opportunistically share its bandwidth with a secondary user (SU). When the secondary users sense the spectrum holes to transmit their information, a competition begins with other users in the network for the available bandwidth. Since no central coordinator is involved in cognitive radio networks, all SUsselfishly try to maximize the throughput. Assuming the restriction of each node having single radio transceiver, only one channel can be accessed by each SU in the network [1]. The throughput of a SU depends upon the number of SUs sharing a spectrum that ultimately results in congestion.

In order to avail channel opportunities, the cognitive radios have the ability to switch the channels quickly, so that significant interference can be avoided [2]. The cognitive radios then use power control or successive waveform adaptations to maintain the cut-off level in SNR that supports the channel allocation and setting power constraints, respectively. Ideally, channel switching of cognitive radios should not cause any disruption in their current activity, but in practice inevitable disturbance is caused. Cognitive radios, therefore, need to balance the channel switching and spectrum sharing benefits and cost altogether. Cognitive radio is a specialized technology for spectrum sharing and coordinating in order to mitigate conflicts among spectrum sharing devices. Interference mitigation is the major objective to deal with in cognitive radio networks. Along with the power control, suitable waveform generation is required to minimize interference. Many waveform adaptation algorithms are used to define suitable waveforms for the channel opted by the CR. The greedy interference avoidance (IA) waveform adaptation algorithms update the codes sequentially [3]. The iterative methodology generates a set of orthogonal sequences todecrease total squared correlation. Normalized MMSE receiver replaces the corresponding sequences. These MMSE algorithms depend upon the stochastic receiver measurements; hence the convergence must be examined. Welch bound Equality is achieved by distributed algorithms but convergence to optimal sequence set cannot be assured [4]. Eigen-Iterative Interference Aware (IA) technique and its stability due to the addition and deletion of nodes in comparison to code division multiple access (CDMA) is discussed in [5]. The IA techniques are further extended for multiple receivers and adaptations in asynchronous CDMA systems are given in [6] - [9].

The cognitive radios are usually selfish, so the spectrum sharing can either be cooperative or non-cooperative. The focus of our study is on cooperative spectrum sharing that considers the amount of interference each node faces due to neighboring nodes. Since each cognitive radio is responsible for her decisions and no central authority is involved in cognitive radio networks, the cooperation problem can be managed with the tool of game theory. In general, game theory is the branch of applied mathematics that models the influence of users' choices on network and analyzes them. Basic analysis of game theory on wireless ad hoc networks is discussed in [10]. However, a game-theoretic framework is established for distributed power and sequence control in CDMA systems in [11]. The congestion game model approach for resource allocation is discussed in [12], [13].

The congestion games are briefly discussed in the following section II. Section III consists of system model and the proposed game model that leads to the Nash Equilibrium. The simulation results are discussed in Section IV and the comparison with an exact potential game. Section V then concludes the work.

II. CONGESTION GAMES

Congestion games are one of the useful tools in game theory when it comes to resource sharing. Rosenthal in 1973 proposed the congestion game model in game theory for the first time which was then followed by Monderer and Shapley (1996). Monderer and Shapley proved that every congestion game is an isomorphic to an exact potential game. The payoff function of each user in a congestion game depends on the choice of resources it makes and the number of users sharing that resource. The payoff function of an exact potential game can be modeled as cost or latency functions in congestion game. The cost function is the negative effect of congestion. This effect increases with increase in number of players sharing the same resource. Further establishing the global function, pure Nash equilibrium can be achieved.

Congestion games can be defined as a tuple $(I, , (S_i)_{i\in I}, (U_r)_{r\in})$, where $I = \{1,2,\dots,N\}$ denotes the set of players, is the finite set of available resources, $(S_i)_{i\in I}$ is the strategy set of each player, $i \in I$ such that S_i is the subset of the and $(U_r)_{r\in}$ is the payoff (cost) function associated to the resources players opt as strategyS_i. The payoff (cost) function depends on the total number of players sharing the same resource. In general, players in congestion games aim to maximize their payoff function or minimize the total cost to achieve the Nash equilibrium.

A. Cooperative Congestion Games

Congestion games deal with both the cooperative and non-cooperative players. In game theory, cooperative games are focused on the joint actions players make and the resultant collective payoff. Congestion externalities or the cooperative factors are involved in the process that may result in non-optimal equilibrium. However, the equilibrium could be socially optimal, regardless of the fixed parameters effecting utilities, if the cost increases with increasing number of players [14]. Thus, the need of cooperation is evident for optimal sharing of resources. In this work, the utility of each player decreases as the size of players set sharing same resource increases. The players are considered to be heterogeneous as they achieve different payoffs by opting same choice of resource.

The equilibrium of cooperative congestion game is considered socially optimal if and only if the cost of players can be interpreted as a negative function. This leads to the ultimate minimization of aggregate cost shown as the maximization of a global function of the network.

III. SYSTEM MODEL

The CR network consists of clusters of transmit and receive node pairs. The SINR of each node is dependent on the correlation with the waveforms of other users sharing the same spectrum; theirtransmit power levels and spectrum characteristics. Wave forms of nodes are represented by the signal space characteristics that are nearly orthogonal signal dimensions (either in time, frequency, or spreading code) [4]. The focus of our work is the efficient spectrum sharing based on the correlation between waveforms of users sharing that spectrum while keeping fixed transmit power levels. Pseudo random sequences are taken as they hold the properties of white noise with minimum auto and cross-correlation. The base data pulses are directly multiplying with the pseudo random sequences and each resultant waveform pulse represents a chip. Resultant waveform signals are non-overlapping rectangular pulses of amplitude +1 and -1 [15].

Considering a cognitive radio of N transmit-receive node pairs that are distributed randomly in the area. The K transmission frequency bands are available in the network, where K<N.

The spectrum sharing of the CRs is modeled as a normal form of congestion game, $G = (N, \{S\}, \{U_{i\in N}\})$. N is the set of players, i.e. node pairs in the network. The strategy space of users is $S = S_1 \times S_2 \times \dots \times S_N$. $S_{i\in N}$ is the strategy set of the player i, consists of two subsets $S_{i1} = \{ch_1, ch_2, \dots, ch_K\}$ (set of available channels within the network) and $S_{i2} = \{s_1, s_2, \dots, s_N\}$ (set of signature sequences), $\forall\, i \in \{1, 2, \dots, N\}$. $U_{i\in N}$ is the utility function of player i that also includes the cost function.

In the proposed game model, inverse signal to interference ratio can be expressed as:

$$ISIR_i = \frac{s_i^H s_j s_j^H s_i p_j h_{ji}^2}{p_i h_{ii}^2} \quad (1)$$

Where, s_i, s_j are the signature sequences of the nodes. p_i is the transmit power of node i that is kept fixed, $p = 1$. And h_{ij} is the link gain of nodes in the network. The gain remains constant throughout the game as the network topology is fixed.

The utility of a player comprises of the benefit of minimum correlation with other players sharing the same channel and the cost of choosing that particular channel.

$$U_i(s_i, s_{-i}) = B_i(s_i, s_{-i}) - C_i(s_i, s_{-i}) \quad (2)$$

where, s_{-i} is the strategy set of all the players except player i that can be denoted as:

$$s_{-i} = s_1 \times s_2 \times \dots s_{i-1} \times s_{i+1} \dots \times s_N$$

IV. COOPERATIVE CONGESTION: INVERSE UTILITY GAME

The purpose of the spectrum sharing congestion game is to reach a suitable utility level at which network approaches to Nash equilibria. The utility function might not be maximized as the cost of spectrum sharing and adaptation of a new suitable channel is involved. The cost function of a player i is:

$$C_i(s_i, s_{-i}) = \frac{b_p I_i(s_i, s_{-i})}{p_i} + c_s \quad (3)$$

Where, b_p is the battery power of node i transmitter, $I_i(s_i, s_{-i})$ is the inverse signal to interference ratio of player i at some particular channel, and c_s is the channel switching cost. The channel switching cost increases as the player keeps on shifting from one channel to another in search of the optimal result. Switching cost can be defined as:

$$c_{switch} = \begin{cases} +1, & \text{if } ch_{i,Iter} \neq ch_{i,Iter-1} \\ 0, & \text{otherwise} \end{cases}$$

The cost increases by the factor of 1 every time a player switch its strategy from one channel to another. But if the channel remains same at next iteration the switching cost becomes 0. Since the benefit of choosing a particular channel and sharing it with other users is in terms of the minimum cross-correlation that is

$$B_i(s_i, s_{-i}) = \frac{s_i^H X s_i}{p_i} \quad (4)$$

The waveforms of users sharing same channel are replaced by the eigenvector corresponding to the smallest eigen value of correlation matrix X. The iterative game helps in reaching to minimum correlation set of each player that enlarges the benefit function by reducing interference at each channel. Equation (2) simplifies the utility function of the proposed game model. The game is played iteratively.

A. Effect of Cost on Utility Function

Equation (2) simplifies the utility function of the proposed game model. The game is played iteratively. Each user measures its benefit and cost at each channel and then opt the channel of maximum utility. The utility function of each user keeps on increasing as the game starts, since the CRs are selfish and opt for their best possible resource. After certain iterations the cost factor starts to dominate players benefit. The channel switching cost increments after every single change. The cost dominance is considered as an influencing factor for CRs to cooperate, resulting in a cooperative congestion game.

The dominance of cost function enforces the CR users to reaches for the suitable utilities instead of maximum. This leads to the negative utility function values, the cost starts to increase and benefit decreases. However, at certain point of equilibrium the players reach their best possible spectrum with minimum interference. Negative resultant utility function models the inverse utility congestion game.

B. Global Function

Utility of each user influences the strategy set s_{-i} of opponents in game theory. This influence is made to minimize the interference with in the network. The sum of influence of utility of each user is projected in the form of a global function. In the proposed game framework, global function is the negative sum utilities of each user.

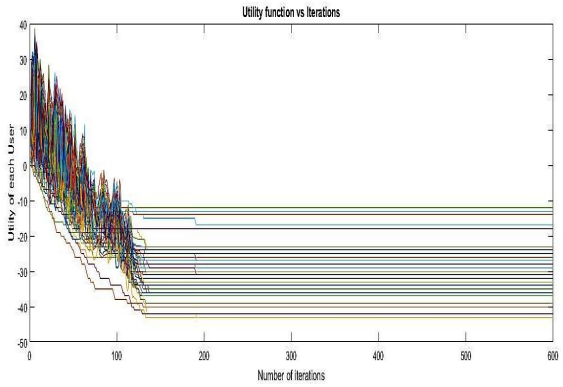


Fig 1: Maximum Utility Function of Each CR, $U_i(s_i, s_{-i})$

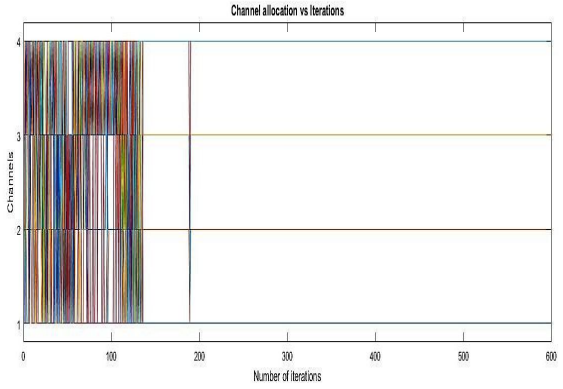


Fig 2: Convergence of CR Channel Allocation Process

$$P_s = -\sum_{i=1, i\neq j}^{N} [\max_{s_i \in S} U_i(s_i, s_{-i})] \quad (5)$$

The convergence of global function shows social stability in the CR network where each user is operating at its best possible channel without creating any hindrance in transmission of other users or even PU (in case of underlay systems).

V. SIMULATIONS RESULTS

The inverse utility congestion game is evaluated using variable number of CR node pairs. A CR network is of area 50m x 50m with 50 transmit-receive node pairs, uniformly distributed to share K available channels, K=4. After iteratively running the game, utilities of players with 3 signal space dimensions are shown in Figure 1.

The utility of nodes start to increase as each node acts selfishly and tries to maximize its own payoff. This selfish behavior increases the cost of nodes and ultimately leads to the negative utility. Users keep on changing their channels until they reach an optimum point of utility. Convergence of channel allocation process is shown in Figure 2. It can be seen that users

select their suitable channels approximately at 140th iteration, but the signature sequences take time to converge. The correlation between waveforms is reaching to minimum level with delay but the change is so small that it hardly

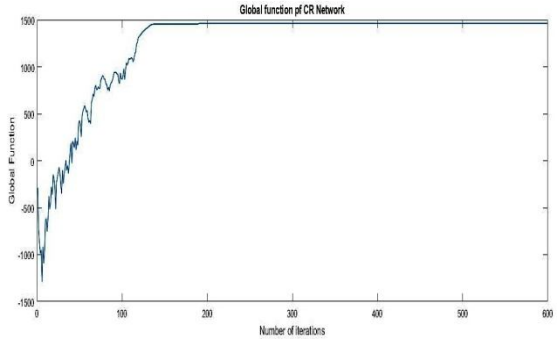


Fig 3: Convergence of Global Function (P_s)

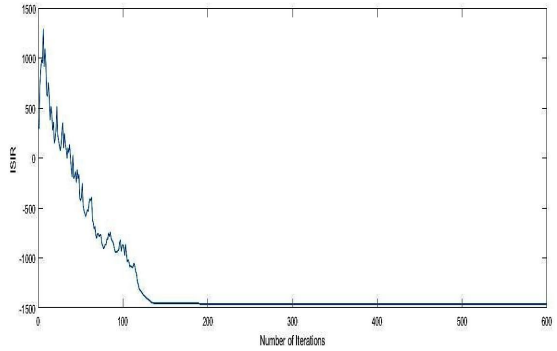


Fig 4: Inverse Signal to Interference Ratio in CR Network

effects the channel allocation. Finally the network converges near 190th iteration. Figure 3 is of the global function of the proposed game model. The Global function converges at the maxima point of the network where users start coordinating with each other and network becomes stable. That stability ensures the existence of a unique Nash Equilibrium. Here the noticeable trend is the switching of convergence point from 140th iteration to 190th iteration. In game theoretic perspective it could be the shifting of local maxima to global one. But trends need further study. The global function of the congestion game is isomorphic to the potential function of the exact potential games. The steady state of the function is pure Nash equilibrium, where no further change in strategy of a user makes any difference. In other words no unilateral deviation from the equilibrium point gives incentive to that user.

Reduction in ISIR within the network is the inverse of potential function that can be seen in Figure 4. The overall throughput of the network is shown in Figure 5.

A. Congeation Game isomorphic to Potential Game

As described above that congestion game is an isomorphic to a potential game. We have observed the results of inverse utility game without cost that can be considered as a potential game model.

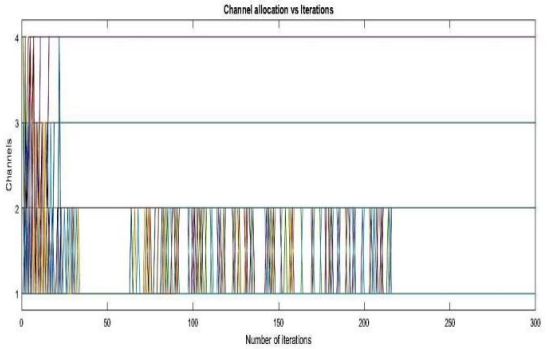


Fig 5: Convergence of CR Channel Allocation Process without Cost Factor

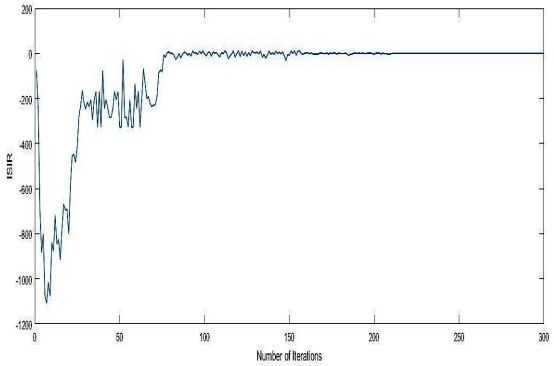


Fig 6: Inverse Signal to Interference Ratio in CR Network without Cost Factor

Similarly, the ISIR of the network remains unstable for a long period of time. Since selfish nodes in CR network does not take into account the cost initially. Later nodes have to bear cost in term of a destabilized network and excessive interference at each channel that enforces them towards cooperation. This process results in system delay and convergence is not always guaranteed. Figure 6 shows the unstable trend of ISIR until stability is achieved.

CONCLUSION

A congestion game framework is proposed to mitigate interference and congestion in CR network. The game model is designed to formulate the waveform adaptation process for the efficient utilization of resources. Efficient spectrum sharing is performed by the users through the adaptation strategy of waveforms. The target SIR is achieved. The utility is not maximum but at the suitable level for each node.

The potential function is best response convergent that ensure the better QoS in CR network. In this paper the comparison of the inverse utility congestion game with and without cost effect is also shown. The Nash Equilibrium is also achieved without the cost function, but the system faces delay in convergence. Hence, the cost dominance is somewhat helpful in attaining cooperation among nodes.

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