Resource Allocation for Cognitive Radio Networks Report 1

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***Abstract*— This document is the first report for the project Resource Allocation for Cognitive Radio Networks written by group 8. In this report, we firstly introduced some basic background information for CR(Cognitive Radio) networks, and described the work we have done in these days. Finally, we also presented some problems we have met and our focus for next step.**

I. Introduction

A. Why cognitive radio is needed?

Demand for greater amount of information has always been growing, while spectrum resource keeps finite. Nevertheless, regulatory bodies in various countries (including the Federal Communications Commission in the United States and Ofcom in the United Kingdom) found that a large amount of the radio frequency spectrum was underutilized. While cellular network bands are overloaded in most parts of the world, amateur radio and paging frequencies are not. And spectrum utilization is tightly related with time and place. Currently used static spectrum allocation fails to authorize unlicensed users to use rarely used frequencies assigned to specific services, even when their transmissions will not interrupt any assigned service.

Cognitive radio network is designed to solve the problem of spectrum idleness mentioned above. Cognitive radio network allows unlicensed users to utilize licensed bands whenever no legitimate user presence is sensed.

B. What is cognitive radio?

Cognitive radio is a paradigm for wireless communication, in which to implement more efficient communication or spectrum reuse, a network or a wireless node changes its transmission or alters reception parameters so as to avoid interference with licensed or unlicensed users.

C. What are main functions of cognitive radio?

There are four main functions of cognitive radio, including spectrum sensing, spectrum management, spectrum mobility and spectrum sharing.

Spectrum sensing is an important requirement of cognitive radio network. Detecting primary users is the most efficient way to detect spectrum holes. And spectrum sensing techniques are classified into three categories, including transmitter detection, cooperative detection and interference based detection.

Spectrum management is aimed to capturing the best available spectrum to satisfy the user. And the management functions can be classified as spectrum analysis and spectrum decision.

Spectrum mobility is defined as the process where a cognitive radio user alters its operating frequency. Cognitive radio network allows the radio terminals to operate in the best available frequency band.

Spectrum Sharing is the most challenging puzzle for a fair spectrum scheduling method.

II. Our Model for Cognitive Radio Network

There are three main steps in our project:

- Modeling
- Analysis
- Simulation

The simulation could be done after the complete analysis, so now our key problem is to find a way to model appropriately and conveniently to make a full analysis on the performance of our algorithm.

Our research will focus on multi-radio multi-hop CR networks, which contains N nodes and M channels. The session is on the hop by hop basis. There are seven elements in our model:

- $\mathcal{N}$: set of nodes in the CR network
- $\mathcal{M}$: set of channels in the CR network
- $\mathcal{S}$: set of sessions in the CR network
- $\mathcal{L}$: $\mathcal{L} = \{l_{ij}^m\}, i, j \in \mathcal{N}, m \in \mathcal{M}$
- $\mathcal{P}$: $\mathcal{P} = \{p_{ij}^m\}, i, j \in \mathcal{N}, m \in \mathcal{M}$
- $\mathcal{F}$: set of footprints in the CR network
- Θ: set of scaling factors for the bandwidth of channels in the CR network in which θ_m is the normalized bandwidth of channel m.

III. Our Plans of Research

We are going to talk about a special kind of cognitive radio network: the multi-hop cognitive radio network. In cognitive radio network, routing, scheduling and power control are some very important technologies. The multi-hop cognitive radio network is more complex than ordinary wireless networks in that the nodes of a network has the ability to learn from the communication environment. For example, in the multi-hop CR networks, the nodes has the ability to learn the frequency bands that their neighboring nodes are using, thereby scheduling the frequency they are using and the transmission power also. The routing algorithm and the scheduling pattern also need to be paid attention to because they are critical in the functionality of the network. Nodes need to make sure that their packages can be sent to distant nodes that may be several hops away, and they have to make sure that the transmission is successful.

Although the concept of CR is relatively new and consists of some widely ranged knowledge, we have some current technologies we can turn to when we study on them. i.e. the Multi-Channel Multi-Radio(MC-MR). There are some differences between CR and MC-MR. For example, the former is more software based while the latter is hardware based (in that each node of the network has several radio antennas from which the node can choose). The bandwidth of the MC-MR are considered to be the same while in CR, bandwidth can be at any size as long as there is a frequency hole. Still, the study on MC-MR is very meaningful in the field of CR because they are include the scheduling of transmission frequency and power in the network. In some sense, an MC-MR network can be considered as a special case of a CR network.

Game theory provides a straightforward tool to study channel allocation problems in competitive wireless networks. As far as known, game theory has been applied to the CSMA /CA protocol, to the Aloha protocol and to the peer-to-peer system. Furthermore, on the basis of graph coloring, Halldorsson et al. use game theory to solve a fixed channel allocation problem. Some concepts in economy such as auction and contract has also been applied to the allocation problem and reached a high level of performance.

IV. Recent Studies on the Design of A Distributed Optimization Algorithm

Virginia Polytechnic Institute and State University has done some works on this issue and published several papers about Optimization Algorithm in CR Network. In the paper, Y. Shi and Y.T.Hou introduced a complete algorithm for the distributed optimization algorithm for CR Network. They modeled the system similar to the MC-MR network and made some additions to it. For example, the bandwidth of each channel can be different. They use a bandwidth-footprint product (BFP) to measure the cost of a route during the routing process. In the special case of MC-MR, the BFP can be reduced to FP. In the design of the distributed optimization algorithm, they introduced two processes in routing and scheduling: the CIP and AIP which stand for conservative and aggressive iterative process. Each contains three steps: routing, minimalist scheduling and power-control and scheduling. Details and realization of the algorithm will be discussed later. In the performance evaluation part, the author points out that the performance is very close to the proved upper bound of the system. Therefore they safely concluded that their algorithm is very close to the optimal solution of the problem.

The model of this problem is to set threshold power P_{ij}^T with which the node i can send packages to node j successfully. Therefore we have:

$$p_{ij}^m \geq P_{ij}^T \tag{1}$$

Where p_{ij}^m denotes the power of the transmission from node i to node j under the band of m. This is a constraint that all the power scheduling processes have to satisfy.

The Flow chart of the algorithm is shown in Fig.1.

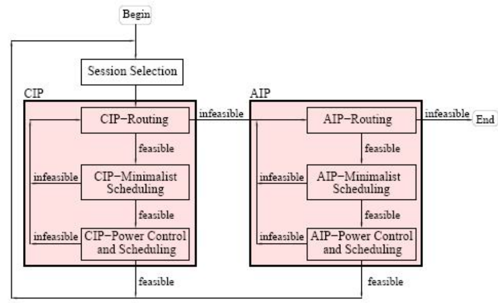

Fig. 1. Flow Chart of the Algorithm

The objective of CIP is to increase $K(l)$ without affecting (decreasing) the current scaling factors of other sessions in $\mathcal{L}$. On the other hand, the objective of AIP is to increase $K(l)$ aggressively by decreasing the current scaling factors of some other sessions in $\mathcal{L}$ as long as they do not fall below the newly increased $K(l)$. With the utilization of both processes, the performance of the allocation can reach a certain level of optimization.

A. Routing Module

We first present the ideas in the routing module under CIP and AIP. During an iteration, the routing, scheduling, and power control for session l in the previous iterations are intact. The CIP-Routing module aims to find an additional route (which could overlap with previous routes) for session l onto which there is a potential to push more data rate. This routing module is based on minimum cost, which can be implemented distributedly. The key step in CIP-Routing is the definition of incremental link cost (ILC) for pushing more data rate onto a link. Obviously, such link cost must capture network resource in terms of both frequency usage (bandwidth) and spatial occupancy (footprint), which indicates the length of the route. In light of this spirit, the so-called bandwidth-footprint product (BFP) is used, which is a unique metric for CR networks. So the incremental link cost for pushing more data rate onto a link can be defined as the incremental BFP per additional data rate. This metric only requires local information and can be computed distributedly. On the other hand, under the AIP-Routing module, all links carrying sessions whose current scaling factors are greater than $K(l)$ will be marked. The cost on these links will be redefined so that session l has the potential of pushing more data rate at the expense of decreasing the data rate of those sessions currently with larger scaling factors.

In this paper, the author assumes that all the bandwidths are the same, therefore the BFP reduces to footprint, and the *incremental link cost* (ILC) is used. Also, they gave some details on how the ILC is calculated. They define the *incremental band cost* as the incremental footprint area over increased band capacity when the transmission power is increased to the minimum required transmission power P_{ij}^T. Therefore the IBC for the band m on link $i \to j$ is

$$IBC(i,j,m) = \frac{\pi(P_{ij}^T/P_I)^{2/\alpha}}{W\log_2(1+\frac{g_{ij}P_{ij}^T}{\eta W})} \tag{2}$$

There are three cases when it comes to the calculation of the ILC.

Case I: If band m is already used but $p_{ij}^m < (p_{ij}^m)_U$, then pm ij may be increased to (pm ij)U and IBC is defined as

$$IBC(i,j,m) = \frac{\pi[(p_{ij}^m)_U/P_I]^{2/\alpha} - \pi(p_{ij}^m/P_I)^{2/\alpha}}{W[\log_2[1+\frac{g_{ij}}{\eta W}(p_{ij}^m)_U] - \log_2(1+\frac{g_{ij}}{\eta W}p_{ij}^m)]} \tag{3}$$

Case II: If band m is not yet used, then IBC can be defined by (2).

Case III: If band m is already fully utilized (i.e., $(p_{ij}^m)_U = p_{ij}^m$), IBC is then defined as 1, since the capacity on this band cannot be further increased.

When determining the route, we have to check whether there is Case I. If so, we will use such band. If not, Case II will be checked. So is Case III. After implementing this method node by node, we finally have the route.

In the AIP routing, the process is similar. However, we should guarantee that the session with the larger scaling factor will not fall below the scaling factor of the session that has just been increased because of itself. Therefore, after many iterations, the total scaling factor will reach an equilibrium point and cannot be increased.

B. Minimalist Scheduling Module.

We now present the ideas in the minimalist scheduling module under CIP and AIP. Since the routing process cannot necessarily provide us with enough capacity on a link, we should decide when and how we can use the capacity on another band.

The approach is of minimalist, in the sense that it only makes necessary scheduling decisions (i.e., frequency band assignments) when there is no alternative options. Specifically, under the CIP-Minimalist Scheduling, if there is no remaining capacity on a hop and current transmission powers on used bands have already reached their maximum allowed transmission power, then it is necessary to assign a new band. If there is only one unassigned band on this link, we will make an assignment of this band (as there is no other options) subject to scheduling constraint at the node. On the other hand, when there are multiple unassigned bands, we will skip the process and leave it to the Power schedule process. The reason for this deferring is that power control may change the conflict relationship among the nodes. Therefore, scheduling decision (band assignment among multiple unassigned bands) is best done with joint consideration of power control. The AIP-Minimalist Scheduling module follows a similar process, with the difference being when a new band should be assigned. This is because under AIP-Minimalist Scheduling, if a hop carries sessions with their current scaling factors greater than $K(l)$, then there is no need to assign a new band since the rates of these sessions can be reduced and thus leave more room for increasing the rate of session $\mathcal{L}$.

C. Power Control/Scheduling Module.

The last module in either CIP or AIP is power control/scheduling. In this module, we will determine all the remaining scheduling assignments (that are not determined in the minimalist scheduling module), transmission powers, and flow rate increase on the minimum cost route.

The algorithm will first check whether there has already been a band assigned in the Minimalist Scheduling Module. If so, it will also check whether the band is still available after the whole hop by hop process. If so, then the power will be set to the threshold value P_{ij}^T. If not, it will choose the band that has remaining capacity with the lowest IBC.

For the AIP-Power Control/Scheduling module, we have one more strategy to explore in order to accommodate the additional flow rate . That is, if there are other sessions with larger scaling factors on this link, then we can obtain some additional capacity by reducing the scaling factor of one of these sessions. Among these sessions, we choose the one with the largest releasable capacity. For this session, we also need to reduce its flow rate on other links along its paths. The transmission power and scheduling on these links may also need to be updated.

V. Mathematical Tools Used in Our Research

A. Analysis and Design of Cognitive Radio Networks

1) Component for A general model for CR networks:

- N–a collection of radios in the CR network
- A–a collection of actions available for radios in the CR network
- $\{\mu_j\}$–A set of utility functions which describe how much value radio j assigns to specific action
- $\{\mathrm{d}_j\}$–a set of decision available for radios in the CR network
- T–The set of all times where decision updates can occur

2) Analysis Objectives:

- What is the expected behavior of the network?
- Does this behavior yield desirable performance?
- What conditions must be satisfied to ensure that adaptations converge to this behavior?
- Is the network stable?
- How good are the steady states of the algorithm?
- Does an optimal action vector exist and how close do the steady states come to achieving optimal performance?

3) Analysis Tools: For a cognitive radio network, we would prefer that the network settle down to a particular steady state and only adapt as the environment changes. Identifying these steady-states also allows a cognitive radio designer to predict network performance. In the context of our state equation, such a steady state is a fixed point of d^t, which is illustrated by Fig. 2. But how can we find out the steady state?

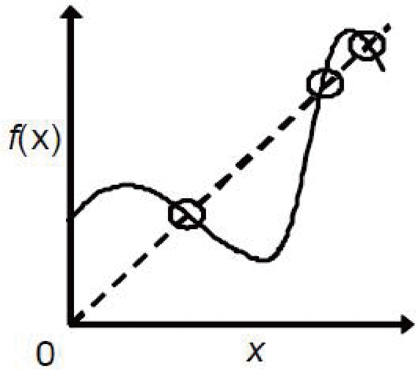

Fig. 2. Example of fixed points

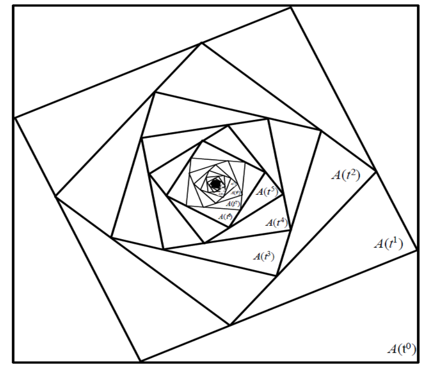

Fig. 3. Example of fixed points

(1) Solving the evolution function $a_i^* = d_i(a^*) \forall \in N$ to find out the steady-state a*
(2) Lyapunovs Direct Method for Discrete Time Systems: Given a recursion $a(t^{k+1}) = d^t(a(t^k))$with fixed point a*, we know that a* is Lyapunov stable if there exists a continuous function (known as a Lyapunov function) that maps a neighborhood of a* to the real numbers, such that the three conditions are satisfied:

- $L(a^*) = 0$
- $L(a) > 0 \forall a \in N(a^*) \backslash a^*$
- $\triangle L(a(t)) \equiv L[d^t(a(t))] - L(a(t)) \leq 0, \forall a \in N(a^*) \backslash a^*$

This method tells us, in effect, that if we can find a function that strictly decreases along all paths created by the adaptations of a cognitive radio network, then that cognitive radio network is asymptotically stable.
In the preceding discussion, we are assumed to know the precise evolution function of the system. However, if we are unable to precisely predict the next network state. However, we are able to bound the network state within a particular set of states A(t^1). Then suppose that armed with the knowledge that the network starts in A(t^1), we could say that after the second iteration, the network state would have to be within another set A(t^2), which is a subset of A(t^1). Extending this concept, suppose that given any set of network states, A(t^k), we know that the decision update rule always results in a network state in the set, A(t^{k+1}), which is a subset of A(t^k). This process is called Contraction Mapping, which is illustrated by Fig. **??**.

4) Markov Models: Perhaps because of uncertainty in the order of adaptation (as would be the case for a randomly or asynchronously timed process) or because of uncertainties in the decision rules (either from noise or a non-deterministic procedural radio), it may be impossible to derive a closed-form expression for an evolution equation or to even to bound the adaptations into sequential subsets. Instead, suppose we can model the changes of the cognitive radio network from one state to another as a sequence of probabilistic events conditioned on past states that the system may have passed through. When the probability distribution for the next state in time, a(t^{k+1}), is conditioned solely on the most recent state as shown in (3.10), the random sequence of states, a(t) is said to be a Markov chain. If we assume that the network is in state a$^m \in$ A at time t^k, then at time t^{k+1}, the network transitions to state a$^n \in$ A with probability p$_{mn}$ where p$_{mn} \geq 0$, $\forall$ a^m,a$^m \in$ A and $\sum_{j \leq |A|} P_{mj} = 1$. Under this model, we have following insights:

- The network has a unique steady-state distribution π^*
- $L(a) > 0 \forall a \in N(a^*) \backslash a^*$
- $\triangle L(a(t)) \equiv L[d^t(a(t))] - L(a(t)) \leq 0, \forall a \in N(a^*) \backslash a^*$

We have studied several examples of building CR network models by transition matrix and diagraph, which is illustrated by Fig. 4 and Fig. 5

$$\mathbf{P} = \begin{array}{c} \\ a^1 \\ a^2 \\ a^3 \\ a^4 \end{array} \begin{array}{c} \begin{array}{cccc} a^1 & a^2 & a^3 & a^4 \end{array} \\ \begin{bmatrix} 0.1 & 0.3 & 0.1 & 0.5 \\ 0.4 & 0.0 & 0.3 & 0.3 \\ 0.4 & 0.1 & 0.3 & 0.2 \\ 0.1 & 0.4 & 0.3 & 0.2 \end{bmatrix} \end{array}$$

Fig. 4. Example of Transition matrix

B. Opportunistic Scheduling with Reliability Guarantees in Cognitive Radio Networks

In the paper of *Opportunistic Scheduling with Reliability Guarantees in Cognitive Radio Networks*, the author introduced one conception of collision probability. The goal of the resource allocation is to trade off between the delay time and the collision in the network. They use the techniques of adaptive queueing and Lyapunov Optimization to design an online flow control.

First, the relationship between the primary user and the channel is shown in the channel access matrix.

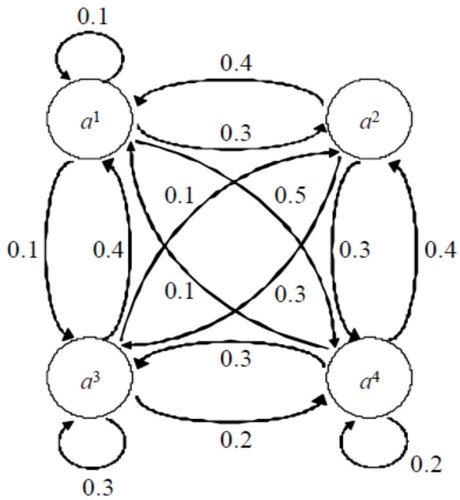

Fig. 5. Example of Transition diagraph

$$h_{nm}(t) = \begin{cases} 1 & \text{if user n can access the channel m in time slot t} \\ 0 & \text{else} \end{cases}$$

And then we get the channel access matrix:

$$\mathbf{H(t)} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

Then introduce the channel state vector for the primary user S(t)=(S_1(t),S_2(t),. . .,S_M(t)). If S_i(t)=1, it means the channel i is not used by the primary user(idle) and can be used by the secondary user in time slot t.

And for the secondary user, define the interference I_{nm} as the set of channels that secondary users n interferes with when it uses channel m.

$$I_{nm}^k = \begin{cases} 1 & \text{if } k \in I_{nm} \\ 0 & \text{else} \end{cases}$$

Thus the necessary condition for the secondary user n on channel m in time slot t is:
1) S_m(t)=1
2) For all the secondary users i transmitting on a channel j∈[1,2,. . .,M], we have m not in I_{ij}.

And for the secondary user n, U_n(t) is defined as the backlog in the network layer queue, and R_n(t) is defined as the new packages in the time slot t. Define μ_{nm}(t) as the attempted packet transmissions. Then the queueing dynamics of the secondary user n is described by:

$$U_n(t+1) = max[U_n(t) - \sum \mu_{nm}(t) S_m(t), 0] + R_n(t) \quad (4)$$

Then the delay time and the collision queue are introduced. The trade off is made between these two aspects. The Optimal control algorithm is a cross-layer control strategy that can be shown to achieve the optimal average time rate r. It operates without knowledge of whether the input rate is within or outside of the bound. Further, it provides deterministic worst case bounds on the maximum backlog at all times and the maximum number of collisions with a primary user in a given time interval. These are much stronger than probabilistic performance guarantees.
The algorithm is decoupled into two separate components. The first component performs optimal flow control at the transport layers and is implemented independently at each secondary user. The second component determines a network wide resource allocation every slot and needs to be solved collectively by the secondary users.

- Flow Control
  The goal of the flow control is to minimize the largest probable delay time.

$$Minimize : R_n(t)[U_n(t) - V\theta_n] \quad (5)$$

  Tip: the optimization is for each user but not for the whole users.

- Resource Allocation
  The goal of resource allocation is to maximize the largest resource avalible and revoid the collision.

$$Max : \Sigma\mu_{nm}(t)[U_n(t)P_m(t) - \Sigma X_k(t)(1 - P_k(t))I_{nm}^k] \quad (6)$$

The performance of this algorithm is shown as following:
1) The worst case queue backlog for all secondary users n is upper bounded by a finite constant U_{max} for all t:

$$U_n(t) \leq U_{max} = V\theta_{max} + A_{max} \quad (7)$$

2) For all m, t such that P_m(t)≠1, letϵ¿0 be such that P_m(t)≤1-ϵ^3. Then the worst case collision queue backlog for all channels m is upper bounded by a finite constant X_{max}:

$$X_m(t) \leq X_{max} = U_{max}(1 - \epsilon)/\epsilon + 1 \quad (8)$$

Further, the worst case number of collision sufferd by any primary user m is no more than ρ_mT+X_{max} over any finite interval.
3) The time average throughput utility achieved by the CNC algorithm is within B/V of the optimal value:

$$\lim\inf \frac{1}{t} \sum\sum \theta_n E R_n(\tau) \geq \sum \theta_n r_n^* - \frac{B^*}{V} \quad (9)$$

Where B^* are determined by V when these processes evolve according to a finite state ergodic Markov model.

VI. Conclusion

In these weeks, our group have spent a lot of hours on reading related papers, such as *A Distributed Optimization Algorithm for Multi-hop Cognitive Radio Network* and *Opportunistic Scheduling with Reliability Guarantees in Cognitive Radio Networks*. We have also obtained some basic concepts and ideas of Cognitive Radio Networks by reading and discussing materials downloaded from IEEE, such as *Analysis and Design of Cognitive Radio Networks.*

We think there are three steps to analyze the resource allocation problem about CR network:

- Modeling
- Analyzing
- Designing

After mastering these basic concepts and techniques to build a cognitive radio networks, we will focus on how to analyze a specific model and put more efforts in studying Game Theory and

References

[1] A Distributed Optimization Algorithm for Multi-hop Cognitive Radio Networks: Yi Shi Y. Thomas Hou

[2] Opportunistic Scheduling with Reliability Guarantees in Cognitive Radio Networks: Rahul Urgaonkar, Michael J. Neely

[3] Analysis and Design of Cognitive Radio Networks and Distributed Radio Resource Management Algorithms: James ODaniell Neel

[4] A Game Approach for Multi-Channel Allocation in Multi-Hop Wireless Networks: L.Gao, X. Wang