Resource Allocation with Flexible Channel Cooperation in Cognitive Radio Networks

S.Jagadeesan MCA., M.Phil., ME., R.Vidya
Assistant Professor, Final Year Mca,
Department Of Computer Application, Nandha Engineering College (Anna University), Erode, Tamilnadu,India.

ABSTRACT-- *We study the resource allocation problem in an OFDMA based cooperative cognitive radio network, where secondary users relay data for primary users in order to gain access to the spectrum. In light of user and channel diversity, we first propose FLEC, a novel flexible channel cooperation scheme. It allows secondary users to freely optimize the use of channels for transmitting primary data along with their own, in order to maximize performance. Further, we formulate a unifying optimization framework based on Nash bargaining solutions to fairly and efficiently allocate resources between primary and secondary networks, in both decentralized and centralized settings. We present an optimal distributed algorithm and a sub-optimal centralized heuristic, and verify their effectiveness via realistic simulations. Under the same framework, we also study conventional identical channel cooperation as the performance benchmark, and propose algorithms to solve the corresponding optimization problems.*

KEYWORDS—Cognitive radio, Cooperative Communication, Resource Allocation, Nash bargaining solutions, OFDMA.

1. INTRODUCTION

A new paradigm where primary users (PUs) can leverage secondary users (SUs) for their own transmissions, termed *cooperative cognitive radio networks* (CCRN). In CCRN, SUs cooperatively relay data for PUs in order to access the spectrum. Assuming that SUs have better channel conditions and also gain opportunities to access the spectrum, resulting in a "win-win" situation.

A single channel network with only one PU has been considered in [1], [2]. We consider multi-channel cellular networks based on OFDMA, e.g. for the primary network, with multiple SUs assisting multiple PUs on the uplink[3]. Multi-channel networks impose unique challenges of realizing the cooperative paradigm The *first* contribution in this paper is a new design for cooperation among SUs and PUs, termed Flexible Channel Cooperation (FLEC), that opens up all dimensions of resource allocation for SUs. It takes advantage of channel and allows SUs to freely*optimize* its use of resources, including channels and time slots leased by PUs.

PUs transmit in the first slot to SUs, and SUs transmit in the second to the primary base station (BS) and to their own access point (AP). A SU strategically optimizes its use of the leased resources. The intuition is that, if sub channel 1 has superior conditions on the SUBS link but poor conditions on the SU-AP link, it is much more efficient using sub channel 1 to relay data from both sub channels. Such channel *swapping* or *shuffling* results in boosted SU throughput, as well as larger relay capacity for PU, since the overall spectral efficiency is improved. The spectral efficiency gain can in turn be translated into more cooperation opportunities, as well as increased network capacity and better performance.

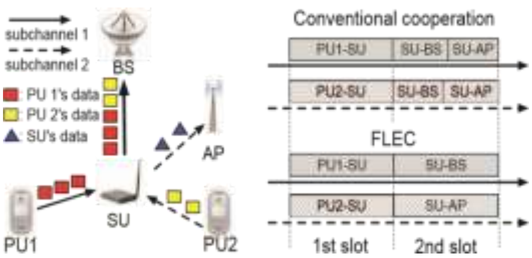

Fig. 1. The motivating scenario for *FlexibleChannel Cooperation (FLEC)*.The*second* contribution is a novel unifying optimization framework that jointly considers relay and sub channel assignment, relay strategy optimization, and power control. PUs and SUs agree to jointly optimize a social cost function, known as the Nash product, which is essentially the product of utility functions of the cooperating PUs and SUs. The solution concept, known as the Nash bargaining solution (NBS), is a unique Nash equilibrium point that is guaranteed to provide Pareto efficiency.We consider both decentralized and centralized FLEC.

2. AN OPTIMIZATION FRAMEWORK

2.1 System Model

Consider the uplink of a single-cell OFDMA network. A number of SUs are located in the cell and perform cooperative transmission for PUs to access the primary spectrum. Cooperative transmissions take place on an OFDMAsub channel basis, and transmissions in different sub channels do not interfere with each other. Decode-and-forward multi-hopping [4] is used when SUs relay primary data. Note that our results are readily applicable when other relaying scheme is used. Moreover, higher rates are achievable with more sophisticated coding/decoding schemes. Here we focus on decode-and-forward multi-hopping only for simplicity of presentation. Our analysis and algorithms are readily applicable to scenarios with other relaying and coding/decoding schemes.We model the fading environment by large scale path loss and shadowing along with small scale frequency-selective Rayleigh fading.

2.2 Basics of Nash bargaining solutions

We present the salient concepts and results from Nash bargaining solutions in this section, which are used in the sequel. For details we refer readers to [5].

The basic setting is as follows: Let N be the set of players, including PUs and SUs. Let Sbe a closed and convex subset of R^N to represent the set of feasible payoff allocations that players can get if they all work together. Let R_n^{min}be the minimal payoff that the *n*-th player would expect; otherwise, he will not cooperate. Suppose $\{R_n \in S | R_n \geq R_n^{min}, \forall n \in N\}$ is a nonempty bounded set. Define $\mathbf{R}^{min} = (R_1^{min},...,R_N^{min})$, then the pair $(S,\mathbf{R}^{min})$ is called a *N*-person bargaining problem.

Within the feasible set S, we first define the notion of Pareto optimality as a selection criterion in a typical game setting.

*Definition :*The point $(R_1,...,R_N)$ is said to be *Pareto optimal* if and only if there is no other allocationthat leads to superior performance for some user without inferior performance for some other user.

Independence of Linear transformations: For any linear scale transformation ψ, $\psi(\phi(\mathcal{S}',\mathbf{R}^{min})) = \varphi(\psi(S),\psi(\mathbf{R}^{min}))$.

Symmetry: If S is invariant under all exchanges of players, then$\phi_i(\mathcal{S},\mathbf{R}^{min}) = \phi_{i'}(\mathcal{S},\mathbf{R}^{min}) \forall i, i'$.

2.3 An Optimization Framework Based on NBS

Each user, being primary or secondary, has $\bar{R}_n$, the average total throughput summed across all sub channels, as its objective function. It is bounded above and has a non-empty, closed, and convex support. $\bar{\mathbf{R}}^{min}$is an *N*-dimensional vector that represents the minimal average performance requirements.For PUs, the minimal requirement will be the optimal average throughput they could obtain should they choose not to cooperate with SUs, given by a multi-user uplink scheduling algorithm. For SUs, their minimal requirement that can be obtained without cooperation is clearly zero. **S** is the feasible set of resource allocation that satisfies $\bar{R}_n > \bar{R}_n^{min}, \forall n$.The problem, then, is to find the NBS, i.e., to solve the optimization problem with $\bar{R}_n$and $\bar{R}_n^{min}$.

For the scheduling and resource allocation problem, it has to be solved in each scheduling epoch because channel conditions change over time. It has been shown that maximizing the aggregate marginal utility at each epoch exactly achieves long-term utility maximization. Therefore, separating the terms for PUs and SUs, the basic resource allocation framework for OFDMA cooperative cognitive radio networks at each epoch is $R_i,\bar{R}_i,R_j,\bar{R}_j$denote the instantaneous and average throughput for PU *i* and SU *j* at current epoch, respectively. Both $\bar{R}_i$and $\bar{R}_j$can be readily obtained by applying the exponential moving averaging technique. $R_i^{min},\bar{R}_i^{min}$are the instantaneous and average throughput requirement respectively, which can be obtained by running a multi-user scheduling algorithm at each epoch and using exponential moving averaging technique.

A final remark is that our optimization framework maximizes throughput gains without considering QoS requirements for both PUs and SUs for reasons of both tractability and conciseness. QoS requirements, such as minimum delay, bit error rate, etc., are usually specific to multimedia applications such as mobile video streaming, and is not addressed in this work that targets a general data transmission application. They can be incorporated as additional constraints into the optimization framework, and new algorithms can be developed as a possible direction of future work.

3 OPTIMAL DISTRIBUTED ALGORITHM

3.1 Problem Formulation

We first consider a decentralized setting where the secondary network is independent from the primary network, and cannot be controlled by the primary BS. Thus, BS allocates resources to PUs *a priori* to any cooperative transmission, and SUs have to “negotiate” distributively with PUs in order to have cooperation taking place.This may correspond to the most immediate implementation scenario of CCRN that does not call for any change in the existing primary infrastructure, and therefore is of practical interest.

In this case, PU channel assignment is done

$$\mathbf{0} \preceq \mathbf{P} \cdot \mathbf{1}^T \preceq \mathbf{p}^{max},$$

$$\max_{,\mathbf{P},\boldsymbol{\alpha}} \sum_{i\in\mathcal{N}_\mathcal{P}} \frac{R_i - R_i^{\min}}{\bar{R}_i - \bar{R}_i^{\min}} + \sum_{j\in\mathcal{N}_\mathcal{S}} \frac{R}{\bar{R}_j}$$

separately by the BS, and is not part of the optimization. The resource allocation problem, including relay assignment, SU sub channel assignment, SU relay strategy optimization using FLEC, and PU-SU power control within the basic framework in Sec. 2.3 can be expressed succinctly

as $\mathbf{R} \succeq \mathbf{R}^{\min}, \mathbf{R} \in \mathcal{C}(\mathbf{P}, \boldsymbol{\alpha})$, where $\mathbf{p}^{\max} = [p^{\max}_1, \ldots, p^{\max}_N]^T$ is the power constraint vector. Since only one PU and one SU can be active on each sub channel, the column vector has at most two non-zero entries, and it also specifies relay and sub channel assignments.

3.2 Dual Decomposition

The decentralized problem (9) is essentially a mixed integer program, with the objective function being neither convex nor concave. However, in an OFDMA system with many narrow subchannels, the optimal solution is always a convex function of $\mathbf{p}^{\max}$, because if two sets of throughputs using two different sets of $\mathbf{P}$ and α are achievable individually, their linear combination is also achievable by a frequency-division multiplexing of the two sets of strategies. In particular, using the duality theory of [22], the following is true:

Proposition 1: The decentralized resource allocation problem (9) has zero duality gap in the limit as the number of OFDM subchannels goes to infinity, even though the discrete selection of subchannels, SUs and relay strategies are involved.

This proposition allows us to solve non-convex problems in their dual domain. Note that although the proposition requires the number of subchannels to go to infinity, in reality the duality gap is very close to zero as long as the number of subchannels is large [13].

Introduce Lagrangian multiplier vectors λ,μ,ν to the power, individual rationality, and flow conservation constraints.

$$\begin{aligned} L(\mathbf{R},\mathbf{P},\boldsymbol{\alpha},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu}) &= \sum_{i\in\mathcal{N}_\mathcal{P}} \frac{R_i - R_i^{\min}}{\bar{R}_i - \bar{R}_i^{\min}} + \sum_{j\in\mathcal{N}_\mathcal{S}} \frac{R_j}{\bar{R}_j} \\ &+ \sum_{n\in\mathcal{N}} \lambda_n \left(p_n^{\max} - \sum_{c\in\mathcal{K}} p_n^c\right) + \sum_{i\in\mathcal{N}_\mathcal{P}} \mu_i \left(R_i - R_i^{\min}\right) \\ &+ \sum_{j\in\mathcal{N}_\mathcal{S}} \nu_j \left(\sum_{c\in\mathcal{K}} R_{j,P}^c - \sum_{c\in\mathcal{K}}\sum_{i\in\mathcal{N}_\mathcal{P}} R_{i,j}^c\right) \end{aligned} \quad (10)$$

The Lagrangian becomes

The dual function becomes

$$g(\lambda,\mu,\nu) = \begin{cases} \max\limits_{\mathbf{R},\mathbf{P},\boldsymbol{\alpha}} & L(\mathbf{R},\mathbf{P},\boldsymbol{\alpha},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu}) \\ \text{s.t.} & \text{Eq. (1)–(4)} \end{cases} \quad (11)$$

3.3 Solving the Per-Sub channel Problem

The main idea is to consider p^c_n as the optimizing variable and express $R_{i,j}^c, R_j^c, R_{j,P}^c$ in terms of p^c_i, p^c_j. The persub channel problem is essentially a joint optimization of transmission strategy, relay assignment, and relay strategy. For each sub channel c, its PU i needs to decide whether to use direct or cooperative transmission, which SU to cooperate with, while the chosen SU j needs to optimize its relay strategy denoted by the time sharing parameter $\alpha_j^c \in \{0,1\}$. Therefore, the exhaustive search is performed over a finite set defined by

- PU transmission strategies: {direct, cooperative}
- SU relay assignment: $j, j \in N_S$
- SU relaying strategies: {primary data only ($\alpha_j^c = 0$), its own data only ($\alpha_j^c = 1$)}

We derive optimal solutions $\tilde{p}_i^c, \tilde{p}_j^c, \tilde{\alpha}_j^c$ under direct or cooperative transmission modes for any combination of sub channel c with its PU i and the SU j.

3.3.1 Direct Transmission

If PU i chooses direct transmission, the problem becomes

$$\max_{p_i^c} \left(\frac{1}{(\bar{R}_i - \bar{R}_i^{\min})} + \mu_i\right) \log(1 + p_i^c g_i^c) - \lambda_i p_i^c$$

3.3.2 Cooperative Transmission

Substituting the rate formulas and regrouping the terms, the objective becomes

$$\frac{\log(1+2p_i^c g_{i,j}^c)}{2(\bar{R}_i - \bar{R}_i^{\min})} + \frac{(\mu_i - \nu_j)\log(1+2p_i^c g_{i,j}^c)}{2} - \lambda_i p_i^c + \frac{\alpha_j^c \log(1+2p_j^c g_j^c)}{2\bar{R}_j} + \frac{\nu_j(1-\alpha_j^c)\log(1+2p_j^c g_{j,P}^c)}{2} - \lambda_j p_j^c$$

To summarize, the per-sub channel problem can be efficiently solved via exhaustive search over a finite set defined by the transmission strategies, SUs, and SU relay strategies with FLEC as discussed above. The size of this discrete set is very limited, making it feasible for a practical network.

3.4 An Optimal Distributed Algorithm

We have shown that the dual function can be decomposed into K per-sub channel problems, the optimal solutions of which can be obtained efficiently through exhaustive search. Then, the primal problem can be optimally solved by minimizing the dual objective. Because of the dual decomposition, dual optimization by sub gradient method can be done in a *distributed* fashion. First, in each iteration, the per-sub channel problems [6].It can be solved simultaneously by the PU of the sub channel exchanging information with neighboring SUs as in *Subroutine* 1, though the objective jointly involves PU's and SU's benefits. Second, sub gradient updates can also be distributive performed by each primary and secondary users. The algorithm can be perceived as an iterative bargaining process. The dual variable $v_j$is exchanged between PUs and SUs and serves as a relay price signal to coordinate the level of cooperation.When the relay traffic demand$\sum_c \sum_i \tilde{R}^c_{i,j}$ from PUs exceeds the supply$\sum_c \tilde{R}^c_{j,P}$ from j, i.e. PUs over-exploit j, j increases its relay price $v_j$for the next round of bargaining to suppress the excessive demand. Similarly, if j has redundant relay capacity $\sum_c \tilde{R}^c_{j,P} > \sum_c \sum_i \tilde{R}^c_{i,j}$, it will decrease the relay price $v_j$to attract more relay traffic and therefore obtain more channels to use. The process continues until it converges to the optimal resource allocation.

The interpretation of other dual variables $\lambda_n$and $\mu_i$is also worth mentioning. For each user, $\lambda_n$is easily understood as a price signal to regulate its power consumption. $\mu_i$for each PU is used to ensure that the resource allocation is individual rational, i.e. it is beneficial for each PU in that the total throughput obtained from cooperation $R_i$is larger than R_i^{min}. When $R_i<R_i^{min}$, $\mu_i$will be increased, and so will $p^{\sim c}{}_i$. Therefore, R_i^cwill be larger in the next iteration. Both dual variables are kept privately and updated independently with only local information.

1. The primary BS runs a multiuser scheduling algorithm to determine $R_i^{min}$for PUs without cooperation.
2. Each primary user initializes $\lambda^{(0)}{}_i$,$\mu^{(0)}{}_i$. Each secondary user initializes both power and relay prices $\lambda^{(0)}{}_j, v_j^{(0)}$.
3. Given $\lambda^{(l)},\mu^{(l)},v^{(l)}$, each PU i coordinates with each neighboring SU j concurrently to solve the per-sub channelresource allocation problem using *Subroutine*.
4. Return to step 3 until convergence.
5. Every user updates $\bar{R}_n$from its total throughput $R_n$in this epoch. Every PU i updates $\bar{R}_i^{min}$from R_i^{min}in Step 1. They will be used for resource allocation in next epoch.

Analyze the amount of message exchanges and complexity here. For a pair of PU-SU, two messages v_j,˜$b_j(i,\lambda_j,v_j)$ need to be exchanged for each c. They can easily be piggybacked in the probing packets from SU to PU to measure the channel gain, resulting in zero message exchange overhead. The complexity of solving K per-sub channel problems by exhaustive search is $O(KN_S)$[7]. The complexity of the subgradient update is polynomial in the dimension of the dual problem, which is K. Therefore, the complete algorithm has complexity polynomial in KN_S. While this may render it infeasible for real-time scheduling within 5–10 ms when the network scales, the distributed nature of the algorithm makes it possible for each PU to *concurrently* solve the persub channel problem, reducing the complexity to only $O(N_S)$. Also, each user can update their own prices as dual variables independently. Further, in reality, only a few SUs residing in the neighborhood of the PU can potentially help and thus have to be considered. Therefore from the network point of view, each round of bargaining has complexity O.

4. CENTRALIZED HEURISTIC ALGORITHM

We now proceed to the centralized setting. Recall that in the decentralized setting, the subchannel assignment to PUs is done by the BS without considering the possibility of cooperative transmission, and thus is not part of the optimization. This enables efficient development of distributed algorithms, but is sub-optimal in general. Here we consider the scenario where the SU cooperative transmission becomes an integral part of primary BS scheduling, and SUs abide by the scheduling decisions, provided that the resource allocation is fair as reflected by the NBS fairness. With centralized FLEC, we have an additional dimension to optimize: *global subchannel assignment* for both PU and SU.

4.1 Motivation for Developing Heuristics

The problem can be formulated in a similar way as the decentralized problem, and optimally solved via dual decomposition and update. Compared to the decentralized version [8]. There are additional variablesi, i', j' to optimize, which represents the global sub channel assignment. Specifically, i is the PU assigned to use c and j is its helping SU, while $j$is the SU assigned to use c and i' is the PU whose data is relayed by j. Note that i (j) needs not to be equal to i' (j'). The solution of this problem thus has to exhaustively search all possible combinations of PU-SU pairs for each subchannel, which has a complexity of $O(KN_P{}^2\ N_S{}^2)$ since distributed concurrent optimization is not possible.Moreover, because of the global impact of centralized subchannel assignment, the speed of convergence of dual variables λ,μ ,$v$scales up with the size of the dual problem which scales quadratically with N_P and N_S, instead of being independent of the dual problem size as in the decentralized case. Note that although the convergence of method is guaranteed, the speed of convergence is not, and often depends heavily on problem conditioning and scaling [9].Given that complexity has been significantly increased, we focus on developing efficient heuristics in this section, which reduce the complexity while maintaining good performance..

4.2 Overview of the Heuristic Algorithm

To make the problem more tractable, we decouple it to three orthogonal dimensions: relay assignment, subchannel assignment, and power control. First, we derive optimal relay assignment using bipartite matching, assuming that each SU is only able to help one distinct PU and one PU can only be matched to one SU. This simplification is reasonable as it ensures a certain level of fairness. Then we assume that power is equally distributed, and derive an subchannel assignment algorithm. Even with optimal relay and equal power assignment, this turns out to be an NP-hard problem. We propose a suboptimal algorithm based on randomized rounding and prove its approximation ratio. Finally, power allocation is solved to maximize performance with the given subchannel assignment. Be reminded that as an initialization step, the BS first performs a multi-user scheduling [10] to determine R_i^{min},$\bar{R}_i^{min}$for PUs before the three component algorithms run. The entire heuristic algorithm is called CentralizedHeuristicforFLEC hereafter.

We do not claim that our heuristic design is the only choice here. In fact other heuristic designs are entirely possible. For example, one may choose to solve the subchannel assignment first, then relay assignment, and finally power control. It is also possible to jointly solve two of the three orthogonal dimensions. For example one may choose to solve the joint problem of relay and subchannel assignment and then compute the power allocation based on the solution of the joint problem. These possibilities are beyond the scope of this paper and left as future research, since they have different formulations and require different solutions. We do not claim that our heuristic design is the best, although simulation studies. It improves performance significantly compared to the conventional identical channel cooperation.

4.3 Relay Assignment

Here, we model each user n as having an *imaginary* channel with a normalized channel gain to noise ratio and power p^{max}_n. Then the optimal FLEC strategy reduces to simple time-sharing on this channel. Assuming each SU can only help one distinct PU and one PU can only be matched to one SU.

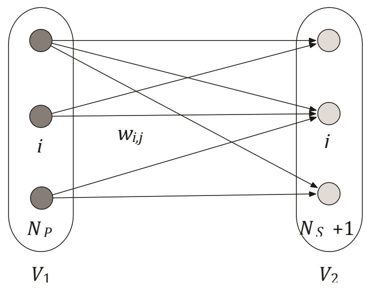

Fig. 2. Weighted bipartite matching for optimal relay assignment.

The above relay assignment is a weighted bipartite matching problem that can be optimally solved.The edge set E corresponds to $N_P(N_S + 1)$ edges connecting all possible pairs of users in the two vertex sets. Each edge (i,j) carries a weight, $w_{i,j}$,

For edges connecting PUs to the void SU that we patched, the edge weights have captured the maximum marginal utility given by direct transmission.

4.4 Subchannel Assignment

For PUs using direct transmission as determined by optimal relay assignment, they do not share resources with SUs, and as such cannot benefit from SU cooperation.For each PU i and its unique helping SU $j(i)$, we assume they will use powerrespectively on each subchannel, such an equal power assumption is widely used and leads to subchannel assignment algorithms with near-optimal performance.

The subchannel assignment problem under the above IP formulation is NP-hard.

Proof: The problem can be reduced from type-dependent multiple knapsack problems (MKP), where each set of knapsacks (users) belongs to a different type (time slot and primary/secondary). The profit of allocating an item (subchannel) depends not only on the knapsacks but also the type of them. The one-type MKP is known to be NP-hard and even hard to approximate [11]. Therefore our problem is NP-hard.

Given the hardness of the problem, we present a rounding based algorithm to solve it as shown in Algorithm 1. It ensures that each subchannel is assigned to at most one user for both slots. We now capture the performance of the algorithm.
Algorithm 1 provides an approximation ratio with high probability.

Therefore, its performance becomes better when there is a larger magnitude of available subchannels to users in the system. Since the number of subchannels in a practical OFDMA system is much bigger than that of users, Algorithm 1can be expected to provide good performance.

4.5 Power Control

For PUs with cooperative transmission, optimal power allocation is performed on a per-pair basis with their unique helping SUs. With sub channels allocated and their use on an SU determined, power allocation on each pair of PU-SU is a standard convex optimization problem and can be readily solved by KKT conditions.

Algorithm 1Rounding-based Sub channelAssignment

Formulate the problem using the IP above. Solve its LP relaxation with $x_i^{c1}, y_i^{c2}, y_j^{c2}$being relaxed to [0,1]. Let the

LP solutions be $\hat{x}_i^{c1}, \hat{y}_i^{c2}, \hat{y}_j^{c2}$ and $\hat{a}_i, \hat{b}_j$.

Adopt the following procedure to round the fractional solutions, to integral values, $\tilde{x}_i^{c1}, \tilde{y}_n^{c2}$, where $n \in \{i \in \mathcal{P}\} \cup \{j \in \mathcal{S}\}$.

- For every c_2, round y_n^{c2} to 1 ($\tilde{y}_n^{c2}$) with probability $\hat{y}_n^{c2}$. If $\tilde{n}$ is the user to whom c_2 is assigned, then $\hat{y}_n^{c2} = 0,\ \forall n \neq \tilde{n}$.
- Update$\tilde{a}_i = \frac{\sum \tilde{y}_i^{c2} w_{j(i),P}^{c2}}{1-\delta}, \tilde{b}_j = \frac{\sum \tilde{y}_j^{c2} w_j^{c2}}{1-\delta}$, where δ is a constant derived in the Appendix. Run the LP again on x_i^{c1} only. Let $\bar{x}_i^{c1}$ be the solutions of the new LP.
- For c_1, round x_i^{c1} to 1 ($\tilde{x}_i^{c1}$) with probability $\bar{x}_i^{c1}$. If $\tilde{i}$ is the PU c_1 is assigned to, then$\tilde{x}_i^{c1} = 0, \forall i \neq \tilde{i}$.

5. IDENTICAL CHANNEL COOPERATION

The present solutions for resource allocation with conventional identical channel cooperation (CC), which makes our analysis complete. The motivation to study CC here is that it can serve as the performance benchmark for our flexible channel cooperative scheme. Also, due to implementation and complexity considerations, FLEC may not be feasible in certain scenarios, whereas CC is comparatively easier to implement due to its simplicity. Similar to FLEC, we also consider both decentralized and centralized CC.

5.1 Decentralized CC

5.1.1 Problem Formulation

Scheduling and resource allocation of decentralized CC can be similarly formulated as that of FLEC. The key difference is that, the per-subchannel flow conservation constraints need to be satisfied for each subchannel, instead of only total flow conservation for FLEC.

From an intuition level, CC has more flexible time sharing strategy, but requires the relay transmission to be on the identical subchannel. FLEC is more flexible in terms of channel sharing strategy for cooperative transmission, but the time sharing strategy is restricted. From an optimization point of view, CC has $N_S K$ per-subchannel flow conservation constraints, while FLEC only has N_S total flow conservation constraints, where N_S is the number of SUs and K the number of subchannels. Given that K is typically on the order of hundreds in a practical OFDMA system, CC formulation has far more constraints than FLEC. Because these flow conservation constraints directly impact SU's throughput for relay and its own transmission they are active constraints that directly impact the optimization objective. Thus, it is not a surprise that FLEC outperforms CC in both decentralized and centralized settings.

5.1.2 Dual Decomposition

The dual variable updates can be understood as coordinating these constraints such that, when combined together, they are satisfied at the end of the process. In the decentralized resource allocation problem of CC, the flow constraint is already in the decoupled form to be satisfied for each subchannel. Thus, we only need to relax the total power and individual rationality constraints.,

By expanding the term R_i, R_j, ignoring constant terms, and realizing that each subchannel is already assigned to a PU, the per-subchannel problem can be written as

$$\begin{array}{ll} \max\limits_{j, p_i^c, p_j^c, \alpha_j^c} & \frac{R_{i,j}^c}{\bar{R}_i - \bar{R}_i^{\min}} + \mu_i R_{i,j}^c + \frac{R_j^c}{\bar{R}_j} - \lambda_i p_i^c - \lambda_j p_j^c \\ \text{s.t.} & (1)-(4), (25), R_{i,j}^c \leq R_{j,P}^c, i = F(c) \end{array}$$

5.1.3 Solutions to the Per-subchannel Problem

Exhaustive search can also be used to solve the per-subchannel problem. As we have seen, to enable such search we need to derive optimal solutions $\tilde{p}_i^c, \tilde{p}_j^c, \tilde{\alpha}_j^c$ under direct and cooperative transmission modes for any combination of subchannel c with its PU i and the SU j. Readily we can see that for direct transmission, the optimal solution $\tilde{p}_i^c$is the same as in[12]. However, for cooperative transmission, the derivations are different from the previous analysis.

The first observation is that, maximization of the problem is achieved with the inequality of the flow conservation constraint achieved as equality. This can be easily verified by observing that increasing $R_{j,P}^c$any further beyond $R_{i,j}^c$will not increase the utility of PU i. On the other hand, it will decrease the utility of SU j in the objective function, since j will inevitably have fewer resources to improve its own throughput.

Essentially, this is a constrained non-linear maximization with respect to two variables with standard solution methods. But it turns out quite difficult to obtain a closed form solution. We resort to numerical methods to obtain solutions efficiently.

Algorithm 2 Distributed Bargaining for CC

1. The primary BS runs a multiuser scheduling algorithm to determine R_i^{min} for PUs without cooperation.
2. Each user initializes its power price $\lambda^{(0)}{}_n$. Each PU initializes the dual variable $\mu^{(0)}{}_i$.
3. Given $\lambda^{(l)}$, each PU i solves the per-subchannel resource allocation problem
4. Each user n bargains by performing a update for the price λ_n. Each PU i also updates μ_i.
5. Return to step 3 until convergence.

6. Every user updates $\bar{R}_n$from its total throughput $R_n$in this epoch. Every PU i updates $\bar{R}_i^{min}$from R_i^{min}in Step 1. They will be used for resource allocation in next epoch.

$$g(\lambda,\mu) = \begin{cases} \max\limits_{\mathbf{R},\mathbf{P},\boldsymbol{\alpha}} & L(\mathbf{R},\mathbf{P},\boldsymbol{\alpha},\boldsymbol{\lambda},\boldsymbol{\mu}) \\ \text{s.t.} & (1)-(4),(24)-(25) \end{cases}$$

5.2 Centralized CC

Finally we consider resource allocation of centralized CC, which takes into account subchannel assignment to PUs and SUs. By the same argument.our focus is on developing efficient heuristics with short running time. We follow the same approach in developing Centralized Heuristics for FLEC and divide the problem into three dimensions, i.e. relay assignment, subchannel assignment, and power control. Readily we can see that the same relay assignment algorithm based on maximum weighted bipartite matching can be used here, since we would have an exactly the same problem formulation with only total flow conservation constraints, when all the channels are combined to form an imaginary channel. It is also straightforward that optimal power allocation follows the famous water-filling solution, given the relay and subchannel assignment. The only difference then lies in solving the subchannel assignment, which turns out to be much easier. The entire algorithm is referred to as Centralized Heuristics for CC thereafter.

5.2.1 Subchannel Assignment

Consider the set of PUs N_P^R that are assigned with an unique helping SU each. Their allocated subchannels K^R in the initialization step is re-assigned by the channel assignment algorithm. The same assumptions are inherited, that each PU i and its unique helping SU $j(i)$ usemaxequal powerrespectively on each subchannel, where K_i is the number of subchannels allocated to i in the initialization step.

From the per-subchannel flow conservation constraint, optimal time sharing $\bar{\alpha}^c_{j(i)}$ can be uniquely determined under equal power allocation $\bar{p}_i$,$\bar{p}_{j(i)}$ on each subchannel. The subchannel assignment problem can be casted as:

$$\max_{x_i^c} \sum_{c\in\mathcal{K}^R} \sum_{i\in\mathcal{N}_P^R} x_i^c u_{i,j(i)}^c$$
$$\sum_{i\in\mathcal{N}_P^R} x_i^c = 1, \forall c \in \mathcal{K}^R$$

The constraint is such that each subchannel is only allocated to one pair of PU-SU. This can be easily solved by assigning each subchannel c to a PU i that has the largest $u^c_{i,j(i)}$. That is, $\tilde{i}_c$= argmax$_{i\in N_P^R} u^c_{i,j(i)}$.

6. RELATED WORK

In networking literature,first proposes the idea of cooperative cognitive radio network, where the secondary users can earn spectrum access in exchange for cooperation with the primary user. A Stackelberg game is formulated where the primary user acts as the leader and determines the optimal time sharing strategy in maximizing its transmission rate. [13] consider a slightly different setting where the traffic demand of primary user is taken into account, and the utility function includes a revenue component from secondary users. Consider the game of one PU and multiple SUs in which the PU decides the portion of access time and the SU decide the relay power level. In a priority queuing system model is developed, and in a credit-based spectrum sharing scheme is studied for cooperative cognitive radio network. These works adopt a single shared channel setting with a single primary user and an ad-hoc network of secondary users[14]. On contrary, in this paper we consider a multi-channel setting where the OFDMA based primary and secondary networks co-locate, which represents a more practical network scenario and has not been considered before.

Resource allocation with cooperative diversity has been extensively studied in general wireless networks. Specifically, our paper is more related to work in cognitive radio or cooperative OFDMA networks. For the former, most work consider maximizing SUs' throughput with constrained interference to PUs. In other words, they all consider the underlay paradigm. For the latter, most related to our work are addresses the problem with a joint consideration of relay assignment, channel allocation, relay strategy optimization, and power control. Our previous work [15]considers the problem with a novel network coding based cooperation strategy, and proposes approximation algorithms with performance guarantees. Compare to these work, we consider the performance of primary and secondary users *jointly*, and apply the concept of Nash bargaining solutions to ensure both parities benefit from cooperation fairly.

7 .CONCLUSION

This work represents an early attempt to study OFDMA cooperative cognitive radio networks. The central question addressed is how to effectively exploit secondary user cooperation when conventional cooperation method becomes inefficient in this scenario, which has not yet been explored. We propose FLEC, a flexible channel cooperation design to allow SUs to customize the use of leased resources in order to maximize performance. We develop a unifying optimization framework based on Nash bargaining solutions to address the resource allocation problem with FLEC, where relay assignment, sub channel assignment, relay strategy optimization and power control intricately interplay with one another. An optimal distributed algorithm as well as an efficient centralized heuristic with near-optimal performance are proposed. We also extend our framework to consider resource allocation with conventional cooperation.

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