Flexible channel allocation using best Secondary user detection algorithm

K.Mathivanan[1] S. Dhayanithi[2] Prof. R. Anbarasu[3]
[1, 3]Associate Professor [2]PG Scholar
[1,2,3] Department of Computer Science & Engineering
[1,2,3] Selvam College of Technology, Namakkal

Abstract –Mobile computing is human–computer interaction by which a computer is expected to be transported during normal usage. The main problem in the existing system is the power allocation algorithm and the channel allocation problem for cooperative multiuser orthogonal frequency division multiplexing (MU-OFDM) cognitive radio (CR) systems. In the flexible channel cooperation, resource allocation is the serious problem. The primary user (PU) can transmit the data through the Secondary User (SU). Then through the number of SU s the data is transferred to the base station. The channel can be allotted based on the two algorithms, the optimal distributed bargaining algorithm and centralized heuristic algorithm. Then in the existing system, inflation attack is the severe problem. The inflation attack is overcome by implementing the Future Peak Detection algorithm. This determines that the PU can decide itself to transmit data through which SU. So the inflation attack problem can be overcome and the data is traversed to the base station with the full security.

I. INTRODUCTION

Cognitive radio, with the ability to flexibly adapt its transmission parameters, has been considered a revolutionary technology to open up dynamic access to the under-utilized wireless spectrum [2], [3]. Recently, a new paradigm where primary users (PUs) can leverage secondary users (SUs) for their own transmissions, termed cooperative cognitive radio networks (CCRN), is advocated [4], [5]. In CCRN, SUs cooperatively relay data for PUs in order to access the spectrum. Assuming that SUs have better channel conditions to the primary receiver, cooperative relaying can greatly increase the primary transmission rate. Meanwhile, SUs 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 [4], [5]. The PU leases its channel to SUs for a fraction of time in exchange for cooperative transmission. SUs allocate a portion out of their time fraction for relaying primary data, and the rest for their own traffic.

In this paper, we investigate cooperative cognitive radio networks from a new perspective. We consider multi-channel cellular networks based on OFDMA, e.g. IEEE 802.16 [6] for the primary network, with multiple SUs assisting multiple PUs on the uplink. Multi-channel networks impose unique challenges of realizing the cooperative paradigm, as we narrate below along with our original contributions. First, we observe that conventional user cooperation permeated through the literature [7] becomes inefficient when directly applied to multi-channel CCRN. It implicitly postulates that data on one channel has to be relayed on exactly the same channel, which may not be amenable to relaying from a performance perspective.

Our 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 user diversities available in multi-channel networks [8], [9], and allows SUs to freely optimize its use of resources, including channels and time slots leased by PUs, as well as power, for relaying primary data along with its own data, as long as all the primary data it received can be delivered. The basic idea of FLEC works as shown in Fig. 1. We consider the simplified case where time is equally divided into two slots among cooperating users1. PUs transmits 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. For example, it can use sub channel 1 solely for relaying data aggregated from both subchannel 1 and 2, and use subchannel 2 solely for sending its own data as in Fig. 1. The intuition is that, if subchannel 1 has superior conditions on the SUBS link but poor conditions on the SU-AP link, it is much more efficient using subchannel 1 to relay data from both subchannels. 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.

The second challenge in multi-channel CCRN is how to schedule the transmissions and allocate resources, in order to maximize performance gains while ensuring fairness among all users. A SU may assist several PUs (as in Fig. 1) simultaneously while a PU may also pair up with several SUs, complicating the resource allocation problem. Our main objective in this paper, therefore, is to develop efficient yet fair resource allocation algorithms for FLEC in multi-channel networks, which has not been addressed yet. To this end, our second contribution is a novel unifying optimization framework that jointly considers relay and subchannel assignment, relay strategy optimization, and power control, based on the concept of Nash bargaining [10].

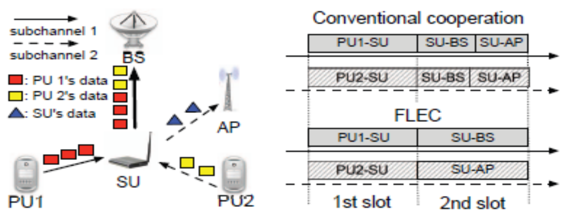

Fig. 1. The motivating scenario for Flexible Channel Cooperation (FLEC).

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 with NBS fairness among Pus and SUs, which is a generalized proportional fairness notion [11]. Therefore, gains from cooperation to individual PU and SU are allocated proportionally according to their channel conditions, i.e. their contributions to the social welfare gain. These properties make NBS favorable in our problem. We consider both decentralized and centralized FLEC as introduced above. In the decentralized case, we wish to develop a distributed algorithm that can be performed by users independently with local information only. We tackle this using a dual decomposition technique to transform the global optimization into many per-subchannel problems that can be solved by the respective Pus distributive and optimally. To account for SUs' utility, we rely on the sub gradient method [12] to allow PUs to bargain with neighboring SUs autonomously to arrive at the optimal solution for the per-subchannel problem, i.e. the Nash bargaining solution

II. AN OPTIMAL DISTRIBUTED ALGORITHM

A. *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 separately by the BS, and is not part of the optimization.

$$\max_{R,P,\propto} \sum_{i\epsilon\mathcal{N}p} \frac{Ri - Rimin}{\bar{R}i - \bar{R}imin} + \sum_{j\epsilon\mathcal{N}s} \frac{Rj}{\bar{R}j}$$

$$0 \preceq \mathrm{P}.1^{\mathrm{T}} \preceq \mathrm{p}^{\max}$$

$$\mathrm{R} \succeq R^{min}, R\epsilon\mathcal{C}(P,\alpha)$$

B. *Dual Decomposition*

The decentralized problem 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 **p** max, because if two sets of throughputs using two different sets of **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.

C. *Solving the Per-Sub channel Problem*

The previous sections show that in a decentralized setting with per-user power constraint and per-SU total flow constraint, the resource allocation problem (9) can be solved optimally and efficiently in the dual domain. However, this hinges upon efficient solutions to the per subchannel problem (12), which is required to solve the dual function g(λ,μ,ν). In this section, we show the per-subchannel maximization problem can be solved efficiently via exhaustive search.

D. *An Optimal Distributed Algorithm*

We have shown that the dual function can be decomposed into K per-subchannel problems, the optimal solutions of which can be obtained efficiently through exhaustive search. Then, the primal problem (9) can be optimally solved by minimizing the dual objective:

$$\begin{array}{ll}\min & g(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu}) \\ \text{s.t.} & \boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu} \succeq 0.\end{array}$$

Subgradient method can be used to solve this dual problem. The updating rules are as follows:

$$\lambda_n^{(l+1)} = \left[\lambda_n^{(l)} + \delta_n^{(l)}\left(\sum_{c\in\mathcal{K}} \tilde{p}_n^c - p_n^{\max}\right)\right]^+,$$

$$\mu_i^{(l+1)} = \left[\mu_i^{(l)} + \epsilon_n^{(l)}\left(R_i^{\min} - R_i\right)\right]^+,$$

$$\nu_j^{(l+1)} = \left[\nu_j^{(l)} + \kappa_j^{(l)}\left(\sum_{c\in\mathcal{K}}\sum_{i\in\mathcal{N}_\mathcal{P}} \tilde{R}_{i,j}^c - \sum_{c\in\mathcal{K}} \tilde{R}_{j,P}^c\right)\right]^+$$

III. A 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.

A. *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. 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 [20] to determine

R^{min}, R^{max} for Pus before the three component algorithms run. The entire heuristic algorithm is called Centralized Heuristic for FLEC hereafter.

B. *Relay Assignment*

Here, we model each user n as having an imaginary channel with a normalized channel gain to noise ratio $\bar{g}_n^c = \frac{1}{K}\sum_c g_n^c$ and power P_n^{max}. 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, the optimal relay assignment under the basic framework.

$$\max_{x_{i,j}\in\{0,1\}} \sum_{i\in\mathcal{N}_\mathcal{P}} \sum_{j\in\mathcal{N}_\mathcal{S}^+} x_{i,j}\left(\frac{\hat{R}_{i,j}-R_i^{\min}}{\bar{R}_i-R_i^{\min}}+\frac{\hat{R}_{j,i}}{\bar{R}_j}\right)$$

$$\text{s.t.}\quad \hat{R}_{i,j}=\frac{1}{2}\min\left(\log(1+2p_i^{\max}\bar{g}_{i,j}),\log(1+2p_j^{\max}\bar{g}_{j,P})\right)$$

$$\hat{R}_{j,i}=\frac{1}{2}\log(1+2p_j^{\max}\bar{g}_j)\left[1-\frac{\log(1+2p_i^{\max}\bar{g}_{i,j})}{\log(1+2p_j^{\max}\bar{g}_{j,P})}\right]^+,$$

$$\forall i\in\mathcal{N}_\mathcal{P}, j\in\mathcal{N}_\mathcal{S},$$

$$\hat{R}_{i,N+1}=\log(1+p_i^{\max}\bar{g}_i), \hat{R}_{N+1,i}=0, \bar{R}_{N+1}=\infty.$$

$$\sum_{i\in\mathcal{N}_\mathcal{P}} x_{i,j}=1, \forall j\in\mathcal{N}_\mathcal{S}, \quad \sum_{j\in\mathcal{N}_\mathcal{S}} x_{i,j}=1, \forall i\in\mathcal{N}_\mathcal{P}$$

IV. IDENTICAL CHANNEL COOPERATION

In previous sections, we have addressed the resource allocation problem with FLEC in both decentralized and centralized settings. In this section, we 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.

A. *Decentralized CC*

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 (5) for FLEC.

B. *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.

1) *Subchannel Assignment*

We only consider the set of PUs $\mathcal{N}_p^R$ that are assigned with an unique helping SU each. Their allocated subchannel $\mathcal{K}^R$ in the initialization step is re-assigned by the channel assignment algorithm. The same assumptions are inherited, the at each PU i and its unique helping SU j(i) use equal power

$$p_i = \frac{p_i^{max}}{K_i},$$

$$\bar{p}_{j(i)} = \frac{p_j^{\max(i)}}{K_i}$$

Ki respectively on each subchannel, where Ki is the number of subchannels allocated to i in the initialization step. From the per-subchannel flow conservation constraint (24), optimal time sharing $\propto_j^C(i)$can be uniquely determined under equal power allocation $p_i, \bar{p}_{j(i)}$ on each subchannel.

V. PERFORMANCE EVALUATION

To evaluate the performance of FLEC with the proposed resource allocation algorithms, we adopt empirical parameters to model the fading environment. There are 128 subchannels centered at 2.5 GHz, each with 312.5 kHz bandwidth. Channel gain can be decomposed into a large-scale log normal shadowing component with standard deviation of 5.8andpath loss exponent of 4, and a small-scale Rayleigh fading component. The inherent frequency selectivity is captured by an exponential power delay profile with delay spread 1.257vsas reported via extensive measurements [26]. The entire40 MHz channel is partitioned into blocks of size equal to the coherence bandwidth Bc ≈ 795.6 KHz. Three independent Rayleigh waveforms are generated for each block using the modified Jakes fading model and a weighted sum is taken to calculate the SNR. A scheduling epoch is of 5 ms duration, and an evaluation period consists of 1000 scheduling epochs. The number of PUs is set to 60, and the number of SUs varies.

A. *Overall performance of FLEC*

We first evaluate the overall performance of distributed and centralized FLEC compared with conventional identical channel cooperation ("CC" in the figures). We use Centralized Heuristic for CC to derive CC performance as the benchmark here. In Fig. 1, we plot the average throughput of both PUs (first three bars) and SUs (last three bars). We can see that Distributed Bargaining for FLEC and Centralized Heuristic for FLEC provide20–40% and 30–60% improvement, respectively. It clearly demonstrates the advantage of FLEC. A similar trend is also observed for SUs, although the improvement becomes marginal when the number of SUs scales up. The reason is that, though a larger number of SUs provides more and better cooperation for PUs and thus improves their throughput, it results in fewer channels leased to each SU, and a lower degree of optimization freedom.

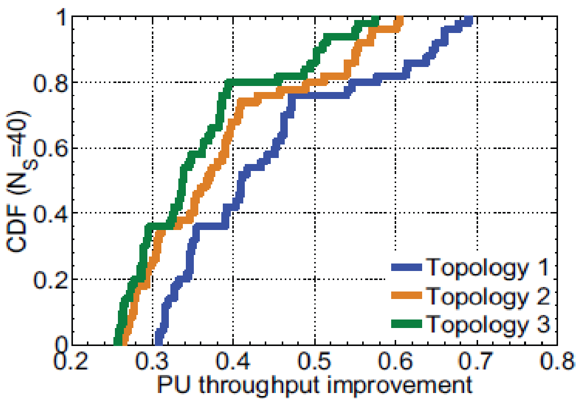

Fig. 1. Near-optimality of Centralized Heuristic.

VI. NEAR-OPTIMALITY OF CENTRALIZED HEURISTIC

We now evaluate the performance loss of Centralized Heuristic compared with that of Centralized Optimization. Recall that Centralized Optimization is developed via the same methodology of dual decomposition and sub gradient update as used in Distributed Bargaining. As seen from Fig. 2, with respect to the average throughput of both PU and SU, Centralized Heuristic losses about 5% in all cases. We also evaluate the performance loss with different values of p_i^{max}, and find that the gap widens when p_i^{max}, decreases. The reason is that our subchannel assignment is based on the assumption of equal power allocation, which becomes invalid when p_i^{max}, is small, and affects the performance of our Centralized Heuristic. Numerical details are not presented because of limited space. Due to slow convergence of Centralized Optimization, we may conclude that Centralized Heuristic achieves a good tradeoff between performance and complexity, and is amenable to practical implementations.

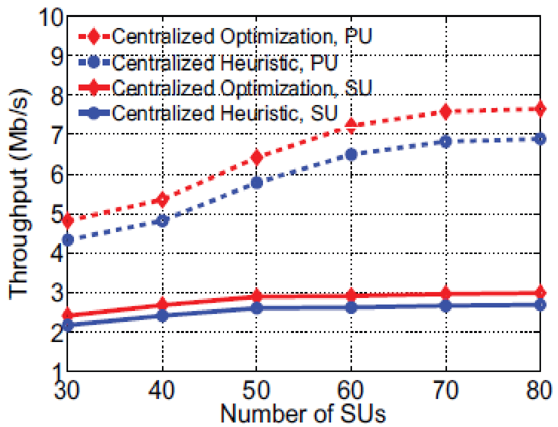

Fig. 2. Near-optimality of Centralized Heuristic.

VII. CONCLUSION AND FUTURE WORK

The central question addressed is how to effectively exploit secondary user co-operation when conventional cooperation method becomes inefficient. FLEC, a flexible channel cooperation design is proposed to allow SUs to customize the use of leased resources in order to maximize performance. The problem of synchronizing the periodic transmissions of nodes in ad hoc networks, in order to enable battery lifetime extensions without missing neighbor's updates is studied. Several solutions, both lightweight and scalable but vulnerable to attacks is proposed. Extension of generic algorithm to use transmission stability as a metric for synchronization is made. The implementation and simulations show that the protocols are computationally inexpensive, provide significant battery savings, are scalable and efficiently defend against attacks. The application works well for given tasks in windows environment. Any node with .Net framework installed can execute the application. The underlying mechanism can be extended to any all kind of web servers and even in multi-platform like Linux, Solaris and more. The system eliminates the difficulties in the existing system. It is developed in a user-friendly manner. The system is very fast and any transaction can be viewed or retaken at any level.

REFERENCES

[1] H. Xu and B. Li, "Efficient resource allocation with flexible channel cooperation in OFDMA cognitive radio networks," in Proc. IEEE INFOCOM, 2010.
[2] J. Zhang and Q. Zhang, "Stackelberg game for utility-based cooperative cognitive radio networks," in Proc. ACM MobiHoc, 2009.
[3] M. Andrews and L. Zhang, "Scheduling algorithms for multi-carrier wireless data systems," in Proc. ACM MobiCom, 2007.
[4] S. Deb, V. Mhatre, and V. Ramaiyan, "Wimax relay networks: Opportunistic scheduling to exploit multiuser diversity and frequency selectivity," in Proc. ACM MobiCom, 2008.
[5] IEEE 802.16j task group. Air Interface for Fixed and Mobile Broadband Wireless Access Systems: Multihop Relay Specification, 802.16j-06/026r4 edition, June 2007.
[6] M. Charafeddine, O. Oymant, and S. Sandhu. System-level performance of
cellular multihop relaying with multiuser scheduling. In CISS, March 2007.
[7] T. S. Rappaport. Wireless Communications: Principles and Practice. Prentice Hall, 2001.
[8] O. Oyman. OFDMA2A: A centralized resource allocation policy for cellular multi-hop networks. In IEEE Asilomar Conference on Signals, Systems and Computers, Nov 2006.