

Dynamic Control Channel Assignment in Cognitive Radio Networks using Swarm Intelligence

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Abstract— In recent years, a variety of algorithms for cognitive radio networks have been proposed. Many of these algorithms rely on the exchange of control information among the cognitive radio nodes and often require the presence of a globally available control channel. This requirement however poses a problem in a practical deployment: First, due to spectrum fluctuations such common control channel may be unknown at deployment stage. Second, when designating a fixed, dedicated control channel (for example in licensed spectrum), this will increase costs and expose vulnerability to the operation of the cognitive radio network. Thus, to overcome this difficulty, control channels should be dynamically assigned and managed in cognitive radio networks.

In this paper, we propose the use of swarm intelligence as a way to dynamically find and manage such control channels in cognitive radio networks. The system we describe is able to independently identify viable control channels and adapt in presence of changing spectrum. We formalize the problem of control channel assignments to the multi-commodity flow problem, measure the performance of our approach in a hardware implementation and software simulation and compare the results against the theoretically optimal solution.

I. INTRODUCTION

In the recent past, a wide variety of algorithms managing various aspects of cognitive radio networks have been proposed. Many of these algorithms that coordinate a cognitive radio network, however, require the existence of a commonly known and globally available control channel, through which spectrum management decisions [1], configuration instructions [2], routing information [3] or multi-channel medium access information [4], [5] is distributed among the network nodes. Without such information, the cognitive radio algorithms' performance is significantly deterred or the algorithm may not function properly at all. Thus, possessing such a common global control channel for active coordination is crucial for many applications.

There exists two basic strategies of how to find such channel: First, one may define a dedicated, fixed channel that is known to all the network nodes at deployment time. If such a channel (located in-band or on a different band for better propagation to eliminate routing and forwarding issues) is statically assigned, one has to make sure that the network nodes are always allowed to use it, i.e., one must license the spectrum or operate in a license-free band, and also be aware of that such channel acts as the critical link in the network. If it becomes suddenly unavailable, the cognitive radio network

loses its ability to coordinate and adapt. As a second strategy, one may dynamically select a control channel at run-time. This will remediate vulnerability concerns, as the network can flexibly change its control channel once necessary, but due to local spectrum heterogeneity extended negotiation among nodes might be necessary to determine a feasible solution. Such negotiation processes however create an additional level of complexity, protocol conformance and compatibility issues, thus making the inner workings of the cognitive radio more complicated.

In this paper, we present a light-weight solution to the problem of dynamic control channel assignment that does *not* require the explicit exchange of coordination messages among the nodes as it was required in previous work. Instead of active negotiation, the algorithm passively observes beacons sent out in the IEEE 802.11 ad-hoc mode. This feature allows the system to consume less resources, remove overhead and eliminate compatibility and interoperability issues. We have shown the feasibility of using swarm intelligence to control cognitive radio networks theoretically, through simulations [6] as well as in an experimental setup [7]. In this work, we build on these previous experiences and show how swarm intelligence can be used to dynamically manage control channel assignments in cognitive radio networks.

The remainder of this paper is structured as follows: Section II describes related work on dynamic control channel assignment in cognitive radio networks. Section III discusses the requirements of dynamic control channel assignment and provides a brief introduction to the concept of managing cognitive radio networks through swarm intelligence. Sections IV formalizes the problem, shows performance results and compares them to the theoretically optimal solution for control channel assignment. Section V concludes our work and summarizes our findings.

II. RELATED WORK

In this section, we describe and discuss related work on control channel assignment and channel management in cognitive radio networks. Even though the existence of working control channels is essential for many cognitive radio algorithms, limited work has been done in the development of algorithms that dynamically manage control channels.

Of the proposals that do dynamically assign control channels in cognitive radio networks, most algorithms make use of

a TDMA-driven schemes to communicate control information. In [8] for example, Zhao, Zheng and Yang describe an architecture for distributed coordination of control channels. In their approach and implementation called “HD-MAC”, all communication inside the network follows a super-frame structure, which is divided into a beacon broadcast period, a coordination window and a data transmission period. All coordination information to form and maintain control channels between nodes is transmitted in the first two parts of this superframe, whereas the last third is available for actual data exchange. This approach however requires that tight clock synchronization among the network nodes which is very difficult to achieve across many wireless nodes [9], furthermore all nodes in the cognitive radio network have to understand and participate in the messaging during the coordination and broadcast period for this solution to work, thus creating significant overhead communication.

As similar problem is associated with Krishnamurthy et al.’s proposal [10], which also builds upon a decentralized TDMA scheme. In this work each node learns its precise time information through a GPS device. Such synchronization however is only achievable in outdoor environments where GPS signals can be received.

Channel assignment strategies have been studied extensively in the area of cellular networks, for example in the management of microcells and to manage co-channel interference. For a comprehensive discussion in the area of cellular networks see for example [11]. In these works however, due to the relatively stable (base station) network topology and centralized control of cellular networks, channel assignments are not as dynamically and distributively managed as it would be required in cognitive radio networks. Other recent work on channel assignment has focused on the area of wireless 802.11 access point planning with the objective to minimize interference among base stations.

In summary, all previously introduction algorithms are built on implicit assumptions and requirements that might limit their applicability to the task of dynamic control channel assignment in cognitive radio networks: First, if the nodes use a time-division channel access scheme, tight synchronization between nodes has to exist. This might be difficult to achieve, given that no coordination link between the nodes yet exists (as this is supposed to be established by the algorithm) and no information about the network topology might be known to each individual node before hand. Second, if that coordination information is exchanged using some special format, i.e., as a message in a particular time slot or through a discovery protocol, all nodes in the system have to be of the same make and model or at least compatible enough to understand and make sense of this negotiation information. This might not be the case in a diverse cognitive radio deployment hosting many different types of secondary users.

III. MANAGING CONTROL CHANNELS IN COGNITIVE RADIO NETWORKS

In this section, we present a novel approach to dynamically manage control channel assignment in cognitive radio

networks that does not have the requirements and limitations of previously proposed approaches such as explicit messaging, protocol compatibility or synchronized clocks. The approach we describe in this section is based on the concept of swarm intelligence and can dynamically and distributively coordinate a cognitive radio network through passive observation of its environment only.

To set the stage for our analysis, we first describe two scenarios for control channel assignment applicable to most deployment environments - first, the case of channel assignment in spectrum homogeneity and second, the case of spectrum heterogeneity. We then describe the details of our proposal to dynamically find control channels using swarm intelligence.

A. Scenarios

As introduced before, many different cognitive radio algorithms, e.g., for spectrum management [1], routing [3], MAC layer scheduling [2] or multi-channel medium access [4], [5], require the exchange of control information to coordinate decision making processes among the cognitive radio network nodes. Since this control information needs to be exchanged prior and in addition to other network flows, researchers and designers frequently rely on the existence of a common control channel that can be accessed and used by all network nodes in the deployment to exchange such coordination information.

There exist two distinct situations for the assignment of control channels, first in spectrum homogeneous and second in spectrum heterogeneous environments. While we have solved both cases using our methodology, due to space limitations in the paper, we only present parts of these results in this paper. Specifically, we limit our discussion to introduce the concept of dynamic control channel assignment through swarm intelligence (Section III-B) and to show results in the first of the two described scenarios (Section IV).

1) *Spectrum Homogeneity: Global Control Channel Assignment:* Figure 1 depicts a situation where a cognitive radio network is encountering spectrum homogeneity, i.e., spectrum is similar enough among the network nodes that a single available channel among them exists. In such a situation the incumbents either have a similar effect on all nodes (for example there exists only one primary user in range of the stations) and/or in the presence of multiple primary users with varying ranges and impacts these incumbents must be allocated to channels in such a way that a set of frequencies is still available to all cognitive radio nodes as indicated in the figure. Note that even in spectrum homogeneous situations, all cognitive radio network nodes do not necessarily have to be in range of each other and that the need to forward control messages might still occur.

2) *Spectrum Heterogeneity: Area-Specific Control Channel Assignment:* Figure 2 shows the situation where a cognitive radio network has to find a control channel assignment in presence of spectrum heterogeneity, i.e., there exists no channel that is available to all network nodes at the same time, thus area-specific channel assignments will have to be found. In these situations, which will typically occur when

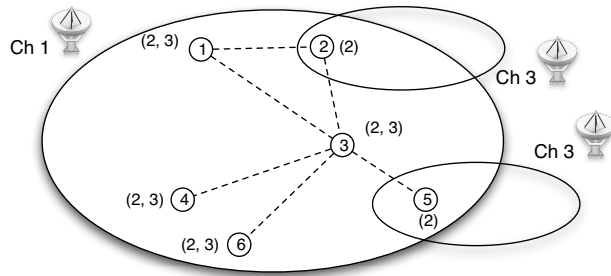


Fig. 1. Global Control Channel Assignment in Spectrum Homogeneous Situations: All nodes can use channel 2 for control communication.

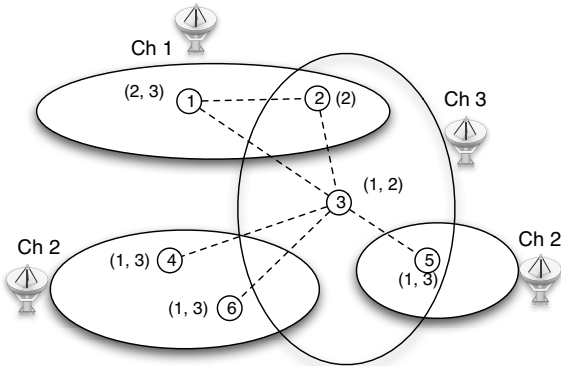


Fig. 2. Area-Specific Control Channel Assignment due to Spectrum Heterogeneity: Nodes 1-3 can use channel 2 for communication, nodes 4-6 channel 1. The boundary node 3 will need to forward control information between the two areas for network-wide control communication.

secondary user networks cover larger areas, nodes that are located at the boundary of two such areas will need to route and forward control flow messages across channels and into areas that cannot be connected using a common control channel assignment.

B. Coordinating Cognitive Radio Networks through Swarm Intelligence

In this subsection, we briefly outline the idea of coordinating cognitive radio networks using emergent behavior, i.e., swarm intelligence as it can for example be observed in schools of fish and flocks of birds. We will present this idea in a high-level, conceptual overview, for a more detailed discussion of the underlying concepts, algorithmic considerations and its implementation in a cognitive radio refer to [6].

1) *Biological Foundation*: The collective, emergent behavior of a school of fish, which to the outside viewer expresses itself as “swarming”, is the result of very simple rules that are followed by every individual in the group. These simple rules, executed by each individual based on its local view of the environment, together give rise to a complex globally coordinated behavior and make it possible that schools of a million fish can move as a cohesive structure, navigate around obstacles and avoid predators in unison.

Even though each fish is only considering its most direct proximity, the school as a whole can manage to react globally meaningful to changes that occur anywhere nearby. Any relevant information that is sensed by a particular individual is propagated through the entire swarm so that all individuals affected finally know this information even though they didn't

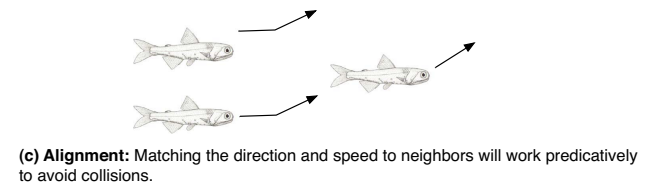
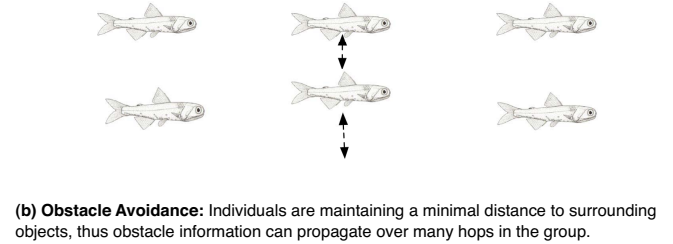
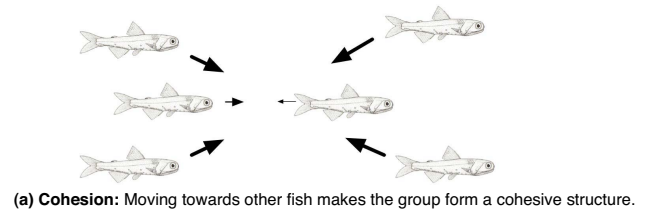


Fig. 3. Following three basic rules at the individual level creates the global property of emergent behavior.

originally sense it. Knowledge is not explicitly communicated as a message. Instead if the information is important enough that the individual, who has originally learned it, is directly acting upon it, it is a good idea for any nearby neighbors seeing the individual's reactions to correspondingly mirror it, i.e., one does not need to see the shark oneself, it is enough to see the next door neighbor fleeing from it to start fleeing.

There are two reasons why swarming behavior is a very compelling solution to coordinate cognitive radio networks: First, swarming works without the existence of a “master fish” that coordinates everyone's actions nor are there distributed negotiations schemes between neighbors at work, thus the entire approach drastically reduces overhead. Second, even though each individual only possesses very limited local knowledge, by following a simple set of rules all relevant information is propagated to all group members keeping even large populations synchronized.

To create this global behavior, each individual follows three rules [12], which are visualized in Figure 3(a)-(c):

- (a) **Cohesion** move towards other fish and stay in their proximity,
- (b) **Obstacle Avoidance** stay at a minimal distance from your neighbors and other foreign obstacles, and
- (c) **Alignment** move in the same direction and speed as those around you.

2) *Applying Swarm Intelligence to Cognitive Radios*: If we plan to transfer this biological behavior to the technical domain, we must follow a series of steps to “translate” the biological algorithm to the requirements and assumptions of wireless networks. More specifically, we must adjust the sensory input and actions of the agents in the source domain, the fish, to senses and actions meaningful in a cognitive radio network.

One corresponding starting point for such an adjustment is to analyze the semantics of the swarming algorithm, and find matching analogies in the target domain: A commonly cited reason why fish stay together in dense swarms is that the group offers protection from outside predators [13], as individuals are easier to seek out and attack when on their own instead of when being part of a larger group. Spatial proximity offers protection from negative outside influences.

This intention is in essence identical to the task a cognitive radio has to achieve, as it too needs to minimize negative influences, for example interference, from the outside. Instead of changing its physical location (which is usually unwanted), the cognitive radio however has more sophisticated ways to adjust. In order to achieve “proximity” to improve communication to its peers and create a sufficient “distance” to negative outside influences, it could for example modify its transmission frequency, change its encoding scheme or adapt its waveform to meet that objective.

Thus, through this and similar mappings for the other two behaviors obstacle avoidance and alignment, we use the swarm algorithm to coordinate cognitive radio networks without explicit communication between nodes and by having each node rely on local information only. The cognitive radio network basically achieves the same objective as the school of fish, follows the identical biological algorithm, while making use of the more sophisticated means of adaptability of a cognitive radio network. While the algorithm can be used to coordinate the network using many different parameters, we explicitly limit it to frequency adaptation only, since we are intending to use this algorithm for the dynamic management of control channels. Using the foundation and process described above, we implemented the cognitive radio algorithm following the swarming approach both in a software simulation and on a hardware platform. Details about the specific implementation in hardware and software, algorithmic considerations and additional results are discussed in further detail in [14].

IV. GLOBAL CONTROL CHANNEL ASSIGNMENT

In this section, we describe our experimental setup and results for an application of swarming as a solution to the dynamic control channel assignment problem in cognitive radio networks. In this discussion, we are specifically interested in the fidelity of the solution, i.e., we investigated the adaptation performance of the algorithm and how well it assigns control channels compared to the theoretically optimal solution found through a linear program.

We therefore begin our discussion by formalizing the problem of common control channel assignments into the multi-commodity flow problem. This formalization can then serve both as a metric for measuring the channel assignment success as well as – when extended into a linear program – to find the theoretical optimum. We then describe our experimental setup for this evaluation and compare the performance of the swarm solution.

A. Problem Statement

When viewed as a multi-commodity flow problem, the problem can therefore be formalized as follows: Assume a

directed graph (N, A) where $N \in [N_0, N_{|N|}]$ denotes the set of nodes and A the set of directed links between a pair of nodes. All nodes are initialized from random and can sense local spectrum which is divided into the set of $C \in [C_0, C_{|C|}]$ channels. The set of locally available frequencies that can be used by node N_i is written as $a(i)$ and due to spectrum homogeneity,

$$\exists k \in [0, |C|] \text{ such that } k \subseteq \left(\bigcup_{i \in [0, |N|]} a(i) \right) \neq \emptyset. \quad (1)$$

To manage the network, there exist control communication flows that need to be fulfilled between given pairs of nodes, where x_{ij} denotes the flow that is originated at node i and terminated at node j . These flows can be made of different commodities which cannot be substituted against each other and must be individually served. Let $x(m)$ denote the flow vector of commodity m where $m = 1..M$, that contains all flows of that commodity between a set of nodes. The collection of all flow vectors of all commodities in the network is given as $x = (x(1), \dots, x(M))$. Since a network that has completely settled on a common, network-wide control channel can fulfill all control flow demands, we can use the ratio of currently fulfillable control flows given the current network configuration as a configuration “goodness” metric.

Since the packets from each node are unique and not interchangeable with other packet streams in the network, let each flow between the origin-destination pair (i_m, j_m) be denoted as a commodity, with $x(m)$ describing the corresponding flow vector. The flow of commodity m begins at node i_m and terminates at node j_m and is forwarded through intermittent nodes if there exists no link connecting i_m and j_m .

Therefore, in the entire network the conservation of flow constraint must be fulfilled to allow a proper accommodation of each flow,

$$\sum_{\{j|(i,j) \in A\}} x_{ij}(m) - \sum_{\{j|(j,i) \in A\}} x_{ji}(m) = \begin{cases} r_m & \text{if } i = i_m, \\ -r_m & \text{if } i = j_m, \\ 0 & \text{otherwise.} \end{cases}$$

i.e., the net amount of commodity m exiting node i is exactly the amount of commodity m that is being injected by node i into the network and the net amount absorbed by node j is the amount of commodity m being consumed by node j . For all other nodes, the net amount of commodity m entering and exiting must exactly be zero. This formalization will capture both unicast and multicast control flows.

We further require that the amount of flow on each network link must be greater than 0 and the sum of all commodity flows must not exceed a link’s capacity c_{ij} .

$$0 \leq x_{ij}(m), y_{ij} = \sum_{m=1}^M x_{ij}(m) \leq c_{ij} \quad \forall (i, j) \in A, m = 1..M$$

The objective is to maximize the overall traffic flowing in the network, i.e.,

$$\text{maximize } f = \sum_{(i,j) \in A} f_{ij}(y_{ij})$$

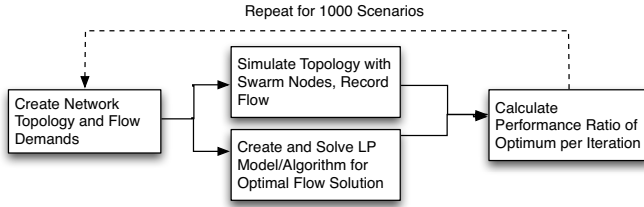


Fig. 4. Automatic setup for evaluating the performance of the swarm-driven cognitive radio network.

where $f_{ij}(y_{ij})$ is a convex function weighted for the utility and cost of the link (i, j) . The sum over all control flows $\sum_{(i,j) \in A} (y_{ij})$ for a maximized f results in the best obtainable solution for this particular class of problems.

B. Reference Solution: Linear Programming Model

Since for the case of control channel assignment in spectrum homogeneity equation 1 is fulfilled, there always exists a feasible solution to the control channel assignment problem that can be found through a linear program. To find the maximal number of commodity flows that can be fulfilled with a valid, network-wide control channel assignment, we can use the formalization of the multi-commodity flow problem populated with the specifics of a given network topology as the input to a linear programming solver. We implemented a toolkit that would read in a particular network topology, automatically create the corresponding populated linear program and solve the problem through the GNU linear programming kit (GLPK) [15] to find the optimal reference solution. We used this reference solution as a benchmark for the experimental evaluation.

C. Experimental Setup

To determine the utility of the approach, we conducted a series of experiments using both software simulations and a hardware testbed.

For the software simulations, all evaluations and performance comparisons were conducted using the experimental setup depicted in Figure 4. For each evaluation, we automatically generated a cognitive radio network topology that included $|N|$ nodes, each in interference distance to at least one of 3 incumbent users and $|N|/2$ control flow demands between the nodes in the topology that needed to be fulfilled. The topologies were generated such that all networks were strongly connected, exhibited some clustering but also contained sparsely linked areas. One actual example topology for the 15 node case is shown in Figure 5.

The automatically generated network topology was then solved in a simulation by cognitive radio nodes running our swarming approach. Then, the fractional performance of the swarm algorithm compared to the theoretically optimal solution was calculated for each iteration that the algorithm was executed, i.e., we determined the relative performance and the steepness of the improvement gradient for our proposed solution technique. For each experiment, this approach was replicated 1,000 times.

For the hardware evaluation, we deployed sets of three of four commodity hardware laptops with off-the-shelf wireless

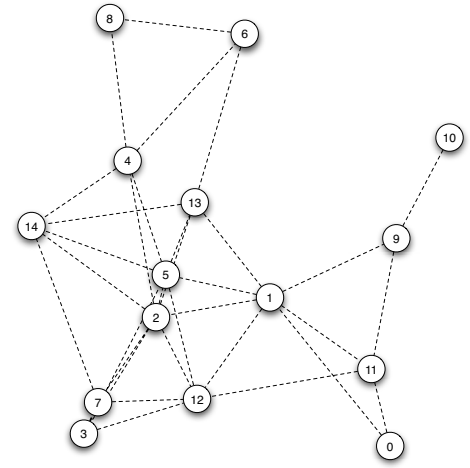


Fig. 5. Example of an topology with network flows automatically generated for 15 nodes.

adapters such that there was full connectivity in the network. Each wireless adapter was using an Atheros chipset, which in conjunction with the MadWifi [16] driver provided us with a low-cost cognitive radio system with limited sensing capabilities. In the hardware experiments, all systems started from a random initial configuration and had to come to a consensus control channel assignment. The hardware experiments for the three and four node deployments were replicated 25 times each.

D. Performance Evaluation and Comparison

Figure 6 summarizes our findings and shows the performance of the swarm intelligence-driven control channel assignment measured in achieved percentage of the optimal solution, for both the hardware implementation (red curves) and the simulated results (black curves). As can be seen in the figure, the decentralized, messaging-less swarm algorithm while starting from a random initialization achieves overall high performance levels; it is able to configure a network-wide control channel that can satisfy 80% of the theoretically possible control flows in the network after 10–15 iterations of the algorithm and achieves near perfect fidelity after 10–50 iterations depending on the network size.

The figure further displays three features that make the swarm algorithm based solution an interesting choice for channel management in a wireless network:

First, scalability is barely an issue. Even though we varied the implemented and simulated network size between 4 and 50 nodes, the algorithm scales well with network size and is able to configure even moderate sized networks in reasonable time. We have analyzed the scalability of the general approach further in [17].

Second, the algorithm performance shows very steep improvement gradients. Thus, even completely uninformed, freshly initialized or recently interrupted cognitive radio networks can expect to achieve good levels of performance within very few iterations of the algorithm, making it an interesting

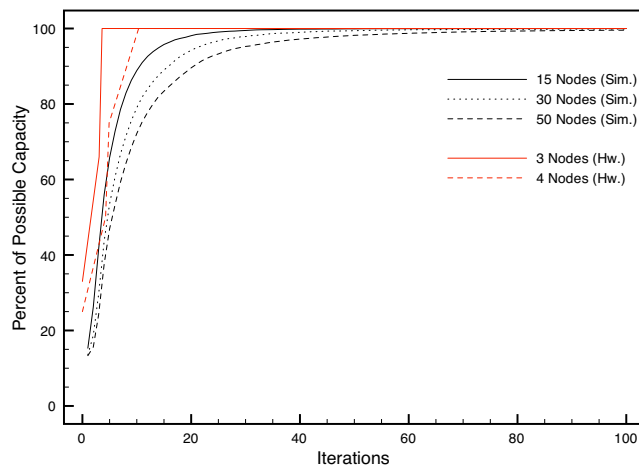


Fig. 6. Comparison of the swarm algorithm's solution to the theoretically achievable optimum.

candidate for managing control channel assignments in highly fluctuant environments.

Third, the simulation data is verified by empirical results. Even though we tested the algorithm in an admittedly small scale hardware testbed, the empirical results also indicate a steep improvement gradient and overall low convergence times for the algorithm, thus further supporting the experimental evidence obtained in simulations.

E. Summary

In summary, we can conclude that an algorithm based on swarm behavior is well suited to dynamically manage common control channel assignments in a cognitive radio network. This is due to several reasons: First, the algorithm operates on local information only and does not explicitly exchange negotiation messages in the network, thus overhead is minimized and potential incompatibility issues or common protocol requirements are avoided. Second, the algorithm operates on a simple set of rules, thus making implementation easy and reduces the potential of unwanted, complex interactions with other algorithms in the cognitive radio. Third, we could demonstrate both in hardware and in software that controlling a cognitive radio network through this algorithm is a feasible solution and yields competitive performance outcomes compared to the theoretically optimal solution.

V. CONCLUSIONS

In this paper, we have introduced and discussed a solution to the dynamic control channel assignment problem in cognitive radio networks. Many algorithms for these networks require the existence of a common, network-wide control channel for proper operation, thus the dynamic identification and management of such channel is for great importance for the functions of such higher-level algorithms.

Previous work to find such channel has relied on a distributed algorithm that either required a common signaling protocol and/or tight clock synchronization in a network,

thus making the deployment of such algorithms in many environments difficult if not impossible.

In this work, we have discussed the use of swarm intelligence to dynamically manage control channel assignments. The algorithm based on this concept is able to find such assignment, but achieves network coordination through passive observation only, thus negating the need for common messaging protocols and removing overall overhead. We have implemented the algorithm both in hardware and software and have shown the general feasibility. We find that this approach results in competitive performance compared to the theoretically optimal solution.

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