

Coexistence Decision Making for Spectrum Sharing Among Heterogeneous Wireless Systems

Behnam Bahrak and Jung-Min “Jerry” Park, *Senior Member, IEEE*

Abstract—This paper focuses on the problem of spectrum sharing between secondary networks that access spectrum opportunistically in TV spectrum. Compared to the coexistence problem in the ISM (Industrial, Scientific and Medical) bands, the coexistence situation in TV whitespace (TVWS) is potentially more complex and challenging due to the signal propagation characteristics in TVWS and the disparity of PHY/MAC strategies employed by the systems coexisting in it. In this paper, we propose a novel decision making algorithm for a system of coexistence mechanisms, such as an IEEE 802.19.1-compliant system, that enables coexistence of dissimilar TVWS networks and devices. Our algorithm outperforms existing coexistence decision making algorithms in terms of fairness, and percentage of demand serviced.

Index Terms—Coexistence decision making, cognitive radio, TV whitespace, IEEE 802.19.1, Boltzmann machine.

I. INTRODUCTION

THE analog-to-digital TV transition has freed up a significant amount of TV spectrum which is referred to as TV white space (TVWS). In 2012, the U.S. Federal Communications Commission (FCC), in its report and order [1], ruled that the TVWS can be used for secondary (i.e., unlicensed) access, and regulators in other countries are following suit.

The opening up of the TV bands to unlicensed access has triggered several standardization efforts such as IEEE 802.22, 802.11af, 802.19.1, and ECMA 392. Based on the ongoing standardization efforts and the industry stakeholders’ growing interest in utilizing TVWS, it is likely that a heterogeneous mix of secondary networks will coexist in TVWS, each with distinct operation parameters (e.g., bandwidth, transmission power, PHY and MAC techniques, etc.). Therefore, enabling “congenial” heterogeneous coexistence in TVWS is emerging as an important research area.

The FCC rules stipulate requirements and mechanisms for protecting incumbent systems such as TV stations. However, neither the FCC nor any other regulatory agency addresses the problem of coexistence of secondary systems/devices operating in the same spectrum. The lack of provisions for coexistence of secondary systems in TVWS may be due to the experience in the Industrial, Scientific and Medical (ISM) bands, where diverse technologies, such as WiFi and Bluetooth, coexist without a common coexistence mechanism. However, the coexistence situation in the TVWS is more

challenging due to the signal propagation characteristics in TVWS and the disparity of PHY/MAC strategies of the coexisting systems. Without coexistence mechanisms in place, secondary networks’ performance can be severely degraded by interference from other secondary networks. Recognizing the criticality of such a problem, the IEEE 802.19 Working Group recently formed the 802.19.1 Task Group. This Task Group has been chartered with the specific task of developing a standard for TVWS coexistence mechanisms.

In a *coexistence enabling system* such as an 802.19.1 compliant system, coexistence decision making (CDM) is a procedure that carries out critical tasks for enabling congenial coexistence among dissimilar networks operating in the same spectrum. Specifically, this procedure sends out reconfiguration commands to coexisting networks and allocates spectrum to those networks. This procedure is the primary function carried out by an 802.19.1 compliant system. In this paper, we define spectrum allocation (by a coexistence enabling system) as the process of allocating a number of TV channels of predetermined bandwidth to the base station of each coexisting TV band device (TVBD) network. Thus, it is different from the notions of traditional link-based or node-based scheduling. Once the spectrum has been allocated, the allocation does not change unless: (1) an incumbent appears in one of the assigned channels (2) a change in a network’s spectrum demand or some other coexisting network’s demand requires readjusting the network’s allocation.

In this paper, we propose an algorithm called *Fair Algorithm for Coexistence decision making in TV whitespace (FACT)*. This algorithm addresses some of the challenges of coexistence between heterogeneous wireless networks, and considers many factors in sharing a channel between two or more networks of different types. Our contributions can be summarized as follows:

- 1) We use a set of constraints to formulate the CDM problem as a multi-objective combinatorial optimization problem. Each of the constraints corresponds to an important prerequisite for the coexistence of heterogeneous wireless networks. Unlike the existing CDM problem formulations, our formulation includes all of the critical constraints.
- 2) We model the optimization problem as an energy minimization problem in a modified Boltzmann machine, and propose an algorithm to find a Pareto optimal feasible solution. Our evaluations show that the proposed algorithm outperforms existing CDM algorithms that have been proposed for use in IEEE 802.19.1 [2][3] in terms of fairness, and percentage of demand serviced.

Manuscript received December 19, 2012; revised June 28 and November 12, 2013; accepted November 28, 2013. The associate editor coordinating the review of this paper and approving it for publication was Y. Yousefi’zadeh.

The authors are with the Department of Electrical and Computer Engineering (MC0111), Virginia Tech, 438 Whittemore Hall, 1185 Perry Street, Blacksburg, VA, 24061, USA (e-mail: {bahrak, jungmin}@vt.edu).

Digital Object Identifier 10.1109/TWC.2014.012314.122009

The rest of this paper is organized as follows. We discuss related works in Section II and provide technical background knowledge in Section III. Section IV provides details on the constraints for CDM and in Section V, we formulate the CDM problem using these constraints. We propose our CDM algorithm in Section VI and then evaluate the performance of this algorithm and compare it with existing algorithms in Section VII. Finally Section VIII concludes the paper.

II. RELATED WORK

Coexistence of wireless networks has always been an issue, however the coexistence of heterogeneous wireless networks become a more serious problem after the introduction of wireless networks in unlicensed bands. The issue began to receive significant press with the introduction of the Bluetooth technology (IEEE 802.15.1) around the same time that WiFi technology (IEEE 802.11b) networks were becoming popular [4]. In 2003, the IEEE formed a task group to quantify the severity of the problem and offer solutions. This ultimately resulted in a published IEEE recommended practice: IEEE 802.15.2. IEEE 802.15.2 [5] addresses the coexistence of wireless personal area networks (WPAN) with other wireless devices operating in unlicensed frequency bands such as wireless local area networks (WLAN).

Coexistence of ZigBee (IEEE 802.15.4) and WiFi (IEEE 802.11) is another example of coexistence of heterogeneous wireless networks that has attracted significant attention since their disparate power levels, asynchronous time slots, and incompatible PHY layers hinders the coexistence of them in 2.4 GHz band. Industrial associations, such as the ZigBee Alliance [6], demonstrated that ZigBee can coexist well with WiFi in home networks. The conflicting coexistence between IEEE 802.15.4 and IEEE 802.11 has been observed in existing measurement studies [7]. In [8], a coexistence mechanism called cooperative busy tone (CBT) is proposed that allows ZigBee to coexist and even contend with WiFi in frequency, spatial and temporal domains.

Coexistence between IEEE 802.16 and IEEE 802.11 is another interesting example of coexistence between heterogeneous wireless networks. The IEEE standard draft 802.16h [9] proposes methods for 802.16 system coexistence. It distinguishes between coordinated and uncoordinated operation. Coordinated operation uses a specified protocol allowing multiple systems to negotiate their resource usage. With uncoordinated operation no explicit messages are exchanged. A system has to sense the medium at the beginning of the frame. If it is busy the system is not allowed to perform any transmissions for the whole frame.

In [10], the coexistence mechanisms provided by IEEE 802.19.1 are analyzed. These mechanisms include neighbor discovery and white space management to guarantee interference mitigation and fairness. In [11] and [12], challenges in addressing the problem of coexistence between heterogeneous wireless networks are discussed. We address some of these challenges in this paper. In [13] a taxonomy of the mechanisms that have been proposed for heterogeneous coexistence in TVWSs is offered. At this point in time, there are only a few CDM algorithms for IEEE 802.19.1 that have been proposed.

To the best of our knowledge, only two such algorithms exist [2] [3]. We have compared our algorithm against these algorithms and showed that our algorithm outperforms them in some aspects.

In [14], the authors propose a standard-independent framework to enable exchange of coexistence-related information based on centralized and distributed mechanisms. Both mechanisms use a multi-radio cluster-head equipment (CHE) as a physical entity that identifies coexistence opportunities and makes coexistence decisions.

III. TECHNICAL BACKGROUND

In this section we provide some technical background and jargon that facilitates the understanding of this paper's technical aspects.

Regulators such as FCC prescribe rules and mechanisms for protecting licensed networks and devices operating in TV bands (i.e. coexistence between secondary and primary networks), but no such rules exist for coexistence among secondary, unlicensed networks (a.k.a *TVBD networks*). To fill this void, the IEEE 802.19 Working Group sponsored the formation of the IEEE 802.19 Task Group 1.

An IEEE 802.19.1 system is consist of three main entities that are briefly described below:

- The *Coexistence Discovery and Information Server* (CDIS) provides coexistence related information to coexistence managers, supporting discovery of coexistence managers, and opening interfaces between coexistence managers. It also collects and aggregates information related to TVWS coexistence, and may connect to the TVWS database to obtain information on primary user spectrum utilization.
- The *Coexistence Manager* can be regarded as the brain of IEEE 802.19.1 compliant systems. It is responsible for discovering other coexistence managers (CMs) and making coexistence-related decisions in order to solve coexistence problems between TVBD networks they serve. They also provide coexistence commands and control information to coexistence enablers and help network operators manage coexistence-related issues.
- The *Coexistence Enabler* is responsible for the communications between a coexistence manager and a TVBD network. It obtains information required for coexistence from the TVBD network or device, and it translates reconfiguration requests/commands and control information received from the coexistence manager into TVBD-specific reconfiguration requests/commands.

In this paper, we focus on a coexistence enabling system that has a centralized topology—e.g., a centralized 802.19.1 topology. In this topology, there is a master coexistence manager (MCM) controlling multiple slave coexistence managers (SCMs), each associated with a TVBD network. The MCM is the central entity that controls the SCMs, and makes coexistence decisions. Fig. 1 illustrates this centralized topology.

As it can be seen in Fig. 1, each TVBD network is associated with an SCM, and all these SCMs are connected to an MCM. Each SCM sends *context information* (CI) messages to the MCM. Context information messages convey fundamental

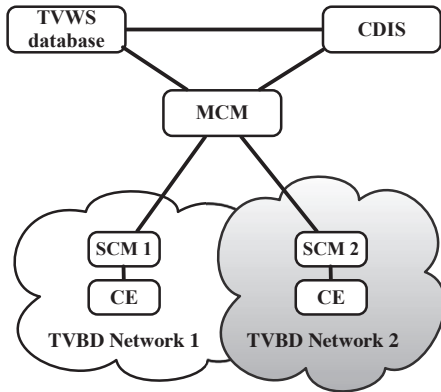


Fig. 1. A coexistence enabling system with a centralized topology.

information required by their corresponding entity for making decisions on radio resource allocation. The MCM uses the context information messages as inputs to a *coexistence decision making* algorithm in order to allocate spectrum resources to coexisting networks under the control of the MCM.

IV. CONSTRAINTS FOR COEXISTENCE DECISION MAKING

The output of the CDM algorithm determines which network is assigned to which part of the TVWS. Allocating spectrum to a heterogeneous mix of coexisting networks is challenging because each network has different spectrum resource requirements and it may employ a different PHY/MAC strategy that affects other coexisting networks. On the other hand the necessity of supporting capabilities such as adaptive channel bandwidth that are unique to nodes in a cognitive radio network and the changing nature of available channels in TVWS hinders the problem of spectrum allocation to these coexisting networks.

The CDM algorithm uses two pieces of critical information to generate its output: (1) each network's *spectrum demand* (i.e., amount of spectrum requested by a network) and (2) the *interference graph* showing the interference relations between the coexisting networks. Interference graph is an undirected graph that its nodes are variables representing the TVBD networks and its edges connect networks that interfere with one another. The weight of an edge shows the minimum frequency separation (i.e. freq separation required to achieve a threshold SINR at either of the networks connected by the edge) between the two interfering networks.

The MCM needs to consider several constraints when performing CDM. In the following paragraphs, we describe the constraints that are critical in maximizing throughput of secondary networks and spectrum utilization. Note that the purpose of these constraints is to enable coexistence among secondary networks/devices, and they do not consider incumbent (i.e., licensed) system protection. We assume that incumbent system protection is ensured by other means (such as the incumbent protection database) and that the TVWS channels that are being allocated by the CDM algorithm are free of incumbent system signals. The constraints are used to formulate the CDM problem as an *energy minimization problem*, which we describe in Section V.

A. Contiguous Channels

The allocation of contiguous channels enables channel aggregation. Prior research has shown that aggregating contiguous channels improves throughput. Chandra et al. [15] have shown that allocating contiguous channels to a network enables the network to support adaptive channel widths, which can result in a throughput increase of more than 60% compared to the best fixed-width configuration under certain conditions.

B. Interference

The CDM algorithm should allocate spectrum to secondary networks in a manner that minimizes co-channel and adjacent-channel interference. To carry out this task, the algorithm utilizes an interference graph that provides quantitative information on the adjacent-channel and co-channel interference between each pair of networks within interference range of each other. The interference level is determined based on a node's location, transmission power, out-of-band emission characteristics, and frequency band. The MCM uses this interference level to find the minimum frequency separation between two interfering networks and update this value in the interference graph.

C. Fairness

Ensuring fairness in spectrum allocation is the main role of the CDM algorithm of the IEEE 802.19.1 coexistence system [10]. In order to satisfy this requirement, FACT considers fairness when allocating spectrum to networks. The algorithm uses the following notion of fairness: spectrum allocation is considered fair if the ratio of the amount of allocated spectrum to the spectrum demand for each of the coexisting networks is the same. This notion of fairness is achieved by the *aggregate spectral efficiency* (ASE) metric [16] which captures the dependence between the given amount of spectrum and data rate based on the received signal strength indicator (RSSI) values of all TVBD devices associated with a TVBD network and the location of the spectrum.

D. Channel Allocation Invariability

The CDM algorithm may need to readjust a network's spectrum allocation under a number of circumstances—e.g., the network's spectrum demand changes, spectrum demand of coexisting networks changes, etc. If such a reallocation needs to be performed for a network, the algorithm ensures that its impact on the other networks is minimized. In other words, the algorithm ensures that the reallocation affects the smallest number of networks as possible. The algorithm evaluates the tradeoff between the advantages of reallocating a new block of spectrum to a network vs. the costs of reallocation. As described in Section V, the algorithm addresses this tradeoff by using two techniques when allocating spectrum: (1) a weight is assigned to each constraint to differentiate each one's impact on the reallocation; and (2) a correlation metric between the previous and the current spectrum assignments are defined, and this value is made as large as possible. The channel allocation invariability constraint prevents triggering

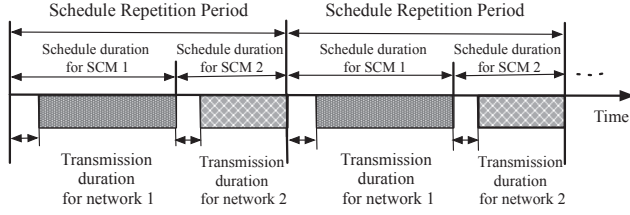


Fig. 2. Scheduling transmission periods for two networks on a channel.

decision-making propagation by a small change in the demand of a network and thus can help the system to reduce the channel switching and communication overhead of coexisting networks.

E. Transmission Scheduling Constraints

When possible, the MCM avoids assigning the same channel to more than one coexisting network that are in the interference range of each other. However, in some highly congested spectrum environments (e.g., dense metropolitan areas), due to the lack of available channels, scheduling transmission periods for different networks on one channel cannot be avoided. Therefore, FACT considers criteria for transmission scheduling.

For two networks, i and j , that need to share a channel, we define a cost value, C_{ij} , that represents the cost of scheduling transmission durations on a channel for these networks in a schedule repetition period (see Fig. 2). The value of C_{ij} is determined based on the following factors.

- *Channel widths*: If the MCM needs to assign a single channel to two or more networks with different channel width requirements, then it assigns a swath of spectrum that is sufficiently large to satisfy the largest channel width requirement. For example, an 802.22 network operates on 6 MHz-wide channels, while an 802.11af network uses 5 MHz-wide channels. If these two networks need to share a channel, then the MCM assigns a 6 MHz channel for transmission scheduling. Such an allocation results in inferior spectral efficiency compared to an allocation in which two networks with the same channel bandwidth share a channel, and this disadvantage is considered by assigning a higher cost value, C_{ij} .
- *MAC strategies*: Scheduling transmission duration to share a channel between two different networks that use incompatible mac strategies, will result in a higher switching delay and packet error rate due to synchronization issues. Thus if i and j use incompatible MAC strategies, we increase C_{ij} .
- *Transmission power*: A large discrepancy in transmission power between two coexisting networks can cause an asymmetric interference relation between the two networks. That is, the impact of interference caused by a high-power network on a low-power network is not the same vice versa. In such a scenario, the CDM algorithm assigns a larger value to C_{ij} compared to the one for a scenario in which the coexisting networks use comparable transmission power.

we make the simplifying assumption that the values of C_{ij} are determined prior to spectrum allocation. These values may be determined by performing field tests or via agreements made between the service providers managing the secondary networks. The methods for determining the values of C_{ij} are outside the scope of this paper.

Note that the above constraints do not include a constraint on limiting the transmission power. We assume that all nodes transmit at its maximum allowed transmission power. In the next section, we formulate the CDM problem as a combinatorial optimization problem that considers the aforementioned constraints.

V. PROBLEM FORMULATION OF COEXISTENCE DECISION MAKING

In this section, we formulate the CDM problem as an energy minimization problem in a modified *Boltzmann machine*. We show that an optimal solution to the latter problem is a solution to the former problem that satisfies all the constraints mentioned in Section IV. We provide a brief overview of the Boltzmann machine before describing the problem formulation.

A. Boltzmann Machine

The Boltzmann machine [17] is a stochastic recurrent artificial neural network that combines the principles of simulated annealing with those of neural networks.

The value of the neuron i 's state, S_i is determined by the output of a thresholding function, f_{out} , whose two inputs are T_i and θ_i . The first input, T_i , is the weighted sum of the state values of all the other neurons, i.e.,:

$$T_i = \sum_j w_{ij} S_j, \quad (1)$$

where w_{ij} is the connection weight between neuron i and neuron j . The second input, θ_i , is an appropriate threshold for T_i that controls the value of S_i .

Each neuron updates its state by using Equation (2):

$$S_i = f_{out}(T_i, \theta_i) = \begin{cases} 1 & \text{with probability } p_i \\ 0 & \text{with probability } (1 - p_i) \end{cases}, \quad (2)$$

where $p_i = \frac{1}{1 + e^{-(T_i - \theta_i)/\tau}}$ and τ denotes the *temperature* parameter. During the convergence of the Boltzmann machine, as with simulated annealing, the *temperature* parameter τ decreases progressively.

Boltzmann machines have a scalar value associated with each state of the network referred to as the *energy*, E , of the network, where:

$$E = -\frac{1}{2} \sum_i \sum_j w_{ij} S_i S_j + \sum_i S_i \theta_i \quad (3)$$

B. Problem Formulation

In this section, we formulate the problem of CDM as an energy-minimization problem in a Boltzmann machine such that minimizing the energy function is equivalent to satisfying all the constraints introduced in Section IV.

In our Boltzmann machine, each neuron is denoted as a triplet (i, j, k) . S_{ijk} is the state of neuron (i, j, k) , which has two possible values: 0 and 1. $S_{ijk} = 1$ means that the CDM algorithm should assign channel i at time slot j to wireless network k , and $S_{ijk} = 0$ means that no channel should be assigned. We assume that the total number of available channels is C , and each channel is divided into T time slots for a schedule repetition period. We assume that N is the number of coexisting networks that have registered with the MCM. With these assumptions, we can define the \mathbb{S} , the set of the states of all neurons, as $\mathbb{S} = \{S_{ijk} | 1 \leq i \leq C, 1 \leq j \leq T, 1 \leq k \leq N\}$. A time-frequency resource block is defined as a timeslot (within a schedule repetition period) of an available frequency channel. Let n_k denote the number of time-frequency resource blocks that network k requires (this can be computed using the ASE metric of network k 's requested data rate), and f_{kr} denote the minimum frequency separation between networks k and r (obtained from the interference graph provided by the CDIS). In the following paragraphs, we derive an energy function for each of the constraints of the CDM problem.

Contiguous Channels: As discussed in Section IV, there are performance advantages associated with allocating contiguous channels to a network, and whenever possible, the CDM algorithm should take this into account. In the context of the Boltzmann machine, allocation of contiguous channels can be expressed as $S_{ijk} = S_{(i+1)jk}$, i.e., if channel i is assigned to network k in time slot j , the algorithm should assign the adjacent channel $(i + 1)$ to the same network in time slot j . Minimizing the following energy function will satisfy this constraint:

$$E_C = \sum_{i=1}^{C-1} \sum_{j=1}^T \sum_{k=1}^N (S_{ijk} - S_{(i+1)jk})^2 \quad (4)$$

Interference: In order to mitigate the co-channel interference and adjacent channel interference for coexisting networks, the CDM algorithm needs to separate the channels of networks k and r in the frequency domain by the value f_{kr} . Here, the value of f_{kr} indicates the minimal amount of separation needed to avoid adjacent-channel interference. In the context of the Boltzmann machine, this is equivalent to two neurons, (i, j, k) and (p, j, r) , satisfying $|i - p| \geq f_{kr}$. As mentioned in IV-B, f_{kr} is a function of the distance between the networks, transmission power, out-of-band emission characteristics, the required spectrum mask, and frequency band, and its value is available through the interference graph in the CDIS. Note that setting $f_{kr} > 0$ implies that networks k and r cannot share a channel without causing non-negligible level of harmful co-channel interference to each other.

To represent the interference constraint using an energy function, we define a new variable X_{ikpr} as follows:

$$X_{ikpr} = \begin{cases} 1 & \text{if } |i - p| < f_{kr} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

The variable X_{ikpr} signifies whether assigning channel i to network k and channel p to network r in the same time slot causes interference or not. Therefore to mitigate the co-channel interference and the adjacent channel interference, the

algorithm needs to minimize the following energy function:

$$E_I = \sum_{j=1}^T \sum_{i=1}^C \sum_{k=1}^N \sum_{p=1}^C \sum_{r=1}^N S_{ijk} S_{pjr} X_{ikpr} \quad (6)$$

Fairness: As we mentioned in IV-C, the notion of fairness used by the proposed algorithm depends on the ratio of the allocated spectrum to each network by the algorithm to the spectrum demanded by the network. Thus, to maximize fairness, the algorithm should assign the spectrum such that the value of $R_k (<= 1)$ for each network, k , is the same or their variance is minimized, where

$$R_k = \frac{\sum_{i=1}^C \sum_{j=1}^T S_{ijk}}{n_k}, \quad (7)$$

is the ratio of the amount of spectrum assigned to network k to network k 's spectrum demand. The R_k value for network k is called the *qualify factor* of the network.

In addition, the algorithm should assign spectrum such that the value of R_k is as close to one as possible in order to meet each network's spectrum demand as much as possible (e.g., if $R_k = 1$, the allocation has met all of the network's spectrum demand). Equivalently, we can say that the algorithm should minimize $(1 - R_k)^2$ for each network.

The algorithm can satisfy both of the above requirements (i.e., maximize fairness and meet the maximum proportion of each network's spectrum demand) by minimizing the value $\sum_{k=1}^N (1 - R_k)^2$. Therefore, the algorithm needs to minimize the following energy function:

$$E_F = \sum_{k=1}^N \left(\frac{n_k - \sum_{i=1}^C \sum_{j=1}^T S_{ijk}}{n_k} \right)^2 \quad (8)$$

The justification for the above energy function's derivation is based on the arithmetic mean (AM)-root mean square (RMS) inequality. The AM-RMS inequality states that for all set of N values $\{x_1, x_2, \dots, x_N\}$ such that $\sum_{k=1}^N x_k = K$, the following inequality holds:

$$\frac{K}{N} \leq \sqrt{\frac{x_1^2 + \dots + x_N^2}{N}} \quad (9)$$

The above inequality indicates that the sum of squares is bounded below by $\frac{K^2}{N}$, which is attained when $x_1 = \dots = x_N = \frac{K}{N}$. Therefore the sum of squares is minimum when $x_1 = x_2 = \dots = x_N$.

Channel Allocation Invariability: As we mentioned in Section IV-D, the CDM algorithm uses an energy function to evaluate the correlation between the current spectrum assignment and the previous spectrum assignment in order to prevent triggering a chain reaction of needless spectrum reallocations and mitigate channel switching and communication overhead. The algorithm needs to minimize the following energy function:

$$E_P = \sum_{i=1}^C \sum_{j=1}^T \sum_{k=1}^N (S_{ijk} - S'_{ijk})^2, \quad (10)$$

where S'_{ijk} represents the output of the previous execution of the algorithm. Note that minimizing E_P is equivalent to maximizing the correlation between \mathbb{S} and \mathbb{S}' .

Transmission Scheduling: As mentioned in Section IV-E, the CDM algorithm should try to assign each channel to only one network, therefore it is desirable to have $S_{ijk} = S_{i(j+1)k}$, i.e. if channel i is assigned to network k in time slot j , the algorithm should assign this channel to the same network in time slot $(j + 1)$. But sometimes due to spectrum limitation, the algorithm must schedule transmission durations for two networks k and r that are in interference range of each other and need to share a channel, and this adds an energy C_{kr} to the total energy function. Minimizing the following energy function will satisfy this constraint:

$$E_S = \sum_{i=1}^C \sum_{j=1}^{T-1} \sum_{k=1}^N C_{kr(k)} (S_{ijk} - S_{i(j+1)k})^2, \quad (11)$$

where $r(k)$ is the network that shares channel i with network k after time slot j .

Therefore the CDM problem reduces to the following multi-objective optimization problem (MOOP):

$$\text{Minimize}_{\mathbf{s}}: \{E_S, E_C, E_I, E_F, E_P\} \quad (12)$$

Finding a solution for the MOOP (12) can be unclear, because a single solution point that minimizes all objectives simultaneously usually does not exist. Consequently, we use the idea of Pareto optimality to describe the solution of (12). A solution point is Pareto optimal if it is not possible to move from that point and improve at least one objective function without detriment to any other objective function [18]. There are numerous methods for solving a MOOP [19]. To solve our problem, we choose weighted-sum method, because it has a simple formulation and provides sufficient condition for Pareto optimality.

Using the weighted-sum method to solve the MOOP (12), we need to select positive scalar weights $\lambda^S, \lambda^C, \lambda^I, \lambda^F$, and λ^P , and minimizing the following composite objective function:

$$E = \lambda^S E_S + \lambda^C E_C + \lambda^I E_I + \lambda^F E_F + \lambda^P E_P, \quad (13)$$

where $\lambda^S, \lambda^C, \lambda^I, \lambda^F$ and λ^P be the weight of the objective functions associated with transmission scheduling, contiguous channels, interference, fairness and channel allocation invariability, respectively. Since the weights are positive, the minimum of (13) is always Pareto optimal [18].

C. Weight Selection

It is necessary to incorporate the decision-maker preferences for various objectives in order to determine a single suitable solution. We use the weights as general gauges of relative importance for each objective function. With methods that incorporate *a priori articulation of preferences*, the decision-maker indicates preferences before running the optimization algorithm and subsequently allows the algorithm to determine a single solution that presumably reflects such preferences.

To establish the relationship between preferences and weights, we use a *paired comparison method* (a.k.a *ratio questioning*). Assuming that the MOOP consists of n objective functions, this method involves $\frac{n(n-1)}{2}$ pairwise comparisons

between objective functions. The judgments result in a comparison matrix A , where the entry a_{ij} is entered in response to the question: How much more important is the criterion of row i when compared with another criterion of column j ? When a criterion is compared to itself, it is of equal importance and is assigned the value of 1. The numbers 3, 5, 7, and 9 correspond to the verbal judgments “moderately more”, “strongly more”, “very strongly more”, and “extremely more”, respectively. The numbers 2, 4, 6, 8 are used when a compromise is in order. This scale from 1 to 9 has proved to be the most appropriate [20]. Also we use $a_{ji} = a_{ij}^{-1}$ to fill the matrix, for instance if criterion i is strongly more important than criterion j , we have $a_{ij} = 5$ and $a_{ji} = \frac{1}{5}$.

To find the weights from the comparison matrix A , we find the principal eigenvector (the eigenvector corresponding to the eigenvalue with the largest absolute value) of the matrix $v = (v_1, \dots, v_n)$ and set the weight of the criterion i as:

$$w_i = \frac{v_i}{\sum_{j=1}^n v_j}.$$

Also note that in order to use this method we need the objective functions to have similar ranges, thus we normalize each objective function E^α of the MOOP (12) using its average value E_{avg}^α . The above discussion will result in the following equation for the weights in the optimization problem (13):

$$\lambda^\alpha = w_\alpha / E_{avg}^\alpha, \quad (14)$$

where $\alpha \in \{C, S, I, F, P\}$.

D. Problem Formulation using Boltzmann Machine

To formulate the energy minimization problem (13) as a Boltzmann machine, we need to find the appropriate connection weights and thresholds. To define these values, we need to use the following three functions:

- The Kronecker delta function:

$$\delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

- The Euclidean distance tester function:

$$\alpha_i(x) = \begin{cases} 1 & \text{if } 1 < i < x \\ 0 & \text{otherwise} \end{cases}$$

- The unit difference function:

$$\gamma_{ij} = \begin{cases} 1 & \text{if } |i - j| = 1 \\ 0 & \text{otherwise} \end{cases}$$

We can show that a Boltzmann machine with connection weight

$$W_{ijkpqr} = 2\lambda^S C_{kr(i,j,k)} \delta_{ip} \gamma_{jq} \delta_{kr} + 2\lambda^C \gamma_{ip} \delta_{jq} \delta_{kr} - \lambda^I \delta_{jq} X_{ipkr} - \frac{2\lambda^F}{n_k^2} ((1 - \delta_{ip}) || (1 - \delta_{jq})) \delta_{kr} \quad (15)$$

between two arbitrary neurons (i, jk) and (p, q, r) and threshold value

$$\theta_{ijk} = \lambda^S (C_{kr(i,j,k)} + C_{kr(i,j-2,k)}) + \lambda^C (1 + \alpha_i(C)) + \lambda^P (1 - 2S'_{ijk}) + \lambda^F \left(\frac{-2n_k + 1}{n_k^2} \right) \quad (16)$$

for an arbitrary neuron (i, j, k) can model the above optimization problem that represents our CDM problem. The derivation of equations (15) and (16) is explained in [21].

In our Boltzmann machine, the total input to neuron (i, j, k) is:

$$T_{ijk} = \sum_{p=1}^C \sum_{q=1}^T \sum_{r=1}^N W_{ijkpqr} S_{pqr} \quad (17)$$

and the final output of the neuron is: $S_{ijk} = f_{out}(T_{ijk}, \theta_{ijk})$, where f_{out} is the following thresholding function:

$$f_{out}(T_{ijk}, \theta_{ijk}) = \begin{cases} 1 & \text{with } p_{ijk} \\ 0 & \text{with } 1 - p_{ijk} \end{cases}, \quad (18)$$

with

$$p_{ijk} = \frac{1}{1 + e^{-(T_{ijk} - \theta_{ijk})/\tau}}.$$

VI. FACT: A FAIR COEXISTENCE DECISION MAKING ALGORITHM

FACT is an update procedure that runs on the Boltzmann machine that we introduced in Section V.

A. The Main Algorithm

Algorithm 1 FACT Algorithm

Require: $f_{kr}, n_k, \lambda^S, \lambda^C, \lambda^F, \lambda^I, \lambda^P, S'_{ijk}, C_{kr}$

Ensure: $BestS_{ijk}$

- 1: Initialize S_{ijk} based on the initialization strategy.
 - 2: $I = 0$.
 - 3: Calculate W_{ijkpqr} for all pairs of neurons using Equation (15).
 - 4: Calculate threshold $\theta_{i,j,k}$ for all neurons using Equation (16).
 - 5: Compute E using Equation (13).
 - 6: $MinE = E$.
 - 7: $BestS_{ijk} = S_{ijk}$.
 - 8: **while** ($E \neq 0$ **and** $I < MaxNumIterations$) **do**
 - 9: **repeat**
 - 10: Pick neuron (i, j, k) based on the updating order strategy.
 - 11: Calculate T_{ijk} using Equation 17.
 - 12: Calculate S_{ijk} using Equation (18).
 - 13: **until** (all neurons are picked)
 - 14: Compute E using Equation (13).
 - 15: **if** $E < MinE$ **then**
 - 16: $MinE = E$.
 - 17: $BestS_{ijk} = S_{ijk}$.
 - 18: **end if**
 - 19: $I = I + 1$
 - 20: **end while**
-

The pseudo-code for the FACT algorithm is given in Algorithm 1. The algorithm uses its inputs—the weight of edges in the interference graph, f_{kr} , network's demand, n_k , cost of channel sharing between networks k and r , C_{kr} , and the constraint weights for each network—to produce the output $BestS_{ijk}$ which indicates the values of S_{ijk} 's that minimize the energy function. In other words, this output indicates

whether the algorithm assigns channel i at timeslot j to network k in order to minimize the value of the total energy function.

The algorithm has an initialization step that assigns binary values to each neuron's state. In general, a random initialization strategy is used to assign these values. However, in order to increase the convergence rate, we use another initialization approach discussed in Section VI-B.

Note that since the connection weights and threshold values of neurons are fixed, the coexistence decision-making algorithm only needs to compute them once. The algorithm repeats the updating procedure until the total energy becomes zero (i.e., minimum value of energy) or a predetermined maximum number of iterations is reached (variable I represents the number of iterations). At each iteration, the algorithm calculates the state of all neurons, and then checks to see whether a minimum value of E has been obtained (up to the current point). The updating order of the neurons' states and initialization strategy are important, because they affect the convergence rate of the algorithm. The convergence of Boltzmann machines is discussed in [22]. The output of the algorithm is $BestS_{ijk}$, and it represents the Pareto optimal feasible solution for our optimization problem. Let M denote the maximum number of iterations of the algorithm. The running time complexity of the algorithms is dominated by computing the total energy E at each iteration. The complexity of energy computation is $O(N^2 C^2 T)$ and as a result the overall complexity of FACT is of $O(MN^2 C^2 T)$.

B. Initialization Strategy

In order to increase the convergence rate of the algorithm, instead of a random initialization of the neurons' states, we propose an initialization strategy based on coexistence constraints. The pseudo-code of the proposed initialization algorithm is given in Algorithm 2.

Algorithm 2 Initialization Sub-Algorithm

Require: f_{kr}, n_k

Ensure: S_{ijk}

- 1: $n = 0$
 - 2: Select a network randomly and assign k as its index value.
 - 3: **repeat**
 - 4: Assign resource blocks $n + 1$ to $n + n_k$ to network k by setting the appropriate neurons' states to 1.
 - 5: $n = n + n_k$
 - 6: Select a network that has not been selected and has minimum frequency separation with current selected network and assign k as its index value.
 - 7: **until** (all networks are picked **or** $n > T \times C$)
-

We consider all frequency-time blocks, r_{ij} , with $1 \leq i \leq C$ and $1 \leq j \leq T$ as a one-dimensional array such that block (i, j) is mapped to entry $T(i-1) + j$. The length of the array is $T \times C$. The algorithm starts with a randomly chosen network k and assigns the first n_k entries of the array to network k by setting the appropriate neurons' states to 1. Then the algorithm selects another network that has minimum frequency separation with the current network (it uses the values of f_{kr}

from the interference graph to determine this network), and assigns a number of remaining entries of the array to this network (if multiple networks satisfying minimum frequency separation, it selects one of them randomly). The number of assigned entries is indicated in line 4 of the algorithm. The algorithm repeats this operation until there is no remaining networks to select or there is no resource block to assign, whichever comes first.

C. Updating Strategy

The updating order of the neurons' states influences the convergence rate of the FACT algorithm. We propose an updating order strategy given in Algorithm 3.

Algorithm 3 Updating Order Sub-Algorithm

Require: n_k, S_{ijk} .

Ensure: Updating order of neurons.

- 1: **for** $i = 1$ to N **do**
 - 2: Calculate $u_k = n_k - \sum_{i=1}^C \sum_{j=1}^T S_{ijk}$.
 - 3: **end for**
 - 4: Put the networks' IDs in array A .
 - 5: Sort array A in descending order of u_k .
 - 6: **for** $i = 1$ to N **do**
 - 7: Update all neurons associated with network $A[i]$.
 - 8: **end for**
-

This algorithm takes two inputs—the spectrum demand of each network and the current state of its neurons—to determine the updating order of neurons for the next iteration. It first computes how many more resource blocks each network requires (by calculating u_k), and then it creates a sorted array of network IDs. This array is sorted in descending order of each network's u_k value. For each network, the algorithm updates the state of the neurons according to the order of the networks in the list. Note that we update the state of a neuron (i, j, k) by computing the state of the neuron using Equation (18) in each iteration of the algorithm.

VII. SIMULATION AND NUMERICAL RESULTS

We compare FACT with two CDM algorithms that have been proposed in [2] and [3] for use in IEEE 802.19.1. We have implemented all three algorithms in MATLAB R2009b on a PC with an Intel Core i5 2.67 GHz CPU, 4 GB memory, and running Windows 7 operating system.

The algorithm that is proposed by Wang et al. in [2] selects a network at each step and assigns spectrum to the network. This algorithm always selects the network with the minimum quality factor (R_k), say network x . Then the algorithm tries to find an unoccupied channel for network x , and if no unoccupied channel is available, the algorithm searches for a channel occupied by a network with the similar MAC/PHY to the network x . If the algorithm finds such a network, it checks to see whether the network supports scheduling, and if it does, it schedules a transmission period for each network on that channel [2]. The complexity of this algorithm is $O(N^2CT)$.

The algorithm that is proposed by Junell et al. in [3] considers the balanced sharing criterion in the coexistence decisions that it makes. The algorithm is based on a parameter

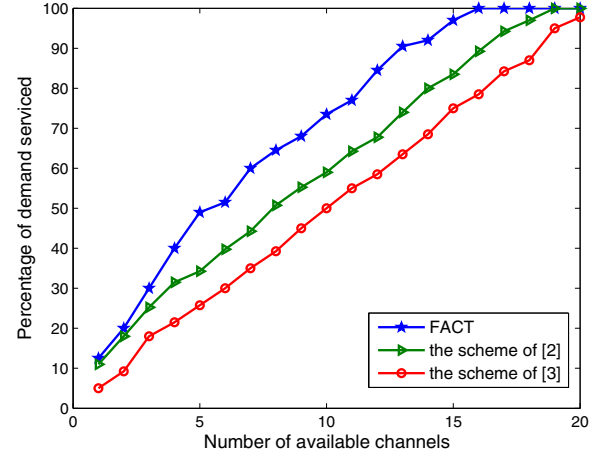


Fig. 3. Percentage of demand serviced vs. number of available channels.

called Coexistence Value (CV), that measures a network's eligibility for resources. This parameter is computed using the number of nodes in the network, channel utility value that the network can achieve, and a possible regulatory preference [3]. The complexity of this algorithm is $O(NCT)$.

Though the running time complexity of FACT is higher than the algorithms of [2] and [3], it is superior to the other two CDM algorithms in terms of percentage of demand serviced and fairness.

In order to compare the performance of FACT with the CDM algorithms of [2] and [3], we have run experiments with 20 networks that are competing for different number of available channels. There are 20 networks of 3 different types. Number of available channels varies between 1 and 20. Each channel is divided to 10 (frequency-time) resource blocks. Each network competes for a number n_k of these resource blocks. n_k is a random number between 5 and 10 resource blocks.

The percentage of demand serviced is defined as the average of allocated resource ratios for all networks, i.e.,

$$\text{PDS} = 100 \times \left(\frac{1}{N} \sum_{k=1}^N R_k \right). \quad (19)$$

This performance measure indicates how well a decision making algorithm satisfies a network's spectrum demands. Fig. 3 illustrates the percentage of demand serviced (PDS) for twenty coexisting networks with different demands. As the figure shows, our algorithm does a better job in satisfying the networks' demands compared to the other two algorithms. However, when the number of channels is increased, the performance gap between the three algorithms narrows. When there are enough resources for all networks (i.e., twenty channels are available), all three algorithms achieve the same performance. The difference in PDS performance among the three algorithms are due to the following reasons: 1) Our algorithm maximizes R_k for all networks in the fairness constraint, i.e. our fairness constraint not only makes an attempt to make the quality factors of all the networks equal but also works on maximizing these values, and 2) the scheme

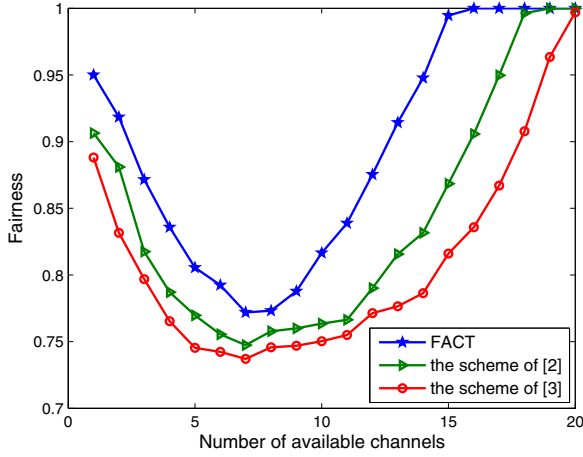


Fig. 4. Fairness vs. number of available channels.

of [2] only allows scheduling between networks of the same air interface and the scheme of [3] does not allow transmission scheduling.

Since ensuring fairness in spectrum allocation is the main role of the CDM algorithm of the IEEE 802.19.1 coexistence system, the fairness metric was the main performance metric that was considered when designing the FACT algorithm. Fig. 4 shows the performance of the three algorithms in terms of fairness vs. the number of available channels. As mentioned in Section IV-C, the notion of fairness that we use, tries to make the quality factor of all networks equal. Specifically, we define fairness F , as one minus the variance of quality factors of all networks. i.e.,

$$F = 1 - \frac{1}{N} \sum_{k=1}^N (R_k - \bar{R})^2.$$

Note that a small variance for the quality factors, shows that the values of quality factors are close, and we have a fair algorithm.

As it can be seen in Fig. 4, FACT allocates the spectrum more fairly among TVBD networks compared to the other two algorithms in general, but when the number of available channels is enough for all networks, all three algorithms have the same fairness. The difference between FACT and the algorithm of [2] in terms of fairness is due to the fact that the latter always assigns spectrum to the network with minimum R_k , whereas the former allocates the spectrum in a way that makes all R_k values equal. The algorithm of [3] shows the worst performance in terms of fairness because it does not consider transmission scheduling. Also note that when the number of available channels is small, the quality factors of most of the networks are close to zero, and as a result we have a high fairness value. By increasing the number of available channels, some networks get more resources than the others, and the fairness decreases. But when the number of available channels is enough for satisfying the demand of most of the networks, the fairness value of all three algorithms increases, and when the number of available channels is enough to satisfy the demand all the networks, all three algorithms achieve the maximum fairness.

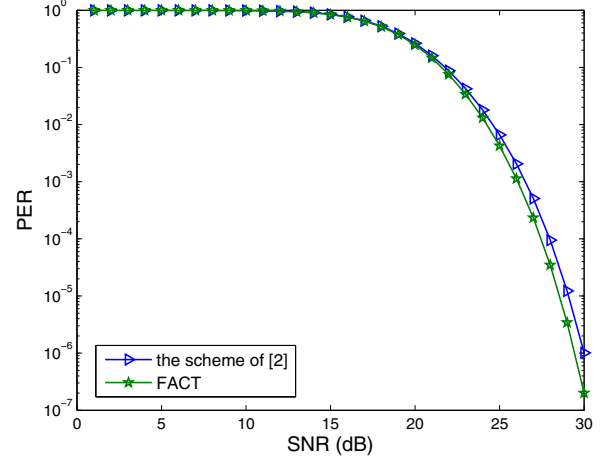


Fig. 5. Packet error rate vs. signal to noise ratio.

Fig. 5 compares FACT with the scheme of [2] in terms of packet error rate (PER) vs. SNR (signal to noise ratio). Here, we assume that the coexistence of heterogeneous networks is managed by an IEEE 802.19.1 system. We use the following PER formula that is derived in [23]:

$$\text{PER} = \sum_{m=0}^N [1 - (1 - p)^m] f_m(M), \quad (20)$$

where p is the symbol error probability, M is a random variable that indicates the number of symbols that collide with an interference pulse, and $f_m(M)$ is the probability mass function of M .

In this experiment, we consider three co-located networks that all use 64-QAM modulation for transmission. Two of the networks are WLANs and the third network is a WPAN. All networks support transmission scheduling and are competing for two available channels. The value of p for 64-QAM modulation is given by:

$$p = 1 - \left(1 - \frac{7}{4} Q\left(\sqrt{\frac{\gamma}{21}}\right)\right)^2,$$

where γ is the SINR and $Q(x)$ is the integral of the tail of a normalized Gaussian probability density function.

We compare FACT only with the algorithm of [2], because it is the only other existing CDM algorithm that uses transmission scheduling. As can be seen in Fig. 5, the algorithm of [2] modestly outperforms FACT in terms of PER. This result is due to the fact that the scheme of [2] only considers transmission scheduling between networks of the same type but FACT uses transmission scheduling between networks of different types as well as similar networks. As a result, the algorithm of [2] assigns one channel to the two WLANs and the other channel to the WPAN. In contrast, depending on the networks' resource demand, FACT selects two out of the three networks, which may be of the same type or of different types, to share a channel and assigns the second channel to the third network. Scheduling transmission between networks of the same type enables a better synchronized transmission scheduling between the coexisting networks, and results in lower PER.

VIII. CONCLUSION

In this paper, we proposed a CDM algorithm called *Fair Algorithm for Coexistence decision making in TV whitespace (FACT)*. FACT is a spectrum allocation algorithm that a coexistence enabling system with a centralized topology (such as an IEEE 802.19.1 system) can utilize to enable coexistence of heterogeneous networks. Our results showed that FACT is superior to the existing CDM algorithms, which have been proposed for IEEE 802.19.1, in terms of fairness, and percentage of demand serviced.

REFERENCES

- [1] FCC, Third Order and Memorandum Opinion and Order, in the Matter of Unlicensed Operation in the TV Broadcast Bands, Additional Spectrum for Unlicensed Devices Below 900 MHz and in the 3 GHz band, Apr. 2012.
- [2] J. Wang, S. Filin, and H. Harada, "Proposal of decision-making algorithm," IEEE 802.19 Wireless Coexistence Working Group, July 2011.
- [3] J. Junell, M. Kasslin, and P. Ruuska, "A coexistence decision approach proposal," IEEE 802.19 Wireless Coexistence Working Group, Jan. 2012.
- [4] J. Lansford, A. Stephens, and R. Nevo, "Wi-fi (802.11b) and Bluetooth: enabling coexistence," *IEEE Netw. Mag.*, vol. 15, pp. 20–27, 2001.
- [5] IEEE 802.15 TG2, IEEE Recommended Practice for Local and Metropolitan Area Networks Part 15.2: Coexistence of Wireless Personal Area Networks with Other Wireless Devices Operating in Unlicensed Frequency Bands, IEEE Standard, Aug. 2003.
- [6] "ZigBee and wireless radio frequency coexistence," Z. Alliance, June 2007.
- [7] S. Pollin, I. Tan, B. Hodge, C. Chun, and A. Bahai, "Harmful coexistence between 802.15.4 and 802.11: a measurement-based study," in *Proc. 2008 Int. Conf. Cognitive Radio Oriented Wireless Netw.*
- [8] X. Zhang and K. G. Shin, "Enabling coexistence of heterogeneous wireless systems: case for ZigBee and WIFI," in *Proc. 2011 ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*
- [9] IEEE 802.16h/D4, IEEE Standard for Local and Metropolitan Area Networks. Part 16: Air Interface for Fixed Broadband Wireless Access Systems. Improved Coexistence Mechanisms for License-exempt Operation, IEEE Standard, Feb. 2008.
- [10] S. Filin, T. Baykas, M. Rahman, and H. Harada, "Performance evaluation of IEEE 802.19.1 coexistence system," in *Proc. 2011 IEEE Int. Conf. Commun.*
- [11] C. Ghosh, S. Roy, and D. Cavalcanti, "Coexistence challenges for heterogeneous cognitive wireless networks in TV white spaces," *IEEE Wireless Commun. Mag.*, 2011.
- [12] T. Baykas, M. Kasslin, M. Cumming, H. Kang, J. Kwak, R. Paine, A. Reznik, R. Saeed, and S. Shellhammer, "Developing a standard for TV white space coexistence: technical challenges and solution approaches," *IEEE Wireless Commun.*, 2012.
- [13] B. Gao, J. M. Park, Y. Yang, and S. Roy, "A taxonomy of coexistence mechanisms for heterogeneous cognitive radio networks operating in TV white spaces," *IEEE Wireless Commun.*, vol. 19, no. 4, pp. 41–48, 2012.
- [14] G. Villardi, Y. Alemseged, S. Chen, S. Chin-Sean, N. Ha, T. Baykas, and H. Harada, "Enabling coexistence of multiple cognitive networks in TV white space," *IEEE Wireless Commun.*, 2011.
- [15] R. Chandra, R. Mahajan, T. Moscibroda, R. Raghavendra, and P. Bahl, "A case for adapting channel width in wireless networks," in *Proc. 2008 ACM Special Interest Group Data Commun.*
- [16] S. Deb, V. Srinivasan, and R. Maheshwari, "Dynamic spectrum access in DTV whitespaces: design rules, architecture and algorithms," in *Proc. 2009 ACM Int. Conf. Mobile Comput. Netw.*
- [17] G. Hinton, T. Sejnowski, and D. Ackley, "Boltzmann machines: constraint satisfaction networks that learn," Carnegie-Mellon University, Tech. Rep., 1984.
- [18] K. Deb, "Multi-objective optimization," in *Multi-Objective Optimization Using Evolutionary Algorithms*. Wiley, 2001, ch. 2, pp. 13–46.
- [19] T. Marler and J. Arora, "Survey of multi-objective optimization methods for engineering," *Structural Multidisciplinary Optimization*, vol. 26, no. 6, pp. 369–395, 2004.
- [20] T. Saaty, "How to use the analytic hierarchy process," in *Fundamentals of Decision Making and Priority Theory*. RWS Publications, 2006, ch. 1, pp. 1-1 – 1-7.
- [21] B. Bahrak and J. Park, "Coexistence decision making for spectrum sharing among heterogeneous wireless systems in TV whitespace," Virginia Tech, Tech. Rep., 2013. Available: <http://www.arias.ece.vt.edu/publications/TechReports/TR-Coexistence.pdf>
- [22] E. Aarts and J. Korst, *Simulated Annealing and Boltzmann Machines: A Stochastic Approach to Combinatorial Optimization and Neural Computing*. John Wiley & Sons Ltd., 1989.
- [23] S. Shellhammer, "Emerging technologies in wireless LANs: theory, design, and deployment," in *Coexistence of Unlicensed Wireless Networks*. Cambridge University Press, 2007, ch. 20, pp. 469–499.



Behnam Bahrak received his bachelor's and master's degrees, both in electrical engineering, from Sharif University of Technology, Tehran, Iran, in 2006 and 2008, respectively. He received the Ph.D. degree from the Bradley Department of Electrical and Computer Engineering at Virginia Tech in 2013. Behnam's research interests include cryptography, network security, and dynamic spectrum access.



Jung-Min "Jerry" Park received a Ph.D. degree in electrical and computer engineering from Purdue University in 2003. He is currently an associate professor in the Department of Electrical and Computer Engineering at Virginia Tech, and the site director of a National Science Foundation (NSF) Industry-University Cooperative Research Center (I/UCRC) called the Broadband Wireless Access & Applications Center (BWAC). As the director of the Advanced Research in Information Assurance and Security (ARIAS) Lab at Virginia Tech, Park is leading several sponsored research projects on wireless networks and network security. He is widely recognized for his pioneering work on enforcement and security problems in cognitive radio networks. His research interests include cognitive radio networks, spectrum sharing technologies, network security and privacy, and applied cryptography. Current or recent research sponsors include the NSF, National Institutes of Health (NIH), Defense Advanced Research Projects Agency (DARPA), Office of Naval Research (ONR), SANS (SysAdmin, Audit, Network Security) Institute, Motorola Solutions, Samsung Electronics, and SCA Techniques. More details on his research interests can be found online at <http://www.arias.ece.vt.edu>. He is a recipient of a 2008 NSF Faculty Early Career Development (CAREER) Award, a 2008 Hoerl Excellence in Research Award (equivalent to a best paper award), and a 1998 AT&T Leadership Award. He is a senior member of the IEEE and the ACM, and a member of the Korean-American Scientists and Engineers Association (KSEA).