Ecology-inspired Coexistence of Heterogeneous Wireless Networks

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***Abstract*—A number of wireless standards (e.g., IEEE 802.11af and IEEE 802.22) have been developed or are currently being developed for enabling opportunistic access in TV white space (TVWS) using cognitive radio (CR) technology. When heterogeneous CR networks that are based on different wireless standards operate in the same TVWS, coexistence issues can potentially cause major problems. Enabling collaborative coexistence via *direct* coordination between heterogeneous CR networks is very challenging due to incompatible MAC/PHY designs of coexisting networks. Moreover, the direct coordination would require competing networks or service providers to exchange sensitive control information that may raise conflict of interest issues and customer privacy concerns. In this paper, we present an architecture for enabling collaborative coexistence of heterogeneous CR networks over TVWS, called *Symbiotic Heterogeneous coexistence ARchitecturE (SHARE)*. By mimicking the symbiotic relationships (i.e., the interspecific competition process) between heterogeneous organisms in a stable ecosystem, SHARE establishes an *indirect* coordination mechanism for spectrum sharing between heterogeneous CR networks via a *mediator* system, which avoids the drawbacks of direct coordination. Analytical and simulation results show that SHARE allocates spectrum among coexisting networks in a weighted-fair manner without any inter-network direct coordination.**

I. Introduction

Industry and research stakeholders have initialized standardization efforts to enable the secondary networks' utilization of TV "white space" (TVWS) by leveraging *cognitive radio* (CR) technology. These efforts include IEEE 802.22 Wireless Regional Area Networks (WRAN) [7], IEEE 802.11af (WiFi over TVWS) [6], ECMA 392 (WPAN over TVWS) [2], etc. All of these standards rely on CR technology to overcome the challenging coexistence issues between primary and secondary networks as well as between secondary networks. In this paper, we focus on the heterogeneous coexistence between secondary networks that employ different wireless technologies in TVWS, and we use the term "CR network" to denote a CR-enabled wireless network operating over TVWS.

The coexistence schemes for wireless networks can be broadly classified into two categories. A *non-collaborative* coexistence scheme is the only feasible approach when there are no means of coordination between the coexisting networks, such as the coexistence of WiFi and ZigBee networks [5], [17]. A *collaborative* coexistence scheme can be employed when coexisting networks can directly coordinate their operations, such as the self-coexistence schemes for 802.22 networks [1], [9].

Existing coexistence schemes fail to adequately address the heterogeneous coexistence problem in TVWS for a number of technical and policy reasons. Non-collaborative schemes cannot facilitate the coexistence among heterogeneous networks due to their incompatible MAC strategies. Collaborative strategies may require the exchange of potentially sensitive information (e.g., traffic load, bandwidth requirements) across different networks to negotiate the spectrum partitioning [14], [15], which could raise conflict-of-interest issues and customer privacy concerns for competing wireless networks or service providers. Moreover, it is difficult to find a third party that can serve as a global or centralized decision maker that supervise all heterogeneous networks and allocate spectrum them.

In this paper, we propose a coexistence framework, called the *Symbiotic Heterogeneous coexistence ARchitectuRE* (*SHARE*), that employs an *indirect* coordination method for enabling collaborative coexistence among heterogeneous CR networks. As its name implies, the proposed framework was inspired by the inter-species relations that exist in biological ecosystems. A *symbiotic* relation is a term used in biology to describe the coexistence of different species that form relations via indirect coordination. SHARE exploits a *mediator* system (e.g., the 802.19.1 system) that forwards *sanitized* data to establish the indirect coordination mechanism between coexisting networks. SHARE employs an *ecology-inspired spectrum sharing* algorithm inspired by an interspecific resource competition model that enables each CR network to autonomously determine the amount of spectrum that it should appropriate without direct negotiation with competing networks. Our analytical and simulation results show that SHARE guarantees weighted-fairness in partitioning spectrum and improves spectrum utilization.

The rest of this paper is organized as follows. We provide background knowledge of the mediator system and theoretical ecology in Section II. In Section III, we give an overview of SHARE. We present the SHARE algorithm and provide analytical results in Section IV. In Section V, we evaluate the performance of SHARE using simulations. We conclude the paper in Section VI.

II. Technical Background

As stated previously, SHARE employs a mediator system to establish an indirect coordination mechanism between CR networks. Note that the mediator is not a global decision maker.

Using the sanitized information forwarded by the mediator, each CR network makes coexistence decisions autonomously using the algorithm proposed in this paper.

A. The Mediator System

The recently formed IEEE 802.19.1 task group (TG) was chartered with the task of developing standardized methods, which are radio access technology-independent, for enabling coexistence among dissimilar or independently operated wireless networks [8]. This standard is currently being developed, and it has yet to prescribe solid solutions. The IEEE 802.19.1 system is a good candidate to serve as the mediator. The IEEE 802.19.1 system [8] defines a set of logical entities and a set of standardized interfaces for enabling coordination between heterogeneous CR networks. In Figure 1, we show the architecture of an 802.19.1 system which includes three entities in the grey box: (1) the coexistence manager (CM) acts as the local decision maker of the coexistence process; (2) the coexistence database and information server (CDIS) provides coexistence-related control information to the CMs, and (3) the coexistence enabler (CE) enables communications between the 802.19.1 system and the TV band device (TVBD) network. The TVWS database indicates the list of channels used by primary users and their locations, and it is connected to the 802.19.1 system via backhaul connections.

B. Interspecific Competition in Ecology

In ecology, interspecific competition is a distributed form of competition in which individuals of different species compete for the same resource in an ecosystem without direct interactions between them [12]. The impact of interspecific competition on populations have been formalized in a mathematical model called the Lotka-Volterra (L-V) competition model [10], [13]. In this model, the impact on population dynamics of species i can be calculated separately by a differential equation given below:

$$\frac{dN_i}{dt} = r_i N_i \left(1 - \frac{N_i + \sum_{j \neq i} \alpha_{ij} N_j}{K_i}\right). \tag{1}$$

In this equation, N_i is the population size of species i, K_i is the carrying capacity (which is the maximum population of species i if it is the only species present in the environment), r_i is the intrinsic rate of increase, and α_{ij} is the competition coefficient which represents the impact of species j's population growth on the population dynamics of species i. The interspecific competition model has been used for modeling the bandwidth allocation problem for TCP flows [3], [4]

III. Overview of SHARE

In this section, we present the system model, underlying assumptions, and the architecture of SHARE.

A. System Model

We assume n heterogeneous networks are co-located, and they coexist in the same spectrum band that includes N channels with an identical bandwidth. Let $\mathcal{K}$ denote this set of networks, and all of these networks in $\mathcal{K}$ are registered with the mediator system. Every network is composed of multiple devices and a base station (BS) (or access point). Channels are labeled with indices $0, 1, ..., N-1$.

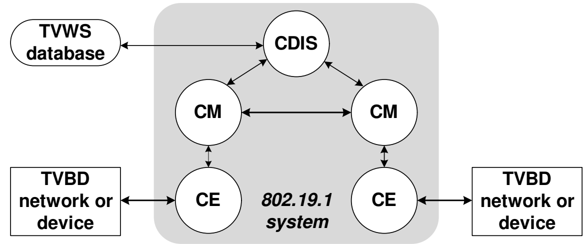


Fig. 1. IEEE 802.19.1 system architecture.

Time-spectrum blocks. Time is divided into periods, each period contains a number of u super-frames, and each super-frame contains f frames (Such a structure based on frames can be found in IEEE 802.16 and 802.22). In this paper, we use a time-spectrum block as the minimum unit for spectrum allocation, which can be defined by a channel index and a frame index. Specifically, we represent a time-spectrum block using a three-tuple (i, j, k)—i.e., the k-th frame in the j-th super-frame over channel i. Over channel i, there are a number of uf blocks that can be allocated during a period. We assume that a BS or network with multiple radios is able to scan and access multiple time-spectrum blocks on different channels simultaneously. Furthermore, we define the capacity, C, as the total number of spectrum-time blocks during a period, given N channels.

The bandwidth requirement. We define the *bandwidth requirement* of a network as the number of time-spectrum blocks that it needs to satisfy the QoS requirements of its traffic load. Let R_i denote the bandwidth requirement of network i.

The mediator-based indirect coordination. SHARE establishes a mediator-based *indirect* coordination mechanism between coexisting networks. There is no direct coordination between the coexisting networks, and they have to interact with each other by exchanging control information through a third-party mediator. Specifically, SHARE utilizes a CDIS (which is one of the components of an 802.19.1 system) as a mediator. Note that CDIS is not a global or centralized decision maker, but rather it is an information directory server with simple data processing capabilities.

Necessity of sanitized information. The mediator helps address conflict-of-interest issues and customer privacy concerns, which may arise when coexisting networks operated by competing service providers are required to exchange sensitive traffic information in order to carry out coexistence mechanisms. The mediator *sanitizes* the sensitive information received from the coexisting networks and then returns the sanitized information back to them. The coexisting networks execute their coordinated coexistence mechanisms using the sanitized data.

B. Ecology-inspired Spectrum Allocation

As mentioned before, spectrum allocation among the coexisting networks through *direct* coordination may not be possible (due to a lack of infrastructure), may be too costly, or may be shunned by the competing network operators because they do not want to provide their sensitive information. Instead of direct coordination, the SHARE framework adopts an indirect coordination mechanism, which is inspired by an interspecific competition model from theoretical ecology.

Design objective. In a spectrum sharing process, a network has to figure out how much spectrum it can appropriate given its bandwidth requirement. Suppose a time-spectrum block is the minimum unit amount of spectrum allocation. Let S_i denote the *number of time-spectrum blocks* allocated to network $i \in \mathcal{K}$. We refer to S_i as the *spectrum share* of network i.

Our objective is that the spectrum sharing process will eventually reach a state of equilibrium, where the number of allocated blocks to each network is proportional to its reported bandwidth requirement.

Inspiration from ecology. In ecology, the population dynamics of a species in the interspecific resource competition process can be captured by the L-V competition model. In the context of network coexistence, we build a *weighted* competition model to help a network to determine the *dynamics of its allocated spectrum*, given its bandwidth requirement.

Information exchange between the mediator and a network. The mediator exchanges two types of control information with every CR network:

1) *Upload of local report*. Network i reports the current value of S_i to the mediator;
2) *Download of sanitized data*. The mediator replies back to network i with the sanitized data, i.e., sum of numbers of time-spectrum blocks of all other coexisting networks, i.e., $\sum_{j \neq i, j \in \mathcal{K}} S_j$.

C. Problem Formulation

Suppose that $\mathcal{K}$ denotes a set of n co-located networks that have individual bandwidth requirements $R_1, R_2, ..., R_n$, and operate over the same WS. The first objective for coexisting networks is to split the WS into n pieces that are proportional to their individual bandwidth requirements, without sharing individual bandwidth requirements with each other.

Let $\mathbf{S}(\mathcal{K}) = [S_1, S_2, \ldots, S_n]$ denote the *spectrum share vector* for $\mathcal{K}$ over the WS[1]. We define the *fairness index*, $F(\mathbf{S}(\mathcal{K}))$, for networks in $\mathcal{K}$ as follows:

$$F(\mathbf{S}(\mathcal{K})) = \frac{\left(\sum_{i \in \mathcal{K}} S_i\right)^2}{\sum_{i \in \mathcal{K}} R_i \cdot \sum_{i \in \mathcal{K}} R_i \left(\frac{S_i}{R_i}\right)^2}. \tag{2}$$

The maximum value of $F(\mathbf{S}(\mathcal{K}))$ is one (the best or weighted-fair case), where the allocated spectrum share value of a network is proportional to its bandwidth requirement.

Let $\mathcal{I}_i$ denote the *set of shared control information* known by network i, and it is easy to see that $R_i \in \mathcal{I}_i$. However, we assume that $R_j \notin \mathcal{I}_i$—i.e., co-located networks, i and j, do not know each other's bandwidth requirements.

We formulate a *weighted-fair spectrum sharing allocation* problem where heterogeneous networks dynamically determine their spectrum share values.

[1]The vector is a row vector or a $1 \times n$ matrix.

TABLE I
A mapping between biological and CR network ecosystems.

Biological ecosystem	CR network system
A species	A network
Population of a species	Spectrum share of a network
Population dynamics (growth or decline)	Dynamics of spectrum share

***Problem** 1:* Given a set of n co-located networks, $\mathcal{K}$, operating over N channels, one has to solve the following problem to find the spectrum share vector for $\mathcal{K}$:

$$\begin{aligned} &\text{Maximize} \quad F(\mathbf{S}(\mathcal{K})) \\ &\text{subject to} \quad \frac{S_i}{S_j} = \frac{R_i}{R_j}, R_j \notin \mathcal{I}_i, \forall i, j \in \mathcal{K}. \end{aligned}$$

The first constraint $\frac{S_i}{S_j} = \frac{R_i}{R_j}$ guarantees the weighted fairness.

IV. An Ecology-inspired Spectrum Share Allocation Algorithm

A. A Weighted-fair Spectrum Competition Model

1) The stable equilibrium of the L-V competition model: The L-V competition model provides a method for defining a state of "stable equilibrium" and finding the sufficient conditions for achieving it. If one considers the interspecific competition process described by equation (1), when $K_i = K_j$ and $\alpha_{ij} = \alpha_{ji}$ for any two species i and j, then the sufficient condition for stable equilibrium is $\alpha_{ij} < 1$.

2) The basic spectrum competition model: In Table I , we identify a number of analogies between a biological ecosystem and a network system. Based on equation (1) and the analogies, we can easily obtain the following *basic* spectrum competition model:

$$\frac{dS_i}{dt} = rS_i \left(1 - \frac{S_i + \alpha \sum_{j \neq i} S_j}{C}\right), \tag{3}$$

where S_i is the spectrum share for network i, and r is an intrinsic rate of increase. In equation (3), the carrying capacity is equal to the number of time-spectrum blocks in a period given N channels. A competition coefficient $\alpha < 1$ will guarantee a stable equilibrium—i.e., all the competing networks will have the same spectrum share value.

Next, we will show how to extend the basic competition model to a weighted-fair spectrum competition model that complies with the weighted-fairness requirement (i.e., $\frac{S_i}{S_j} = \frac{R_i}{R_j}$ for any two networks i and j) in a state of stable equilibrium.

3) The weighted-fair spectrum competition model: The basic spectrum competition model guarantees a stable equilibrium where all the competing networks have the same spectrum share value. However, solutions to Problem 1 must satisfy the requirement of weighted fairness, which implies that the competing networks' spectrum share values are proportional to their bandwidth requirements. For example, if network i has a bandwidth requirement that is twice that of network j, then network i's allocated spectrum share should also be twice the allocated spectrum share of network j.

To support the weighted-fairness in spectrum share allocation, we construct a weighted-fair spectrum competition model by introducing the concept of "sub-species". A network with a higher bandwidth requirement would have a greater number of sub-species than a network with a lower bandwidth requirement. We use the bandwidth requirement R_i as the number of sub-species of network i.

Let $S_{i,k}$ denote the spectrum share allocated to the sub-species k of network i, where $k \in [1, R_i]$. In the *weighted* competition model, every sub-species k of network i calculates the change in its spectrum share according to the following equation:

$$\begin{aligned}\delta_{i,k} &= \frac{dS_{i,k}}{dt} \\ &= rS_{i,k}\left(1 - \frac{S_{i,k} + \alpha\sum_{\kappa \neq k} S_{i,\kappa} + \alpha\sum_{j \neq i} S_j}{C}\right).\end{aligned} \tag{4}$$

Then, network i obtains its spectrum share value by combining the spectrum share values of all its sub-species, i.e., $S_i = \sum_k S_{i,k}$.

In SHARE, every network i periodically sends its spectrum share value S_i to the mediator, and then the mediator sends back the sanitized data $\beta_i = \sum_{j \neq i} S_j$ to network i. The spectrum share allocation process terminates when $\delta_{i,k} = 0$ for all i and k. Note that the sanitized data β_i is used (instead of actual bandwidth requirement information) to mitigate conflict of interest and privacy issues that may arise between competing networks. The use of sanitized data coincides with the second constraint of Problem 1. We show the pseudo code in Algorithm 1 and describe the procedure of SHARE as below.

1) A network i starts its spectrum share allocation process by creating a number of R_i sub-species.
2) At the beginning of every frame, every sub-species calculates the change rate of its spectrum share (i.e., $\frac{dS_{i,k}}{dt}$) using the sanitized data β_i obtained from the mediator.
3) If the change rate of the spectrum share is positive (or negative), a sub-species increases (or decreases) its spectrum share by randomly selecting a number of time-spectrum blocks to access (or releasing/freeing a number of occupied time-spectrum blocks).
4) At the end of every iteration, every network i calculates its new spectrum share value by $S_i = \sum_k S_{i,k}$, and sends S_i to the mediator. Meanwhile, the network updates the value of β_i from the mediator.
5) Last three steps are repeated until there is no sub-species with a non-zero change rate of spectrum share; that is $\frac{dS_{i,k}}{dt} = 0$ for every sub-species k of any network i.
6) The allocated spectrum share for network i is $\sum_k S_{i,k}$.

B. Characteristics of the Stable Equilibrium

Weighted-fairness. We first prove that the spectrum share allocation algorithm satisfies the requirement of weighted-fairness defined in Problem 1.

***Lemma** 1:* Given n coexisting CR networks in $\mathcal{K}$, when $\alpha < 1$, the spectrum share allocation process of Algorithm 1 is weighted-fair in partitioning the spectrum consisting of C time-spectrum blocks.

Proof: Suppose network $i \in \mathcal{K}$ has a number of R_i sub-species. The spectrum share allocation problem is equivalent to a problem where all sub-species compete for the resource using the L-V competition model. Since the sufficient condition for the equilibrium in the L-V competition model, $\alpha < 1$, is satisfied, the algorithm will terminate after a finite number of iterations, and all sub-species obtain the same spectrum share at the equilibrium point [3], [4], which is equal to $\frac{C}{\sum_{j \in \mathcal{K}} R_j}$. Hence, network i with R_i sub-species will obtain a spectrum share $R_i \frac{C}{\sum_{j \in \mathcal{K}} R_j}$, and thus $\frac{S_i}{S_{i'}} = \frac{R_i}{R_{i'}}$, $\forall i, i' \in \mathcal{K}$. ∎

Algorithm 1 The Spectrum Share Allocation Algorithm.

Input: competition coefficient α, capacity C, intrinsic rate of increase r, the sanitized data β_i.
Output: spectrum share, S_i, for network i.

Network i generates a number of R_i sub-species.
Update the value of β_i from the mediator.
while $(\exists k \in [1, R_i], s.t.\ \delta_{i,k} \neq 0)$ **do**
  for $k = 1$ to R_i **do**
    if $\delta_k \neq 0$ **then**
      $S_{i,k} = S_{i,k} + \delta_{i,k}$.
    end if
  end for
  Send $S_i = \sum_k S_{i,k}$ to the mediator and update the value of β_i.
end while
$S_i = \sum_k S_{i,k}$.

Stable equilibrium. We now show that the equilibrium point achieved by the weighted-fair competition model is stable.

***Theorem** 1:* Let $l = \sum_{i \in \mathcal{K}} R_i$ represent the total number of sub-species in the system. The differential equations (4) describe an l-dimensional system where the equilibrium when $S_i = R_i \frac{C}{l}$ is stable.

Proof: Suppose networks in $\mathcal{K}$ generate a total number of l sub-species. For the sake of simplicity, we assign every sub-species an index from $\{1, ..., l\}$. Let $\mathbf{S}^* = [s_1^*, ..., s_l^*]$ be the spectrum share vector at the equilibrium point for all sub-species in the system, where s_i^* is the allocated spectrum share of sub-species i at the equilibrium point.

By Lemma 1, we have $s_i^* = \frac{C}{l}$, where $i \in [1, l]$. Equation (4) is equivalent to

$$\frac{ds_i^*}{dt} = rs_i^*\left(1 - \frac{s_i^* + \alpha\sum_{j \neq i, j \in [1,l]} s_j^*}{C}\right) = 0. \tag{5}$$

That is, $s_i^* + \alpha\sum_{j \neq i, j \in [1,l]} s_j^* = C$.

We will prove the equilibrium $\mathbf{S}^*$ is stable by linearizing the system equations at this equilibrium point. Let $\mathbf{S} = [s_1, ..., s_l]$ be a spectrum share vector for all sub-species at a non-equilibrium point. We denote the differential equation at this point as

$$G_i(\mathbf{S}) = rs_i\left(1 - \frac{s_i + \alpha\sum_{j \neq i, j \in [1,l]} s_j}{C}\right). \tag{6}$$

Let $\Delta s_i = s_i - s_i^*$. By linearizing equation (6) at the equilibrium point, we obtain

$$G_i(\mathbf{S}) = G_i(s_1^*, ..., s_l^*) + \sum_{i\in[1,l]} \left(\frac{\partial G_i(\mathbf{S})}{\partial s_i}\bigg|_{s_1^*,...,s_l^*} \cdot \Delta s_i \right)$$
$$= -\left(\frac{r}{l}\right)\Delta s_i - \frac{r\alpha}{l}\sum_{j\neq i, j\in[1,l]} \Delta s_j. \quad (7)$$

We derive the l by l Jacobian matrix for the above equation (7) as follows

$$A = \begin{vmatrix} -\frac{r}{l} & -\frac{r\alpha}{l} & -\frac{r\alpha}{l} & \cdots & -\frac{r\alpha}{l} \\ -\frac{r\alpha}{l} & -\frac{r}{l} & -\frac{r\alpha}{l} & \cdots & -\frac{r\alpha}{l} \\ \vdots & \ddots & \ddots & \cdots & \vdots \\ -\frac{r\alpha}{l} & -\frac{r\alpha}{l} & \cdots & -\frac{r\alpha}{l} & -\frac{r}{l} \end{vmatrix},$$

which is a symmetric matrix. This matrix has two eigenvalues $\lambda = -\frac{r}{l} - \frac{(l-1)r\alpha}{l}$ and $\frac{r(\alpha-1)}{l}$. Since $0 < \alpha < 1$, the two eigenvalues are negative. Based on the stability theory, the system is stable if all eigenvalues are negative. Hence, the differential equations shown by (4) describe an l-dimensional system and the equilibrium $\mathbf{S}^* = \{s_i^* | s_i^* = \frac{C}{l}, \forall i \in [1,l]\}$ is stable. ∎

Convergence time. Next, we analyze the time required for the proposed algorithm to converge to the stable equilibrium.

***Theorem** 2:* Consider N networks that compete for the same spectrum band, then the time-to-convergence to the SHARE's equilibrium is $T_c = O(ln(C/l))$.

Proof: Similar to the proof of Theorem 1, there are a total number of l sub-species. Let $A = \sum_{j\neq i, j\in[1,l]} s_j = (l-1)s_0$, and equation (5) can be rewritten as

$$\frac{ds_i}{dt} = rs_i\left(1 - \frac{s_i + \alpha A}{C}\right) = 0. \quad (8)$$

By integrating (8), we can obtain

$$s_i(t) = \frac{s_0 e^{rt\left(1-\frac{\alpha A}{C}\right)}(C-\alpha A)}{s_0(e^{rt\left(1-\frac{\alpha A}{C}\right)} - 1) + (C - \alpha A)}. \quad (9)$$

To calculate the time-to-convergence, we consider the time which is required to increase the spectrum share for network i from s_0 to $s_i(t) = s^* = C/l$. By solving (9), the time T_c becomes:

$$T_c = \frac{C}{r(C-\alpha A)} ln\left(\frac{s_i(t)(C - \alpha A - s_0)}{s_0(C - \alpha A - s_i(t))}\right).$$

The time of convergence of SHARE is $O(ln(C/l))$, and it is exponentially fast. ∎

V. Performance Evaluation

In this section, we evaluate the performance of SHARE in two steps. We first look into the the stable equilibrium achieved by the weighted-fair spectrum share allocation scheme. Then, we compare the foraging-based channel selection scheme and the random channel selection strategy in terms of system fitness.

A. The Stable Equilibrium

In the first set of simulations, we simulate two CR networks that coexist in a block of spectrum that is divided into 20 channels. We fix the bandwidth requirements of the two networks as $R_1 = 2$ and $R_2 = 3$, which implies that network 1 has two sub-species and network 2 has three in the spectrum share allocation process. In the L-V competition model, the competition coefficient $\alpha < 1$ and the intrinsic rate of increase $r < 2$ [11]. The discussions on how to choose appropriate parameter values to achieve fast convergence to an equilibrium can be found in [3], [11]. In this set of simulations we used $\alpha = 0.9$ and $r = 1.95$. Next, we show that the coexisting networks under SHARE achieve an equilibrium, where the spectrum share of each network is proportional to its bandwidth requirement.

Convergence to an equilibrium. From Figure 2, we observe the dynamics of the spectrum share value of each network and each sub-species within a network. "Sub-species (i, j)" in the figure legend represents sub-species j within network i. The system converges to an equilibrium state in finite time where all sub-species of every network are allocated the same spectrum share value. The aggregate spectrum share value allocated to a network is proportional to its bandwidth requirement.

Stability of the equilibrium. To test the stability of the equilibrium point, we introduce two types of disturbance in bandwidth requirement by: 1) silencing the sub-species $(2, 3)$ for a short time period (from the 120^{th} to 140^{th} iteration), and 2) deleting the sub-species $(2, 3)$ at the 360^{th} iteration. Figure 3 shows the dynamics of spectrum share values when the disturbance is introduced. As can be seen in the figure, the disturbance causes the system to deviate away from equilibrium, but the coexisting networks quickly converge to a new equilibrium point where the allocated spectrum share values are proportional to the new values of bandwidth requirements.

B. Weighted Fairness

We vary the number of coexisting CR networks, and in each simulation run, the bandwidth requirement, R_i, of each network i is randomly chosen from the range $[1, 5]$. We compare SHARE with a "non-collaborative" allocation scheme where every coexisting network determines its spectrum share value without coordinating with others. This is equivalent to splitting the available spectrum "randomly" to n pieces and allocates them to n coexisting networks. We measure the fairness values using the fairness index defined in (2). Figure 4 clearly shows that SHARE allocates spectrum in a weighted-fair manner, whereas the non-collaborative allocation scheme does not.

C. System Satisfaction

We define the *satisfaction* of network i as the ratio between its allocated spectrum share to its bandwidth requirement, $f_i = \frac{S_i}{R_i}$. Then, the system satisfaction is the network satisfaction value of the network that has the minimum satisfaction, such as

$$\Phi = \min\{f_0, f_1, ..., f_{P-1}\}.$$

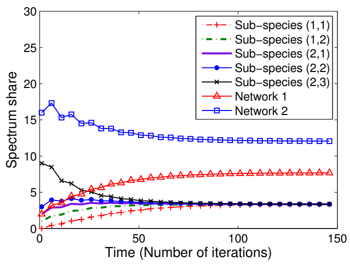


Fig. 2. Convergence to the equilibrium.

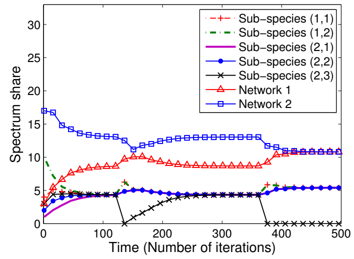


Fig. 3. Stability of the equilibrium.

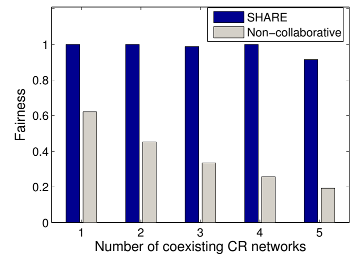
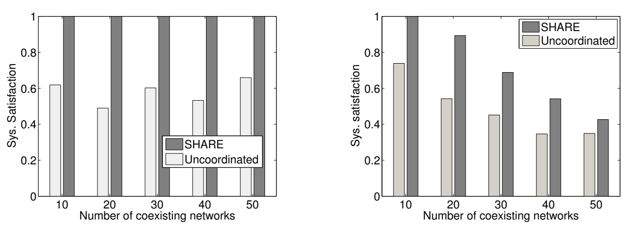


Fig. 4. Measured fairness values.

Then, we vary the number of networks when their bandwidth requirement values are identical or uniformly distributed in a range $[1, N]$. From simulation results in Figure 5, we observe that SHARE's system satisfaction value is close to one when the bandwidth requirement values are identical; when random bandwidth requirements are employed, SHARE's performance is much better that the random spectrum sharing strategy.

Summary. A centralized is always the best strategy when global information is available. However, in this paper, due to incompatible interface, conflict of interests, privacy issues, we cannot deploy a centralized approach. Instead, we compare a mediator-based approach with the totally uncoordinated methods (the random strategy).



(a) (b)

Fig. 5. System satisfaction: (a) coexisting networks have identical bandwidth requirement given sufficient spectrum; (b) coexisting networks have random values of bandwidth requirement given insufficient spectrum;.

VI. Conclusions

Inspired by symbiotic coexistence in ecology, in this paper we presented a framework called Symbiotic Heterogeneous coexistence ARchitecturE (SHARE), which enables collaborative coexistence among heterogeneous CR networks over TVWS. SHARE enables two heterogeneous CR networks to coexist in TVWS through a mediator-based *indirect* coordination mechanism between them, which avoids the drawbacks of direct coordination mechanisms. The SHARE framework adopts two algorithms that are executed by each coexisting network to autonomously complete the following two spectrum sharing tasks: (1) dynamically determine its spectrum share that is proportional to its bandwidth requirement, and (2) select channels in such a way to achieve a very high value of system fitness. Analytical and simulation results show that SHARE enables the networks' spectrum allocation to converge to a stable equilibrium, and that in this allocation, weighted-fairness is ensured and the system fitness is maximized.

Acknowledgements

This work was partially supported by National Natural Science foundation of China under grant numbers 61201245, 61073155 and 61001075; and by the US National Science Foundation through grants CNS-0746925, CNS-0963578, CNS-1022552, and CNS-1065444.

References

[1] S. Brahma and M. Chatterjee. Mitigating Self-Interference Among IEEE 802.22 Networks: A Game Theoretic Perspective. *IEEE Globecom*, pp. 1–6, Nov. 2009.
[2] Ecma International. ECMA-392: MAC and PHY for Operation in TV White Space. 1st Ed., Dec. 2009.
[3] G. Hasegawa and M. Murata. TCP symbiosis: Congestion control mechanisms of TCP based on Lotka-Volterra competition model. *ACM Inter-Perf*, Oct. 2006.
[4] X. Huang, F. Ren, G. Yang, and Y. Wu. End-to-end Congestion Control for High Speed Networks Based on Population Ecology Models. *IEEE ICDCS*, pp. 353–360, June 2008.
[5] J. Huang, G. Xing, G. Zhou, and R. Zhou. Beyond Co-existence: Exploiting WiFi White Space for ZigBee Performance Assurance. *IEEE ICNP*, Oct. 2010.
[6] IEEE P802.11 task group af. Wireless LAN in the TV White Space. http://www.ieee802.org/11/Reports/tgaf_update.htm/.
[7] IEEE 802.22 Working Group. http://www.ieee802.org/22/.
[8] IEEE 802.19 Task Group 1. Wireless Coexistence in the TV White Space. http://www.ieee802.org/19/pub/TG1.html.
[9] C. Ko and H. Wei. Game Theoretical Resource Allocation for Inter-BS Coexistence in IEEE 802.22. *IEEE Trans. on Vehi. Tech.*, 59(4):1729–1744, May 2010.
[10] A. Lotka. Elements of Physical Biology. *Williams&Wilkins*, 1925.
[11] J. Murray. *Mathematical Biology I: An Introduction*. Springer Verlag, 2002.
[12] M. Tokeshi. *Species Coexistence: Ecological and Evolutionary Perspectives*. Wiley-Blackwell, 1998.
[13] V. Volterra. Variations and Fluctuations of the Number of Individuals in Animal Species Living Together. *Animal Ecology*, R.N. Chapman, (ed.), McGraw-Hill, 1931.
[14] T. Wang, L. Song, and Z. Han. Coalitional Graph Games for Popular Content Distribution in Cognitive Radio VANETs. , *IEEE Transactions on Vehicular Technologies*, to appear.
[15] R. Yu, Y. Zhang, Y. Liu, S. Xie, L. Song, and M. Guizani. Secondary Users Cooperation in Cognitive Radio Networks: Balancing Sensing Accuracy and Efficiency. *IEEE Wireless Communications Magazine*, 19(2):30–37, Apr. 2012.
[16] Y. Yuan, P. Bahl, R. Chandra, T. Moscibroda, Y. Wu. Allocating Dynamic Time-spectrum Blocks in Cognitive Radio Networks. *ACM MobiHoc*, pp. 130–139, Sept., 2007.
[17] R. Zhou, Y. Xiong, G. Xing, L. Sun, and J. Ma. ZiFi: Wireless LAN Discovery via ZigBee Interference Signatures. *ACM Mobicom*, pp. 49–60, Sept. 2010.