When Brands fight over Bands: Sociality in the Cognitive Radio Ecosystem

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***Abstract*—As wireless devices continue to proliferate, spectrum management is essential to a healthy and functioning digital ecosystem. Here we present an evolutionary analysis of how inter-brand relationships can be expected to evolve in the cognitive radio domain over long time scales. We find that a range of trajectories are possible, and that the eventual outcomes depend on a variety of system parameters including the number of users and transmission band switching costs. Starting from previous bio-socially inspired fair spectrum sharing protocols, we put forward an extended model of secondary user etiquette that allows for a range of inter-group dynamics to arise in the natural course of competition over and co-use of spectrum resources. We show that as populations grow, increases in transmission switching costs lead to evolutionary pressures toward increasing antagonism between brands, and that in such scenarios devices tend to segregate by brand across bands. Understanding the drivers behind emerging inter-brand dynamics from an evolutionary perspective is an important input to the long term view of the successful application of distributed spectrum access and cognitive radio.**

***Index Terms*—Cognitive radio networks; bio-social networking; self-coexistence; dynamic spectrum access; contention-sensing**

I. Introduction

Remarkable advances in wireless device technologies continue to be driven by the demands of an increasingly diverse set of *new* higher bandwidth end-user applications. These technological advances have over time, yielded corresponding reductions in hardware production costs. Not surprisingly, this positive feedback loop has led to an exponential growth of total numbers of devices and their cumulative bandwidth demands, while available radio spectrum has remained largely unchanged. The current scenario (or the one which we are inexorably headed) is one in which wireless devices face severe problems of "coexistence" as co-users of the limited resource of radio spectrum. Dynamic Spectrum Access (DSA) networks [1] using Cognitive radio (CR) technology [2] has been proposed to alleviate contention in spectrum bands [3], [4]. The historical approach of static spectrum assignment has led to underutilization in some bands because spectrum license holders (primary users) transmit periodically leaving "spectrum holes" while being idle [5]. With CR technology "secondary users" (SUs) can transmit in a licensed spectrum band provided they immediately leave the band upon primary user arrival to avoid interference. SUs dynamically identify and opportunistically forage for unused spectrum, adjusting transmission/reception parameters accordingly. In addition to primary user avoidance, SUs compete with other SUs over limited resources. We attempt to map out the most plausible long-term evolutionary trajectories of spectrum co-use strategy under the pressures and dynamics of inter-group competition.

We consider a population where all SUs belong to one out of two groups. We think of these groups as being identified by **brands**. Our goal is to understand how the relationship between brands might evolve over time. In answering this question about brands competing over spectrum, we draw upon prior work from the bio-social domain where the competition between species over natural resources has been extensively studied [1]

We start from a previous bio-social model of CR nodes [9], wherein each SU can at each point in time either "forage" (search) for good spectrum bands or "consume" (transmit in) its present band of interest. While the SU is foraging, it is accumulating untransmitted data; following the bio-social metaphor, we say that it is experiencing increasing "hunger". An SU decides to transmit stochastically based on its hunger

[1]The leap is not that far fetched, given that CR networks in DSA environments are autonomous and (at least in theory) capable of sensing, learning, and adaptation, they may evolve over time, much as humans and other social animal species have in analogous contexts of resource sharing/conflict [6]. Computer science research on resource allocation in networks recognizes the potential relevance of knowledge on resource use in human and animal societies. There has been considerable prior work seeking to apply models of animal foraging strategies (and derivative theories of marginal use) to the design of protocols in the domain of CR networks [7], [8].

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level and contention in the channel; elevated hunger or low contention levels make consuming more likely, foraging is more likely when hunger is low or contention is high. By operating according to these simple rules, the CR society implicitly achieves some measure of fair access–those SUs that need to transmit are able to–without paying the price of explicit resource coordination [9].

Here we extend the model to include heterogeneous groups, to reflect distinct CR brands. Our goal is to understand how the relationship between brands might evolve in response to environmental conditions. Where in the earlier model, SUs had a bias towards avoiding contention (with *any* SUs), here they will *only* avoid contention with individuals *of their own group*. In addition, each SU is averse to consuming in a band if there are "too many" SUs belonging to the other group present there. The definition of "too many" is governed by a system-wide parameter, and one of our objectives here is to understand what the evolutionary pressures on this parameter may be. If we can understand when and why this parameter can be expected to change, we will understand how inter-brand relationships can be expected to evolve, under different assumptions within the CR ecosystem.

II. Mathematical Model

There are m orthogonal spectrum bands $b \in \mathcal{B}$, and S is a set of n secondary users. Each SU has a transmission buffer of size $H_{\max}$ Kbits which accumulates data at a constant rate of $(A \cdot H_{max})$ Kbits/sec. SUs operate according to the finite state machine (FSM), shown in Figure 1 (following [10]), having a "consume" state q_c and a "forage" state q_f. At any point in time, each SU has a band of interest (BoI), which is one of the m spectrum bands; each SU can autonomously change its BoI over time. When an SU is in the consume state, it is transmitting in its BoI. When an SU is in the forage state, it is tuned to its BoI, listening but not transmitting. An SU transitions from the forage state to the consume state (Figure 1) with probability P. This probability P depends on the amount of untransmitted data accumulated in the SU's transmission buffer (i.e. its "hunger level"). As more buffered data awaits transmission, the SU's hunger level increases, and its probability to transition to consume state (and begin transmitting) increases. In consume state, as the SU transmits buffered data, its hunger level decreases, and the probability to transition back to the forage state rises. This mechanism allows SUs with low hunger level to (implicit) defer to SUs with higher hunger level, since SUs with high hunger level will have higher probability to transmit in the band; this need-based deference occurs without (explicit) coordination. The performance benefits of such a deference scheme among secondary users was established by Wisniewska et al [9].

In this work we extend this bio-social model further by considering the implication of co-existing groups and inter-group dynamics. Our goal is to move towards understanding the possible evolution of inter-brand dynamics within the commercial-digital ecosystem. For simplicity, we begin by supposing that each of the n secondary users in set S belong

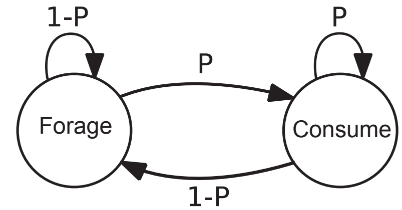

Fig. 1: A general behavioral finite state machine for SUs.

to one of just *two* identifiable groups G_1 and G_2. Each of the two groups has size $\frac{n}{2}$, and the membership of the groups is assumed to be invariant over time. There are two key components of SU behavior we will consider:

- **In-group Deference**. SUs have a tendency to not transmit in a band if they detect that SUs from their *own group* are presently transmitting. Deference is, in effect, a kind of "backoff" algorithm operating within each group.
- **Out-group Avoidance**. SUs from one group have a tendency to switch bands if they detect that "too many" SUs from the *other group* are present (i.e. a fraction exceeding some system-wide **comfort threshold** parameter $\theta \in [0, 1]$). Avoidance behavior is natural in the face of deference, since within-group-only "backoff" penalizes those who are in the out-group.

A. Behavioral Model

The following **time-varying state variables** are maintained by each SU s:

- Its current BoI (band of interest), denoted $\alpha_t(s)$.
- Its hunger level $h_t(s)$, the amount of queued data.
- Its FSM state $\gamma_t(s)$ which is either in forage q_f or in consume q_c.

At each time t, each SU s observes the set of co-consumers in its current BoI:

$$K_t(s) = \{s' \in S \mid \alpha_t(s') = \alpha_t(s) \wedge \gamma_t(s') = q_c\}.$$

It then measures its own "congruence" with this set of co-consumers, by computing the fraction that are in its own group:

$$f_t(s) = |\{s' \in K_t \mid g(s') = g(s)\}|/|K_t|.$$

Each SU s maintains an archive of recent "congruence" measurements in a queue of bounded size $\max$; the size limit is enforced by dropping the oldest entries in a FIFO manner. The mean "congruence" over the last $\max$ measurements is computed and referred to as $f_{ave}(s)$.

While in the forage state untransmitted data is enqueued in s's transmit buffer, causing hunger level to increase. Over a time interval ΔT, we take

$$h_{(t+\Delta T)}(s) = h_t(s) + A \cdot \Delta T \cdot H_{max}.$$

Finally, hunger level is clipped at a maximum value of $H_{\max}$ to reflect the bounded size of the transmit buffer. The probability that a foraging SU begins transmitting increases linearly with the relative occupancy level of its transmission buffer *provided* *no other members of the group are currently consuming*. If SUs from its own group are *not* consuming its BoI, i.e. $f_t(s) = 0$, then with probability $P = h_t(s)/H_{\max}$ the SU transitions into the consume state. If it decides to remain in forage state, it then determines whether or not to switch bands by comparing its "congruence" measurements against the system-wide comfort threshold. If the congruence $f_{ave}(s)$ is below the comfort threshold parameter θ, the SU switches BoI with a probability $1 - f_{ave}(s)/\theta$. If the SU decides to switch bands, it chooses its new BoI uniformly at random, and upon switching, flushes its queue of "congruence" measurements.

While in the consume state the SU transmits data, causing its hunger level to decrease. The probability for a consuming SU to transition to forage state is inversely proportional to the hunger level. Over a time interval ΔT, we take

$$h_{t+\Delta T}(s) = h_t(s) - R(|K_t(s)|) \cdot \Delta T.$$

Here the effective rate of throughput R is determined by Shannon's formula [11], [12]

$$R(k) \stackrel{def}{=} B \cdot log_2 \left(1 + \frac{G_z P_z}{\sum_{y=1}^{k} G_{zy}\, P_y + \epsilon}\right) \qquad (1)$$

where k is the number of co-consumers in the band, the transmission power of SU z (resp. y) are denoted P_z (resp. P_y); B is the channel bandwidth; G_z is the channel gain for transmissions by z, G_{zy} represents the channel gain for the transmission between z and y, and ϵ is the power level of the ambient white Gaussian noise. In this work we do not consider path losses and consider only a homogeneous network wherein all SUs send (to a base station) at the same power P and experience the channel gain G.

With probability $1-P = 1-(h_t(s)/H_{\max})$, the consuming SU transitions into the forage state q_f; otherwise, it remains in consume state q_c (see Figure 1).

B. Utility

Gross utility (per SU) at time t is determined by

$$U_t = \frac{1}{n} \sum_{i=1}^{m} |K_t(i)| \cdot R(|K_t(i)|)$$

where $|K_t(i)|$ is the number of co-consumers of the band, and R is the utility obtained by each consumer as determined by Shannon's formula (1). The average utility U_T is defined as the average value of U_t over the previous T steps.

Switching costs. When an SU switches transmission bands $\alpha_t(s) \neq \alpha_{t-1}(s)$ expensive (in terms of time) hardware reconfiguration is required. To account for the possibility that changing transmitter and receiver bands may require different amounts of time, and hence opportunity costs in terms of transmission, we keep track of L_t which is the number of SUs who switch BoI at time t and F_t the number of SUs who switched from forage to consume state at time t. The former are receiver reconfiguration events; the latter are transmitter reconfigurations. The cost paid by the system at time t is $C_t = c_1|F_t| + c_2|L_t|$. As it turns out, and as we shall see in the Results section, once the system reaches "convergence", $L_t \approx 0$; this will justify our taking $c_2 = 0$ and considering just one parameter $c_1 = c$.

Net utility (per SU) at time t is taken as $I_t = \frac{1}{n}(U_t - C_t)$. The average utility U_{net} is defined as the average value of I_t over the previous T steps.

C. Convergence

To avoid the possibility of drawing conclusions about system performance that are unduly impacted by stochastic effects, we introduce a formal criterion for convergence of the dynamic system. Informally, we say that the system has converged when each of the SUs individually is in a "steady state". We say that an SU in "steady state" if it has a relatively stable frequency with which it is switches bands. Formally, the SU is in steady state at time t_0 if (i) $t_0 >$ 10,000 and (ii) the ratio of the number of band switches in the first half of $[t_0 -$ 10,000$, t_0]$ is between 0.95 and 1.05 times what the number of band switches in the second half of the same interval. Stated equivalently, the frequency of BoI switches has remained consistent over an interval of 10,000 time steps with fluctuations bounded by $\pm 5\%$. The system reaches steady state when all consumers are found to be in steady state.

D. Segregation

Beyond utility maximization, one epiphenomenon we will be interested in examining is the possibility of segregation; that is the exclusive use of certain bands by certain groups. To help quantify segregation, each band records $m_1(b)$ (resp. $m_2(b)$), the fraction of time post-convergence that band b was occupied by a majority of consumers from G_1 (resp. G_2). We take $e(b)$ represent the fraction of time post convergence that the two groups were equinumerous in the band. For example, if $m_1(b) = 0.7$, $m_2(b) = 0.2$ and $e(b) = 0.1$ then post-convergence 70% of the time band b was being consumed by mostly SUs from G_1, 20% of the time by mostly SUs from G_2, and 10% of the time by an equal number from both groups. The segregation measure for each non-empty band b is defined as:

$$\omega(b) = \left| \frac{m_1(b)}{m_1(b) + m_2(b) + e(b)} - \frac{m_2(b)}{m_1(b) + m_2(b) + e(b)} \right|$$

A segregation measure of 1 occurs when one group has a monopoly over the band; a segregation measure of 0 occurs when both groups occupy majority status with equal frequency. In the example, $\omega(b) = |0.7 - 0.2| = 1/2$. The segregation level in the system as a whole Ω, is taken to be the average $\omega(b)$ over all bands $b \in \mathcal{B}$. Segregation dynamics have been studied previously in social science starting with the work of Schelling [13], although that body of work considers spatially distributed agents and does not include resource sharing/competition as one of its processes.

III. Experimental Platform

We use a stochastic discrete event simulator [14] to obtain utility measurements for different SU societies over time. Consumers transition asynchronously according to the appropriate previously defined finite state machine. The parameters used in the simulation are listed in Table I below:

TABLE I: Baseline Parameters

Parameter	Description	Value
m	Number of bands	5
P_z	Transmission power of node z	4 W
B	Capacity per band	20 MHz
A	Hunger accumulation rate	0.2
H_{max}	Max hunger level	$R(0) \sim 7$
$c_1 = c$	Cost of transmitter reconfig	varies
c_2	Cost of receiver reconfig	0
max	Memory buffer size	100

IV. Experimental Results

In what follows, we will refer to CR societies in which the comfort threshold parameter $\theta = 0.0$ as **tolerant**, and CR societies where $0.1 \leq \theta \leq 1.0$ as **intolerant**. We will always be comparing the performance of intolerant CR societies *relative* to the performance of tolerant CR societies. All measurements are made post-convergence – as defined in Section II-C.

Gross utility is elevated at intermediate values of comfort threshold. We begin by comparing the gross utility of intolerant versus tolerant CR societies. In Figure 2 the X axis varies the comfort parameter θ, while the Y axis shows the percentage difference in gross utility obtained by an intolerant society, *normalized by the utility obtained by a tolerant CR society of the same size*. For example, when $n = 120$ in a tolerant society $U_T = 2.0$ while in a society with $\theta = 0.5$ $U_T = 2.5$, the difference in utility is 0.5 which normalized yields $0.5/2.0 = 25\%$. In Figure 2 there is a significant increase in utility U_T when SUs operate at intermediate values of comfort threshold (between $0.2 \leq \theta \leq 0.8$). The percentage difference in utility U_T increases with population size. For example, when $n = 30$ and $\theta = 0.5$ there is an 9% increase in utility over the tolerant society's baseline; by comparison, when $n = 480$ and $\theta = 0.5$ that increase goes up to 62%.

There is evolutionary pressure towards intermediate values of the comfort threshold parameter. In a hypothetical setting where two parallel, side-by-side societies exist, one tolerant, and one with intermediate values of comfort threshold, the latter would obtain higher per-SU gross utility (see Figure 2). Thus, we can say that (in the absence of switching costs) there is an evolutionary pressure toward intermediate (non-zero) values of the comfort threshold parameter.

Larger tolerant CR systems are more evolutionarily stable with respect to their comfort threshold values. Although this pressure exists at all population sizes we considered, larger tolerant populations appeared more evolutionarily stable. From Figure 2 we see that when the population is relatively small ($n < 120$) there is an immediate increase in gross utility when θ increases above 0. On the other hand, at larger population sizes a significant and discontinuous jump in θ is required for the system to receive any payoff in gross utility. For example, when $n = 480$, all SUs must increase θ to > 0.3 for any benefits to be achieved.

Post-convergence, the number of BoI switches contribute insignificantly to the net utility, regardless of the value of comfort threshold. At each time step, an SUs that switches BoI pays a cost c_2 (receiver reconfigurations). Figure 3 shows the average number of BoI transitions per consumer per unit time (the mean value of $|L_t|/n$). We see that (regardless of comfort threshold θ and population size n) this number is below 0.01. Even though the frequency of band transitions increases when the comfort threshold is large, the contribution of $\sum_{t=1}^{T} L_t \sim 0$ remains small. This is not surprising, since these measurements are all post-convergence, when BoI switching rates have stabilized. To summarize, switching cost is thus approximable $C_t \sim c_1|F_t|$ by the costs of transitioning from forage to consume, which we discuss next.

Post-convergence, the frequency of transitions from forage to consume decreases for intermediate values of comfort threshold. At each time step, an SUs that switches to consume state pays a cost c_1 (transmitter reconfigurations). In Figure 4, the X axis varies the comfort parameter θ, while the Y axis shows the difference in frequency of forage to consume transitions in an intolerant society, *normalized by the frequency in a tolerant CR society of the same size*. There is a significant decrease in transitions (and hence costs) when SUs operate at intermediate values of comfort threshold (between $0.2 \leq \theta \leq 0.8$). The percentage difference in forage to consume transitions $|F_t|$ decreases with population size. For

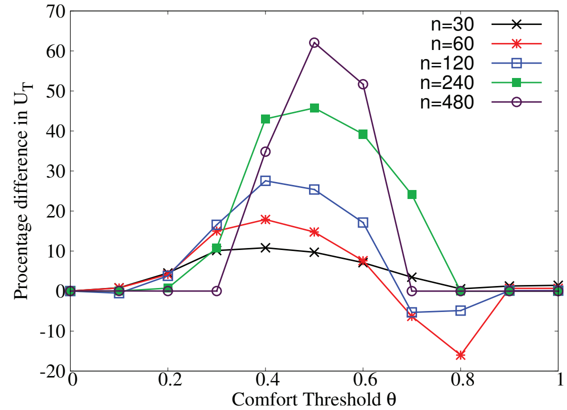

Fig. 2: Gross utility U_t, normalized by tolerant society.

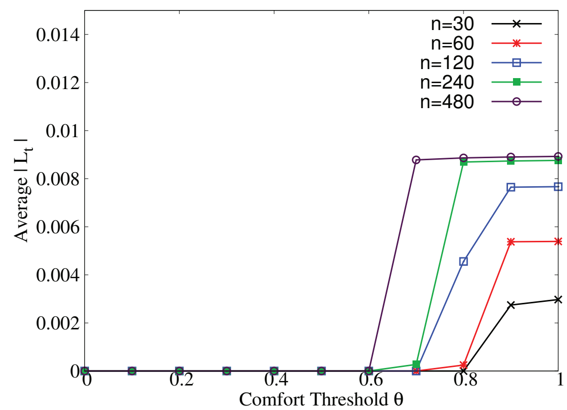

Fig. 3: BoI switch rate, normalized by tolerant society.

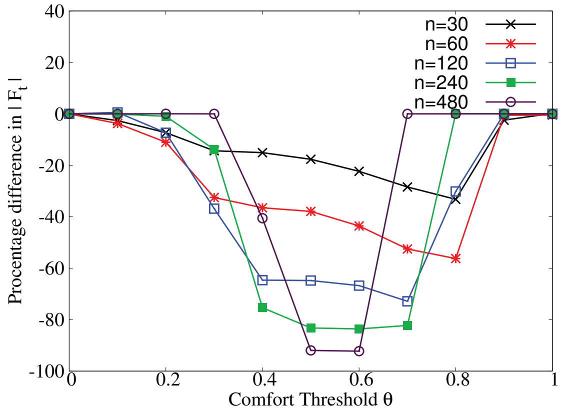

Fig. 4: F-to-C switch rate, normalized by tolerant society.

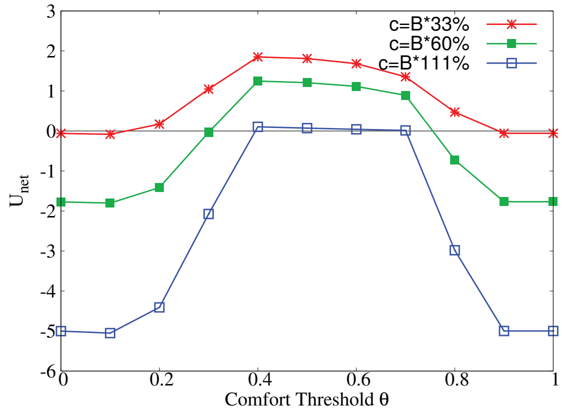

Fig. 5: U_{net}, normalized by tolerant society $n = 120$.

example, when $n = 30$ and $\theta = 0.5$ there is an 20% decrease in utility over the tolerant society's baseline; by comparison, when $n = 480$ and $\theta = 0.5$ that decrease goes up to 90%.

Including switching costs does not alter conclusions about evolutionary pressure towards intermediate values of the comfort threshold parameter. In a hypothetical setting where two parallel, side-by-side societies exist, one tolerant, and one with intermediate values of comfort threshold, the latter would have lower forage to consume transitions, and lower associated costs (see Figure 4). Combined with our previous conclusions (above) we now can say that *even in the presence of switching costs* there is an evolutionary pressure toward intermediate (non-zero) value of the comfort threshold parameter.

Including switching costs does not alter conclusions about larger tolerant CR systems being more evolutionarily stable. From Figure 4, we see that when the population is relatively small ($n < 120$) there is an immediate decrease in the frequency of transitions when θ increases above 0. On the other hand, at larger population sizes a significant and discontinuous jump in θ is required for the system to receive any reduction in switching costs. For example, when $n = 480$, all SUs must increase θ to > 0.3 for any switching cost reduction to be achieved. Although this pressure exists at all population sizes we considered, larger tolerant populations can be seen to be more evolutionarily stable.

Forage to consume switching costs amplify the evolutionary pressure to depart from tolerance. We begin by consider the impact of switching cost c_1 on net utility U_{net}. Figure 5 shows U_{net} for population size $n = 120$ where cost $c_1 = c$ is varied. When cost is 33% of the bandwidth B, net utility $U_{net} \approx 0.0$ for tolerant populations with $\theta \in [0, 0.1]$ and positive only when $\theta > 0.1$. At this **critical value** of switching cost, intolerance is *required* for the society's survival–that is, to ensure a positive utility for each SU. As cost increases, societies must further increase the comfort parameter even higher to remain viable. For example, if $c = 0.6 \cdot B$, the society must adopt $\theta \in [0.3, 0.75]$ if SUs are on average to obtain positive utility. Finally, there is some **maximum value** of the switching cost for which the society ceases to be viable regardless of its choice of comfort parameter θ. In the example of Figure 5, this occurs when $c \approx 1.1 \cdot B$.

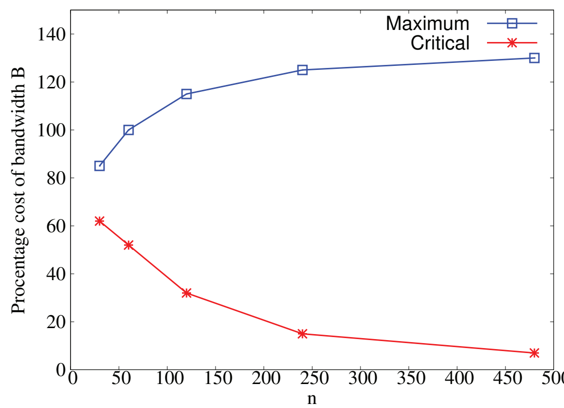

Fig. 6: Critical & max cost for various n.

There is a "rational" threshold (in terms of forage-to-consume transition cost) beyond which a population of any given size will find it necessary to deviate from tolerance. The previous example is intended to demonstrate that each population of SUs has an associated critical cost value; when forage-to-consume switching cost exceeds this critical value, intolerance is required for survival. Each population also has an associated maximum cost value; when forage-to-consume switching cost exceeds this maximum value the comfort parameter is unable to save the SU population from starvation. Figure 6 shows how the critical and maximum cost values vary with population size. We note that for larger populations, even small forage-to-consume transition costs are a sufficient inducement for adopting a position of intolerance. For example, when $n = 30$ the switching cost must exceed $0.6 \cdot B$ for the society to be incentivized to depart from tolerance; when $n = 480$ it need only exceed $0.06 \cdot B$ for the departure to be "rational" and evolutionarily advantageous.

Segregation as epiphenomenon. In Figure 7, we consider the system-wide segregation measure Ω defined in Section II-D. Recall that $\Omega = 1$ when each band is monopolized by

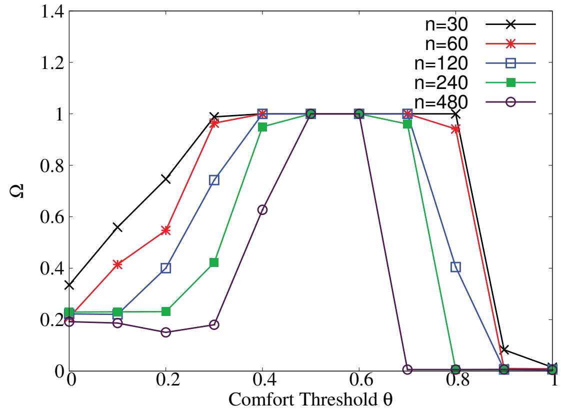

Fig. 7: Band based segregation Ω for varying comfort thresholds.

some group and $\Omega = 0$ when both groups occupy majority status with equal frequency in all bands. The graph shows Ω for different population sizes n and different comfort threshold θ settings. Regardless of populations size, societies will segregate at intermediate values of θ. When consumers have low comfort threshold levels, the population does not segregate since consumers are comfortable with a large fraction of consumers from the other group consuming in their BoI. On the other hand, when comfort threshold levels are high, SUs are only comfortable consuming their BoI if a large fraction of co-consumers are from their own group; this results in frequent switching (Figure 3) and failing to segregate (Figure 7).

V. Conclusion

The diverse device population in the Internet of Things poses coexistence challenges. The protocol presented here builds on earlier bio-socially inspired "fair" need-to-transmit based protocols [9]. Our objective in this paper was to determine *what could be expected to happen in the future*, if SUs with similar characteristics (e.g. the same brand) group together and act according to two basic principles (i) in-group deference and (ii) out-group avoidance. Holding in-group deference fixed, we considered CR societies with a range of out-group avoidance. This was implemented using a comfort threshold parameter θ. By examining societies with different θ settings side-by-side and through the lens of a fitness function (net utility), we came to see the evolutionary pressures at play. We showed that there are always pressures towards the emergence of (intermediate) non-zero comfort threshold societies, but that large tolerant CR societies are more robust (evolutionarily stable) in this regard, compared to smaller ones. We showed that the strength of evolutionary pressures is closely linked to both population size and transmitter reconfiguration costs. Larger CR societies are more susceptible to responding to small increases in transmitter reconfiguration cost by deviating from policies of tolerance; the emergence of such discriminatory and avoidant behaviors can be explained directly in terms of survival needs (the requirement that per SU net utility be positive). We also saw that band-based segregation can arise as an epiphenomenon in societies with such intermediate comfort threshold value.

Future Work The proposed scheme considers only two groups of CR devices; we intend to consider the dynamics of multiple groups, and settings in which the groups can be of different sizes. We hope to extend the model so that CR nodes can evolve by independently choosing the comfort thresholds based on collective beliefs about the relative merits of different settings. We intend to implement the proposed scheme in real hardware testbed in the CR and IoT context, using nodes that are capable of switching Wi-Fi channels using a microcontroller together with ns-3 emulation/testbed engine.

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References

[1] C. Cordeiro, K. Challapali, D. Birru, and S. Shankar, "IEEE 802.22: The first worldwide wireless standard based on cognitive radios," *Proc., IEEE Symposium of New Frontiers in Dynamic Spectrum Access Networks (DySPAN'2005)*, pp. 328–337, Nov. 2005.

[2] J. Mitola and G. Maguire, "Cognitive radio: Making software radios more personal," *IEEE Personal Commun.*, vol. 6, no. 4, pp. 13–18, Aug. 1999.

[3] M. Murroni, R. Prasad, P. Marques, B. Bochow, D. Noguet, C. Sun, K. Moessner, and H. Harada, "IEEE 1900.6: spectrum sensing interfaces and data structures for dynamic spectrum access and other advanced radio communication systems standard: technical aspects and future outlook," vol. 49, no. 12, pp. 118–127.

[4] H. Pohls, V. Angelakis, S. Suppan, K. Fischer, G. Oikonomou, E. Tragos, R. Diaz Rodriguez, and T. Mouroutis, "RERUM: Building a reliable IoT upon privacy- and security- enabled smart objects," in *2014 IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, pp. 122–127.

[5] FCC, "In the matter of unlicensed operation in the TV broadcast bands," *Second Report and Order and Memorandum Opinion and Order*, no. FCC-08-260A1, Nov. 2008.

[6] F. Ge, Q. Chen, Y. Wang, C. Bostian, T. Rondeau, and B. Le, "Cognitive radio: From spectrum sharing to adaptive learning and reconfiguration," pp. 1 –10, march 2008.

[7] B. Atakan and O. B. Akan, "Biologically-inspired spectrum sharing in cognitive radio networks," in *Wireless Communications and Networking Conference, 2007. WCNC 2007. IEEE*, 2007, pp. 43–48.

[8] P. Di Lorenzo, S. Barbarossa, and A. Sayed, "Bio-inspired decentralized radio access based on swarming mechanisms over adaptive networks," *IEEE Transactions on Signal Processing*, vol. Early Access Online, 2013.

[9] A. Wisniewska, B. Khan, A. Al-Fuqaha, K. Dombrowski, and M. A. Shattal, "Social deference and hunger as mechanisms for starvation avoidance in cognitive radio societies." IEEE, Sep. 2016, pp. 1063–1068.

[10] A. Wisniewska and B. Khan, "Contention-sensing and dynamic spectrum co-use in secondary user cognitive radio societies," in *Wireless Communications and Mobile Computing Conference (IWCMC), 2014 International*, Aug. 2014, pp. 157–162.

[11] C. E. Shannon, "Communication in the presence of noise," *Proc. Institute of Radio Engineers*, vol. 37, no. 1, pp. 10–21, 1949.

[12] T. M. Cover and J. A. Thomas, *Elements of Information Theory*. John Wiley & Sons, Jul. 2006.

[13] T. C. Schelling, "Dynamic models of segregation," *Journal of Mathematical Sociology*, Aug. 2010.

[14] B. Khan, K. Dombrowski, and M. Saad, "A stochastic agent-based model of pathogen propagation in dynamic multi-relational social networks," *SIMULATION,Transactions of SCS*, vol. 90(4), pp. 460–484, 2014.