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From Blindness to Foraging to Sensing to Sociality: an Evolutionary Perspective on Cognitive Radio Networks

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Abstract Wireless communication is an increasingly important aspect of the digital ecosystem. The Internet of Things reached 4+ billion devices in 2014, and is expected to exceed 25 billion by 2020. In this paper, we formalize the notion of evolutionary pressures in Cognitive Radio (CR) societies, and show how it can be expected to drive the emergence of more advanced sensing capabilities, and correspondingly more sophisticated models of resource sharing. We put forth four evolutionary stages for CR societies, based on well-established biological analogs, and demonstrate that at each stage of CR evolution, a subpopulation that is able to engage more advanced sensing capabilities and co-use strategies is able to better extract greater utility from spectrum resources. In this manner, we see that each stage of CR evolution prepares the way for the next: the present societies of non-foragers facilitate the emergence of foragers; foragers give way to contention-sensing rational CR societies; these, in turn, will likely facilitate the emergence of sociality. We find this progression to depend crucially in population size, and to be robust to consideration of primary user activity. We use a sensitivity analysis to isolate salient factors most likely to accelerate or inhibit the anticipated natural evolutionary trajectory.

1 Introduction

Opportunities afforded by cheaper hardware, wireless services, and increased demand for end-user applications, have led to rapid population growth in the Internet of Things (IoT). As wireless devices become more sophisticated, Dynamic Spectrum Access (DSA) networks [15] using Cognitive Radio (CR) technology offers a potential solution to relieve over-crowded wireless channels as has been argued by many [14, 40, 45, 66].

Current spectrum assignment policies have resulted in suboptimal use of spectral resources [55]—over-use in some bands and under-utilization in others [3, 23, 24]. Few segments of spectrum remain unassigned, and yet, the licensed spectrum is underutilized because licensed ("primary") users are often idle [22] and "spectrum holes" [31] arise. This has motivated DSA policy by the U.S. Federal Communications Commission (FCC), as well as **Cognitive Radio** (CR) [1, 39] wherein nodes dynamically identify unused spectrum bands [1, 7, 15, 16, 25, 29].

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Multiple CR networks operated by a multitude of WSPs compete with each other as **secondary** users (SUs) of limited spectrum, seeking efficiency and quality of service (QoS). Although the FCC reforms "allow unlimited numbers of unlicensed [secondary] users to share frequencies", it "does not provide any right to protection from interference" [23, 24]. Since there are many secondary users, each SU's selection of band and decision to transmit, potentially impacts other secondary users [5, 12, 26, 51].

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 [9, 27, 28, 61]. Mapping evolutionary trajectories of IoT CR societies is the subject of inquiry in the present work.

2 Prior work

Most prior research has focused on the interaction of primary users (PUs) with secondary users (SUs). Spectrum sensing has been applied to detect primary user arrival and departure (see [65] for a survey). By sensing spectrum holes, SUs can find bands for opportunistic use [57]. Many researchers have developed PU-SU solutions for spectrum sensing [31, 64, 65], fewer have looked at SU-SU interactions (see [62, 67]). Non-cooperative game theory has been used to describe the competition between SUs [42, 52]. Unfortunately (see Xu et. al., and others), a frequent limitation of these approaches is that the game is repeatedly played for just one step [63].

Computer science research on resource allocation in networks recognizes the potential relevance of knowledge on resource use in human and animal societies; for a recent survey of bio-socially inspired approaches, see [21, 38, 41], and books [43, 60]. 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 Internet [36, 44, 58], toward routing and management in mobile ad-hoc networks [8, 11, 13, 20, 34, 35, 49], within sensor networks [6, 10, 30, 50], and now most recently, in the domain of cognitive radio (CR) networks [2, 19, 37, 47, 48]. Previous bio-inspired approaches have depended on *inductive* analyzes of biosocial foraging, wherein idealized formal models are proposed for animal societies (e.g. termites, ants, birds, bacteria, etc.)—a strategy whose weakness was recognized long ago [54]. These inductively derived models of resource consumption were then applied to the design of networking protocols, e.g. termites [49], ants [46], birds [18], bacteria [11] etc. In assuming an inductively derived model of behavior, previous bio-inspired advances assume a basic level of coordination, namely that the individuals in the networked society abide by a parametrized set of rules of resource-sharing that have been agreed upon beforehand. As such, these approaches fail to recognize the long-term evolutionary optimization processes that underlie and give rise to the observed structural patterns of co-use within *specific instances* of bio-social collectivities—our perspective here precisely addresses this omission.

3 Our approach

In this paper, we evaluate the hypothesis that CR evolution could plausibly be expected to parallel the evolution of animal species in conditions of resource sharing and conflict [28, 61]. Toward this, we put forward four successively more sophisticated biologically inspired evolutionary stages of CR capabilities: non-foraging, foraging, contention-sensing, and sociality.

- Evolutionary Stage 1: "Consuming". SUs are always consuming bandwidth in some spectrum hole.
- Evolutionary Stage 2: "Foraging". SUs can either consume a channel's bandwidth or "forage".
- Evolutionary Stage 3: "Contention-Sensing". SUs can estimate co-consumers, and this environmental data bias when they transition between forage/consume states and/or switch channels.
- Evolutionary Stage 4: "Sociality". SUs can sense some characteristics of other co-consumers, and this social data bias when they transition between forage/consume states and/or switch channels.

First, we develop a general parametric behavioral model which encompasses the four evolutionary stages above. The resulting CR strategies are then rendered as parametrized non-cooperative mixed-strategy games, extending the ideas put forth by Tan et al. [56]. In contrast to formal analysis of repeated one step game play [63], our evaluation here is based on simulation experiments in which SUs continuously apply the prescribed strategies over long time intervals. By considering heterogeneous societies consisting of two different types of SUs (a majority with more primitive capabilities, and a minority with more advanced capabilities), we quantify the anticipated evolutionary pressures in utility-maximizing SU societies [4, 32].

4 Mathematical model

We assume a discrete time stochastic system of n secondary users $\mathcal{S} = \{z_1, z_2, ..., z_n\}$ and m orthogonal spectrum bands $\mathcal{B} = \{b_1, b_2, ..., b_m\}$ in which individuals operate according to a two-state finite state machine (FSM) shown in
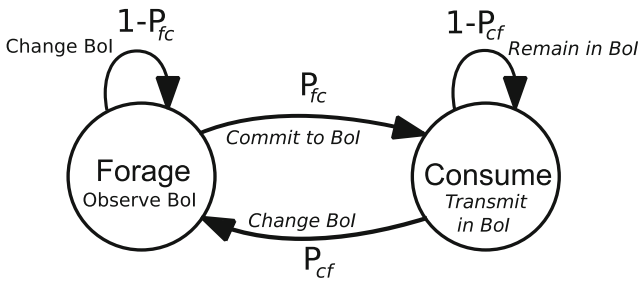
Fig. 1 Finite state machine for SUs

Fig. 2 Finite state machine for SUs in stage 1

Fig. 1 (following [59]). The FSM consists of two states $Q = \{q_c, q_f\}$ and one state variable, the band of interest (BoI) which takes a time varying value $b \in \mathcal{B}$.

State q_c represents "consuming" state, during which an SU is transmitting in the BoI; q_f represents a "forage" state, during which the SU is tuned to a BoI but only passively listening. We introduce a time indexed function $\gamma_t : \mathcal{S} \to \{q_f, q_c\}$ where $\gamma_t(z)$ is the state of SU z at time t. At time t, each SU $z \in \mathcal{S}$ has band of interest $\rho_t(z) \in \mathcal{B}$; this defines a set of time-indexed maps $\rho_t : \mathcal{S} \to \mathcal{B}$ assigning SUs to bands. At time t, each SU $z \in \mathcal{S}$ faces decisions: If z was consuming, then with probability P_{cf}, at time $t + 1$ it switches to a new BoI (chosen uniformly at random), and starts foraging. If z was foraging (at time t), then with probability P_{fc}, at time $t + 1$, it starts consuming its current BoI.

In the consume state q_c each consumer receive reward R while transmitting with k co-consumers:

$$R(k) \overset{def}{=} B \cdot log_2 \left(1 + \frac{G_z P_z}{\sum_{y=1}^{k} G_{zy} P_y + \omega} \right) \quad (1)$$

Equation 1 is Shannon's formula [53],[1] often used in models of spectrum sharing [17]. Here we do not consider path losses, and consider a homogeneous network where SUs send to a base station at uniform power P and channel gain G.
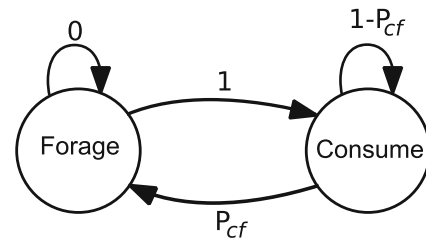
4.1 Behavioral models

The above mathematical model is specialized below to capture the four evolutionary stages of SU capabilities.

4.1.1 Evolutionary stage 1: "non-foraging"

In this stage, SUs are always consuming bandwidth in some spectrum hole, and autonomously decide when to switch

channels (e.g. when a PU arrives). This model is widely used in CR literature (see e.g. [56, 59, 63]). The model is obtained by tying $P_{fc} = 1$, yielding the FSM of Fig. 2. We refer to this concrete stage 1 society as **Non-Foraging (NF)**.

4.1.2 Evolutionary stage 2: "foraging"

In this stage, SUs can either consume a channel's bandwidth or be silent ("forage") and decide when to transition between these two states and when to switch channels. A stage 2 behavioral model is obtained by allowing P_{fc} to be set to any value in the interval $[0, 1]$, so that SU's can inhabit the forage state rather than continuously consume. We refer to this concrete stage 2 behavioral model as **Foraging-Blind (FB)**. The advantage of foraging is based on sublinear regimes of R, as the next proposition shows.

Proposition 1 *Consider a system of $n > 1$ SUs competing over $m = 1$ bands. If for some $k = \{1, \ldots, n-1\}$ we have $R(k - 1) > R(n - 1) \cdot n/k$, then if all users forage their utility will be higher than if they don't.*

Proof If n SUs consume simultaneously, they each receive $R(n-1)/n$ utility. If the SUs organize as an FB society, and forage with probability $P_f = (n - k)/n$, then the expected occupancy in the band becomes $(1 - P_f)n$. Thus each SU gets $(1 - P_f)n - 1$ and so receives utility $[P_f \cdot 0 + (1 - P_f) \cdot R(k-1)]/n = (1 - P_f)R(k-1) = k \cdot R(k-1)$ utility. But $R(n-1) \cdot n < k \cdot R(k-1)$ by assumption; the proposition is proved. □

4.1.3 Evolutionary stage 3: "contention-sensing"

In this stage, SUs can estimate the number of other SUs that are concurrently consuming the channel, and this environmental data (which in practice may be obtained at the physical or MAC layers) biases their decision on when to transition between forage/consume states and when to switch channels. **Foraging with Contention-Sensing** is a behavioral model for Stage 3 SUs, obtained by allowing the transition probabilities $P_{fc}, P_{cf} \in [0, 1]$ to be biased by the contention level in the band of interest $\mu_t(z) = |\rho_t^{-1}(\rho(z)) \cap \gamma_t^{-1}(q_c)|$.

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[1]In expression (1), the transmission power for SU z (resp. y) are denoted P_z (resp. P_y); B is the channel bandwidth; G_z is the channel gain for the transmissions by z, G_{zy} is the channel gain for the transmission between z and y, and ω is the power level of the ambient white Gaussian noise.

Here we only assume that SUs are able to determine whether the band's occupancy is "low" $\mu_t(z) \leqslant \tau$ or "high" $\mu_t(z) > \tau$ (for some system-wide parameter τ). If the band has high occupancy, the FSM probabilities are biased by a system-wide parameter $\epsilon \in [0, 1]$, making it less likely to be in the consume state and more likely to be in forage state; the reverse bias is manifested when bands have low occupancy (see Fig. 3).

We consider three different etiquettes:

- Foraging-Rational (FR) etiquette, $\tau = \frac{n}{m}$.
- Foraging-Apathetic (FA) etiquette, $\tau \gg \frac{n}{m}$.
- Foraging-Intolerant (FI) etiquette, $\tau = 0$.

4.1.4 Evolutionary stage 4: "sociality"

In this stage, each SU is additionally capable of sensing some characteristics of the other co-consumers of its current BoI, and this social data biases its decision on when to transition between forage/consume states and when to switch channels. Toward analyzing the fundamental implications of sociality, we assume that stage 4 SUs have a single differentiating characteristic χ, and an enhanced sensing capability $\mu_t^*(z)$ by which they estimate the number of the co-consumers that share the same characteristic value (χ might represent vendor, organizational affiliation, task, network carrier, etc.) This could be implemented in a distributed manner or through a centralized entity [31, 64, 65, 67] the details of which are beyond the scope of this paper.

For simplicity, in this work, we assume that $\chi : \mathcal{S} \to \{0, 1\}$ is binary-valued and consider one concrete etiquette: splitting. If n SUs are sharing m channels each with bandwidth B, the system *splits* into two independent subsystems: $\mathcal{S}_0 = \{s \in \mathcal{S} \mid \chi(s) = 0\}$ consuming m bands, each of capacity $\frac{|\mathcal{S}_0|}{n}B$, and $\mathcal{S}_1 = \{s \in \mathcal{S} \mid \chi(s) = 1\}$ consuming m

bands, each of capacity $\frac{|\mathcal{S}_1|}{n}B$. Figure 4 shows a system of 8 SUs (where 4 have characteristic $\chi = 0$ and 4 have $\chi = 1$) and $m = 3$ bands of capacity B. The system undergoes a 2-way split, yielding two subsystems of half the scale (in terms of the number of SUs and channel capacity).

4.2 Benefit, costs, and net utility

Since benefit is only obtained when an SU z is in the consume state q_c, the utility achieved at time t is

$$W_t(z) = \begin{cases} R(k_t(\rho_t(z))) & \gamma_t(z) = q_c \\ 0 & \gamma_t(z) = q_f \end{cases} \quad (2)$$

where $k_t(i) = |\rho_t^{-1}(i) \cap \gamma_t^{-1}(q_c)|$. The total system utility at t is:

$$W_t = \sum_{i=1}^{m} k_t(i) R(k_t(i)). \quad (3)$$

When an SU switches transmission bands on entering (or re-entering) q_c, transmitter reconfiguration is required. We assume this to be expensive compared to receiver reconfigurations upon entering (or re-entering) q_f. We charge each SU a fixed cost c when it switches from q_f to q_c.

$$C_t(s) = \begin{cases} c & \gamma_{t-1}(s) = q_f \wedge \gamma_t(s) = q_c \\ 0 & otherwise \end{cases}$$

The set of SUs charged at time $t \geqslant 2$ is

$$M_t = \{s \in \mathcal{S} \mid \gamma_{t-1}(s) = q_f \wedge \gamma_t(s) = q_c\} \quad (4)$$

so the total cost paid at time t is $C_t = c|M_t|$, and the mean utility (per SU per unit time) up to time T is

$$U_T = \frac{1}{T} \sum_{t=1}^{T} \frac{1}{n}(W_t - C_t) \quad (5)$$

4.3 Evolutionary pressure

To study evolutionary pressures on the emergence of new SU capabilities and etiquettes, we evaluate a range of heterogeneous CR societies. We denote a system in which αn
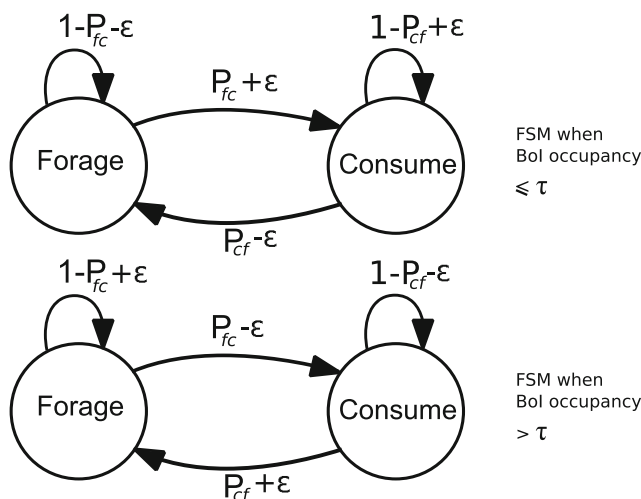

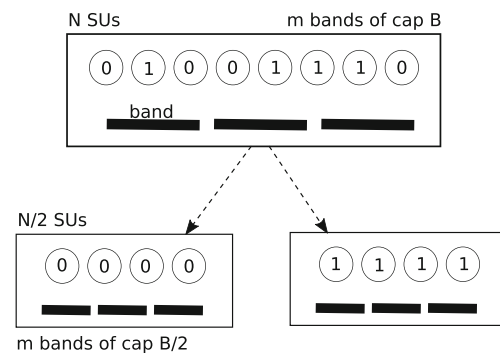**Fig. 3** Finite state machine for SUs in stage 3

Fig. 4 2-way splitting of consumers/resources

Table 1 Baseline Parameters

Parameter	Description	Value
n	Number of SUs	30
m	Number of bands	5
P_z	Transmission power of node z	4 W
B	Capacity per band	20 MHz
C	Switching cost	$0.3 \cdot B$
P_{fc}	Prob. of commencing consume	0.12
P_{cf}	Prob. of commencing foraging	0.21
ϵ	Bias based on occupancy	5%
τ	Rational occupancy threshold	n/m

SUs operate according to model Y, while $(1 - \alpha)n$ operate according to model X heterogeneous society $(X, Y)_\alpha$; here X, Y are one of the previously described strategies: NF, FB, FR, FI, FA. By varying α from 0 to 1, we can evaluate the incentives for or against the emergence of a subsociety following behavioral model Y within an ambient society following behavioral model X. Within $(X, Y)_\alpha$ we define the evolutionary pressure of an α fraction invasion as:

$$\lambda(X, Y, \alpha) = 100 \cdot \frac{\Lambda_{Y,\alpha,n} - \Lambda_{X,1-\alpha,n}}{|\Lambda_X|} \tag{6}$$

where

$$\Lambda_{Y,\alpha,n} = \sum_{t=1}^{T} \frac{1}{\lceil \alpha n \rceil} \sum_{y \in Y} W_t(y) - C_t(y)$$

$$\Lambda_{X,1-\alpha,n} = \sum_{t=1}^{T} \frac{1}{\lfloor (1-\alpha)n \rfloor} \sum_{x \in X} W_t(x) - C_t(x)$$

5 Experimental results

We use a stochastic discrete event simulator [33] to obtain utility measurements for different SU societies over time. In the graphs below, each plotted data point is an experiment, which is repeated for 10 independent trials; error bars indicate the standard deviations. To facilitate comparison with the work of Tan and others [56, 59] in many experiments, we use the same parameter values as these previous researchers. These values are listed in Table 1.

5.1 Blind foraging

To begin, we describe the circumstances under which foraging behavior (FB) might plausibly emerge within (NF) societies of non-foragers. Figure 5 shows the utility achieved in a $(NF, FB)_{0.1}$ society where 10% of the population is foraging and 90% is not. We see that when the population
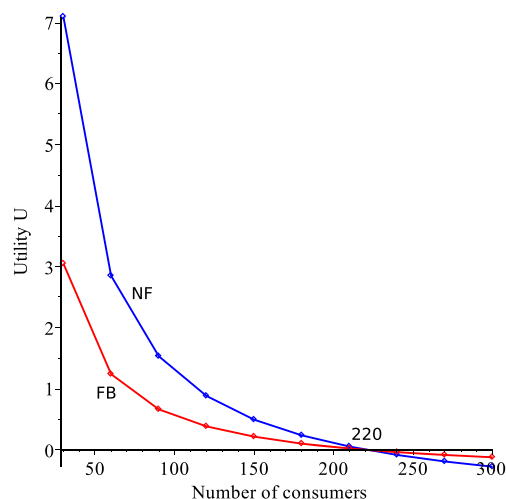
Fig. 5 Merits of foraging, n increasing

grows (but resources are held constant at the baseline values listed in Table 1) there is a critical size at which a blind foraging strategy (FB) outperforms non-foraging behavior (NF); this breakpoint occurred at $n = 220$.

When $n \ll 220$, the adoption of foraging behavior is penalized, and hence is expected to be selected against in evolutionary terms. This phenomenon is seen in Fig. 6, which considers a population of $n = 30$ SUs, of which $\lfloor 30 \cdot \alpha \rfloor$ are blind foragers (while the rest are non-foragers); all other experiment parameters are set as specified in the baseline (see Table 1). We see that for low values of α (e.g. when the first forager emerges) the utility attained by the foraging minority subpopulation (2.9) is significantly smaller than that which is enjoyed by non-foraging majority subpopulation (6.5). The dotted curves in Fig. 6 represent a system in which the primary user decides to return to the band 30% of the time. We can see that even with primary
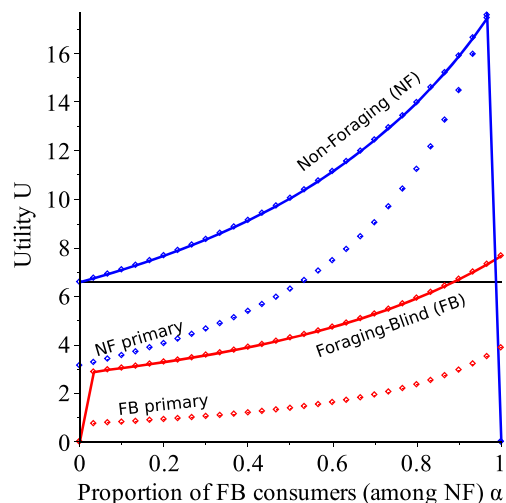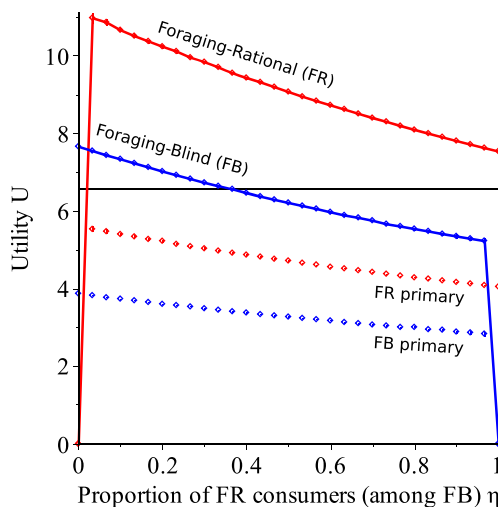

Fig. 6 Rise of foraging ($n = 30$)

Fig. 7 Rise of foraging ($n = 300$)
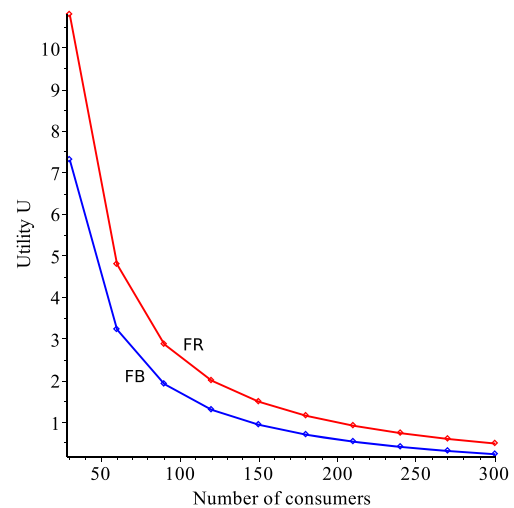

Fig. 9 Rational foraging, n increasing
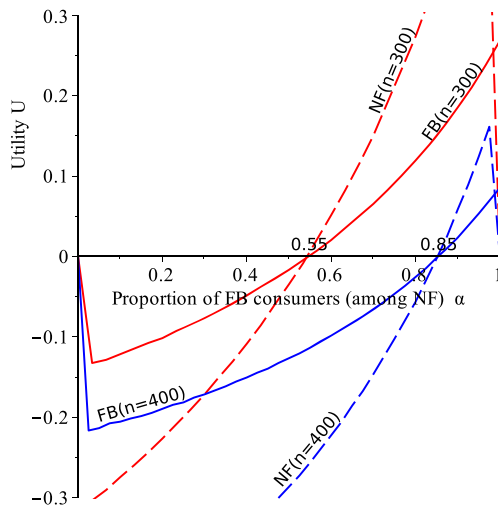
user interruption, non-foragers continue to outperform as the foraging population emerges.

In contrast, when $n \gg 220$, the adoption of foraging behavior is systemically rewarded, and hence is expected to be selected in evolutionary terms. This phenomenon is seen in Fig. 7, which considers a population of $n = 300$ SUs, of which $\lfloor \alpha \cdot 300 \rfloor$ are blind foragers (and the rest are non-foragers). We see that for low values of α, the utility attained by the foraging minority subpopulation is greater (-0.13) than that enjoyed by non-foragers (-0.31). Thus, the longer a growing society waits to move to foraging behavior, the more a widespread change of behavior promises to be in the rational self-interest of individuals.

Regardless of n, monotonic positive first derivatives with respect to α (Figs. 6 and 7) imply that once foraging behavior arises, each individual (regardless of their behavior

model) experiences an increase in utility if a greater percentage of the population adopts the foraging model. This is evidence of the evolutionary pressure toward the emergence and widespread adoption of foraging behavior in CR societies of non-foragers.

5.2 Sensing and rationality

We describe the circumstances in which contention sensing capabilities (i.e. the FR model) might plausibly emerge within (FB) societies of blind foragers. In Fig. 8, we consider a population of $n = 30$ SUs, of which $\lfloor 30 \cdot \beta \rfloor$ are sensing their environment and responding according to the rational etiquette (FR), while the rest are blind foragers (FB). We see that for low values of β (e.g. when the first rational forager appears) the utility attained by FR nodes is

Fig. 8 Sensing and rationality
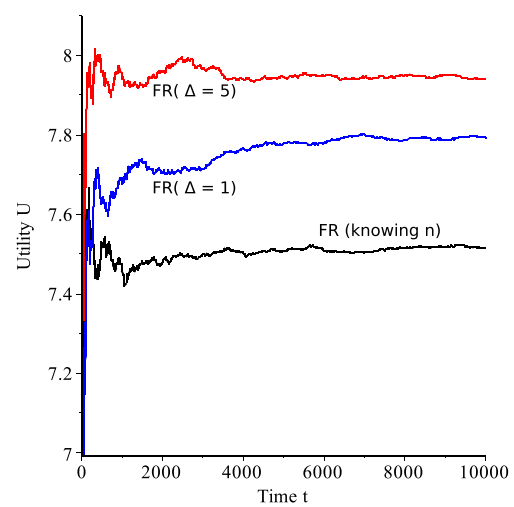
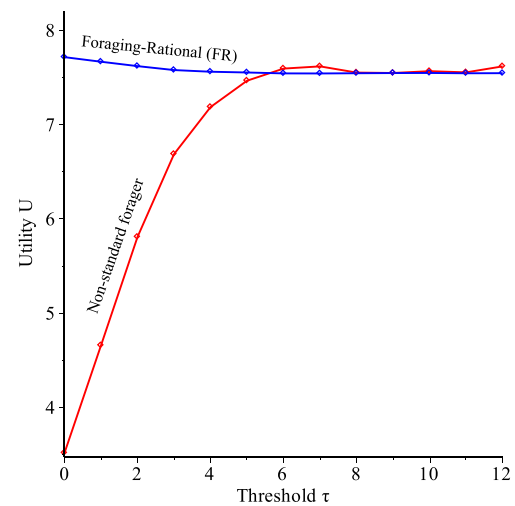

Fig. 10 Population size estimation
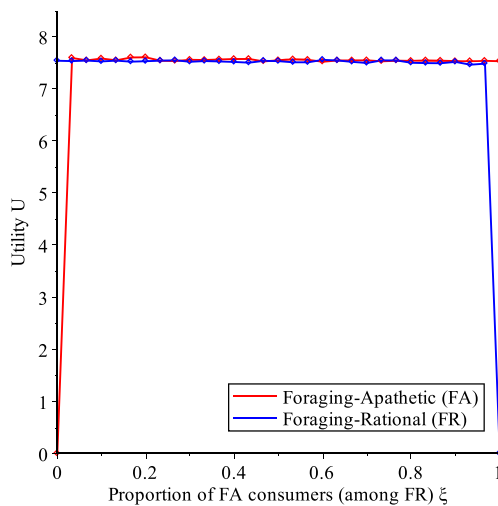
Fig. 11 Futility of apathy, n increasing

Fig. 13 A non-standard forager inside FR

significantly greater (11.0) than the mean utility attained by blind foragers (7.6). This systemic reward is experimental evidence of evolutionary pressure toward the emergence of sensing capabilities and rational etiquettes in CR societies of blind foragers. As β increases, each SU that changes behavior from blind foraging to rational foraging experiences a benefit (albeit at the expense of everyone else, as implied by the monotonic negative first derivatives with respect to β). The observation continues to hold in a system where the primary user decides to return to the band 30% of the time (dotted line in Fig. 8).

As the population size n increases, FR continues to outperform FB in terms of utility and is expected to be selected in evolutionary terms. Figure 9 shows the utility achieved in a $(FB, FR)_{0.1}$ society. We see that the subpopulation that

follows the FR etiquette consistently outperforms the larger ambient FB population at all population sizes. We also see that as the population grows (but resources are held constant) the *relative* advantage of the FR model increases. For example, when $n = 30$ the advantage was 145% (11.0/7.6); by the time the population grows to $n = 300$ the minority's advantage from using the FR model (compared to the ambient population using the FB model), is 250% (0.5/0.2). This indicates that the evolutionary pressure to adoption a rational sensing model increases as the total population grows larger.

In FR societies, the etiquette of "rationality" mandates that each SU set its occupancy threshold to $\tau = n/m$, and thus requires each SU to know both the size of the population n and the number of resources m. This can be a
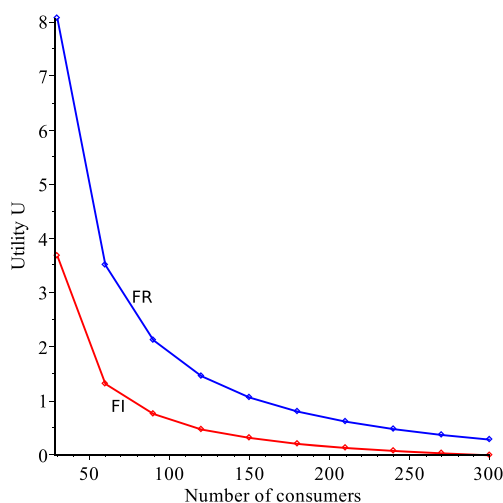
Fig. 12 Intolerance, n increasing
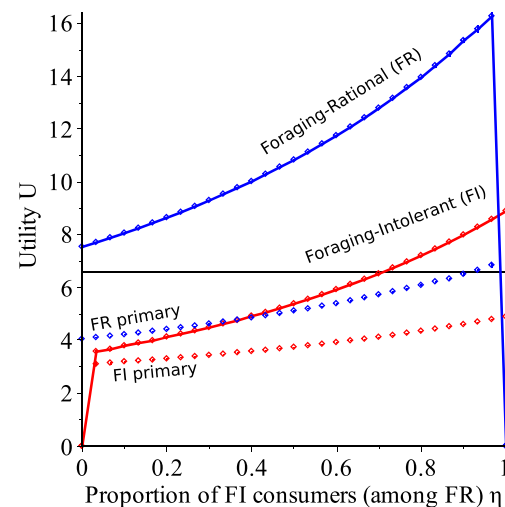
Fig. 14 Intolerance, $n = 30$

Table 2 Evolutionary pressure $n = 30$

n=30	90% NF	90% FB	90% FR	90% FA	90% FI
10% NF	0	138	62	61	230
10% FB	−57	0	−32	−31	31
10% FR	−41	46	0	0	97
10% FA	−37	46	1	0	97
10% FI	−76	−23	−54	−54	0

Table 4 Evolutionary pressure $n = 300$

n=300	90% NF	90% FB	90% FR	90% FA	90% FI
10% NF	0	132	−71	−70	401
10% FB	56	0	−73	−73	105
10% FR	89	107	0	0	245
10% FA	91	108	0	0	247
10% FI	49	−63	−105	−105	0

problematic assumption in growing SU societies. We find that each SU can estimate the total number of consumers as

$$\tilde{n}_t = m \cdot \frac{1}{\Delta} \sum_{\delta=0}^{\Delta-1} \mu_{t-\delta(z)} \qquad (7)$$

over a time window Δ, and then setting its threshold occupancy level to $\tau_t = \frac{\tilde{n}_t}{m}$. Figure 10 shows that such dynamic estimation of population sizes is successful in quickly converging to the performance of systems that are pre-configured with offline knowledge about the true population size n.

5.3 Alternative sensing etiquettes

In what follows, we consider the evolutionary pressure for or against the emergence of sub-populations that deviate from the rational etiquette, within an FR society where threshold occupancy $\tau = n/m$. Here we consider extreme deviations from this value: the "Apathetic" (FA) etiquette, in which the threshold is taken to be much higher $\tau = 2n/m$; the "Intolerant" (FI) etiquette, in which $\tau = 0$. As we shall see, based on evolutionary considerations, neither is expected to emerge.

The etiquette of apathy Figure 11 shows the change in utility for rational and apathetic societies as the proportion of apathetic consumers increases. As can be seen, regardless of their proportion within the population, apathetic SUs do not gain any advantage over rational consumers (7.5) by choosing a higher than rational threshold.

The etiquette of intolerance Figure 12 shows the utility achieved in a $(FR, FI)_{0.1}$ society where 10% of the population is following an intolerant etiquette while 90% is foraging rationally. We see that a rational etiquette consistently outperforms the minority of intolerant foragers at all population sizes. We also see that as the population grows (but resources are held constant) the *relative* advantage of the FR model over the FI model, increases. For example, when $n = 30$ the advantage was 210% (7.6/3.4); by the time the population grows to $n = 300$ the minority's advantage from using the FR model (compared to the ambient population using the FI model), is 4500% (0.45/0.01). This indicates that the evolutionary pressure against an intolerance etiquette increases as the total population grows larger. The above analysis demonstrates beyond some scale, there will be significant evolutionary pressure against deviations from rational etiquette.

The structural explanation for why the transition to FI is impeded can be best understood by examining Fig. 13. Here we consider a minor perturbation of the baseline experiment settings (see Table 1). Specifically, we consider a society of 29 standard FR nodes (who set rational threshold $\tau = n/m = 30/5 = 6$), together with one non-standard deviant player who chooses to set their threshold τ autonomously. The graph shows what the utility of the deviant player is (compared to the utility of the law-abiding standard FR majority), for each possible nonstandard setting of τ that might be used. Utilities obtained when $\tau = 0$ (intolerant) and $\tau = 12$ (apathetic) are consistent with Figs. 11 and 14 for low values of η and ξ, respectively. What we see is

Table 3 Evolutionary pressure $n = 150$

n=150	90% NF	90% FB	90% FR	90% FA	90% FI
10% NF	0	130	33	33	328
10% FB	−57	0	−41	−41	83
10% FR	−11	59	0	0	177
10% FA	−5	59	0	0	178
10% FI	−87	−48	−71	−71	0

Table 5 Varying parameters for FB vs. NF

Parameter Name	min val	max val	U_T FB/NF mean	mean U_T FB/NF flux
m	1	11	0.43	3.49%
B	10	30	0.43	3.25%
C	1	11	0.43	3.82%
P_z	2	6	0.43	1.56%

Table 6 Varying parameters for FR vs. FB

Parameter Name	min val	max val	U_T FR/FB mean	mean U_T FR/FB flux
m	1	11	1.47	10.68%
B	10	30	1.46	3.96%
C	1	11	1.46	2.82%
P_z	2	6	1.45	2.15%

that any unilateral deviation from the rationally determined value may result in a performance penalty and never yields an advantage.

5.4 Evolutionary pressure revisited

To help us evaluate the potential emergence of new strategies Y to emerge within a society X, we introduced the formalization (6) of evolutionary pressure. In our next experiments, we computed $\lambda(X, Y, 0.10)$, allowing X and Y to vary over all pairs of strategies. Tables 2, 3, and 4 provide this data for population sizes $n = 30$, $n = 150$, and $n = 300$, respectively. Whenever $\lambda > 0$, there is an evolutionary pressure to adopt strategy Y within an ambient population X.

Restricting our attention to column 1 of the three tables, we observe that no other strategy can emerge in an NF society at population sizes $n = 30$ and $n = 150$. At $n = 300$ (Table 4), however, evolutionary pressures are seen and we can expect competing strategies to emerge. Which evolutionary stage actually emerges depends on the costs of the enhanced sensing capabilities relative the benefits of

increased utility; of the candidates, the FB model is the least advanced competing strategy which might invade an established NF society. Considering column 2, we see that in a foraging-blind (FB) society, there is an evolutionary pressure for all strategies except for foraging-intolerant to emerge. Examining column 3, we see that in a foraging-rational (FR) society, once the size $n \geqslant 150$, no other strategy can emerge. Looking at column 4, we see that in a foraging-apathetic (FA) society, if the size $n \leqslant 150$, the non-foraging strategy can emerge. Reviewing column 5, we see that in a foraging-intolerant (FI) society, there is an evolutionary pressure for all other strategies to emerge.

5.5 Sensitivity analysis

In this section we investigate the robustness of our findings regarding evolutionary pressure by performing a sensitivity analysis. We vary the number of resources m, channel bandwidth B, switching cost C, and transmission power P_z, number of consumers n, congestion bias ϵ, and FSM transition probabilities P_{cf}, P_{fc}—one at time—*while keeping all other parameters at the baseline values* (see Table 1). The first four of these parameters, produced less than 11% fluctuations in the mean difference in utility. These results for $(NF, FB)_{0.1}$ and $(FB, FR)_{0.1}$ societies are seen from the data in Tables 5 and 6, respectively. Although the tables only provide evidence of small partial derivatives (with respect to m, B, C, and P_z) at the baseline, similar results were confirmed at a wider range of settings.

On the other hand, the number of consumers n, congestion bias ϵ, and FSM transition probabilities P_{cf}, P_{fc}, all were found to significantly impact the utility of each SU,

**Fig. 15** $(NF, FB)_{0.1}$: $P_{cf} - P_{fc}$ heatmap
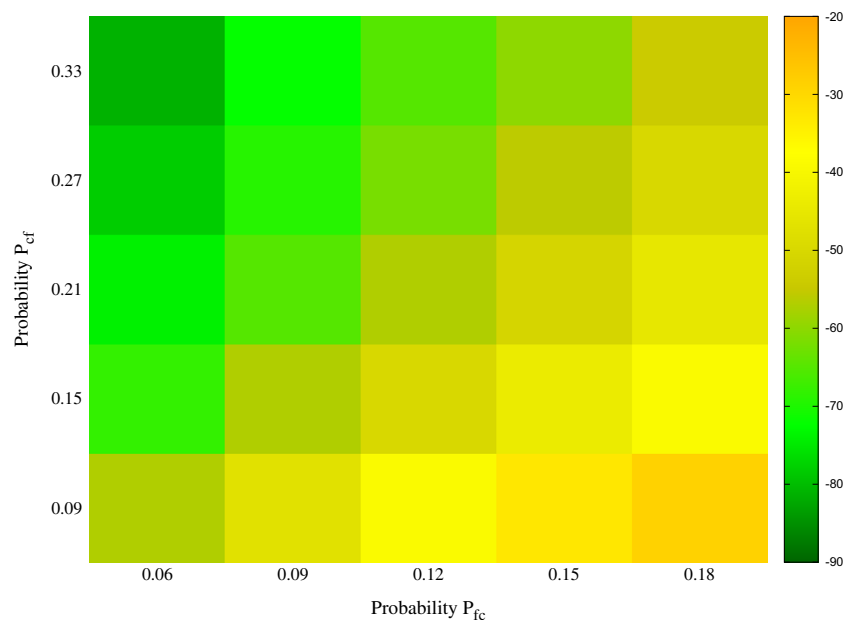
Fig. 16 $(FB, FR)_{0.1}$: $P_{cf} - P_{fc}$ heatmap
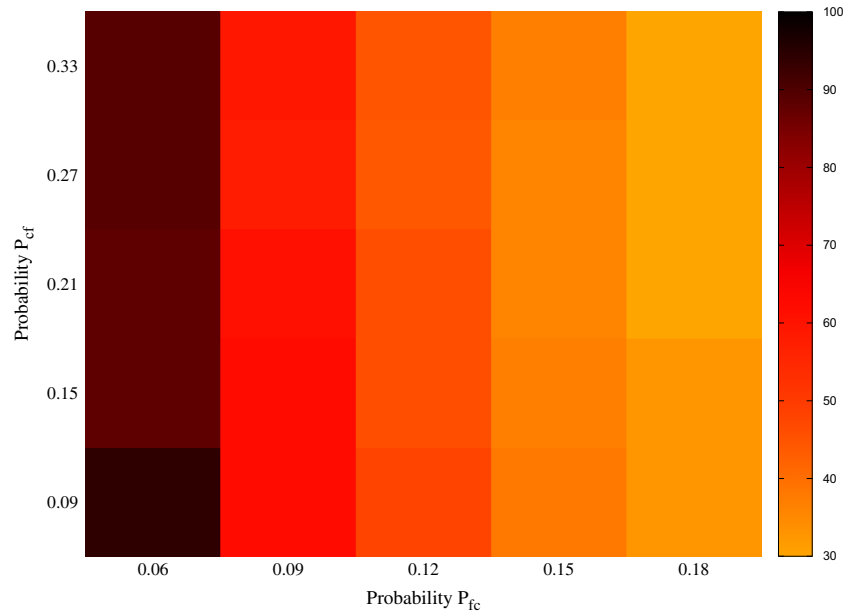
and hence potentially impact evolutionary pressure. Varying FSM transition probabilities P_{fc} and P_{cf} (see Fig. 1) altered the evolutionary pressure in both $(NF, FB)_{0.1}$ and $(FB, FR)_{0.1}$ societies, albeit in different ways; this is shown in the heat maps of Figs. 15 and 16. In $(NF, FB)_{0.1}$ society, evolutionary pressure is negative (i.e. invasion by FB is not possible), but is minimized when P_{cf} is small and P_{fc} is large. In $(FB, FR)_{0.1}$ society, evolutionary pressure is positive (i.e. invasion by FR is possible), and maximized when P_{fc} is small (independent of P_{cf}).

We further investigate the $(FB, FR)_{0.1}$ society by varying the contention-bias parameter ϵ (see Fig. 3). Figure 17 shows a near-linear relationship between ϵ and evolutionary pressure λ. As ϵ increases, SUs in the FR society become
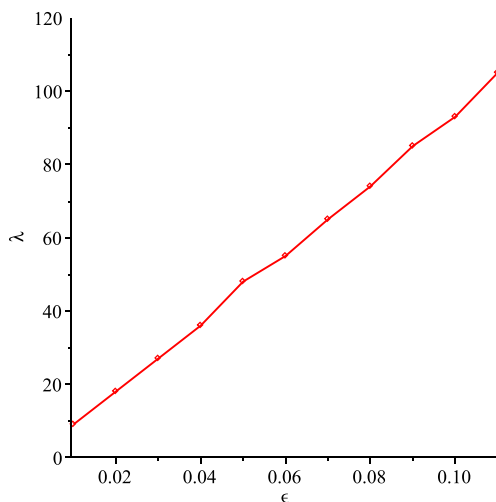
more reluctant to enter a resource when contention is high and less reluctant to leave a resource if contention is low (see Section 5.2), and these behavioral traits are precisely the source of evolutionary advantage.

5.6 Subdivision

In this section, we consider the potential benefits of SU diversity, assuming that CR nodes have an intrinsic characteristic χ, which can be sensed, and used to implement

Fig. 17 Varying ϵ, 10% FR + 90% FB
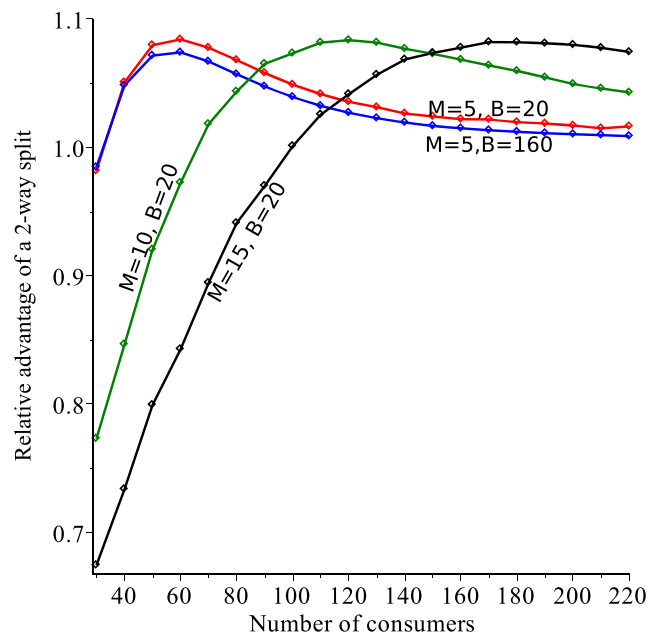
Fig. 18 Benefits of a single 2-way split

splitting. We show that emergence of SU diversity in the splitting context is only beneficial for specific population sizes. There are of course countless other ways in which diversity could be harnessed socially—here we consider whether splitting, by itself, presents enough advantages to predict the plausible emergence of SU diversity. In effect, we view splitting as the analog of ecological niche formation in the CR domain. The question we are asking then is: Does niche formation produce advantages which would justify the emergence of species diversity χ among CRs?

How is the benefit obtained by splitting impacted by the system's size? Figure 18 shows the performance advantage of splitting a society of n nodes into two societies of $n/2$ nodes each receiving m bands of capacity $B/2$ (normalized by the performance attained in societies which do not choose to split). For example, when $m = 10$ and $B = 20$ there is a critical value of system size $n = 80$ beyond which splitting yields a marginal advantage — but this advantage which is maximal (9% at $n = 120$) vanishes for $n \gg 80$. The same qualitative behavior is seen for other experiment settings ($m = 15$ and $m = 5$), albeit with different local maxima and rates of asymptotic convergence to 1. We conclude that splitting only makes sense in a critical range of society size–if a society is too small, or too large, no benefit is derived from splitting.

6 Conclusions

In this paper, we considered an evolutionary sequence of increasingly sophisticated capabilities for CR nodes in societies of secondary users of radio spectrum as the IoT population adjusts to saturated resources.

We showed that:

– In a society of SUs which are constantly consuming (stage 1), when the capability to forage for spectrum emerges, there is an evolutionary pressure for a subpopulation to switch to a foraging etiquette, and this subpopulation is expected to grow. This was shown in Section 5.1.

We saw that at a critical population size it becomes advantageous (with respect to utility) for an SU to unilaterally adopt the more advanced strategy. This "first conversion" acts as a seed, since any increase in the fraction of SUs following the new strategy yields a differential improvement in the utility of all SUs (regardless of strategy) thus driving the "upgrading" of the entire population. Next, we saw that:

– In a society of foraging SUs (stage 2), when the capability to sense channel characteristics emerges, there is an evolutionary pressure for a subpopulation

to bias transition probabilities accordingly to rational expectations of contention levels. This was shown in Section 5.2.

Regardless of population size, we saw that it becomes advantageous (with respect to utility) for an SU to unilaterally adopt the more advanced strategy.

– In a population of contention sensing foragers, it is not advantageous for a subpopulation to deviate from the rational contention threshold by adopting an attitude of apathy or intolerance to contention. This was seen in Section 5.3. We demonstrated that the rational threshold can be estimated dynamically by the SUs, making FR viable in growing populations.

Although many etiquettes based on sociality are conceivable, here we considered one based on splitting.

– Division based on a boolean differentiating characteristic is marginally profitable up to a certain population sizes; larger diverse societies do not profit by splitting into homogeneous subsocieties. This was seen in Section 5.6.

In practice of course, the evolutionary selection of device capabilities and behavioral strategies arises from consumer pressure on manufacturers to deliver increased bandwidth for a rapidly growing IoT device population. Taken together, the projections presented in this paper determine a quantifiably plausible evolutionary trajectory for IoT devices adopting cognitive radio capabilities (and corresponding behavioral strategies) that one might expect to see implemented by manufacturers as they compete for increasing numbers of consumers with increasing bandwidth requirements.

6.1 Future work

We seek to ascertain the extent to which the phenomena reported in this paper are replicable in real hardware testbed of software-defined radio systems. Our plan is to experiment with the different evolutionary stages using ns-3 in conjunction with different channel models to provide more insight into the practical implications of the evolutionary stages. In addition, we plan to experiment with actual IoT nodes that utilize a low power microcontroller with the capability to switch the Wi-Fi channel to study the evolution behavior experimentally.

The general question on whether the emergence of CR diversity is evolutionarily selected for remains open. Answering it requires deeper exploration of social structures by which CR societies might harness node diversity in a manner that benefits its members. The study of more

complex social structures supported by differentiation and sensing is an area of active research.

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