Evolution of Bio-Socially Inspired Strategies in Support of Dynamic Spectrum Access

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***Abstract*—Human and animal societies exhibit complex cognitive and social processes of coordination, cooperation, and competition among their members. Among other functions, these processes can facilitate fairer sharing of resources among community members and enhance individual survival outcomes. In this work, three bio-socially inspired models for secondary users of spectrum in cognitive radio networks are defined and compared to one other within an evolutionary framework. The proposed models reflect successively more sophisticated capabilities of secondary users in distributed spectrum access. The simplest of the three, blind channel access, is shown to be evolutionarily dominant when residual channel capacities are homogeneous. The second more advanced model assumes a capability to sense channel utilization; this model is shown to dominate when the channels have intermediate load and heterogeneous capacities. Finally, the most complex model (additionally) allows for social coalitions and within-group deference; this model is seen to dominate in high load heterogeneous resource settings. We explore the long term evolutionary pressures within societies whose members choose between these three schemes, with natural selection operating via a utility-based fitness function. Our research is based on systematic ns-3 simulation experiments of heterogeneous societies under a range of assumed channel conditions, population sizes, resource demands, and initial user attributes. Our results demonstrate that the secondary user population always evolves to adopt a unique and stable strategy, but that the winning strategy selected depends strongly on channel conditions. Our results further show that this kind of leaderless evolution leads to a significant 12-116% overall improvement in performance compared to systems in which a fixed strategy is deployed. In summary, we conclude that evolving bio-social behavioral models can be applied to great advantage in understanding dynamic environments such as those envisioned by distributed spectrum access.**

***Index Terms*—Dynamic Spectrum Access; Cognitive Radio; Bio-Social Spectrum Access Strategies; Strategy Evolution.**

I. Introduction

The Federal Communications Commission (FCC), and similar regulatory bodies around the world are responsible for licensing the inherently scarce resource of radio spectrum. In spite of this, spectrum bands are typically underutilized by their licensed owners (i.e. the "Primary Users" or PUs); indeed the findings of Wang et al. [1] and others show spectrum occupancy in the U.S. is presently below 6%. The FCC prompted the research community for innovative solutions to spectrum underutilization, resulting in the development of cognitive Radio (CR) and distributed spectrum (DSA) access models [2] which allow unlicensed "Secondary Users" (SUs) to access licensed spectrum while guaranteeing transmission priority for PUs.

In the DSA paradigm, managing SU-SU interactions is crucially important. Uncoordinated SU access to resources can lead to unbalanced resource usage, and leave some channels crowded and others underutilized. In this work, we investigate SU-SU interactions within a bio-socially inspired evolutionary framework, to obtain more efficient spectrum utilization strategies long term. In our framework, we allow SUs to adapt their strategies gradually over time by mimicing their more successful peers. Our approach to CR societies reflects what we know about its biological counterparts, wherein we observe a variety of individuals with different capabilities and behaviors, adapting over time. We consider three types of SUs:

- **Baseline:** Users select their transmission channel randomly, operating in the absence of external data about the states of the different channels.
- **Foraging Behavior:** Users can dynamically sense the channel state information, and use this external data to determine their channel selection and data transmission strategy.
- **Social Behavior:** Users can dynamically sense the channel state information as well as the properties of its co-users, and use this external data to determine their channel selection and data transmission strategy.

In this paper, we will consider heterogeneous ecosystems containing a mix of SUs spanning the three behav-

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ioral paradigms above. We show that, contrary to naïve expectations, more complex behavioral paradigms are not always advantaged. We characterize the extent to which each paradigm above is evolutionarily advantages in each of a range of spectrum environments. We describe the settings in which behaviors like *foraging* and *deference* are likely to emerge through natural selection within DSA networks. We demonstrate that spectrum utilization can be enhanced using the proposed bio-social behaviors within the proposed evolutionary framework: a performance improvement of 12-116% in system throughput is achieved.

The remainder of this paper is organized as follows: Prior work is discussed in Section II. Section III formally decribes the behavioral models that are considered and Section IV presents our strategy evolution model. Simulation results are discussed in Sections V. Section VI provides conclusions of the study and describes future research directions.

II. Prior Related Work

Most prior research in DSA focuses primarily on PU-SU dynamics (e.g., [3] and others), ignoring SU-SU interactions. Exceptions are the recent work of Dixit et al. [4], Xing et al. [5] and Wisniewska et al. [6]. Our work here also serves to elucidate the nature of SU-SU dynamics.

Prior research related to DSA falls broadly into three categories: (a) machine learning, (b) bio-socially inspired, and (c) game-theoretic approaches. Previous bio-socially inspired approaches typically begin by defining user behavioral models (e.g., preferential bias [7], peer recommendations [8] and selfishness [9]). In our work, two elements are considered: environmental *foraging* and social *deference*.

Behavioral models based on bio-social interactions are by now well recognized as the basis of a wide range of resource allocation problems, for MANET routing [10] and sensor network management [11]. In the context of CR, bio-socially inspired models have been developed for spectrum sensing [11], channel selection [12], and efficient routing [10]. Genetic algorithms have been used to tune CR parameters for better spectrum usage [13], and recommendation systems have been applied to minimize sensing and decision-making time required for channel selection [14].

Unfortunately, idealized bio-social models based on animal societies (e.g. termites [15], ants [16], etc.) all assume a level of *coordination of strategy choice* among population members [17]. This assumption that all members agree to follow a pre-agreed upon strategy fails to take into consideration possible long-term evolution of strategies for users; our approach, which allows SU strategies to evolve, sidesteps this shortcoming. Whereas almost all prior work in this area tends to compare *homogeneous* societies each of which prescribe a some uniform behavior to all of its members [5], in this work we consider *heterogeneous* societies in which individual behaviors can change, either due to natural selection (long term) or rationally-driven mimicry (short term).

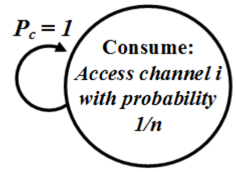


Fig. 1. FSM for ACU

III. Behavioral Models

In what follows, we assume a community of N secondary users. Each of the SUs seeks to transmit data at a rate of R bits/s. SUs operate within an ecosystem of M spectrum channels. Each channel i ($i = 1..M$) has capacity C_i bit/s, and a fraction $\alpha_i \in [0, 1]$ of the overall channel capacity that is available for SU communications. When $\alpha_i = 0$, SUs are not permitted to transmit (i.e., a PU is present). When $\alpha_i = 1$ all SUs who are tuned to channel i may transmit at rate R (e.g., because the PU is absent).

In this work, we will vary (i) the range of channel selection strategies used by the SU population, and (ii) the channel characteristics, towards quantifying the impact of these two factors on (iii) actual throughput attained by the SUs. Attained throughput will define system utility, and its maximization will act as the fitness function driving evolutionary pressure on SU etiquette. We denote as $\gamma(c, n, r)$ the expected instantaneous **fractional throughput** (between 0 and 1) obtained by each SU **in a homogeneous system** when *n* SUs are simultaneously transmitting at rate r on the same channel having capacity c. In practice, this function is dependent on the particular link layer technology and protocols used. The function γ will play an important role in quantifying the performance of the model that follow.

We introduce three different channel selection strategies; namely: Always Consume User (ACU), Forage-Consume User (FCU), Social Forage-Consume User (SFCU) paralleling the categories presented in Section I. We discuss and model the details of these strategies in the following paragraphs.

The Always-Consume User (ACU) is always transmitting in some channel at this selected uniformly at random, following the Finite State Machine (FSM) in Figure 1. This simple strategy (used previously in [18]) allows the ACU to act with a naïve view to capture utility using the set of channel resources. The ACUs strategy has the advantage that it can be implemented cheaply since no sensing capability is needed. The channel selection process itself is fast, requiring minimal computational resources and no coordination overhead. In practice, an ACU may access congested channels instead of using channels that have higher residual capacity. The performance of ACUs serves as a baseline for the incremental benefits of more sophisticated foraging and social behaviors. In a homogeneous environment consisting of just N ACUs, the expected utility of each ACU is given by:

$$U_{ACU} = \frac{1}{M} \sum_{i=1}^{M} \gamma(\alpha_i C_i, N/M, R)$$

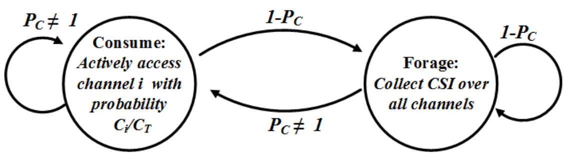


Fig. 2. FSM for FCU

Advancing from ACU, the **Forage-Consume User (FCU)** has the ability to engage in two distinct activities. It may either sense the channel state information but abstain from transmission (forage), or it may transmit data on a channel (consume). The FCUs choice to consume may, in turn, be based on information about the channel's state information (CSI) sensed while foraging. Interference level, noise level, and capacity are examples of potential CSI. The FCU forgoes short-term utility benefits while in the foraging state, but may stand to gain more long-term utility by acquiring data about the channels. On the other hand, too much foraging could yield inefficient usage of spectrum resources and decreased users utility.

As depicted in the Figure 2, an FCU is in one of two states. The FCU is in the consume state with asymptotic relative frequency P_c; in this state it transmits data and switches between channels with stochastic bias proportional to its estimates of the channels relative capacities. The FCU is in the forage state with asymptotic relative frequency $1-P_c$; in this state it forages for channels by switching over channels and sensing and collecting CSI for each channel.

In this work, FCUs consider the relative capacity of channel i as the CSI of interest:

$$\overline{\mathrm{C_i}} = \alpha_i C_i / \sum_j \alpha_j C_j$$

While foraging, FCUs bias their stochastic selection of each channel proportionally to the channel's relative capacity (which is in turn, estimated as described above). This encourages FCUs to utilize the channels with higher relative capacity.

Unfortunately, SUs cannot measure $\overline{\mathrm{C_i}}$ directly for every channel i, especially in the dynamic presence of PUs. Instead, they estimate the relative capacity of channel via the throughput recently attained on the channel. In particular, each FCU considers its recently attained fractional throughput as a proxy estimate for the relative capacity of its current transmission channel. Thus, if n SUs ($1 \leq n \leq N$) are co-consuming channel i, each of the FCUs will estimate $\overline{\mathrm{C_i}}$ as follows:

$$\overline{\mathrm{C_i}} \approx \frac{\gamma(\alpha_i C_i, n, P_c R)}{\sum_j \gamma(\alpha_j C_j, n, P_c R)} \tag{1}$$

This estimate reflects the actual relative capacity of the channels; it is also responsive to the presence of PUs. For example, if the users have access to 4 channels each with 1Mbps available capacity and a PU arrives in channel 1, then $\overline{\alpha_1}$ will change from 1 to 0, and the updated estimate (1) will reflect the presence of the PU. The low (proxy measure of) CSI now ensures that FCUs will not switch into channel 1.

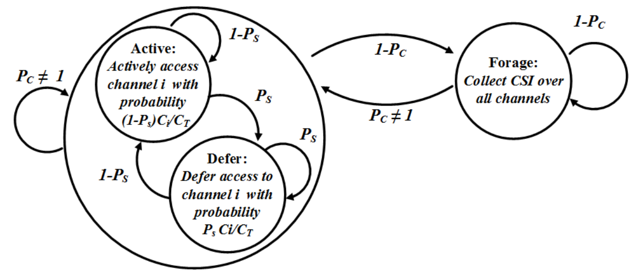


Fig. 3. FSM for SFCU

When the FCU forages it receives no utility, and when it consumes, it consumes channel i with probability $\overline{\mathrm{C_i}}$ In a homogeneous environment consisting of just N FCUs, the expected utility of each FCU is thus:

$$U_{FCU} = P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \gamma(\alpha_i C_i, \overline{\mathrm{C_i}} N, R)$$

Advancing from FCU, the **Social Forage-Consume User (SFCU)** incorporates sociality as an additional factor in its channel selection logic. Sociality presumes enhanced sensing capabilities beyond the mere measurement of relative capacity levels, as it requires SUs to sense some aspect of the *identities* of co-users in the channels. SFCUs may choose *not* to transmit in a channel because of the presence of other users with whom a social relationship exists.

In this work, we consider a particular type of social relationship among the SFCUs; we refer to this phenomenon as **deference**. Specifically, we consider the situation in which whenever a SFCU decides to begin transmitting in a channel, the other SFCUs who are also presently transmitting in the channel tend to defer by exhibiting a bias towards not transmitting. The SFCU behavioral model reflects well-known findings from the structure of animal [19] and those of non-human primates [20] where sociality plays a significant organizing function and helps towards species survival. For example, we can utilize deference behavior in animals' societies in order to maximize benefits for user(s) in the society which leads to less conflict over resources.

As depicted in Figure 3, a SFCU operates using the same FSM as the FCU but with the consume state split into *Active* and *Defer* substates. While in the consume state, the SFCU is in the Defer substate with asymptotic relative frequency P_S; in this "social" state, the SU does not transmit or switch channels, deferring for the benefit of other SFCUs in the DSA society. A stochastic process governed by P_S allows SFCUs in Defer state to switch to Active state. While in the Active substate with asymptotic relative frequency $1-P_S$, the SFCU transmits data at an elevated rate $(1+S_+)R$ to make use of the additional bandwidth made available by deferrers and continues switching between channels with stochastic bias proportional to its estimates of the channels' relative capacities.

To account for the costs of coordination among the SFCUs consuming a channel, we will assume that each gives up S_- fraction of its utility towards coordination overhead. In a homogeneous environment consisting of just N SFCUs, the expected utility of each SFCU is thus:

$$U_{SFCU} = P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}}(1+S_+)R \cdot (1-S_-) \cdot \gamma(\alpha_i C_i, \overline{\mathrm{C_i}}N, R)$$

Heterogeneous systems. In what follows, we will assume a heterogeneous ecosystem consisting of a *total* of $N = N_{ACU} + N_{FCU} + N_{SFCU}$ secondary users, of which N_{ACU} are ACUs, N_{FCU} are FCUs, and N_{SFCU} are SFCUs. The expected number of SUs of each type consuming *in each* channel i is then given by:

$$\begin{aligned} n_{ACU} &= \frac{N_{ACU}}{M} \\ n_{FCU} &= \overline{\mathrm{C_i}} N_{FCU} \\ n_{SFCU} &= \overline{\mathrm{C_i}} \cdot (1-P_S) \cdot N_{SFCU} \end{aligned}$$

Note that when the ACUs and FCUs transmit they do so at rate R, whereas when the SFCUs transmit they do so at the elevated rate $(1+S_+)R$. Thus, we are considering a heterogeneous environment where there are two types of users in channel with capacity $c = \alpha_i C_i$: There are $n_1 = n_{ACU} + n_{FCU}$ users of type 1 transmitting at a rate $r_1 = R$ and $n_2 = n_{SFCU}$ users of type 2 transmitting at $r_2 = (1+S_+)R$. We introduce two functions capture the expected instantaneous **fractional throughput** (between 0 and 1) obtained by each SU **in a heterogeneous system**; $\gamma_1(c, n_1, r_1, n_2, r_2)$ is the fractional throughput obtained by users of type 1 (i.e. ACU/FCUs), while γ_2 is what is obtained by type 2 users (i.e. SFCUs) in such a setting. The quantity

$$X_{i,t} = \gamma_t(\alpha_i C_i, n_{ACU} + n_{FCU}, R, n_{SFCU}, (1+S_+)R)$$

then represents the instantaneous *fractional* throughput of SUs of type t in channel i (where $t = 1, 2$). The expected utility obtained by each of the three types of users is then expressible as follows:

$$U_{ACU} = \frac{1}{M} \sum_{i=1}^{M} R \cdot X_{i,1} \tag{2}$$

$$U_{FCU} = P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot R \cdot X_{i,1} \tag{3}$$

$$U_{SFCU} = P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot (1+S_+)R \cdot (1-S_-) X_{i,2} \tag{4}$$

and the total expected utility achieved in such a system is the sum of the utility of all users in the system:

$$U_S = N_{ACU} \cdot U_{ACU} + N_{FCU} \cdot U_{FCU} + N_{SFCU} \cdot U_{SFCU}$$

IV. Strategy Evolution

Based on the formal model description and analysis of expected utilities in the previous section, we see that utility achieved by an SU is a function of its strategy, the available channel capacity, the numbers of co-users of each type in the channel, and their transmission rates. For fixed settings, each SU receive some computable utility based on these factors, as specified by equations (2), (3), and (4).

We now extend the model to allow SUs to evolve over time by changing their strategy. For example, an ACU might choose to change and become an FCU, or vice versa. An SFCU might become an ACU briefly, and then later return to behaving like an SFCU[1]. We justify the extended model by appealing to the long term phenomenon of natural selection and the short term phenomenon of mimicry. In the bio-social sphere, long term natural selection processes are driven through fitness and reproductive viability. In the cognitive radio context, we anticipate an analogous fitness function to be implemented through free market dynamics. We also anticipate that the more sophisticated SUs of the future may attempt to imitate one another's strategies if they are determined to be superior; in nature this is the phenomenon of mimicry.

In our simulations of **strategy evolution**, we make some simplifying assumptions: (1) strategy evolution takes place only at the end of discrete "phases"; (2) at the end of each phase, users truthfully share information about the throughput they attained during the phase; (3) we allow only a small randomly chosen set of SUs to change their strategy at the end of discrete phases. Assumption (1) is inconsequential to our conclusions, and made mainly so that (3) can be easily implemented; assumption (3) is made so as to observe the diffusion of successful strategies and prevent thrashing. In practice, assumption (2) incurs some coordination costs, but in this work, we ignore this constant overhead and focus on the performance impact of strategy evolution.

The work here raises important research questions:

1) *For each possible environmental scenario (channel conditions and SUs), which strategy emerges as dominant over time?*
2) *Does the community of SUs always evolve to a homogenous system in which all SUs are using the same strategy?*
3) *In which scenarios do short-term strategies (ACUs) eventually dominate? Which scenarios drive the dominance of long-term strategies (FCUs)?*
4) *In which scenarios do selfish behaviors (FCUs) eventually dominate? Which scenarios drive the dominance of altruistic social behavior (SFCUs)?*

V. Simulation Experiments

In our simulations, we consider a range of CR scenarios. Throughout, we assume 4 channels and 80 SUs. We always

[1]Each SU employs one and only one strategy (i.e., ACU, FCU, or SFCU) at each point in time, in a community of heterogeneous population (i.e., a community of SUs in which the nodes utilize dissimilar pure strategies). No SU ever employs a "mixed strategy" in the game-theoretic sense.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Total number of SUs	80
Number of Channels	4
Channel capacity (Mbps)	hom.: [1,1,1,1] and het.:[1, 1, 11, 11]
Modulation Scheme	DSSS
WLAN Standard	IEEE 802.11g
Distance from AP	10m
Transmission power	16.0206 dBm (default) [22]
Channel Propagation Model	Log Distance Propagation Model [21]
CBR transmission rate per SU (kbps)	10 Kbps (light), 40 Kbps (intermediate) 60 Kbps (heavy)

start with 20 SUs per channel, with 80% of the SUs being of one type, and 10% of each of the other two types. Channel capacities are taken to be either *homogeneous* with all channels having capacity 1 Mbps, or *heterogeneous* with two channels having capacity 1 Mbps and two having capacity 11 Mbps. We take the traffic load to be either *light*, where each SUs transmits at either a *light* rate ($R = 10$ Kbps) or *intermediate* rate ($R = 40$ Kbps), or a *heavy* rate ($R = 60$ Kbps). The total offered traffic thus ranges from light (20x10 = 200Kbps) to heavy (20x40=800Kbps). The simulation parameters are listed in Table I. Network nodes, representing SUs, are distributed around the Access Point (AP) on a circle of a 10m radius. This eliminates the effect of variability of the distance between AP and SUs on the SUs' throughput. A standard log-distance channel propagation model is used [21]. Every node transmits to a pre-determined node via the AP. For simplicity, mobility is not considered in our simulations. While the IEEE 802.11g WLAN standard is used at the MAC layer for our simulation experiments, other MAC layer protocols could be utilized.

Each simulation experiment is broken into phases; namely, channel switching and strategy evolution (c.f. Figure 4). Each phase is broken into iterations where the duration of each iteration is 10 seconds of simulation clock time. Within a channel switching phase, each SU operates by switching channels and transmitting data according to the logic of its chosen strategy, as described in the previous sections. At the end of each iteration, we tabulate the total throughput within each channel; this data is used as a proxy measurement for the CSI (residual channel bandwidth) during the next iteration. In addition, we aggregate the average utility achieved by each of three SU types (ACU, FCU, SFCU) in the previous iteration. Prior to the start of next iteration, a small number of randomly selected SUs are permitted to use the aggregated data as the basis for changing strategies; in our simulation, this small set of "evolving" SUs choose a strategy which outperformed their current strategy in the previous phase. In this way, SUs use their communal experiences within phases to learn about the strategy better suited to the spectrum environment scenario. As we shall see, depending on the initial channel conditions and population demographics, different strategies emerge as dominant over long (multi-phase) timescales.

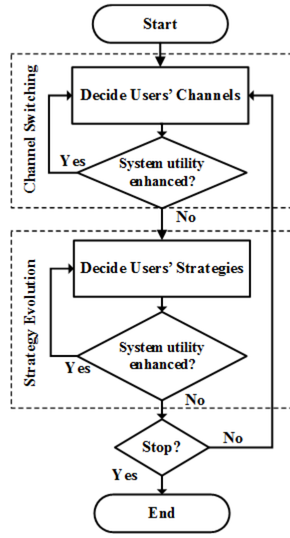


Fig. 4. Channel Switching and Strategy Evolution of SUs

A. Results

We describe $3 \times 3 = 9$ different scenarios covering all the possibilities in which one of the 3 strategies (ACU, FCU, SFCU) was dominant at the beginning, and one was eventually dominant post-evolution. These experiments are illustrated in TABLE II. The column represents the initially dominant strategy in each scenario, while the row represents the final dominant strategy. Each cell of the table is labelled by its environmental parameters (above) and an informal description (below). Together the 9 experiments show that (A) the specific winning strategy that emerges as the eventual winner in the evolutionary process is determined by the environmental parameters; (B) more sophisticated strategies are not always preferred; (C) in each case, the population evolves to a homogeneous configuration in which all SUs employ the same strategy. Most significantly, (D) strategy evolution yields a significant improvement in the aggregate throughput of the overall system, as illustrated in the Figure 5.

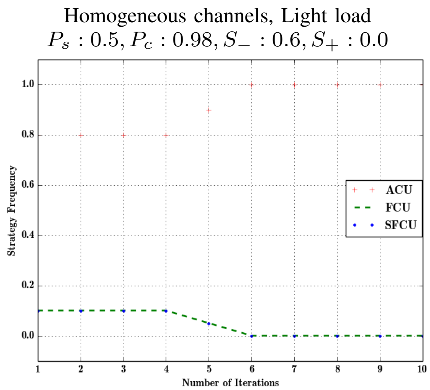
The results of these simulation experiments as summarized in the following paragraphs, answering Research Questions 1 and 2:

The ACU strategy outperforms the other strategies in scenarios that involve channels with homogeneous capacities under light load; see Table II (a-c). In these scenatios, the ACU strategy outperforms the other strategies because of foraging and sociality incur unnecessary overhead that negatively impacts system utility.

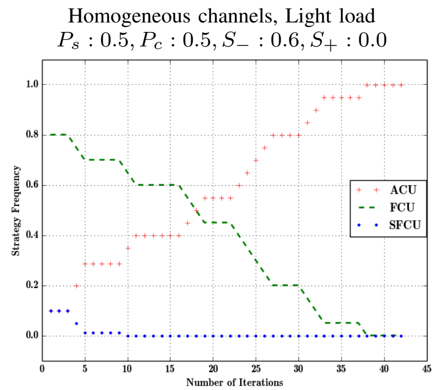
The FCU strategy outperforms the other strategies in scenarios that involve channels with heterogenous capacities under intermediate load; see Table II (d-f). In such scenarios, employing the foraging behavior is advantageous (relative to ACUs) because it allows the SUs to find and use better channels. Social behavior is not advantageous because deference does not yield significant advantage in light load scenarios.

The SFCU strategy outperforms other strategies in scenarios

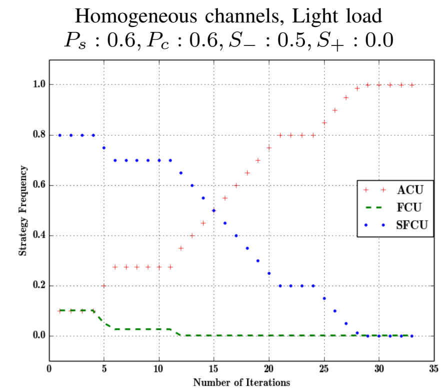
TABLE II
SIMULATION RESULTS: EVALUATION OF ACU, FCU, SFCU STRATEGIES UNDER VARIOUS CHANNEL CONDITIONS



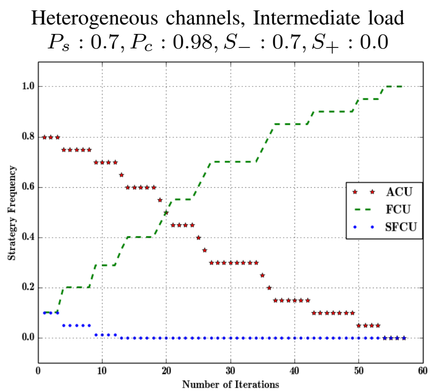
(a) ACU initially dominant, ACU eventual winner



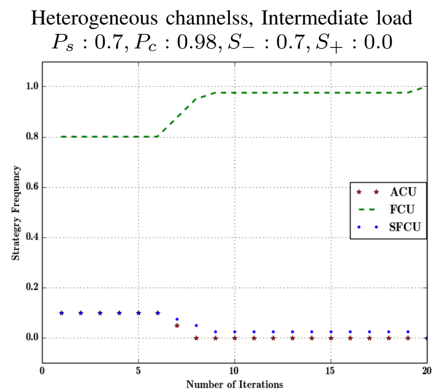
(b) FCU initially dominant, ACU eventual winner



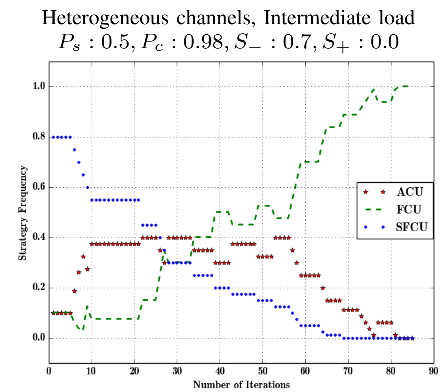
(c) SFCU initially dominant, ACU eventual winner



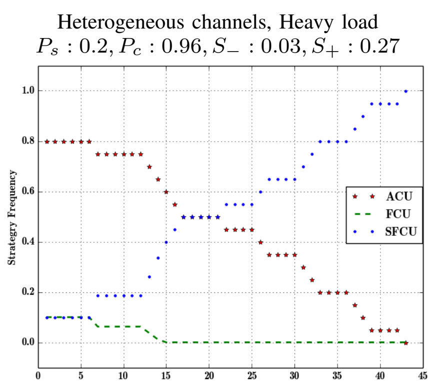
(d) ACU initially dominant, FCU eventual winner



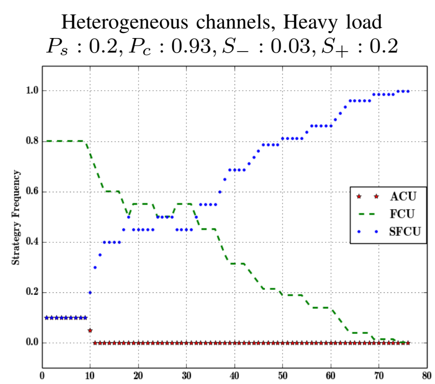
(e) FCU initially dominant, FCU eventual winner



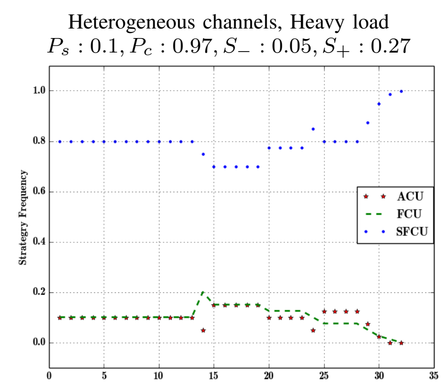
(f) SFCU initially dominant, FCU eventual winner



(g) ACU initially dominant, SFCU eventual winner



(h) FCU initially dominant, SFCU eventual winner



(i) SFCU initially dominant, SFCU eventual winner

that involve channels with heterogenous capacities under high load; see Table II (g-i). Allowing all SFCUs to transmit in such scenarios negatively impacts the utility for the overall system. By engaging in social deference behavior, only a P_S fraction of the SFCUs transmit (at a higher rate), while the remaining defer—this yields higher system utility.

Long-term versus Short-term: The FCU strategy outperforms the ACU strategy when the channel capacities are heterogeneous and under intermediate load; the conclusion is reversed when channel capacities are homogeneous and under light load—see Table II (b) and (e). This answers research question 3 as to when short-term strategies (ACUs) dominate versus long-term strategies (FCUs).

Altruism versus Selfishness: The SFCU strategy outperforms the FCU strategy when the channel capacities are heterogeneous and under heavy load; the conclusion is reversed when channel capacities are homogeneous and under lighter load—see Table II (h) and (f). This answers research question 4 as to when selfish strategies (FCUs) dominate versus altruistic social strategies (SFCUs).

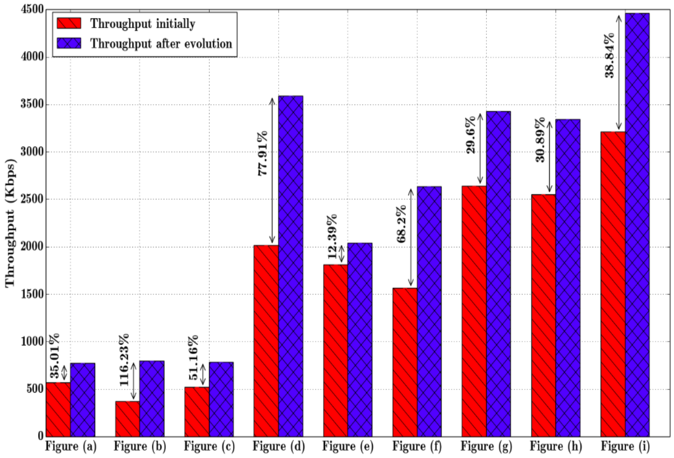


Fig. 5. Throughput improvement due to strategy evolution

VI. Conclusions and Future Work

In this work we presented three bio-socially inspired strategies for DSA by secondary users. We demonstrated through simulation experiments that each of these strategies has the potential to dominate the others over long time scales where natural selection is at play. We showed that the winning strategy depends on the underlying channel conditions and the demographics of the SUs. ACUs emerge when the channel capacities are homogeneous and under light load; FCUs emerge when the channels capacities are heterogeneous and under intermediate load; SFCUs emerge when the channels capacities are heterogeneous and under heavy load.

In our future research work, we plan to replicate the experimental results of this paper formally using evolutionary game theory. We also plan to verify the conclusions in a experimental hardware testbed in which some of the simplifying assumptions of the simulation models are no longer present.

Acknowledgment

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