Bio-Socially Inspired Strategies in Support of Dynamic Spectrum Access: An Evolutionary Game Theory Perspective

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BIO-SOCIALLY INSPIRED STRATEGIES IN SUPPORT OF DYNAMIC SPECTRUM ACCESS: AN
EVOLUTIONARY GAME THEORY PERSPECTIVE

by
Mohammad Ali Marzouq Abu Shattal

A dissertation submitted to the Graduate College
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
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Dynamic Spectrum Access (DSA) has been introduced to fulfill the expanded need for spectrum by different wireless networks and applications. Within the realm of spectrum access, the problem of "spectrum crunch" is present since some of the spectrum bands are overcrowded and others are underutilized. DSA aims to alleviate the problem of spectrum crunch. In DSA, Primary Users (PUs) allow Secondary Users (SUs) to access the spectrum as long as they do not interfere with PU transmissions beyond a pre-agreed acceptable level. In this work, a bio-socially inspired approach is proposed for SU interactions in support of better throughput for the whole community of SUs.

Two representative and biologically-inspired spectrum access strategies are proposed and evaluated relative to a baseline strategy that provides anti-social random access to the underlying spectrum. A formal analysis of the interactions among SUs is carried out using Evolutionary Game Theory (EGT). Within the EGT, the problem is formulated as “a game against the field,” in which the replicator dynamics is used to derive insights into the physical conditions necessary for each of the strategies to be evolutionarily stable. This study shows that the physical channels’ conditions almost always uniquely determine which one of the three (pure) strategies is selected, and that no mixed strategy ever survives. Extensive ns-3 simulation and hardware testbed experiments confirm the validity of the analytical conclusions.

The proposed strategies are applied within the Vehicular Networks (VANET) domain, and demonstrated throughput improvement for the infotainment traffic in VANETs. This study also addresses the feasibility of employing combined social avoidance and deference behaviors among SUs for dynamic spectrum access. The employment of these behaviors in the DSA is studied using a simulation framework and an experimental testbed.
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* Members of Jordanian Community in Kalamazoo, whom I always appreciate their help and support.

Mohammad Ali Marzoug Abu Shattal
Dedication

To my father Ali Abu Shattal and my mother Aziza Alnaimt, for their effort raising me, encouraging me and believing in me over the years. To my wife Rawan Alnaimat for her effort helping and supporting me, and taking care of me, Omar and Elaf during my PhD degree. To Omar and Elaf, believing that they will write their own PhD dissertations in the future. To all of you, I dedicate this work.

Mohammad Ali Marzoug Abu Shattal
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Chapter 1

Introduction

Dynamic Spectrum Access (DSA) is a new paradigm in wireless networking, wherein radio spectrum frequencies may be assigned dynamically to remediate spectrum scarcity. Opportunistic Spectrum Access is a prominent DSA model in which any “secondary user” (SU) is allowed to use radio spectrum already licensed to a “primary user” (PU), as long as the PU is not subjected to interference. Opportunistic spectrum access naturally gives rise to the concerns of spectrum sensing (see [1], [2] and others), since its implementation requires detecting the presence of primary users[3], or equivalently, their absence, i.e. spectrum “holes.”

Cognitive Radio (CR) is a framework of enabling technologies which facilitate the implementation of self-configured DSA networks [4], providing for spectrum sensing, management, mobility and sharing. Here we anticipate that the sensing technologies originally developed to coordinate PU-SU interactions [5], might be adapted and re-appropriated within the CR paradigm, to enable more harmonious SU-SU co-existence to ensure more effective resource sharing. Channel selection is an inherently complex task in multi-channel CR networks, since each SU can (potentially) take a wide range of variables into consideration in its channel selection strategy, including: instantaneous channel state information, social environment, user preferences, and history. The following question is the central focus of this work:

As SU sensing capabilities advance to make more variables accessible to the channel selection strategy, how can we reasonably expect population-level behaviors of rationally driven SUs to evolve, assuming that spectrum utilization is the main objective of each user?

Towards resolving the question, we consider three successively more advanced spectrum users:

- **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.

Together, the strategies above represent categories of hypothetical behavioral adaptation by secondary users, to the feasibility of more sophisticated spectrum sensing technology. The question remains as to whether advances in sensing capability are sufficient to necessarily drive behavioral adaptation in rational users. We will show here that this is not the case and that environmental context plays a critical role in evolutionary outcomes. Through analysis, simulation, and hardware testbed experiments we describe which of the three strategies (or mixture thereof) will dominate in any given environmental context. By arriving at a complete quantitative description of the evolutionary equilibrium point in SU spectrum access etiquette, we reveal the factors affecting the strategic decision-making of rational secondary users with respect to opportunistic spectrum access. Knowing these factors is a necessary prerequisite to ensuring that SU-SU co-existence benefits from advances in spectrum sensing to the maximum extent possible long-term.

In this work, we will consider heterogeneous ecosystems containing a mix of SUs spanning the three behavioral 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 advantageous 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.

**Statement of the Problem**

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.
Purpose of the Research

In this work, we investigate SU-SU interactions within a bio-socially inspired evolutionary framework, to obtain long term efficient spectrum utilization strategies. In our framework, we allow SUs to adapt their strategies gradually over time by mimicking 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.

Significance of the Study

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. [6] 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 CR and DSA models [7] which allow unlicensed SUs to access licensed spectrum while guaranteeing transmission priority for PUs.

Research Questions

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 homogeneous 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)?

5. Which social deference structure leads the best SU interactions that enhance the spectrum utilization?
Contributions

The work of this dissertation embodies the research work done in the following publications:


The work of this dissertation also contributed to the following publications:


Structure of the Dissertation

The overall structure of the dissertation is as follows:

- Chapter I: Introduction
- Chapter II: Paper I
- Chapter III: Paper II
- Chapter IV: Paper III
- Chapter V: Paper IV
- Chapter VI: Conclusions and future work.
Chapter 2

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

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.

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. [6] 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 [7] 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 behavioral 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 describes 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.

Prior Related Work

Most prior research in DSA focuses primarily on PU-SU dynamics (e.g., [5] and others), ignoring SU-SU interactions. Exceptions are the recent work of Dixit et al. [8], Xing et al. [9] and Wisniewska et al. [10][11][12][13]. Our work here also serves to elucidate the nature of SU-SU dynamics and extends the work of Shattal et al. [14][15]. The work utilizes the findings in the work of Dombrowski et al. [16] for hierarchical resource sharing in the Inuit community in Labrador, Canada.

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 [17], peer recommendations [18] and selfishness [19]). 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 [20] and sensor network management [21]. In the context of CR, bio-socially inspired models have been developed for spectrum sensing [21], channel selection [22], and efficient routing [20]. Genetic algorithms have been used to tune CR parameters for better spectrum usage [23], and recommendation systems have been applied to minimize sensing and decision-making time required for channel selection [24].

Unfortunately, idealized bio-social models based on animal societies (e.g. termites [25], ants [26], etc.) all assume a level of coordination of strategy choice among population members [27]. 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 [9], 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).
In what follows, we assume a community of $N$ secondary users. Each of the SUs seeks to transmit data at a rate of $R \text{ bits/s}$. SUs operate within an ecosystem of $M$ spectrum channels. Each channel $i$ ($i = 1..M$) has capacity $C_i \text{ bit/s}$, 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 $\gamma$ 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 [28]) allows the ACU to act with a naïve view to capture utility using the set of channel resources. The ACU’s 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:

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

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 FCU’s 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 user’s 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:

$$\overline{C_i} = \frac{\alpha_i C_i}{\sum_j \alpha_j C_j}$$

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 $\overline{C_i}$ 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 $\overline{C}_i$ as follows:

$$\overline{C}_i \approx \frac{\gamma(\alpha_i C_i, n, P_c R)}{\sum_j \gamma(\alpha_j C_j, n, P_c R)}$$  \hspace{1cm} (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 $\overline{\alpha}$ will change from 1 to 0, and the updated estimate (2) will reflect the presence of the PU. The low (proxy measure of) CSI now ensures that FCUs will not switch into channel 1.

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

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

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 [29] and those of non-human primates [30] 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:

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

**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:

$$n_{ACU} = \frac{N_{ACU}}{M}$$

$$n_{FCU} = \overline{c_i} N_{FCU}$$

$$n_{SFCU} = \overline{c_i} \cdot (1 - P_S) \cdot N_{SFCU}$$

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 $\gamma_2$ 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:

\[
U_{ACU} = \frac{1}{M} \sum_{i=1}^{M} R \cdot X_{i,1} \quad (2)
\]

\[
U_{FCU} = P_e \sum_{i=1}^{M} C_i \cdot R \cdot X_{i,1} \quad (3)
\]

\[
U_{SFCU} = P_e \sum_{i=1}^{M} C_i \cdot (1 + S_+)R \cdot (1 - S_-)X_{i,2} \quad (4)
\]

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

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

**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 biosocial 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

\(^1\)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 1: Simulation Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of SUs</td>
<td>80</td>
</tr>
<tr>
<td>Number of Channels</td>
<td>4</td>
</tr>
<tr>
<td>Channel capacity (Mbps)</td>
<td>hom.:[1,1,1,1] and het.:[11, 11, 11]</td>
</tr>
<tr>
<td>Modulation Scheme</td>
<td>DSSS</td>
</tr>
<tr>
<td>WLAN Standard</td>
<td>IEEE 802.11g</td>
</tr>
<tr>
<td>Distance from AP</td>
<td>10m</td>
</tr>
<tr>
<td>Transmission power</td>
<td>16.0206 dBM (default) [31]</td>
</tr>
<tr>
<td>Channel Propagation Model</td>
<td>Log Distance Propagation Model [32]</td>
</tr>
<tr>
<td>CBR transmission rate per SU (kbps)</td>
<td>10 Kbps (light), 40 Kbps (intermediate)</td>
</tr>
<tr>
<td></td>
<td>60 Kbps (heavy)</td>
</tr>
</tbody>
</table>

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)?

Simulation Experiments

In our simulations, we consider a range of CR scenarios. Throughout, we assume 4 channels and 80 SUs. We always 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 \( R = 10 \text{ Kbps} \) or intermediate rate \( R = 40 \text{ Kbps} \), or a heavy rate \( R = 60 \text{ Kbps} \). The total offered traffic thus ranges from light (20x10 = 200Kbps) to heavy (20x40=800Kbps). The simulation parameters are listed in Table 7. 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 [32]. 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

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**Figure 4: Channel Switching and Strategy Evolution of SUs**

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```plaintext

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“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.

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 8. 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 8 (a-c). In these scenarios, 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 heterogeneous capacities under intermediate load; see Table 8 (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 that involve channels with heterogeneous capacities under high load; see Table 8 (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 8 (b) and (e). This answers research question
Table 2: Simulation Results: Evaluation of ACU, FCU, SFCU Strategies Under Various Channel Conditions

Homogeneous channels, Light load

\[ P_s : 0.5, P_c : 0.98, S_- : 0.6, S_+ : 0.0 \]

(a) ACU initially dominant, ACU eventual winner.

Homogeneous channels, Light load

\[ P_s : 0.5, P_c : 0.5, S_- : 0.6, S_+ : 0.0 \]

b) FCU initially dominant, ACU eventual winner.

Homogeneous channels, Light load

\[ P_s : 0.6, P_c : 0.6, S_- : 0.5, S_+ : 0.0 \]
(c) SFCU initially dominant, ACU eventual winner.

Heterogeneous channels, Intermediate load

\[ P_s : 0.7, P_c : 0.98, S_- : 0.7, S_+ : 0.0 \]

(d) ACU initially dominant, FCU eventual winner.

Heterogeneous channels, Intermediate load

\[ P_s : 0.7, P_c : 0.98, S_- : 0.7, S_+ : 0.0 \]

(e) FCU initially dominant, FCU eventual winner

Heterogeneous channels, Intermediate load

\[ P_s : 0.5, P_c : 0.98, S_- : 0.7, S_+ : 0.0 \]
(f) SFCU initially dominant, FCU eventual winner.

Heterogeneous channels, Heavy load

\[ P_s : 0.2, P_c : 0.96, S_- : 0.03, S_+ : 0.27 \]

(g) ACU initially dominant, SFCU eventual winner

Heterogeneous channels, Heavy load

\[ P_s : 0.2, P_c : 0.93, S_- : 0.03, S_+ : 0.2 \]

(h) FCU initially dominant, SFCU eventual winner.

Heterogeneous channels, Heavy load

\[ P_s : 0.1, P_c : 0.97, S_- : 0.05, S_+ : 0.27 \]
Figure 5: Throughput improvement due to strategy evolution

(i) SFCU initially dominant, SFCU eventual winner.

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 8 (h) and (f). This answers research question 4 as to when selfish strategies (FCUs) dominate versus altruistic social strategies (SFCUs).

**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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Chapter 3

Evolutionary Game Theory

Perspective on Dynamic Spectrum Access Etiquette

abstract: In this work, we describe the long-term evolution of societies of secondary users in dynamic spectrum access networks. Such an understanding is important to help us anticipate future trends in the organization of large-scale distributed networked deployments. Such deployments are expected to arise in support of a wide variety of applications including vehicular networks and the Internet of Things. Two new biologically-inspired spectrum access strategies are presented here, and compared with a random access baseline strategy. The proposed strategies embody a range of plausible assumptions concerning the sensing capabilities and social characteristics of individual secondary users. Considering these strategies as the basis of “a game against the field,” we use replicator dynamics within an evolutionary game-theoretic analysis to derive insights into the physical conditions necessary for each of the strategies to be evolutionarily stable. Somewhat surprisingly, we find that the physical channel conditions almost always uniquely determine which one of the three (pure) strategies is selected, and that no mixed strategy ever survives. We show that social tendencies naturally become advantageous for secondary users as they find themselves situated in network environments with heterogeneous channel resources. Hardware testbed experiments confirm the validity of the analytic conclusions. Taken together, these results predict the emergence of social behavior in the spectrum access etiquette of secondary users as cognitive radio technology continues to advance and improve. The experimental results show an increase in the throughput of up to 90%, when strategy evolution is continuously operational, compared to any static strategy. We present use cases to envision the potential application of the proposed evolutionary
Introduction

Dynamic Spectrum Access (DSA) is a new paradigm in wireless networking, wherein radio spectrum frequencies may be assigned dynamically to remediate spectrum scarcity. Opportunistic Spectrum Access is a prominent DSA model in which any “secondary user” (SU) is allowed to use radio spectrum already licensed to a “primary user” (PU), as long as the PU is not subjected to interference. Opportunistic spectrum access naturally gives rise to the concerns of spectrum sensing (see [33], [2] and others), since its implementation requires detecting the presence of primary users [34], or equivalently, their absence, i.e. spectrum “holes.”

Cognitive Radio (CR) is a framework of enabling technologies which facilitate the implementation of self-configured DSA networks [4], providing for spectrum sensing, management, mobility, and sharing. Here we anticipate that the sensing technologies originally developed to coordinate PU-SU interactions [5], might be adapted and re-appropriated within the CR paradigm, to enable more harmonious SU-SU co-existence, thus ensuring more effective resource sharing. Channel selection is an inherently complex task in multi-channel CR networks, since each SU can (potentially) take a wide range of variables into consideration in its channel selection strategy, including: instantaneous Channel State Information (CSI), social environment, user preferences, and history. The following question is the central focus of this work:

As SU sensing capabilities advance to make more variables accessible to the channel selection strategy, how can we reasonably expect population-level behaviors of rationally driven SUs to evolve, assuming that spectrum utilization is the main objective of each user?

Towards resolving the question, we consider three successively more advanced spectrum users:

- “Primitive” users who are not capable of sensing channel characteristics, or responding to them behaviorally.
- “Foraging” users who are capable of sensing channel characteristics, and can respond behaviorally by either consuming (transmitting) or foraging for (listening) resources;
- “Social” users who are additionally capable of sensing the identities of co-users within their environment, and can respond by deferring to them (or not).

Through analysis and experimental studies, we describe which of the three strategies (or mixture thereof) dominates in any given environmental context. By arriving at a complete quantitative description of the evolutionary equilibrium point in SU spectrum access etiquette, we reveal the factors affecting the strategic decision-making of rational secondary users with respect to opportunistic spectrum access.
Knowing these factors is a necessary prerequisite to ensuring that SU-SU co-existence benefits from advances in spectrum sensing to the maximum extent possible long-term. We demonstrate that spectrum utilization can be enhanced using the above bio-social behaviors within an evolutionary framework. The experimental results indicates an increase in the throughput of up to 90% when evolution is continuously operational, compared to when any one strategy is statically deployed.

The remainder of this paper is organized as follows: Prior work is discussed in Section 5. Section III introduces the behavioral models and the utility functions being maximized. Section IV presents several use cases for the devised strategies. The results of formal analysis and experimental based studies of system dynamics are presented in Sections 5, and 5, respectively. Finally, conclusions and future research directions are discussed in Section 5.

Prior Related Work

Most prior research in cognitive radio focuses primarily on PU-SU dynamics (e.g. [5] and others), ignoring SU-SU interactions. Exceptions are the recent work of Dixit et al. [8] and Xing et al. [9] as well as that of Wisniewska et al. [35] [10] [11] [12][13]. Our work serves to address the nature of SUs dynamics and expands the work of Shattal et al. [14] [15]. The work utilizes the outcome of the work of Dombrowski et al. [16] for resource sharing in the Inuit community in Labrador, Canada. Research into PU-SU and SU-SU interactions can be classified in three broad categories: (a) machine learning formulations, (b) biologically or socially inspired schemes, and (c) game-theoretic approaches. The results presented here serve to address the research gap emanating from the scarcity of studies that address the role of SU interactions in support of enhanced DSA. This research gap is illustrated in Figure 18 relative to the different DSA/CR-related research areas addressed in the recent literature.

Machine learning approaches have been applied extensively to spectrum sharing [36], spectrum sensing [37] and channel selection [38]. Specifically, different types of machine learning algorithms have been incorporated into CR network protocols (see [39] for a survey), including support vector machines [40], re-enforcement learning [41] and Q-Learning [42]. Unfortunately, in machine learning approaches it is difficult to provide the SU with the correct action that is best for the current situation, especially for DSA systems in dynamic environments. This problem can be seen, for example, in reinforcement learning approaches where decision making depends on a trial and error process with evaluative feedback [43].

Biologically or socially inspired approaches typically begin by incorporating a social component to users’ behavioral models (e.g., preferential bias [17], peer recommendations [18], and selfishness [19]).
These approaches consider the CR ecosystem as a social network [44] [45] for which cooperative schemes are designed [22]. Such approaches recognize the optimization inherent in evolving biological systems, and seek to apply the outcomes of biological natural selection processes to the realm of CR networks.

Behavioral models based on animal social interactions are by now well recognized as the basis of a wide range of resource allocation problems, including MANET routing [46], Vehicular Network (VANET) routing [47], and sensor network management [21]. In the context of CR, bio-socially inspired models have been developed for spectrum sensing [21], channel selection [22], and efficient routing [46]. Genetic algorithms have been used to tune CR parameters for better spectrum usage [23], and recommendation systems have been applied to minimize sensing and decision-making times required for channel selection [24]. Unfortunately, idealized bio-social models based on animal societies (e.g., termites [48], ants [26], etc.) require a level of coordination among population individuals [27]. The assumption of pre-agreed upon coordination fails to take into consideration possible long-term evolution of strategies for users. Our approach, which allows SU strategies to evolve, sidesteps this shortcoming.

Game theory approaches have been used as a mathematical framework for scenario-based analysis and modeling of CR networks (see [49] and [50] for a survey of prior work in this area). Competition among SUs over network resources has been modeled as a non-cooperative game [51]. Unfortunately, most game-theoretic research relies on the availability of spectrum statistics in order to formulate the game and cope with spectrum dynamic changes, especially in stochastic [52] and repeated games [53]. Such information is not known a priori, limiting the applicability of this approach [54].

Evolutionary game theory (EGT) has captured the attention of researchers in DSA because of its impressive ability to model potential PU-SU dynamics as an evolving game [55]. In some cases, evolutionary stable strategies have been found to exhibit in-simulation performance improvements of almost...
Figure 7: Finite State Machine for the proposed bio-social users.

35% [37]. EGT is also attractive because it relaxes the traditional rationality assumptions of game theory [56], which require all players to have complete knowledge of the game. Yet another advantage of EGT is that its framework of replicator dynamics can provide computable rates of convergence to an Evolutionarily Stable Strategy (ESS), and thus generate concrete predictions of the distribution of the deployed strategies and a picture of the adaptation of users over time. Despite the fact that “uncoordinated” access to the spectrum by SUs would likely result in poor long-term spectrum utilization, SU interactions have not been studied thoroughly in the literature. One exception, however, is the work of Jiang et al. [2] which studied the SUs’ spectrum access jointly with spectrum sensing based on EGT.

In this work, we apply EGT to the DSA/CR domain to shed light on what we can reasonably expect to witness as SU etiquette in the long-term. We focus on the emergence of bio-socially inspired foraging and socializing behaviors, and the potential impacts of these behaviors on the overall performance of the system as measured by spectrum utilization.
Behavioral Models

In what follows, we assume a community of $N$ SUs. Each SU 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). While $C_i$ depends on the channel conditions including noise and interference, $\alpha_i$ only depends on the presence of the PU, and defined as follows:

$$\alpha_i = \begin{cases} 0 & ; R_{PU_i} > 0 \\ 1 & ; R_{PU_i} = 0 \end{cases}$$

where $R_{PU_i}$ is the PU transmission rate on the channel $i$.

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 the system’s utility, and its maximization will act as the fitness function driving evolutionary pressure on SU etiquette.

We introduce three different channel selection strategies, namely: Always Consume User (ACU), Forage-Consume User (FCU), Social Forage-Consume User (SFU).

**The Always-Consume User (ACU)** is always transmitting on some channel that is selected uniformly at random, following the Finite State Machine (FSM) in Figure 19-(a). This simple strategy (used previously in [28]) allows the ACU to act with a naïve view to capture utility using the set of channel resources. The ACU’s 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.

Advancing from the ACU, the **Forage-Consume User (FCU)** has the ability to engage in two distinct activities. It may either sense the CSI (“forage”) but abstain from transmission, or it may transmit data on a channel (“consume”). The FCU’s choice to consume may, in turn, be based on information about the CSI sensed while foraging. Interference level, noise level, and capacity are examples of potential CSI\(^1\). The FCU forgoes short-term utility benefits while in the foraging state, but may stand

\(^1\)In this work, we do not focus on contributions toward the problem of spectrum sensing, but rather assume that an FCU has access to “sufficient” information about the channel at the moment of decision-making. In our analysis, simulation and hardware experiments (described in later sections), the FCU has access to basic CSI on noise and interference levels, implemented as channel sniffing spectrum sensing at the MAC layer.
to gain more long-term utility by acquiring information about the channels. On the other hand, too much foraging could yield inefficient usage of spectrum resources and decreased utility. As depicted in Figure 19-(b), 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 forage state with asymptotic relative frequency $1 - P_c$. In this state, it only collects CSI as it switches across all channels.

Based on the CSI, each FCU establishes preferential access to specific channels.

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

$$\overline{C}_i = \frac{\alpha_i C_i}{\sum_j \alpha_j C_j}$$

where $j = 1, 2, \ldots, M$. While foraging, FCUs bias their stochastic selection of each channel proportionally to the channel’s relative capacity. This behavior encourages FCUs to utilize channels with higher relative capacities.

Unfortunately, SUs cannot measure $\overline{C}_i$ directly (especially in the dynamic presence of PUs). To circumvent this obstacle, here we allowed SUs to estimate the relative capacity of the channel via the throughput recently attained within it. The throughput $R_{th}$ can be drawn from the Shannon’s formula:

$$R_{th} = B \cdot \left(1 + \frac{G_z P_z}{\sum_{y=1}^{k} G_{zy} P_y + W}\right)$$

where $k$ is the number of co-consumers (i.e., interferers) in the channel $i$, 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 $W$ is the power level of the ambient white Gaussian noise. Each FCU considers its recently attained fractional throughput $\gamma(\alpha_i C_i, n_i, P_c R)$ reflected from $R_{th}$ as a “learned” proxy estimate for the capacity of its current transmission channel. Thus, if $n_i$ SUs ($1 \leq n_i \leq N$) are co-consuming channel $i$, the FCUs estimate the relative channel capacity $\overline{C}_i$ as follows:

$$\overline{C}_i \approx \frac{\gamma(\alpha_i C_i, n_i, P_c R)}{\sum_j \gamma(\alpha_j C_j, n_j, P_c R)}$$

where $j = 1, 2, \ldots, M$. 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 $\alpha_1$ drops from 1 to 0, and the updated estimate (2) reflects the presence of a PU. The low (proxy measure of) CSI now ensures that FCUs will not switch to channel 1. When the FCU forages, it receives no utility, and when it consumes, it consumes channel
i with probability $C_i$.

Advancing from FCU, the Social Forage-Consume User (SFU) 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. SFUs may choose not to transmit on 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 SFUs. We refer to this phenomenon as deference. Specifically, we consider the situation in which whenever a SFU decides to begin transmitting on a channel, the other SFUs who are also presently transmitting on the channel tend to defer by exhibiting a bias towards not transmitting. The SFU behavioral model reflects well-known findings from the structure of animal [29] and non-human primate [30] societies. In these societies, sociality plays a significant organizing function and helps ensure species survival. In our work, the social deference behavior witnessed in animal societies is leveraged to yield benefits for secondary users in terms of reduced conflict over resources.

As depicted in Figure 19-(c), a SFU 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 SU 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 SFUs in the DSA society. A stochastic process governed by $P_s$ allows SFUs in Defer state to switch to Active state. While in the Active substate with asymptotic relative frequency $1 - P_s$, the SFU transmits data at an elevated rate $(1 + S_+)R$. This increase helps in using the additional bandwidth that has been relinquished by deferrers. $S_+ \in [0,1]$ is the percentage that represents this increase in the rate. Each SFU 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 SFUs consuming a channel, we will assume that each gives up $S_-$ fraction of its utility towards coordination overhead. $S_- \propto c_0 N^h$: $h \in [1,2]$ represents the social penalty due to coordination overhead among SFUs to access the channel. $S_-$ increases proportionally with the number of SFUs (i.e., $N$). $h$ is an exponent that represents the degree to which SFUs coordinate their social attributes. For full coordination among social users $h = 2$ (i.e., $N N$ coordination among SFUs). $S_-$ is protocol-specific coordination overhead with some constant $c_0$. The $S_-$ factor encompasses the effect of the sociality coordination overhead. The exact coordination overhead is scenario specific (network architecture, network protocol and standard, and channel assignment scheme). This factor is impacted by the nature of the coordination and cooperation among SFUs. For example, if the interaction comprises of a prioritized access among the SFUs, the overhead will be different than for schemes where all SFUs have the same priority to access the channels.
In the next sub-sections, we discuss the utility of SUs utilizing the proposed strategies in two different systems, namely: homogeneous and heterogeneous. In homogeneous systems, all SUs utilize the same strategy. In heterogeneous systems, different SUs utilize different strategies. In both cases, the utility is presented for single and multi-channel systems. These utilities will be the basis for our analysis (Section 5) and experimental studies (Section 5).

Utility of the SUs in Homogeneous Systems

Consider a homogeneous system $S$ in which there are $N$ SUs of ACUs, FCUs, or SFUs, acting on one channel of capacity $C$ and the SUs transmit at a rate of $R$. Such a system is specified by a 3-tuple

$$Z = (C, N, R)$$

The fractional throughput of the SUs in $Z$ is written as:

$$X_\eta(Z) := \eta(\alpha C, N, R)$$

Where $\eta(\alpha C, N, R)$ denotes 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 $\alpha$ of the overall capacity $C$ available for SU communications. In practice, this function is dependent on the particular link layer technology and protocols used. The function $\eta$ plays an important role in quantifying the performance of the model that follows.

Now, when we consider a system $Z^*$

$$Z^* = (C, N, R)$$

having access to $M \geq 1$ channels of capacities $C_1, \ldots, C_M$. Assuming $Z^*$ is in steady state, $O^i_s$ represents the expected number of SUs employing strategy $s$ on channel $i$. Therefore, the occupancy of the SUs employing the ACU, FCU, and SFU strategies on channel $i$ can be represented as follows:

$$O^i_{ACU} = \frac{N}{M}$$

$$O^i_{FCU} = \overline{C}_1 \cdot N$$

$$O^i_{SFU} = \overline{C}_1 \cdot (1 - P_S) \cdot N$$

The total demand for channel \(i\) is computable as

\[ D_i(Z^*,s) = O_s^i \cdot R \] (7)

and the fractional throughput of users in channel \(i\) is:

\[ X_i^\eta(Z^*,s) = \eta(\alpha_i C_i, O_s^i, R) \] (8)

While the precise form of \(\eta\) is intractable, we will take

\[ X_i^\eta(Z^*,s) \approx \begin{cases} 1 & \text{if } D_i(Z^*,s) < \rho C_i \\ \frac{1}{\exp[D_i(Z^*,s) - \rho C_i]} & \text{if } D_i(Z^*,s) \geq \rho C_i \end{cases} \] (9)

Here \(\rho\) is a fitting parameter chosen so that \(\eta\) mirrors experimental measurements. In a homogeneous environment consisting of \(N\) ACUs, the expected utility of each ACU is given by:

\[ U_{s=ACU}(Z^*) = \frac{1}{M} \sum_{i=1}^{M} R \cdot X_i^\eta(Z^*,s) \] (10)

In a homogeneous environment consisting of \(N\) FCUs, the expected utility of each FCU is thus:

\[ U_{s=FCU}(Z^*) = P_c \sum_{i=1}^{M} C_i \cdot R \cdot X_i^\eta(Z^*,s) \] (11)

In a homogeneous environment consisting of \(N\) SFUs, the expected utility of each SFU is thus:

\[ U_{s=SFU}(Z^*) = P_c \sum_{i=1}^{M} C_i(1 + S_+) \cdot R \cdot (1 - S_-) \cdot X_i^\eta(Z^*,s) \] (12)

**Utility of the SUs in Heterogeneous Systems**

In heterogeneous systems, each SU chooses one strategy to employ, although different SUs may make different choices. Consider a heterogeneous system \(S\) in which there are \(k_1\) ACUs, \(k_2\) FCUs, ad \(k_3\) SFUs. In \(S\), there is just one channel of capacity \(C\) and the ACUs and the FCUs transmit at a rate of \(r_1\) while SFUs transmit at a rate of \(r_2\). Such a system is specified by a 5-tuple

\[ S = (k_1, k_2, k_3, r_1, r_2) \] (13)
The fractional throughput of the SUs in \( S \) is written as:

\[
X_\gamma(S) := \gamma(\alpha C, k_1 + k_2, r_1, k_3, r_2)
\]  

(14)

Considering a multi-channel system \( S^* \), we have:

\[
S^* = (k_1, k_2, k_3, r_1, r_2)
\]  

(15)

having access to \( M \geq 1 \) channels of capacities \( C_1, \ldots, C_M \). In what follows, \( S^* \) will always consist of a set of SUs who each follow a pure strategy. We will, however, sometimes subject the system to the possibility that some fraction of its players could “mutate” to different (possibly mixed) strategy.

Assuming \( S^* \) is in steady state, the expected number of ACUs, FCUs and SFUs in channel \( i \) is given by

\[
O_{ACU}^i = \frac{N_{ACU}}{M}
\]  

(16)

\[
O_{FCU}^i = \overline{C}_i N_{FCU}
\]  

(17)

\[
O_{SFU}^i = \overline{C}_i (1 - P_S) N_{SFU}
\]  

(18)

The total demand for channel \( i \) is computable as

\[
D_i(S^*) = (O_{ACU}^i + O_{FCU}^i) \cdot R + O_{SFU}^i \cdot (1 + S_+) \cdot R
\]  

(19)

and the fractional throughput of users in channel \( i \) is:

\[
X_{\gamma}^i(S^*) = \gamma(\alpha_i C_i, O_{ACU}^i, O_{FCU}^i, R, O_{SFU}^i, (1 + S_+) \cdot R)
\]  

(20)

While the precise form of \( \gamma \) is intractable (as in the \( \gamma \) in the homogeneous system), we will take

\[
X_{\gamma}^i(S^*) \approx \begin{cases} 
1 & \text{if } D_i(S^*) < \rho C_i \\
\frac{1}{\exp(D_i(S^*) - \rho C_i)} & \text{if } D_i(S^*) \geq \rho C_i
\end{cases}
\]  

(21)

Here \( \rho \) is a fitting parameter chosen so that \( \gamma \) mirrors experimental measurements. In system \( (S^*) \), the
utility achieved by each ACU, FCU, and SFU, respectively is:

\[ U_{ACU}(S^*) = \frac{1}{M} \sum_{i=1}^{M} R \cdot X_i^i(S^*) \]  \hspace{1cm} (22)

\[ U_{FCU}(S^*) = P_c \sum_{i=1}^{M} C_i \cdot R \cdot X_i^i(S^*) \]  \hspace{1cm} (23)

\[ U_{SFU}(S^*) = P_c \sum_{i=1}^{M} C_i \cdot R \cdot G_s \cdot X_i^i(S^*) \]  \hspace{1cm} (24)

where \( G_s = (1 + S_+) \cdot (1 - S_-) \) is the sociality gain. The system utility is expressed as:

\[ U_S(S^*) = N_{ACU} \cdot U_{ACU}(S^*) + N_{FCU} \cdot U_{FCU}(S^*) + N_{SFU} \cdot U_{SFU}(S^*) \]  \hspace{1cm} (25)

When an individual user gains more utility due to channel switching or strategy evolution, the system’s utility \( U_S(S^*) \) increases accordingly. The system utility is a measure of how SUs are acting on the system and provide us with a basis of judgment for the long term benefits of strategies in the system. Formal performance analysis is provided in section 5, in which limits and conditions for each SU strategy to maximize the system utility are established.

Use Cases and Applications

In this section, two real-world scenarios are introduced to address the applicability of the proposed strategies.

Internet-of-Things: Electronic Health Services

Electronic Health Services (EHS) is an application in the Internet-of-Things (IoT) domain, in which vital data is transmitted and processed to advance human health. In this application, wireless sensors are connected to the patients to sense and transmit vital data (i.e., heart rate, blood pressure, etc.). These sensors transmit data to the nursing stations to be monitored and reviewed for fast recommendations and quick response.

In cases where the number of the patients is large, spectrum access becomes a critical aspect of system since delayed or dropped packets affect the availability of the data for medical staff. This issue is particularly important in unlicensed bands where spectrum is also simultaneously accessed by other networks (e.g., WiFi, Bluetooth, etc.) that are outside the control of the EHS system. Leveraging
foraging behaviors and social interactions between secondary users (EHS sensors) can potentially yield throughput gains for the overall EHS system. In short, DSA approaches can provide a flexible self-configuring solution for devices to utilize in multichannel unlicensed bands.

Considering the proposed DSA strategies, we anticipate the following three cases, for potential benefits for EHS applications:

*Case 1 - Potential benefits from ACU strategies:* This strategy potentially provides better performance when the traffic demand from EHS sensors is low. It represents a primitive candidate strategy for channels with lower contention levels. However, this strategy fails to benefit from channels with better conditions, in the cases where channels have different contention levels. The implementation of this strategy is cost effective since it does not require sensing, and requires minimal computation resources to randomize the channel access.

*Case 2 - Potential benefits from FCU strategies:* In this strategy, sensors transmit traffic intelligently on channels that have fewer co-users by actively sensing the channels characteristics. An effective implementation of this strategy’s must specify an appropriate balance between the time used for sensing and the time used for transmission. This strategy needs more computation and network resources to implement the decision making and channel sensing processes compared to the ACU strategy.

*Case 3 - Potential benefits from SFU strategies:* SFUs have potential advantage when devices are able to socialize within groups in a hierarchical or prioritized manner. Sensors could be potentially classified into groups based on their traffic demand. Sensitive data might be transmitted with higher priority and SFUs might form deference hierarchies to coordinate and prioritize their transmissions. An effective use of this strategy’s must address the trade-off between the overhead of social coordination, channel sensing, and the gain from the social deference.

**Infotainment Traffic throughput: Internet of Vehicles**

Our approach can be potentially applied to VANETs, where vehicles communicate over channels that are rapidly changing in terms of the number of SUs. The load is completely generated by SUs (vehicles) since VANETs utilize Dedicated Short Range Communications (DSRC) service and control channels, and (unlike in the EHS setting) do not coexist with other networks. In this application, we optimize the throughput of infotainment traffic. The interplay between infotainment and safety traffic in VANETs ensures that optimizing the throughput of infotainment traffic will yield greater (residual) bandwidth to support safety traffic.

Considering the proposed DSA strategies, we can anticipate the following three cases:

*Case 1 - Potential benefits from the ACU strategy:* If the infotainment traffic is evenly distributed
across the service channels, the ACU strategy provides fast channel access with minimal decision making overhead. The cost of implementing this strategy is low, similar to the cost of its deployment in the EHS use case.

**Case 2 - Potential benefits from the FCU strategy:** Applying the FCU strategy helps the SUs to access the service channels that have less contention on average to enhance the overall throughput of the system. The cost of implementing this strategy is similar to the cost of the FCU strategy discussed in Case 2 of the EHS use case.

**Case 3 - Potential benefits from the SFU strategy:** Applying the grouping and socializing primitives of the SFU strategy, we can provide different groups of users with prioritized access to the channels. This is especially important in cases where channels are heavily loaded, and deference among vehicles can lead to better channel utilization in favor of the infotainment and safety traffic. The cost of implementing this strategy is similar to the cost of the SFU strategy discussed in Case 3 of the EHS use case.

**Formal Performance Analysis**

Evolutionary Game Theory (EGT) originated as an application of game theory in the context of biological sciences [57], based on the understanding that frequency dependent fitness introduces a strategic aspect to evolution. Within EGT, *population games* consider the behavior of populations of strategically interacting players. There are two types of population games, “pairwise” games and “games against the field.”

In pairwise games, each player is assumed to play against a random player in the population and the overall utility is determined based on statistical analysis of the utility of players in the population. The individual utility obtained by the user is calculated based on the game structure.

Mynard in [58] describes advantages of “games against the field” over pairwise games. In the former game, the player plays against the whole population or against a subsection of it. Unlike pairwise games, the field approach does not require complete knowledge about the structure of the game. Rather, it relies on the accumulation of empirical information about the relative advantages of individual pure strategies. This idea was first put forth by Nash in [59], and has since been described in many textbooks (e.g., see [60]).

In general game theory, Nash equilibrium is an optimal outcome of the game such that no player gains more utility by unilaterally deviating “or changing” his strategy, under the assumption that other player(s) strategies remain unchanged. When the game is in Nash equilibrium, all players reach their maximum utilities and have no incentive to deviate from their strategies. The ESS is thus a strategy that, once employed by the whole population, renders impossible for any other strategy to spontaneously
arise. If the whole population employs the ESS then the population is, by definition, at Nash equilibrium.

EGT analysis of the proposed system is motivated by the fact that each user in the system is competing simultaneously over the channels against all other users. The assumptions of pair-wise games are not realistic, since these games assume that the player plays against an individual opponent. By making the assumption that only a small number of users evolve to employ a better strategy over time, we can thus analyze our system using the framework of evolutionary game theory.

We follow the standard formal definitions of the ESS [61]. A strategy \( \sigma^* \) is an ESS, if mutants that adopt any other strategy \( \sigma \) leave fewer offsprings in the post-entry population \( x_\epsilon := (1 - \epsilon)\sigma^* + \epsilon\sigma \), assuming that the proportion of mutants \( \epsilon \) is sufficiently small \((0 < \epsilon < 1)\). For \( \sigma^* \) to be ESS then:

\[
U(\sigma^*, x_\epsilon) > U(\sigma, x_\epsilon)
\]

where \( U(\sigma^*, x_\epsilon) \) is the payoff (utility) of players that play \( \sigma^* \) and \( U(\sigma, x_\epsilon) \) is the payoff of the mutants that play \( \sigma \) in the post-entry population, respectively.

In what follows, we define \( U(S^*; s, x_\epsilon) \) as the utility received by users employing strategy \( s \) in a system \( S^* \) of a mixed population that utilizes multiple strategies. For convenience, \( U(S^*; s, x_\epsilon) \) is denoted as \( U_{s}(S^*) \). The stability of the strategy, when it exists, is guaranteed only when the number of users deviating from strategy \( s \) is sufficiently small.

**Existence of ESS—the general framework**

In this section, we describe the conditions in which a homogeneous system of SUs is an ESS—that is, invasion by any competing mixed strategy will fail, provided the invading population is sufficiently small.

We will first state a general formulation of conditions for an ESS in the lemma below. This lemma will be specialized and applied to homogeneous systems of ACUs, FCUs, and SFUs in the next section. The next definition is helpful in the results that follow.

**Definition 1.** Let \( S^* \) be the system in (3), and \( \sigma^* = (p^*, q^*, k^*) \) and \( \sigma = (p, q, k) \) are mixed strategies where ACU, FCU, SFU are used with probabilities \( p^*, q^*, k^* \), for \( \sigma^* \) and \( p, q, k, \) for \( \sigma \), respectively; where \( (p^* + q^* + k^* = 1) \) and \( (p + q + k = 1) \). Define

\[
A(S^*, \sigma^*, \sigma) = p^*(p^* - p) \cdot U_{ACU}(S^*) + q^*(q^* - q) \cdot U_{FCU}(S^*) + k^*(k^* - k) \cdot U_{SFU}(S^*)
\]

\[
B(S^*, \sigma^*, \sigma) = (p^* - p)^2 \cdot U_{ACU}(S^*) + (q^* - q)^2 \cdot U_{FCU}(S^*) + (k^* - k)^2 \cdot U_{SFU}(S^*)
\]
Lemma 1. Let $S^*$ be the system in (3), and suppose that the majority $1-\epsilon$ of SUs employ $\sigma^* = (p^*, q^*, k^*)$ where the ACU, FCU, SFU strategies are used with probabilities $p^*$, $q^*$, $k^*$, respectively. When a small $\epsilon$ fraction of SUs contemplate a defection to a mixed strategy $\sigma = (p, q, k)$ where ACU, FCU, and SFU strategies are used with probabilities $p$, $q$, $k$, respectively, then for $\epsilon$ sufficiently small, the defection fails to be rational. In particular, $S^*$ is evolutionarily stable as long as

$$\epsilon < \frac{A(S^*, \sigma)}{B(S^*, \sigma)}$$  \quad (29)$$

Proof. Since $\epsilon \approx 0$ the payoff for a defecting player is:

$$U_\sigma(S^*) = p \cdot U_{ACU}(S^*) + q \cdot U_{FCU}(S^*) + k \cdot U_{SFU}(S^*)$$ \quad (30)$$

The existence of an ESS in an EGT game requires the inequality condition of Equation (2) to hold. Suppose $\sigma^* = (p^*, q^*, k^*)$ is the strategy employed in $S^*$ and $\sigma = (p, q, k)$ is the strategy of the defectors. The utility achieved by the defectors is

$$U_\sigma = p [p^* - \epsilon(p^* - p)] \cdot U_{ACU}(S^*) + q [q^* - \epsilon(q^* - q)] \cdot U_{FCU}(S^*) + k [k^* - \epsilon(k^* - k)] \cdot U_{SFU}(S^*)$$ \quad (31)$$

while the non-defectors achieve

$$U_{\sigma^*} = p^* [p^* - \epsilon(p^* - p)] \cdot U_{ACU}(S^*) + q^* [q^* - \epsilon(q^* - q)] \cdot U_{FCU}(S^*) + k^* [k^* - \epsilon(k^* - k)] \cdot U_{SFU}(S^*)$$ \quad (32)$$

It is easy to check that $U_{\sigma^*} > U_\sigma$ if and only if $\epsilon < A/B$. \qed

Existence of ESS

Since we have three pure strategies and one mixed strategy, we need the following five propositions to study the existence of ESS:

Proposition 1. If $S^*$ is a homogeneous system of ACUs, a defection to strategy $\sigma = (p, q, k)$ by an $\epsilon$ fraction of players fails to be rational if $\epsilon$ is less than

$$\frac{(1 - p) \cdot U_{ACU}(S^*)}{(1 - p)^2 \cdot U_{ACU}(S^*) + q^2 \cdot U_{FCU}(S^*) + k^2 \cdot U_{SFU}(S^*)}$$
Proof. Using Lemma 2, we specialize Definition 2 to the situation \( \sigma^* = (1, 0, 0) \) to obtain

\[
A(S^*, \sigma) = (1 - p) \cdot U_{\text{ACU}}(S^*)
\]

(33)

\[
B(S^*, \sigma) = (1 - p)^2 \cdot U_{\text{ACU}}(S^*) + q^2 \cdot U_{\text{FCU}}(S^*) + k^2 \cdot U_{\text{SFU}}(S^*)
\]

(34)

The proposition is proved. \( \square \)

As \( U_{\text{ACU}}(S^*) \) decreases, we see that the bound on \( \epsilon \) in Proposition 6 approaches 0, making it more likely that users will defect away from the homogeneous ACU society. Conversely, as \( U_{\text{ACU}}(S^*) \) increases relative to \( U_{\text{FCU}}(S^*) \) and \( U_{\text{SFU}}(S^*) \), we see that the bound on \( \epsilon \) approaches 1, making it so users will be unable to defect away from the homogeneous ACU society without group coordination.

**Proposition 2.** If \( S^* \) is a homogeneous system of FCUs, a defection to strategy \( \sigma = (p, q, k) \) by an \( \epsilon \) fraction of players fails to be rational if \( \epsilon \) is less than

\[
\frac{(1 - q) \cdot U_{\text{FCU}}(S^*)}{p^2 \cdot U_{\text{ACU}}(S^*) + (1 - q)^2 \cdot U_{\text{FCU}}(S^*) + k^2 \cdot U_{\text{SFU}}(S^*)}
\]

Proof. Using Lemma 2, we specialize Definition 2 to the situation \( \sigma^* = (0, 1, 0) \) to obtain

\[
A(S^*, \sigma) = (1 - q) \cdot U_{\text{FCU}}(S^*)
\]

(35)

\[
B(S^*, \sigma) = p^2 \cdot U_{\text{ACU}}(S^*) + (1 - q)^2 \cdot U_{\text{FCU}}(S^*) + k^2 \cdot U_{\text{SFU}}(S^*)
\]

(36)

The proposition is proved. \( \square \)

As \( U_{\text{FCU}}(S^*) \) decreases, we see that the bound on \( \epsilon \) in Proposition 7 approaches 0, making it more likely that users will defect away from the homogeneous FCU society. Conversely, as \( U_{\text{FCU}}(S^*) \) increases relative to \( U_{\text{ACU}}(S^*) \) and \( U_{\text{SFU}}(S^*) \), we see that the bound on \( \epsilon \) approaches 1, making it so users will be unable to defect away from the homogeneous FCU society without group coordination.

**Proposition 3.** If \( S^* \) is a homogeneous system of SFUs, a defection to strategy \( \sigma = (p, q, k) \) by an \( \epsilon \) fraction of players fails to be rational if \( \epsilon \) is less than

\[
\frac{(1 - k) \cdot U_{\text{SFU}}(S^*)}{p^2 \cdot U_{\text{ACU}}(S^*) + q^2 \cdot U_{\text{FCU}}(S^*) + (1 - k)^2 \cdot U_{\text{SFU}}(S^*)}
\]
Proof. Using Lemma 2, we specialize Definition 2 to the situation \( \sigma^* = (0, 0, 1) \) to obtain

\[
A(S^*, \sigma) = (1 - k) \cdot U_{SFU}(S^*)
\]  
(37)

\[
B(S^*, \sigma) = p^2 \cdot U_{ACU}(S^*) + q^2 \cdot U_{FCU}(S^*) + (1 - k)^2 \cdot U_{SFU}(S^*)
\]  
(38)

The proposition is proved. \( \square \)

As \( U_{SFU}(S^*) \) decreases, we see that the bound on \( \epsilon \) in Proposition 7 approaches 0, making it more likely that users will defect away from the homogeneous SFU society. Conversely, as \( U_{SFU}(S^*) \) increases relative to \( U_{ACU}(S^*) \) and \( U_{FCU}(S^*) \), we see that the bound on \( \epsilon \) approaches 1, making it so users will be unable to defect away from the homogeneous SFU society without group coordination.

**Proposition 4.** If \( S^* \) is a system in which

\[
U_{ACU}(S^*) = U_{FCU}(S^*) = U_{SFU}(S^*)
\]

then no evolutionary stable strategy exists in \( S^* \).

**Proof.** If all utilities of all strategies are equal then players may switch and mix strategies without penalty, and because the strict inequality in (2) cannot be made to hold for any strategy, no strategy is evolutionarily stable. \( \square \)

**Proposition 5.** If \( S^* \) is a system in which \( U_{ACU}(S^*) \), \( U_{FCU}(S^*) \) and \( U_{SFU}(S^*) \) are pairwise distinct, and \( \sigma \) is evolutionary stable strategy in \( S^* \), then \( \sigma \) is a pure strategy.

**Proof.** Suppose \( \sigma \) is the ESS. The payoff for this strategy is

\[
U_\sigma(S^*) = p \cdot U_{ACU}(S^*) + q \cdot U_{FCU}(S^*) + k \cdot U_{SFU}(S^*)
\]

This function is convex combination, and so is maximized by placing all the probability mass on the unique strategy which has the highest utility. Thus, precisely one of the values \( p, q, k \) is equal to 1. \( \square \)

**Corollary 1.** If \( S^* \) is a system in which \( U_{ACU}(S^*) \), \( U_{FCU}(S^*) \) and \( U_{SFU}(S^*) \) are pairwise distinct, and
\(\sigma\) is evolutionary stable strategy in \(S^*\), then

\[
\sigma = \begin{cases}
ACU & \text{if } U_{ACU}(S^*) > U_{FCU}(S^*), U_{SFU}(S^*) \\
FCU & \text{if } U_{FCU}(S^*) > U_{ACU}(S^*), U_{SFU}(S^*) \\
SFU & \text{if } U_{SFU}(S^*) > U_{ACU}(S^*), U_{FCU}(S^*)
\end{cases}
\]  

(39)

Finding an ESS

**Theorem 1.** For a system \(S^*\) where \(X_i(S^*) \approx 1\), ACU is a winning strategy iff: \(P_c < \min(1, \frac{1}{G_s})\).

**Proof.** Corollary 2 mandates that \(U_{ACU}(S^*) > U_{FCU}(S^*)\) and \(U_{ACU}(S^*) > U_{SFU}(S^*)\), which implies:

\[
\frac{1}{M} \sum_{i=1}^{M} X_i(S^*) > P_c \sum_{i=1}^{M} C_i \cdot X_i(S^*)
\]  

(40)

\[
\frac{1}{M} \sum_{i=1}^{M} X_i(S^*) > P_c \sum_{i=1}^{M} \frac{C_i}{M} \cdot G_s \cdot X_i(S^*)
\]  

(41)

Substituting \(X_i(S^*) = 1\) and \(\sum_{i=1}^{M} C_i = 1\), we get

\[
P_c < 1
\]  

(42)

\[
P_c \cdot G_s < 1
\]  

(43)

The theorem is proved.

**Theorem 2.** For a system \(S^*\), where

\[
\forall i, j : 1 \ldots M, \ C_i = C_j
\]

ACU is a winning strategy iff: \(P_c < \min(1, \frac{1}{G_s})\).

**Proof.** Since \(C_i = C_j\) for all \(i, j\) it follows that

\[
\overline{C}_i = \overline{C}_j = 1/M
\]

Substituting into inequalities (8) and (9), we get

\[
P_c < 1
\]  

(44)

\[
P_c \cdot G_s < 1
\]  

(45)

The theorem is proved.
Reflections on Theorems (5) and (6): The antecedent in Theorem (5) means that all channels are able to accommodate the demand, and thus, from the nodes’ perspective, their demand is fulfilled regardless of their channel choices. The ACUs benefit directly from this condition as they randomly access the channels. The SFUs and FCUs detect this condition using their foraging capability, but to gain this knowledge, they sacrifice some of their channel access time by foraging some fraction \( (P_f = 1 - P_c) \) of the time. This behavior hinders their ability to gain utility relative to the ACUs. On the other hand, SFUs can recapture some of this loss by the advantage derived from social behavior \( (G_s) \). As long as the effects of foraging and social gain are less than 1; however, the SFUs cannot outperform the ACUs under this condition. The antecedent in Theorem (6), states that the utilities of all channels are equal but not necessarily equals 1. This happens when the different channels provide similar throughput; this uniformity implies that the utility lost due to time spent foraging was in vain since it yielded no information about the channel environment; leading to the same conclusion as that of Theorem (5).

**Theorem 3.** For a system \( S^* \), FCU is a winning strategy iff:

\[
P_c > \frac{1}{M} \sum_{i=1}^{M} C_i \cdot X_i^c(S^*)
\]

\[
G_s < 1
\]  

**Proof.** Corollary 2 mandates that \( U_{FCU}(S^*) > U_{ACU}(S^*) \) and \( U_{FCU}(S^*) > U_{SFU}(S^*) \), which implies:

\[
P_c \sum_{i=1}^{M} C_i \cdot X_i^c(S^*) > \frac{1}{M} \sum_{i=1}^{M} X_i^c(S^*)
\]

\[
P_c \sum_{i=1}^{M} C_i \cdot X_i^c(S^*) > P_c \sum_{i=1}^{M} C_i \cdot G_s \cdot X_i^c(S^*)
\]

Rearranging the terms of the two inequalities, the theorem is proved.

Reflections on Theorem 7: The antecedent in Theorem (7) asserts a lower-bound on the probability of consuming, that is the ratio of the ACU and FCU utilities, and indicate that the social gain is smaller than 1. We know already from Theorems (5) and (6), that the ACUs outperform all strategies when channels have uniform conditions. In non-uniform settings, the FCUs and SFUs have the tendency to access channels with better throughput, based on the values of \( C_i \). In non-uniform channel settings, the weighted average in the denominator is greater than the unweighted average in the numerator, and so the ratio of the ACU to the FCU utilities decreases below 1; the lower bound on \( P_c \) then drops correspondingly, and (for appropriately chosen \( P_c < 1 \)) foraging wins. The second antecedent lower-bounds the sociality gain \( (G_s) \) to be less than 1. This condition restricts the antecedent lower-bounds the SFUs from compensating for their
social coordination overhead and ensures that FCUs outperform SFUs.

**Theorem 4.** For a system $S^*$, SFU is a winning strategy iff:

$$ P_c > \frac{1}{M} \sum_{i=1}^{M} \frac{X_i^i(S^*)}{C_i \cdot G_s \cdot X_i^i(S^*)} $$

(50)

and

$$ G_s > 1 $$

(51)

**Proof.** Corollary 2 mandates that $U_{FCU}(S^*) > U_{ACU}(S^*)$ and $U_{FCU}(S^*) > U_{SFU}(S^*)$, which implies:

$$ P_c \sum_{i=1}^{M} C_i \cdot G_s \cdot X_i^i(S^*) > \frac{1}{M} \sum_{i=1}^{M} X_i^i(S^*) $$

(52)

$$ P_c \sum_{i=1}^{M} C_i \cdot G_s \cdot X_i^i(S^*) > P_c \sum_{i=1}^{M} C_i \cdot X_i^i(S^*) $$

(53)

Rearranging terms of the two inequalities, the theorem is proved.

**Reflections on Theorem 8:** The antecedent in Theorem (8) asserts a lower-bound the probability of consume, that is the ratio of the ACU and the SFU utilities, and prescribe a sociality gain greater than 1. We know already from Theorems (5) and (6), that the ACUs outperform all strategies when channels have uniform conditions. In non-uniform settings, the FCUs and the SFUs have the tendency to access channels with better throughput, based on the values of $C_i$. In non-uniform channel settings, the weighted average in the denominator is greater than the unweighted average in the numerator, and so the ratio of the ACU to the SFU utilities decreases below 1; the lower bound on $P_c$ then drops correspondingly, and (for appropriately chosen $P_c < 1$) foraging wins. The second antecedent lower-bounds the sociality gain ($G_s$) to be greater than 1. This condition allows the SFUs to benefit from their social coordination and ensures that SFUs outperform FCUs.

**Replicator Dynamics and Rate of Convergence**

The Nash equilibrium doesn’t describe the evolution process of the population to reach equilibrium, especially in games with multiple equilibria [62]. On the other hand, the replicator dynamics details the evolution mechanisms through which the population arrives at an ESS. Following the general equation for replicator dynamics, we define $x_i$ as the portion of the population playing strategy $i$ and $f_i(x)$ as the fitness of strategy $i$:

$$ \dot{x}_i = x_i [f_i(x)] - \sum_{j}^n x_j \cdot f_i(x) $$

(54)
where $\dot{x}$ represents the rate of change of $x$ per unit time. In order to study the rate of convergence to an ESS, we define $c_1$, $c_2$ and $c_3$ as follows:

\[ c_1 = [U_{ACU} \cdot (1 - x_{ACU}) - U_{FCU} \cdot x_{FCU} - U_{SFU} \cdot x_{SFU}] \]  \hspace{1cm} (55)\]
\[ c_2 = [U_{FCU} \cdot (1 - x_{FCU}) - U_{ACU} \cdot x_{ACU} - U_{SFU} \cdot x_{SFU}] \]  \hspace{1cm} (56)\]
\[ c_3 = [U_{SFU} \cdot (1 - x_{SFU}) - U_{ACU} \cdot x_{ACU} - U_{FCU} \cdot x_{FCU}] \]  \hspace{1cm} (57)\]

The replicator dynamics of the ACU, FCU, and SFU strategies is represented as:

\[ \dot{x}_{ACU} = c_1 \cdot x_{ACU} \]  \hspace{1cm} (58)\]
\[ \dot{x}_{FCU} = c_2 \cdot x_{FCU} \]  \hspace{1cm} (59)\]
\[ \dot{x}_{SFU} = c_3 \cdot x_{SFU} \]  \hspace{1cm} (60)\]

Solving for $x_{ACU}$, $x_{FCU}$ and $x_{SFU}$ yields:

\[ x_{ACU} = x_{ACU}(0)e^{c_1 t} \]  \hspace{1cm} (61)\]
\[ x_{FCU} = x_{FCU}(0)e^{c_2 t} \]  \hspace{1cm} (62)\]
\[ x_{SFU} = x_{SFU}(0)e^{c_3 t} \]  \hspace{1cm} (63)\]

The number of users in the community is constant, and hence:

\[ x_{ACU} + x_{FCU} + x_{SFU} = 1 \]  \hspace{1cm} (64)\]

implying that:

\[ \frac{N_{ACU}}{N} + \frac{N_{FCU}}{N} + \frac{N_{SFU}}{N} = 1 \]  \hspace{1cm} (65)\]

at any point of time.

This implies that users leaving one strategy will be captured by another strategy in the system. The rate of convergence differs based on the values of $c_1$, $c_2$ and $c_3$. That means the time needed for every strategy to evolve in the system depends on the deviation of population from this strategy. This evolution converges exponentially; therefore, making the system stable to temporal changes.
Discussions

We can conclude the following based on the analytical results presented in this work:

*Similar vs. dissimilar channels’ capacities:* For channels with dissimilar capacities, the FCU and SFU strategies perform better than the ACU strategy, under proper forage and social tendencies. This is due to the fact that the ACU strategy suffers from degraded throughput over crowded channels, while the FCU and SFU strategies balance their losses among channels based on their relative capacities. For channels with similar capacities, the ACU strategy outperforms as it does not have the overhead associated with foraging and social coordination as that of the FCU and SFU strategies.

*Mixed strategies vs. pure strategies:* The utility of a mixed strategy is the weighted sum of the utilities of the three constituent strategies. A given SU can play a mixed strategy to maximize its benefit. Since the sum of probabilities for the three strategies equals 1, the maximum utility is obtained when a player maximizes the weight that corresponds to the maximum utility. By maximizing this probability, the mixed strategy changes to be closer to the pure strategy that has the maximum utility. Furthermore, no combination maximizes the utility if one of the strategies is better than others as described in Proposition 5. If the utilities of all strategies are equal, there is no ESS in the system since the user can arbitrary choose different strategies that achieve the same utility.

*Replicator dynamics:* The rate of convergence of the population towards the ESS strategy is important to quantify the time needed for the population to reach an ESS. This rate depends on the relative fitness of the strategies.
Table 3: Experimental Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of SUs</td>
<td>80</td>
</tr>
<tr>
<td>Number of Channels</td>
<td>4</td>
</tr>
<tr>
<td>PU traffic (Mbps)</td>
<td>Homogeneous:[1, 1, 1, 1]</td>
</tr>
<tr>
<td></td>
<td>Heterogeneous:[19, 19, 25, 25]</td>
</tr>
<tr>
<td>WLAN Standard</td>
<td>IEEE 802.11g</td>
</tr>
<tr>
<td>WLAN channel capacity</td>
<td>ns-3 network: 11Mbps</td>
</tr>
<tr>
<td></td>
<td>Physical network: 54Mbps</td>
</tr>
<tr>
<td>Distance from AP</td>
<td>10m for ns-3 network</td>
</tr>
<tr>
<td>Transmission power</td>
<td>16.0206 dBm (default) [31]</td>
</tr>
<tr>
<td>Channel Propagation Model</td>
<td>Log Distance Propagation Model [32]</td>
</tr>
<tr>
<td>CBR transmission rate per SU (kbps)</td>
<td>10 Kbps (light), 40 Kbps (intermediate)</td>
</tr>
<tr>
<td></td>
<td>65 Kbps (heavy)</td>
</tr>
</tbody>
</table>

Experimental Results

In this section, a testbed is presented to experiment with channel switching and strategy evolution in Wireless Local Area Networks (WLANs). The testbed design and implementation are described next, followed by experimental results and discussions.

Experimental Testbed

For experimental purposes, a testbed was developed; its architecture is shown in Figure 26. Five Small-Form Factor Singe-Board Computers (SBCs) are setup with Ubuntu Linux. The SBCs are UDOO devices with ARM i.MX6 NXP® processor. Each SBC is equipped with a Netgear-N150 Wireless-N USB adapter, enabled with Atheros device driver. ns-3 is installed on two SBCs to transmit and receive SUs traffic. The ns-3 network in these two SBCs runs as a WLAN 802.11g network: network nodes (SUs) are uniformly distributed around an Access Point (AP) on a circle with 10m radius, eliminating the impact of distance on the SUs’ throughput variability. A standard log-distance channel propagation model is used [32]. System parameters are listed in Table 7. At the same time, a second pair of SBCs are dedicated for emulating the behavior of primary users. To experiment with channels that have different capacities, PU traffic is generated on the channel using the iperf tool in Linux and the back-off algorithm is turned off on the WiFi devices so that PUs have priority over the SUs to access the channels. This behavior is realized by changing the register values in the ModWiFi [63] device driver and verified experimentally (see Table 4). Finally, a 5th SBC represents the node manager that controls the experiments and monitors the traffic over the physical channel using wireshark.

Each experiment is split into two phases: (1) channel switching and (2) strategy evolution (see Figure 9). Each phase, in turn, is divided into iterations, and the duration of each iteration is 60 seconds. Within a channel switching phase, each SU operates by switching channels, transmitting data, and following its
strategy. At the end of each iteration, the total throughput within each physical channel is tabulated; this data is used as a proxy measurement for the CSI, and is then used to inform strategy selection for the next iteration.

In this work, the channel estimation is sent to the SUs in centralized fashion. The node manager collects the channels estimations and send it to the SUs. In general, the SUs can implement both types of sensing, namely: channel sensing: to obtain channel capacity and social sensing: to obtain the identities of co-users, in a distributed or centralized fashion. Only SFUs exchange and coordinate information (as part of their social functions) to implement the deference behavior. ACUs and FCUs act independently and FCUs obtain their own channels estimates, without exchanging information with other SUs.

In our experiments, we consider a range of CR scenarios. Throughout, we assume a network of 80 SUs sharing 4 channels (each with 11 Mbps channel capacity) in ns-3 real-time mode. We always start with 20 SUs on each ns-3 channel, with 80% of the SUs being of one type, and 10% of each of the other two types. After each iteration is completed the node manager reports CSI to all SUs so they can update their channel selection probabilities as well as for strategy evolution decisions.

In some experiments, residual channel capacities are taken to be homogeneous: all channels having the PUs transmitting at 1 Mbps. In other experiments, channels are assumed heterogeneous: two channels have the PUs transmitting at 19 Mbps and two having the PUs transmitting at 0.25 Mbps. We take the SUs’ load to be either light: each SU transmits at a rate of $R = 10$ Kbps, moderate $R = 40$ Kbps, or heavy $R = 65$ Kbps. The total offered traffic thus ranges from 200 Kbps to 1300 Kbps.

Figure 16 illustrates the steps followed in each iteration. These steps are detailed in the following paragraphs:

1. The experiment starts by preparing the configuration for nodes in the setup phase (see Figure 16). The node manager sends commands to the PU-Rx node to be ready for receiving data from the PU-Tx node.

2. The node manager sends commands to the PU-Tx node to start transmission using the iperf tool with a pre-defined transmission rate. The PU data transmission is initiated first to ensure that the channel is loaded with PU traffic prior to SU transmissions on the channel.

3. The node manager sends commands to the SU-Rx and SU-Tx nodes to start receiving and transmitting data, respectively.

4. For SU traffic, UDP packets from the SU-Tx node are passed from the ns-3 network through the tap-bridge device to the WiFi device on the UDOO SBC.

5. Packets are then transmitted over the air on the physical WLAN channel, under the presence of
Table 4: Results of a Single Iteration

<table>
<thead>
<tr>
<th>Channel Number</th>
<th>PU’s demand (Theoretical) (Mbps)</th>
<th>PU’s throughput (Experimental) (Mbps)</th>
<th>SU throughput per user ACU, FCU, SFU (Kbps)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20</td>
<td>20.00</td>
<td>0.073, 0.034, 0.103</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>19.70</td>
<td>0.047, 0.021, 0.239</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>0.497</td>
<td>17.70, 24.88, 42.97</td>
</tr>
<tr>
<td>4</td>
<td>0.5</td>
<td>0.497</td>
<td>14.91, 22.66, 34.58</td>
</tr>
</tbody>
</table>

the PU traffic.

6. In the corresponding SU-Rx node, packets that received by WiFi devices are passed to the ns-3 SU-Rx node through the tap-bridge.

7. Throughput counters are used to calculate the throughput for data flows.

8. Throughput values for different SUs are sent to the node manager in order to make channel switching and strategy evolution decisions.

9. The node manager waits for the results and checks the connectivity among the PU and SU devices and saves the results used for the next experiment.

10. The node manager receives CSI details (i.e., throughput) from the SU-Rx node.

11. Prior to starting the next iteration, a small number of randomly selected SUs are permitted to use the aggregated data as the basis for changing strategies; in our experiments, this small set of “evolving” SUs choose a strategy which outperformed their current strategy in the previous phase. Consequently, SUs use their communal experiences within phases to learn about the strategy that is better suited to the given DSA scenario.

If no system utility enhancement is achieved and the SUs strategies stable for 5 iterations, the system is considered as converged and the experiment is terminated.

A result of one iteration is shown in Table 4. These results are associated with the results in Table 5-Figure (g). It can be clearly seen that the PUs obtained the required throughput, while the SUs (ACUs, FCUs, and SFUs) obtained throughput based on the remaining capacity during the PU transmissions.

**Results**

We describe $3 \times 3 = 9$ different scenarios covering all the possibilities in which one of the 3 strategies (ACU, FCU, SFU) is dominant at the beginning, and another is eventually dominant post-evolution. These experiments are illustrated in Table 5. Each column represents the initially dominant strategy in
Figure 9: Channel switching and strategy evolution of SUs.

Each of the scenarios, while the row represents the final dominant strategy. Each cell of the table is labeled by its environmental parameters (above) and an informal description (below). 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 11. Running the experiment with different values for media access eagerness (reflected in $P_c$), social preferences (captured by $P_s$), and channel characteristics (i.e. PU traffic assumptions) results in different evolution patterns. While PU traffic affects all three strategies, $P_c$ only mediates the performance of FCU and SFU strategies.

To assess the efficacy of the ACU strategy, we conducted 3 experiments using the experimental channel and strategy parameters detailed in Table 7 and in the headers above each of the figures in Table 5-Figure (a)-(c). In these scenarios, all channels were lightly loaded with PUs (0.25Mbps). In these experiments, the ACUs are uniformly distributed over the channels. The FCU and SFU strive to maximize their utility by accessing better channels more often. Hence, all strategies end up distributing their users equally over the channels. Since the FCUs and SFUs have less probability to transmit over the channel due to their probability of foraging $1 - P_c = 0.1$, the utilities of the FCUs and SFUs decrease and the ACU
strategy dominates the community. In our experiments, the ACU baseline strategy showed (2.6 – 21.3%) improvement over other strategies as shown in Figure 11-Columns (a)-(c). The SFU strategy utility decreased in the community since the probability of deference is high (i.e., $P_s = 0.9$). The ACU strategy still had the potential to be the winning strategy since ACUs transmit on all channels while the FCU and SFU transmissions are decreased due to their foraging behavior.

To assess the efficacy of the FCU strategy, we conducted 3 experiments using the experimental channel and strategy parameters detailed in Table 7 and in the headers above each of the figures in Table 5-Figure (d)-(f). In these scenarios, two channels were highly loaded with PUs (19Mbps), and two channels were lightly loaded (250kbps). In these scenarios, the ACU strategy does not adapt to the channel conditions since ACUs are distributed quasi equally over channels. In contrast, the FCUs and SFUs are distributed with more probability on channels 3 and 4 since they have more benefit in terms of throughput due to better channel conditions. Notice that even though the FCU and the SFU strategies lose $1 - P_c$ amount of their utility on the channels, they compensate that by switching to better channels. Furthermore, the FCU strategy has more potential in the community since the SFU strategy suffers from $S_-$ which decreases its utility especially in scenarios in which $S_+$ is low. The three scenarios also present the FCU strategy with different initial number of users where it needs to be the ESS in the community. In our experiments, the FCU strategy showed (20.3 – 42.2%) improvement over other strategies as shown in Figure 11-Columns (d)-(f).

To assess the efficacy of the SFU strategy, we conducted 3 experiments using the experimental channel
Figure 11: Experimental throughput improvement.

Table 5: Experimental Evaluation of the ACU, FCU, and SFU Strategies

<table>
<thead>
<tr>
<th>Homogeneous channels, Light load</th>
<th>$P_s : 0.9, P_c : 0.9, S_\infty : 0.15, PU_i(Mbps) : 1, 1, 1$</th>
</tr>
</thead>
</table>

(a) ACU initially dominant, ACU eventual winner

<table>
<thead>
<tr>
<th>Homogeneous channels, Light load</th>
<th>$P_s : 0.9, P_c : 0.85, S_\infty : 0.15, PU_i(Mbps) : 1, 1, 1$</th>
</tr>
</thead>
</table>
(b) FCU initially dominant, ACU eventual winner.

Homogeneous channels, Light load

\[ P_x : 0.9, P_c : 0.85, S_- : 0.15, S_+ : 0.05, \text{PU}_i (Mbps) : 1, 1, 1 \]

(c) SFU initially dominant, ACU eventual winner.

Heterogeneous channels, Moderate load

\[ P_x : 0.8, P_c : 0.98, S_- : 0.31, S_+ : 0.04, \text{PU}_i (Mbps) : 19, 19, 0.25, 0.25 \]

(d) ACU initially dominant, FCU eventual winner.

Heterogeneous channels, Moderate load

\[ P_x : 0.9, P_c : 0.97, S_- : 0.32, S_+ : 0.05, \text{PU}_i (Mbps) : 19, 19, 0.25, 0.25 \]
(e) FCU initially dominant, FCU eventual winner.

Heterogeneous channels, Moderate load

\( P_s : 0.8, P_c : 0.95, S_- : 0.3, S_+ : 0.05, \ PU_i(Mbps) : 19, 19, 0.25, 0.25 \)

(f) SFU initially dominant, FCU eventual winner.

Heterogeneous channels, Heavy load

\( P_s : 0.5, P_c : 0.98, S_- : 0.07, S_+ : 0.3, \ PU_i(Mbps) : 19, 19, 0.25, 0.25 \)

(g) ACU initially dominant, SFU eventual winner.

Heterogeneous channels, Heavy load

\( P_s : 0.5, P_c : 0.95, S_- : 0.04, S_+ : 0.27, \ PU_i(Mbps) : 19, 19, 0.25, 0.25 \)
(h) FCU initially dominant, SFU eventual winner.

Heterogeneous channels, Heavy load

\[ P_s : 0.5, P_c : 0.98, S_- : 0.06, S_+ : 0.31, \text{PU}_l(Mbps) : 19, 19, 0.25, 0.25 \]

(i) SFU initially dominant, SFU eventual winner.

and strategy parameters detailed in Table 7 and in the headers above each of the figures in Table 5-Figure (g)-(i). In these scenarios, two channels were highly loaded with PUs (19Mbps), and two channels were lightly loaded (250kbps). The SFUs had less overhead due to cooperation (i.e., \( S_- \) decreased), and receive more enhancement (i.e., \( R \) increased by \( S_+ \)). The FCU and SFU strategies had more potential over the ACU strategy due to channel switching, and the SFU strategy had more benefits due to the social behavior, by allowing \( P_s \) percent of SFUs users (50%) to transmit over better channels with the elevated rate. The SFU strategy then dominates the community and evolve to be the ESS. In our experiments, the SFU strategy showed (39.1 – 78.3%) improvement over other strategies as shown in Figure 11-Columns (g)-(i).
Discussions

The experimental results are discussed further below.

*The ACU strategy* outperforms the other strategies in scenarios that involve lightly loaded channels with similar capacities. In such scenarios, the ACU strategy outperforms since the foraging and sociality incur unnecessary overhead that negatively impacts the SUs’ utilities and the overall system utility.

*The FCU strategy* outperforms the other strategies in scenarios that involve moderately loaded channels with dissimilar capacities. In such scenarios, employing the foraging behavior is advantageous (relative to the ACU strategy) because it allows the SUs to find and use better channels. Social behavior is not advantageous since the deference behavior does not yield significant advantage to reduce the contention on the channels since the channels are not heavily loaded.

*The SFU strategy* outperforms other strategies in scenarios that involve heavily loaded channels with dissimilar capacities. By employing the social deference behavior, only $1 - P_s$ fraction of the SFUs transmit at a higher rate, while the remaining defer—this yields higher system utility. This is due to the reduction in contention over channels.

*Long-term versus Short-term*: The ACU strategy represents a short-term behavior, in which SUs tend to access channels immediately. The FCU and SFU strategies show more long-term behavior, in which they sacrifice part of their time to sense the channels and then access better resources in later time.

*Altruism versus Selfishness*: The SFU strategy shows an altruistic behavior, in which SUs are deferring to each other based on their social relationships. In contrast, the ACU and FCU strategies show self-centered selfish behaviors, in which they access channels ignoring the identity of other SUs on the channels.

Conclusion

In this work, we devised three different strategies in order to address the social aspects of DSA etiquette. We proved analytically that each strategy has a potential to win or lose in a system of SUs, based on the condition of the channels utilized and social attributes of the users. Given channel conditions and users’ behaviors, SUs evolve to one and only one strategy that is considered evolutionary stable. We showed analytically that no mixed strategies yield a stable strategy for the system. Furthermore, we showed that, under some conditions, SUs with more social tendency gain more benefits on the long run when compared with selfish SUs, who prefer myopic, short-term benefits. The proposed analytical framework, can be extended to study new strategies that exhibit a distinct social and cognitive behaviors, depending on observed community of SUs and network metrics. Future work includes, but not limited to, applying the proposed strategies in different use cases such as EHS, IoT, and VANETs.
Acknowledgments

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Chapter 4

From Channel Selection to Strategy Selection: Enhancing VANETs using Foraging and Deference

Abstract: Dynamic Spectrum Access (DSA) has been hailed as a possible panacea for the “spectrum crunch,” drawing significant attention from researchers and industry alike. Here we describe a novel system architecture for vehicular ad-hoc networks (VANETs) that relies on the DSA framework. In our system, nodes continuously and independently choose one of three strategies for channel selection. Two of these strategies are bio-socially inspired, based on resource sharing behaviors known to have been prevalent in human societies over the course of their natural evolution. We view the strategy selection problem as an evolutionary game, proving that the only evolutionarily stable strategy is one in which all nodes utilize the same strategy that depends on the social characteristics of the nodes and the current channel conditions. Within our system, a specialized Road Side Unit (RSU) continuously computes the game-theoretically optimal evolutionarily stable strategy and broadcasts this recommendation to all VANET nodes. Through ns-3 simulation experiments across a range of social characteristics and channel condition scenarios, we demonstrate a significant and robust improvement in utility (between 3% – 136%) is achieved when a large fraction of VANET nodes adopt the RSU’s recommendation. The approach represents a bold departure from previous research which sought to track and micro-manage channel resources, to one that provides VANET nodes with channel selection strategy recommendations.
that is both optimized for throughput and robust against attempts at circumvention by deviant users.

**Introduction**

Intelligent transportation systems promise to deliver new safety and efficiency applications including pedestrian and vehicular safety, reduced fuel consumption, and reduced pollution. The design focus of new systems typically prioritizes one of several broad areas: safety, efficiency, convenience, and infotainment applications [64].

Vehicular Ad-hoc Networks (VANETs) are a key technology enabling intelligent transportation systems (Vegni *et al.* provide a good recent survey [65]). In VANETs, vehicles communicate directly with each other and with road-side infrastructure. VANETs are critical communication environments due to the fast mobility of vehicles. The Dedicated Short Range Communications (DSRC) licensed spectrum helps address some of the communication needs of VANETS. Using DSRC spectrum resources in a manner that scales with VANET size, however, requires robust resource sharing protocols.

Dynamic Spectrum Access (DSA) is a new resource sharing paradigm in wireless networking, in which radio spectrum frequencies are assigned dynamically to users in order to combat spectrum scarcity. Cognitive Radio (CR) is a framework of enabling technologies which facilitate the implementation of self-configuring DSA networks [4] that allow spectrum sensing, management and sharing. The sensing technologies developed to coordinate PU-SU interactions [5] can be adapted within the CR paradigm to enable more harmonious SU-SU co-existence, and ensure more effective resource sharing.

Here we will develop a bio-socially inspired approach to DSA, with the objective of enhancing the throughput of infotainment applications in VANETs. The impact of this is ensured by the multi-channel structure of the DSRC in the IEEE Wireless Access to Vehicular Environment (WAVE) standard: by improving infotainment throughput, greater residual bandwidth becomes available for safety traffic. Generally speaking, bio-socially inspired algorithms leverage knowledge about social and biological communities to design resource management solutions in a variety of domains. Here we apply prior findings on observed behaviors and structures of resource sharing and co-use in human societies [66] to design a new and highly effective DSA scheme for VANETs. In keeping with the bio-social paradigm in what follows, we will use the phrase “consuming a resource” and “transmitting in a channel” interchangeably. Likewise, the phrase “foraging” will signify passively listening to traffic for the purpose of collecting channel state information, without transmitting.

This work considers 3 models of resource sharing behaviors:

- **Always Consume User (ACU):** A user who always consumes, choosing the resource to consume blindly at random.
• **Forage-Consume User (FCU):** A user who only sometimes consumes, and otherwise forages, using information gathered during foraging to choose where next to consume.

• **Social Forage-Consume User (SFU):** An FCU who sometimes “defers” to other SFUs, that is, refrains from consuming so as to allow other SFUs more exclusive access to the resource they are consuming.

To quantify the merit of our proposed behaviors, we will use both simulations and formal analysis using evolutionary game theoretic techniques. Game theory is a mathematical formalism that can model strategic interactions among agents, which has been used in a wide range of domains, including wireless spectrum sharing and sensing [67] [68]. We will rely on the sub-discipline of evolutionary game theory (EGT), which is specialized to strategic aspects of evolution in terms of individual fitness within a community [57]. Figure 18 depicts the relationships between our method and several closely related approaches in previous literature.

The remainder of this paper is organized as follows: Prior work is discussed in Section 4. Section 4 introduces the proposed approach followed by Section 4 in which we introduce the system model, and how the three proposed bio-socially inspired strategies are applied in the context of VANETs. Simulation results are discussed in Section 4. The formal analysis comparing the three strategies (two of which are bio-socially inspired) is presented in section 4. Finally, Section 4 provides a discussion of the implications, and an outlines of future research directions.

**Prior Work**

Different aspects of VANETs have been the subject of active and ongoing research. Several recent surveys consider VANETs from the specialized perspectives of routing [69], security [70], and new tech-
nologies [71]. Pagadarai et al. [72] were among the first to explore the potential application of DSA into vehicular communications, while Khabbas et al. [73] considered the application of DSA in Vehicle to Infrastructure (V2I) systems.

Some researchers have explored the possibility of using other bands, such as TV White Spaces (TVWS) [74, 75, 76]. Lim et al. use both TVWS and DSRC bands [75] by using TVWS for Emergency Safety Messages and DSRC for data and control messages. TVWS have also been utilized in the context of VANETs for route selection [77], minimizing channel switching overhead due to mobility [78], media streaming [79] and for VANET data offloading [80] [72]. In this paper, we limit consideration to the DSRC band and to its use for infotainment services.

The notion of “foraging” is of course closely related to spectrum sensing, which is in turn a central aspect of DSA and the subject of a lot of prior research (see the survey by Abeywardana et al. [81]). In the VANET context, Kremo et al. developed cooperative spectrum sensing mechanisms for TVWS [82]. Doost-Mohammady et al. developed a system using spectrum sensing base station for database-assisted cognitive vehicular networks [83]. Tradeoffs between local (vehicular) and global (database-assisted) spectrum sensing are considered by the work of Al-Ali et al. [84]. Along those lines, in this paper, we are less concerned with accurate sensing, and more concerned with understanding when sensed information (that is assumed to be accurate) can be profitably leveraged towards higher throughput, and when it cannot.

Huang et al. explored the potential of spectrum sensing to increase safety traffic throughput [85]; we are considering an analogous problem here for infotainment traffic.

Many researchers have designed and evaluated services that assist users in finding a good band. In contrast, in this paper, we propose a cloud-based solution that assists users in choosing a good channel selection strategy. Examples of previous approaches include that of Rawat et al. who proposed a cloud-based solution in which each vehicle downloads spectrum availability information on one fixed-channel device while actual vehicular communications take place on a second tunable-channel device [86]. Similarly, Luo et al. develop a database-assisted white space system incorporating technical and economic features [87]. In their system, white space information is updated periodically by spectrum licensees, and users send location-based queries to obtain current regional white space listings.

Several authors have previously proposed solutions with a bio-social component. Fei et al., for example, introduce the benefits of leveraging social centrality among users with common interests to enhance DSA in VANETs [88]. Sociality also plays a role in Frigau et al. proposal for an adaptive multi-channel social relay strategy [89] that optimizes the transmission of service updates. A social approach for SS is proposed in [90]. Perhaps closest to our own work is the that of Aygun et al., who developed novel bio-social DSA schemes for VANETs based on the social foraging and consumption behavior of bumblebees [91]. In this paper, our schemes are based on more complex cognitive and social processes which give rise
to a range of resource-sharing behaviors observed in human societies of the work of Wisniewska et al. [35] [10] [11] [12] [13] and Shattal et al. [14] [15]. The work benefits from the study provided by Dombrowski et al. [16] for resource sharing and management in the Inuit community in Labrador, Canada.

Approach

We begin with two observations: (1) Each user does not compete against one other user for a channel, but rather simultaneously against all other users and over all channels; (2) If users gradually change strategies over time by mimicking the strategies of peers who are achieving greater utility, then the system can be considered to be evolving. These two observations naturally point to an evolutionary game. Playing the field games consider the behavior of a large population of strategically interacting players [58], each of whom plays against the whole community (or a subset thereof). While pair-wise games require complete knowledge of the utilities (prior to the game), playing the field games involve the accumulation of empirical information on relative advantages of pure strategies (see Nash [59]). An Evolutionary Stable Strategy (ESS) is defined to be any strategy which, once adopted by a community, cannot be displaced by any different “invading” strategy. The ESS may be viewed a Nash equilibrium since players who unilaterally deviate from the ESS see no gain. Having recognized that our DSA problem in VANETs can be cast as a game against the field, the ESS of our game will turn out to be critical to our understanding of the VANET’s performance.

In the proposed architecture (see Figure 13), a community of vehicles moves along a network of roads that are covered by a set of fixed Road Side Units (RSUs), each of which is connected to a back-end cloud-based service. VANET nodes are responsible for periodically reporting their local Channel State Information (CSI) and sending it to their local RSU, stamped with the current time. Interference level, noise level, and capacity are examples of potential CSI. In this work, the CSI is simply each node’s measurement of its own recent throughput in its current channel; we take this as a proxy for the channel’s residual capacity. Each RSU receives this CSI information from VANET nodes, and continuously updates a geo-indexed spectrum availability database, effectively producing a live channel-by-channel residual capacity heatmap (see Figure 14). Each RSU periodically examines this live data, and then via a game-theoretic analysis computes a strategy recommendation, which it sends to all VANET nodes within its broadcast radius. It is important to note that the RSU’s recommendation is not for specific users to use specific channels\(^1\)—rather the RSU simply recommends that all users (uniformly) follow a particular strategy.

\(^1\)Indeed, individual channel occupancies are likely to be fluctuating so rapidly as to render specific channel recommendations useless.
System Model

Our proposed system supports \( N \) VANET nodes, each of which sends/receives infotainment data at a combined rate of \( R \) bits/s. The system is designed over the DSRC 5.9 GHz band in alternating mode (see WAVE standard [92] for details). In this mode, flexible alternating access is provided to support \( n = 6 \) service channels (SCHs) and 1 control channel (CCH). VANET nodes synchronize their transmission across a 100ms synchronization interval which is, in turn, divided into SCH (\( \alpha \) ms), CCH (\( \beta \) ms) and guard subintervals (see Figure 15, \( \alpha + \beta \approx 100\)ms). The node send/receives infotainment data (over IP) to the RSU during the SCH interval, as well as receiving any strategy recommendations broadcast by the RSU. During the CCH interval, the user broadcasts Basic Safety Messages (BSMs), WAVE short messages, and WAVE Service Announcements (WSAs). The last of these is used by vehicles to announce their SCH during the next SCH interval (SCHI). Each SCH has a residual capacity of \( C_i \) bit/s (\( i = 1, 2, ..., n \)); and nodes’ recent measurements of their throughput in channel \( i \) collectively serve as a proxy for \( C_i \). The normalized residual channel capacity of channel \( i \) is defined as \( C_i^\prime = C_i / \sum_j C_j \).

For system evaluation, we use throughput \( \gamma \) as a metric for infotainment traffic, and Packet Delivery Ratio (PDR) as the metric for BSM broadcast messages.

Figure 16 provides an interaction diagram for the key entities in our system; the sequence of interactions is as follows.

1. A User enters a coverage area handled by a given RSU.
2. The RSU sends the most recently computed ESS as a strategy recommendation to the user, who then starts accessing the bands using the recommended strategy.

3. During the Service Channel Interval, the user sends/receives infotainment traffic to/from the RSU.

4. During the Control Channel Interval, the user sends BSMs.

5. The User reports sensed CSI along with its corresponding time stamp to the RSU.

6. Reported CSI and selected channel access strategies are stored in a geo-location spectrum database for strategy analysis.

7. A cloud-based entity computes the ESS strategy based on the geo-location spectrum database entries for the given service area and time. Steps 2 through 7 repeat periodically.

By providing the ESS as its strategy recommendation to the VANET nodes, the RSU ensures that (if almost all nodes adopt its recommendation) no small group of opportunistic nodes will be able to gain unfair advantage by deviating from the recommended strategy. As we shall see in Section 4, the RSU can actually compute the ESS-based recommendation as a closed-form expression, based on the aggregated CSI data.

In this work, we consider a “menu” of three strategies (two of which are bio-socially inspired):
The **Always Consume User (ACU)** is always transmitting on an SCH that is uniformly selected from all SCHs. This strategy was used previously by Xin *et al.* [28], and allows the ACU to act with a naive opportunistic view to capture utility using the set of channel resources. The ACU’s strategy 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. When transmitting, an FCU chooses to transmit on channel $i$ with probability $\frac{1}{n}$.

The **Forage Consume User (FCU)** engages in two different activities stochastically. With probability $P_f$ it “forages,” sensing CSI$^2$ while ceasing transmission, while with probability $P_c = 1 - P_f$, it “consumes” or transmits data on a SCH. When transmitting, an FCU chooses to transmit on channel $i$ with probability $C_i$. 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 user’s utility. FCU accesses channels based on channel characteristics, favoring channels with higher residual capacity.

Advancing from FCU, the **Social Forage Consume User (SFU)** incorporates sociality as an additional factor in its channel selection logic. This type of user has sensing capabilities beyond the measurement of relative capacity levels. In particular, SFUs may be biased against not transmitting on channels where other SFUs are transmitting. We refer to this phenomenon as deference. The SFU strategy model reflects well-known findings from the structure of animal societies [29] and well as those of non-human primates [30], where sociality plays a significant organizing function and helps towards species survival. To model this phenomenon concretely, we assume that while consuming, an SFU can either be in Defer state (relative frequency $P_s$) or Active state (relative frequency $1 - P_s$). While in Defer, a user does not transmit at all; in contrast, while in Active, the user transmits at an elevated rate $(1 + S_+)R$, making use of the additional bandwidth made available by the deference of their peers. To

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$^2$In this work, we do not focus on contributions toward the problem of spectrum sensing, but rather assume that an FCU has access to “sufficient” information about the channel at the moment of decision-making. In our analysis and simulation experiments (described in later sections), the FCU has access to basic CSI on noise and interference levels, implemented as channel sniffing spectrum sensing at the MAC layer.
account for the potential costs of deference coordination among the SFUs, we will assume that each gives up $S_-$ fraction of its utility towards coordination overhead. We take $S_- \propto c_0 N^h$ where $h \in [0, 2]$ is the penalty due to coordination overhead among SFUs to access the channel. The parameter $h$ represents the extent of coordination, with $h = 2$ being full coordination and $h = 0$ being no coordination.

The RSU aggregates and relays per-band throughput measurements from its area nodes to the cloud. The cloud service uses this data to compute the evolutionary stable strategy through simulations. The existence of such a strategy is analyzed in Section 4. Having computed the ESS, the cloud relays this optimal strategy to the RSU, which then broadcasts it onwards to its area nodes; the data flow is shown in Figures (13) and (16). The performance advantage of such a scheme is explored in Section 4. Note that the recommendation only specifies the strategy type (e.g., ACU, FCU or SFU), and not node attributes (e.g., $P_c, P_s, S_+$) which are assumed to be static and external to the optimization process. The dynamic optimization of node-specific parameters, and a fine-grained analysis of control traffic overhead are beyond the scope of this work and are planned for future research. Here we seek to evaluate the feasibility of the proposed bio-social strategies and their optimal dynamic selection in the VANET domain, and to understand the impact of social attributes on the performance of the infotainment traffic.

**Research Questions**

The potential of using a bio-social model to enhance spectrum access in the context of the VANETs prompts the following research questions:
Table 6: System Parameters

<table>
<thead>
<tr>
<th></th>
<th>Symbol</th>
<th>Parameter</th>
<th>Value/Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constants</td>
<td>n</td>
<td>Number of service channels</td>
<td>6SCHs</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>Number of vehicles</td>
<td>162, 210</td>
</tr>
<tr>
<td></td>
<td>C_i^{max}</td>
<td>Maximum service channel capacity</td>
<td>10Mbps</td>
</tr>
<tr>
<td>Input Parameters</td>
<td>C_i</td>
<td>Service channel capacity</td>
<td>varies in [0, C_i^{max}]</td>
</tr>
<tr>
<td></td>
<td>α</td>
<td>Service channel interval</td>
<td>varies in [0, 100]ms</td>
</tr>
<tr>
<td></td>
<td>P_c</td>
<td>Probability of consume</td>
<td>varies in [0, 1]</td>
</tr>
<tr>
<td></td>
<td>P_s</td>
<td>Probability of Sociality</td>
<td>varies in [0, 1]</td>
</tr>
<tr>
<td></td>
<td>S_+</td>
<td>enhancement due to sociality</td>
<td>varies in [0, 1]</td>
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<tr>
<td></td>
<td>S_-</td>
<td>Overhead of sociality</td>
<td>varies in [0, 1]</td>
</tr>
<tr>
<td>Calculated Parameters</td>
<td>C_i</td>
<td>Relative service channel capacity</td>
<td>C_i / ∑_j C_j</td>
</tr>
<tr>
<td></td>
<td>β</td>
<td>Control channel interval</td>
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<td></td>
<td>G_s</td>
<td>Sociality gain</td>
<td>(1 - S_-)(1 + S_+)</td>
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<tr>
<td>Output Parameters</td>
<td>γ(.)</td>
<td>Fraction of attained vehicle throughput</td>
<td>[0, 1]</td>
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Table 7: Simulation Parameters

<table>
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<tr>
<th>Parameter</th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>Number of Channels ((n))</td>
<td>6 SCHs, 1 CCH</td>
</tr>
<tr>
<td>Number of vehicles ((N))</td>
<td>162, 210</td>
</tr>
<tr>
<td>Vehicle transmission rate ((R))</td>
<td>10 kbps (once every 100ms)</td>
</tr>
<tr>
<td>Channel Capacity ((C_i))</td>
<td>OFDM 3Mbps</td>
</tr>
<tr>
<td>(P_c, P_s, S_+ , S_-)</td>
<td>Varies based on the experiment</td>
</tr>
<tr>
<td>Number of packets</td>
<td>IP: 1, 6, 14, BSM: 10</td>
</tr>
<tr>
<td>Transmission Range</td>
<td>500m</td>
</tr>
<tr>
<td>WLAN Standard</td>
<td>IEEE 802.11p</td>
</tr>
<tr>
<td>Simulation Time</td>
<td>10 seconds</td>
</tr>
<tr>
<td>Number of replications</td>
<td>10</td>
</tr>
</tbody>
</table>

Simulation Performance Analysis

Our experiments are carried out using ns-3 [93] to simulate an 802.11p environment with 6 service channels and 1 control channel, all OFDM channels with a data rate of 3Mbps (see Table 7 for details). When experiments required a heterogeneous spectrum environment, we set channels 1,2,3 to have an energy detection level of \(-61.1dBm\), while the channels 4,5,6 operate at a \(-91.1dBm\) setting. When we needed to consider scenarios with homogeneous spectrum environment, we set all 6 channels to operate at a \(-91.1dBm\) setting.

Within each experiment, 162–210 DSA vehicles generate infotainment traffic in conformance with the IEEE WAVE 802.11p standard in multi-channel operation mode [92]. Each vehicle transmits on a channel that is dynamically updated in a continuous stochastic manner, as prescribed by the vehicle’s chosen bio-social channel selection strategy. Each vehicle must choose between three channel selection strategies: ACU, FCU and SFU (the latter two being bio-socially inspired). To compare the efficacy of the different strategy choices, we consider 3 homogeneous systems where 100% of the population use the same strategy; we also consider 3 heterogeneous populations where 80% of the vehicles employ one strategy, while the remaining 20% of the population is deviant, with 10% adopting each of the remaining two strategies. There are thus 6 distinct simulation scenarios in each experiment (3 homogeneous and corresponding to each, a heterogeneous system). By measuring the performance of each homogeneous strategy in various settings, we can determine which is dominant across a range of environmental conditions. By comparing the performance of nodes in each homogeneous strategy with the performance achieved by deviant nodes in the corresponding heterogeneous system, we can measure the evolutionary stability of the homogeneous system.

Simulation Results and Discussion

In this section, we address research questions (1) and (2) from the previous section.
Can the FCU channel selection strategy outperform all other strategies in some circumstances? We hypothesize that scenarios which favor FCUs are marked by heterogeneous channel characteristics, or when the cost of sociality is high $P_s(1-S_-)$ relative to its benefit. To test this hypothesis, we configured our simulation to consist of $n = 6$ channels with normalized residual capacities $\overline{C_i} = (\frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{2}{9}, \frac{2}{9}, \frac{2}{9})$. In such a system, FCUs and SFUs have probability of $\frac{1}{3}$ to access “good” channels 1,2,3 ($-61.1dBm$) and probability of $\frac{2}{3}$ to access “bad” channels 4,5,6 ($-91.1dBm$). Within this environment, we placed $N = 162$ vehicles, 80% of which adopted the FCU channel selection strategy, while the remaining 20% utilized the ACU and SFU strategies evenly. This is compared with populations that totally employed FCU strategy. Each vehicle sent 6 IP packets per $\alpha = 10..50$ ms, yielding transmission rates $R = 60KBytes/sec = 480Kbps$. For FCUs and SFUs, the probability of foraging was set at 2% ($P_c = 0.98$). SFUs deferred to peers 30% of the time ($P_s = 0.3$) but then transmitted at rate elevated 5% above normal when in active state ($S_+ = 0.05$). To implement this social structure, SFUs were charged 60% overhead to account for group coordination costs ($S_- = 0.6$). Table 8-Figure (a) shows the throughput achieved in each of the three homogeneous and heterogeneous scenarios. As shown in Table 8-Figure (b), FCUs obtain 82.6% - 136.8% improvement in throughput over ACUs and SFUs. Even though FCUs spend time not consuming ($P_c < 1$), they are able to compensate for this loss and outperform ACUs because they can choose better channels for transmission as a result of their sensing capabilities. FCUs also outperform SFUs in this scenario because SFU defer too readily, and the cost of their deference and coordination is high.

Can the SFU channel selection strategy outperform all other strategies in some circumstances? We hypothesize that the SFU strategy outperforms the other strategies in highly loaded network scenarios. In these scenarios, channels are not able to accommodate all the demand and there will be an emergent need for social deference. In order to test this hypothesis, we configured the simulation to consist of $n = 6$ channels with normalized residual capacities $\overline{C_i} = (\frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{2}{9}, \frac{2}{9}, \frac{2}{9})$. In such a system, FCUs and SFUs have probability of $\frac{1}{3}$ to access “good” channels 1,2,3 ($-61.1dBm$) and probability of $\frac{2}{3}$ to access “bad” channels 4,5,6 ($-91.1dBm$). Within this environment, we placed $N = 210$ vehicles, 80% of which adopted the SFU channel selection strategy, while the remaining 20% utilized the ACU and FCU strategies evenly. This is compared with populations that totally employed SFU strategy. Each vehicle sent 14 IP packets per $\alpha = 10..50$ ms, yielding transmission rates $R = 140KBytes/sec = 1120Kbps$. For FCUs and SFUs, the probability of foraging was set at 1% ($P_c = 0.99$). SFUs deferred to peers 80% of the time ($P_s = 0.8$) but then transmitted at rate elevated 40% above normal when in active state ($S_+ = 0.4$). To implement this social structure, SFUs were charged 4% overhead to account for group coordination costs ($S_- = .04$). Table 8-Figure (c) shows the throughput achieved in each of the three homogeneous and heterogeneous scenarios. As shown in Table 8-Figure (d), SFUs obtain 3.1% - 10.5%
improvement in throughput over ACUs and FCUs. In such scenarios, nodes with social behavior will be able to gain more utility by coordinating so that only $P_s$ fraction of them are deferring, while only $1 - P_s$ fraction are actively transmitting, albeit at an elevated rate. This results in decreased contention over the channels and helps users to access better channels more frequently in order to improve their utility. Under such network conditions, ACUs and FCUs fail to achieve better utility since these nodes do not defer to others, and therefore, experience higher contention on channels. Notice that as the number of vehicles and their load increases, the SFU strategy gains more utility compared to other strategies as shown in Table 8-Figures (c).

**Under what conditions does ACU outperform the bio-social FCU and SFU strategies?** We hypothesize that the ACU strategy outperforms the other strategies in lightly loaded network scenarios where channel conditions are homogeneous. In these scenarios, channels are able to accommodate all the demand and there is no need for foraging and social behaviors. In order to test this hypothesis, we configured the simulation to consist of $n = 6$ channels with normalized residual capacities $C_i = \left( \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6} \right)$. In such a system, FCUs and SFUs have probability of $\frac{1}{6}$ to access all 6 channels configured with $(-91.1dBm)$ energy detection threshold. Within this environment, we placed $N = 162$ vehicles, 80% of which adopted the ACU channel selection strategy, while the remaining 20% utilized the FCU and SFU strategies evenly. This is compared with populations that totally employed ACU strategy. Each vehicle sent 1 IP packets per $\alpha = 10.50$ ms, yielding transmission rates $R = 10KBytes/sec = 80Kbps$. For FCUs and SFUs, the probability of foraging was set at 40% ($P_c = 0.6$). SFUs deferred to peers 40% of the time ($P_s = 0.4$) but then transmitted at rate elevated 5% above normal when in active state ($S_+ = 0.05$). To implement this social structure, SFUs were charged 30% overhead to account for group coordination costs ($S_- = .3$). Table 8-Figure (e) shows the throughput achieved in each of the three homogeneous and heterogeneous scenarios. As shown in Table 8-Figure (f), ACUs obtain 97.7% to 1839.2% higher throughput than FCUs and SFUs. Thus, FCUs and SFUs receive less throughput than the baseline strategy (i.e., ACU) in scenarios with light infotainment traffic. In such settings, the foraging behavior employed by FCUs and SFUs offers little benefit, since the time spent in foraging and sensing decreases the utility of the nodes and provides little useful information; similarly, the social deference of SFUs leads $P_s$ fraction of the nodes to defer transmissions, which is unnecessary given the traffic conditions, and only lowers throughput.

In all the simulations above, in addition to evaluating throughput for infotainment traffic, we also measured the packet delivery ratios for safety traffic. The ACU, FCU, and SFU strategies only concern the transmission for infotainment IP packets, and do not affect the transmission of safety traffic such as BSM messages. Figure 17 shows the PDR for safety traffic in networks corresponding to experiments of Table 8-Figure (e) and (f) where the efficacy of the ACU strategy was being evaluated. The figure shows
the PDR for BSM broadcasts in a scenario with 162 nodes transmitting 10 BSMs per CCH interval. The figure clearly shows that as SCH interval increases, the CCH interval decreases, yielding a decreased delivery ratio of the BSM packets.

These results demonstrate the interplay between infotainment and safety traffic. As the SCH interval increases, the throughput for infotainment traffic increases and the PDR for safety traffic decreases; the reverse is true as well, and hence the trade off. This work does not address the optimal design of the SCHI and CCHI values. However, it shows the feasibility of employing the proposed bio-socially inspired strategies in the realm of vehicular networks that utilize DSA in support of infotainment applications.

We have arrived at an experimentally derived intuition concerning questions (1) and (2): it appears that the bio-socially inspired FCU, and SFU strategies can indeed sometimes enhance spectrum access and utilization in VANETs (compared to the baseline performance of ACUs), but the best strategy choice depends on the environmental conditions. The FCU and SFU strategies have two distinct behaviors. FCUs tend to immediately benefit from the knowledge about the underlying channel conditions and try to access better channels more frequently (i.e., with higher probability). SFUs provide the users with the ability to grant their share of the bandwidth to other fellow nodes in the SFU group (i.e., altruistic behavior), and prefer to let others transmit on channels when the channels are crowded in favor of obtaining more utility from a group perspective. We say that FCUs tend to have a short-term view and selfish behavior, while SFUs which have a long-term view and altruistic behavior. Experimentally, we observe that both strategies benefit (relative to ACUs), under suitable channel and traffic conditions. These experimental intuitions will be proven in the next section.

Analytical Performance Analysis

Here will will prove the experimental intuitions of the previous section concerning research questions (1) and (2), as well as address research question (3).

Preliminaries

We distinguish the concept of a mixed strategy from that of a heterogeneous population. A node that employs a mixed strategy switches between pure strategies over time at random; it might act like an ACU 10% of the time, like an FCU 60% of the time, and like an SFU 30% of the time. We will not consider mixed strategies in this paper. A heterogeneous population on the other hand, is a population in which each SU employ a “pure” strategy (an ACU, or an FCU, or an SFU, and uses the corresponding strategy 100% of the time); different nodes in the population, however, may use different strategies. In this paper, a homogeneous population will be one in which all the nodes use the same pure strategy.
Table 8: Simulation Results for Proposed Strategies Under Various Channels’ Conditions and Nodes’ Properties

Heterogeneous channel capacity, Lightly loaded: $P_c : 0.98, P_s : 0.3, S_+ : 0.05, S_- : 0.6$

(a) FCU strategy outperforms, utility increases with SCHI

(b) Improvement on throughput corresponding to Figure (a)

Heterogeneous channel capacity, Highly loaded: $P_c : 0.99, P_s : 0.8, S_+ : 0.4, S_- : 0.04$

(c) SFU strategy outperforms, utility increases with SCHI
Heterogeneous channel capacity, Highly loaded: $P_c: 0.99, P_s: 0.8, S_+: 0.4, S_-: 0.04$

(d) Improvement on throughput corresponding to Figure (c)

Homogeneous channel capacity, Lightly loaded: $P_c: 0.6, P_s: 0.4, S_+: 0.05, S_-: 0.3$

(e) ACU strategy outperforms, utility increases with SCHI

Homogeneous channel capacity, Lightly loaded: $P_c: 0.6, P_s: 0.4, S_+: 0.05, S_-: 0.3$

(f) Improvement on throughput corresponding to Figure (e)

We follow the analysis presented in [61] for a formal definition of ESS. A strategy $\sigma^*$ is an ESS, if
mutants that adopt another strategy $\sigma$ leave fewer offsprings in the post-entry population $x_\epsilon$ where:

$$x_\epsilon = (1 - \epsilon)\sigma^* + \epsilon\sigma$$  \hspace{1cm} (1)$$

assuming that the proportion of mutants $\epsilon$ is sufficiently small ($0 < \epsilon < \bar{\tau}$). Hence, for $\sigma^*$ to be ESS, then:

$$U(\sigma^*, x_\epsilon) > U(\sigma, x_\epsilon)$$  \hspace{1cm} (2)$$

where $U(\sigma^*, x_\epsilon)$ is the payoff (i.e., utility) of players that play $\sigma^*$ and $U(\sigma, x_\epsilon)$ is the payoff of the mutants that play $\sigma$ in the post-entry population $x_\epsilon$.

**Mathematical Model**

Consider a heterogeneous system $\mathcal{S}$ in which there are $k_1$ ACUs, $k_2$ FCUs, $k_3$ SFUs. In $\mathcal{S}$, there is just one channel of capacity $C$ and ACUs and FCUs transmit at a rate of $r_1$ while SFUs transmit at a rate of $r_2$. Such a system will be specified by a 5-tuple

$$\mathcal{S} = (k_1, k_2, k_3, r_1, r_2)$$

The fractional throughput of each SU in $\mathcal{S}$ will be written as

$$X_\gamma(\mathcal{S}) := \gamma(C, k_1 + k_2, r_1, k_3, r_2)$$

we will say more about the functional form of $\gamma$ shortly.

Now, when we consider a system $\mathcal{S}^*$

$$\mathcal{S}^* = (n_{ACU}, n_{FCU}, n_{SFU}, R, (1 + S_+)R)$$  \hspace{1cm} (3)$$

having access $M \geq 1$ channels of capacities $C_1, \ldots, C_M$. In what follows, $\mathcal{S}^*$ will always consist of a set of SUs who each follow a pure strategy. We will, however, sometimes subject system to the possibility that some fraction of its players could “mutate” or “defect” or “switch” to different (possibly mixed) strategy.

Assuming $\mathcal{S}^*$ is in steady state, the expected number of ACUs, FCUs and SFUs in channel $i$ is given by

$$O^i_{ACU} := \frac{N_{ACU}}{M}$$

$$O^i_{FCU} := C_i N_{FCU}$$

$$O^i_{SFU} := C_i (1 - P_S) N_{SFU}$$
The total demand for channel $i$ is computable as

$$D_i(S^*) = (O_{ACU}^i + O_{FCU}^i) \cdot R + O_{SFU}^i \cdot (1 + S_+)R$$

and the fractional throughput of users in channel $i$ is:

$$X_i^i(S^*) := \frac{1}{\exp(D_i(S^*) - \rho C_i)}$$

while the precise form of $\gamma$ is intractable, we will take

$$X_i^i(S^*) = \begin{cases} 
1 & \text{if } D_i(S^*) < \rho C_i \\
\frac{1}{\exp(D_i(S^*) - \rho C_i)} & \text{if } D_i(S^*) \geq \rho C_i
\end{cases}$$

Here $\rho$ is a fitting parameter chosen so that $\gamma$ mirrors experimental measurements.

In what follows we define $U(S^*; s, x)$ as the utility received by users employing strategy $s$ in a multiband system $S^*$ of a mixed population that utilize employing strategies different from $s$. For convenience, $U(S^*; s, x)$ is denoted as $U_s(S^*)$. The stability of the strategy, when it exists, is guaranteed only when the number of users deviating from strategy $s$ is sufficiently small.

In system $(S^*)$, the utility achieved by each ACU, FCU, and SFU respectively is:

$$U_{ACU}(S^*) = \nu \frac{1}{M} \sum_{i=1}^{M} R \cdot X_i^i(S^*)$$

$$U_{FCU}(S^*) = \nu P_c \sum_{i=1}^{M} C_i R \cdot X_i^i(S^*)$$

$$U_{SFU}(S^*) = \nu P_c \sum_{i=1}^{M} C_i R \cdot G_s \cdot X_i^i(S^*)$$

where $\nu = \frac{\alpha}{\alpha + \beta}$ is the service channel duty cycle, and $G_s = (1 + S_+) \cdot (1 - S_-)$ is the sociality gain.

**Existence of ESS—the general framework**

In this section, we describe the conditions in which a homogeneous system of SUs is an ESS—that is, invasion by any competing mixed strategy will fail, provided the invading population is sufficiently small. Towards this, we will first state a general formulation of conditions for an ESS in the Lemma below. This lemma will be specialized and applied to homogeneous systems of ACUs, FCUs, and SFUs in the next section. The next definition will be helpful in the results that follow.

**Definition 2.** Let $S^*$ be the system in (3), and $\sigma^* = (p^*, q^*, k^*)$ and $\sigma = (p, q, k)$ are mixed strategies
where \( ACU, FCU, SFU \) are used with probabilities \( p^*, q^*, k^* \), for \( \sigma^* \) and \( p, q, k \), for \( \sigma \), respectively; where \( (p^* + q^* + k^* = 1) \) and \( (p + q + k = 1) \). Define

\[
A(S^*, \sigma^*, \sigma) = p^*(p^* - p) \cdot U_{ACU}(S^*) + q^*(q^* - q) \cdot U_{FCU}(S^*) + k^*(k^* - k) \cdot U_{SFU}(S^*)
\]

\[
B(S^*, \sigma^*, \sigma) = (p^* - p)^2 \cdot U_{ACU}(S^*) + (q^* - q)^2 \cdot U_{FCU}(S^*) + (k^* - k)^2 \cdot U_{SFU}(S^*)
\]

**Lemma 2.** Let \( S^* \) be the system in (3), and suppose that the majority \( 1 - \epsilon \) of SUs employ \( \sigma^* = (p^*, q^*, k^*) \) where \( ACU, FCU, SFU \) are used with probabilities \( p^*, q^*, k^* \), respectively. When a small \( \epsilon \) fraction of SUs contemplate a defection to a mixed strategy \( \sigma = (p, q, k) \) where \( ACU, FCU, SFU \) are used with probabilities \( p, q, k \), respectively, then for \( \epsilon \) sufficiently small, the defection fails to be rational. In particular, \( S^* \) is evolutionarily stable as long as

\[
\epsilon < \frac{A(S^*, \sigma^*, \sigma)}{B(S^*, \sigma^*, \sigma)}
\]  

\[
(4)
\]

**Proof.** Since \( \epsilon \approx 0 \) the payoff for a defecting player is:

\[
U_{\sigma}(S^*) = p \cdot U_{ACU}(S^*) + q \cdot U_{FCU}(S^*) + k \cdot U_{SFU}(S^*)
\]  

\[
(5)
\]

The existence of an ESS in an EGT game requires the inequality condition of Equation (2) to hold. Suppose \( \sigma^* = (p^*, q^*, k^*) \) is the strategy employed in \( S^* \) and \( \sigma = (p, q, k) \) is the strategy of the defectors. The utility achieved by the defectors is:

\[
U_{\sigma} = p[p^* - \epsilon(p^* - p)] \cdot U_{ACU}(S^*) + q[q^* - \epsilon(q^* - q)] \cdot U_{FCU}(S^*) + k[k^* - \epsilon(k^* - k)] \cdot U_{SFU}(S^*)
\]  

\[
(6)
\]
while the non-defectors achieve

\[ U_{\sigma^*} = p^* [p^* - \epsilon(p^* - p)] \cdot U_{ACU}(S^*) + q^* [q^* - \epsilon(q^* - q)] \cdot U_{FCU}(S^*) + k^* [k^* - \epsilon(k^* - k)] \cdot U_{SFU}(S^*) \]

(7)

It is easy to check that \( U_{\sigma^*} > U_\sigma \) if and only if \( \epsilon < A/B \).

Existence of ESS—Applied to VANETs

Since we have three pure strategies and one mixed strategy we need the following five propositions to study the existence of ESS:

**Proposition 6.** If \( S^* \) is a homogeneous system of ACUs, a defection to strategy \( \sigma = (p, q, k) \) by an \( \epsilon \) fraction of players fails to be rational if \( \epsilon \) is less than

\[
\frac{(1 - p) \cdot U_{ACU}(S^*)}{(1 - p)^2 \cdot U_{ACU}(S^*) + q^2 \cdot U_{FCU}(S^*) + k^2 \cdot U_{SFU}(S^*)}
\]

**Proof.** Using Lemma 2, we specialize Definition 2 to the situation \( \sigma^* = (1, 0, 0) \) to obtain

\[
A(S^*, \sigma^*, \sigma) = (1 - p) \cdot U_{ACU}(S^*)
\]

\[
B(S^*, \sigma^*, \sigma) = (1 - p)^2 \cdot U_{ACU}(S^*) + q^2 \cdot U_{FCU}(S^*) + k^2 \cdot U_{SFU}(S^*)
\]

The proposition is proved.

As \( U_{ACU}(S^*) \) decreases, we see that the bound on \( \epsilon \) in Proposition 6 approaches 0, making it more likely that users will defect away from the homogeneous ACU society. Conversely, as \( U_{ACU}(S^*) \) increases relative to \( U_{FCU}(S^*) \) and \( U_{SFU}(S^*) \), we see that the bound on \( \epsilon \) approaches 1, making it so users will be unable to defect away from the homogeneous ACU society without group coordination.

**Proposition 7.** If \( S^* \) is a homogeneous system of FCUs, a defection to strategy \( \sigma = (p, q, k) \) by an \( \epsilon \) fraction of players fails to be rational if \( \epsilon \) is less than

\[
\frac{(1 - q) \cdot U_{FCU}(S^*)}{p^2 \cdot U_{ACU}(S^*) + (1 - q)^2 \cdot U_{FCU}(S^*) + k^2 \cdot U_{SFU}(S^*)}
\]
Proof. Using Lemma 2, we specialize Definition 2 to the situation $\sigma^* = (0, 1, 0)$ to obtain
\[
A(S^*, \sigma^*, \sigma) = (1 - q) \cdot U_{FCU}(S^*)
\]
\[
B(S^*, \sigma^*, \sigma) = p^2 \cdot U_{ACU}(S^*) + (1 - q)^2 \cdot U_{FCU}(S^*) + k^2 \cdot U_{SFU}(S^*)
\]
The proposition is proved. \qed

As $U_{FCU}(S^*)$ decreases, we see that the bound on $\epsilon$ in Proposition 7 approaches 0, making it more likely that users will defect away from the homogeneous FCU society. Conversely, as $U_{FCU}(S^*)$ increases relative to $U_{ACU}(S^*)$ and $U_{SFU}(S^*)$, we see that the bound on $\epsilon$ approaches 1, making it so users will be unable to defect away from the homogeneous FCU society without group coordination.

**Proposition 8.** If $S^*$ is a homogeneous system of SFUs, a defection to strategy $\sigma = (p, q, k)$ by an $\epsilon$ fraction of players fails to be rational if $\epsilon$ is less than
\[
\frac{(1 - k) \cdot U_{SFU}(S^*)}{p^2 \cdot U_{ACU}(S^*) + q^2 \cdot U_{FCU}(S^*) + (1 - k)^2 \cdot U_{SFU}(S^*)}
\]

Proof. Using Lemma 2, we specialize Definition 2 to the situation $\sigma^* = (0, 0, 1)$ to obtain
\[
A(S^*, \sigma^*, \sigma) = (1 - k) \cdot U_{SFU}(S^*)
\]
\[
B(S^*, \sigma^*, \sigma) = p^2 \cdot U_{ACU}(S^*) + q^2 \cdot U_{FCU}(S^*) + (1 - k)^2 \cdot U_{SFU}(S^*)
\]
The proposition is proved. \qed

As $U_{SFU}(S^*)$ decreases, we see that the bound on $\epsilon$ in Proposition 7 approaches 0, making it more likely that users will defect away from the homogeneous SFU society. Conversely, as $U_{SFU}(S^*)$ increases relative to $U_{ACU}(S^*)$ and $U_{FCU}(S^*)$, we see that the bound on $\epsilon$ approaches 1, making it so users will be unable to defect away from the homogeneous SFU society without group coordination.

**Proposition 9.** If $S^*$ is a system in which
\[
U_{ACU}(S^*) = U_{FCU}(S^*) = U_{SFU}(S^*)
\]
then no evolutionary stable strategy exists in $S^*$.

Proof. If all utilities of all strategies are equal then players may switch and mix strategies without penalty, and because the strict inequality in (2) cannot be made to hold for any strategy, no strategy is evolutionarily stable. \qed
Proposition 10. If $S^*$ is a system in which $U_{ACU}(S^*)$, $U_{FCU}(S^*)$ and $U_{SFU}(S^*)$ are pairwise distinct, and $\sigma$ is evolutionary stable strategy $S^*$, then $\sigma$ is a pure strategy.

Proof. Suppose $\sigma$ is the ESS. The payoff for this strategy is

$$U_\sigma(S^*) = p \cdot U_{ACU}(S^*) + q \cdot U_{FCU}(S^*) + k \cdot U_{SFU}(S^*)$$

This function is convex combination, and so is maximized by placing all the probability mass on the unique strategy which has the highest utility. Thus, precisely one of the values $p, q, k$ is equal to 1. \qed

Corollary 2. If $S^*$ is a system in which $U_{ACU}(S^*)$, $U_{FCU}(S^*)$ and $U_{SFU}(S^*)$ are pairwise distinct, and $\sigma$ is evolutionary stable strategy $S^*$, then

$$\sigma = \begin{cases} 
ACU & \text{if } U_{ACU}(S^*) > U_{FCU}(S^*), U_{SFU}(S^*) \\
FCU & \text{if } U_{FCU}(S^*) > U_{ACU}(S^*), U_{SFU}(S^*) \\
SFU & \text{if } U_{SFU}(S^*) > U_{ACU}(S^*), U_{FCU}(S^*) 
\end{cases}$$

Finding an ESS

Theorem 5. For a system $S^*$ where $X_i^\gamma(S^*) \approx 1$, $ACU$ is a winning strategy iff: $P_c < \min(1, \frac{1}{G_s})$.

Proof. Corollary 2 mandates that $U_{ACU}(S^*) > U_{FCU}(S^*)$ and $U_{ACU}(S^*) > U_{SFU}(S^*)$, which implies:

$$\frac{1}{M} \sum_{i=1}^{M} X_i^\gamma(S^*) > P_c \sum_{i=1}^{M} C_i \cdot X_i^\gamma(S^*)$$  \hspace{1cm} (8)$$

$$\frac{1}{M} \sum_{i=1}^{M} X_i^\gamma(S^*) > P_c \sum_{i=1}^{M} C_i \cdot G_s \cdot X_i^\gamma(S^*)$$  \hspace{1cm} (9)$$

Substituting $X_i^\gamma(S^*) = 1$ and $\sum_{i=1}^{M} C_i = 1$, we get

$$P_c < 1$$

$$P_c \cdot G_s < 1$$

The theorem is proved. \qed

Theorem 6. For a system $S^*$, where

$$\forall i, j : 1 \ldots M, \ C_i = C_j$$

$ACU$ is a winning strategy iff: $P_c < \min(1, \frac{1}{G_s})$. 
Proof. Since $C_i = C_j$ for all $i, j$ it follows that

$$\overline{C_i} = \overline{C_j} = 1/M$$

Substituting into inequalities (8) and (9), we get

$$P_c < 1$$

$$P_c \cdot G_s < 1$$

The theorem is proved. \qed

**Reflections on Theorems (5) and (6):** The antecedent in Theorem (5) means that all channels are able to accommodate the demand, and thus, from the nodes’ perspective, their demand is fulfilled regardless of their channel choices. ACUs benefit directly from this condition as they randomly access the channels. SFUs and FCUs detect this condition using their foraging capability, but to gain this knowledge, they sacrifice some of their channel access time by foraging some fraction ($P_f = 1 - P_c$) of the time. This hinders their ability to gain utility relative to ACUs. On the other hand, SFUs can recapture some of this loss by the advantage derived from social behavior ($G_s$). As long as the effects of foraging and social gain are less than 1, however, SFUs cannot outperform ACUs under this condition. The antecedent in Theorem (6), states that the utilities of all channels are equal but not necessarily 1. This happens when the different channels provide similar throughput; this uniformity implies that the utility lost to time spent foraging was in vain since it yielded no information about the channel environment. This leads to the same conclusion as that of Theorem (5).

**Connections to previous ns-3 experiments:** The conclusion from Theorem (6) is also observed in our ns-3 experimental results as can be seen in Table 8-Figure (e)-(f). These figures are based on scenarios in which the different channels have similar conditions.

**Theorem 7.** For a system $S^*$, FCU is a winning strategy iff:

$$P_c > \frac{1}{M} \frac{\sum_{i=1}^{M} X^i_{\gamma}(S^*)}{\sum_{i=1}^{M} \overline{C_i} \cdot X^i_{\gamma}(S^*)}$$

and

$$G_s < 1$$
Proof. Corollary 2 mandates that $U_{FCU}(S^*) > U_{ACU}(S^*)$ and $U_{FCU}(S^*) > U_{SFU}(S^*)$, which implies:

$$P_c \sum_{i=1}^{M} C_i \cdot X_i(S^*) > \frac{1}{M} \sum_{i=1}^{M} X_i(S^*)$$

$$P_c \sum_{i=1}^{M} C_i \cdot X_i(S^*) > P_c \sum_{i=1}^{M} C_i \cdot G_s \cdot X_i(S^*)$$

Rearranging terms of the two inequalities, the theorem is proved.

Reflections on Theorem 7: The antecedent in Theorem (7) assert a lower-bound on the probability of consuming that is the ratio of the ACU and FCU utilities, and indicate that the social gain is smaller than 1. We know already from Theorems (5) and (6), that ACUs outperform all strategies when channels have uniform conditions. In non-uniform settings, FCUs and SFUs have the tendency to access channels with better throughput, based on the values of $C_i$. In non-uniform channel settings, the weighted average in the denominator is greater than the unweighted average in the numerator, and so the ratio of ACU to FCU utilities decreases below 1; the lower bound on $P_c$ then drops correspondingly, and (for appropriately chosen $P_c < 1$) foraging wins. The second antecedent upper-bounds the sociality gain ($G_s$) to be less than 1. This condition restricts the SFUs from compensating for their social coordination overhead and ensures that FCUs outperform SFUs.

Connections to previous ns-3 experiments: The conclusion from Theorem (7) is also observed in our ns-3 experimental results as can be seen in Table 8-Figure (a)-(b). These figures are based on scenarios in which the channels have non-uniform conditions and the sociality overhead ($S_-$) limits ($G_s$) and curtails SFU utilities.

Theorem 8. For a system $S^*$, SFU is a winning strategy iff:

$$P_c > \frac{1}{M} \sum_{i=1}^{M} X_i(S^*)$$

$$G_s > 1$$

Proof. Corollary 2 mandates that $U_{FCU}(S^*) > U_{ACU}(S^*)$ and $U_{FCU}(S^*) > U_{SFU}(S^*)$, which implies:

$$P_c \sum_{i=1}^{M} C_i \cdot G_s \cdot X_i(S^*) > \frac{1}{M} \sum_{i=1}^{M} X_i(S^*)$$

$$P_c \sum_{i=1}^{M} C_i \cdot G_s \cdot X_i(S^*) > P_c \sum_{i=1}^{M} C_i \cdot X_i(S^*)$$

Rearranging terms of the two inequalities, the theorem is proved.
**Reflections on Theorem 8:** The antecedent in Theorem (8) assert a lower-bound the probability of consume that is the ratio of the ACU and SFU utilities, and prescribe a sociality gain greater than 1. We know already from Theorems (5) and (6), that ACUs outperform all strategies when channels have uniform conditions. In non-uniform settings, FCUs and SFUs have the tendency to access channels with better throughput, based on the values of $C_i$. In non-uniform channel settings, the weighted average in the denominator is greater than the unweighted average in the numerator, and so the ratio of ACU to FCU utilities decreases below 1; the lower bound on $Pc$ then drops correspondingly, and (for appropriately chosen $Pc < 1$) foraging wins. The second antecedent lower-bounds the sociality gain ($Gs$) to be greater than 1. This condition allows the SFUs to benefit from their social coordination and ensures that SFUs outperform FCUs.

**Reflections on the ns-3 experiments:** The conclusion from Theorem (8) is also observed in our ns-3 experimental results as can be seen in Table 8-Figure (c)-(d). These figures are based on scenarios in which the channels have non-uniform conditions and the sociality overhead ($S_{-}$) is low enough such that SFUs are able to acquire greater utility ($Gs$) than their non-social foraging counterparts.

**Conclusions and Future Work**

The advent of large-scale VANETs heralds the emergent problems of device co-existence and the potential of device sociality in the ecosystem of the radio spectrum. Here we considered two bio-socially inspired strategies for VANETS, based on resource foraging and social deference; we compared them to a baseline strategy driven by continuous blind consumption. We found (see Section 4) that one of these three strategies is always dominant, and while the winning strategy depends on channel conditions, it is stable against defections by small numbers of deviating nodes. The intuitions for these theoretical results, and the empirical evaluation of their merits were obtained through extensive simulation experiments (see Section 4)—where we saw that the optimal strategy enjoys utility gains of 3%-136% relative to baseline.

Taken together, these results together point to a new way of thinking about resource allocation problem: one where optimal and stable channel selection strategies are computed and uniformly recommended, rather than the current view where individual channels are micromanaged and allocated by a central authority. This new model is envisioned at the core of a VANET communications system, where a road-side unit aggregates and relays per-band throughput measurements from its area nodes to the cloud. The cloud service then uses the data to compute the evolutionary stable strategy based on the collected data. Having computed the optimal stable strategy, the cloud relays it to the RSU, which then broadcasts it onwards to its area nodes.

The present work considers recommendations of strategy type (i.e., ACU, FCU or SFU) only, and
not node attributes (i.e., $P_c, P_s, S_\pm$). The dynamic optimization of node-specific parameters, and a fine-grained analysis of control traffic overhead is planned for future research. Hardware implementation of an experimental testbed based on the proposed bio-socially inspired DSA systems are planned, to complement and validate the analytic and simulation findings presented here.

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Chapter 5

Social Avoidance and Deference
Etiquettes in Support of Dynamic
Spectrum Access

Abstract: Dynamic Spectrum Access leverages different approaches and solutions to provide better spectrum utilization over scarce underutilized expensive spectrum. In this work we seek biologically and socially approach mimicking humans and prime-mates behaviors over resources to enhance the spectrum utilization. Specifically, two bio-socially inspired behaviors are introduced and combined to enhance the SU interactions over channels, for enhancing throughput of SU communities. The social behaviors are compared with a baseline behavior, in which no social deference or avoidance takes place. That is the SUs are fixed on the channels and always transmit on the allocated channels. The proposed behaviors are: (1) The social deference, in which SUs altruistically defer transmission for the SUs within their group, and (2) The social avoidance, in which SUs cautiously avoid transmission on channels that have large number of SUs out of their group. The former behavior shines on overcrowded channels, while the latter shines on channels that have relatively noticeable difference on the available channel capacities. The difference in th channels capacities either comes from the channel condition or from the distribution of the SUs when they follow the social avoidance behavior and their demand. For better performance, the two proposed behaviors can be combined to achieve better throughput for the SUs community. An ns-3 Simulation framework demonstrated that throughput improvement up to 134.4% with average improvement of 54.1% with different values of social and deference thresholds for large SUs communities with high demand.
Introduction

Dynamic Spectrum Access (DSA) is a recent paradigm in wireless communications, in which spectrum channels are allocated dynamically for users to combat spectrum scarcity. The research in DSA addresses a set of challenges including spectrum management, spectrum sharing, spectrum mobility, and spectrum sensing [33], [2].

The most widely adopted model for DSA is the Opportunistic Spectrum Access (OSA) [94]. In this model, the licensed Primary User (PU) and the unlicensed Secondary Users (SUs) have mutual access on the spectrum. SUs detect the presence of PUs [34], and access the spectrum when the PUs are absent (i.e., detecting white space). Different approaches are followed to address the PU-SU and SU-SU interactions including: (a) game-theoretic [49][50][52][53] (b) machine learning [40][41][42] and (c) biologically or socially inspired approaches [47] [46] [23]. This work addresses the SU-SU interactions for spectrum access using bio-socially approach.

Cognitive Radio (CR) is a set of enabling technologies dedicated for the implementation of self-organizing networks and DSA networks [4]. Here we anticipate that the CR spectrum sensing technologies, can be combined with social sensing (i.e., awareness of the identity of peer SUs) to harmonize SU-SU co-existence on the spectrum, and ensuring more effective spectrum sharing. This is important since poor SUs interactions leads to unbalanced spectrum access, in which some channels are congested and other channels are underutilized.

The following question is the central focus of this work: For a community of SUs, who are distributed over different groups, what is the recommended SU behaviors across channels that maximize the community throughput and enhance the spectrum utilization?

Towards resolving the question, we introduce the following SU capabilities:

1. The SU is able to transmit on the channels as long as the PUs are absent, following the OSA model.
2. The SUs able to socially sense the channels, and understand social structure of the SUs on the channel.
3. The SU has the tendency to avoid transmission over channels that has presumably a large number of SUs belonging to groups other than its own group. The avoidance also serves as the SU response to the presence of the PUs on the channel.
4. The SU has the tendency to defer transmission over channels that has presumably a large number of SUs belonging to its own group.

The first and second capabilities provide the SUs with the channel and social sensing, respectively. The social out-of-group avoidance capability helps to distribute the SUs belonging to different groups.
over channels. This is anticipated to enhance the fairness among groups across channels, in which SUs from different groups will likely to experience the same level of channel conditions. Social segregation might arise in cases where some groups has a little tendency to avoid transmission and others have more tendency to avoid transmission on that channel. The social in-group deference capability allow SUs to act altruistically on the channels that have excessive demand. In this case, SUs sacrifice some of their time to defer to other co-SUs to help them gain more utility on the channel. A starvation avoidance technique is employed to avoid deteriorating utilities of the deferring SUs.

Through ns-3 Simulation, the proposed bio-socially inspired behaviors demonstrated throughput improvement up to 134.4% with average improvement of 54.1% in scenarios where large SUs communities have high demand on channels, under different tendencies of social avoidance and deference.

The remainder of this paper is organized as follows: Prior work is discussed in Section 5. Section 5 introduces the system model. Section IV presents two use cases for the proposed behaviors. The results of simulation studies and formal analysis of the system dynamics are presented in Sections 5 and 5, respectively. Section 5 introduces an experimental testbed for future experimental research directions. Finally, conclusion and future directions are discussed in Section 5.

**Prior Related Work**

Previous work in CR focuses on PU-SU dynamics (e.g. [5] and others), ignoring SU-SU interactions over resources. This point is recently addressed in the work of Dixit et al. [8] and Xing et al. [9], and the work of Wisniewska et al. [10] [12][11][13]. Our work here also serves to elucidate the nature of SU-SU dynamics and extends the work of Shattal et al. [14] [15]. The work utilizes the findings in the work of Dombrowski et al. [16] for hierarchical resource sharing in the Inuit community in Labrador, Canada. Research into PU-SU and SU-SU interactions can be classified into three main categories: (a) machine learning formulations, (b) game-theoretic approaches, and (c) biologically or socially inspired schemes.
The results presented here serve to address the role of SU interactions towards the enhancement of DSA systems. This research gap is illustrated in Figure 18 relative to the recent DSA/CR research, briefly explained next.

**Machine learning** approaches have been applied extensively for spectrum allocation and spectrum sharing, using various support vector machine techniques [95], for spectrum sensing using Q-learning [96] in comparison with other HMM model techniques, and for security in cognitive radio networks [97]. Different types of machine learning algorithms are applied into CR network protocols (see [43] for a survey). The problem associated with machine learning approaches, is that the SU doesn’t have access to updated, correct action that is best fit for the current DSA environment. Example of this is the reinforcement learning approaches, where decision making depends on an evaluative feedback for a trial and error process, as discussed in the survey [43].

**Game theory** approaches have been used in CR domain as a mathematical tool to analyze and model the CR networks as a common form games (see [49] and [50] for a survey of prior work). For example, SUs over competition over channels has been modeled as a non-cooperative game [98]. Unfortunately, most game-theoretic research relies on the availability of spectrum statistics in order to formulate the game and cope with spectrum dynamic changes, especially in stochastic [52] and repeated games [53]. Such information is not known a priori, limiting the applicability of this approach [54].

**Biologically or socially inspired** incorporate social components to users’ behavioral models (e.g., preferential bias [17], peer recommendations [18], and selfishness [19]). These approaches treat the CR ecosystem as a social network [44] [45] for which cooperative schemes are designed [22]. Such approaches follow the optimization resulting from the evolution of the biological systems, and apply the of biological natural selection process to the CR Networks domain. Behavioral models of biological and social systems were used for resource allocation problems, including MANET routing [46], Vehicular Network (VANET) routing [47], and sensor network management [21]. In the context of CR, bio-socially inspired models have been developed for spectrum sensing [21], channel selection [22], and efficient routing [46]. Unfortunately, idealized bio-social models based on animal societies (e.g., termites [48], ants [26], etc.) require a level of coordination among population individuals [27].

Priority among SUs groups in CR Networks (CRNs) were studied based on social approach. The work of Ezirim et al. [99], proposed a deference structure among “networks” to support an altruistic behavior in social coalition. This helps CRNs to minimize the chances of conflict over homogeneous channels. The proposed model consider the CR from network perspective, in which networks, not the SUs, forms the coalition to interact over resources. In our approach, CRN is divided into social groups. Each SU defers or avoids transmission on channels based on his group membership. There is no group-wise decision involved in the deference, avoidance or transmission decisions. The work of Kedun et al.
[100] proposed a single channel and multi-channels CR systems. Both analyzed based on preemptive and non-preemptive priority queuing approaches. From social point of view the work can be considered as an example of studying greedy SUs interactions over channels. Our approach addresses the priority over channels based on social relations among SUs within different groups. The grouping can be tackled based on SUs' transmission rate, sensitivity to delay or channel conditions and/or pure social relations among SUs. This point is further explained in the use cases section (see Section 5).

A similar work to ours, is the work of Xing et al. [101]. Their work addresses the SUs interaction under two constraints: the QoS and the interference temperature. The work formulates the problem as an optimization problem by maximizing the utility of SUs. SUs are divided into groups based on their priority. The model forms a potential game to address the priority among SUs. Regarding social deference, priority model in Xing’s work can be considered as social deference among SUs on a single channel. However, this is needed to be re-formulated for multi-channel systems in which SUs with more priority have more incentives to access better channels, which empowers the role of social avoidance. Our work addresses multi-channel bio-socially inspired CR systems.

System Model

In what follows, we assume a community of $N$ SUs. Each SU $S_j$ seeks to transmit data at a rate $R_j$ bits/s: $j = 1 \ldots N$. The community of SUs is distributed over a set of $z$ groups: $G = \{g_1, g_2, \ldots, g_z\}$. SUs operate within an ecosystem of $M$ spectrum channels, and follows the FSM depicted in Figure 19. Each channel $B_i$ ($i = 1 \ldots M$) has a capacity $C_i$ bit/s, and a fraction $\alpha_i \in [0,1]$ of the overall channel capacity that is available for SUs transmission. When $\alpha_i = 0$, a PU is present and SUs are not permitted to transmit; when $\alpha_i = 1$, all SUs who are tuned to channel $B_i$ may transmit each at rate $R_j$.

Initially, $S_j$ is in Transmit substate and transmits on channel $i$. Based on the deference probability $q_j$, it may defer to other SUs from its own group. We define: $U_{j,i,z}$ as a set of all SUs belong to group $g_z$ and transmitting on channel $B_i$ as seen by the secondary user $S_j$. Then, the total number of SUs seen
by $S_i$ is defined as:

$$N_{j,i} = \sum_z ||U_{j,i,z}|| \quad (1)$$

Within $U_{j,i,z}$, the number of SUs that are in $S_j$’s group $z$ is:

$$N_{j,i,z} = \sum_s ||U_{j,i,s} : S_j \in g_z|| \quad (2)$$

and the probability of deference for $S_j$ on channel $B_i$ is:

$$q_{j,i} = \frac{N_{j,i,z}}{N_{j,i}} \quad (3)$$

Notice that at any point of time, $q_{j,i} = 0$ for all channels other than the $S_j$’s current channel $B_i$. $S_j$ defers only when $q_{j,i}$ exceeds the deference threshold $\beta$. For large values of $\beta$, $S_j$ is less likely to defer to other SUs and tends to act selfishly on the channel, and vice versa.

When deferring, the SU stops transmission on the channel and stay tuned on the same channel. To avoid starvation, a probability of hunger $r_H$ is introduced for the SU. $r_H$ is proportional to the hunger level $H$ which is limited by the maximum allowable hunger level $H_{\text{max}}$. If the SU reaches $H_{\text{max}}$, SU stops acting altruistically and start transmitting on the channel.

Regardless of the SU being in the Defer sub-state or in the Transmit sub-state, the SU avoids transmission on channels that has large number of SUs from other groups, based on the probability of the avoidance $p_{j,i}$. To define $p_{j,i}$, we have the number of SUs that are not in $S_j$’s group $z$ as:

$$N_{j,i,-z} = \sum_s ||U_{j,i,s} : S_j \notin g_z|| \quad (4)$$

and the probability of avoidance for $S_j$ on channel $B_i$ is:

$$p_{j,i} = \frac{N_{j,i,-z}}{N_{j,i}} \quad (5)$$

$S_j$ avoids transmission on the channel only when $P_{j,i}$ exceeds the avoidance threshold $\alpha$. For large values of $\alpha$, $S_j$ has less tendency to leave the channel for other groups. In the avoidance, SU tunes to another channel, that is randomly chosen from the set of channels. The social avoidance is associated with a switching cost $S_c$ that is compensated by switching to less congested channels.
Use Cases and Applications

In this section, two real-world scenarios are introduced to address the applicability of the proposed strategies.

Hierarchical SUs DSA Systems

The principle of OSA among SUs and PUs can be extended to include hierarchical DSA among SUs. An example of this approach is the model introduced by Federated Wireless [102], for Spectrum Access System (SAS) of three levels of Spectrum Access. In the first level is the incumbent Users representing Military and other users who allocate the spectrum as they need (i.e., the PU). The second level represents the commercial users who are provided with prioritized access. The third level represents the general users, who can benefit from the spectrum, while guaranteeing spectrum access for the two former types of users. Our work can is aligned with this model, in which SU forms two groups of SUs that access channels based on their social avoidance tendency. Priority access can be studied by providing SUs in the two groups with different social avoidance threshold $\alpha$, to balance the co-existence of SUs from different groups on the channels, based on their priority.

Mice and Elephant transmission

The concept of *mice and elephants* was used in the context of TCP/IP networks to distinguish between two levels of IP connections: connection with large demand (i.e., elephants) and connections with lower demand (i.e., mice). The work in [103] claims that majority (e.g., 80%) of the Internet connections are mice and the rest are *elephants*. Elephants are likely to win the competition against mice since they can reflect from details of connections. Recently, Chai et al. [104], employed this concept in support of Cloud-Radio Access Network (RAN), by dividing each elephant connection into multiple mice connections.

We can employ the concept of *mice and elephants*, by allowing different transmission rates for different users. Two groups of SUs can be modeled based on their demand on the channels, with different social avoidance thresholds. One example of this approach can be spectrum access for multimedia and IoT applications. In general, multimedia is throughput hungry applications in which we expect less number of multimedia users are accessing the channels. On another hand, IoT applications generate data from large number of users, each has little data to be transmitted. In this model, SU not only able to avoid transmission based on the other SUs identities on the channels, but also this decision can be combined with the estimation of demand on the channels. This carried out by SU since they know their group type (e.g., mice or elephants) and also the other group type. This might lead to combined channel and
Simulation Performance Analysis

In our simulation model, \( N \) SUs access \( M \) different WLAN 802.11g channels in infrastructure mode, in which SUs of each band are managed by an Access Point (AP). SUs are free to switch among channels via associating with different APs. Initially, each SU load its avoidance list and deference list and start consuming on its pre-designated band.

Simulation Setup

Network Setup: To simulate \( M = 5 \) different bands in WLAN network, We setup \( M \) Access points (AP) that manage traffic of the network segments (i.e. wireless channel) in infrastructure mode. We setup \( N \) different nodes each equipped with \( M \) WiFi devices. Each device is connected to different AP. When nodes decide to switch from one band to another band it turn off the current device and turn on the device corresponds to the intended band and associate with the new AP. The transmission is a unicast UDP traffic generated from the nodes and sent to the AP. When device decides to defer to other nodes in the channel it stop its own UDP application.

The Social Deference Behavior: In order to simulate the deference behavior using ns-3, we can install an IP application (either UDP or TCP) and then schedule the start time and stop time the application on given node. In this case, stopping the application simulates the deference behavior. Deference behavior happens asynchronously for nodes. Every nodes determines its Deference Time \( T_d \) independently based on values of \( \beta \) and \( \gamma \).

The Social Avoidance Behavior: The avoidance behavior takes place, when the SU decides to switch from the current channel to another channel when it realizes that there is a large number of SUs, with respect to \( \alpha \), from the other groups. The cost of channel switching is networks/system dependent. In our simulation framework, SUs switch channels by associating from the current interface on the AP and associating with the new interface on the AP. Despite the fact that this operation is costly, the system shows throughput improvement due to the avoidance behavior. Other systems have different cost of switching based on there operations, since the channel switching involves hardware and/or software reconfiguration for different wireless devices.

Determining the Hunger Level: If SUs are transmitting with a constant rate \( R \), then the hunger level can be determined based on the waiting time that SU spent without transmission. the hunger level is a function of the demand of SU, in which it accumulate data in its buffer to transmit. Also, the hunger level should be determined in the forage state and not in the consume state. Furthermore, the hunger
Table 9: System Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>Parameter</th>
<th>Value/Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constants</td>
<td>$M$</td>
<td>Number of channels</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>$N$</td>
<td>Number of SUs</td>
<td>40 per channel</td>
</tr>
<tr>
<td></td>
<td>$C_i$</td>
<td>Channel capacity</td>
<td>$[1, 1, 2, 2]$ Mbps, respectively</td>
</tr>
<tr>
<td>Input Parameters</td>
<td>$R_i$</td>
<td>SU transmission rate</td>
<td>varies in $[10, 25, 40]$ Kbps</td>
</tr>
<tr>
<td></td>
<td>$\theta_1$</td>
<td>Avoidance Threshold</td>
<td>varies in $[0, 1]$</td>
</tr>
<tr>
<td></td>
<td>$\theta_2$</td>
<td>Deference Threshold</td>
<td>varies in $[0, 1]$</td>
</tr>
<tr>
<td></td>
<td>$\theta_3$</td>
<td>Hunger Level Threshold</td>
<td>varies in $[0, 1]$</td>
</tr>
<tr>
<td>Calculated Parameters</td>
<td>$\alpha$</td>
<td>Avoidance probability</td>
<td>varies in $[0, 1]$</td>
</tr>
<tr>
<td></td>
<td>$\beta$</td>
<td>Deference probability</td>
<td>varies in $[0, 1]$</td>
</tr>
<tr>
<td></td>
<td>$\gamma$</td>
<td>Relative Hunger level</td>
<td>varies in $[0, 1]$</td>
</tr>
<tr>
<td>Output Parameters</td>
<td>$\Gamma(\cdot)$</td>
<td>SU fractional throughput</td>
<td>$[0, 1]$</td>
</tr>
</tbody>
</table>

level affect the probability of which the SU will avoid/defer to other SUs on the channel. The hunger level should be determined in timely manner, such that each SU recalculate its own hunger level every step of time.

**Sniffing the MAC Headers:** In ns-3, access to the MAC Frames on the channel by enabling Promiscuous Mode on the devices in $\texttt{ns3::NetDevice::SetPromiscReceiveCallback( PromiscReceiveCallback cb)}$. This helps the devices to pass all packets, from all sources to all destinations, to the upper network layers as seen by the device. An event handler should be setup and wired to the callback of each received packet in Promiscuous mode. MAC headers, then, can be classified and added to the corresponding queue. Notice that the sniffing of the MAC frame is limited only for Data MAC frames that associated with real data packets. Other management MAC frame are not sniffed using this callback.

The algorithm below describes the operations that is based on MAC Frames sniffing process. This algorithm accept the users queues $Q_1$ and $Q_2$ and the current system time as an input parameters. It update the queues to add new entries and remove old obsolete entries based on the system timer and Time to Live TTL for entries of avoidance queue ($T_1$) and TTL for entries in deference queue($T_2$). The output of the algorithm is the hunger level $H$, the number of unique MAC addresses $K$ from $Q_2$ and $\alpha$ and $\beta$, where $\alpha$ is the ratio of number of the mac address in $Q_1$ to the max length for avoidance list $B_1$, and $\beta$ number of the mac address in $Q_2$ to the max length of defer list $B_2$. Notice that even that this algorithm takes the system time as an input value, it is not synchronized with the system timer and it is only prompted by the reception of MAC frames in promiscuous mode.

1: Given: $Q_1, Q_2, T_1, T_2, B_1, B_2, T_s$
2: while System is running do
3:   SniffMACHeaders()
4:   AddNewEntries($Q_1, Q_2, T_s$)
5:   RemoveObseleteEntries($Q_1, Q_2, T_1, T_2$)
6. Calculate $H, K, \alpha, \beta, \gamma$

**The Core Logic:** The core logic encapsulate all aspects of the proposed deference system. The Algorithm 5 describe the operation done in user wise every $C$ seconds. As a result the algorithm evaluate the effect of the social deference behavior on the community utility in term of throughput perceived by the nodes in the network. The algorithm combines all previously described parameters and the content of the queues to determine the current state of the node.

1: Given: $Q_1, Q_2, B_1, T_1, B_2, B_3, T_2, R, \theta_1, \theta_2, \theta_3, C, M$

2: while System is running do

3: if $C \% T_s = 0$ then

4: if In Transmit State then

5: if $Q_1.\text{SIZE} == B_1$ and $\alpha > \theta_1$ then

6: BoI = ChooseABand($M, \alpha, \theta_1$)

7: if BoI != Current Band then

8: SwitchToBand(BoI)

9: SendData($R, \text{BoI}$)

10: else

11: if $Q_2.\text{SIZE} == B_2$ and $\beta > \theta_2$ then

12: BoI = Current Band

13: DeferTransmission($H, \text{BoI}$)

14: else

15: SendData($R, \text{BoI}$)

16: else

17: if In Defer State then

18: if $\gamma > \theta_3$ then

19: BoI = Current Band

20: SendData($R, \text{BoI}$)

21: else

22: DeferTransmission($H, \text{BoI}$)

Mainly, the node either transmit or stop transmission on the channels, due to avoidance or deference. The system wise throughput is used a metric to evaluate the feasibility of implementing the deference and avoidance social behaviors and conditions of their application.
Simulation Results

To study the feasibility of employing the social avoidance behavior in the CR networks, a set of simulation experiments are setup, with 40 SUs transmitting on 4 channels. The SUs are distributed equally between two groups, with different social avoidance thresholds $\alpha_1$, $\alpha_2$, and social deference thresholds $\beta_1$ and $\beta_2$ for groups 1 and 2, respectively. SUs transmit at the same rate: 10, 25, and 40 Kbps, as shown in Figures (20), (21), and (22). In these experiments, the effect of social deference is neutralized by setting the social deference threshold values $\beta_1$ and $\beta_2$ equals 1. In this case, SUs does not defer to each other, and only left with two choices: either to transmit on the current channel or to switch to a different channel and transmit on the new channel.

Referring to Figure (20), the Social avoidance show lower performance in comparison to the baseline case (i.e., $\alpha_1 = \alpha_2 = 1$), in which, no social avoidance is established. This is understood from the fact that the social avoidance is associated with switching overhead accumulating while SUs are avoiding SUs from the other group on the channel. Since the channels are already underutilized, the social avoidance
Figure 22: Effect of social avoidance for SUs with high demand on channels.

shows redundant behavior, leaving the baseline case with better performance.

In contrast, social behavior shows better performance when the demand on the channels is medium (25 Kbps per SU) as shown results in Figure (21). The 1 Mbps channels are near capacity and the 2 Mbps are relaxed. The overhead of channel switching, in this case, is compensated since the SUs are switching to channels with better residual channel capacity (e.g., channels 3 and 4). The baseline behavior, shows lower performance since SUs are fixed on the channels, and are not able to benefit from the 2 Mbps channels. Aggressive avoidance also leads to lower performance, (e.g., $\alpha_1 = \alpha_2 = 0.1$), due to the overhead of the social avoidance.

The social avoidance has no benefits under congested channels. As in Figure (22), SUs transmit at 40 Kbps, and demand on the channels exceeds the the channel capacities. The social avoidance has no advantage since the SUs waste the time switching among channels that are already crowded. **In general,** the social avoidance can be advantageous, in cases where the avoidance overhead can be compensated by allocating channels with better conditions (e.g., residual channel capacities).

**The effect of combined social avoidance and deference behaviors:** In the next experiments, we vary the social avoidance and deference thresholds for the two groups in the community together. Both groups have the same thresholds for avoidance and deference. We experiment with communities of 50, 150, and 250 SUs, respectively, over 5 channels. Again the community is divided between the two groups and data transmission occur only within the same group. The experiments are repeated for different transmission rates to address the effect of contention level on the community throughput. Results for 50 SUs community is illustrated in Figure (23). In these we notice that the base line behavior (i.e., no social avoidance or deference), is preferable over any combination of the social behaviors in the system. The difference between maximum and minimum throughput start to decrease as the SU rate changes from 10 to 75 to 125 Kbps for Figure (23) (a), (b), and (c), respectively. Notice that also the sudden throughput change for avoidance thresholds ($\alpha > 0.5$), which reflect the actual division of the SUs on the community among the two groups. This implies that below this threshold values, the
avoidance provide redundant social behavior. Furthermore, the throughput is sensitive to the deference avoidance as seen in Figure (23) (a)-(c). Aggressive deference leads to underutilization of the channels since it prevents the SUs to transmit on channels (e.g., shaded areas for $\beta = 0.4$ and below).

For 150 SUs community, almost the same load generated in the 50 SUs community in Figure (23) (a)-(c), is generated for 150 SUs community, in Figure (24) (a)-(c), respectively. However, different throughput patterns of the throughput is noticed for this case, especially in Figure (24) (b)-(c). In this case, this is due to the fact that the number SUs in this case is larger, and SUs start experiencing different avoidance behaviors over the set of channels. Notice that the social deference in the 150 SUs community demonstrate better performance, in comparison with the 50 SUs in which it shows poor performance. (e.g., $\alpha = 0.1, \beta = 0.9$) in Figure (23) (a) vs. in Figure (24)). Similar conclusion can be seen comparing (23) (b)-(c) with (24) (b)-(c), respectively, in which social deference becomes more preferable. The baseline performance still be the most beneficial behavior for the whole community and preferred over any other social behaviors in cases of lower and medium load channels (Figure 24 (a)-(b)).

The baseline is beneficial under high load on channels, in which combined social avoidance-deference demonstrate better throughput for the community.

The experiments are repeated for 250 SUs community. The role of social deference and avoidance becomes more crucial and demonstrated better performance for the SUs on the community. This is due to the fact that the altruistic social deference helps to decrease the contention over channels and allow the community of SUs to gain better throughput. The social avoidance and deference behaviors demonstrated, in this experiment, throughput improvement up to 134.4% with average improvement of 54.1% with different values of social and deference thresholds. Failing to follow the social avoidance and deference decreases the SUs' throughout as seen in Figure (25) (b)-(c), for the baseline values ($\alpha = 1.0, \beta = 1.0$). Notice that if the channels are lightly loaded, the baseline behavior is still preferred as in (25) (a), drawing the same conclusion for 50 SUs, and 150 SUs communities, (23) (a) and (24) (a), respectively.

**Formal Performance Analysis**

In what follows, we assume that the SU switches from the current channel to one of its two adjacent channels. This assumption is valid for small number of channels, since all states are accessible by the SU, and the probability of moving to adjacent channel is approximately equal to the probability of hopping randomly between channels. For example, in a eco-system of 3 channels, the probability of moving from the current channel to other adjacent channel equals to $\frac{1}{2}$. The probability of hopping among channels equals to $\frac{1}{N-1} = \frac{1}{2}$, which is equal to the probability of switching to adjacent channels.
Figure 23: Combined Social Avoidance and Deference effect on the community throughput (50 SUs).
Figure 24: Combined Social Avoidance and Deference effect on the community throughput (150 SUs).
Figure 25: Combined Social Avoidance and Deference effect on the community throughput (250 SUs).
for large number of channels, this assumption is invalid, and the analysis should be carried for $N^{N-1}$ equations.

Applying this assumption, and following the analysis of the FSM in Figure 18, we have:

$$\pi_{T,i} \cdot q_{j,i} = \pi_{D,i} \cdot r_{H,i}$$

(6)

Where $\pi_{T,i}$ and $\pi_{D,i}$ are the probability that $S_j$ is transmitting on the channel $i$, and deferring transmission, respectively.

We are specially interested in $\pi_{T,i}$ since it governs the transmission on the channels and consequently, affects the throughput obtained by the SU. Then:

$$\pi_{T,i} = \pi_{D,i} \cdot \frac{r_{H,i}}{q_{j,i}}$$

(7)

Furthermore, we have:

$$\pi_{i-1} \cdot p_{j,i-1} = \pi_i \cdot p_{j,i}$$

(8)

Where $\pi_i$ is the probability that the SU is in state $i$. While in this state it is either deferring, or transmitting. Applying for the $k$th state:

$$\pi_k \cdot p_{j,k} = \pi_{k+1} \cdot p_{j,k+1}$$

(9)

Arranging equation (9) to obtain the probability of being in $k$th state, iteratively, from the 1st state, we have:

$$\pi_k = \pi_1 \cdot \prod_{i=1}^{k-1} \frac{p_{j,i}}{p_{j,i+1}}$$

(10)

The probability that the SU is transmitting on channel $i$:

$$P_{T,i} = \pi_i \cdot \pi_{T,i}$$

(11)

and also, we have:

$$\sum_{i=1}^{N} \pi_i = 1$$

(12)

From equations (10) and (12), we have:

$$\pi_1 \cdot \sum_{i=1}^{N} \prod_{m=1}^{i-1} \frac{p_{j,m}}{p_{j,m+1}} = 1$$

(13)

$$\pi_1 = \frac{1}{\sum_{i=1}^{N} \prod_{m=1}^{i-1} \frac{p_{j,m}}{p_{j,m+1}}}$$

(14)
The $S_i$ transmits on channel $i$ at rate:

$$R_{j,i} = P_{T,i} \cdot R_j$$

and the total demand on the channel $i$:

$$D_i = \sum_{j=1}^{N} R_{j,i}$$

### Experimental Results

In this section, a testbed is presented to experiment with channel switching and strategy evolution in Wireless Local Area Networks (WLANs). The testbed design and implementation are described next, followed by experimental results and discussions.

### Experimental Testbed

The experimental testbed is designed as an extension of the simulation framework to evaluate the proposed model on the physical channels. Due to the reconfigurability and cost of implementing network with large number of devices, one machine can be used to emulate large number of nodes while allowing nodes to transmit traffic over the WiFi channels. In this case, all emulated nodes experience the same level of contention over the channels and allow the behaviors of social deference and avoidance to be studied across the allocated channels.

In this model, packets from ns-3 nodes from one machine are directed to their corresponding nodes on the other machine through the physical WiFi channels. ns-3 nodes are connected to the physical
machine through software tap-bridge, installed on the host Ubuntu platform. The machine redirects packets from tap-bridge to the WiFi device, which sends it over air for physical transmission.

Each band in the simulation part, which represented by an AP, is connected to a given tap-bridge. Five different WiFi devices (Netgear WNA1100 USB wireless adapters) are connected to the machine using USB HUB, the devices should be able to support Atheros WiFi device driver for its known flexibility and reconfigurability. This driver is especially used since it supports disabling the backoff, which is needed for the experiment. This model is re-utilized from the work of Vanhoef [63] which used originally for security purposes.

When SU decides to transmit on a given channel, it sends its packet to the corresponding AP. When it decides to switch to another channel it dissociates from that AP and associates with the new AP. Each simulated AP traffic is directed to different physical channels as depicted in Figure 26.

To maintain a persistent level of traffic on the channels, PU Tx-Rx pair is setup. In this setup five Atheros devices are connected to both the PU-Tx and PU-Rx and the backoff setting, for these devices, is disabled to allocate the needed level of PU traffic.

The experiment manager machine is responsible for experiment initiation and monitoring in timely manner. This machine sends the configuration for all other machines through the Ethernet switch. This is needed to isolate the management traffic among machines from the real traffic generated by the experiments. At the end of experiments, results gathered in the SUs-Rx machine are sent to the experiment manager for further analysis. For traffic logging during the experiments, experiment manager sniffs all channels and logs the data using Wireshark. The hardware used in the experiments:

- 5 Dekstop Machines: Intel® Xeon (R) CPU E3-1240 v5 @ 3.50GHz × 8 with 64GB of RAM.
- 5 USB Hubs.
- 25 WiFi Devices: Netgear WNA1100 USB adapters with Atheros AR9002U/AR9271 Chipset.
- 1 1000Mbps Ethernet Switch.
- 5 1000Mbps Ethernet Cables.

The platforms and applications used in the experiments:

- Ubuntu Linux Operating System for hosting the SUs traffic.
- network simulator 3 (ns-3) for generating and receiving SUs data.
- Python programming language for logging, data analysis and visualization.
- ModWiFi Device Driver [63] for modifying the appropriate WiFi settings.
Conclusion

In this work, two bio-socially behavior were introduced and compared with baseline approach for SUs transmission across the available channels. The proposed behaviors shows improvement under conditions where channels are highly loaded with large SUs community. Future work can be extended to address different properties of SUs, different number of groups, different SUs demand level. More social behaviors can be introduced and studied in similar manner. These properties can be studied using the simulation framework and the experimental testbed introduced in this work.

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Chapter 6

Conclusions and Future Work

This chapter concludes the current work and points the future directions of the research.

Conclusions

The main conclusions that can be drawn from this work are:

• 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.

• We proved analytically that each strategy has a potential to win or lose in a system of SUs, based on the condition of the channels utilized and social attributes of the users. Given channel conditions and users’ behaviors, SUs evolve to one and only one strategy that is considered evolutionary stable.

• We showed analytically that no mixed strategies yield a stable strategy for the system. Furthermore, we showed that, under some conditions, SUs with more social tendency gain more benefits on the long run when compared with selfish SUs, who prefer myopic, short-term benefits.

• The advent of large-scale VANETs heralds the emergent problems of device co-existence and the potential of device sociality in the ecosystem of the radio spectrum.
• We found that for Vehicular Networks, one of these three strategies is always dominant, and while the winning strategy depends on channel conditions, it is stable against defections by small numbers of deviating nodes.

• Taken together, these results together point to a new way of thinking about resource allocation problem: one where optimal and stable channel selection strategies are computed and uniformly recommended, rather than the current view where individual channels are micromanaged and allocated by a central authority.

• This new model is envisioned at the core of a VANET communications system, where a road-side unit aggregates and relays per-band throughput measurements from its area nodes to the cloud.

**Future Work**

This work can be extended to the following research directions:

- The proposed analytical framework, can be extended to study new strategies that exhibit a distinct social and cognitive behaviors, depending on observed community of SUs and network metrics. Future work includes, but not limited to, applying the proposed strategies in different use cases such as EHS, IoT, and VANETs.

- Implementation of VANET hardware testbed, based on the proposed bio-socially inspired DSA systems is planned, to complement and validate the analytic and simulation findings presented here.

- The dynamic optimization of node-specific parameters, and a fine-grained analysis of control traffic overhead is planned for future research.
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