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Evolutionary Game Theory Perspective on Dynamic Spectrum Access Etiquette

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ABSTRACT In this paper, 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 test-bed 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 with any static strategy. We present use cases to envision the potential application of the proposed evolutionary framework in real-world scenarios.

INDEX TERMS Dynamic spectrum access, cognitive radio, evolutionary game theory, bio-social networking.

I. 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 userİ (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, thus ensuring more effective resource sharing. Channel selection is an inherently complex task in multichannel 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 II. 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 V, and VI, respectively. Finally, conclusions and future research directions are discussed in Section VII.

II. 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.* [6] and Xing and Chandramouli [7] as well as that of Wisniewska *et al.* [8], [9]. Our work here also serves to elucidate the nature of SU-SU dynamics and extends the work of Shattal *et al.* [10]. 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 aucity of studies that address the role of SU interactions in support of enhanced DSA. This research gap is illustrated in Figure 1 relative to the different DSA/CR-related research areas addressed in the recent literature.

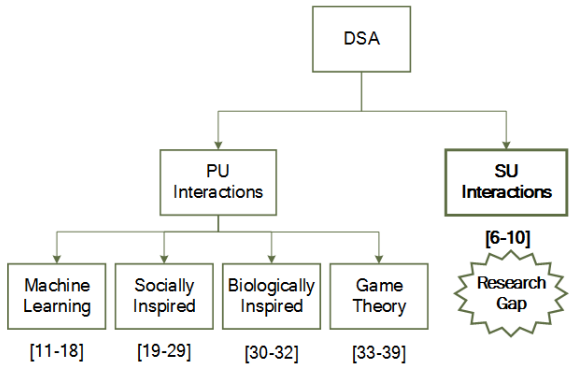
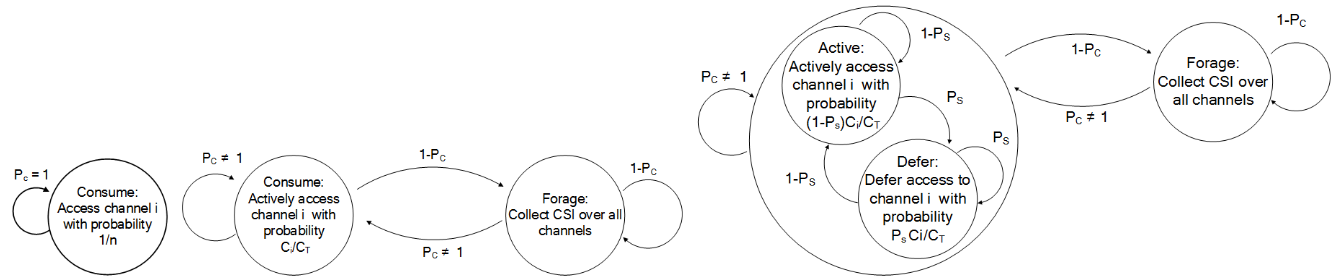


FIGURE 1. Taxonomy of DSA problems and approaches.

Machine learning approaches have been applied extensively to spectrum sharing [11], spectrum sensing [12] and channel selection [13]. Specifically, different types of machine learning algorithms have been incorporated into CR network protocols (see [14] for a survey), including support vector machines [15], re-enforcement learning [16] and Q-Learning [17]. 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 [18].

Biologically or socially inspired approaches typically begin by incorporating a social component to users' behavioral models (e.g., preferential bias [19], peer recommendations [20], and selfishness [21]). These approaches consider the CR ecosystem as a social network [22], [23] for which cooperative schemes are designed [24]. 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 [25], Vehicular Network (VANET) routing [26], and sensor network management [27]. In the context of CR, bio-socially inspired models have been developed for spectrum sensing [27], channel selection [24], and efficient routing [25]. Genetic algorithms have been used to tune CR parameters for better spectrum usage [28], and recommendation systems have been applied to minimize sensing and decision-making times required for channel selection [29]. Unfortunately, idealized bio-social models based on animal societies (e.g., termites [30], ants [31], etc.) require a level of coordination among population individuals [32]. The assumption of pre-agreed upon



(a) FSM for ACU (b) FSM for FCU (c) FSM for SFU

FIGURE 2. Finite State Machine for the proposed bio-social users. (a) FSM for ACU. (b) FSM for FCU. (c) FSM for SFU.

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 [33] and [34] for a survey of prior work in this area). Competition among SUs over network resources has been modeled as a non-cooperative game [35]. 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 [36] and repeated games [37]. Such information is not known a priori, limiting the applicability of this approach [38].

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 [39]. In some cases, evolutionary stable strategies have been found to exhibit in-simulation performance improvements of almost 35% [12]. EGT is also attractive because it relaxes the traditional rationality assumptions of game theory [40], 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 uncoordinatedİ 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.

III. 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, α_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 2-(a). This simple strategy (used previously in [41]) allows the ACU to act with a naïve view to capture utility using the set of channel resources. The ACUs strategy has the advantage that it can be implemented cheaply since no sensing capability is needed. The channel selection process itself is fast, requiring minimal computational resources and no coordination overhead. In practice, an ACU may access congested channels instead of using channels that have higher residual capacity. The performance of ACUs serves as a baseline for the incremental benefits of more sophisticated foraging and social behaviors.

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 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 2-(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:

$$\overline{\mathrm{C_i}} = \alpha_i C_i / \sum_j \alpha_j C_j \tag{1}$$

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 $\overline{\mathrm{C_i}}$ 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:

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

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 $\overline{\mathrm{C_i}}$ as follows:

$$\overline{\mathrm{C_i}} \approx \frac{\gamma(\alpha_i C_i, n_i, P_c R)}{\sum_j \gamma(\alpha_j C_j, n_j, P_c R)} \tag{2}$$

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 α_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 $\overline{\mathrm{C_i}}$.

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 [42] and non-human primate [43] 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 2-(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 SFU 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., NxN 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

[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.

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 V) and experimental studies (Section VI).

A. UTILITY OF THE SUs IN HOMOGENEOUS SYSTEMS

Consider a homogeneous system $\mathcal{S}$ 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

$$\mathcal{Z} = (C, N, R)$$

The fractional throughput of the SUs in $\mathcal{Z}$ is written as:

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

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 α 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 η plays an important role in quantifying the performance of the model that follows.

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

$$\mathcal{Z}^* = (C, N, R) \tag{3}$$

having access to $M \geqslant 1$ channels of capacities $C_1, \ldots C_M$. Assuming $\mathcal{Z}^*$ is in steady state, O_s^i 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:

$$O^i_{ACU} = \frac{N}{M} \tag{4}$$

$$O^i_{FCU} = \overline{\mathrm{C_i}} \cdot N \tag{5}$$

$$O^i_{SFU} = \overline{\mathrm{C_i}} \cdot (1 - P_S) \cdot N \tag{6}$$

The total demand for channel i is computable as

$$D_i(\mathcal{Z}^*, s) = O^i_s \cdot R \tag{7}$$

and the fractional throughput of users in channel i is:

$$X^i_\eta(\mathcal{Z}^*, s) = \eta(\alpha_i C_i, O^i_s, R) \tag{8}$$

While the precise form of η is intractable, we will take

$$X^i_\eta(\mathcal{Z}^*, s) \approx \begin{cases} 1 & \text{if } D_i(\mathcal{Z}^*, s) < \rho C_i \\ \dfrac{1}{\exp^{D_i(\mathcal{Z}^*, s) - \rho C_i}} & \text{if } D_i(\mathcal{Z}^*, s) \geq \rho C_i \end{cases} \tag{9}$$

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

$$U_{s=ACU}(\mathcal{Z}^*) = \frac{1}{M} \sum_{i=1}^{M} R \cdot X^i_\eta(\mathcal{Z}^*, s) \tag{10}$$

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

$$U_{s=FCU}(\mathcal{Z}^*) = P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot R \cdot X^i_\eta(\mathcal{Z}^*, s) \tag{11}$$

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

$$U_{s=SFU}(\mathcal{Z}^*) = P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}}(1 + S_+) \cdot R \cdot (1 - S_-) \cdot X^i_\eta(\mathcal{Z}^*, s) \tag{12}$$

B. 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 $\mathcal{S}$ in which there are k_1 ACUs, k_2 FCUs, ad k_3 SFUs. In $\mathcal{S}$, 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

$$\mathcal{S} = (k_1, k_2, k_3, r_1, r_2) \tag{13}$$

The fractional throughput of the SUs in $\mathcal{S}$ is written as:

$$X_\gamma(\mathcal{S}) := \gamma(\alpha C, k_1 + k_2, r_1, k_3, r_2) \tag{14}$$

Considering a multi-channel system $\mathcal{S}^*$, we have:

$$\mathcal{S}^* = (k_1, k_2, k_3, r_1, r_2) \tag{15}$$

having access to $M \geqslant 1$ 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 the system to the possibility that some fraction of its players could "mutate" 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

$$O^i_{ACU} = \frac{N_{ACU}}{M} \tag{16}$$

$$O^i_{FCU} = \overline{\mathrm{C_i}} N_{FCU} \tag{17}$$

$$O^i_{SFU} = \overline{\mathrm{C_i}}(1 - P_S) N_{SFU} \tag{18}$$

The total demand for channel i is computable as

$$D_i(\mathcal{S}^*) = (O^i_{ACU} + O^i_{FCU})\cdot R + O^i_{SFU} \cdot (1 + S_+)\cdot R \tag{19}$$

and the fractional throughput of users in channel i is:

$$X^i_\gamma(\mathcal{S}^*) = \gamma(\alpha_i C_i, O^i_{ACU} + O^i_{FCU}, R, O^i_{SFU}, (1 + S_+) \cdot R) \tag{20}$$

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

$$X^i_\gamma(\mathcal{S}^*) \approx \begin{cases} 1 & \text{if } D_i(\mathcal{S}^*) < \rho C_i \\ \dfrac{1}{\exp^{D_i(\mathcal{S}^*)-\rho C_i}} & \text{if } D_i(\mathcal{S}^*) \geq \rho C_i \end{cases} \tag{21}$$

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

$$U_{ACU}(\mathcal{S}^*) = \frac{1}{M}\sum_{i=1}^{M} R \cdot X^i_\gamma(\mathcal{S}^*) \tag{22}$$

$$U_{FCU}(\mathcal{S}^*) = P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot R \cdot X^i_\gamma(\mathcal{S}^*) \tag{23}$$

$$U_{SFU}(\mathcal{S}^*) = P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot R \cdot G_s \cdot X^i_\gamma(\mathcal{S}^*) \tag{24}$$

where $G_s = (1 + S_+) \cdot (1 - S_-)$ is the sociality gain.

The **system utility** is expressed as:

$$U_S(\mathcal{S}^*) = N_{ACU} \cdot U_{ACU}(\mathcal{S}^*) + N_{FCU} \cdot U_{FCU}(\mathcal{S}^*) + N_{SFU} \cdot U_{SFU}(\mathcal{S}^*) \tag{25}$$

When an individual user gains more utility due to channel switching or strategy evolution, the system's utility $U_S(\mathcal{S}^*)$ 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 V, in which limits and conditions for each SU strategy to maximize the system utility are established.

IV. USE CASES AND APPLICATIONS

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

A. 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.

B. 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 throughout 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.

V. FORMAL PERFORMANCE ANALYSIS

Evolutionary Game Theory (EGT) originated as an application of game theory in the context of biological sciences [44], 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.

Smith in [45] 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 [46], and has since been described in many textbooks (e.g., see [47]).

In general game theory, Nash equilibrium is an optimal outcome of the game such that no player gains more utility by unilaterally deviating or changingİ 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 [48]. A strategy σ^* is an ESS, if mutants that adopt any other strategy σ leave fewer offsprings in the post-entry population $x_\epsilon := (1-\epsilon)\sigma^*+\epsilon\sigma$, assuming that the proportion of mutants ϵ is sufficiently small ($0 < \epsilon < \overline{\epsilon}$). For σ^* to be ESS then:

$$U(\sigma^*, x_\epsilon) > U(\sigma, x_\epsilon) \tag{26}$$

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

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

A. 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 $\mathcal{S}^*$ be the system in (15), 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 σ^* and p, q, k, for σ, respectively; where $(p^* + q^* + k^* = 1)$ and $(p + q + k = 1)$. Define

$$\begin{aligned} A(\mathcal{S}^*, \sigma^*, \sigma) = p^*(p^* - p) \cdot U_{ACU}(\mathcal{S}^*) \\ + q^*(q^* - q) \cdot U_{FCU}(\mathcal{S}^*) \\ + k^*(k^* - k) \cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{27}$$

$$\begin{aligned} B(\mathcal{S}^*, \sigma^*, \sigma) = (p^* - p)^2 \cdot U_{ACU}(\mathcal{S}^*) \\ + (q^* - q)^2 \cdot U_{FCU}(\mathcal{S}^*) \\ + (k^* - k)^2 \cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{28}$$

Lemma 1: Let $\mathcal{S}^*$ be the system in (15), 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 ϵ 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 ϵ sufficiently small, the defection fails to be rational. In particular, $\mathcal{S}^*$ is evolutionarily stable as long as*

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

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

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

The existence of an ESS in an EGT game requires the inequality condition of Equation (26) to hold. Suppose $\sigma^* = (p^*, q^*, k^*)$ is the strategy employed in $\mathcal{S}^*$ and $\sigma = (p, q, k)$ is the strategy of the defectors. The utility achieved by the defectors is

$$\begin{aligned} U_\sigma = {} & p\left[p^* - \epsilon(p^* - p)\right] \cdot U_{ACU}(\mathcal{S}^*) \\ & + q\left[q^* - \epsilon(q^* - q)\right] \cdot U_{FCU}(\mathcal{S}^*) \\ & + k\left[k^* - \epsilon(k^* - k)\right] \cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{31}$$

while the non-defectors achieve

$$\begin{aligned} U_{\sigma^*} = {} & p^*\left[p^* - \epsilon(p^* - p)\right] \cdot U_{ACU}(\mathcal{S}^*) \\ & + q^*\left[q^* - \epsilon(q^* - q)\right] \cdot U_{FCU}(\mathcal{S}^*) \\ & + k^*\left[k^* - \epsilon(k^* - k)\right] \cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{32}$$

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

B. 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 $\mathcal{S}^*$ is a homogeneous system of ACUs, a defection to strategy $\sigma = (p, q, k)$ by an ϵ fraction of players fails to be rational if ϵ is less than

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

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

$$A(\mathcal{S}^*, \sigma) = (1-p) \cdot U_{ACU}(\mathcal{S}^*) \tag{33}$$

$$\begin{aligned} B(\mathcal{S}^*, \sigma) = {} & (1-p)^2 \cdot U_{ACU}(\mathcal{S}^*) \\ & + q^2 \cdot U_{FCU}(\mathcal{S}^*) + k^2 \cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{34}$$

The proposition is proved. □

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

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

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

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

$$A(\mathcal{S}^*, \sigma) = (1-q) \cdot U_{FCU}(\mathcal{S}^*) \tag{35}$$

$$\begin{aligned} B(\mathcal{S}^*, \sigma) = {} & p^2 \cdot U_{ACU}(\mathcal{S}^*) \\ & + (1-q)^2 \cdot U_{FCU}(\mathcal{S}^*) + k^2 \cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{36}$$

The proposition is proved. □

As $U_{FCU}(\mathcal{S}^*)$ decreases, we see that the bound on ϵ in Proposition 2 approaches 0, making it more likely that users will defect away from the homogeneous FCU society. Conversely, as $U_{FCU}(\mathcal{S}^*)$ increases relative to $U_{ACU}(\mathcal{S}^*)$ and $U_{SFU}(\mathcal{S}^*)$, we see that the bound on ϵ approaches 1, making it so users will be unable to defect away from the homogeneous FCU society without group coordination.

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

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

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

$$A(\mathcal{S}^*, \sigma) = (1-k) \cdot U_{SFU}(\mathcal{S}^*) \tag{37}$$

$$\begin{aligned} B(\mathcal{S}^*, \sigma) = {} & p^2 \cdot U_{ACU}(\mathcal{S}^*) \\ & + q^2 \cdot U_{FCU}(\mathcal{S}^*) + (1-k)^2 \cdot U_{SFU}(\mathcal{S}^*) \end{aligned} \tag{38}$$

The proposition is proved. □

As $U_{SFU}(\mathcal{S}^*)$ decreases, we see that the bound on ϵ in Proposition 2 approaches 0, making it more likely that users will defect away from the homogeneous SFU society. Conversely, as $U_{SFU}(\mathcal{S}^*)$ increases relative to $U_{ACU}(\mathcal{S}^*)$ and $U_{FCU}(\mathcal{S}^*)$, we see that the bound on ϵ approaches 1, making it so users will be unable to defect away from the homogeneous SFU society without group coordination.

Proposition 4: If $\mathcal{S}^*$ is a system in which

$$U_{ACU}(\mathcal{S}^*) = U_{FCU}(\mathcal{S}^*) = U_{SFU}(\mathcal{S}^*)$$

then no evolutionary stable strategy exists in $\mathcal{S}^*$.

Proof: If all utilities of all strategies are equal then players may switch and mix strategies without penalty, and because the strict inequality in (26) cannot be made to hold for any strategy, no strategy is evolutionarily stable. □

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

Proof: Suppose σ is the ESS. The payoff for this strategy is

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

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. □

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

$$\sigma = \begin{cases} ACU & \text{if } U_{ACU}(\mathcal{S}^*) > U_{FCU}(\mathcal{S}^*), U_{SFU}(\mathcal{S}^*) \\ FCU & \text{if } U_{FCU}(\mathcal{S}^*) > U_{ACU}(\mathcal{S}^*), U_{SFU}(\mathcal{S}^*) \\ SFU & \text{if } U_{SFU}(\mathcal{S}^*) > U_{ACU}(\mathcal{S}^*), U_{FCU}(\mathcal{S}^*) \end{cases} \quad (39)$$

C. FINDING AN ESS

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

Proof: Corollary 1 mandates that $U_{ACU}(\mathcal{S}^*) > U_{FCU}(\mathcal{S}^*)$ and $U_{ACU}(\mathcal{S}^*) > U_{SFU}(\mathcal{S}^*)$, which implies:

$$\frac{1}{M}\sum_{i=1}^{M} X^i_\gamma(\mathcal{S}^*) > P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X^i_\gamma(\mathcal{S}^*) \quad (40)$$

$$\frac{1}{M}\sum_{i=1}^{M} X^i_\gamma(\mathcal{S}^*) > P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X^i_\gamma(\mathcal{S}^*) \quad (41)$$

Substituting $X^i_\gamma(\mathcal{S}^*) = 1$ and $\sum_{i=1}^{M} \overline{\mathrm{C_i}} = 1$, we get

$$P_c < 1 \quad (42)$$

$$P_c \cdot G_s < 1 \quad (43)$$

The theorem is proved. □

Theorem 2: For a system $\mathcal{S}^*$, where

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

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

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

Substituting into inequalities (40) and (41), we get

$$P_c < 1 \quad (44)$$

$$P_c \cdot G_s < 1 \quad (45)$$

The theorem is proved. □

1) REFLECTIONS ON THEOREMS (1) AND (2)

The antecedent in Theorem (1) 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 (2), 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 (1).

Theorem 3: For a system $\mathcal{S}^*$, FCU is a winning strategy iff:

$$P_c > \frac{1}{M} \frac{\sum_{i=1}^{M} X^i_\gamma(\mathcal{S}^*)}{\sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X^i_\gamma(\mathcal{S}^*)} \quad (46)$$

and

$$G_s < 1 \quad (47)$$

Proof: Corollary 1 mandates that $U_{FCU}(\mathcal{S}^*) > U_{ACU}(\mathcal{S}^*)$ and $U_{FCU}(\mathcal{S}^*) > U_{SFU}(\mathcal{S}^*)$, which implies:

$$P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X^i_\gamma(\mathcal{S}^*) > \frac{1}{M}\sum_{i=1}^{M} X^i_\gamma(\mathcal{S}^*) \quad (48)$$

$$P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X^i_\gamma(\mathcal{S}^*) > P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X^i_\gamma(\mathcal{S}^*) \quad (49)$$

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

2) REFLECTIONS ON THEOREM 3

The antecedent in Theorem (3) 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 (1) and (2), 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 $\overline{C_i}$. 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 SFUs from compensating for their social coordination overhead and ensures that FCUs outperform SFUs.

Theorem 4: For a system $\mathcal{S}^*$, SFU is a winning strategy iff:

$$P_c > \frac{1}{M} \frac{\sum_{i=1}^{M} X^i_\gamma(\mathcal{S}^*)}{\sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X^i_\gamma(\mathcal{S}^*)} \quad (50)$$

and

$$G_s > 1 \quad (51)$$

Proof: Corollary 1 mandates that $U_{FCU}(\mathcal{S}^*) > U_{ACU}(\mathcal{S}^*)$ and $U_{FCU}(\mathcal{S}^*) > U_{SFU}(\mathcal{S}^*)$, which implies:

$$P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X^i_\gamma(\mathcal{S}^*) > \frac{1}{M}\sum_{i=1}^{M} X^i_\gamma(\mathcal{S}^*) \quad (52)$$

$$P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot G_s \cdot X^i_\gamma(\mathcal{S}^*) > P_c \sum_{i=1}^{M} \overline{\mathrm{C_i}} \cdot X^i_\gamma(\mathcal{S}^*) \quad (53)$$

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

3) REFLECTIONS ON THEOREM 4

The antecedent in Theorem (4) 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 (1) and (2), 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 $\overline{C_i}$. 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.

D. 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 [49]. 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:

$$\dot{x} = x_i[f_i(x) - \sum_j^n x_j \cdot f_i(x)] \tag{54}$$

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:

$$c_1 = [U_{ACU} \cdot (1 - x_{ACU}) - U_{FCU} \cdot x_{FCU} - U_{SFU} \cdot x_{SFU}] \tag{55}$$

$$c_2 = [U_{FCU} \cdot (1 - x_{FCU}) - U_{ACU} \cdot x_{ACU} - U_{SFU} \cdot x_{SFU}] \tag{56}$$

$$c_3 = [U_{SFU} \cdot (1 - x_{SFU}) - U_{ACU} \cdot x_{ACU} - U_{FCU} \cdot x_{FCU}] \tag{57}$$

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

$$\dot{x}_{ACU} = c_1 \cdot x_{ACU} \tag{58}$$

$$\dot{x}_{FCU} = c_2 \cdot x_{FCU} \tag{59}$$

$$\dot{x}_{SFU} = c_3 \cdot x_{SFU} \tag{60}$$

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

$$x_{ACU} = x_{ACU}(0)e^{c_1 t} \tag{61}$$

$$x_{FCU} = x_{FCU}(0)e^{c_2 t} \tag{62}$$

$$x_{SFU} = x_{SFU}(0)e^{c_3 t} \tag{63}$$

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

$$x_{ACU} + x_{FCU} + x_{SFU} = 1 \tag{64}$$

implying that:

$$\frac{N_{ACU}}{N} + \frac{N_{FCU}}{N} + \frac{N_{SFU}}{N} = 1 \tag{65}$$

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.

E. 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 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.

VI. 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.

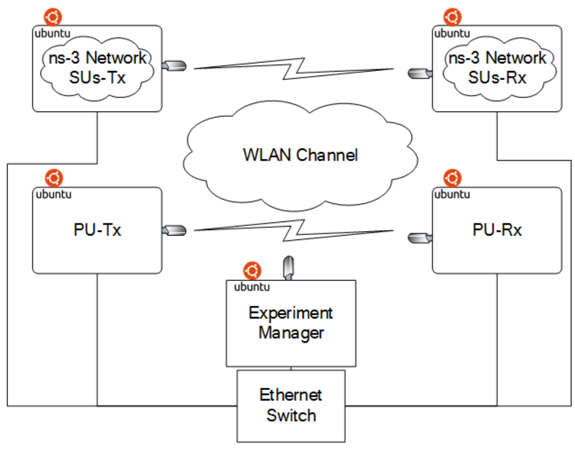


FIGURE 3. Experimental testbed.

TABLE 1. Experimental parameters.

Parameter	Value
Total number of SUs	80
Number of Channels	4
PU traffic (Mbps)	Homogeneous:[1, 1, 1, 1] Heterogeneous:[19, 19, .25, .25]
WLAN Standard	IEEE 802.11g
WLAN channel capacity	`ns-3` network: 11Mbps Physical network: 54Mbps
Distance from AP	$10m$ for `ns-3` network
Transmission power	16.0206 dBm (default) [50]
Channel Propagation Model	Log Distance Propagation Model [51]
CBR transmission rate per SU (kbps)	10 Kbps (light), 40 Kbps (intermediate) 65 Kbps (heavy)

A. EXPERIMENTAL TESTBED

For experimental purposes, a testbed was developed; its architecture is shown in Figure 3. 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 [51]. System parameters are listed in Table 1. 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` [52] device driver and verified experimentally (see Table 2). 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 4). 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.

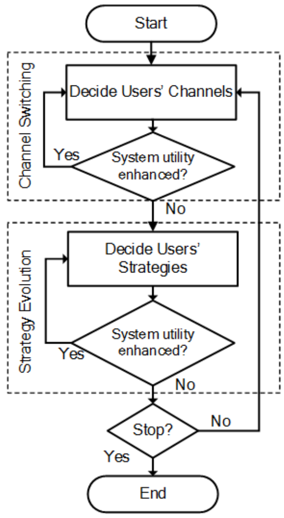


FIGURE 4. Channel switching and strategy evolution of SUs.

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.

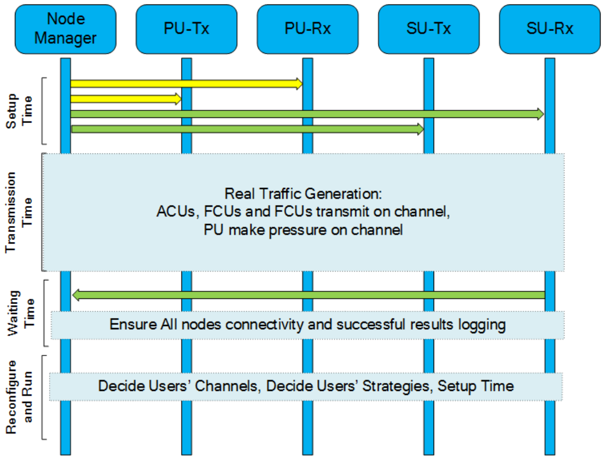


FIGURE 5. Timeline of actions during each experiment.

Figure 5 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 5). 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 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 2. These results are associated with the results in Table 3-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.

TABLE 2. Results of a single iteration.

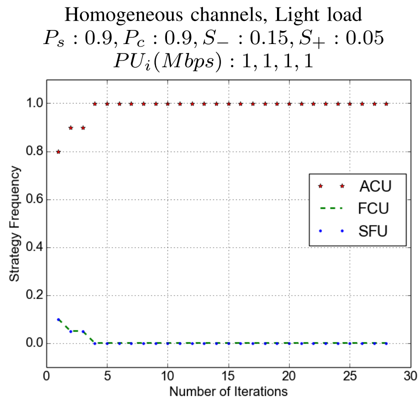
Channel Number	PU's demand *(Theoritical)* (Mbps)	PU's throughput *(Experimental)* (Mbps)	SU throughput per user ACU, FCU, SFU (Kbps)
1	20	20.00	0.073, 0.034, 0.103
2	20	19.70	0.047, 0.021, 0.239
3	0.5	0.497	17.70, 24.88, 42.97
4	0.5	0.497	14.91, 22.66, 34.58

B. RESULTS

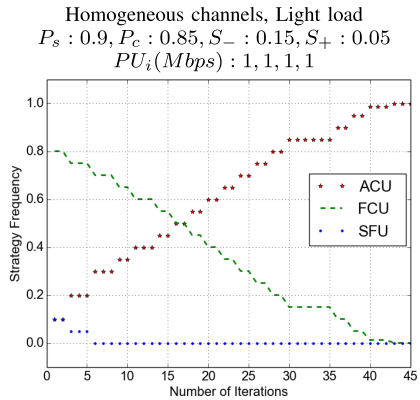
We describe $3 \times 3 = 9$ different scenarios covering all the possibilities in which one of the 3 strategies (ACU, FCU, SFU) is dominant at the beginning, and another is eventually dominant post-evolution. These experiments are illustrated in Table 3. Each column represents the initially dominant strategy in 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 6. 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 1 and in the headers above each of the figures in Table 3-Figure (a)-(c). In these scenarios, all channels were lightly loaded with PUs (0.25*Mbps*). 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

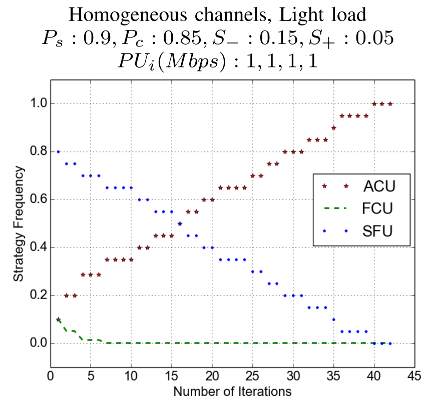
TABLE 3. Experimental evaluation of the ACU, FCU, and SFU strategies. (a) ACU initially dominant, ACU eventual winner. (b) FCU initially dominant, ACU eventual winner. (c) SFU initially dominant, ACU eventual winner. (d) ACU initially dominant, FCU eventual winner. (e) FCU initially dominant, FCU eventual winner. (f) SFU initially dominant, FCU eventual winner. (g) ACU initially dominant, SFU eventual winner. (h) FCU initially dominant, SFU eventual winner. (i) SFU initially dominant, SFU eventual winner.



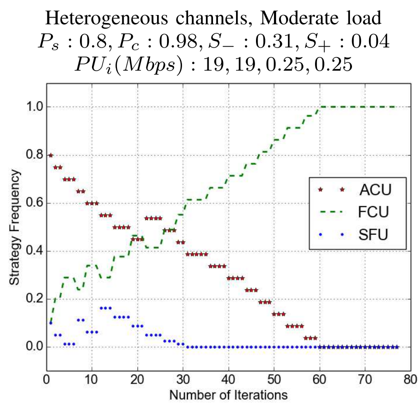
(a)



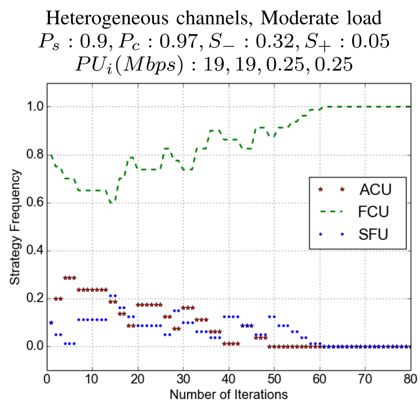
(b)



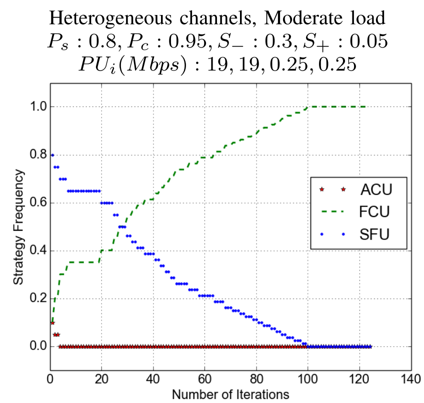
(c)



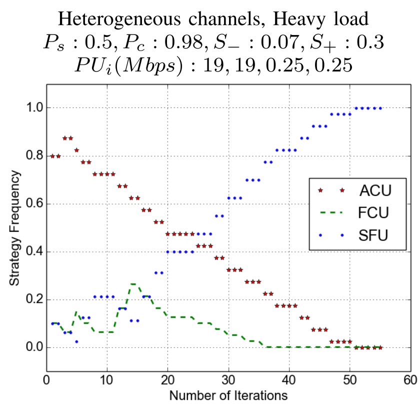
(d)



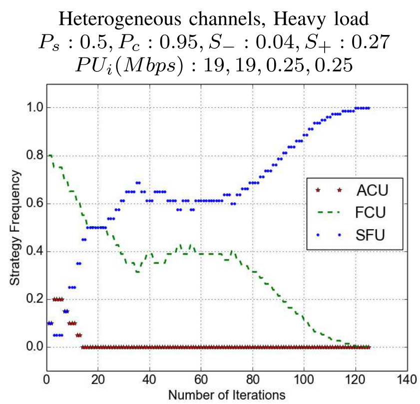
(e)



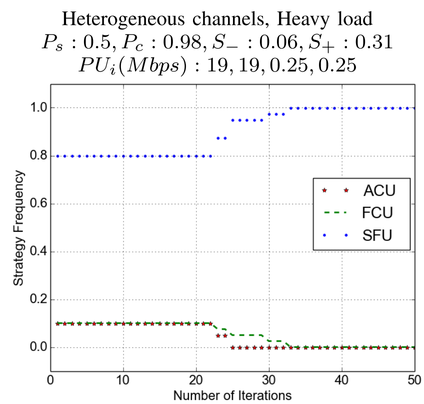
(f)



(g)



(h)



(i)

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 6-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 1 and in the headers above each of the figures in Table 3-Figure (d)-(f). In these

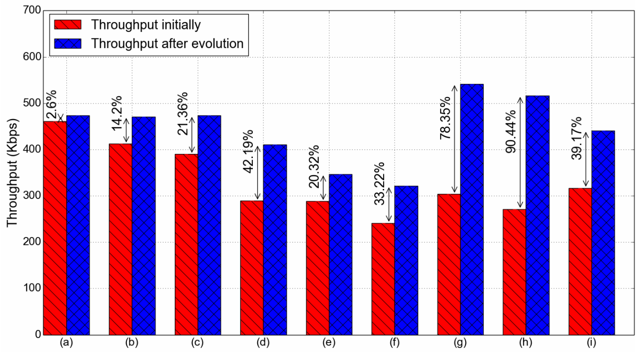


FIGURE 6. Experimental throughput improvement.

scenarios, two channels were highly loaded with PUs (19*Mbps*), and two channels were lightly loaded (250*kbps*). 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 6-Columns (d)-(f).

To assess the efficacy of the SFU strategy, we conducted 3 experiments using the experimental channel and strategy parameters detailed in Table 1 and in the headers above each of the figures in Table 3-Figure (g)-(i). In these scenarios, two channels were highly loaded with PUs (19*Mbps*), and two channels were lightly loaded (250*kbps*). 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 6-Columns (g)-(i).

C. 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.

VII. 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.

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REFERENCES

[1] A. Ali and W. Hamouda, "Advances on spectrum sensing for cognitive radio networks: Theory and applications," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 1277–1304, 2nd Quart., 2017.

[2] C. Jiang, Y. Chen, Y. Gao, and K. J. R. Liu, "Joint spectrum sensing and access evolutionary game in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 2470–2483, May 2013.

[3] A. Salman, I. M. Qureshi, K. Sultan, and S. Saeed, "Joint spectrum sensing for detection of primary users using cognitive relays with evolutionary computing," *IET Commun.*, vol. 9, no. 13, pp. 1643–1648, Oct. 2015.

[4] X. Liu, Y. Zhang, Y. Li, Z. Zhang, and K. Long, "A survey of cognitive radio technologies and their optimization approaches," in *Proc. 8th Int. ICST Conf. Commun. Netw. China (CHINACOM)*, Aug. 2013, pp. 973–978.

[5] W. Gabran, C.-H. Liu, P. Pawelczak, and D. Cabric, "Primary user traffic estimation for dynamic spectrum access," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 3, pp. 544–558, Mar. 2013.

[6] S. Dixit, S. Periyalwar, and H. Yanikomeroglu, "A distributed framework with a novel pricing model for enabling dynamic spectrum access for secondary users," in *Proc. IEEE 70th Veh. Technol. Conf. Fall (VTC-Fall)*, Sep. 2009, pp. 1–5.

[7] Y. Xing and R. Chandramouli, "Human behavior inspired cognitive radio network design," *IEEE Commun. Mag.*, vol. 46, no. 12, pp. 122–127, Dec. 2008.

[8] A. Wisniewska and B. Khan, "Contention-sensing and dynamic spectrum co-use in secondary user cognitive radio societies," in *Proc. Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Aug. 2014, pp. 157–162.

[9] A. Wisniewska, B. Khan, A. Al-Fuqaha, K. Dombrowski, and M. A. Shattal, "Social deference and hunger as mechanisms for starvation avoidance in cognitive radio societies," in *Proc. Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Sep. 2016, pp. 1063–1068.

[10] M. A. Shattal, A. Al-Fuqaha, B. Khan, K. Dombrowski, and A. Wisniewska, "Evolution of bio-socially inspired strategies in support of dynamic spectrum access," in *Proc. IEEE Int. Conf. Commun., Workshop Flexible Netw. (FlexNets)*, Paris, France, May 2017, pp. 289–295.

[11] J. Zhang, D. I. Kountanis, and A. Al-Fuqaha, "Two novel learning algorithms to solve the spectrum sharing problem in cognitive radio networks," in *Proc. Int. Conf. Syst. Inform. (ICSAI)*, May 2012, pp. 1472–1476.

[12] K. Thilina, K. W. Choi, N. Saquib, and E. Hossain, "Machine learning techniques for cooperative spectrum sensing in cognitive radio networks," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 11, pp. 2209–2221, Nov. 2013.

[13] I. Macaluso, D. Finn, B. Ozgul, and L. A. DaSilva, "Complexity of spectrum activity and benefits of reinforcement learning for dynamic channel selection," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 11, pp. 2237–2248, Nov. 2013.

[14] M. Bkassiny, Y. Li, and S. K. Jayaweera, "A survey on machine-learning techniques in cognitive radios," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1136–1159, 3rd Quart., 2013.

[15] O. P. Awe and S. Lambotharan, "Cooperative spectrum sensing in cognitive radio networks using multi-class support vector machine algorithms," in *Proc. 9th Int. Conf. Signal Process. Commun. Syst. (ICSPCS)*, Dec. 2015, pp. 1–7.

[16] C. Robert, C. Moy, and C.-X. Wang, "Reinforcement learning approaches and evaluation criteria for opportunistic spectrum access," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2014, pp. 1508–1513.

[17] N. Morozs, T. Clarke, and D. Grace, "Distributed heuristically accelerated Q-learning for robust cognitive spectrum management in LTE cellular systems," *IEEE Trans. Mobile Comput.*, vol. 15, no. 4, pp. 817–825, Apr. 2016.

[18] L. Gavrilovska, V. Atanasovski, I. Macaluso, and L. A. DaSilva, "Learning and reasoning in cognitive radio networks," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 4, pp. 1761–1777, 4th Quart., 2013.

[19] S. Li, Z. Zheng, E. Ekici, and N. B. Shroff, "Maximizing social welfare in operator-based cognitive radio networks under spectrum uncertainty and sensing inaccuracy," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 953–961.

[20] X. Chen, J. Huang, and H. Li, "Adaptive channel recommendation for opportunistic spectrum access," *IEEE Trans. Mobile Comput.*, vol. 12, no. 9, pp. 1788–1800, Sep. 2013.

[21] T. AlShammari, B. Hamdaoui, M. Guizani, and A. Rayes, "Overcoming user selfishness in DSA systems through credit-based resource allocation," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2014, pp. 318–323.

[22] P. Li, S. Guo, W. Zhuang, and B. Ye, "On efficient resource allocation for cognitive and cooperative communications," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 2, pp. 264–273, Feb. 2014.

[23] H. Wu, R. Yu, and Y. Zhang, "Exploiting primary user social features for reliability-driven routing in multi-hop cognitive radio networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2014, pp. 215–220.

[24] B. Atakan and O. B. Akan, "Biological foraging-inspired communication in intermittently connected mobile cognitive radio ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 61, no. 6, pp. 2651–2658, Jul. 2012.

[25] O. Castillo, R. Martínez-Marroquín, P. Melin, F. Valdez, and J. Soria, "Comparative study of bio-inspired algorithms applied to the optimization of type-1 and type-2 fuzzy controllers for an autonomous mobile robot," *Inf. Sci.*, vol. 192, pp. 19–38, Jun. 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0020025510001003

[26] S. Bitam, A. Mellouk, and S. Zeadally, "Bio-inspired routing algorithms survey for vehicular ad hoc networks," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 2, pp. 843–867, 2nd Quart., 2015.

[27] C. Charalambous and S. Cui, "A biologically inspired networking model for wireless sensor networks," *IEEE Netw.*, vol. 24, no. 3, pp. 6–13, May/Jun. 2010.

[28] M. Zeeshan and S. Ali, "A spectrum exploitation scheme with channel assignment for Genetic Algorithm based adaptive-array smart antennas in cognitive radio networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2012, pp. 1555–1559.

[29] C. Güven, S. Bayhan, and F. Alagöz, "Effect of social relations on cooperative sensing in cognitive radio networks," in *Proc. 1st Int. Black Sea Conf. Commun. Netw. (BlackSeaCom)*, Jul. 2013, pp. 247–251.

[30] K. Manjappa and R. M. R. Guddeti, "Mobility aware-termite: A novel bio inspired routing protocol for mobile ad-hoc networks," *IET Netw.*, vol. 2, no. 4, pp. 188–195, Dec. 2013.

[31] C. R. Reid, D. J. T. Sumpter, and M. Beekman, "Optimisation in a natural system: Argentine ants solve the towers of Hanoi," *J. Experim. Biol.*, vol. 214, no. 1, pp. 50–58, 2010. [Online]. Available: http://jeb.biologists.org/content/214/1/50

[32] E. A. Smith *et al.*, "Anthropological applications of optimal foraging theory: A critical review [and comments and reply]," *Current Anthropol.*, vol. 24, no. 5, pp. 625–651, 1983. [Online]. Available: http://www.jstor.org/stable/2743169

[33] A. Bhattarai, C. Charoenlarpnopparut, P. Suksompong, and P. Komolkiti, "Developing policies for channel allocation in Cognitive Radio Networks using Game Theory," in *Proc. 11th Int. Conf. Elect. Eng./Electron., Comput., Telecommun. Inf. Technol. (ECTI-CON)*, May 2014, pp. 1–6.

[34] W. Liang, S. X. Ng, and L. Hanzo, "Cooperative overlay spectrum access in cognitive radio networks," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 3, pp. 1924–1944, 3rd Quart., 2017.

[35] D. Niyato and E. Hossain, "Competitive pricing for spectrum sharing in cognitive radio networks: Dynamic game, inefficiency of Nash equilibrium, and collusion," *IEEE J. Sel. Areas Commun.*, vol. 26, no. 1, pp. 192–202, Jan. 2008.

[36] Y. Xu, J. Wang, Q. Wu, A. Anpalagan, and Y.-D. Yao, "Opportunistic spectrum access in unknown dynamic environment: A game-theoretic stochastic learning solution," *IEEE Trans. Wireless Commun.*, vol. 11, no. 4, pp. 1380–1391, Apr. 2012.

[37] Y. Xiao, J. Park, and M. V. D. Schaar, "Repeated games with intervention: Theory and applications in communications," *IEEE Trans. Commun.*, vol. 60, no. 10, pp. 3123–3132, Oct. 2012.

[38] Y. Xu, A. Anpalagan, Q. Wu, L. Shen, Z. Gao, and J. Wang, "Decision-theoretic distributed channel selection for opportunistic spectrum access: Strategies, challenges and solutions," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 4, pp. 1689–1713, 4th Quart., 2013.

[39] F. Zhang and X. Zhou, "Location-oriented evolutionary games for spectrum sharing," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2014, pp. 1047–1052.

[40] H. Roh, C. Jung, W. Lee, and D.-Z. Du, "A stackelberg game for cooperative cognitive radio network with active SUs," in *Proc. Int. Conf. Comput., Netw. Commun. (ICNC)*, Jan. 2013, pp. 911–915.

[41] C. Xin, M. Song, L. Ma, G. Hsieh, and C.-C. Shen, "On random dynamic spectrum access for cognitive radio networks," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Dec. 2010, pp. 1–5.

[42] X. Mao and H. Ji, "Biologically-inspired distributed spectrum access for cognitive radio network," in *Proc. 6th Int. Conf. Wireless Commun. Netw. Mobile Comput. (WiCOM)*, Sep. 2010, pp. 1–4.

[43] R. Yao, K. He, Y. Sun, and Y. Wang, "Learning engine for cognitive radio based on the immune principle," in *Proc. NASA/ESA Conf. Adapt. Hardw. Syst. (AHS)*, Jul. 2014, pp. 210–217.

[44] J. M. Alexander, *The Stanford Encyclopedia of Philosophy*. Stanford, CA, USA: Metaphysics Research Lab, Stanford Univ., 2009.

[45] J. M. Smith, *Evolution and the Theory of Games*. Cambridge, U.K.: Cambridge Univ. Press, 1982. [Online]. Available: http://dx.doi.org/10.1017/CBO9780511806292
[46] J. Nash, "The bargaining problem," *Econometrica*, vol. 18, no. 2, pp. 155–162, 1950. [Online]. Available: http://EconPapers.repec.org/RePEc:ecm:emetrp:v:18:y:1950:i:2:p:155-162
[47] Y. Zhang and M. Guizani, *Game Theory for Wireless Communications and Networking*, 1st ed. Boca Raton, FL, USA: CRC Press, 2010.
[48] V. Křivan, "Evolutionary games and population dynamics," in *Proc. Seminar Differ. Equ.*, vol. 2. Kamenice nad Lipou, Czech Republic, 2009, pp. 223–233.
[49] C. P. Roca, J. A. Cuesta, and Á. Sánchez, "Evolutionary game theory: Temporal and spatial effects beyond replicator dynamics," *Phys. Life Rev.*, vol. 6, no. 4, pp. 208–249, 2009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1571064509000256
[50] *ns-3 WifiPhy Class Reference*. Accessed on Dec. 16, 2016. [Online]. Available: https://www.nsnam.org/doxygen/classns3_1_1_wifi_phy.html#details
[51] *ns-3 Yans-WiFi-Helper Class Reference*. Accessed Dec. 16, 2016. [Online]. Available: https://www.nsnam.org/doxygen/yanswifihelper_8cc_source.html
[52] M. Vanhoef and F. Piessens, "Advanced Wi-Fi attacks using commodity hardware," in *Proc. 30th Annu. Comput. Secur. Appl. Conf. (ACSAC)*, Dec. 2014, pp. 256–265.

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