Emergence of pecking order in social Cognitive Radio societies

Anna Wisniewska
Computer Science Department
City University of New York, GC
New York, NY 10016, U.S.A
Email: awisniewska@gradcenter.cuny.edu

Mohammad Abu Shattal
Electrical and Computer Engineering
Western Michigan University
Kalamazoo, MI 49008, U.S.A
Email: mohammad.a.shattal@wmich.edu

Bilal Khan
Department of Sociology
University of Nebraska-Lincoln
Lincoln, NE 68583, U.S.A
Email: bkhan2@unl.edu

Ala Al-Fuqaha
Computer Science Department
Western Michigan University
Kalamazoo, MI 49008, U.S.A
Email: ala.al-fuqaha@wmich.edu

Kirk Dombrowski
Department of Sociology
University of Nebraska-Lincoln
Lincoln, NE 68583, U.S.A
Email: kdombrowski2@unl.edu

***Abstract*—In the face of the exponential growth of Internet of Things (IoT) devices, the limited capacity of radio spectrum is likely to reach saturation. Cognitive Radio technology has been proposed to relieve over-saturated channels by allowing for licensed channels to be opportunistically accessed by unlicensed users during periods of time when the license holder is absent from its channel. Un-coordinated competition over a limited number of resources among unlicensed spectrum users leads to complex co-existence challenges. Here we present a new bio-social inspired paradigm for cognitive radio, extending our previous work where we showed a plausible evolutionary trajectory of intra-groups dynamics over time as groups abide by two social behavioral rules, in-group deference and out-group avoidance. In this paper, we relax these social behavior rules in order to allow groups to organize into different social structures. More specifically, we observe how a hierarchical society compares to a classless society. We show that as the system scales, the hierarchical social structure is more likely to emerge in a distributed cognitive radio network. The bio-social paradigm presented here has consequences both in suggesting potential improvements for dynamic spectrum access, and in understanding the natural evolvement of social structures as cognitive radio devices form groups to gain advantage in the competition over resources.**

I. Introduction

The rapid growth of the Internet of Things (IoT) is expected to significantly impact wireless service demands. Limited spectrum availability, more affordable hardware, and increased demand for end-user applications lead to device coexistence challenges. Although IoT devices are most often thought of as low power sensors with limited hardware capabilities, the need to support Big Data transmission is inevitable. As IoT devices become more sophisticated, Dynamic Spectrum Access (DSA) networks [4] using Cognitive Radio (CR) technology offers a potential solution to relieve over-crowded wireless channels [11], [13].

The current approach of static spectrum assignment by the FCC has led to underutilization in some bands since spectrum license holders (primary users) transmit periodically leaving behind "spectrum holes" while being idle [8]. Cognitive Radio technology alleviate underutilized bands by allowing CR equipped devices "secondary users" (SUs) to transmit in a licensed spectrum band as long as they abandon the band upon the primary user's arrival. To avoid interference with primary users, SUs are capable of dynamically identifying and opportunistically forage for unused spectrum bands by adjusting transmission/reception parameters accordingly. In addition to primary user avoidance, SUs compete with other SUs while foraging for a limited amount of resources.

Computer science research on resource allocation in networks recognizes the potential relevance of knowledge on resource use in human and animal societies [7], [12]. There has been considerable prior work seeking to apply models of animal foraging strategies to the design of protocols in the Internet [17], [9], towards routing and management in mobile ad-hoc networks [6], [2], within sensor networks [14], [3], and now most recently, in the domain of cognitive radio (CR) networks [1], [10], [5], [15].

As competition over resources becomes increasingly more challenging in wireless networks, a bias toward devices belonging to the same group (e.g. the same manufacturer, carrier, etc.) could potentially alter the resource sharing efficiency. In our previous work [19], we introduced two simple social behavioral rules, in-group deference and out-group avoidance. In-group deference allows SUs to avoid causing interference with its group members by waiting to transmit. Out-group avoidance causes SUs to switch bands if they detect that too many SUs from competing groups are present in their band, i.e. a fraction exceeding some system wide comfort threshold parameter. We showed that this behavioral model significantly increases system utility for intermediate comfort threshold values as it results in the epiphenomenon of group based segregation across bands.

In this work, we extend our previous bio-social scheme by relaxing the deference and avoidance rules to allow for more

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general social structures in the network. Specifically, we are interested in comparing networks where groups have different priorities to resources (social rank), to networks where groups have equal access to resources. The formation of a dominance hierarchical social structure (pecking order) is commonly observed as animals compete over resources [16]. The dominance hierarchy is characterized by its linear ranking order, where each animal is dominant over all animals with lower ranks and submissive to all animals with higher rank. On the other end of the spectrum, animals form a classless (egalitarian) social structure where all animals have the same social status. Here we consider groups forming either a hierarchy or a classless social structure with respect to deference/avoidance. We aim to answer the following question: Is there an evolutionary pressure with respect to utility for a distributed heterogeneous CR network to adopt hierarchy over a classless social structure?

II. Mathematical Model

We begin by briefly outlining the key feature of the bio-social behavioral model. In the following subsections, these key features are formally defined.

Foraging/Consuming. There are a distinct set of groups of SUs where each SU is a member of exactly one group. SUs can dynamically choose which channel to occupy, selecting from a fixed set of channels (resources). Each SU can dynamically choose to be either consuming or foraging in its channel. In the former state, it is transmitting data and accumulating utility. In the latter state, it is merely passively sensing co-users in the channel without receiving utility. Switching between states incurs a cost due to transmitter reconfiguration.

Hunger. While foraging, an SU accumulates the data that it needs to transmit at a constant rate. We refer to this as "hunger". Higher hunger levels make it more likely for an SU to choose to be in the consuming state.

Deference/Avoidance. Even when hunger levels are high, an SU can choose to defer to members of its own group who are attempting to use its current channel. Each SU can choose to avoid being in channels that appear to have been recently frequented by too many members of a different group. Here we generalize the avoid and defer features where each group of SUs can avoid/defer to any other group of SUs. This configuration data is referred to as the social structure of SUs. The objective is to explore two extreme cases; first, a classless society referred to as mutual-avoidance (MA) where each group avoids all others, and defers to itself; second, hierarchy (H) where each group avoids all groups with a lesser ID and defers to all groups with a lesser or equal ID.

A. Forage-Consume FSM

We assume a discrete time stochastic system of n secondary users $\mathcal{S} = \{s_1, s_2, ..., s_n\}$ and m orthogonal spectrum bands $\mathcal{B} = \{b_1, b_2, ..., b_m\}$. Each SU operate according to the finite state machine (FSM) shown in Figure 1 (following [18]). The FSM consists of two states $Q = \{q_c, q_f\}$ and one state variable, the band of interest (BoI) which takes a time varying value $b \in \mathcal{B}$. Each SU keeps track of its current FSM state and

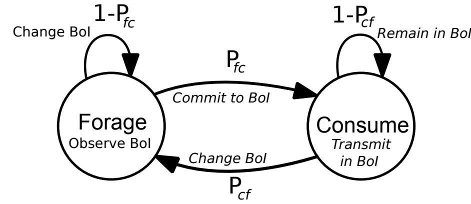

Fig. 1: Forage-Consume FSM

its current band of interest. The time indexed function $\gamma_t(s)$ indicates the state of SU s at time t where $\gamma_t : \mathcal{S} \rightarrow \{q_f, q_c\}$. The time indexed function $\alpha_t(s)$ indicated the BoI of SU s at time t where $\alpha_t : \mathcal{S} \rightarrow \mathcal{B}$.

SUs transition between the two FSM states asynchronously. If an SU s is scheduled to transition according to the FSM at time t, it will make its decision as described next.
If s is in the consume state at time t, i.e. $\gamma_t(s) = q_c$ then at time $(t + \Delta t)$ it chooses:

1) With probability P_{cf} to stop consuming BoI $\alpha_t(s)$, switch to a new band randomly chosen from $\mathcal{B} \setminus \alpha_t(s)$ and begin foraging $\gamma_{t+\Delta t}(s) = q_f$.
2) With probability $(1 - P_{cf})$ to continue consuming BoI $\alpha_t(s)$, i.e. $\gamma_{t+\Delta t}(s) = q_c$.

If s is the forage state at time t, i.e. $\gamma_{t+\Delta t}(s) = q_f$ then at time $(t + \Delta t)$ it chooses:

1) With probability P_{fc} to start consuming the BoI $\alpha_t(s)$, i.e. $\gamma_{t+\Delta t} = q_c$.
2) With probability $(1 - P_{fc})$ to remain in the forage state, i.e. $\gamma_{t+\Delta t}(s) = q_f$, and switch to a new BoI randomly chosen from $\mathcal{B} \setminus \alpha_t(s)$.

While an SU is in the forage state, it is not transmitting data but rather foraging for an appropriate BoI and, therefore, it is not receiving any reward. While an SU s is in the consume state, it is transmitting data and its rate of throughput R is determined by Shannon's theorem

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

where k is the number of co-consumers transmitting in its BoI, B is the channel bandwidth, P_z is the transmission power of SU z, G_z is the channel gain experienced by an SU z, G_{zy} is the channel gain between SU z and SU y, and ϵ is the white Gaussian noise. To isolate the impact of the proposed behavioral model we assume homogeneous SUs transmitting at the same power level and experiencing the same channel gain.

Hunger level. SUs dynamically determine their FSM transition probabilities P_{fc} and P_{cf}. Each SU has a transmission buffer of size $H_{\max}$ Kbits which accumulates data at a constant rate of $(a \cdot H_{max})$ Kbits/sec. While foraging, SUs acquire a growing level of "hunger" (accumulate data to transmit). If an SU is in the consume state, hunger dissipates at a rate of -R(k) per unit time. If an SU is in the forage state, hunger accumulates at a rate of $a \cdot H_{max}$ per unit time. The instantaneous hunger level $h(t)$ updates at each time step according to the above rates, depending on the state of the SU. If an SU is in the forage state q_f at time t it will determine its transition probability P_{fc} as follows; if hunger is 0, the probability $P_{fc} = 0$; if hunger is not 0, the probability $P_{fc} = h(t)/H_{max}$. Thus SUs who experience low hunger level will have higher probability to leave the consume state when compared to SUs with high hunger level.

Utility and switching cost. The instantaneous system utility per SU at unit time t is

$$I_t = \frac{1}{n} \sum_{i=1}^{m} |K_t(b_i)| \cdot R(|K_t(b_i)|) \tag{2}$$

where $|K_t(b_i)|$ the number of co-consumers of band i

$$K_t(b) = \{s' \in S \mid \alpha_t(s') = b \wedge \gamma_t(s') = q_c\} \tag{3}$$

and R is the reward function according to equation (1). Average gross utility per SU per unit time for total time T is

$$U_{gross} = \frac{1}{T} \sum_{t=1}^{T} I_t. \tag{4}$$

We consider a transmission reconfiguration cost (in terms of time) every time an SU transitions from the forage state to the consume state

$$C_T = \frac{1}{nT} \sum_{t=1}^{T} |F_t| \cdot c \tag{5}$$

where $F_t = \{s' \in S \mid \gamma_t(s') = q_c \wedge \gamma_{t-\Delta t}(s') = q_f\}$ is the fraction of SUs who switched from forage to consume at time t, T is total time, and c is a constant. Finally, the net utility (average utility per SU per unit time) for total time T is

$$U_{net} = U_{gross} - C_T. \tag{6}$$

B. Behavioral model

In this work we are interested in examining the impact of social structures in cognitive radio networks. Here we extend the in-group deference and out-groups avoidance model defined in our previous work [19] by allowing each group's defer and avoid sets to consist of any groups in the network. This allows for more flexible social network structures.

We assume that each SU $s \in S$ belongs to precisely one group G_i. The network consist of the total number of groups $G_T = \{G_1, G_2, ..., G_g\}$, where each group is of equal size $\frac{n}{g}$. Each SU s belonging to group G_i will operate according to an avoid set $A_i \subseteq S \setminus s$ and a defer set $D_i \subseteq S \setminus s$. These two sets together make up group G_i's set of essential SUs $E_i = A_i \cup D_i$. The remaining SUs in S, who are not part of set E_i, are simply ignored by members of group G_i. Each SU will follow two simple rules:

- **Deference.** SUs avoid causing interference while transmitting with SUs in their defer set. If an SU detects that SUs from the defer set are transmitting in the BoI, it will defer by waiting to transmit. This can be seen as a "backoff" algorithm.

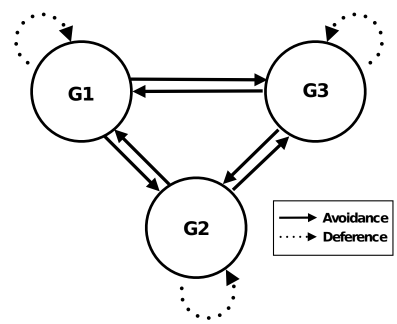

Fig. 2: Mutual-Avoidance (MA)

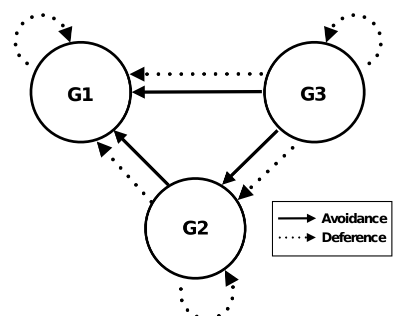

Fig. 3: Hierarchy (H)

- **Avoidance.** By applying avoidance, SUs switch bands if they detect that too many SUs from their avoid set are present in their BoI, i.e. a fraction exceeding some system wide **comfort threshold parameter** $\theta \in [0, 1]$.

More formally, deference overrides hunger level $h(t)$ when determining P_{cf} (FSM transition probability in Figure 1). If an SU s belonging to group G_i detects that there are SUs from its defer set in the BoI (at time t $|K_t(\alpha(s)) \cap D_i| > 0$), it will remain in the forage state, i.e. $P_{cf} = 0.0$. Avoidance influence BoI switching in Figure 1. Each SU s belonging to group G_i will sample the channel periodically and record the fraction of consumers to avoid $f_t(s) = |K_t(\alpha(s)) \cap A_i| / |K_t(\alpha(s)) \cap E_i|$. Each of these samples will be stored in a memory array of fixed size max where the oldest sample will be dropped in a FIFO manner. Each time an SU s is in the forage state q_f it will make a stochastic choice to switch BoI. Once SU s has gathered enough samples and the memory buffer is full, it will calculate the mean fraction of consumers belonging to the avoid set f_{avg}. If the comfort threshold is not met, i.e. $(1 - f_{avg}) \leq \theta$, the SU will switch BoI with probability $p = (f_{avg}/\theta)$.

We consider two social structures with respect to the defer and avoid sets, mutual-avoidance (MA) and Hierarchy (H).

Mutual-Avoidance (MA). In the mutual-avoidance society, SUs belonging to group G_i avoid SUs from the set $A_i =$

$G_T \setminus G_i$. The defer set D_i consists of SUs belonging to group G_i. Thus each SU defers to SUs belonging to its own group and avoids SUs belonging to other groups. In Figure 2, the avoidance and deference group relationships are shown for mutual-avoidance when the population is evenly divided into three groups G_1, G_2 and G_3.

Hierarchy (H). In the hierarchical society, the avoid set depends on each group's priority in the network. Here we assume that priority is indicated by the subscript of the group where lower subscript values have higher priority, i.e. a linear hierarchy where G_1 has the highest priority and G_g has the lowest priority. Avoid set A_i for group G_i consists of all groups G_j where $j < i$. The defer set D_i consists of all groups G_j where $j \leq i$. Thus each SU avoids SUs of higher rank and defers to its group members in addition to SUs of higher rank. In Figure 3 the avoidance and deference group relationships are shown for hierarchy when the population is evenly divided into three groups G_1, G_2 and G_3.

III. Experimental Results

We use a stochastic discrete event simulator (DES) to obtain utility measurements for different SU societies over time [20], [18]. In the graphs below, each plotted data point is an experiment, which is repeated for 10 independent trials; error bars indicate the standard deviations. These values are listed in Table I below:

TABLE I: Baseline Parameters

Parameter	Description	Value
g	Number of groups	3
n	Number of SUs	480
m	Number of bands	5
c	cost	1
P_s	Transmission power of node s	4 W
B	Capacity per band	20 MHz
a	Hunger accumulation rate	0.2
H_{max}	Max hunger level	$R(0)$
max	Memory buffer size	100

A. Emergence of Hierarchy

We begin by comparing social structure organizations as population size n increases while all other parameters are held constant at the baseline values listed in Table I.

As population density (n/m) grows, hierarchy (H) outperforms mutual-avoidance (MA) with respect to utility, except for a narrow range of comfort threshold values θ. In the discussion of the emergence of hierarchy, transmission reconfiguration cost C_T is the determining factor of net utility U_{net} since the difference in gross utility U_{gross} between the two social structures is negligible for the majority of comfort threshold values. Figures 4 and 5 show switching cost C_T for different population sizes as the comfort threshold parameter is varied for hierarchy and mutual-avoidance, respectively. In a hierarchical society (Figure 4), there is a significant decrease in switching cost C_T for most choices of comfort threshold θ as population size n increases. A mutual-avoidance society

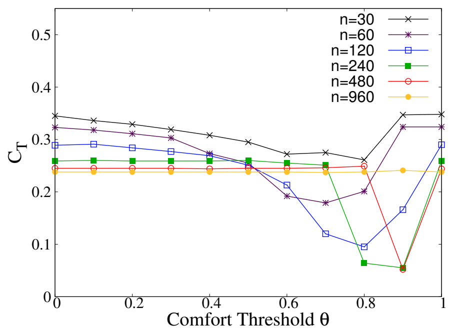

Fig. 4: Hierarchy (H) increasing n

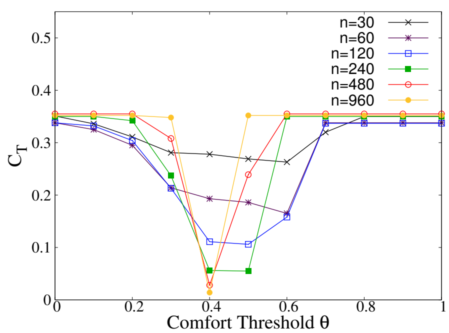

Fig. 5: Mutual-avoidance (MA) increasing n

(Figures 5) only experiences a significant decrease in switching cost for intermediate values of comfort threshold θ. This window of comfort threshold values narrows as population size n grows.

To describe the circumstances under which hierarchy is more likely to be adopted when compared to mutual-avoidance, we separate comfort threshold values into three intervals, small (Figure 6), intermediate (Figure 7), and large (Figure 8).

For small values of comfort threshold θ (Figure 6), there is a significant decrease in C_T in a hierarchical society when compared to mutual-avoidance as the population grows. When population size is small $n < 60$, the difference in C_T between the two social structures is insignificant. As population size increases, hierarchy experiences a decrease in switching cost while mutual-avoidance experiences an increase. For example, in Figure 6 when comfort threshold $\theta = 0.1$, societies choosing mutual-avoidance experience a 5% increase $(0.352/0.336)$ in switching cost C_T as the population grows from $n = 30$ to $n = 960$. In contrast, when $\theta = 0.1$ the hierarchical society experiences a 29% decrease $(0.238/0.336)$ in C_T when comparing population size $n = 30$ to $n = 960$. Thus there is a significant difference in utility between the two social structures since the hierarchical society enjoys 32% less $(0.238/0.352)$ switching cost when compared to mutual-avoidance.

For intermediate values of comfort threshold θ (Figure 7), mutual-avoidance experiences lower switching cost C_T when compared to hierarchy. Although, with a growing population

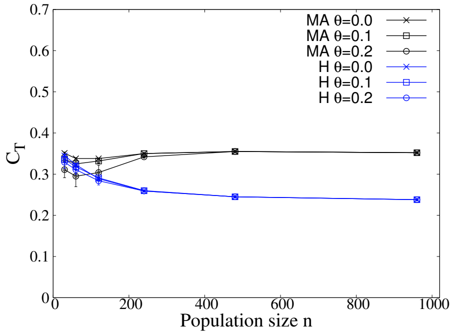

Fig. 6: H vs. MA when $0.0 \leq \theta \leq 0.2$

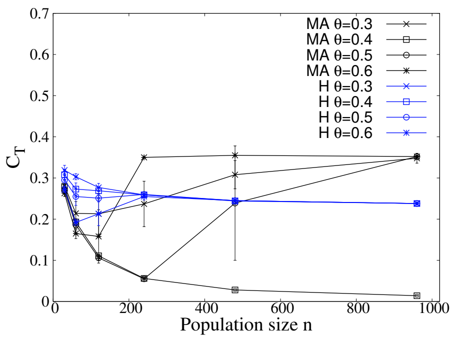

Fig. 7: H vs. MA when $0.3 \leq \theta \leq 0.6$

size, the range of comfort threshold values that yield an advantage in the mutual-avoidance community narrows. For example, when the population size is relatively small $n = 120$ (Figure 7), mutual-avoidance experiences lower switching cost C_T when compared to hierarchy for comfort threshold values $\theta = 0.3$ through $\theta = 0.6$. As population size grows to $n \geq 480$, mutual-avoidance outperforms hierarchy only when comfort threshold $\theta = 0.4$.

For large values of θ (Figure 8), a hierarchical society experiences significantly lower switching cost C_T when compared to mutual-avoidance as the population size grows. Note that constant c in C_T is relatively small (see Table I). Increasing c would only amplifies the results.

The window of comfort threshold values when mutual-avoidance enjoys higher net utility than the hierarchical society narrows as the population size increases (Figures 6,7,8). Thus hierarchy outperforms mutual-avoidance with respect to net utility for the majority of comfort threshold values as the population scales and is more likely to be selected in evolutionary terms.

In the next subsection we take a closer look at the increase in net utility U_{net} in a mutual-avoidance society when specific comfort threshold values are chosen. To be able to understand the reason for this increase in utility, we introduce the measure of entropy as described next.

Entropy. Beyond utility maximization, we are interested in the epiphenomenon of segregation. More precisely, the emergent exclusive use of certain bands by certain groups. In our previous work [19] we developed a band-centric measure

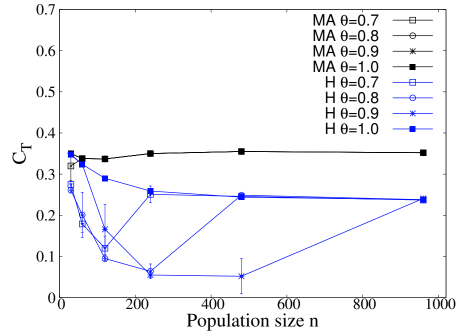

Fig. 8: H vs. MA when $0.7 \leq \theta \leq 1.0$

of segregation by determining the fraction of time that an average band was used by a majority from a single group. Such a measure is intuitive and easy to visualize, but it is difficult to generalize to many groups and suffers from quantization effects. To overcome these difficulties, here we introduce an entropy-based measure of segregated resource allocation, whose calculation is now described. Post convergence[1], each band j collects data on its occupancy over a series of $i \in [1..W = 1000]$ intervals, where each interval consists of $t = [1..100]$ time steps. Denote the group that was most dominant in band $j \in [1..m]$ during interval i time step t, as $o_{ij}(t) \in [1..g]$. Let X_{jk} be the random variable that "band j experiences dominance by group $k \in [1..g]$ at a random time post convergence". Then we can use the collected data $o_{ik}(t)$ to produce a point estimate:

$$P(X_{jk} = 1) \approx \frac{\sum_{i=1}^{W} |o_{ij}^{-1}(k)|}{100 \cdot W}$$

Each band $j \in [1..m]$ now calculates its entropy as:

$$\omega(j) = -\sum_{k=1}^{g} P(X_{jk} = 1) \cdot log_2 P(X_{jk} = 1)$$

Note that $\omega(j) \geqslant 0$, and is equal to zero precisely when band j is used exclusively by some group, i.e. $P(X_{jk_0} = 1) = 1$ for some $k_0 \in [1..g]$ and $P(X_{jk_0'} = 1) = 0$ for all $k_0' \neq k_0$. Total organizational entropy of the system is then defined as:

$$\Omega = \sum_{j=1}^{m} \omega(j).$$

[1]To avoid the possibility of drawing conclusions about system performance that are unduly impacted by stochastic effects, we introduced a formal criterion for convergence of the dynamic system in [19]. Informally, we say that the system has converged when each of the SUs individually is in a "steady state". We say that an SU in "steady state" if it has a relatively stable frequency with which its switches bands. Formally, the SU is in steady state at time t_0 if (i) $t_0 > 10{,}000$ and (ii) the ratio of the number of band switches in the first half of $[t_0 - 10{,}000, t_0]$ is between 0.95 and 1.05 times what the number of band switches in the second half of the same interval. Stated equivalently, the frequency of BoI switches has remained consistent over an interval of 10,000 time steps with fluctuations bounded by $\pm 5\%$. The system reaches steady state when all consumers are found to be in steady state.

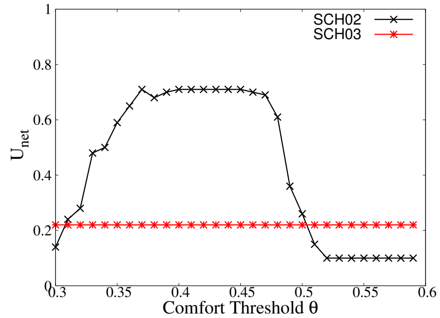

Fig. 9: Net utility U_{net} for MA vs. H

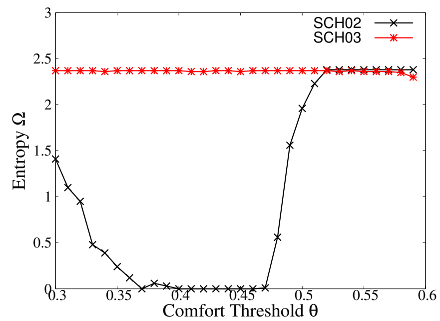

Fig. 10: Entropy Ω for MA vs. H

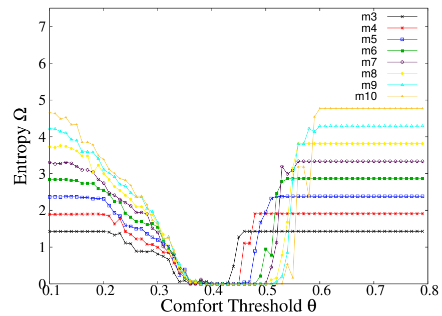

Fig. 11: Increasing bands-to-SUs ratio

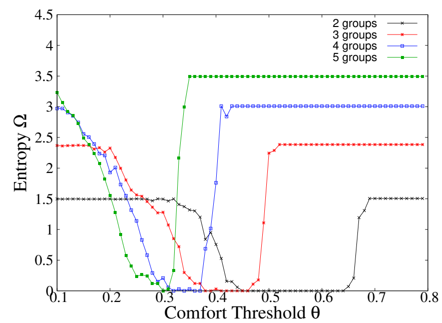

Fig. 12: Increasing groups-to-bands ratio

B. Mutual-Avoidance together with low entropy

The mutual-avoidance social structure outperforms hierarchy when comfort threshold is chosen carefully since a narrow window of comfort threshold values result in SUs segregating across bands and forming a low entropy configuration.

To understand why utility reaches its maximum in a mutual-avoidance society we look at net utility U_{net} and entropy Ω for tolerance threshold 0.3 through 0.6 in a population of size $n = 480$. Here we consider net utility U_{net} as opposed to only considering switching cost C_T since a low-entropy state decreases switching cost C_T while simultaneously increasing gross utility U_{gross}.

Figure 9 shows net utility U_{net} for mutual-avoidance compared to hierarchy. There is a significant gain in net utility U_{net} in the mutual-avoidance society for tolerance threshold values $\theta = 0.33$ through $\theta = 0.49$ when compared to the hierarchal social structure. Maximum utility U_{net} is reached when comfort threshold values lie between $\theta = 0.37$ and $\theta = 0.47$.

Figure 10 shows entropy Ω in a mutual-avoidance society compared to hierarchy. We can see that the mutual-avoidance society experiences low entropy $\Omega \approx 0$ for the corresponding comfort threshold values that maximize utility, namely $\theta = 0.37$ through $\theta = 0.47$. We refer to this interval of comfort threshold values for which the mutual-avoidance society converges to a low-entropy state as the **segregation interval**. Entropy Ω remains high during the same interval in the hierarchical society.

The peak in utility while in a low-entropy state is due to groups segregating across bands. This exclusive use of bands by groups maximizes utility since each group takes full advantage of the deference behavioral rule. When SUs defer to group members, interference while transmitting is minimized as groups operate in their own bands.

In the following subsection we vary the number of bands and groups in the system to understand the influence of these parameters on the segregation interval.

C. Varying groups and bands

To further understand the parameters that influence the choice of social structure, we vary the number of bands and the number of groups in the system. We show that in addition to the segregation interval narrowing as population size n increase, it similarly narrows as the number of groups g increase and as the number of bands m decreases.

Varying bands-to-SUs ratio. In Figure 11, resource entropy Ω is shown for a population of size $n = 480$ as the number of bands in the network varies from $m = 3$ to $m = 10$. We can see that the segregation interval narrows as the number of resources m decreases. Thus as the bands to population size decreases, the segregation interval narrows and the hierarchical social structure has a higher chance of being adopted.

Varying groups-to-bands ratio. In Figure 12, the number of groups varies while resources are kept fixed at $m = 5$ in a population of size $n = 480$. We can see that the segregation interval narrows as the number of groups g increases. For example, if the population is divided into 2 groups, the society experiences a low-entropy state $\Omega = 0$ when tolerance threshold lies between $\theta = 0.47$ and $\theta = 0.63$. In a society of 5 groups, a low entropy state $\Omega = 0$ only occurs between

$\theta = 0.30$ and $\theta = 0.31$. The benefit in utility that a low-entropy state yields in a mutual-avoidance society becomes harder to achieve as the group-to-bands ratio increase since the segregation interval narrows. Similar utility benefits are obviously not achievable if the number of groups exceeds the number of bands in the network.

IV. Conclusion

A dense heterogeneous IoT population competing over a limited amount of resources poses complex co-existence challenges. Considering bio-inspired approaches and the study of animal foraging strategies, may play an important role in addressing these challenges. Here we extended our previously defined bio-social paradigm [19] to incorporate different social structures. Our objective was to determine if there is an evolutionary pressure with respect to utility for the emergence of hierarchy in a social SU population.

We showed that a hierarchical social structure is more likely to emerge when compared to mutual-avoidance as the population size grows. Mutual-avoidance outperforms hierarchy when the society experiences a low-entropy state (segregation across bands) since defering to group members lowers transmission interference. This occurs for a narrowing range of comfort threshold choices (segregation interval) as population size increases. Thus hierarchy is more likely to emerge since it yields higher utility when compared to mutual-avoidance for a broader range of comfort threshold values.

We showed that as the number of bands-to-SUs ratio decreases or the number of groups-to-bands ratio increases, the range of the segregation interval in mutual-avoidance narrows and a hierarchical society is more likely to emerge.

Given that the precise values defining the segregation interval are a complex function of population size n, the number of bands m, and the number of groups g, if these parameters are dynamic, SUs would need to coordinate their comfort threshold settings. We do not dismiss mutual-avoidance since it yields maximum utility but argue that in the absence of global coordination, SUs have an incentive to choose a hierarchical social structure. In a system that is growing, hierarchy will arise and mutual-avoidance will be abandoned.

A. Future work

We intend to implement the proposed scheme in real hardware testbed in the CR and IoT context, using nodes that are capable of switching Wi-Fi channels using a microcontroller together with ns-3 emulation/testbed engine.

We hope to extend the model where CR nodes can evolve by independently choosing group membership to allow for dynamic social structures.

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