Social Deference and Hunger as Mechanisms for Starvation Avoidance in Cognitive Radio Societies

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***Abstract*—Wireless communication is an increasingly ubiquitous and important resource substrate of the digital ecosystem. In the face of the rapid growth in the population of Internet of Things (IoT), however, uncoordinated access to limited resources of radio spectrum is likely to lead to mass starvation. Here we put forward a new bio-social paradigm for cognitive radio, extending previous models in which the secondary users of spectrum alternate stochastically between foraging and consuming behaviors. In this paper, we ask and resolve two questions: (1) What costs and benefits does social deference to the group yield for each of the *individuals* therein? and (2) Can a notion of individual "hunger" form the basis of a distributed social deference scheme that is free of group coordination costs? Through a series of simulation experiments grounded in a well-specified formal model, we show that social deference improves both the fairness and the reliability of spectrum resource allocation, and moreover, that the concept of individual "hunger" can be used to implement social deference with minimal group coordination overhead. The results have consequences both in suggesting potential improvements for distributed spectrum access, and in understanding the evolutionary pressures on the behaviors of individual devices within emerging digital IoT societies.**

***Index Terms*—Cognitive radio networks, bio-social networking, Internet of Things, self-coexsitence, dynamic spectrum access, contention-sensing.**

I. Introduction

Ubiquitous wireless service together with decreasing hardware costs have led to rapid population growth in the Internet of Things (IoT). Although the present IoT consists largely of primitive low power sensors, the demand to support richer data streams is unquestionable. As the population and sophistication of IoT devices increases, it is widely expected that they will engage Dynamic Spectrum Access (DSA) networks [3] as secondary users (SUs) of radio spectrum, using Cognitive Radio (CR) technologies [12], [14], [2].

Unfortunately, the FCC's frequency assignment policies over the years have resulted in suboptimal use of spectral resources. Few segments of spectrum remain unallocated, and yet spectrum is underutilized because licensed ("primary") users are frequently idle. To address this, the FCC proposed DSA within the CR paradigm. However, although the FCC reforms "allow unlimited numbers of unlicensed [secondary] users to share frequencies", they do "not provide any right to protection from interference" [7]. Since there are many secondary users, each SU's selection of band and decision to transmit, potentially impacts other secondary users, whose channel bandwidth degrades when greater numbers of SUs share a channel. Taken together, bandwidth scarcity and "no right to protection from interference" present serious challenges to performance for SUs in CR and DSA environments. In short, DSA can "kick the can further down the road" but the problem remains looming.

Prior research on resource allocation in networks recognizes the potential relevance of our knowledge on resource co-use in human and animal societies; for a recent survey of bio-socially inspired approaches, see [6], [13]. In particular, since SUs in CR and DSA environments are potentially capable of sensing, learning, and adaptation, there has been considerable prior work seeking to apply models of animal foraging strategies to the design of protocols in CR networks [1], [5], [11].

In their previous work [17] the authors considered cognitive radio societies in which secondary users (SUs) of radio spectrum can alternate stochastically between two distinct behavioral modes: searching for spectrum holes ("foraging") and transmitting in a band ("consuming"), rather than always consuming. They showed that if, while in foraging mode, SUs measure ("sense") congestion (i.e. number of other SUs transmitting) in a band, and then use this measurement to bias the individual decisions to start consuming the band, such **social contention avoidance** behaviors significantly improve channel utilization metrics (28%).

Here, we continue to extend the above bio-social model to leverage prior understanding of resource conflict/sharing in the context of humans and other social animals [8], [9], [18]. Specifically, we consider **social deference**, by which we mean behavior in which an SU may voluntarily stop consuming a band prematurely (i.e. before it has finished sending all its queued data). We ask and answer the question: *What costs and benefits does social deference to the group yield for each of the* individuals *therein?* Of course, a naively implemented form of social deference might require group coordination, and hence communication–with the adverse consequence of further contributing to bandwidth resource scarcity. Here we show how the biological notion of individual "hunger" (whose analogue in the CR context is total data queued for transmission at an SU) can be basis of a distributed social deference scheme that is free of group coordination overhead.

Towards answering the above question, we conduct simulations of two distinct populations of SUs. In both populations, SUs are either foraging (searching for spectrum holes) or consuming (transmitting in a band) and exhibit social contention avoidance behavior (see above). The SUs in one population (DCons) exhibit social deference behavior (implemented via a coordination-free scheme based on individual hunger); in the second population (Econs) SUs do not exhibit social deference.

Deferent-Consumer (DCon): Each DCon SU forages for an underutilized spectrum band, and as it does so, its "hunger" increases linearly with time, until a hunger value upper bound is reached, at which point the SU is said to experience an "injury". This metaphor corresponds to queuing unsent data for a constant bit-rate stream until its network interface's buffer becomes exhausted and data loss occurrs. Once a DCon finds a channel free of contention and decides to switch to consume mode (begin transmitting queued data), causing its residual hunger to decrease linearly with time until either: a lower bound of 0 is reached, *or* the SU chooses to "defer", that is, to pre-emptively stop consuming and return to foraging mode. The likelihood of deferring is inversely proportional to the DCon's residual hunger.

Ego-Consumer (ECon): While DCon SUs may leave a band before their hunger is fully sated, thereby implicitly defering to the group, ECon SUs, by comparison, lack such behavior: Once an ECon SU finds a channel free of contention and decides to switch to consume mode (begin transmitting queued data), causing its residual hunger to decrease linearly with time until a lower bound of 0 is reached. Econ SUs never "defer", that is, they never stop transmitting if they still have more queued data, even if other SUs may be hungrier.

Here we explore the costs and benefits of deference behavior, and show that the DCon behavior is evolutionarily advantagous as a means for fair resource co-use, that it makes rational sense from the perspective of individual self-interest and minimization of injury ("data loss"), and that it requires minimal group coordination overhead.

II. Mathematical Model

We consider a discrete time stochastic system of n secondary users $\mathcal{S} = \{s_1, s_2, ..., s_n\}$ and m orthogonal spectrum bands $\mathcal{B} = \{b_1, b_2, ..., b_m\}$. Individuals operate according to a finite state machine (FSM) shown in Figure 1 (following [17]). The FSM consists of two states $Q = \{q_c, q_f\}$ and one state variable, the band of interest (BoI) which is one of the m spectrum bands $b \in \mathcal{B}$.

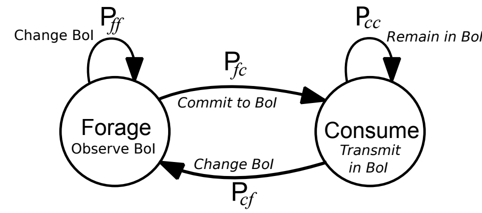

Fig. 1: A general behavioral finite state machine for SUs.

State q_c represents a "consume" state, during which the SU is transmitting in the BoI; q_f represents a "forage" state, during which the SU is merely tuned to the next randomly chosen BoI but it is not consuming any bandwidth. To keep track of instantaneous state, we introduce a time indexed function $\gamma_t : \mathcal{S} \to \{q_f, q_c\}$, where $\gamma_t(s)$ indicates the state of SU s at time t. At time t, each SU $s \in \mathcal{S}$ is either foraging or consuming some bands $\alpha_t(s) \in \mathcal{B}$; this implicitly defines a set of time-indexed maps $\alpha_t : \mathcal{S} \to \mathcal{B}$ assigning SUs to bands. At time t, each SU $s \in \mathcal{S}$ faces a decision to move from state q to state q', governed by an independent Markov process with the transition matrix $P_{qq'}$ where $q, q' \in Q$ and $\sum_{q'} P_{qq'} = 1$.

If s is consuming resources at time t (i.e. $\gamma_t(z) = q_c$), then at time $t+1$ it chooses:

- With probability P_{cf} to stop consuming $\alpha_t(s)$, switch to a new band α_{t+1} from $\mathcal{B} \backslash \alpha_t(s)$, and begins foraging.
- With probability $P_{cc} = 1 - P_{cf}$, continues consuming $\alpha_t(s)$.

If s is foraging at time t (i.e. $\gamma_t(s) = q_f$), at time $t+1$ it chooses:

- With probability P_{fc}, to start consuming band $\alpha_t(s)$.
- With probability $P_{ff} = 1 - P_{fc}$, continues foraging but switches to a new band α_{t+1} from $\mathcal{B} \backslash \alpha_t(s)$.

Since benefit is only obtained when an SU s is consuming, the total system utility is captured by

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

where the number of co-consumers of band i is given by $k_t(i) = |\alpha_t^{-1}(i) \cap \gamma_t^{-1}(q_c)|$ and

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

is the bandwidth utility (1) as given by Shannon's formula [4], [15]. In expression (1), the transmission power for SU z (resp. y) are denoted P_z (resp. P_y); B is the channel bandwidth; G_z represents the channel gain for the transmissions by z, G_{zy} represents the channel gain for the transmission between z and y, and ω is the power level of the ambient white Gaussian noise. To isolate the impact of the proposed paradigms, here we do not consider path losses, and consider a homogeneous network wherein all SUs send (to a base station) at the same power P and experience the channel gain G.

When an SU switches transmission bands on entering (or re-entering) q_c, expensive transmitter reconfiguration is required (we assume receiver reconfiguration costs to be insignificant). To capture this, our model charges each SU a fixed cost c whenever it switches from forage to consume state. The cost paid by the system at time t is $C_t = c|M_t|$, where M_t is the number of SUs $\{s \in \mathcal{S} \mid \gamma_{t-1}(s) = q_f \wedge \gamma_t(s) = q_c\}$ who switched to consuming state at time t. The instantaneous average utility (per SU) at time t is thus $A_t = \frac{1}{n}(W_t - C_t)$ and the average utility (per SU per unit time) up to time T is

$$U_T = \sum_{t=1}^{T} A_t / T.$$

1) ***Hunger level:*** 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 H_{max}/T_f per unit time; here T_f is a system parameter governing the rate of hunger accumulation (data transmission request rate) and H_{max} is the maximum hunger possible (the size of the network output buffer). The instantaneous hunger level $h(t)$ updates at each time step according to the above rates, depending on the state of the SU, and is clipped so as to always lie in the range $[0, H_{max}]$.

2) ***Population Fitness & Injuries:*** We define fitness of the CR society in terms of the frequency with which SUs experience data loss due to their output buffer being full. This occurs if an SU reaches hunger level $h(t) = H_{max}$ while foraging (and so experiences "injury"). We quantify population fitness as the number of injuries over time experienced by an average SU in the population. The fitness is then the average number of injuries per unit time

$$F_T = \frac{1}{nT} \sum_{t=0}^{T} \sum_{s \in \mathcal{S}} I(s,t) \tag{2}$$

where $I(s,t)$ is an indicator variable which is 1 if and only if SU s has reached hunger H_{max} at time t.

III. Bio-social behavioral models

Here we formally describe how DCon and ECon SUs operate by detailing the necessary modifications of the finite state machine shown in Figure 1.

A. Egoistic behavior with contention-sensing

To maximize utility we consider the contention-sensing model introduced in [17] where each consumer can estimate the contention level in the BoI.

If the ECon is in the forage state q_f at time t it will determine its transition probability P_{fc} as follows:

- If BoI is empty, the transition probability $P_{fc} = 1.0$.
- If BoI is not empty, transition probability $P_{fc} = 0.0$.

If the ECon is in the consume state q_c at time t it will determine its transition probability P_{cf} as follows:

- If hunger is 0, the transition probability $P_{cf} = 1.0$.
- If hunger is not 0, transition probability $P_{cf} = 0.0$.

In other words, as soon as the ECon finds a resource that is free from other consumers, it will access the resources, and consume until it satiate its hunger.

B. Deferent behavior with contention-sensing

To achieve fair resources sharing, DCons, in addition to the contention-sensing, will determine the FSM transition probabilities based on the current hunger level $h(t)$:

If the DCon is in the forage state q_f at time t it will determine its transition probability P_{fc} as follows:

- If BoI is empty, the probability $P_{fc} = h(t)/H_{max}$.
- If BoI is not empty, probability $P_{fc} = 0.0$.

Thus DCon SUs who experience low hunger level will have lower probability to enter consume state, when compared to SUs with high hunger level.

If the DCon is in the consume state q_c at time t it will determine its transition probability P_{cf} as follows:

- If hunger is 0, the probability $P_{cf} = 1.0$.
- If hunger is not 0, probability $P_{cf} = 1 - \frac{h(t)}{H_{max}}$.

Thus DCon SUs who experience low hunger level will have higher probability to leave consume state, when compared to SUs with high hunger level.

An consequence of this hunger-based behavior is social deference: consumers with low hunger will defer to consumers with high hunger level. Creating the phenomenon of social deference in the DCon society does not require communication/coordination overhead.

IV. Optimal Offline analysis

To understand how well DCon SUs fare relative to ECon SUs, it will be helpful to have a sense of what an offline fully coordinated system might achieve. Towards this, consider an offline system where n consumers receive equal globally scheduled access to m resources ($n > m$) in round-robin manner. In this system, each SU transmits for one time step and spends $(n/m) - 1$ time steps being idle. Two SUs never share a band (i.e. $k = 0$ always) and each consumer obtains the optimal average utility:

$$U_{opt} = \frac{m}{n}(R(k) - c). \tag{3}$$

Each SU accumulates hunger H_{max} while in the forage state (over T_f units of time) and then transmits this data once it is in consume state (over $T_c = H_{max}/R(0)$ units of time). The quantity $D^* = (T_f^* + T_c^*)$ is referred to as the system's "duty cycle". Whenever T_c and T_f satisfy the equation

$$T_f = \left(\frac{n}{m} - 1\right) T_c$$

the offline system's resources are being fully utilized; such a pair of matched values are denoted T_f^* and T_c^*.

V. Experimental Results

We use a stochastic discrete event simulator [10] to obtain utility measurements for different SU societies over time. Consumers transition asynchronously according to the appropriate previously defined finite state machines (FSM). To facilitate

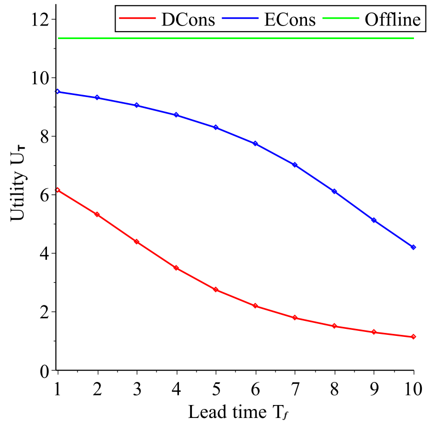

Fig. 2: Utility with switching cost U_T.

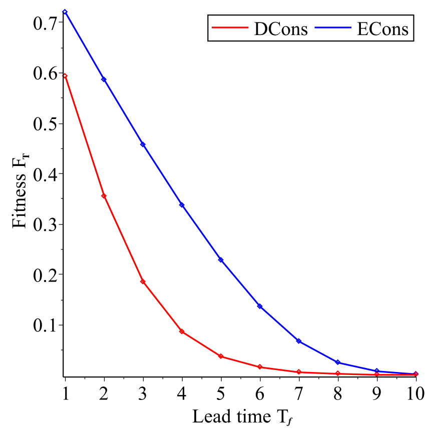

Fig. 4: Frequency of hunger level $h(t) = H_{max}$.

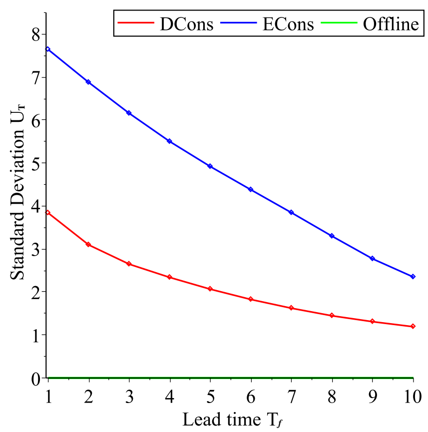

Fig. 3: Standard deviation of utility U_T in each time interval D^*.

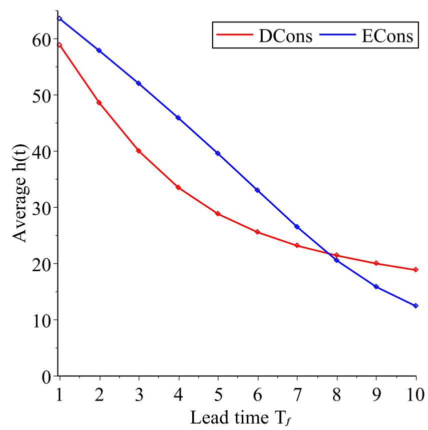

Fig. 5: Average instantaneous hunger level $h(t)$ over time.

comparison with the work of Tan and others [16], [17], in many experiments we use the same parameter values as these previous researchers. These values are listed in Table I below:

TABLE I: Baseline Parameters

Parameter	Description	Value
n	Number of SUs	30
m	Number of bands	5
P_z	Transmission power of node z	4 W
B	Capacity per band	20 MHz
C	Switching cost	$0.3 \cdot B$

A. Fair Access to Resources

Figure 2 shows the utility U_T achieved by the ECon and DCon populations compared to offline U_{opt}. When T_f is equal to the expected time foraging $T_f^* = 5$, DCons receive $U_T = 2.74$ while ECons receive utility $U_T = 8.28$. Both DCons and ECons experience a significant decrease in utility compared to the optimal utility $U_{opt} = 11.33$. With increasing T_f, both populations experience a decrease in utility although ECons outperform DCons regardless of lead time T_f. The decrease in utility as lead time T_f increase in the ECon society is due to consumers entering resources with hunger level $h(t) < H_{max}$ causing ECons to switch out of consume more often. When the hunger level $h(t)$ accumulates at a slow rate, lead time $T_f > T_f^*$, DCons will forage for a longer period of time causing underutilized resources.

Offline SUs experience fair distribution of resources and will receive an equal amount of utility in interval D^*, i.e. the standard deviation of the utility across the population is zero each time through duty cycle D^*. In figure 3 standard deviation of utility U_T across the population is measured in each time interval D^*. Although ECons receive higher utility than DCons (figure 2), the standard deviation of utility in time interval D^* in the DCon society is lower. At $T_f = 5$ DCons standard deviation of utility is 4.92 while ECons standard deviation of utility is 2.06. As T_f increase, standard deviation for both ECons and DCons decreases and both populations experience an increase in fair resource distribution. Although, DCons experience less variation in utility than ECons regardless of lead time T_f. ECons achieve higher utility than DCons but also a higher variance in utility across the population in each time interval D^*. DCon experience low variance in utility in each time interval D^* at the cost of lower overall average utility.

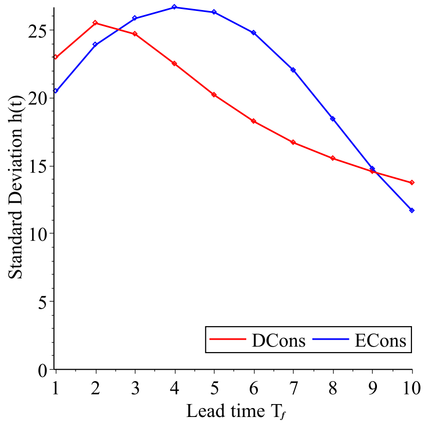

Fig. 6: Standard deviation of instantaneous hunger level $h(t)$.

B. Reliable Access to Resources

While offline SUs wait in the forage state to transmit, each SU buffer H_{max} data uniformly over the fixed time interval T_f^*. Once the data accumulation reaches H_{max}, SU enter the consume state. This process allows SUs to experience consistent QoS. If an SU spend more time in forage than it takes to accumulate maximum data H_{max}, the SU experience a congested network and QoS suffers. In bio-social context, if consumers reach their maximum hunger level before finding a resource, they will starve. In figure 4 we determine the fitness F_T of the population by calculating the fraction of time that an individual in the population experience an "injury". Injuries indicate the fraction of time that an individual in the population on average spend with H_{max} data, ready to transmit to maintain desired QoS, although unable to find an empty band. When $T_f = 5$, each individual in the ECon society experience injuries 22.8% of the time while DCons experience injuries for 3.7% of the time. As T_f increase and hunger accumulation rate decreases, the fraction of time that individuals in both populations experience injuries decrease. Although both populations experience a decrease in injuries, DCons injury level decrease more rapidly. When T_f increases from 1 to 2 units of time, DCons experience a 40% decrease in injuries while ECons only experience an 18% decrease in injuries. As T_f increases ECons will spend up to 11.2 more time with injuries compared to DCons. This indicates that each individual in the DCon population will experience less data loss (injuries) and more consistent QoS compared to ECons.

C. Discussion

The number of injuries experienced in each society can be explained by measuring the average instantaneous hunger level $h(t)$ (figure 5) and the standard deviation of the instantaneous hunger level $h(t)$ (figure 6). When T_f is small, both populations experience high average hunger level and high standard deviation of hunger level. As T_f increases, average hunger level decreases more rapidly in the DCon society compared to the ECons. In addition, the standard deviation of hunger level in the DCon society reaches its peak at $T_f = 2$ while the standard deviation of hunger level continuous to increase until $T_f = 4$ for ECons. In other words, while the average hunger level decreases in both societies, ECons experience more injuries than DCons since the standard deviation of the hunger level start decreasing with smaller T_f in the DCon society compared to the ECon society. Although DCon consumers experience higher average hunger level when $T_f \geq 8$ (figure 5) and higher standard deviation when $T_f \geq 10$ (figure 6), this has no impact on the number of injuries since the average hunger level is low. DCons experience higher average hunger level than the ECons when $T_f \geq 8$ since the hunger level accumulation is lower than the expected time $T_f^* = 5$ (underutilized network) and DCons spend longer time intervals foraging since transition probabilities are calculated based on hunger level.

VI. Conclusion and Future Work

A. Conclusion

In this paper, we have introduced two behavioral models to determine if fair access to resources can be achieved in autonomous SU networks. In the first scheme, consumers act on their own behalf while trying to maximize utility (ECons). Consumer in the second scheme are willing to share resource to increase population fitness at the expense of individual fitness (DCons). Although we do not dismiss ECons as they can achieve higher utility over time, we argue that DCons experience fair access to resources by deferring to other individuals in the population based on hunger level. As DCons sacrifice utility to achieve lower variance in instantaneous utility, the population fitness increases, and each DCon experience more consistent QoS compared to ECons.

B. Future Work

We seek to implement the proposed behavioral models in real hardware testbed of software-defined radio systems. We plan to experiment with actual IoT nodes that utilize a low power microcontroller with the capability to switch the Wi-Fi channel to study the behaviors experimentally.

VII. Acknowledgments

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References

[1] B. Atakan and O. B. Akan. Biologically-inspired spectrum sharing in cognitive radio networks. In *Wireless Communications and Networking Conference, 2007. WCNC 2007. IEEE*, pages 43–48, 2007.

[2] T. Chiwewe, C. Mbuya, and G. Hancke. Using cognitive radio for interference-resistant industrial wireless sensor networks: An overview. 11(6):1466–1481.

[3] C. Cordeiro, K. Challapali, D. Birru, and S. Shankar. IEEE 802.22: The first worldwide wireless standard based on cognitive radios. *Proc., IEEE Symposium of New Frontiers in Dynamic Spectrum Access Networks (DySPAN'2005)*, pages 328–337, Nov. 2005.
[4] T. M. Cover and J. A. Thomas. *Elements of Information Theory*. John Wiley & Sons, July 2006.
[5] P. Di Lorenzo, S. Barbarossa, and A. Sayed. Bio-inspired decentralized radio access based on swarming mechanisms over adaptive networks. *IEEE Transactions on Signal Processing*, Early Access Online, 2013.
[6] F. Dressler and O. B. Akan. A survey on bio-inspired networking. *Computer Networks*, 54(6):881–900, Apr. 2010.
[7] FCC. In the matter of unlicensed operation in the TV broadcast bands. *Second Report and Order and Memorandum Opinion and Order*, (FCC-08-260A1), Nov. 2008.
[8] F. Ge, Q. Chen, Y. Wang, C. Bostian, T. Rondeau, and B. Le. Cognitive radio: From spectrum sharing to adaptive learning and reconfiguration. pages 1 –10, march 2008.
[9] S. Haykin. Cognitive radio: brain-empowered wireless communications. *Selected Areas in Communications, IEEE Journal on*, 23(2):201 – 220, feb. 2005.
[10] B. Khan, K. Dombrowski, and M. Saad. A stochastic agent-based model of pathogen propagation in dynamic multi-relational social networks. *SIMULATION,Transactions of SCS*, 90(4):460–484, 2014.
[11] X. Mao and H. Ji. Biologically-inspired distributed spectrum access for cognitive radio network. In *2010 6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM)*, pages 1–4, 2010.
[12] M. Murroni, R. Prasad, P. Marques, B. Bochow, D. Noguet, C. Sun, K. Moessner, and H. Harada. IEEE 1900.6: spectrum sensing interfaces and data structures for dynamic spectrum access and other advanced radio communication systems standard: technical aspects and future outlook. 49(12):118–127.
[13] T. Nakano. Biologically inspired network systems: A review and future prospects. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 41(5):630–643, 2011.
[14] H. Pohls, V. Angelakis, S. Suppan, K. Fischer, G. Oikonomou, E. Tragos, R. Diaz Rodriguez, and T. Mouroutis. RERUM: Building a reliable IoT upon privacy- and security- enabled smart objects. In *2014 IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, pages 122–127.
[15] C. E. Shannon. Communication in the presence of noise. *Proc. Institute of Radio Engineers*, 37(1):10–21, 1949.
[16] Y. Tan, S. Sengupta, and K. P. Subbalakshmi. Human society inspired dynamic spectrum access networks: The effect of parochialism. In *Global Telecommunications Conference (GLOBECOM 2011), 2011 IEEE*, pages 1–5, 2011.
[17] A. Wisniewska and B. Khan. Contention-sensing and dynamic spectrum co-use in secondary user cognitive radio societies. In *Wireless Communications and Mobile Computing Conference (IWCMC), 2014 International*, pages 157–162, Aug. 2014.
[18] Y. Xing and R. Chandramouli. Human behavior inspired cognitive radio network design. *Communications Magazine, IEEE*, 46(12):122 –127, december 2008.