Human Behavior Inspired Cognitive Radio Network Design

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ABSTRACT

Cognitive radio networks are supposed to be capable of sensing their operating environment (with little or no prior information) and learning to adapt their behavior accordingly. We note that such a cognitive process is inherent in human behavior as well. One application of these networks is in dynamic spectrum access. Human beings evolve by learning to interact with each other for survival, common good, economic gain, and so on. Can models for these interactive behaviors be used by nodes in a cognitive radio network? Will we then see cognitive radio networks evolve into some human societies? Will we observe previously unseen societal behaviors emerge as a result of random perturbations due to fading, mobility, and sensory failures? We also note that some shortcomings (e.g., inability to address irrational behavior) in using microeconomic game theory and Nash equilibrium to study interacting cognitive radio nodes may be overcome by using anthropological models.

INTRODUCTION

Cognitive radio networking is a new paradigm in wireless communications in which either the network or the cognitive radio nodes themselves change particular transmission, reception, or radio environment sensing parameters to execute their tasks efficiently without interfering with other cognitive radio nodes or networks. This parameter adaptation or learning is based on several factors measured from the external and internal cognitive radio environment, such as the radio frequency spectrum, node or user behavior, the network state, and economics. The realization of cognitive wireless access networks requires intelligent management functionality, which will be in charge of finding the best reconfigurations. A cognitive resource manager (CRM) enables autonomic optimization of the communication stack as a whole, instead of focusing solely on the spectrum problem and thus going well beyond simplistic radio resource managers (RRMs) and medium access control techniques [1]. These managers may perform cross-layer optimization using a toolbox of advanced reasoning methods and a great variety of information from the application layer, the underlying networking and data link layers, as well as the operating system.

In this article we present some key missing links between human societies and societies of cognitive radio networks. This provides new ideas to study and design the toolboxes (e.g., in the CRM scheme) needed to build truly cognitive radio networks. The article is organized as follows. The next section presents a discussion of cognitive radio networks within the context of human societies. This framework and its implications are further explained using three specific anthropological models in the following section. Concluding remarks are provided in the final section.

HUMAN SOCIETY AND COGNITIVE RADIO NETWORKS

The analogy between human society and cognitive radio society can be represented by Fig. 1. Human beings living together in a society exhibit some basic behaviors that can be categorized as:

- Individual behavior
- Group behavior

Individual behavior is represented by self-interest, rationality, or irrationality. For example, neoclassical economic theory studies the behavior of a rational agent maximizing an objective function over an appropriate set of choices. Group behavior includes groupings formed for a common public good (survival etc.), some of which can be irrational.

Individual and social behavior evolve over time due to resource constraints, externalities, stability reasons, and so on. Society provides choices and alternatives to individuals and groups. There is usually a trade-off between private gains and public good. For example, increasing the property tax contributes to the community welfare at increased cost to the individual. The trade-offs may be quantitative (e.g., economic value) or qualitative (e.g., ethical value). Measuring this trade-off may be addressed via utility theory. Clearly, different aspects of the individual and group behavior must be well represented in the utility function.

Cognitive radio networks by definition should be capable of making their decisions and con-

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trolling their fate themselves. Similar to a human society, the cognitive radio society could also be a hierarchical society having similar attributes. Similar to a nation's central government and law system, in a cognitive radio society there would be some basic etiquettes to which all the cognitive radio nodes must comply. These basic etiquettes aim to reduce unnecessary and excessive interference, promoting channel access efficiency and fairness. Possible basic etiquettes could be listen before transmitting (LBT), or if the radio unit does not have any packets to transmit, it should never hold the channel needlessly.

Microeconomic game theory has been used widely to study individual and group behavior in wireless networks. Nash equilibrium is perhaps the most popular equilibrium concept investigated in these games. However, as noted in [2] there are several shortcomings in using Nash equilibrium as a solution concept. Among these are the failures to address irrational behavior, colluding nodes or players, and so forth. *Some of these shortcomings in microeconomic game theoretical analysis of wireless networks may be addressed using more general social or psychological models derived directly from human behaviors*.

A cognitive radio network society can mimic human societies. Cognitive radio networks may behave rationally while competing and cooperating for resources, survival, and social efficiency, just like human beings in a society. However, irrational behavior due to Byzantine failures may also be exhibited by nodes (e.g., nodes that sense the radio environment). This may lead to security vulnerabilities, loss of spectral efficiency, instability in the cognitive process, and other problems.

The available resources for cognitive radios may include the network transmission capacity, battery power, latency, frequency of operation, and security. Also, there are questions about whether or not to cooperate. It is known that cooperation in an ad hoc wireless network may increase transport capacity. On the other hand, non-cooperative resource usage could lead to the tragedy of commons. Distributed control of the resources in a cognitive radio network is equivalent to the behavioral evolution of individuals who learn by experience to cooperate or not in a society.

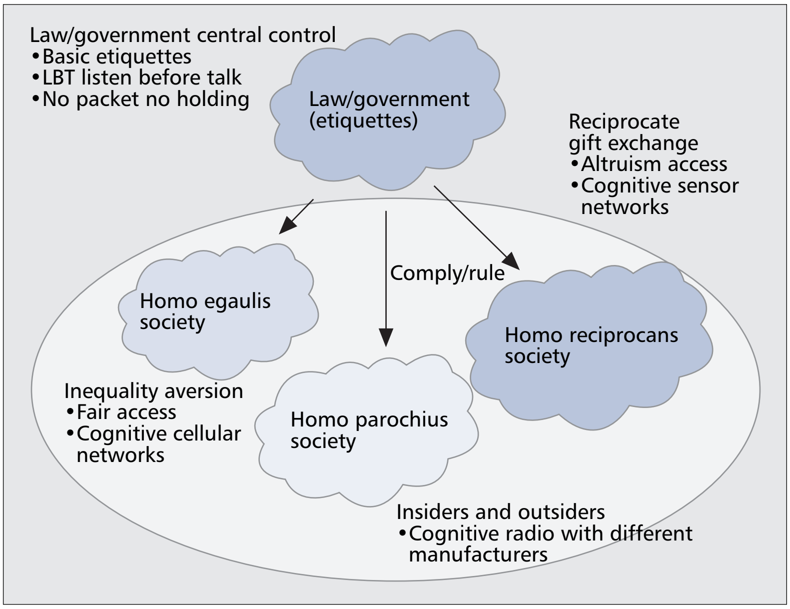


Figure 1. *Analogy between human societies and cognitive radio networks.*

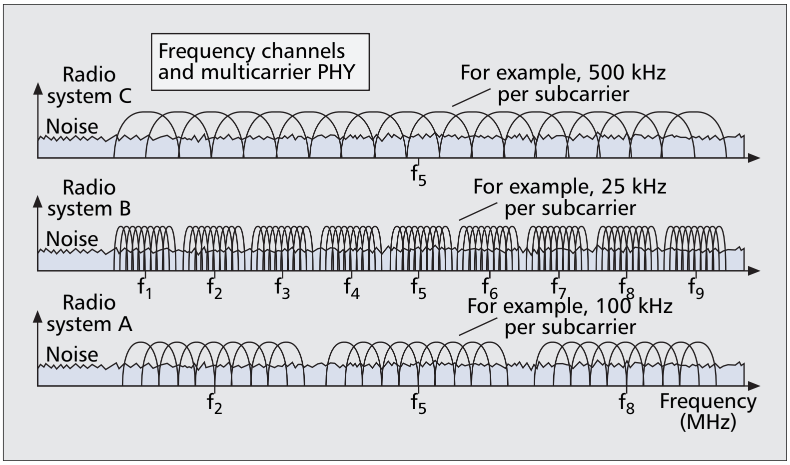


Figure 2. *Frequency channels and multi-carrier PHY.*

Three Examples

Apart from these basic etiquettes, a cognitive radio network's behavior can be modeled by different human societies depending on their types and applications. We provide examples of three societies in this section to illustrate our ideas: Homo Egualis, Homo Parochius, and Homo Reciprocans. Also, note that the cognitive radio nodes can be controlled and regulated distributively by a *hidden hand* (e.g, [3]). By the evolution and interaction of these cognitive radio nodes' behaviors, efficient and fair spectrum access may be achieved autonomously.

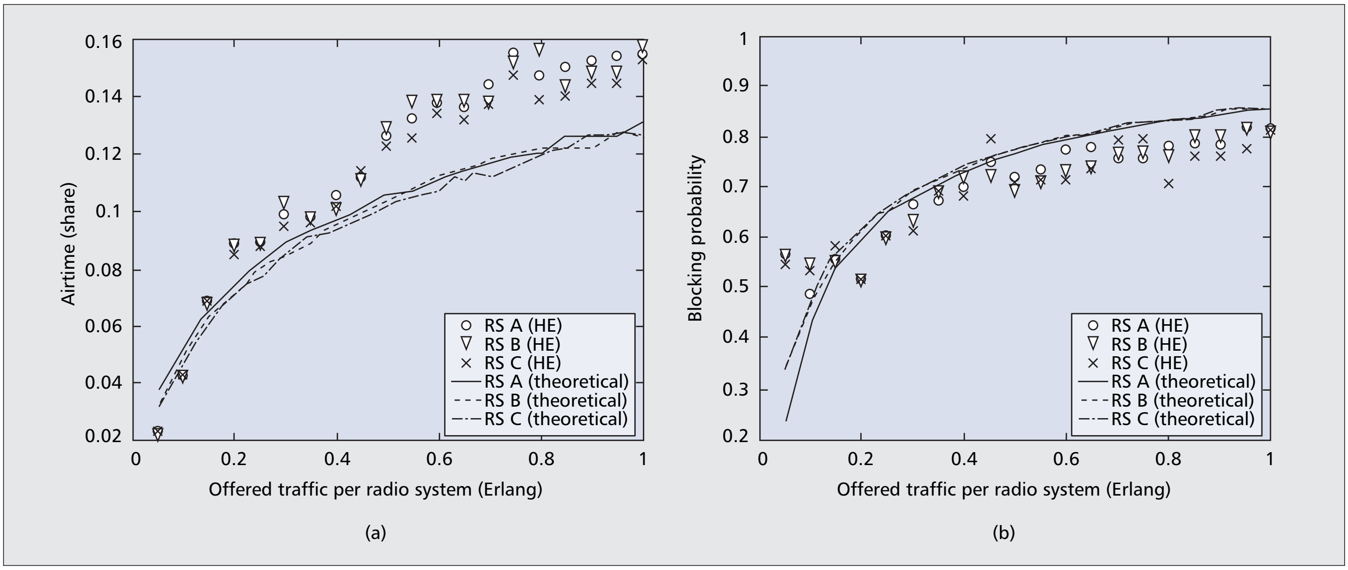
Homo Egualis Society

In the human society, homo sapiens evolved in small hunter-gatherer groups. Such societies have no centralized structure of governance (e.g., state and judicial system). So the enforcement of norms depends on the voluntary participation of peers.

An agent in a Homo Egualis society cares not only about its own payoff but also about how it compares with the payoff of others. A Homo Egualis society [4] can be modeled as follows, where the utility function of player i, u_i, in an n-player society is

$$u_i = x_i - \frac{\alpha_i}{n-1}\sum_{x_j > x_i}(x_j - x_i) - \frac{\beta_i}{n-1}\sum_{x_j < x_i}(x_i - x_j), \quad (1)$$

where $x = (x_i, \ldots, x_j)$ are the payoffs for each player and $0 \le \beta_i < \alpha_i \le 1$. In Eq. 1, $\beta_i < \alpha_i$ reflects the fact that the utility decreases by a smaller value when $x_i > x_j$; that is, there is a weak urge to inequality when doing better than others and a strong urge to reduce inequality when doing worse than others. In [4] it is shown that in this model the salient behaviors in ultimatum and public goods games, where fairness does matter, can be reproduced.



■ **Figure 3.** *Comparison of HE and theoretically optimal solution: a) airtime; b) blocking probability.*

A distributed dynamic spectrum access scheme for dissimilar cognitive radio networks discussed in [5] is based on a Homo Egualis society. The unlicensed frequency bands are good candidates for a large set of radio services that may be supported with spectrum etiquettes. Consider the abstract model of an unlicensed frequency band [5] illustrated in Fig. 2. Here, three different types of radio systems (RSs) are assumed to operate in a band with overlapping frequency channels.

Let us define airtime as the ratio of transmission time allocated per RS type with respect to the total reference time. Efficiency and fairness are two major goals of any spectrum etiquette. If every radio system accesses the unlicensed band in a greedy manner, the RS requiring a broader band to operate will suffer from an unacceptably low airtime share. So one way to provision higher fairness would be to require each RS to work in a cooperative manner. One option would be for each RS i to contend for the spectrum with probability p_i. After the RS has decided to contend for the spectrum, it accesses the spectrum using the LBT etiquette. If perfect fairness is achieved and each RS maximizes its airtime share, it can be shown that the resulting optimal channel access probability vector ($p_{a_{opt}}$, $p_{b_{opt}}$, $p_{c_{opt}}$) corresponds to the strategy that no RSs can do better in terms of the airtime share without harming the other coexisting RSs. So in this sense, both efficiency and fairness are obtained by using this optimal probability vector. Obviously, without considering any fairness issues, the most efficient access in the sense of pure spectrum utilization would be for all the users to compete for the spectrum greedily. In this case some networks may be totally blocked out of spectrum access. If different types of RSs have different traffic loads, equalizing the airtime may cause low spectrum utilization. Exact fairness does not always apply as far as a network operator is concerned, since they are likely to be more concerned with revenue. So users who pay more will get more access, which means that different networks may have different priorities. Therefore, to properly address these issues we have to define the fairness and efficiency carefully.

A cognitive RS can distributively learn the optimal values of p_a, p_b, and p_c using only the local information or measurement. The inequality aversion property of the Homo Egualis agents can be utilized to learn these values. That is, each RS learns its access probability p_i by computing the utility function (1) and adapting it correspondingly. For an example of such an adaptive estimation algorithm we refer to [5]. It is seen from Figs. 3a and 3b that HE-model-based adaptive channel access produces airtime and blocking probabilities that are almost fair. The theoretical solution [5] is obtained from a Markov model. The probabilities p_a, p_b, and p_c are changed iteratively in the HE-based access scheme, whereas it is assumed to be fixed in the theoretical analysis. This is the reason the HE-based access scheme is observed to produce a performance gain slightly higher than the optimal theoretical solution in both airtime share and blocking probability.

HOMO PAROCHIUS SOCIETY

Homo Parochius is the society that divides the world into insiders and outsiders according to context-dependent and even apparently arbitrary characteristics. They value insiders' welfare more than that of outsiders, evaluate insiders' personal qualities higher than those of outsiders, and partially suppress personal goals in favor of the goals of the group of insiders. In human society, race, ethnicity, common language, and nationality are well-known examples of characteristics that are used to distinguish "insiders" from "outsiders."

Similarly, in the cognitive radio society, the cognitive radio nodes of one manufacturer, or belonging to the same service provider or association may provide expedient access to other members by preferential means such as sharing more airtime or offering higher spectrum opportunities. Therefore, when the spectrum market is opened up widely and cognitive radio nodes have the freedom to utilize any possible spectrum opportunity, will some kind of "trust" be formed in a cognitive radio society so that within that group nodes are not treated as outsiders? The answers to this question have several important implications.

A price war indicates a state of intense competitive rivalry accompanied by a multilateral series of price reductions. That is, when one competitor lowers its price, the others will also lower their prices to match. If one of the players reduces its price below the original price cut, a new round of reductions is initiated. In the short term price wars are good for consumers who are able to take advantage of lower prices. Price reduction means that profit margins for a seller decrease, which could even threaten its survival. But a consumer will benefit from such a price competition in a dynamic spectrum access market. They can fulfill their differentiated quality requirements at a lower spectrum access price along with the flexibility to switch among multiple service providers.

Consider a limited geographical region where a spectrum provider operates. A competitive spectrum seller network model explored in [6] is shown in Fig. 4. Assume that all the sessions established between users and operators are of fixed duration. Thus, the time parameter is not included in the problem formulation. Furthermore, we do not consider the multiple access protocol in this article when multiple consumers are subscribing to one provider.

The buyer's decision making process can be modeled as follows. Each buyer b has a utility function $u_b(P, Q)$, which is a single-valued function of the perceived price P and perceived quality Q of a prospective spectrum supplier. The buyer b will select a single seller k for which $u_b(P, Q)$ is maximize as long as that maximal utility is positive within the price budget. If the maximal utility is zero or negative, the buyer does not purchase a unit from any seller. Clearly, there are two types of buyers in this case:

- *Quality sensitive*: Choose the seller with the highest quality as long as the price is below an upper bound.
- *Price sensitive*: Choose the seller with the lowest price as long as the quality is higher than a lower bound.

While there are several candidate choices for the function $u_b(P, Q)$, following [7] let us choose

$$u_b = (\gamma_b(q - \bar{q}_b) + (1 - \gamma_b)(\bar{p}_b - p))\,\Theta(\bar{p}_b - p)\Theta(q - \bar{q}_b), \qquad (2)$$

where $\bar{p}_b$ is the buyer's price ceiling (the maximum price it is willing to pay), $\bar{q}_b$ is its quality floor (the minimum quality it is willing to accept), γ_b is a parameter that ranges between 0 and 1, and $\Theta(x)$ represents the step function: 1 for $x > 0$ and 0 otherwise. A buyer with $\gamma_b = 0$ price sensitivity and $\gamma_b = 1$ is quality sensitivity.

The quality of the spectrum provided by the seller may be evaluated differently, for example:

- Not all spectrum is created equal. Generally, the lower the frequency for a given constant power, the greater the distance the signal can travel and still be received. But the ability to directionalize the signal is less.

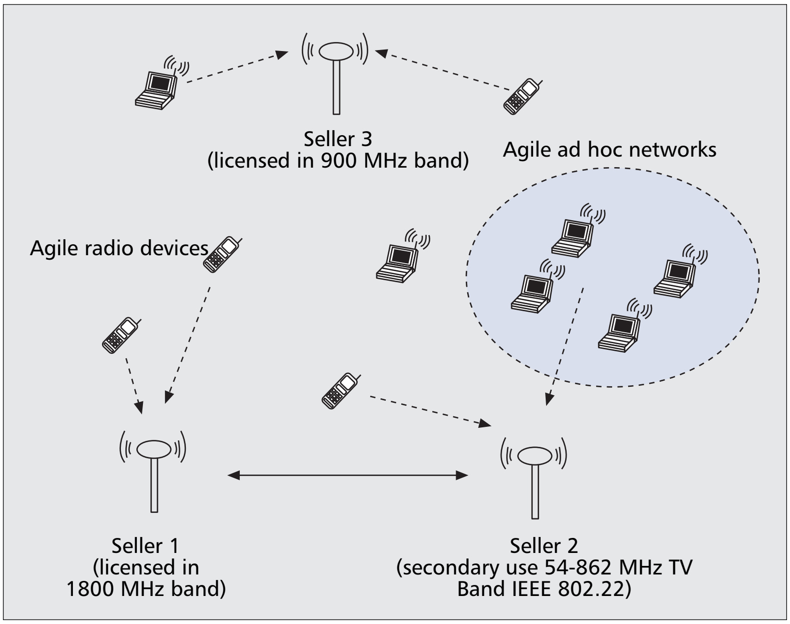


Figure 4. *Competitive spectrum seller or provider network.*

- The spectrum band provided may be contiguous or discontiguous segments. The total bandwidth offered may also be different, and affects the maximum transmission rate.

The sellers could exhibit a complex behavior. At time t, several events may occur. First, at most one randomly selected seller k is given the opportunity to revise and publicize its price P_k and/or quality Q_k Then each buyer is given the opportunity to revise its choice of seller based on this information. Finally, each seller receives P_k from each buyer that has selected it, and pays a cost c_k (assumed to be partially correlated with Q_k) to produce this service and deliver it to the buyer. For example, the cost for seller k could be proportional to the bandwidth it provided, $c_k = W_k$. For the sake of simplicity let us assume that these costs are fixed.

When a seller has the opportunity to modify its price and/or quality, its decision is based on an attempt to maximize its own profit. Let us consider the seller price dynamics when the buyers are quality sensitive. Assume that each buyer b has $\gamma_b = 1$ and $\bar{q}_b = 0$; that is, it is extremely quality sensitive, seeking the highest-quality seller for which the price does not exceed $\bar{p}_b$. Assume that the number of buyers $N \rightarrow \infty$, and $\bar{p}_b$ is distributed uniformly between 0 and 1. Furthermore, assume that every buyer has access to perfect, completely up-to-date information about the sellers' prices and qualities. We define the payoff for seller i to be $u_i = (P_i - c_i)z_i$, where z_i is the fraction of buyers that choose seller i.

Then there are cases when some of the sellers form a cooperative group (of insiders), and they compete as a group against other sellers or groups (of outsiders). Under these conditions, it is interesting to investigate if cooperation increases the profit for the spectrum sellers in the group.

Consider a case of 1000 quality sensitive buyers and 3 spectrum sellers. The profit dynamic

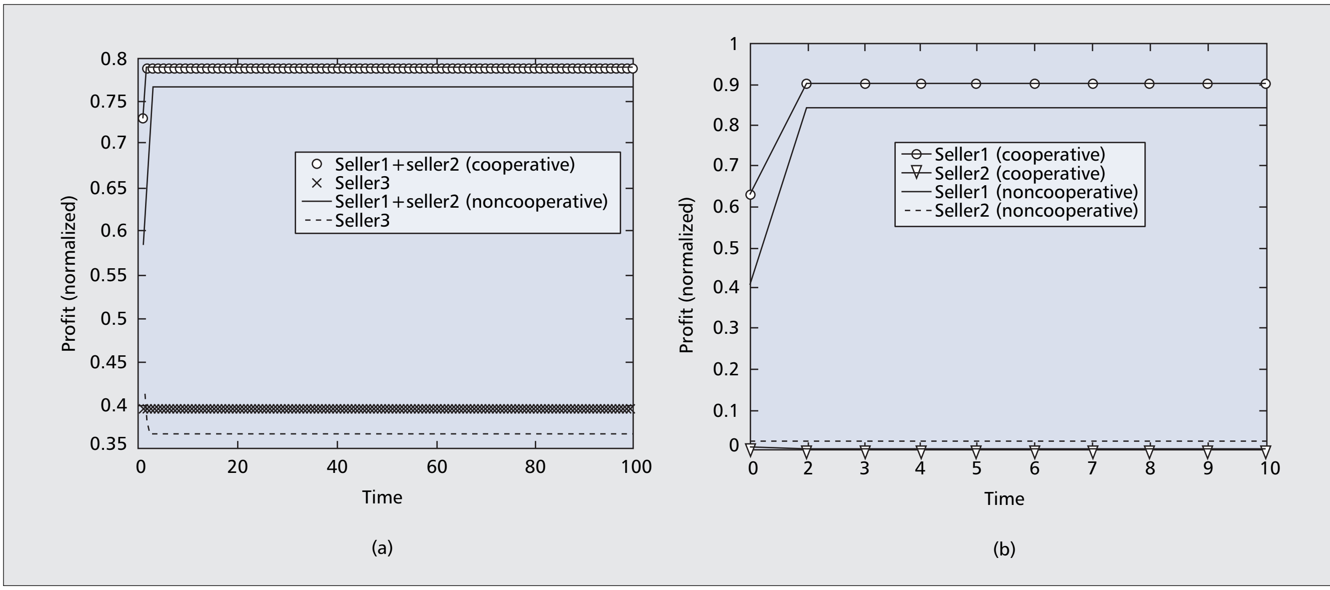


Figure 5. *Profit dynamics of three sellers with quality-sensitive buyers: a)* $c_1 = 0.1$, $c_2 = 0.4$, $c_3 = 0.2$; *b)* $c_1 = 0.1$, $c_2 = 0.8$, $c_3 = 0.5$.

when sellers 1 and 2 cooperate is shown in Fig. 5a. Let the sellers' cost be $c_1 = 0.1$, $c_2 = 0.4$, $c_3 = 0.2$. It is seen that the social profit for all the sellers in the cooperating group increases. This is intuitively correct because if two sellers cooperate they can jointly optimize their profit. Interestingly, in this case seller 3, who is not in the group, also benefits from the cooperation between sellers 1 and 2. The free ride phenomenon can also be observed when two sellers cooperate. For example, as shown in Fig. 5b, when seller 2's cost is much higher than seller 1's cost, after cooperation, seller 2 will completely shut down, but seller 1 will makes a higher profit, and the resulting total social profit for seller 1 and 2 will increase. So in this case seller 2 is free riding on seller 1.

HOMO RECIPROCANS SOCIETY

Homo reciprocans interact strategically with a propensity to cooperate. They respond to cooperative behavior by maintaining or increasing the level of cooperation, and retaliate against offenders that exhibit noncooperative behavior even if this comes at a cost. That the retaliatory action could lead to a loss of future personal gains does not matter to the Homo reciprocan. Homo reciprocans are not selfish in that they try to maximize their own payoffs, but they are not selfless altruists of Utopian theory either (when other forms of punishment are not available, homo reciprocan responds to defection with defection, leading to a downward spiral of noncooperation). Gift exchange is a good example of reciprocal behavior where one agent behaves more kindly than required toward another, with the hope and expectation that the other will respond kindly as well. In human society employers can pay higher than market-clearing wages in hopes that employees will reciprocate by supplying a higher level of effort.

This gift exchange behavior is valuable when a cognitive sensor network is considered, where cooperation between individual nodes is required and valuable in the signal relaying process. If each node acts selfishly and only maximizes its own current payoff, there is no reason for it to forward packets for other nodes at the expense of its own battery power and bandwidth. Furthermore, similar to the ultimatum game, in the unlicensed band, if one radio network A occupies a spectral band W_1 and another radio network B intends to access the same spectral band, radio network A (proposer) should consider giving radio network B a share of the spectrum access opportunity (e.g., by employing time-division multiple access). Radio network B (recipient) will decide to accept or reject this offer. If A's offer is unacceptable and therefore rejected, radio network B may jam radio network A's communication. Hence, both of them cannot complete their communication. On the other hand, if the offer is accepted by B, they will coexist with the agreed share of the right to utilize the spectrum resource. In this situation, if both radio networks operate only by maximizing their individual payoffs, by classical game theory, the subgame perfect equilibrium would be that radio network A provides radio network B with the minimum share of the spectrum, and B would accept this offer; otherwise, it will get nothing.

When actually played by people, the subgame perfect outcome is almost never attained or even approximated. In fact, ultimatum game experiments have shown, under varying conditions and with varying amounts of resources, proposers routinely offer recipients substantial amounts (50 percent of the total being the modal offer), and recipients frequently reject offers below 30 percent. Basically, people like things to be fair, and if they do not perceive what is going on as fair, they are prepared to suffer in order to punish those they see as the source of the unfairness. So they would reject any extreme unfair treatment. This situation may also happen in cognitive radio networks. As an intelligent agent, network B may reject A's unfair offer. So a better choice would be for both of them to behave in a reciprocal way, where in the utility function not only the payoff is considered, but terms corresponding to fairness and kindness are also included. This utility function reflects the fact that homo reciprocans care not only about payoffs, but also about the actions of the other players. The equilibrium reached by maximizing this utility function can be called the reciprocity equilibrium; that is, when radio network A proposes a higher offer then radio network B will accept that offer with probability 1. Hence, the precious spectrum resource is allocated efficiently.

It will be interesting to mathematically model and study the effects of the homo reciprocans behavior in dynamic spectrum access networks. What types of spectrum information sharing policies will evolve? How will spectrum sensors that behave like homo reciprocans interact with each other? Suppose some spectrum sensors fail (e.g., hardware failure) to sense or share information; will the reciprocal behavior from other sensors destabilize the entire network? These are key questions that open up new research themes linking human behavior modeling and cognitive spectrum sensing.

Conclusion

The major conclusions of this article are the following:

- It is possible to use the proposed socio-psychological framework to study and design cognitive radio networks.
- At the outset it may seem that the proposed framework has similarities with the microeconomic game theoretical analysis of wireless networks. But we note that irrational behavior (e.g., Byzantine failure of spectrum sensors), collusion, and some other characteristics are not captured by the traditional microeconomic analysis. Modeling such behaviors is very important for efficient exploitation of spectrum white spaces. Also, using the Nash equilibrium as a solution concept has some shortcomings. Some of these shortcomings can be overcome by using dynamic spectrum access models derived directly from anthropology.
- Fairness in spectrum consumption in a cognitive radio network can be achieved in a distributed manner if homo egualis behavior is mimicked.
- Free riding phenomenon can be observed in a spectrum access market where the players are homo parochians.
- Cognitive radio nodes may be willing to suffer in order to punish other nodes that exhibit unfair behavior.
- It will be interesting to study other human behavioral models for open spectrum access, coexistence of heterogeneous networks, interference suppression, the effect of a hidden hand for distributed sensing and control, and so on.
- The effects of random perturbations in the normal behavior of nodes caused due to channel fading, mobility, hidden nodes, sensor failures, and so on on network stability is another interesting aspect that needs to be explored. Will new kind of behaviors previously unseen in human evolution emerge?

Basically, people like things to be fair, and if they do not perceive what is going on as being fair, they are prepared to suffer in order to punish those they see as the source of the unfairness. So they would reject any extreme unfair treatment. This situation may also happen in cognitive radio networks.

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