Cooperative Sensing among Cognitive Radios

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***Abstract*— Cognitive Radios have been advanced as a technology for the opportunistic use of under-utilized spectrum since they are able to sense the spectrum and use frequency bands if no Primary user is detected. However, the required sensitivity is very demanding since any individual radio might face a deep fade. We propose light-weight cooperation in sensing based on hard decisions to mitigate the sensitivity requirements on individual radios.**

We show that the "link budget" that system designers have to reserve for fading is a significant function of the required probability of detection. Even a few cooperating users (∼10-20) facing independent fades are enough to achieve practical threshold levels by drastically reducing individual detection requirements. Hard decisions perform almost as well as soft decisions in achieving these gains. Cooperative gains in a environment where shadowing is correlated, is limited by the cooperation footprint (area in which users cooperate). In essence, a few independent users are more robust than many correlated users.

Unfortunately, cooperative gain *is* very sensitive to adversarial/failing Cognitive Radios. Radios that fail in a known way (always report the presence/absence of a Primary user) can be compensated for by censoring them. On the other hand, radios that fail in unmodeled ways or may be malicious, introduce a bound on achievable sensitivity reductions. As a rule of thumb, if we believe that $\frac{1}{N}$ users can fail in an unknown way, then the cooperation gains are limited to what is possible with N trusted users.

I. Introduction

Over the past years, traditional approaches to spectrum management have been challenged by new insights into the actual use of spectrum. In most countries, all frequencies have been completely allocated to specific uses. For example, the National Telecommunication and Information Administration (NTIA) frequency allocation chart (see Figure 1) indicates multiple allocations over essentially all of the frequency bands. Thus, within the current regulatory framework, spectrum appears to be a scarce resource. On the other hand, actual measurements indicate low utilization, (see spectrogram in Figure 1) [1]. This view is also supported by studies conducted by the FCC's Spectrum Policy Task Force which have reported vast temporal and geographic variations in the usage of allocated spectrum [2] [3].

As the measurements clearly show, many who have been allocated frequency bands (Primary users) by the regulatory agency are not using them all of the time, at all places. At the same time, others may like to use spectrum locally, but do not have a right to use the corresponding frequencies. Therefore, one way of increasing spectrum utilization is to enable these other secondary users to get access to frequency bands already allocated to Primary users while these are not using it. One of the ways of achieving this [1] is called Opportunistic Spectrum Sharing. Under such a regime, secondary users are allowed to operate in frequency bands without the consent of the Primary users of these bands, as long as they do not interfere with the Primary user. The FCC has already legalized this type of sharing in the 5.4GHz band (5.470GHz to 5.725GHz) [4]. Devices in this spectrum range have to periodically sense for the presence of military radars.

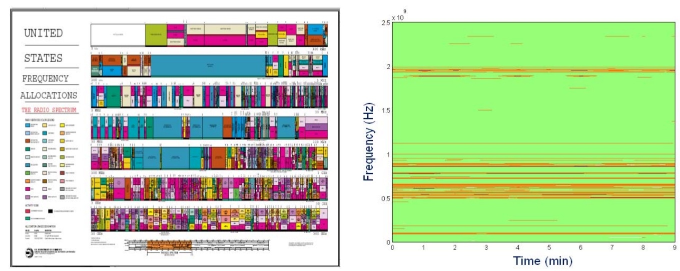

Fig. 1. NTIA spectrum allocation and the measured usage at the Berkeley Wireless Research Center. The measurements were performed at 0-2.5GHz frequencies over a period of 10mins.

A. Cognitive Radios

Cognitive Radios have been proposed as a technology to implement Opportunistic sharing since they are able to sense the spectrum and adapt their usage accordingly. Cognitive Radios must be able to demonstrate usage with minimal harm to the Primary user. This task is rendered difficult due to challenges in sensing the spectrum in a reliable manner. If a Cognitive Radio does not see energy in a particular band can it assume that the Primary user is not present? The answer depends on what level of energy it can reliably "see".

After all, a secondary user may suffer unlucky multipath and/or severe shadowing with respect to the primary transmitter. At the same time, its own transmissions may interfere with a primary receiver should it decide to transmit.[2] To account for possible losses from multipath, shadowing and building penetration, the secondary user must be significantly more

[1] Another paradigm for spectrum sharing involves negotiated sublicensing of bands from primary users through either long term contracts, or the use of secondary "spot markets" in spectrum. We do not discuss that approach here.

[2] This is related to the well known "hidden terminal problem" in wireless networking.

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sensitive in detecting than the Primary receiver [5]. To get a better understanding of the problem, consider this: a typical Digital TV receiver operating in a 6MHz band must be able to decode a signal level of at least -83dBm without significant errors [6]. The typical thermal noise in such bands is -106dBm. Hence a Cognitive Radio which is 30dB more sensitive has to detect a signal level of -113dBm, which is below the noise floor.[3]

B. The Motivation for Cooperative Sensing

The two major sources of degraded signals are multipath and shadowing. For a given frequency, multipath varies significantly with a displacement of $\frac{\lambda}{4}$ as discussed in [7] (where λ is the wavelength). In the absence of multiple antennas, multiple radios can act as a proxy for displacement or movement. The presence of multiple radios helps to reduce the effects of severe multipath at a single radio since they provide multiple independent realizations of related random variables. With multiple realizations, the probability that all users see deep fades is extremely low. In essence we wish to make Cognitive Radios' spectrum sensing robust to severe or poorly modeled fading environments. Cooperation allows us to achieve this robustness without drastic requirements on individual radios.

C. Objectives and key insights

Use of cooperation in wireless has been studied extensively especially with respect to achieving diversity gains and lowering outage probabilities via cooperation of mobile users [8]. In the Cognitive Radio context, we would like to exploit this cooperative effect in a different way. Rather than improving confidence by increasing cooperation, we want to maintain confidence while reducing competence! Hence our chosen metric is the reduction in sensitivity requirements once cooperation is employed (See Figure 2). Sensitivity of a radio is inherently limited by cost and delay requirements. Thus the device designer can figure out the implications of cooperation on the device specification through the well understood metric of detection sensitivity, thereby isolating the issue from unrelated concerns like the access regime, etc.

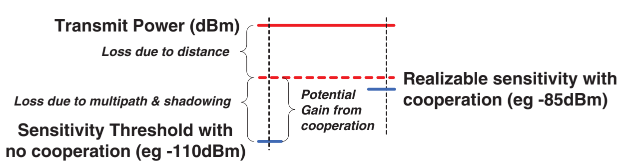

Fig. 2. Cooperation allows us to mitigate the effects of multipath and shadowing and hence the detection threshold can be set closer to the value of nominal path loss.

In this paper, we show the following results:

[3]Of course, being below the noise floor does not automatically make the detection problem impossible. The correlation structure of the primary transmissions, in particular the presence of known pilot tones, can make it possible to detect. However, it is always harder to detect weaker signals as compared to stronger ones.

- Cooperation allows independently faded radios to collectively achieve robustness to severe fades while keeping individual sensitivity levels close to the nominal path loss. Furthermore, a small number of radios ($\sim$10-20) are enough to achieve practical sensitivity levels.
- Practical "link budgets" for dealing with fading depend strongly on the target probability of detection which in turn depends on the tolerable probability for harmful interference at the Primary receiver and the number of non-cooperating Cognitive networks.
- Communicating tentative hard decisions can achieve cooperative gains nearly identical to sharing soft decisions.
- In a correlated fading environment, we cannot necessarily operate robustly with the sensitivity levels predicted by the analysis of independent users. In this case, polling a few independent users is better than polling many correlated users.
- Radios that fail in unmodeled ways or may be malicious, introduce a bound on achievable sensitivity reductions. As a rule of thumb, if we believe that a fraction $\frac{1}{N}$ of users can fail in an unknown way, then the cooperation gains are limited to what is possible with N trusted users.

II. Preliminaries

A. Cooperative Regimes

The level of cooperation is determined by the bandwidth of the control channel and the quality of the detector. Using these two metrics we can define three regimes of interest:

Low bandwidth control channel, Energy detector radios: In this regime, we expect a low bandwidth control channel which is especially true of initial setup stages. Under such a scenario, it is realistic to assume that the radios exchange decisions or summary statistics rather than long vectors of raw data. Furthermore, we assume radios that have no prior information about the correlation structure of the signal and hence must integrate the received energy. In [9], it has been shown that in the presence of noise uncertainty, energy detectors cannot detect a signal below a certain SNR value (called SNR_{wall}). This is the regime of interest in this paper since it gives us the lower bound on cooperative performance.

Low bandwidth control channel, Detectors utilizing signal statistics: An example of such detectors are cyclo-stationary detectors which utilize the correlation in the signal and hence perform better than energy detectors [10]. However, given the presence of a low bandwidth control channel, only summary statistics can be exchanged.

High Bandwidth Control channel, All possible detectors: In this regime, Cognitive Radios can exchange entire raw data and hence sophisticated detection can be performed. In this scenario, it may be possible for tightly synchronized radios to collectively overcome the SNR_{wall}.

B. Radio Sensitivity as a metric for Cooperative Gain

Cognitive Radios must be constrained not to exceed the target probability of harmful interference at the Primary receiver

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(P_{HI}). If there are K non-cooperating systems potentially contributing to the interference, then each individual system or network must ensure that its probability of detection is at least $P_{D,system} \approx 1 - \frac{P_{HI}}{K}$ (this can be derived by applying the union bound to the event that any system interferes with the Primary receiver). As the number of cooperating radios (N) in a given Cognitive network is increased, the required probability of detection of an individual radio $P_{D,radio}$ is reduced as (assuming independent observations at each radio) [11], [12]:

$$\begin{aligned} P_{D,radio} &= 1 - \sqrt[N]{1 - P_{D,system}} \\ &= 1 - \sqrt[N]{\frac{P_{HI}}{K}} \end{aligned}$$

Viewing this equation on the log scale reveals that N scales as the logarithm of K which implies that an order of magnitude increase in the deployment of non-cooperating systems can be compensated by a linear increase in the number of cooperating users within each system. As N increases beyond $\log K - \log P_{HI}$, the required $P_{D,radio}$ rapidly approaches 0.

The reliability of an energy detector depends on the receiver's noise characteristics, the received signal strength, and the length of time that is used for integration. The received signal strength is our focus for two reasons:

- In the presence of noise uncertainty, users below the SNR_{wall} cannot improve their performance even with infinite integration times.
- Limits on integration time may be imposed by the dwell times of the Primary Users.

Based on this discussion, our model of the radio is simple: given a threshold for the received signal strength t, the radio declares that the Primary user is present if and only if the received signal strength is greater than t. To meet the target $P_{D,radio}$, it is necessary that the received signal strength exceed t even in the worst $P_{D,radio}$ fraction of the fades. Since cooperation makes $P_{D,radio}$ close to zero, the system as a whole becomes robust to the details of the fading environment.

C. The Radio Channel

The Radio channel has three different elements which are important for our analysis:

Distance dependent Path Loss: Path loss forms the most significant portion of the energy loss. A realistic model of cooperative cognitive usage is a group of users localized in a small area ($\sim 1km^2$). In such a situation, differences due to path loss are negligible (.1-.5dB)[4]. In this paper, we consider a group of Cognitive Radios situated at a distance of 60km from a TV transmitter of 100kW power. The distance of 60km is well beyond the grade B service contour of TV reception [6].

[4]The cooperation footprint (area in which users cooperate) is limited by the Primary user's coverage area. The cooperation footprint for detecting a wireless microphone is a lot smaller than that required for a TV transmitter. Also note that the usage footprint (area in which users communicate with each other, for e.g. a cell) may be vastly different from the cooperation footprint. When the usage footprint is larger than the cooperation footprint, collective decisions may not be applicable to all users.

Multipath We assume that small scale fading is flat and exhibits a Rayleigh distribution. For Primary user detection, flat fading yields the worst case performance since frequency selectivity provides multiple 'looks' at the same signal. Similarly, Rayleigh fading is considered, since the case of interest is when we cannot count on line of sight between the Cognitive Radio and the Primary transmitter. It is important to note that multipath cannot be relied upon to yield gains (our aim is only to avoid severe multipath losses) since we could easily end up in a deployed scenario where there is Ricean fading.

Shadowing Shadowing on the log scale has been assumed to be normally distributed [13] based on the application of Central Limit Theorem to a large number of small absorptive losses. The standard mechanism to derive the shadowing environment is to take measurements at various locations for a fixed transmitter-receiver separation and attribute the variance in the measurements to shadowing. A naive interpretation would indicate that shadowing can lead to a gain — however it must be realized that the mean received power level in this case has no physical significance. To relate the shadowing to the distance dependent path loss, we used a different model of shadowing where shadowing is viewed as losses via a series of obstacles. For each obstacle, there is a small probability that the obstacle will be missed. Using this model, shadowing is viewed as *extra* loss beyond the distance dependent path loss. Hence,

$$Y_i = \begin{cases} 0 & w.p.\ 0.2 \\ \text{unif}(0, x)dB & w.p.\ 0.8 \end{cases}$$

and the net shadowing is expressed as:

$$S = \frac{1}{\sqrt{M}} \sum_{i=1}^{M} Y_i \tag{1}$$

The loss per obstacle was adjusted to fit the variance of the measured log-normal standard variable of around 3.5dB [14]. The resulting value of M (number of obstacles encountered) was 15 while x was 10.25dB. The Complementary Cumulative Distribution Function (CCDF) of the resulting shadowing random variable is shown in Figure 3 along with the CCDF of multipath.

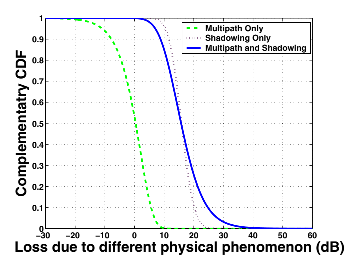

Fig. 3. Complementary CDF of Loss (in dB) due to different physical effects.

It is also important to keep in mind that shadowing is notoriously hard to model accurately and its statistics can vary widely with deployment environment.

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III. Gains from Cooperation

A. Impact of number of users

Using the loss model discussed in the previous section, we simulated the allowed reduction in sensitivity of individual radios as the number of users is increased. This simulation assumes path loss predictions by the NTIA model at a confidence level of 15% as the nominal distance dependent path loss [15]. This model accounts for losses due to frequency, distance, antenna heights, polarization, surface refractivity, electrical ground constants and climate and hence yields realistic loss levels. The setup of the Cognitive Radio system is shown in Figure 4. Radios send their decisions to a designated Controller (which could be one of the radios) that combines these decisions. The controller decides that the Primary User is present if any one of the radios has detected the Primary. Using this scheme, Figure 5 shows the change in sensitivity with increasing number of users under three different effects: multipath only, shadowing only and multipath together with shadowing. We consider gains beyond the nominal path loss as artificial and these should be ignored. When multipath is considered together with shadowing, the threshold asymptotically approaches the nominal path loss. Half the gain is achieved by using $\sim$10-20 users, beyond which the gains exhibit a 'law of diminishing returns' as the number of users is increased.

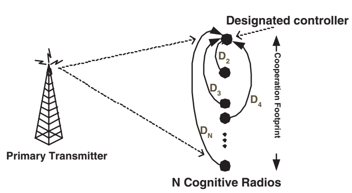

Fig. 4. Cooperation setup. The designated controller collects samples/decisions from the individual radios and makes the final decision.

It is important to realize that a single user acting alone must be robust to extremely rare events. These events are not well modeled by the Central Limit theorem, and may in fact not be properly modeled by any single statistical model given the uncertainty that surrounds actual deployment scenarios. At these levels, sensitivity predictions are no better than pure guesswork in the single user context. One of the major advantages of cooperative sensing is that it allows us to have collective robustness to fading while not requiring us to have great faith in the fading model for even moderately uncommon fades.

B. Soft versus Hard cooperation

It has been argued that soft decision combining of sensing results yields gains that are much better than hard decision combining [16]. This is true when radios are tightly synchronized in which case they can collectively overcome the SNR_{wall}. From [9] we know that the physical noise uncertainty gives a lower bound on signal strength that a user can reliably detect. This lower bound is increased further to

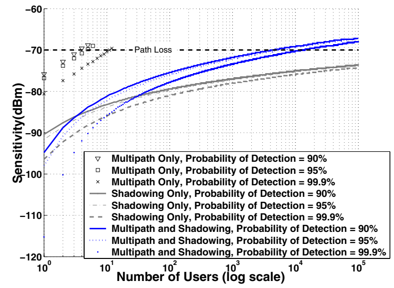

Fig. 5. Sensitivity variation with number of users (Frequency = 800MHz, Distance=60km, TV transmitter height=200m, CR height=3m). With multipath only, results show an unbounded improvement in sensitivity as the number of users is increased. Multipath together with shadowing causes the threshold to asymptotically approach the nominal path loss.

keep the probability of false alarm tolerable. To understand this better, consider the problem of detecting a signal in additive white Gaussian noise (AWGN) with an noise uncertainty α [9]. For user i, our goal is to distinguish between the hypotheses:

$$\begin{aligned} \mathcal{H}_0 : Y_i[n] &= \qquad \alpha W_i[n] & n = 1, \ldots, M \\ \mathcal{H}_s : Y_i[n] &= X[n] + \alpha W_i[n] & n = 1, \ldots, M \end{aligned}$$

Given that we are using a simple energy detector, the test statistics available under $\mathcal{H}_0$ is [17]:

$$\mathcal{T}(Y_i) = \frac{1}{M} \sum_{j=1}^{M} \alpha^2 W_i[n]^2 \tag{2}$$

Its can be shown that:

$$\frac{M\mathcal{T}(Y_i)}{\alpha^2 \sigma_w^2} \sim \chi_M^2 \tag{3}$$

For large M, this behaves as $\mathcal{N}(M,\ 2M)$. Hence we can approximate $\mathcal{T}(Y_i)$ as $\mathcal{N}(\alpha^2\sigma_w^2, \frac{2\alpha^4\sigma_w^4}{M})$.

If we wish to have a net probability of false alarm (P_{FA}) to be around 0.14 percent, the threshold should be set 3 standard deviations away from the mean. This places the threshold[5] at: $\alpha_{max}^2\sigma_w^2(1 + \frac{\sqrt{2(9+\ln N)}}{\sqrt{M}})$. The factor $\alpha_{max}^2\sigma_w^2$ is the worst case noise power.

For soft decoding, we can bound performance by assuming that all the samples are provided to the user with the best channel. In that case the probability of false alarm threshold can be set at: $\alpha_{\max}^2\sigma_w^2(1 + \frac{3\sqrt{2}}{\sqrt{MN}})$, where N is the number of users.

To observe the differences between soft and hard decoding we simulated a group of users at a distance of 60km from the TV transmitter. The number of users in this group was varied and the effect on radio sensitivity for a 95% probability of detection was observed. The results of this simulation can be seen in Figure 6. The small difference between hard and soft

[5] We need to introduce the tiny $\sqrt{\log N}$ correction term to translate system-level false alarm probabilities to radio-level false alarm probabilities.

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decision arises from the effectively longer integration times in the soft case, but is less than a fraction of a dB. When the dominant limits come from uncertainty, this gain in effective integration times is not useful.

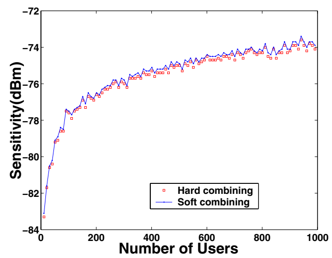

Fig. 6. Radio sensitivity for soft versus hard decoding. The small difference between the two is due to the effectively larger integration time in the soft case.

IV. Shadowing Correlation

In [11] the received signal is treated as a complex Gaussian process and the effect of correlation is identified. The optimal detector is derived assuming that a single entity has access to all the data and performs optimal detection. These results show that higher correlation yields a higher probability of false alarm for the same probability of detection.

It is important to understand that the main source of correlation between the channels observed by two radios is shadowing. Multipath at different radios is essentially uncorrelated since multipath exhibits correlation on the scale of $\frac{\lambda}{2}$. Radio placements on this scale can be safely assumed to be uniformly distributed and independent of each other. Shadowing on the other hand, can exhibits high correlation if two radios are blocked by the same obstacle. Shadowing correlation displays distance dependence which has been studied extensively [18].

To study the effect of shadowing correlation, we simulated a group of Cognitive users in a line at a distance of 60km from a TV transmitter as shown in Figure 4. The designated controller examines the detection results of users.[6] The effect of increasing cooperation on the sensitivity threshold of an individual radio can be seen in Figure 7(a). It must be noted that we ignore multipath effects in this simulation.

Increased correlation decreases our chances of getting a user with a very good channel and hence more users need to be polled for independent looks at the same random variable. For distance dependent correlation, this translates into a desire to poll users which are further away i.e. a large enough cooperation footprint. This effect can be seen in Figure 7(b). Here, we are interested in studying the sensitivity gains as the number of users and their cooperation footprint is varied. Each set of points represents increased user density. Increasing the number of users for a given cooperation footprint asymptotically reaches a limit which is dependent on the cooperation footprint. A similar effect can be seen in [16] where the probability of missed opportunity does not go to zero in a spatially bounded correlated fading environment.

[6]We choose a linear increase model since the shadowing correlation model as proposed in [18] only predicts one dimensional correlation. Furthermore, we have used the conservative suburban model fit from [18] where the correlation is always positive.

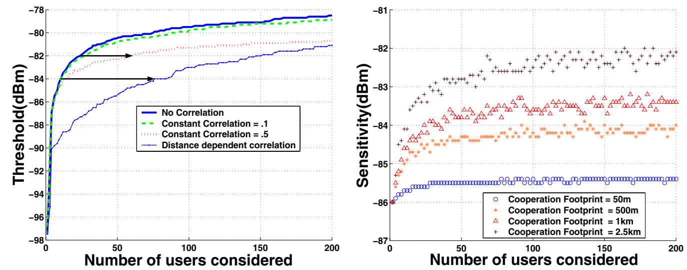

Fig. 7. (a) Sensitivity variation with number of users under different correlation characteristics (no multipath). Correlation causes the system to poll more users to achieve a given threshold. (b) Comparing the impact of varying users versus varying the cooperation footprint. The plot emphasizes the need for independent samples; gains from increasing the number of users is asymptotically limited in a correlated environment.

V. Impact of untrusted users

The results presented so far have established that collectively sensing spectrum availability can deliver tremendous gains even with a small to moderate number of perfectly trusted users as long as they occupy a large enough cooperation footprint. These gains are significant enough to justify revisiting the current per-device model of licensing that is used globally. At this point, a key question emerges — what is the impact of a few malfunctioning devices on the collective?

Such trust issues are natural in cooperation since there are incentives in reporting results in a certain way. For example, Cognitive Radios may assert the presence of a Primary user, in which case they deny others the opportunity to take advantage of the available bandwidth, or deny the presence of Primary users (when users want to use the channel at any cost). Radios may be simply malicious and/or failing in unknown ways. Uncertainty due to trust also provides a way of modeling user uncertainty in decision making. For example, sensing results of a user may be inaccurate in the presence of other secondary transmissions. Such a radio may erroneously decide that a Primary is present.

A. Dealing with malicious Adversaries

Dealing with radios that always report the absence of a Primary does not require knowledge of the number of liars in the system. Such users effectively reduce the number of actual users in the system and can be compensated for by a corresponding increase in the total number of users. For example, if 50% of users always report the absence of a Primary then we can double the number of users in the system.

On the other hand, unknown/malicious radios can severely impact cooperative performance. Figure 8 shows the impact of having a α fraction ($\alpha \in [0,1]$) of N users behave unpredictably (this fraction may swing between reporting presence of Primary and its absence in a random fashion). To be robust to the case when this fraction always reports the

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presence of a Primary, we must set the detection threshold at βN where $\beta > \alpha$ ie. we declare that a Primary user is present if βN Cognitive Radios see the Primary user. The problem arises when these radios start reporting the absence of a Primary user. Not only do they effectively reduce the number of real users in the system to $N(1-\alpha)$, but they also now require a fraction $\frac{\beta}{1-\alpha}$ of the trustworthy users to detect the signal. Explicitly, the resulting probability of detection for a given threshold t is given by:

$$P_{d,t} = 1 - \sum_{i=0}^{\beta N-1} \binom{N(1-\alpha)}{i} (1-F(t))^i F(t)^{N(1-\alpha)-i} \quad (4)$$

where $F(t)$ is the cdf of the received signal strength.

The individual sensitivity threshold tolerable for a group with a fraction of $\frac{1}{N}$ liars is the same as that achievable by a trusted system with N users. This threshold forms an upper bound even when the actual number of users is increased beyond N. Hence for 1% liars, the final achievable threshold is -76dBm which is the threshold for a trusted system with 100 users. The mathematical intuition for this result can be obtained by seeing that even when the number of users is large, for a fraction $\frac{\beta}{1-\alpha}$ of them to detect the primary requires that the threshold be such that $F(t) \leq 1 - \frac{K\beta}{1-\alpha}$ where K is a function of P_{MD} and so the threshold t must be small enough and cannot be made any larger than that. When the proportion of malicious users is high, it does require a moderately large number of users to reach these asymptotic limits.

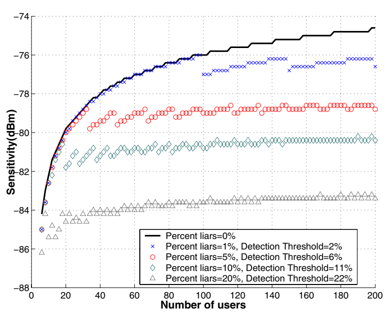

Fig. 8. Sensitivity Variation with malicious adversaries. The threshold achievable for a group with a fraction of $\frac{1}{N}$ liars is the same as that achievable by a trusted system with N users

VI. Conclusions

In this paper, we have suggested light-weight cooperation as a means to reduce the sensitivity requirements on an individual Cognitive Radio. Exploiting cooperation among multiple users may be the only mechanism to achieve a target system-level probability of detection in the case when each Cognitive radio faces an SNR_{wall} below which it is unable to reliably detect a Primary. With enough trusted cooperation, we only need to be sensitive enough to deal with the nominal path loss. However, this requires cooperation among users facing more or less *independent* fading. Shadowing is likely to be correlated across space. When correlation is distance-dependent, cooperation is desired among more distant users. Increasing the number of users in a distance-dependent correlated setting is asymptotically limited by the cooperation footprint. Furthermore, a hard decision scheme performs as well as soft decisions, with small differences arising from the finite number of samples.

Even so, trust is critical for such a cooperative systems to operate reliably. Users that fail in a known fashion (assert/deny the presence of a Primary user), can be compensated for, by increasing the number of users polled. Unfortunately, malicious users or users that fail in unmodeled ways impose an upper bound on achievable sensitivity reductions. As a rule of thumb, if one out of every N users is untrustworthy, then the sensitivity of an individual receiver may not be reduced below what is possible with N trusted users.

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