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Selective reporting - a half signalling load algorithm for distributed sensing

Atílio Gameiro[1], Carlos Ribeiro[2*] and José Quaresma[2]

Abstract

Spectrum sensing is a powerful tool of the cognitive cycle to help circumvent the apparent spectrum scarcity faced by wireless transmission systems. To overcome the challenging issues faced by the localized sensing, multiple cognitive radios can cooperate to explore the multiuser diversity and generate a more reliable decision on the presence of a signal in the frequencies of interest. In such a cooperative sensing scenario, a common reporting channel is needed for the transmission of the information of each element. As the number of elements that participate in the sensing operation increases, so does the bandwidth demanded for the reporting channel, quickly becoming the limiting factor in this scenario. To tackle the issue of reducing the sensing report overhead, this paper introduces a new cooperative sensing scheme that introduces silence periods in the reporting and, relying on information theory principles, explores the information present in these periods to reduce by 50% the sensing reporting overhead while maintaining the same performance of standard reporting schemes. Numerical and experimental results confirm the theoretical analysis and show the predicted reduction in reporting overhead and performance preservation.

Keywords: Sensing; Distributed centralised sensing scheme; Hard-decision; Sensing reporting reduction

1. Introduction

The ever increasing demand for higher data rates is unstoppable. A report from CISCO predicts a 39-fold increase in data traffic in the period 2009 to 2014 [1]. A considerable portion of this data traffic will use wireless infrastructures, increasing the pressure on the efficient management of the available spectrum. The licensed spectrum is largely underutilized [2] as proven by the Federal Communication Commission in [3]. This study shows that the utilization of the licensed spectrum ranges from 15% to 85%.

Today, it is generally accepted that cognitive radio (CR) [4] is a promising solution to the apparent spectrum scarcity faced by the operators [5]. A CR adapts its operating parameters (i.e. centre frequency, bandwidth, etc.) to avoid interfering with (or be interfered by) other licensed or unlicensed wireless systems in the vicinity. This tuning is based on the radio environment monitoring operation, commonly termed sensing. A comprehensive

survey of spectrum sensing techniques can be found in [6]. If a CR is to autonomously assess the availability of a given channel, it needs to overcome challenging issues posed by the varying wireless channel conditions: hidden node problem, deep fading, shadowing, etc., that will deteriorate CR sensing performance. To alleviate this problem, multiple CRs can cooperate to jointly perform the spectrum sensing, exploiting the multiuser diversity in the sensing process [7-9].

In the cooperative spectrum sensing, each CR usually performs the sensing individually and then reports the local observations to a common fusion unit (FU). This unit gathers the information from all sensors involved in the sensing process, generates the decision on the presence of other users in the channel of interest and broadcasts the decision to the CRs. If a large number of CRs participate in the sensing process, it is expectable that even though some will suffer from the localized sensing limitations (hidden node, deep fading, shadowing and sensing performance), others will output correct reports and the overall decision will be more reliable. A survey on cooperative sensing can be found in [10].

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To transmit the local sensing reports to the FU, a bandwidth-limited common reporting channel is generally assumed, and the overhead needed for the CRs to send the reports is a critical issue in cooperative sensing. Although the information by itself may be a simple binary indication, it always requires the setup of the channel, which requires resources. Moreover, the transmissions from the sensors require energy. It is therefore highly convenient for energy reduction and overhead minimization purposes to devise cooperative sensing schemes that minimize the number of transmissions from the localized sensors to the FU.

The reduction of the reporting overhead in cooperative sensing has been addressed in the literature and can be divided into three categories: the CR network throughput optimization schemes [11-13], the user selection schemes [14-17] and the censorship algorithms [18-22].

The CR network throughput optimization schemes aim at maximizing the CR network throughput subject to a given detection probability. The work in [11] optimizes the number of sensors and sensing time that maximizes the network throughput when using energy detection at the sensors and the hard fusion OR decision rule at the FU. An extension for the k-out-of-K decision rule at the FU can be found in [12]. An additional energy constraint per CR is added to the problem in [13] to derive the optimal number of sensors, reporting time and probability of false alarm (PFA) that maximizes the throughput.

The user selection schemes use different criteria to select the sensors that will participate in the cooperative sensing, limiting the dimension of the group and lowering the reporting overhead. The confidence level that each sensor builds on its own decision (when comparing with the decisions of remaining sensors) is used in [14] to limit the set of sensors that report back to the FU. The distance to the primary user (PU) is the criteria adopted in [15] for choosing the k-out-of-K CR users that will participate in cooperative sensing when the positions of CR users and PU are known. The degree of knowledge of the positions of the CR users is the criteria used in the three selection algorithms proposed in [16] to address the shadow correlation problem in cellular systems. A trade-off between the sensing reliability and the reporting overhead is used in [17] to induce the sensors with the best detection performance to join the cooperative sensing.

The censoring algorithms aim at limiting the number of reports sent by each sensor involved in the cooperative sensing by refraining the CR users from transmitting uninformative data. The local decisions made at each sensor are sent to the FU only if they are considered informative. The most common procedure defines two thresholds as shown in Equation 1. Information is sent only if:

$$
\begin{aligned}
&U > L_u \text{ (and 1 is sent)}\\
&\text{or} \qquad\qquad\qquad\qquad\qquad (1)\\
&U < L_l \text{ (and 0 is sent)}
\end{aligned}
$$

If the statistic U belongs to the uncertainty interval $L_l\,L_u$ then no reporting is performed because the binary information corresponding to the local decision is not reliable enough to justify the usage of transmitted power and radio resources. Although one can significantly reduce the overhead with such a scheme, optimization requires a careful setting of the thresholds L_u and L_l, which are dependent of the probabilities of having a primary signal or not. If such *a priori* probabilities are not known or cannot be guessed, then a random choice of the thresholds does not guarantee a good receiver operating characteristic (ROC). This can be improved with learning procedures, but this again takes time to stabilize.

To tackle the issue of reducing the sensing report overhead, a new cooperative scheme is proposed that essentially relies on basic information theory principles which say that silence periods may also convey information. The new cooperative sensing scheme reduces the average number of transmissions by 50% without any loss of performance and could be used in conjunction with the other two groups of distributed sensing algorithms to further reduce the signalling overhead.

The remainder of the paper is organized as follows. The next section introduces the proposed selective reporting algorithm and analyzes its performance under fading channels. Numerical and experimental results are presented and discussed in Section 3. Finally, the main conclusions of this work are drawn in Section 4.

2. Selective reporting algorithm

The selective reporting cooperative sensing algorithm explores the information present in silence periods to reduce the sensing report signalling overhead and associated energy and resource usage. The section starts with a concise background review, introduces the proposed cooperative sensing scheme with silence periods and analyzes the distribution of the number of transmitted messages. An information theory interpretation of the new scheme follows, ending with the investigation of the behaviour of the algorithm subject to fading channels.

2.1. Background review

Considering a node k out of the K cognitive radios in the scenario of Figure 1, the mathematical model for binary hypothesis testing problem is the following:
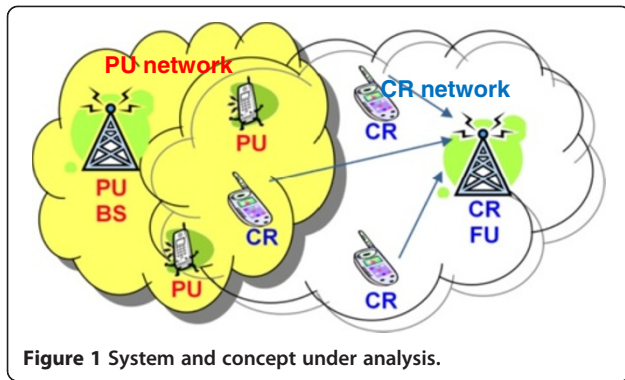
Figure 1 System and concept under analysis.

$$\text{Primary user absent } H_0: \quad y[n] = w[n]$$
$$\text{Primary user present } H_1: \quad y[n] = ax[n] + w[n]$$

$$(2)$$

where the following notation is used:

$x[n]$: transmitted signal, usually modelled as zero-mean additive white Gaussian noise (AWGN) with variance σ_x^2
$w[n]$: zero-mean AWGN noise with variance σ_w^2
$y[n]$: received signal
a: complex coefficient that accounts for channel fading
$n = 0, 1, \cdots, (N-1)$, were N is the number of samples in the observation window of the received signal.

Considering an energy detector, the decision statistic is formed summing up the energy of the received samples during the observation interval, i.e. considering that N samples are collected. The decision statistic U is given by:

$$U = \frac{1}{N} \sum_{n=0}^{N-1} |y[n]|^2 \qquad (3)$$

and using this statistic, the classical decision rule is simply:

$$\begin{cases} \text{Decide } H_0 \text{ if } U < L \\ \text{Decide } H_1 \text{ if } U \geq L \end{cases} \qquad (4)$$

where L is the decision threshold, chosen as to achieve a given operating point on the sensor's ROC curve.

Let us now extend the observation for the entire distributed sensing scheme of Figure 1. Assuming that the localized sensing variables are sent to the FU, the dominant fusion model has its origins in the distributed detection theory: the parallel fusion technique [23] combines the observations to improve the detection performance. The adoption of this fusion model, and its variants, for cooperative sensing can be found in [9,24].

The combining at the FU can be divided into two major categories depending on the result reported by the sensors. If the sensors report the full samples (or its quantized versions), the FU performs a soft combining, achieving the best performance of both categories, at the cost of a higher signalling load. The optimal soft combining algorithm was proposed by [25], where a Neyman-Pearson criterion was used for the weighted combination of the local samples. If the sensors report the binary local decision, the FU performs a simple hard combining. The most commonly used fusion decision rules are the AND, OR and majority decision. These rules can be generalized in the k-out-of-K rule [23] (for $k = 1$, K, $\lceil K/2 \rceil$ the rule becomes, respectively, the OR, AND and majority decision rules). The ideal k value depends on the type of channel affecting the transmission, the detection threshold and the total number of sensors [26]. For a large threshold, the OR rule tends to give the best performance, and due to its simplicity, it is commonly used for scenarios where, subject to a given PFA, the goal is to reduce the probability of missed detection (PMD). At each sensor, from Equation 4:

$$\begin{cases} \text{Decide } H_0 \text{ if } U < L \text{ and send } 0 \\ \text{Decide } H_1 \text{ if } U \geq L \text{ and send } 1 \end{cases}$$

$$(5)$$

The final decision is made at the FU by employing the OR rule: if at least one sensor reports 1, decides H_1, otherwise H_0. With such a rule, and assuming K identical sensors, the global PFA, q_D, is given by:

$$q_D = 1 - (1-q)^K, \qquad (6)$$

where q is the localized (at each sensor) PFA.

Similarly, the PMD, v_D, is simply expressed as a function of the localized PMDs:

$$v_D = \prod_{i=1}^{K} v_i, \qquad (7)$$

where v_i is the localized PMD for sensor i ($i = 1,2,...,K$).

Equation 6 can be extended, in the case of non-identical sensors, to:

$$q_D = 1 - \prod_{i=1}^{K} (1-q_i), \qquad (8)$$

where q_i is the localized PFA for sensor i ($i = 1,2,...,K$).

The localized probabilities, considering the energy detector, are amenable to analytical formulation under certain conditions. Assuming that the number of samples N is high so that we can invoke the central limit

theorem, and resorting to the Gaussian hypothesis, it can be expressed as [27]:

$$
\begin{cases}
q_i = Q\left(\dfrac{K - \sigma_{w(i)}^2}{\sigma_{w(i)}^2 \sqrt{2}}\sqrt{N}\right) \\[3ex]
v_i = Q\left(\dfrac{K - \left(\sigma_{w(i)}^2 + |a_i|^2 \sigma_x^2\right)}{\sqrt{2\left(\sigma_{w(i)}^2 + |a_i|^2 \sigma_x^2\right)^2}}\sqrt{N}\right)
\end{cases} \tag{9}
$$

where a_i is the complex coefficient that accounts for the channel fading of sensor i; $\sigma_{w(i)}{}^2$ is the individual sensor noise variance, and $Q(.)$ is the complementary error function $\frac{1}{\sqrt{2\pi}}\int_x^\infty e^{-x^2/2}dx$.

2.2. Cooperative sensing with silence periods

The basis of the proposal relies on the use of two types of sensors that report if different events occur at each one, i.e.:

- Type 1: report only if decision is H_1. Do not report if decision is H_0.
- Type 2: report only if decision is H_0. Do not report if decision is H_1.

The operating mode of the type 1 sensor is shown in Figure 2 (left). In this figure, the columns represent the hypothesis that is really occurring, and the lines represent the decision made by the sensor. The cells contain the type of message that is sent along with the joint probability of $(\hat{H}_i; H_j)i, j \in \{0; 1\}$. The equivalent figure for a type 2 sensor is shown in Figure 2 (right). In this figure, E indicates that no message is sent (from the word erasure) and M that a message is sent. The type of message (M) is rather irrelevant.

The type of node is decided on the initialization procedure, and the FU must keep an up-to-date list with the sensors integrating each group. When a new sensing report arrives, the only thing that counts is the identification of the transmitting node. In fact, upon receiving a message, the FU knows that if it is coming from a type 1 sensor, it means that this node has detected a primary signal, whereas if it is coming from a type 2 sensor, it means that no primary signal was locally detected.

Table 1 illustrates the operation of the scheme considering that there are only two sensors, one type 1 and one type 2.

Let us consider the number of messages that are transmitted assuming that P type 1 sensors and $P - K$ type 2 sensors are deployed. As a starting assumption, it is considered that localized PMD and PFA are equal for all sensors.

1. Hypothesis H_0

   Let us assume hypothesis H_0 where no primary signal is present. Conditioned to this hypothesis, a type 1 sensor transmits if it makes an erroneous detection, and thus, the average number of messages (T_1) coming from type 1 sensors is given by:

$$
E(T_1|H_0) = Pq, \tag{10}
$$

   while type 2 sensors transmit when they make the correct decision, and then, the average number of messages (T_2) coming from type 2 sensors is given by:

$$
E(T_2|H_0) = (K-P)(1-q). \tag{11}
$$

   Therefore the average number of transmitted messages is given by:

$$
\begin{aligned}
E(T_1 + T_2|H_0) &= Pq + (K-P)(1-q) \\
&= P(2q-1) + K(1-q)
\end{aligned} \tag{12}
$$

2. Hypothesis H_1

   Under hypothesis H_1, type 1 sensors transmit if they make the correct detection, while type 2 sensors transmit if they miss the detection. Thus, the average number of messages coming from type 1
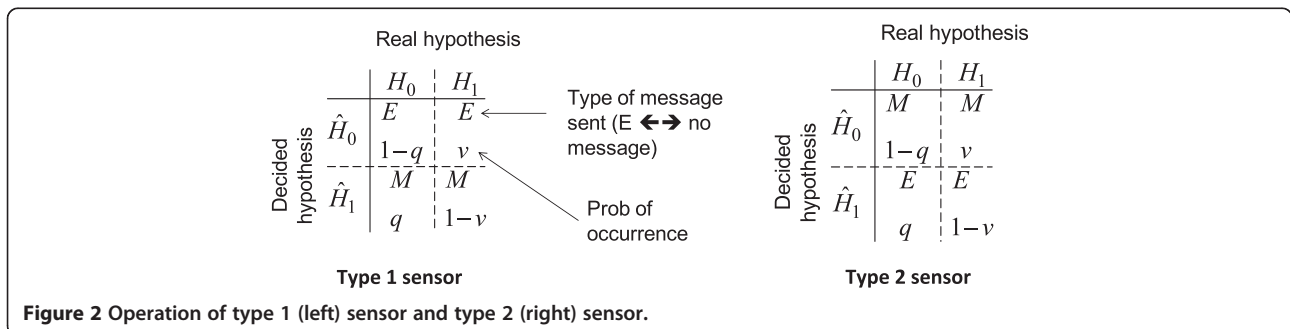

Figure 2 Operation of type 1 (left) sensor and type 2 (right) sensor.

Table 1 Illustration of the selective reporting scheme with two sensors of different types

Type 1 sensor			Type 2 sensor			FU decision (OR rule)
Local decision	Message sent to FU	Interpretation at FU	Local decision	Message sent to FU	Interpretation at FU	
0	E	0	0	M	0	0
0	E	0	1	E	1	1
1	M	1	0	M	0	1
1	M	1	1	E	1	1

and type 2 sensors is given by:

$$\begin{cases} E(T_1|H_1) = P(1-v) \\ E(T_2|H_1) = (K-P)v \end{cases} \quad (13)$$

and, therefore, the average number of total transmissions is given by:

$$E(T_1 + T_2|H_1) = P(1-2v) + Kv. \quad (14)$$

2.3. Analysis of the distribution of transmitted messages

Let us now consider the distribution of the number of transmitted messages.

1. Hypothesis H_0

   Under the assumptions of identical sensors, the distribution of the number of transmitted messages (see Appendix), conditioned to H_0, is given by:

$$f_0(m) = (1-q)^P q^{K-P} \left(\frac{1-q}{q}\right)^m \sum_{l=0}^{m} \binom{P}{l} \binom{K-P}{m-l} \left(\frac{q}{1-q}\right)^{2l} \quad (15)$$

   from which the average and variance can be computed:

$$\begin{cases} E[T|H_0] = P(2q-1) + K(1-q) \\ Var[T|H_0] = Kq(1-q) \end{cases} \quad (16)$$

2. Hypothesis H_1

   Under the assumption of identical sensors, the distribution of the number of transmitted messages (see Appendix), and respective average and variance conditioned to H_1, is given by:

$$\begin{cases} f_1(m) = (1-v)^{K-P} v^P \left(\frac{v}{1-v}\right)^m \sum_{l=0}^{m} \binom{K-P}{l} \binom{P}{m-l} \left(\frac{1-v}{v}\right)^{2l} \\ E[T|H_1] = P(1-2v) + Kv \\ Var[T|H_1] = Kv(1-v) \end{cases} \quad (17)$$

Now, let us consider what would be the best choice of P. Assuming that we have no prior information on the presence or absence of the primary signal, we would like

to choose P that minimizes the average value of required transmissions, whatever the value of the hypothesis,

$$\min_P \{ \max\{E[T|H_0; P]; E[T|H_1; P]\}\} \quad (18)$$

The problem is illustrated graphically in Figure 3. The thick segments represent the maximum value of the average required transmissions for both hypotheses. The optimum values is achieved when

$$\begin{aligned} &E[T|H_0] = E[T|H_1] \Leftrightarrow \\ &P(2q-1) + K(1-q) = P(1-2v) + Kv \Leftrightarrow \\ &(2P-K)(q+v-1) = 0 \end{aligned} \quad (19)$$

For the values of PFA, q and PMD, v, of interest, the only solution to Equation 19 is $P = K/2$. This result will be used throughout the remaining of the paper.

Let us update the solution of Equation 19 in the most relevant equations. Under hypothesis H_0, Equation 12 can be written as:

$$E(T_1 + T_2|H_0) = \frac{K}{2}(2q-1) + K(1-q) = \frac{K}{2}. \quad (20)$$

The result in Equation 20 proves that, irrespective of the localized PFA, the average number of transmissions is $K/2$, i.e. in average, only half of the sensors transmit.

The distribution of the number of transmitted messages, conditioned to H_0, is given by:
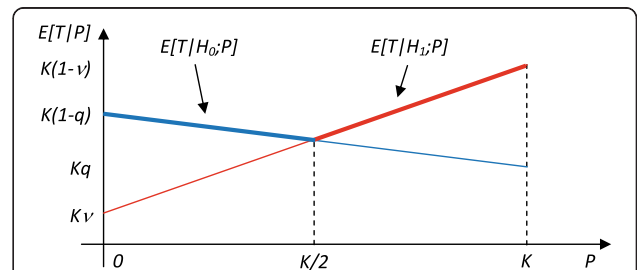

Figure 3 Illustration of the problem of minimizing the average value of required transmissions.

$$f_0(m) = (1-q)^{K/2} q^{K/2} \left(\frac{1-q}{q}\right)^m \sum_{l=0}^{m} \binom{K/2}{1} \binom{K/2}{m-l} \left(\frac{q}{1-q}\right)^{2l}$$

$$(21)$$

The variance is given by Equation 16.

Under hypothesis H_1, Equation 14 can be written as:

$$E(T_1 + T_2 | H_1) = \frac{K}{2}(1-2v) + Kv = \frac{K}{2} \qquad (22)$$

Irrespective of the localized PMDs, the average number of transmissions is $K/2$, i.e. in average, only half of the sensors transmit.

From Equations 20 and 22, one concludes that, irrespective of the hypothesis, the average number of transmissions from the sensors to the FU is $K/2$, which means that, when there is no fading, the average number of messages when using a total of K sensors with half being of type 1 and half of type 2 is equal to $K/2$.

The distribution of the number of transmitted messages, conditioned to H_1, is given by:

$$f_1(m) = (1-v)^{K/2} v^{K/2} \left(\frac{v}{1-v}\right)^m \qquad (23)$$
$$\sum_{l=0}^{m} \binom{K/2}{l} \binom{K/2}{m-l} \left(\frac{1-v}{v}\right)^{2l}$$

The variance is given by Equation 17.

As the PFA and PMD coincide with the ones of K sensors with classical transmission/detection employing an OR rule at the FU, it can be concluded that with the proposed scheme, the number of transmissions can be reduced by a factor of 2 with no penalty in the ROC.

For typical designs, the number of transmissions is much more concentrated around the mean for hypothesis 0 than for hypothesis 1. Let us just point out some numbers for a scenario with ten sensors (five of each type). If the global PFA is designed to be $q_D = 0.2$, using Equation 6, this requires a localized PFA at each sensor $q_i = 0.022$, and therefore, $\sigma_{H_0} = \sqrt{Var[T]|H_0} = \sqrt{10 \times 0.022 \times (1-0.022)} = 0.46$, whereas designing for a global PMD $v_D = 10^{-5}$, using Equation 7, the required localized PMD is $v_i = 0.316$, resulting in $\sigma_{H_1} = \sqrt{Var[T|H_1]} = \sqrt{10 \times 0.316 \times (1-0.316)} = 1.47$.

It may be surprising that with the selective reporting scheme one gets, with fewer transmissions, the same ROC as in the case of a conventional distributed detector, where the results of the local detection are always sent. This may be explained using basic concepts of information theory which states that no transmission (silent periods) may carry information. Let us consider

two sensors (one type 1 and one type 2) as shown in Figure 4, where E stands for no transmission.

It is easy to verify that the mutual information between A and B is the same if one replaces, in the output alphabet of type 1 sensors, E by 0, and, for the type 2 sensors, E by 1. The mutual information can be increased if we allow the use of three symbols, leaving the promise that using a double threshold can lead to improved performance.

2.4. Algorithm behaviour with fading channels

Let us now consider the case of fading between the primary system and the sensors. It is clear that when the primary signal is absent, nothing changes. Assuming that the sensors are identical, Equations 20 and 21 can still be used, i.e. it can be expected that the average number of transmissions is still equal to half the number of sensors.

However, the analysis under hypothesis H_1 is different. As the signal from the primary system arrives at the sensors with different powers, the PMD is different for the various sensors.

Let us now consider hypothesis H_1, assuming K sensors labelled 0, 1, ..., $K/2 - 1$ for sensors of type 1 and $K/2$, $K/2 + 1$, ..., $K - 1$ for sensors of type 2. The PMD i, v_i, is given (under the asymptotic Gaussian approximation) by Equation 9. Sensors of type 1 transmit therefore with probability $(1 - v_i)$ and sensors of type 2 with probability v_i. Although an analytic expression for the distribution of the number of transmissions is not amenable, the first and second order moments are quite easy to derive since it is a sum of Bernoulli variables that are independent. The additivity of the mean and variance can be invoked. The average number of transmissions for sensor i is given by:

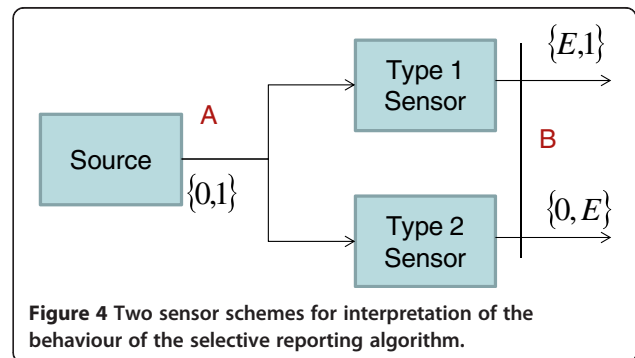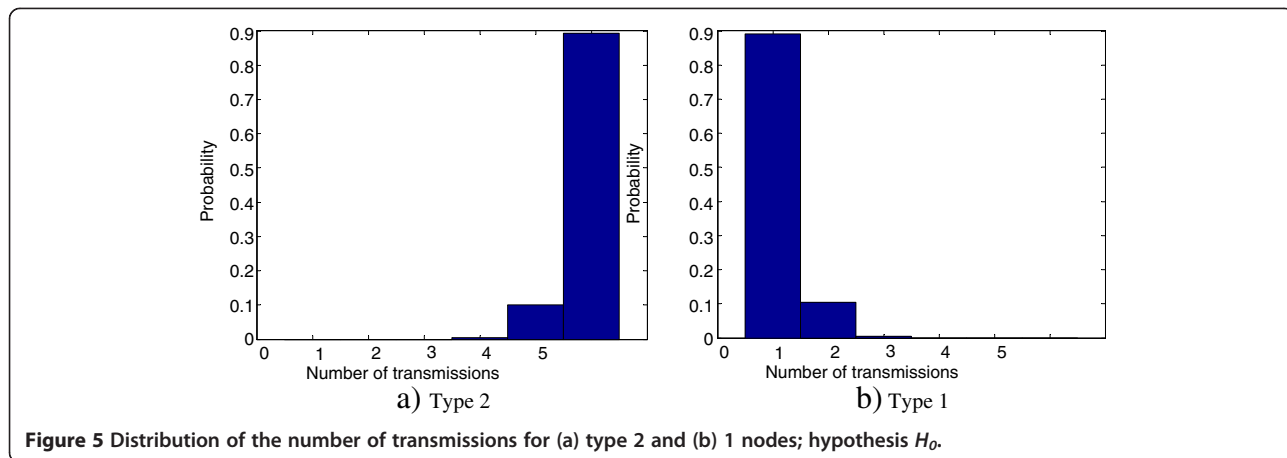$$E[T_i | H_1] = \begin{cases} 1-v_i & 0 \le i \le K/2 - 1 \\ v_i & K/2 \le i \le K - 1 \end{cases} \qquad (24)$$

Figure 4 Two sensor schemes for interpretation of the behaviour of the selective reporting algorithm.

Figure 5 Distribution of the number of transmissions for (a) type 2 and (b) 1 nodes; hypothesis H_0.

Therefore,

$$E[T|H_1] = \sum_{i=0}^{K/2-1} 1-v_i + \sum_{i=K/2}^{K-1} v_i$$
$$= \frac{K}{2} + \sum_{i=0}^{K/2-1} v_{i+K/2} - v_i \qquad (25)$$

Over the long term, if the environment is stationary, the average value of transmissions will be $K/2$, but for the reporting at a specific instant, this will depend on the specific distributions of the fading from the primary source to the sensors.

The variance of a Bernoulli variable with parameter α is $\alpha(1 - \alpha)$. Therefore, for a sensor, we get a variance $v_i(1 - v_i)$, either with parameter v_i or $(1 - v_i)$. As the variables are independent, we get, for the total number of transmissions, the variance:

$$\text{var}[T|H_1] = \sum_{i=0}^{K-1} (1-v_i)v_i \qquad (26)$$

By introducing a new level of randomness in the PMDs, the variability of the number of transmissions will clearly increase.

3. Performance assessment

This section presents numerical results related to the number of transmissions achieved with the proposed algorithm and experimental results of the implementation of the selective reporting scheme in a distributed sensing test bed [28].
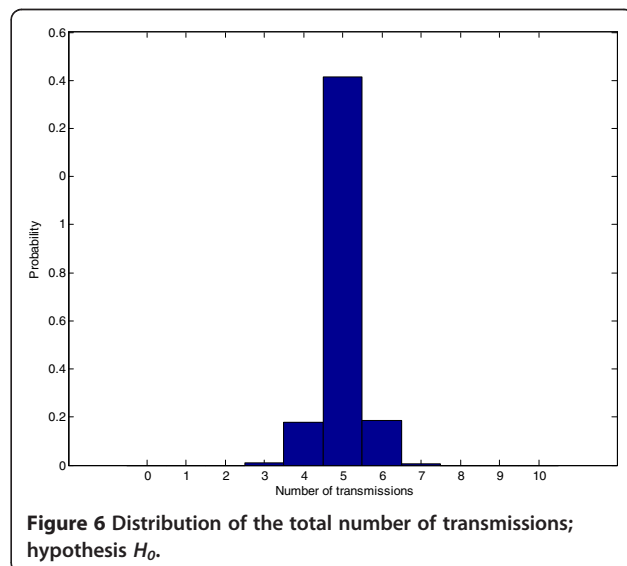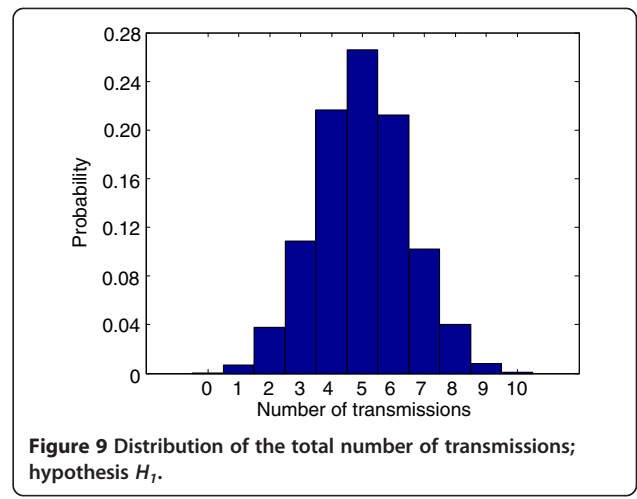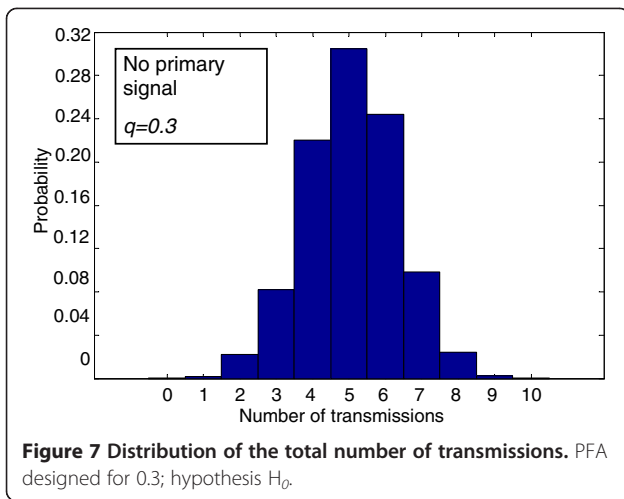
3.1. Numerical results

To assess the performance of the proposed algorithm, several simulations were performed with the following parameters:

- Number of sensing nodes: 10
  - Type 1 nodes: 5
  - Type 2 nodes: 5
- Global PFA designed for $q_D = 0.1$
- Transmitted signal and noise Gaussian
- Signal to noise ratio at the sensors in the case a primary signal is present
  - 0 dB for the case when no channel fading is considered
  - Uniformly distributed between [−8; 10] dB for the case when fading is considered
- Number of samples used in the energy detector: 20

Figures 5 and 6 report the distribution of the number of transmissions for the two different types of nodes for the case where no primary signal is present.

Figure 5 clearly shows the expected asymmetry between the distributions. The type 1 nodes are silent most

Figure 6 Distribution of the total number of transmissions; hypothesis H_0.

Figure 7 Distribution of the total number of transmissions. PFA designed for 0.3; hypothesis H_0.

Figure 9 Distribution of the total number of transmissions; hypothesis H_1.

of the time whereas the type 2 nodes are transmitting with a high probability.

In Figure 6, it is easy to identify the symmetry around the average value which is equal to half the number of sensors, i.e. five, with the distribution highly concentrated near this value.
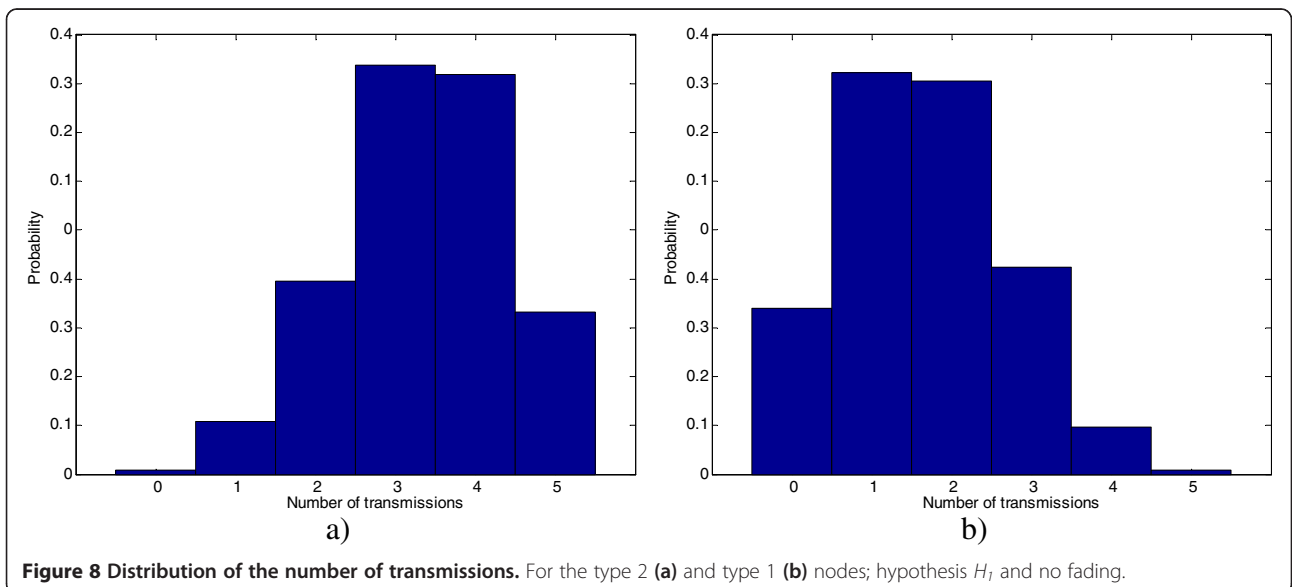
The average value of transmissions in the case reported in Figure 6 is very close to the statistical mean as it can be seen by the high concentration of transmissions around five and the symmetry of the histogram. A wider spread will occur if the threshold is changed to give a larger PFA. However, to notice significant asymmetry, one has to increase the PFA to 0.3, which is a design value seldomly used in practical systems. The resulting distribution is shown in Figure 7 where a much larger dispersion around the mean and an asymmetry
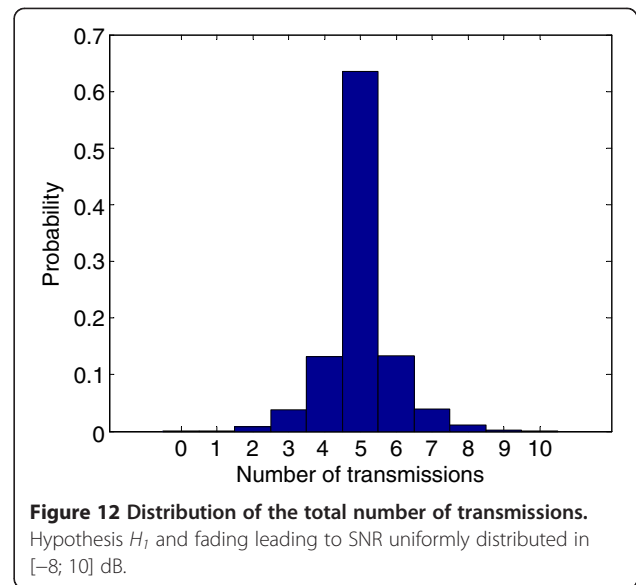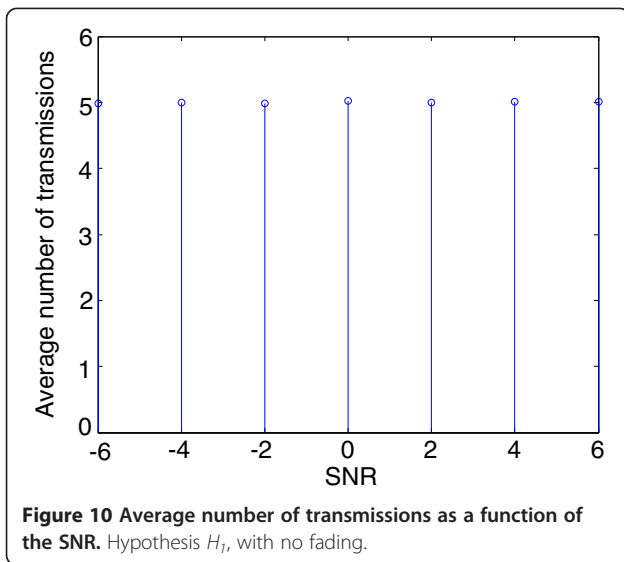
can be seen (in this particular simulation for values above the mean).

Figures 8 and 9 report the distribution of the number of transmissions for the two different types of nodes for the case where the primary signal is present. No fading is assumed, and the path loss is such that the signal-to-noise ratio (SNR) at each node is equal to 0 dB. In these figures, a larger spread in the distributions can be seen, as it was anticipated in the theoretical analysis. However, the mean is very close to half the number of nodes in Figure 9.

In Figure 10, the behaviour in the average number of transmissions is evaluated as a function of the SNR (equal for all nodes). The figure shows that within a 12 dB fluctuation range, the results are very close to the theoretical statistical mean.

Figures 11 and 12 show the probability distributions in the presence of fading, i.e. the SNRs at each node may be
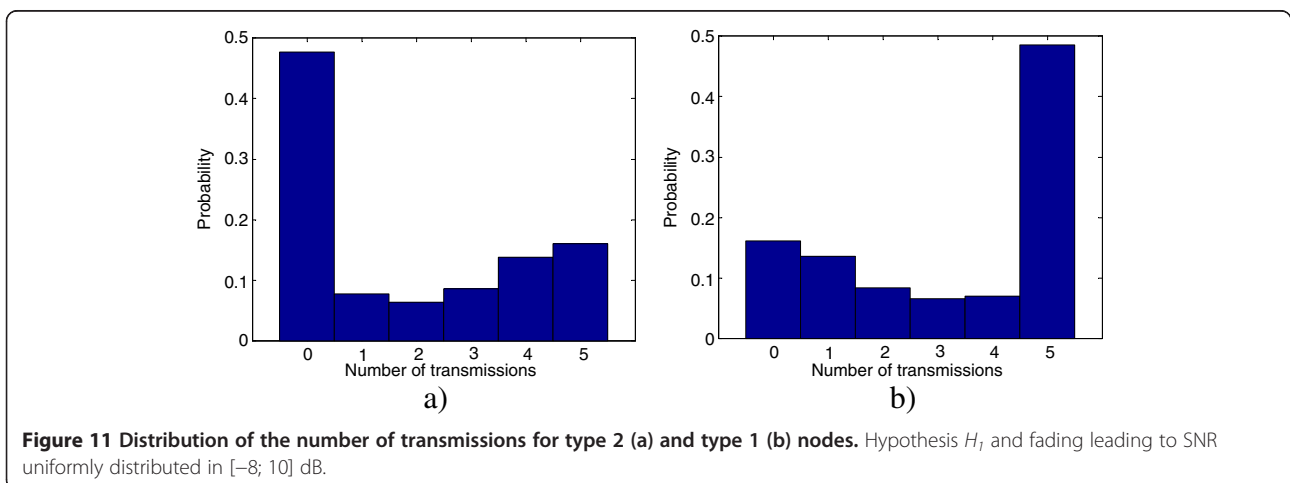

a)

b)

Figure 8 Distribution of the number of transmissions. For the type 2 **(a)** and type 1 **(b)** nodes; hypothesis H_1 and no fading.

Figure 10 Average number of transmissions as a function of the SNR. Hypothesis H_1, with no fading.

Figure 12 Distribution of the total number of transmissions. Hypothesis H_1 and fading leading to SNR uniformly distributed in [−8; 10] dB.

different. For these figures, the SNR is assumed to vary uniformly in the interval [−8; 10] dB. Figure 11 shows a wider spread in the number of transmissions. In both plots (a and b), one can notice that at the opposite edge of the point where the probability is expected to be maximum there is an increase in the density. This arises because, for type 1 sensors, there may be nodes with very low SNR that simply cannot detect the primary signal and contribute to an enhancement of the value of 0. The opposite arises for type 2 nodes. Nevertheless, the distribution of Figure 12 turns out to be very symmetric, and the mean is very close to 5.
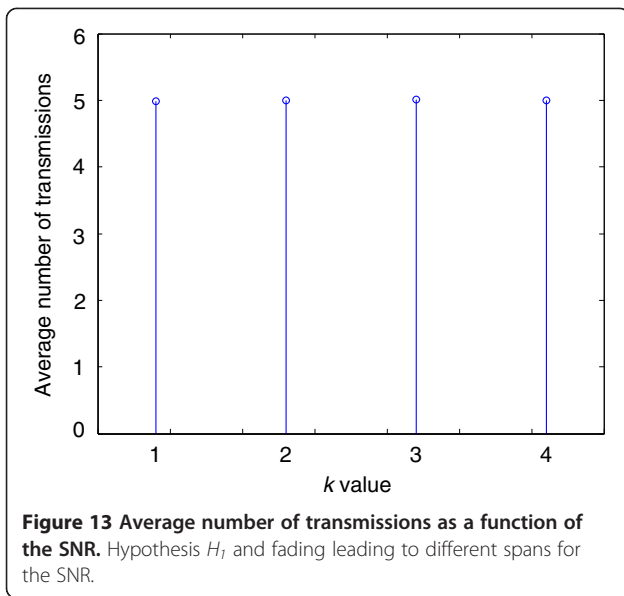
To evaluate the expected value of the number of transmissions, higher deviations in the SNR span were considered. In Figure 13, four cases are presented. The SNRs at the different nodes may vary in the intervals [−8k; 10k] dB with k taking the values 1, 2, 3 and 4. The results show that although the SNRs vary, the average

number of transmissions is still very close to the theoretical statistical value. In general, one can say that for the parameters of interest (that can be summarized as $q_D < 0.1$ and $\nu_D < 10^{-3}$) and for a moderately large number of sensors, the distributions are quite sharp and the number of transmissions are very close to the mean.

3.2. Experimental results
The selective reporting scheme was implemented in the distributed sensing test bed depicted in Figure 14 to evaluate the performance of the proposed algorithm in a close-to-real scenario. The test bed was composed of four sensing nodes, a FU and a primary scene emulator (baseband signal generator, channel emulator and RF up-converters). The sensing nodes and the FU were implemented in the open SDR platform GNU Radio [29]. The sensors used Ettus USRP [30] hardware to

Figure 11 Distribution of the number of transmissions for type 2 (a) and type 1 (b) nodes. Hypothesis H_1 and fading leading to SNR uniformly distributed in [−8; 10] dB.

Figure 13 Average number of transmissions as a function of the SNR. Hypothesis H_1 and fading leading to different spans for the SNR.
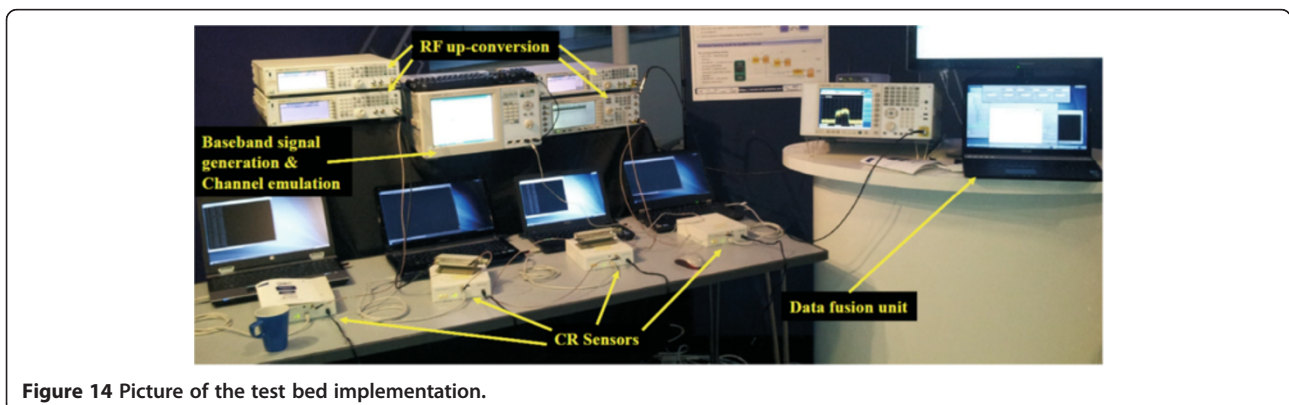
- Number of samples used in the energy detector: {10, 20, ..., 90}
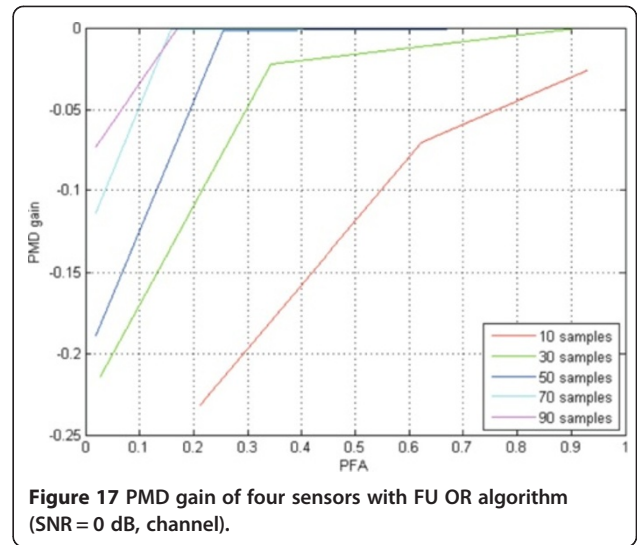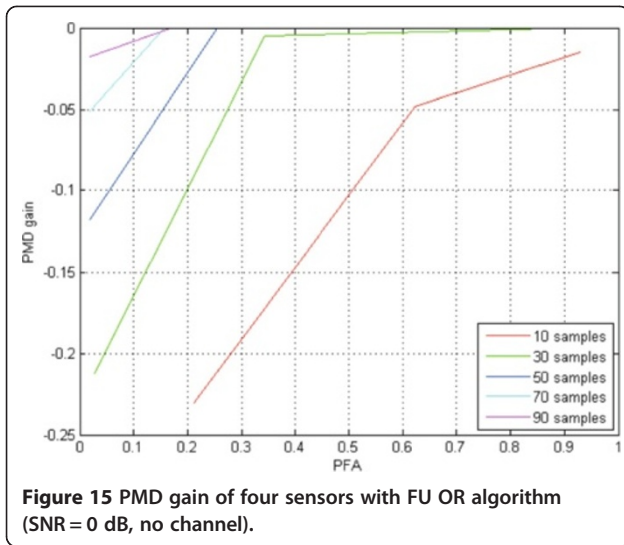- Local decision thresholds: {0 dB, 1 dB, 2 dB}

Figures 15, 16, 17 and 18 show the ROC gains [28] of using a distributed sensing scheme with four sensors and an OR decision rule implemented in the FU, when compared to a single sensor. The plots in Figures 15 and 16 show the ROC gains when no fading channel is affecting the received signal and all sensors have similar SNR (0 dB and 2 dB, respectively, in Figures 15 and 16). The plots in Figures 17 and 18 depict the ROC gains when independent fading channels affect the signals received by the different sensors. Like in the previous figures, the average SNR of all sensors is similar (0 dB and 2 dB, respectively, in Figures 17 and 18). The PMD gains are clearly visible for low values of PFA and decrease as PFA values increase, because the single sensor's probability of detection approaches the unit value.

Figure 19 presents a comparison of the PFA for the four-sensor OR decision rule distributed sensing and four-sensor selective reporting. The plots show that for the tested thresholds, there is no significant difference in the performance between the reference OR-based scheme and the proposed scheme. Figures 20 and 21 plot the PMD differences between the proposed scheme and the reference OR-based, with and without fading channel. Observing both figures, one can easily conclude that the PMD difference is negligible, proving that the proposed method yields the same performance as the reference.

The plots in Figure 22 report the distribution of the number of transmissions (left vertical axis) for the two different types of nodes for different values of PFA (right vertical axis) when no primary signal is present.

In coherence with the theoretical analysis and the numerical results presented in the plots of Figure 5, the asymmetry between the distributions of type 1 and type 2 nodes is clearly visible. As the PFA decreases, two consequences can be observed: type 2 nodes (top plot)

implement the physical layer algorithms. The sensors communicate with the FU over standard Fast Ethernet. The primary scene emulation was performed by the Agilent Technologies, Santa Clara, CA, USA [31] equipments in Figure 14. Further details on the test bed can be found in [28]. The main parameters used in the tests were as follows:

- Number of sensing nodes: 4
  - → Type 1 nodes: 2
  - → Type 2 nodes: 2
- Primary signal represented by an 8MHz bandwidth Digital Video Broadcasting - Terrestrial signal with a 0.8GHz carrier frequency
- Tests performed with and without independent fading channels; used fading channel model - LTE extended typical urban low Doppler channel [32]
- SNR at the sensors in the case a primary signal is present: {0 dB, 2 dB}

Figure 14 Picture of the test bed implementation.

Figure 15 PMD gain of four sensors with FU OR algorithm
(SNR = 0 dB, no channel).

Figure 17 PMD gain of four sensors with FU OR algorithm
(SNR = 0 dB, channel).

become increasingly silent and type 1 nodes (bottom plot) transmit with a high probability; the distribution of the number of transmissions becomes narrower.
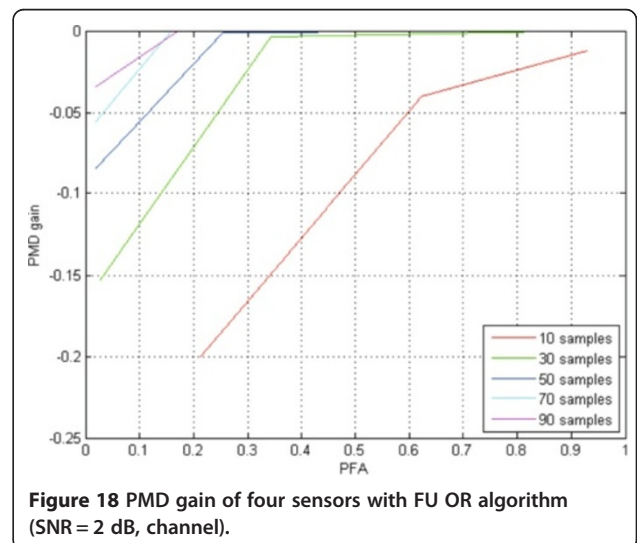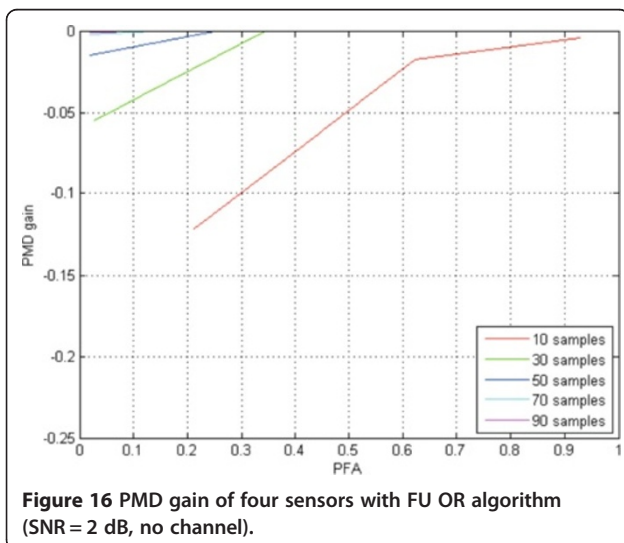
Figure 23 reports the distribution of the total number of transmissions (left vertical axis) for different values of PFA (right vertical axis) when no primary signal is present. As observed previously in Figure 22, as the PFA decreases, the distribution of the number of transmissions becomes narrower. Another consequence that should be pointed is the asymmetry of the distribution. The leftmost set of bars (corresponding to the lowest PFA) presents a distribution shifted to the right, in coherence to the numerical results depicted in Figure 7. As the PFA increases, the distribution widens and the distribution shifts to the left. The rightmost set of bars (corresponding to the largest PFA >0.5) already shows a left-shifted distribution that, actually, can be correlated with the results presented in Figure 9,
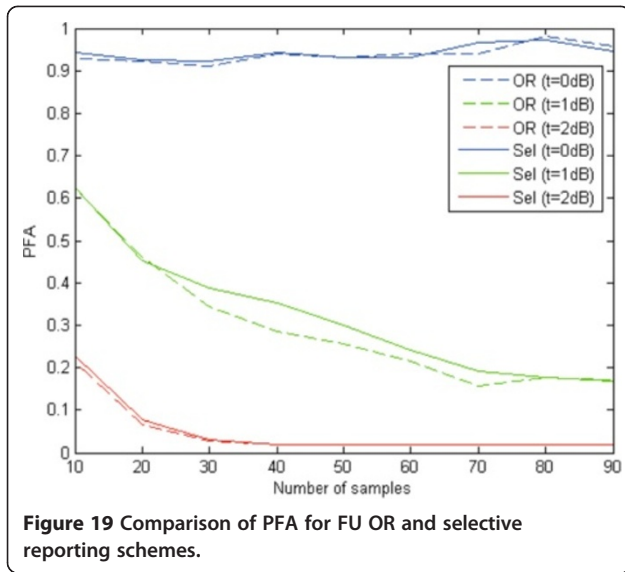
associated with the case where the primary signal is present.

4. Conclusions

The use of cognitive radios is becoming more and more an unquestionable reality to fight the apparent spectrum scarcity and efficiently explore the available spectrum. Spectrum sensing is a fundamental tool of cognitive radios to acquire the spectrum and decide on the best resources to use. The multiuser diversity provided by cooperative spectrum sensing schemes boosts the reliability of the spectrum acquisition, but the available sensing report channels easily become the bottleneck to the number of participants.

This paper proposes a new cooperative sensing scheme that introduces silence periods in the sensing reporting to lower the reporting bandwidth by 50%.

Figure 16 PMD gain of four sensors with FU OR algorithm
(SNR = 2 dB, no channel).

Figure 18 PMD gain of four sensors with FU OR algorithm
(SNR = 2 dB, channel).

Figure 19 Comparison of PFA for FU OR and selective reporting schemes.

Figure 21 PMD difference for FU OR and selective reporting schemes with fading channel.

Using the principles of information theory, the algorithm explores the information present in the silence periods to maintain the same performance of standard reporting schemes. The article presents a theoretical analysis of the distribution of transmitted messages, an information theory interpretation of selective reporting sensing scheme and a study on the behaviour of the algorithm when the received signal is subject to fading caused by the wireless channel that links primary transmitter and cognitive radio user. The theoretical analysis is backed up by numerical and experimental results that show that the PFA and PMD are similar to standard reporting schemes, validating the proposed algorithm. Furthermore, the proposed scheme can be used jointly with censorship and user selection algorithms to further
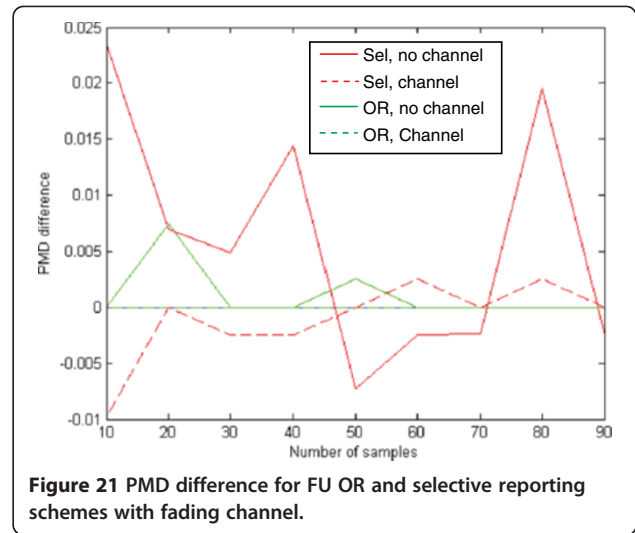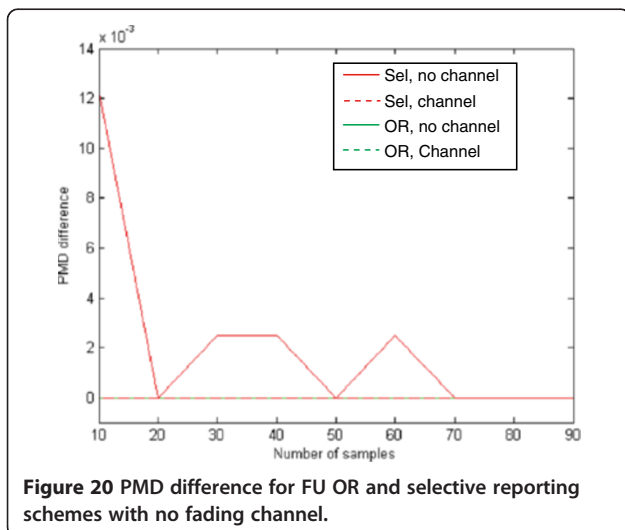
reduce the bandwidth demanded of the sensing report channel.

Appendix

Under the assumptions of identical sensors and hypothesis H_0, the transmission of type 1 sensors represents P independent and identically distributed (i.i.d.) Bernoulli trials. The variable that accounts for the number of transmitted messages coming from these sensors follows a binomial distribution, $X_0^{T1} \sim B(P, q)$ with a probability distribution function:

$$f_0^{T1}(l;P,q) = \binom{P}{l} q^l (1-q)^{P-l}. \tag{27}$$

The transmission of type 2 sensors represents $K - P$ i.i.d. Bernoulli trials. The variable that accounts for the number of transmitted messages coming from these sensors follows a binomial distribution, $X_0^{T2} \sim B(K - P, 1 - q)$ with a probability distribution function:

$$f_0^{T2}(l;K-P,1-q) = \binom{K-P}{l} (1-q)^l q^{K-P-l}. \tag{28}$$

Considering that X_0^{T1} and X_0^{T2} are independent, the distribution of the overall number of transmitted messages, conditioned to H_0, is therefore given by:

$$
\begin{aligned}
f_0(m) &= \sum_{l=0}^{m} f_0^{T1}(l;P,q) f_0^{T2}(m-l;K-P,1-q) \\
&= \sum_{l=0}^{m} \binom{P}{l} q^l (1-q)^{P-l} \binom{K-P}{m-l} (1-q)^{m-l} q^{K-P-m+l} \\
&= (1-q)^P q^{K-P} \left(\frac{1-q}{q}\right)^m \sum_{l=0}^{m} \binom{P}{l}\binom{K-P}{m-l}\left(\frac{q}{1-q}\right)^{2l}
\end{aligned}
$$
$$\tag{29}$$

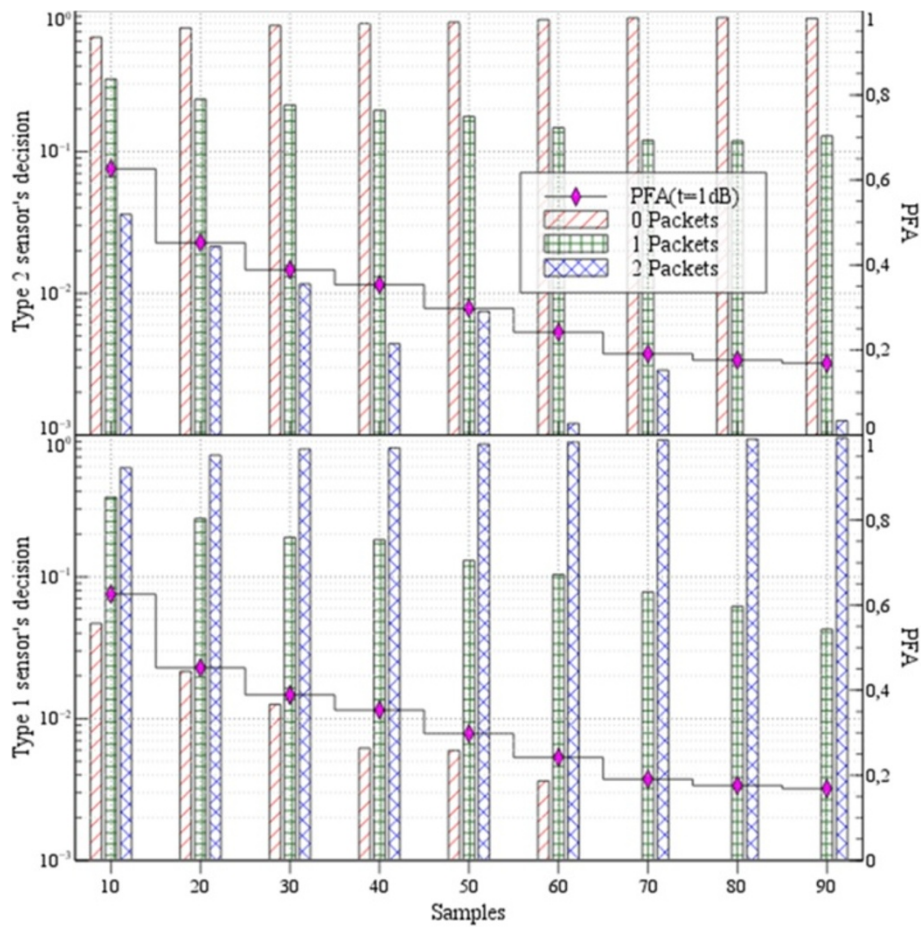**Figure 20 PMD difference for FU OR and selective reporting schemes with no fading channel.**

Figure 22 Experimental normalized distribution of the number of transmissions. For type 2 (top) and type 1 (bottom) nodes with different PFA; hypothesis H_0.
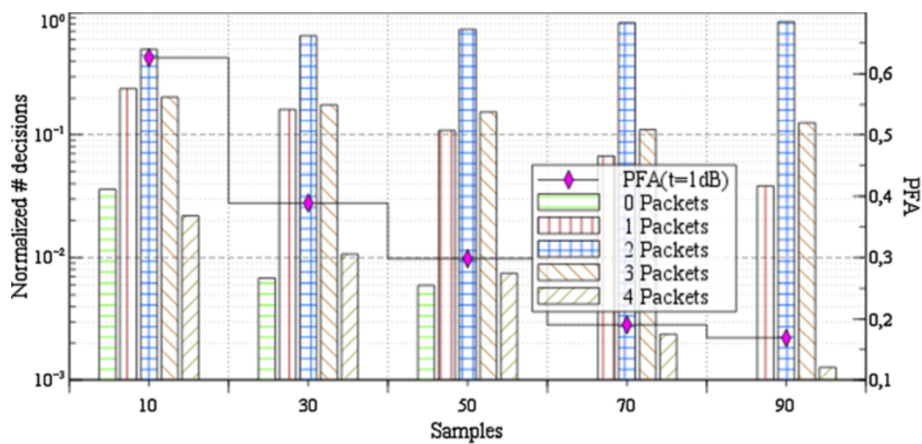

Figure 23 Experimental normalized distribution of the total number of transmissions with different PFA; hypothesis H_0.

For hypothesis H_1, the transmission of type 1 sensors represents P i.i.d. Bernoulli trials with probability $(1 - v)$, $X_1^{T1} \sim B(P, 1 - v)$, with a probability distribution function:

$$f_1^{T1}(l; P, 1-v) = \binom{P}{l}(1-v)^l v^{P-l} \tag{30}$$

For type 2 sensors, we have $X_1^{T2} \sim B(K - P, v)$, with a probability distribution function:

$$f_1^{T2}(l; K-P, v) = \binom{K-P}{l}v^l(1-v)^{K-P-l} \tag{31}$$

The distribution of the overall number of transmitted messages, conditioned to H_1, is therefore given by:

$$\begin{aligned}
f_1(m) &= \sum_{l=0}^{m} f_1^{T1}(l; P, 1-v) f_1^{T2}(m-l; K-P, v) \\
&= \sum_{l=0}^{m} \binom{P}{l}(1-v)^l v^{P-l}\binom{K-P}{m-l}v^{m-l}(1-v)^{K-P-m+l} \\
&= (1-v)^{K-P}v^P\left(\frac{v}{1-v}\right)^m \sum_{l=0}^{m}\binom{P}{l}\binom{K-P}{m-l}\left(\frac{1-v}{v}\right)^{2l}
\end{aligned} \tag{32}$$

Competing interests

The authors declare that they have no competing interests.

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