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# Chapter 6

# Cooperative sensing of spectrum opportunities

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## Abstract

**Reliability and availability of sensing information gathered from Local Spectrum Sensing (LSS) by a single Cognitive Radio is strongly affected by the propagation conditions, period of sensing and geographical position of the device. For this reason, Cooperative Spectrum Sensing (CSS) was largely proposed in order to improve LSS performance by using cooperation between Secondary Users (SUs).**

**The goal of this chapter is to provide a general analysis on Cooperative Spectrum Sensing for Cognitive Radio Networks (CRNs). Firstly, the theoretical system model for centralized CSS is introduced, together with a preliminary discussion on several fusion rules and operative modes. Moreover, three main aspects of CSS that substantially differentiate the theoretical model from realistic application scenarios are analyzed: 1) the presence of spatio-temporal correlation between decisions by different SUs; 2) the possible mobility of SUs; 3) the non-ideality of the control channel between the SUs and the Fusion Center (FC). For each aspect, a possible practical solution for network organization is presented, showing that, in particular**

**for the first two aspects, cluster-based CSS, in which sensing SUs are properly chosen, could mitigate the impact of such realistic assumptions.**

## 6.1 Introduction

It was largely demonstrated that RF spectrum scarcity is due to the ineffective fixed frequency assignments rather than actual spectrum shortage **[1][2]**. Engineering, economics and regulation communities consider Dynamic Spectrum Access with Cognitive Radio (CR) **[3]** a possible solution for the definition of new spectrum management policies **[4]**. A CR is a context-aware radio capable of autonomous reconfiguration by adapting to the communication environment. By using the CR paradigm, the final goal is to design networks that (cooperatively or not) coexist with other networks, by avoiding mutual interference and efficiently using the available frequency spectrum.

Although regulators in US, Europe and UK introduced geolocation databases as a solution to check the presence of users on a given frequency band, FCC in US left open the possibility of using Spectrum Sensing (SS), that is a functionality allowing a CR (also Secondary User (SU)) to detect the presence/absence of eventually incumbent users (also Primary Users (PUs)). If the PU signal is unknown, the most common choice for SS consists in using an Energy Detector, a solution referred to as Energy Detector Spectrum Sensing (ED-SS) **[5]**. Noting that reliability and availability of sensing information gathered from Local Spectrum Sensing (LSS) carried out by a single CR is strongly affected by the propagation conditions, period of sensing and geographical position, Cooperative Spectrum Sensing (CSS) was proposed in order to improve LSS performance **[6]**. In a typical CSS scenario, all the nodes in a Cognitive Radio Network

(CRN) share their sensing results to other nodes (distributed) or to a central unit (centralized), through a dedicated common control channel, potentially increasing the probability of correct identification of spectrum usage.

The goal of this chapter is to provide a general analysis of Cooperative Spectrum Sensing for Cognitive Radio Networks. In particular, the theoretical system model is discussed in Section 2, focusing on centralized CSS in which the central unit (in the following Fusion Center (FC) or Base Station (BS)) takes a sensing decision for the entire network by fusing the local decisions from the SUs. Fusion rules and operative modes are also discussed in the Section, in order to evaluate performance and comparative analysis for different sensing strategies. Moreover, a preliminary analysis of flat CSS vs clustered CSS completes the Section, addressing motivations, advantages and disadvantages of using the first or the second approach. Section 3 shortly reviews three main aspects of CSS that substantially differentiate the theoretical model from realistic application scenarios: 1) the presence of spatio-temporal correlation between sensing measurements (and decisions) by different SUs; 2) the possible mobility of SUs; 3) the non-ideality of the control channel (also reporting channel) used by the SUs to exchange their sensing decision with the FC. For each aspect, a possible practical solution for network organization and management is presented, showing that, in particular for the first two aspects, cluster-based CSS, in which sensing SUs are properly chosen, could mitigate the impact of the realistic assumptions. Finally, Section 4 concludes the chapter, by discussing the results and identifying open issues and future work directions.

## 6.2 System Model for Cooperative Spectrum Sensing

Spectrum Sensing is very important for a CR device, allowing to measure and be aware of parameters regarding the transmission channel. Because its low computational and design complexities, a widely adopted choice consists of using energy detection, referred to hereinafter as Energy Detector Spectrum Sensing (ED-SS). In ED-SS, CR receivers do not need any knowledge on the PUs signal; they evaluate the energy of the received waveform in the band of interest over an observation time window of $T$ (seconds) and comparing the test statistic $Y$ (approximating the signal energy in the interval $(0,T)$), with a threshold $\lambda$, whose optimum value depends on the noise floor [5]: if the evaluated energy is larger (resp. lower) than the threshold, then SU decides for PU presence (resp. absence). Framing this problem into a decision problem, the two hypotheses, denoted by $\mathrm{H}_0$ and $\mathrm{H}_1$, are thus defined as follows:

$$\begin{aligned} H_0 &: Y < \lambda, \\ H_1 &: Y \geq \lambda. \end{aligned}$$

In a LSS scenario, a CR node opportunistically transmits when it does not detect presence of any PUs, and its decision is not related to SS results of other SUs. In a non-fading environment, denoting with $\gamma$ the PU signal-to-noise ratio (SNR) at the SUs within a channel of bandwidth $W$ (Hertz) and assuming for the test statistic $Y$, in hypothesis $\mathrm{H}_0$ and $\mathrm{H}_1$, respectively, central and non-central (with parameter $2\gamma$) chi-square distributions with $2TW$ degrees of freedom, probability of correct detection, $P_{\mathrm{d}}$, and probability of false alarm, $P_{\mathrm{fa}}$, are as follows:

$$P_{\mathrm{d}} = P\{Y > \lambda \mid H_1\} = Q_m(\sqrt{2\gamma}, \sqrt{\lambda}), \qquad (1)$$

$$P_{\mathrm{fa}} = P\{Y > \lambda \mid H_0\} = \frac{\Gamma(m, \frac{\lambda}{2})}{\Gamma(m)}, \qquad (2)$$

where it is assumed that Time-Bandwidth product $TW$ is the integer number $m$, $\Gamma(\cdot)$ and $\Gamma(\cdot,\cdot)$ are the complete and incomplete gamma functions, and $Q_m(\cdot,\cdot)$ is the generalized Marcum $Q$-function, defined from the $I_{m-1}(\cdot)$ modified Bessel function of $(m-1)$th order **[6]**.

For large values of $m$, the Gaussian Approximation can be applied to the test statistic $Y$ under either $\mathrm{H}_0$ or $\mathrm{H}_1$ **[5]**. Under the $\mathrm{H}_0$, $Y$ is the sum of $2m$ statistically independent random variables. Therefore, since $\mathrm{E}[Y] = 2m$ and $\mathrm{Var}[Y] = 4m$, $Y$ is distributed as a Gaussian random variable denoted by $\mathrm{N}\ (2m, 4m)$, and the $P_{\mathrm{fa}}$ is given by:

$$P_{\mathrm{fa}} = \frac{1}{\sqrt{8\pi m}} \int_{Y}^{\infty} e^{-\frac{(x-2m)^2}{8m}} \mathrm{d}x = \frac{1}{2}\mathrm{erfc}\left(\frac{\lambda - 2m}{2\sqrt{2m}}\right). \qquad (3)$$

Under $\mathrm{H}_1$, $\mathrm{E}[Y] = 2m + 2\gamma$ and $\mathrm{Var}[Y] = 4(m + 2\gamma)$, and therefore $Y \sim \mathrm{N}\ (2m + 2\gamma, 4(m + 2\gamma))$. $P_{\mathrm{d}}$ is given by:

$$P_{\mathrm{d}} = \frac{1}{2}\mathrm{erfc}\left(\frac{\lambda - 2m - 2\gamma}{2\sqrt{2}\sqrt{m + 2\gamma}}\right). \qquad (4)$$

When the channel gain $h$ is varying due to shadowing/fading, (1) is conditioned on the instantaneous $\gamma$. In this case, $P_{\mathrm{d}}$ is derived by averaging (1) over fading statistics:

$$P_{\mathrm{d}} = \int_{\gamma} Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) f_{\Gamma}(\gamma) \mathrm{d}\gamma, \qquad (5)$$

where $f_{\Gamma}(\gamma)$ is the pdf of SNR under fading.

### *6.2.1 Centralized CSS with Hard Decision Fusion Rules*

In hard decision centralized CSS, CR nodes take independent decisions and share them with the FC, that will apply the fusion rule and then will broadcast the cooperative decision. The generic hard fusion rule is the $k-out-of-n$ rule: if $k$ or more nodes decide the hypotheses $\mathrm{H}_1$, then the FC will decide for $\mathrm{H}_1$. When $k=1$, the rule becomes the OR rule; when $k=n$ the fusion rule works as the AND rule; when $k=(n+1)/2$, the fusion rule becomes the Majority rule. Let $N$ be the number of cooperative SUs, experiencing independent and identically distributed fading/shadowing with same average SNR. The SUs employ ED-SS with threshold $\lambda$. If the FC receives decisions from $N-1$ users and it applies the generic $n-out-of-N$, then the probabilities of detection and false-alarm for the collaborative scheme ($Q_\mathrm{d}$ and $Q_\mathrm{fa}$, respectively) are **[6]**:

$$Q_\mathrm{d}=\sum_{k=n}^{N}\binom{N}{k}P_\mathrm{d}^{\,k}(1-P_\mathrm{d})^{N-k}, \qquad (6)$$

$$Q_\mathrm{fa}=\sum_{k=n}^{N}\binom{N}{k}P_\mathrm{fa}^{\,k}(1-P_\mathrm{fa})^{N-k}, \qquad (7)$$

under the simplifying assumption that all sensors experience the same fading

where $P_\mathrm{d}$ and $P_\mathrm{fa}$ are the individual probabilities of detection and false alarm as defined before. Using the OR rule, (6) and (7) become:

$$Q_\mathrm{d}=1-(1-P_\mathrm{d})^{N}, \qquad (8)$$

$$Q_\mathrm{fa}=1-(1-P_\mathrm{fa})^{N}. \qquad (9)$$

Formulas for Majority rule are:

$$Q_\mathrm{d}=\sum_{k=\lceil N/2\rceil}^{N}\binom{N}{k}P_\mathrm{d}^{\,k}(1-P_\mathrm{d})^{N-k}, \qquad (10)$$

$$Q_{\mathrm{fa}} = \sum_{k=\lceil N/2 \rceil}^{N} \binom{N}{k} P_{\mathrm{fa}}^{k} (1 - P_{\mathrm{fa}})^{N-k}. \tag{11}$$

For the AND rule, one obtains:

$$Q_{\mathrm{d}} = P_{\mathrm{d}}^{\;N}, \tag{12}$$

$$Q_{\mathrm{fa}} = P_{\mathrm{fa}}^{\;N}. \tag{13}$$

### *6.2.2 Operating Modes: CFAR vs CDR*

From previous formulas, one can note the existing tradeoff between $P_{\mathrm{d}}$ (and its complementary probability of Miss-Detection, $P_{\mathrm{md}}$) and $P_{\mathrm{fa}}$: high $P_{\mathrm{md}}$ implies increases interference to the PU. Conversely, high $P_{\mathrm{fa}}$ decreases the SUs spectrum utilization. For this reason, one can conclude that the $P_{\mathrm{d}}$ , or the $Q_{\mathrm{d}}$ in the cooperative scenario, should be maximized in order to minimize interference, while the, $P_{\mathrm{fa}}$ ($Q_{\mathrm{fa}}$) should be minimized in order to increase spectrum utilization by the CRN. These two different perspectives lead to the definition of two different Spectrum Sensing operating modes: the Constant False Alarm Rate (CFAR) and the Constant Detection Rate (CDR) mode. Focusing on the cooperative scenario, in the CFAR mode it is assumed that the overall CRN has fixed a target probability of false alarm $\overline{Q}_{\mathrm{fa}}$. Given $\overline{Q}_{\mathrm{fa}}$, each cooperating SUs can evaluate the corresponding $\overline{P}_{\mathrm{fa}}$ by inverting the chosen fusion rule formula ((9), (11) or (13), respectively). This leads to the evaluation of the threshold $\lambda$, inverting (3), and the consequent evaluations of $P_{\mathrm{d}}$ and $Q_{\mathrm{d}}$, for a given value of $\gamma$. In this case, the generic formulation of the threshold $\lambda$ is as follows:

$$\lambda^{\mathrm{CFAR}} = \operatorname{erfc}^{-1}(2\bar{P}_{\mathrm{fa}})[2\sqrt{2m}] + 2m. \qquad (14)$$

At this point, one can note that in the case of OR and AND fusion rules, the inversion of (9) and (13), in order to fix the local SUs false alarm target, is quite simple. On the contrary, the inversion of (11), for Majority rule, is quite challenging. For this reason, an approximation of (11) has been proposed in **[7]**, in order to easily evaluate the local probability of false alarm in this case too.

Conversely, in the CDR mode it is assumed that a target $\bar{Q}_{\mathrm{d}}$ was selected for the CRN. Given $\bar{Q}_{\mathrm{d}}$, the corresponding $\bar{P}_{\mathrm{d}}$, is obtained by inverting the formula of the chosen fusion rule ((8), (10) or (12), respectively). This leads to the evaluation of the threshold $\lambda$, inverting (4) for a given value of $\gamma$, and the consequent evaluations of $P_{\mathrm{fa}}$ and $Q_{\mathrm{fa}}$. In this case, the generic formulation of $\lambda$ is as follows:

$$\lambda^{\mathrm{CDR}} = \operatorname{erfc}^{-1}(2\bar{P}_{\mathrm{d}})[2\sqrt{2(m+2\gamma)}] + 2(m+\gamma). \qquad (15)$$

Similarly to the CFAR case, an approximation of (10) has been proposed in **[7]**, in order to easily evaluate the local probability of detection requested to meet the cooperative detection target.

### *6.2.3 Flat vs Clustered CSS*

In order to support decisions fusion through an efficient design, the CRN can be organized using clustering schemes. In general, clustering is the process of hierarchizing nodes in a network, by dividing them into virtual groups called clusters and by assigning up to three different states: clusterhead (CH) (local coordinator), clustergateway (CG) (inter-clusters coordinator), or clustermember (CM) (ordinary node) **[8][9]**. Clustering has been proposed for CRNs, but historically has been extensively analyzed for

MANETs, showing that it can lead to performance improvements thanks to a more efficient resource utilization.

In the context of CSS, the network hierarchy created by clustering can be exploited into several ways. In particular, sensing performance improvement can be achieved by using two levels of sensing cooperation between CR users: a low level, conducted within the cluster and a high level, executed among CHs. On the other hand, sensing overhead reduction, including energy consumption, time delay and bandwidth occupation can be obtained by using only the selected CHs for sensing purposes.

## 6.3 CSS under realistic conditions

In this Section, a short review of three aspects regarding CSS and its practical design and application is presented. These aspects, substantially, differentiate the traditional theoretical model introduced in Section 2 by taking into account realistic conditions regarding, as example, channel propagation and terminals' behavior that, de facto, affect the spectrum sensing performance. In particular the impact of 1) the presence of spatio-temporal correlation between sensing measurements (and decisions) by different secondary users, 2) the mobility of SUs and 3) the non-ideality of the control channel used by the SUs to exchange their sensing decision with the FC is investigated and analyzed. Moreover, starting from the idea that such aspects should be taken into account in the design of robust and efficient CSS algorithms and, in general, for network management and organization procedures, possible practical solutions for each aspects are presented, showing that, cluster-based CSS, in which sensing SUs are properly chosen, could mitigate the impact of such realistic assumptions.

### *6.3.1 Impact of Spatio-Temporal Correlation*

Several works on CSS demonstrated that the performance increase by cooperation depends on the degree of correlation between measurements and sensing decisions of SUs; this because it exists a direct proportionality between the number of SUs and the correlation between the SUs' themselves measurements and an inverse proportionality between the degree of correlation and CSS performance. This leads to the result that the effect of cooperation increases as the number of SUs increases as well, until no further performance increase can be obtained by further increasing the number of collaborating SUs, because of correlation. The main idea is that efficient CSS schemes should rely on the selection of a subset of SUs on the basis of clustering algorithms and according to, eventually, sensing-related metrics **[10][11][12]**.

#### 6.3.1.1 Moran's I-based Nodes Selection Framework for CSS

The work in **[13]** analyzed the problem of CSS in presence of correlation between measurements by defining a novel node selection metric based on the statistical index known as Moran's I, widely used to test for the presence of spatial dependence in observations taken on a lattice **[14]**. In the proposed framework, this index is used to determine the degree of correlation between decisions taken by different SUs in different locations of the environment, in order to select a sub-optimal group of quasi-uncorrelated SUs to be involved in CSS; To this aim, the environment is divided by $n$ squared cells. Assuming that the SUs are able to provide to the FC information about their spatial position, for each SS phase, they transmit to the FC their sensing decisions and position. When the FC receives two or more decisions from the a given cell, it evaluates Moran's I for that cell, defined as in **[14]**:

$$I \,@\, \frac{N}{\sum_k \sum_j w_{ij}} \frac{\sum_k \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i \left(X_i - \bar{X}\right)^2}, \qquad (16)$$

where $N$ in our scheme, is the number of cooperating SUs in the cell under test); $X$ is the variable of interest (the sensed energy); $\bar{X}$ is the mean of $X$ and $w_{ij}$ is an element of a matrix of spatial weights (in the proposed scheme, the shorter the distance between two SUs, the higher the assigned spatial weight). From its definition, Moran's I is defined in the interval $[-1 \quad 1]$; if, for a given cell, $I \approx 0$ , it means that the decisions used to evaluate $I$ are uncorrelated. For this reason, the proposed scheme defines an interval of uncorrelation $\mathrm{C} : I \in [-0.25 \quad 0.25]$. If $I \notin \mathrm{C}$, the FC will conclude that the measurements are correlated. At this point, the FC will determine the average value of the decision variable in the cell and inform the SUs in the cell with a value lower than such average value that they are excluded from the next CSS. This is done iteratively during each sensing phase. No discarding process occurs when the evaluated statistic $I \in \mathrm{C}$. The proposed scheme is analyzed by means of computer simulations under accurate models for propagation channel. The simulation environment foresees the presence of a DVB-T-like transmitter (Primary User) and a set of devices forming a CRN (Secondary Users). The PU is located in the top left corner of a square area of $10 \times 10$ km$^2$, and it uses a fixed transmitter power (200 kW) and a single DVB-T 8 MHz channel in the UHF band for its own licensed transmission. The CRN is located at the lower right $700 \times 700$ m$^2$ area, centered on the position of the FC. The SUs communicate among them and with the FC using a maximum transmission power of 110 mW. The SUs forming the CRN can be static or mobile; when mobility is present, the SUs are allowed to move within the working area using a Gauss-Markov mobility model **[15]** with an average speed $v = [5 \quad 10 \quad 15 \quad 20]$ m/s. To the purpose of the proposed Moran's I-based CSS scheme, the CRN playground is divided by 16 $175 \times 175 \text{ m}^2$ squared cells. The implementation was carried out within the OMNeT++ simulation environment, taking advantage of the MiXiM framework **[16]**. Each run covers 1 hour of simulated time, during which each collaborating SU takes a local decision exploiting a sensing phase of $T = 50\mu$s and then transmits its decision to the FC during the subsequent exchange phase of 1 second. Finally, a global decision is taken by the FC each 5 seconds. The proposed scheme is compared with a scheme where each SU cooperates for sensing, sending its own local decision to the FC. The FC will apply then a fusion rule, obtaining a global decision.

Figure 1 presents the impact on nodes selection in the proposed correlation-based scheme, in terms of the average number of SUs collaborating in the CSS during the simulation, for both static and mobile cases and for different values of SUs in the CRN.

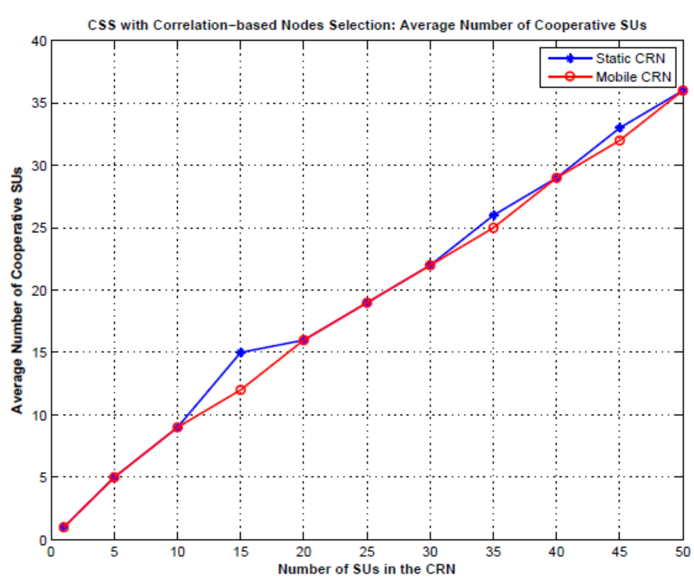


Fig. 1. Average Number of cooperative SUs for CSS with proposed 'Node Selection' scheme.

commas?

One can note that: 1) the chosen mobility model impacts, slightly downward, the nodes selection, 2) until the number of SUs is lower than the number of cells, practically no nodes selection occurs (on average, the SUs are spatially dispersed in the playground). Finally, when the number of SUs is higher that the number of cells, 3) the higher the number of SUs in the network, the higher the number of discarded SUs, thanks to the direct proportionality between the number of SUs and the degree of correlation of the SUs' decisions. Figures 2 and 3 show, the measured $Q_{\mathrm{d}}$ for CSS with Majority rule, as a function of the CFAR target $\bar{Q}_{\mathrm{fa}}$ and the number of SUs ($N = [1 \quad 5 \quad 15 \quad 25 \quad 35 \quad 45]$), for schemes without and with nodes selection. For the evaluation of the single user $P_{\mathrm{d}}$ an average $\gamma = 5\,\mathrm{dB}$ is assumed: after a significant improvement given by cooperation of SUs, the performance does not improve significantly with the number of SUs to similar values, making the use of more SUs less and less useful. Therefore, from this point of view, the scheme with nodes selection achieves comparable performance with respect to the previous scheme even if with a lower number of cooperative SUs. Similar results were obtained for AND and OR rules.

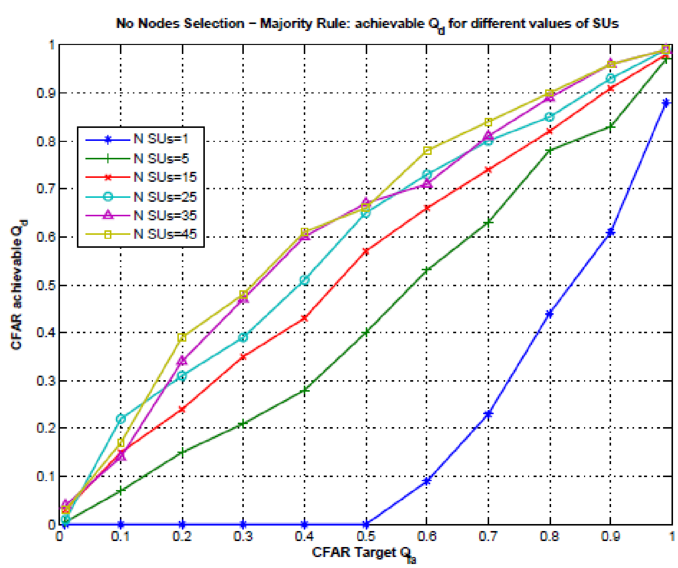

Fig. 2. CSS performance without 'Node Selection' scheme.

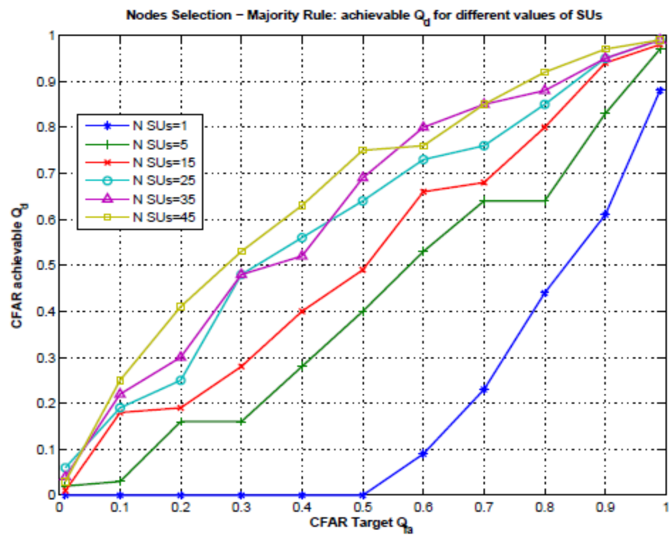


Fig. 3. CSS performance with 'Node Selection' scheme.

### *6.3.2 Impact of SUs' Mobility*

Mobility is a another phenomenon influencing both CSS and LSS performance. Analysis and results in **[17]** and **[18]** show that SUs mobility could increase the sensing performance by increasing the spatial diversity in the collection of signal samples for sensing purposes. However these results have been obtained under several simplifying assumptions, including same speed and constant direction of movement for all SUs, as well as total uncorrelation of measurements taken by different SUs, irrespectively of their positions; in addition, changes in connectivity between SUs induced by mobility were not taken into account.

#### 6.3.2.1 SENSIC: Mobility-aware Cluster-based Framework for CSS

The work in **[19]** proposes a framework for the organization of a mobile CRN, analyzing the network performance in terms of cooperative spectrum sensing and data throughput.

It relies on cooperation between secondary devices, that organize themselves in clusters defined according to both spectrum sensing reliability and mobility behavior of each SU. The algorithm, dubbed SENSIC (SENSing + mobIC), integrates sensing reliability and mobility parameters in order to evaluate a novel metric for clusterheads selection. It basically enhances the so-called MOBIC clustering algorithm **[20]** by defining a novel sensing-related metric and by introducing revised re-clustering conditions. The ultimate goal of SENSIC is to elect as CHs the SUs showing good sensing performance and lower relative mobility with respect to their neighbors.

The evaluation of the mobility-related metric follows the approach in **[20]**: this work, focused on the definition of a clustering algorithm for a generic mobile ad-hoc network (MANET), defines a mobility metric for clusterheads selection. On the other hand, the sensing metric evaluation takes place when the CRN enters in a particular TRAINING state. In this phase, each SU performs $N_{Sensing}$ sensing operations and sends the results to the FC. After collecting the local decisions, the FC replies with the cooperative decision, obtained with the chosen fusion rule. The SUs receive the FC decision and update a wrong decisions counter ($N_{Errors}$) if their local decision is different from the cooperative one. At the end of TRAINING, each SU evaluates the sensing metric ($M_{Sensing}$) as follows:

$$M_{Sensing} = \frac{N_{Errors}}{N_{Sensing}}. \qquad (17)$$

Next, the generic SU combines the mobility metric with the sensing one:

$$M_{Sensic} = M_{Mobic} * M_{Sensing}. \qquad (18)$$

$M_{Sensic}$ is defined so that the nodes with good sensing performance and low mobility have a higher probability to be chosen as CH. In order to select the CHs, the SUs exchange packets containing the $M_{Sensic}$ value. The SUs with the best $M_{Sensic}$ will automatically take the role of clusterheads: they will assume that each neighbor will enter in their cluster but, In the case of a SU contended between two CHs, the SU will choose as CH the node from which it has received packets at higher power and will inform the contending CHs of updating the list of nodes within their clusters.

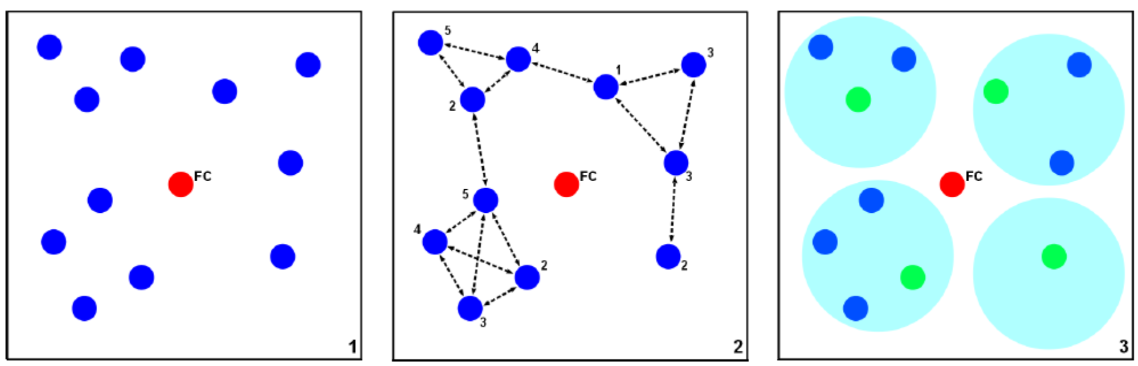


Fig. 4. SENSIC Clustering Algorithm Phases: 1) Non-Clustered SUs (blue); 2) Exchange of SENSIC Metric between neighboring SUs; 3) Election of clusterheads (green) and formation of clusters.

Figure 4 highlights the main phases of the procedure. When the network leaves the TRAINING state each SU resets the $N_{Errors}$ counter and starts switching between the DATA state (data transmission plus sensing operations because, in the previous sensing phase, some of the channels under test were declared FREE) and SENSING state (only sensing operations because, in the previous sensing phase, all the channels under test were declared BUSY). It is important to note that while in DATA/SENSING state, only clusterheads will sense the channels, will take local decisions and will transmit to the FC. Note also that re-clustering procedures are defined in order to modify the clusters and to elect new CHs for the whole network or part of it, when specific conditions occur. Two classes of re-clustering conditions are defined: sensing-related, triggered by a deterioration in sensing performance, and mobility-related, triggered by topology changes due to mobility.

The proposed SENSIC framework is compared by means of computer simulations with a simpler, non cluster-based scheme and with a cluster-based scheme in which the formation of the clusters and the election of the clusterheads are only related to the MOBIC metric.

The simulation environment foresees the presence of a PU and a set of 10 SUs. The PU is located in a fixed position ($[300,\ 300]\ \mathrm{m}$) within a square area of $700 \times 700\ \mathrm{m}^2$ centered on the position of the FC. It alternates Activity and Pause periods, with durations of the periods randomly chosen following an exponential distribution with mean equal to 20 seconds. At the beginning of each Activity period, the PU chooses one of four possible 20 MHz Wi-Fi channels for its own data transmissions, using a fixed power of 110 mW. The SUs communicate among them and with the FC using the same power of the PU, both on data channels (when transmission is allowed) and on the control channel (modeled as well as a 20 MHz 802.11 channel). Both static and mobile SUs were considered; when mobility is present, SUs move within the playground according to a Gauss-Markov mobility model with an average speed $v = 5$ m/s. Also in this case, the implementation of the environment was carried out within the OMNeT++ simulation environment **[16]**. Each run covered 3 hours of simulated time, during which each collaborating SU took local decisions with a CFAR sensing target $P_{\mathrm{fa}} = 0.05$, exploiting a sensing phase of $T = 50\mu\mathrm{s}$ and then transmitting its decision to the FC during the subsequent exchange phase of 1 second. Finally, a global decision was taken by the FC each 5 seconds. Figures 5 and 6 present the cooperative sensing performance in both static and mobile cases for a network clustered with the SENSIC framework, compared with a non-clustered network (all the SUs are involved in CSS) and with a network clustered using the MOBIC algorithm. Figures 7 and 8 present the throughput performance in both static and mobile cases for the same network scenarios.

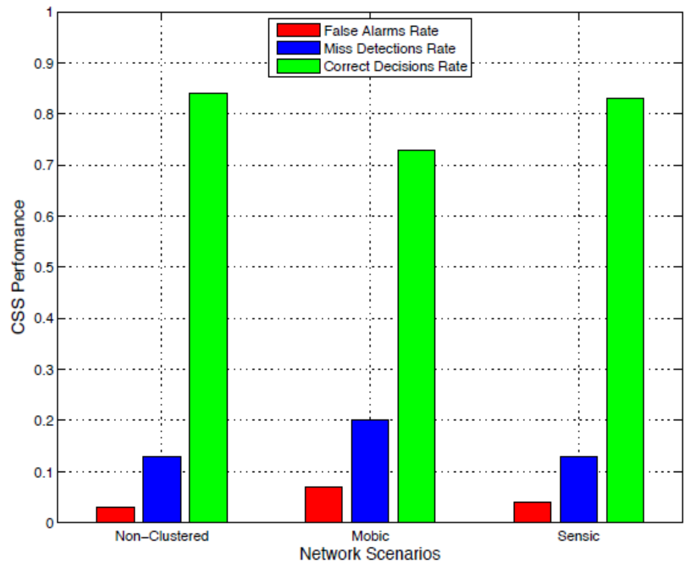


Fig. 5. CSS performance in a Static Scenario for Non-Clustered, MOBIC Clustered and SENSIC-Clustered Networks

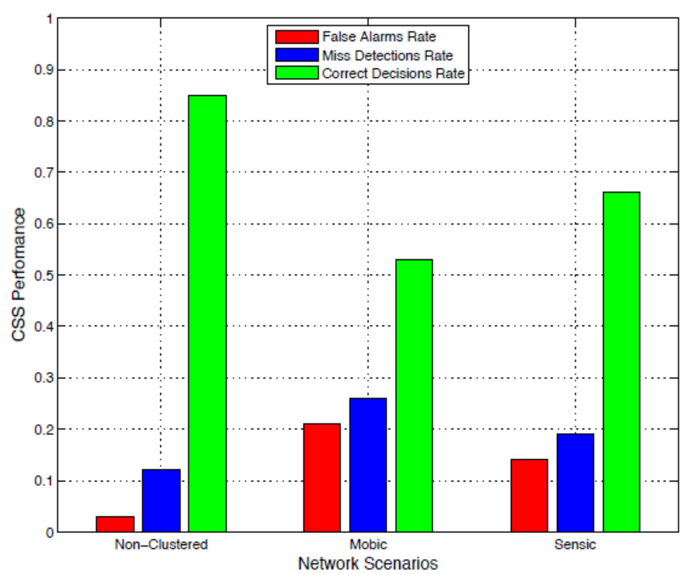


Fig. 6. CSS performance in a Mobile Scenario for Non-Clustered, MOBIC Clustered and SENSIC-Clustered Networks

In the static case, results show that SENSIC matches the sensing performance of the non-clustered algorithm while involving a lower number of cooperating SUs. The use of a lower number of sensing SUs could lead to significant energy savings, and could be very important in particular for energy-limited scenarios, such as in sensors networks.

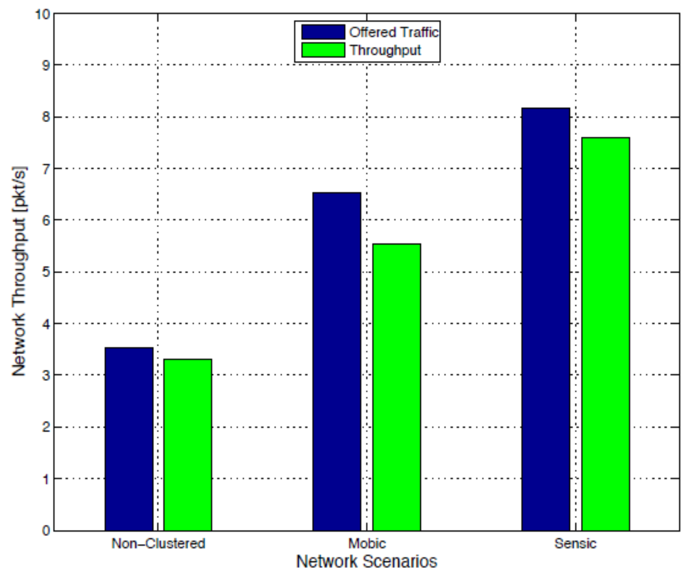


Fig. 7. Offered Traffic and Throughput performance [pkt/s] in a Static Scenario for Non-Clustered, MOBIC Clustered and SENSIC-Clustered Networks

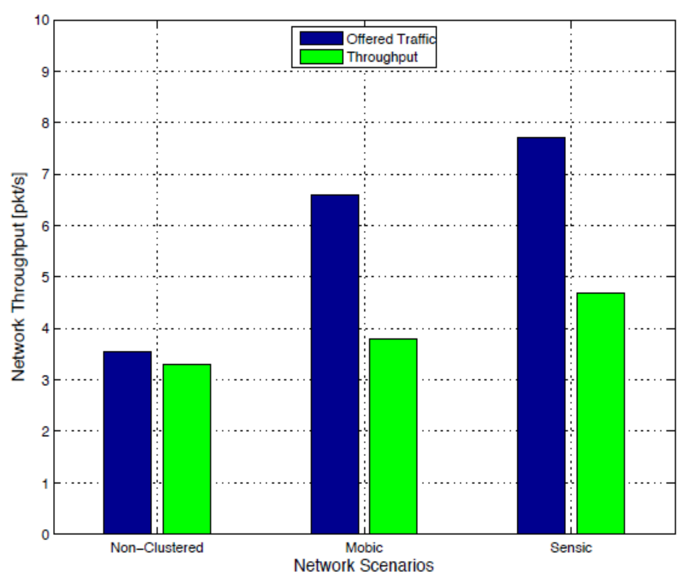

Fig. 8. Offered Traffic and Throughput performance [pkt/s] in a Mobile Scenario for Non-Clustered, MOBIC Clustered and SENSIC-Clustered Networks

Figures 7 and 8 show a significant increase in the offered data traffic for the clustered models: in the case of a non-clustered scenario, it may happen that although the last decision by the FC was of channel IDLE, in the next sensing time some of the SUs sense the channel as BUSY. In this case, in order to protect PUs in the area, those SUs decide to conservatively stop their own data generation and transmission, waiting for the next decision by the FC. This does not happen in the clustered models, where some of the SUs do not even sense: the SUs completely refer to the last cooperative decision, continuing in the data generation and assuming that, at least, they can transmit data to the clusterheads (in a sort of underlay access with a reduced amount of *intra-cluster* power). SENSIC, compared with MOBIC, seems to better manage this traffic growth, with a significant throughput increase. On the other side, it looks clear from Figure 6 that the introduction of a mobility model degrades the sensing performance in the clustered models. In this case as well SENSIC behaves better than MOBIC; it can be expected that additional performance improvements can be obtained with the definition of a more specific mobility metric. In terms of throughput, SENSIC reaches good results, even if the difference between offered traffic and throughput starts to be more pronounced when compared to the static case.

In any case, one can conclude that results highlight that the adoption of a sensing plus mobility-aware clustering algorithm can lead to a sensing reliability comparable with the non-clustered solution (but involving on average a lower number of sensing nodes) and to a desirable improvement in data throughput of the secondary network, also leading to improved energy efficiency.

### *6.3.3 Impact of non-ideal reporting channel*

## 6.4 Discussions & Conclusions

This chapter presents a theoretical and simulative analysis of several centralized CSS schemes under CFAR and CDR constraints, adopting hard decision fusion rules (OR, AND and Majority). In particular, moving from the theoretical system model, the chapter introduces several main aspects of CSS for its application to realistic scenario. In particular, the study of the impact of spatio-temporal correlation and mobility confirms the idea that efficient CSS schemes should based on the selection of a subset of sensing SUs. In particular, in **[13]** a novel framework for nodes selection, based on the Moran's I statistical index was proposed to overcome the effect of correlation between SUs measurements. On the other hand, in **[19]** a further cluster-based solution for the organization of mobile cognitive radio networks in introduced, in order to manage the effect of SUs mobility. Simulation results show that both the proposed schemes achieve sensing performance comparable to CSS relying on all network nodes while only involving a reduced number and confirm that clustering can be an effective way to manage the entire CRN. Future work should focus on the accurate evaluation of the overhead introduced by the proposed algorithms, as well as on the impact of different mobility and channel models. In addiction new CSS schemes should be analyzed, as the distributed scheme with more refined and specific soft fusion rules.

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