

# Analysis of Hybrid Techniques for Energy Consumption Optimization in Cognitive Wireless Sensor Networks

Fabrcio Braga Soares de Carvalho  
Universidade Federal da Paraiba (UFPB)  
Departamento de Engenharia Eltrica (DEE)  
Centro de Energias Alternativas e Renovaveis (CEAR)  
Cidade Universitaria - P.O. Box 5115  
58051-900 - Joao Pessoa - PB - Brazil  
fabricio@cear.ufpb.br

Waslon Terllizzie Araujo Lopes, Marcelo Sampaio de Alencar  
Instituto de Estudos Avancados em Comunicacoes (Iecom)  
Universidade Federal de Campina Grande (UFCG)  
Departamento de Engenharia Eltrica (DEE)  
Rua Aprigio Veloso, 882 - Bairro Universitario  
58429-900 - Campina Grande - PB - Brazil  
waslon@dee.ufcg.edu.br, malencar@dee.ufcg.edu.br

**Abstract**—Energy consumption is one of the main challenges in the operation of wireless sensor networks. This issue is more relevant to cognitive wireless sensor networks, in which the sensor nodes sense the available spectrum before transmitting and receiving data. In this context, the objective of this paper is to investigate and analyze hybrid spectrum sensing techniques applied to cognitive wireless sensor networks. The paper also shows how these techniques can contribute to optimize energy consumption. Simulation results compare hybrid algorithms with individual techniques usually employed for spectrum sensing in terms of mean detection time.

**Index Terms**—Cognitive Radio, Wireless Sensor Networks, Energy Consumption.

## I. INTRODUCTION

The electromagnetic spectrum is overloaded in some frequency bands, and the government agencies stipulate technical criteria to authorize additional frequency bands for allocation of new services [1]. The objective is to reduce the interference among devices operating in near frequencies. As most of the spectrum is already allocated, it is complicated to grant new licenses or to increase the quality of the services in operation. On the other side, some bands face low spectrum usage [2].

Spectrum scarcity and the inefficient use of this important resource led to the development of new techniques to better explore the electromagnetic range. In this context, Cognitive Networks (or Cognitive Radio Networks) aim to extend the spectral efficiency, with opportunistic access, for the available frequency bands [3].

Cognition refers to the process of knowing through perception, reasoning, knowledge and intuition by the observation of an environment [4]. Cognitive radio is a wireless communication technique that monitors the frequency spectrum and adapts its transceivers to occupy an available specific radio frequency channel (when temporarily not occupied by primary or licensed users) in that time [5].

Cognitive radio and its dynamic access capacity can be employed in several wireless applications. One of the most

promising areas of cognitive radio is Wireless Sensor Networks (WSN). Its combination with cognitive radio led to the Cognitive Radio – Wireless Sensor Networks (CR–WSN) or Cognitive Radio Sensor Network (CRSN) [6].

This paper analyzes the energy consumption optimization in cognitive wireless sensor networks using hybrid techniques for spectrum sensing. The remaining of the paper is organized as follows: Section II details the concept of cognitive WSN and the related spectrum sensing techniques; Section III presents a brief literature review about different hybrid strategies used for spectrum sensing; Section IV correlates the time detection of a vacant or occupied channel with the energy consumption optimization in CRSN; and Section V details the conclusions and the perspectives for future works.

## II. COGNITIVE WSN

A CRSN is defined as a network composed of several wireless nodes, equipped with cognitive transceivers and sensor circuits, that allow the observation of a specific event; look for available channels; and to communicate opportunistically with its neighbor nodes. The goal is to transmit monitored data to the sink node of the network in an efficient and reliable way, and with reduced energy consumption [7].

Traditional wireless sensor networks can benefit from cognitive radio advantages. Ordinary wireless sensor networks operate in a specific frequency band and its main characteristics are the low range of the sensors and the limited data transmission rate. Different practical applications for wireless sensor networks can be mentioned, as agriculture and environment monitoring, disaster prevention, health care and emergency and surveillance [8].

The main advantage of a CRSN is the operation of several different wireless sensor networks in the same geographic area with minimal interference among them. The Secondary User (SU), Cognitive Radio (CR) or Non Licensed User should sense the available spectrum to check if there is a Primary User (PU) or Licensed User operating in that moment. If so,

the PU has the priority to operate and the SU should look for another available channel. If the channel is idle, the SU can start transmitting on it opportunistically, although it should regularly monitor the band occupied: if a PU desires to use it, the SU must vacate the channel for the licensed user [9]

There are some fundamental challenges related to the wireless networks. The major issues are the physical limitation of the sensor nodes; the monitoring of the spectrum to verify possible vacant channels to be occupied; the modification of the operating channels; the energy consumption of the nodes with any additional requirements; and the opportunistic communication over licensed and unlicensed spectral bands when the network is composed of several nodes [6], [9].

#### A. Spectrum Sensing

Spectrum sensing is one of the main tasks of a CRSN when compared to traditional WSN. Advantages of opportunistic spectrum allocation (such as higher bandwidth and lower error rates in the transmission) contrast with the additional energy consumption required for cognitive operation. Several researchers are proposing algorithms to make the consumption of energy in cognitive sensor networks more efficient.

The detection problem is analyzed as a binary hypothesis model, defined as [10], [11]:

$$x(t) = \begin{cases} n(t), & \text{if } H_0 \\ n(t) + h \cdot s(t), & \text{if } H_1 \end{cases} \quad (1)$$

in which  $x(t)$  is the signal received by the CR during the observation time;  $s(t)$  is the transmitted signal of the PU;  $n(t)$  is additive white Gaussian noise (AWGN) with zero mean and variance  $\sigma^2$ , and  $h$  is the channel gain [10], [11].

$H_0$  indicates the absence of primary signal in the channel, while  $H_1$  indicates that the spectrum is occupied by a PU (this occupancy can refer to a PU or to a SU). Based on these hypotheses, one can define the probability of detection  $P_d = \text{Prob}(\text{signal detected}|H_1)$  and the probability of false detection  $P_f = \text{Prob}(\text{signal detected}|H_0)$ . The objective is to maximize  $P_d$  while minimizing  $P_f$  [11], [12].

Another important parameter is the probability of missed detection  $P_m$ , which is the complement of  $P_d$ :  $P_f = 1 - P_d = \text{Prob}(\text{signal not detected}|H_1)$ . The probability of a wrong decision in the band occupancy is the weighted sum of  $P_f$  and  $P_m$  [11], [12].

The following spectrum sensing techniques for cognitive radio can be employed in cognitive sensor networks [11]:

- Energy Detection (ED): if the level of energy measured in the channel is below a specific threshold, the channel is considered free or non-occupied by primary users. The simplicity of this technique and its low signal processing demands are the positive aspects, although the energy detection requires longer measurements periods (which results in higher energy consumption). The effect of fading channels in the detection scheme is a remarkable issue in this problem [13].
- Matched Filtering detection (MF): it is the best technique when the licensed user characteristics are known *a priori*

to optimize the filtering. Also, it requires additional hardware to be installed in the sensor nodes of the CRSN to synchronize with the primary user.

- Cyclostationary (or Feature) Detection (CD): if some characteristics of the primary user are known *a priori* (e.g., carrier frequency or modulation scheme), this detection technique can be used. It demands extra computational complexity.
- Covariance based detection: this detection technique is based on the correlation between the received PU signals samples with the dispersive nature of wireless channel and background noise [14].
- Interference Temperature: sensor nodes calculate the level of interference they would cause at the PU receiver and should adjust their transmission power (plus the noise floor) to not exceed a specific interference temperature level [6].
- Other techniques can be employed to improve the CRSN operation. Also, the combination of two or more spectrum sensing techniques can be investigated to obtain better results when compared to these techniques individually. This approach is known as hybrid sensing techniques [6], [9].

### III. RELATED WORK

Recent papers propose hybrid techniques for spectrum sensing in cognitive radio networks. The goal is to achieve better performance results in terms of more reliable spectrum sensing and small mean detection time when compared to the main sensing techniques applied individually.

An intelligent spectrum sensing scheme is proposed in [10] based on the energy detection, matched filter and cyclostationary detection. The SU performs a matched filter detection if the PU waveform is previously known; otherwise, it performs an energy detection associated to a cyclostationary detection.

A two-stage sensing scheme is presented in [15]. Energy detection is firstly used. If required, cyclostationary detection is used at the second stage (the cyclostationary detection is employed only if the channel is declared occupied in the first stage).

A hybrid model approach is proposed in [16]. The suggested scheme uses an association of the three techniques (energy detection, matched filter and cyclostationary detection) in the same algorithm. However, no simulation results are presented by the authors.

Two different-based detector implementations are proposed in [17]. The first detector estimates the spectral correlation density of the signal, and the second is based on estimating the magnitude squared coherence.

Another two-stage spectrum sensing scheme is suggested in [18]. A fast spectrum sensing algorithm based on the energy detection is used for coarse detection. In the sequence, a fine spectrum sensing algorithm is adopted based on cyclostationary feature detection. The authors also investigate bi-thresholds for energy detection and other spectrum sensing strategies in [19].

A novel high speed two-stage detector for spectrum sensing is proposed in [20]. This methodology decreased the sensing time by using energy detection for a coarse sensing. If the measured energy is under a specific threshold, the signal-to-noise ratio (SNR) of the device is computed. If the SNR is less than the theoretical SNR, the second stage of sensing is performed with the usage of covariance absolute value.

The mean detection time is the focus in [21]. Energy detection is employed; before the second stage, the algorithm estimates the SNR of the received signal and determines if the measurements from the ED are reliable. If not, a second spectrum sensing is executed with cyclostationary detection.

Spectrum-sensing algorithms based on the sample covariance matrix (this matrix is calculated from a limited number of received signal samples) are proposed in [14].

#### A. Energy Consumption in CRSN

Energy consumption is one of the main challenges in spectrum sensing for wireless sensor networks. Energy efficiency of the sensor nodes and its hardware limitations are important issues in the project of a cognitive WSN [7].

Research is under way to evaluate the energy consumption in cognitive sensor networks. Different approaches have been presented in the technical literature. The main investigation lines are related to: inactivity of sensors and censoring of the gathered data [2]; efficient spectrum management [22]; packet dimension optimization [7] and optimal duty cycle for cognitive sensor networks [23].

Although, to the best of the authors' knowledge, no work that jointly considers hybrid spectrum sensing techniques and energy consumption optimization in cognitive sensor networks has been carried out.

#### IV. MEAN DETECTION TIME AND ENERGY CONSUMPTION

In this paper, the goal is to correlate the time required for decision of occupancy after sensing the channel (mean detection time, according to the literature) with the energy consumption of the entire network. If the sensors need less time to sense the environment and to confirm if the band is available or not, the performance of the nodes and of the entire network can be improved.

The literature presents few results that discuss the mean detection time. Generally, efforts are focused in the evaluation of the probability of detection and the probability of false detection, while the mean detection time is a secondary issue to be analyzed.

In order to evaluate the mean detection time of the main individual spectrum sensing techniques (energy detection; cyclostationary detection; matched filter detection) with a hybrid technique, the work developed by [10] and [15] were considered. In these papers, as mentioned before, hybrid strategies were adopted to improve the algorithm's spectrum sensing. It is important to highlight that the authors of these papers did not consider the energy issue.

Algorithms presented in [10] and [15] were adopted to study the mean detection time of the spectrum sensing techniques

ED, CD and MF individually and to be compared with the proposed hybrid techniques.

For the proposed algorithms  $Pr$  ranges from 0 to 1; it indicates the probability that a channel would be sensed using a hybrid strategy. There are two distinct scenarios to be evaluated [15]:

- $0 \leq Pr < 0.5$  for most of the channels: the SU should adopt matched filter detection for most of the channels as the PU waveform is known.
- $0.5 < Pr \leq 1$  for the majority of the evaluated channels: there is a uncertainty related to the PU waveform, then the SU will perform the combined techniques (hybrid algorithms).

#### V. SIMULATION RESULTS

The simulation results presented in this paper compare two hybrid techniques ([10] and [15]) with respect to the mean detection time over AWGN channels. As mentioned, a small mean detection time would indicate less energy consumption by the sensor nodes, as compared to a large detection time.

An important parameter in the hybrid algorithms proposed is the probability  $P$  that the channel would be sensed by the cyclostationary detector; as both hybrid techniques uses CD to improve its algorithms, the value of  $P$  also refers to the probability that hybrid techniques would be selected.

Because the values of  $P$  can assume vary between zero and one, three different probabilities were selected to analyze the behavior of the techniques ( $P = 0.2$ ,  $P = 0.5$  and  $P = 0.7$ ), which are the same ones adopted in [10] to analyze the individual characteristics.

The number of channels considered in the simulation is 10. The detection times for the individual techniques were fixed. Adopted values were  $t(ED) = 0.1$  s,  $t(CD) = 0.2$  s and  $t(MF) = 0.3$  s.

Figures 1, 2 and 3 compare the mean detection time for each individual detection technique with the two hybrid techniques selected. The algorithm from [10] is graphically indicated as *Hybrid 1* while the strategy from [15] is named as *Hybrid 2*.

One can compare the two hybrid methods based on Figures 1, 2 and 3. For lower values of  $Pr$ , the probability of using a hybrid algorithm is small. In this context, the second method (*Hybrid 2*) is more efficient in terms of mean detection time. Although, as the probability for a hybrid sensing increases, the first method (*Hybrid 1*) surpasses the performance of the second technique. In effect, as  $Pr$  increases, the mean detection time of (*Hybrid 2*) expands rapidly.

Another analysis refers to the comparison of the hybrid techniques selected with the individual performance of energy detection, cyclostationary detection and matched filter detection. It is important to highlight that the values of  $t(ED)$ ,  $t(CD)$  and  $t(MF)$  are fixed in the simulation algorithms. Figure 4 presents the behavior of both hybrid techniques analyzed when compared to the individual spectrum sensing strategies. As the performance of the hybrid methods is similar for different values of  $P$ , we chose  $P = 0.2$ .

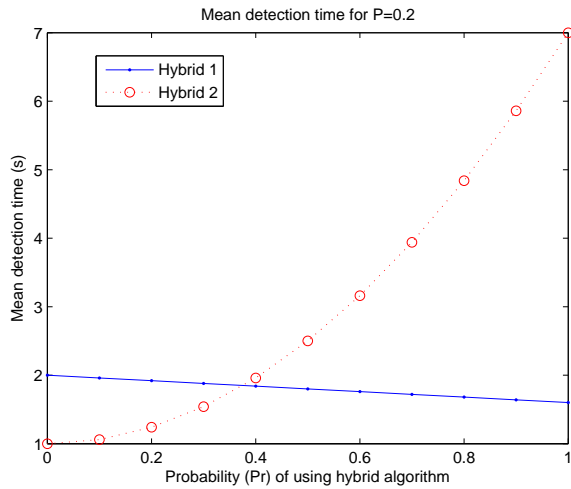


Fig. 1. Mean detection time for a probability  $P=0.2$ .

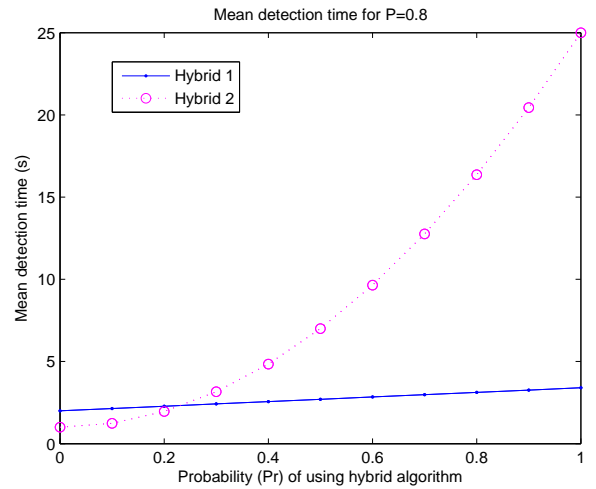


Fig. 3. Mean detection time for a probability  $P=0.8$ .

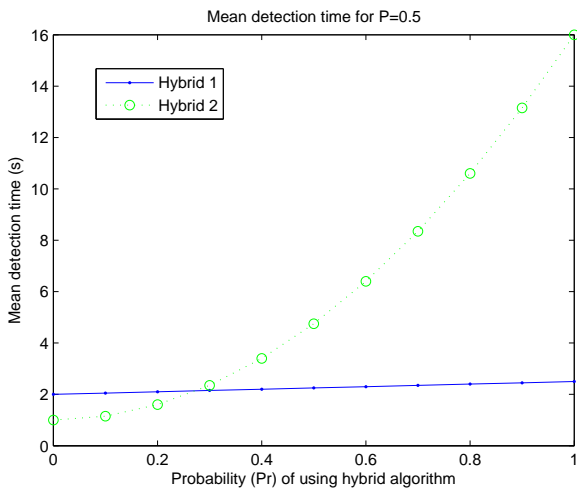


Fig. 2. Mean detection time for a probability  $P=0.5$ .

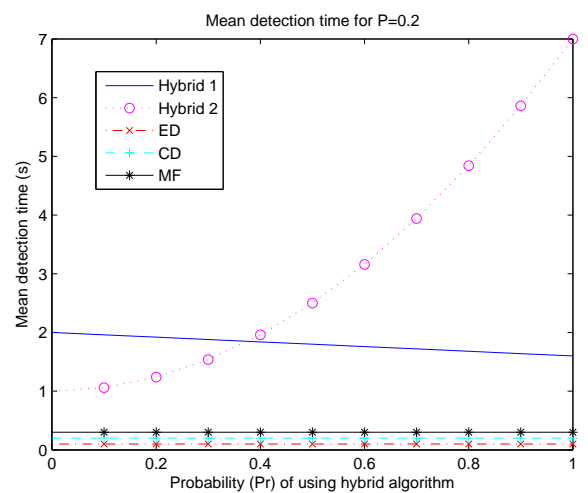


Fig. 4. Mean detection time of the individual techniques compared to the hybrid ones for a probability  $P=0.2$ .

It can be seen from Figure 4 that the individual spectrum sensing techniques present lower mean detection time when compared to the hybrid strategies adopted in this work. This is an expected result, as the time necessary for sensing *Hybrid 1* and *Hybrid 2* is a junction of two or three of these techniques. It is important to highlight that a faster detection time for a single detection (as ED, CD or MD) does not necessarily indicate that the sensing was performed with efficiency. In fact, the reasonability of the hybrid methods is very superior to the individual techniques, as ED, CD and MF normally perform a coarse sensing that would be improved by another sensing step. And that is exactly the purpose of the hybrid methods.

## VI. CONCLUSIONS

Simulation results corroborate the search for an optimum hybrid detection technique that would maximize the spectrum sensing while minimizing the detection time of the sensing

strategy.

By the evaluation of the mean detection time for two recent hybrid techniques available in the literature, one can remark that those algorithms require a larger amount of time to properly sense the spectrum. On the other hand, such hybrid strategies reduce the measurement uncertainty, and consequently increase the detection probability while minimizing the probability of false detection

In this context, an important trade-off should be considered when choosing spectrum sensing strategies: to choose individual techniques (to perform faster but with a coarse sensing) or to adopt improved strategies with hybrid techniques (to perform slowly but with a better accuracy). The decision for one of these strategies will have an impact on the energy consumption of the sensor nodes and on the network performance.

For the continuation of this work, the goal is to propose one or more hybrid techniques that would overcome the

gain and benefits of the ordinary sensing techniques when considered independently in terms of mean detection time. It is the authors' intention to evaluate the correlation between the time necessary for sensing the spectrum with the energy consumption and improve the results achieved by the hybrid techniques studied in this paper.

#### REFERENCES

- [1] D. Raychaudhuri and N. B. Mandayam, *Frontiers of Wireless and Mobile Communications*. Proceedings of the IEEE, Vol. 100, N<sup>o</sup> 4, pp. 824-840, 2012.
- [2] S. Maleki, A. Pandharipande and G. Leus, *Energy-Efficient Distributed Spectrum Sensing for Cognitive Sensor Networks*. IEEE Sensors Journal, Vol. 11, N<sup>o</sup> 3, pp. 565-573, 2011.
- [3] M. P. Sousa, W. T. A. Lopes, F. Madeiro and M. S. Alencar, *Cognitive LFAnt: A Novel Protocol for Healthcare Wireless Sensor Networks*. Sensors (Basel), Vol.12, pp. 10463-10486, 2012.
- [4] G. Vijay et al, *Cognition in Wireless Sensor Networks: A Perspective*. IEEE Sensors Journal, Vol.11, N<sup>o</sup> 3, pp. 582-592, 2011.
- [5] S. Haykin, *Cognitive Radio: Brain-Empowered Wireless Communications*. IEEE Journal on Selected Areas in Communications, Vol. 23, N<sup>o</sup> 2, pp. 201-220, 2005.
- [6] O. B. Akan, O. B. Karli and O. Ergul, *Cognitive Radio Sensor Networks*. IEEE Networks, Vol. 23, N<sup>o</sup> 4, pp. 34-40, 2009.
- [7] M. C. Oto and O. B. Akan, *Energy-Efficient Paket Size Optimization for Cognitive Radio Sensor Networks*. IEEE Transactions on Wireless Communications, Vol. 11, N<sup>o</sup> 4, pp. 1544-1553, 2012.
- [8] M. P. Sousa e W. T. A. Lopes, *Desafios em Redes de Sensores Sem Fio*. Revista de Tecnologia da Informação e Comunicação. Iecom - Instituto de Estudos Avançados em Comunicações. Vol.1, pp. 41-47, 2011.
- [9] A. Ghasemi and E. S. Sousa, *Spectrum Sensing in Cognitive Radio Networks: Requirements, Challenges and Design Trade-offs*. IEEE Communications Magazine, N<sup>o</sup> 4, pp. 32-39, 2008.
- [10] W. Ejaz et al, *I3S: Intelligent Spectrum Sensing Scheme for Cognitive Radio Networks*. EURASIP Journal on Wireless Communications and Networking, 2013.
- [11] R. Umar and A. U. H. Sheikh, *A Comparative Study of Spectrum Awareness Techniques for Cognitive Radio Oriented Wireless Networks*. Physical Communication. Available online 24 August 2012.
- [12] T. Yücek and H. Arslan, *A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications*. IEEE Communications Surveys & Tutorials, Vol. 11, Issue 1, pp 116 - 130, 2009.
- [13] F. F. Digham and M. S. Alouini and M. K. Simon, *On the Energy Detection of Unknown Signals Over Fading Channels*. IEEE Transactions on Communications, Vol. 55, N<sup>o</sup> 1, pp. 21-24, 2007.
- [14] Y. Zeng and Y. C. Liang, *Spectrum-Sensing Algorithms for Cognitive Radio Based on Statistical Covariances*. IEEE Transactions on Vehicular Technology, Vol. 58, N<sup>o</sup> 4, 2009.
- [15] S. Maleki and A. Pandharipande and G. Leus, *Two-Stage Spectrum Sensing for Cognitive Radios*. 2010 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), pp. 2946 - 2949, 2010.
- [16] S. Kapoor and G. Singh, *Non-Cooperative Spectrum Sensing: A Hybrid Model Approach*. 2011 International Conference on Devices and Communications (ICDeCom), pp. 1-5, 2011.
- [17] D. Bhargavi and C. R. Murthy, *Performance Comparison of Energy, Matched-Filter and Cyclostationarity-Based Spectrum Sensing*. 2010 IEEE Eleventh International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), pp. 1-5, 2010.
- [18] W. Yue et al, *Combined Energy Detection and One-order Cyclostationarity Feature Detection Techniques in Cognitive Radio Systems*. The Journal of China Universities of Posts and Telecommunications, Vol. 17, Issue 4, pp. 18-25, 2010.
- [19] W. Yue and B. Zheng, *Spectrum Sensing Algorithms for Primary Detection Based on Reliability in Cognitive Radio Systems*. Computers and Electrical Engineering, Vol. 36, N<sup>o</sup> 3, pp. 469-479, 2010.
- [20] S. Geethu and G. L. Narayanan, *A Novel High Speed Two Stage Detector for Spectrum Sensing*. Elsevier Procedia Technology, Vol. 6, pp. 682-689, 2012.
- [21] P. R. Nair et al, *Fast Two-Stage Spectrum Detector for Cognitive Radios in Uncertain Noise Channels*. IET Communications, Vol. 6, Issue 11, pp. 1341-1348, 2012.
- [22] J. A. Han and W. S. Jeon and D. G. Jeong, *Energy-Efficient Channel Management Scheme for Cognitive Radio Sensor Networks*. IEEE Transactions on Vehicular Technology, Vol. 60, N<sup>o</sup> 4, pp. 1905-1910, 2011.
- [23] R. Deng et al, *Energy-Efficient Cooperative Spectrum Sensing by Optimal Scheduling in Sensor-Aided Cognitive Radio Networks*. IEEE Transactions on Vehicular Technology. Vol. 61, N<sup>o</sup> 2, pp. 716-725, 2012.