# Energy-Aware Multiband Communications in Heterogeneous Networks

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*Abstract*—**This paper investigates the energy-efficiency of well-known spectrum sensing algorithms that exploit the sensed signal's energy, autocorrelation or cyclostationarity features to estimate the presence or absence of that signal in a given spectrum. We investigate the trade-off between energy-efficiency, complexity, and sensing accuracy of those detectors and, their suitability for energy-efficient WiFi spectrum sensing that enables interoperability of Long Term Evolution Advanced (LTE-A) and WiFi systems. Results obtained show significant improvement in correct detection probability and reduced sensing time using the low complexity autocorrelation detectors when compared to other detectors under low signal to noise ratio channel conditions.**

## I. Introduction

The surge in demand for bandwidth-intensive applications hosted on advanced mobile devices from video streaming to online gaming and social networking services is pushing operators to redesign their networks for an overall shift from conventional macro-cell only architectures to heterogeneous and small-cell topologies, and to seek access to additional licensed/unlicensed (e.g., TV white-space) spectrum. The expected growth in the number of deployed small cells that use cellular technology (e.g., micro, pico, or femto cells) and licensed spectrum, not to mention the need for advanced interference mitigation techniques, may eventually increase overall operational and capital expenditures (OPEX and CAPEX) and energy consumption of heterogeneous cellular networks [1].

To this end, Mobile Network Operators (MNO) have considered offloading cellular traffic to small cells through opportunistic WiFi access points [2], since this solution remains the most cost-effective alternative to provide high capacity wireless communication services. More importantly, promising technical advances in the areas of WiFi/3GPP interoperability, optimised offloading to WLAN in 3GPP-RAT mobility [3], and advanced Radio Frequency equipment, are pushing further the concept of WiFi integration into cellular networks.

In the interoperability of LTE and WiFi: LTE is primarily used to provide the macrocell coverage and high mobility where licensed-band performance characteristics are essential while Wi-Fi will provide an underlay of smaller cells. Nonetheless, to ensure the expected improvement in user data rate due to the LTE and WiFi interoperability, it is critical to sense the two standards over a wide band of spectrum. Several multi-band sensing studies have been presented in the cognitive radio (CR) literature [4], [5].

Spectrum sensing techniques are in general divided into three categories based on how much prior information on the signal is available at the detection stage [6]. Energy detectors (ED) [7], compares the received signal energy to a threshold value that depends on the signal to noise ratio (SNR) in the channel. ED are low complexity detectors and may offer an optimal signal detection under the assumption of an accurate knowledge of the noise statistics. One major drawback of EDs is their inability to classify the detected signals according to radio standards (i.e., LTE, WiFi, etc.). On the other hand, feature detection schemes such as autocorrelation detectors (AD) [8] and cyclostationary features detectors (CFD) [9] require prior knowledge about the statistical properties of the sensed signals. AD and CFD algorithms achieve higher detection probability than ED in practical communication systems [9] and are able to classify the detected signal. Finally, matched filter detectors are suitable for the detection of a particular type of signals (e.g., DVB-T) of features explicitly known to the detector (preamble or pilot waveform) [6]. It is desirable that future mobile terminals will be able to perform multi-band sensing to find unoccupied bands. This emphasise the need for low complexity sensing and/or classification schemes with efficient energy usage that are suitable for implementation in battery-constrained mobile devices. To this end, several papers have studied the problem of energy-efficiency of spectrum sensing methods in CR networks [10], [11], [12]. While [10] suggests that incorporating some knowledge about the sensed primary user (PU) signal into the CFD algorithm can reduce its computational-complexity and improve its detection performance compared to ED, [11] proposes an adaptive spectrum sensing algorithm that dynamically adjusts the sensing period in order to improve the detector's energy-efficiency. This algorithm requires the knowledge of two thresholds for different hypotheses and a sequential sensing policy [11]. In [12], the authors consider the energy-efficiency of both the spectrum sensing and spectrum handoff and sensing/throughput tradeoff for CR networks. In general most of the existing studies of energy efficiency of spectrum sensing mainly consider a general model of signals that are assumed to be compact in time and frequency, under medium to high SNR ratios.

In this paper we investigate the energy-efficiency of three classical signal sensing methods: the energy detector, autocorrelation detector, and cyclostationarity detector, and their suitability for the signal detection in future multi-standard

LTE-A and WiFi signals under low SNR channel conditions, and without previous assumption of knowledge of sensed signals. The energy consumption calculations are performed for the most important step related to WiFi spectrum sensing. The remaining part of this paper is organized as follows. In Sec. II we give a background review of the spectrum sensing problem and the relevant formulation and key metrics related to studied detectors. Sec. III presents energy-efficiency of studied spectrum sensing approaches. Sec. IV provides the numerical results obtained. Finally in Sec. V we present our conclusions and future work.

## II. SPECTRUM SENSING APPROACHES

### A. Spectrum Sensing Principles

In this system, the received signal at time $n$, denoted by $y_n$, can be modeled as:

$$y_n = A_n s_n + e_n \tag{1}$$

where $A_n$ is the transmission channel gain, $s_n$ is the transmitted signal sent from the primary user (PU), and $e_n$ is an additive noise.

In order to avoid interferences with the primary (licensed) system, the CR needs to sense its radio environment whenever it wants to access available spectrum resources. The goal of spectrum sensing is to decide between two conventional hypotheses modeling the spectrum occupancy:

$$y_n = \begin{cases} e_n & \mathcal{H}_0 \\ A_n s_n + e_n & \mathcal{H}_1 \end{cases} \tag{2}$$

The sensed sub-band is assumed to be a white area if it contains only a noise component, as defined in $\mathrm{H}_0$; while, once there exist PU signals drowned in noise in a specific band, as defined in $\mathrm{H}_1$, we infer that the band is occupied. The key parameters of all spectrum sensing algorithms are the false alarm probability $P_F$ and the detection probability $P_D$. $P_F$ is the probability that the sensed sub-band is classified as it contains a PU data while actually it is only a noise signal, thus $P_F$ should be kept as small as possible. On the other hand, $P_D$ is the probability of classifying the sensed sub-band as a PU data when it is truly present, thus sensing algorithms tend to maximize $P_D$. To design the optimal detector based on Neyman-Pearson criterion, the aim is to maximize the overall $P_D$ under a given overall $P_F$. Based on those definitions, $P_F$ is the probability of the spectrum detector sensing a user signal given the hypothesis $H_0$, and is given by:

$$P_F = P(\mathcal{H}_1 \mid \mathcal{H}_0) = P(\text{ PU is detected} \mid \mathcal{H}_0) \tag{3}$$

while $P_D$ is the probability of the spectrum detector sensing a user signal under the hypothesis $\mathcal{H}_1$. $P_D$ is given by:

$$\begin{aligned} P_D &= 1 - P_M = 1 - P(\mathcal{H}_0 \mid \mathcal{H}_1) \\ &= 1 - P(\text{ PU is not detected} \mid \mathcal{H}_1) \end{aligned} \tag{4}$$

where $P_M$ indicates the probability of missed detection.

In order for the detector to decide the presence of absence of a signal in a given spectrum, a decision threshold that is determined based on the required $P_F$ needs to be known at the detector. The threshold $\gamma$ for a given value of $P_F$ is determined by solving the following equation:

$$P_F = P(y_n \text{ is present} \mid \mathcal{H}_0) = 1 - F_{\mathcal{H}_0}(\gamma) \tag{5}$$

where $F_{\mathcal{H}_0}$ denotes the cumulative distribution function (CDF) under $\mathcal{H}_0$. In this paper, the values of $\gamma$ are computed for the three detectors (ED, AD, CFD) using a Monte Carlo simulation.

### B. Energy Detection

The ED is the most common method for spectrum sensing because of its non-coherent detection and low complexity. ED simply measures the received energy during a finite time interval and compares it to a predetermined threshold. The decision statistic of ED is given by:

$$\Lambda_{ED}(y) = \sum_{n=1}^{N} |y_n|^2 \tag{6}$$

where $N$ is the number of samples of the received signal $y_n$. The computed energy is compared to a predetermined $\gamma$, given in equation (5), to make a decision about the presence/absence of a user signal. A major drawback of ED that may diminish their advantage of low implementation complexity is their sensitivity to changing noise levels.

### C. Autocorrelation Detection

AD exploits the fact that many communication signals contain a built-in redundancy (cyclic prefix, channel coding) to ensure a robust signal detection even at low SNR channel conditions [8]. This redundancy is represented by non-zero autocorrelation peaks at time lags $l$. The signal autocorrelation function at time lag $l$ can be estimated from:

$$\hat{r}_l(y) \quad = \quad \frac{1}{p-l} \sum_{n=0}^{p-l-1} y_{n+l}\ y_n^* \qquad l \geq 0 \tag{7}$$

where $p$ is the length of the PU signal in samples. Any signal except for the white noise case will have non-zero autocorrelation peaks for $l \geq 0$ [1]. In this purpose, the signal autocorrelation function in Eq. (7) can be used to detect the presence or absence of a signal in a given spectrum. Therefore, the autocorrelation-based decision statistic is given by [13]:

$$\Lambda_{AD}(y) \quad = \quad \sum_{l=1}^{L} w_l \frac{\mathrm{Re}\{\hat{r}_l\}}{\hat{r}_0} \tag{8}$$

where the number of lags, $L$, is selected to be an odd number. The weighting coefficients $w_l$ could be computed to achieve the optimal performance, and are given by:

$$w_l \quad = \quad \frac{L+1+|l|}{L+1} \tag{9}$$

[1]Some autocorrelation peaks values might be close to or exactly zero depending on the zero crossings.

### D. Cyclostationary Features Detection

Digitally modulated features exhibit second order cyclic properties that can be used to enhance the signal detection process. In this purpose, a second order Cyclostationarity Detector (CFD) is used to sense and classify OFDM-based signals. For example, the authors in [14] use a CFD for LTE/WiMAX signals detection that exploits the second-order cyclostationarity features of OFDM signals, based on the Cyclic Autocorrelation Function (CAF) $R_y^\alpha(\tau) \neq 0$ at cyclic frequency $\alpha = 0$ and delay $\tau = D_F$ ($D_F$ is the frame duration) for all OFDM transmission modes. The CAF of the received signal $y_n$ is estimated from $N_s$ samples at the delay $\tau$ and CF $\alpha$, using the vector: $\widehat{R}_y^\alpha = [\mathrm{Re}(R_y^\alpha(\tau))\mathrm{Im}(R_y^\alpha(\tau))]$ in order to compute the test statistic given by:

$$\Lambda_{CFD} = N_s \widehat{R}_y^\alpha \widehat{\Sigma}^{-1} (\widehat{R}_y^\alpha)^t \tag{10}$$

where $\widehat{\Sigma}$ is the estimate of the $\widehat{R}_y^\alpha$ covariance matrix.
The test statistic $\Lambda_{CFD}$ is compared to a predefined threshold value $\lambda$ to make the detection decision. As previously stated, $\Lambda_{CFD}$ is function of $P_F$. In our case, and given the test statistic, a possible definition of $P_F$ could be: the probability of deciding that the tested frequency $\alpha$ is a CF at the delay $\tau$ when it is not a CF. Following this definition, $P_F = \Pr(\Lambda_{CFD} \geq \lambda|\mathrm{H}_0)$. Since the value of $\Lambda_{CFD}$ follows a chi-squared distribution [14], [15], the threshold $\gamma$ is obtained from chi-squared distribution tables for a given value of $P_F$.

## III. Energy Efficiency of Spectrum Sensing

In order to evaluate the energy efficiency of the studied sensing techniques, in the following we address some of their key characteristics that impact their energy consumption:

### A. Complexity

Algorithms complexity are measured in terms of the number of complex operations that the detection algorithm has to perform in order to complete the decision statistics on the spectrum occupancy[2].

Assuming that $N$ samples of the sensed signal are available, and that the length of the signal's cyclic prefix and the useful data block are given by $T_c$, $T_d$, respectively, we can estimate the complexity of the sensing algorithm using Table I that shows the number of operations (multiplications, divisions) required to perform the signal detection [6].

| Detector | Multiplications (Complex) | Divisions |
|---|---|---|
| ED | N | 0 |
| AD | 2(N- $T_d$) | 1 |
| CFD | (2N + 4L) + 0.5N$log_2$(N) | 0 |

TABLE I
Theoretical complexity analysis [6]

[2]Note that measuring the complexity of estimating nuisance parameters (e.g., noise variance) is beyond the scope of this paper.

### B. Energy Consumption

The energy efficiency of the considered sensing detectors ED, AD and CFD is calculated assuming the use of ARMs Cortex-A8 and Cortex-A9 processor cores. We use the published energy consumption figures for the Qualcomm Scorpion central processing unit (CPU) of these ARM processors that is featured in the Snapdragon mobile chipset range [10], [18], [19]. Based on the computation complexity values of the chosen sensing algorithm in Table I, we can then use an embedded processors power usage to estimate the detector's energy-efficiency. For example, If we assume that Scorpion CPU can achieve this using one Single Instruction Multiple Data (SIMD) multiplication and one SIMD addition instruction, and that this is comparable to two Dhrystone instructions, then using the DMIPS/mW figures from Table II, we can estimate how much energy is consumed per detection operation.

| | |
|---|---|
| Benchmark, DMIPS/MHz | 2.1 |
| Assumed clock rate | 1.0GHz |
| Total DMIPS | 2100 |
| Frequency-flat | Single path |
| Typical power usage | 350mW |
| Energy effciency, DMIPS/mW | 6 |

TABLE II
QUALCOMM SCORPION CPU DETAILS

## IV. Simulations and Results

The results presented in this section in terms of sensing, complexity and energy efficiency were derived using WiFi compliant signals. For more information about the used WiFi PHY simulation, please refer to [22], [23].

### A. Multiband Spectrum Sensing Techniques Evaluation

Fig. 1 compares the detection performance, given in $P_D$ vs. SNR, of the studied sensing techniques, for a WiFi OFDM-based signal, with $P_F$ = 0.0001 and 1ms sensing period. The ED performance is evaluated assuming a perfect or inaccurate knowledge or the noise variance at the detector. As expected, the performance of the ED, with perfect noise variance, outperforms that achieved using both the AD and the CFD. However, the fact that the ED performance is highly sensitive to noise uncertainty, a noise variance inaccuracy even as low as 0.25dB would result in a significant performance. For example, a loss of almost 7dB in SNR at $P_D$ = 80%, when compared to the perfect noise knowledge case. On the other hand, the AD performance is better than that of CFD, with almost 4dB gain in SNR at $P_D$ = 80%. These observations agrees with those obtained in [8] for the single cyclic frequency CFD.

Fig. 2 shows another key performance metric in spectrum sensing the Receiver Operating Characteristic (ROC). ROC curves present the detection performance of the sensing algorithm in terms of $P_D$ vs. $P_F$. Fig. 2 confirms the same performance trends as those in Fig. 1 with the ED outperforming the AD and CFD, and the AD outperforming the CFD.

Fig. 3 shows that for a given $P_F$ and SNR values the more samples are sent to the detector (i.e., longer sensing period),

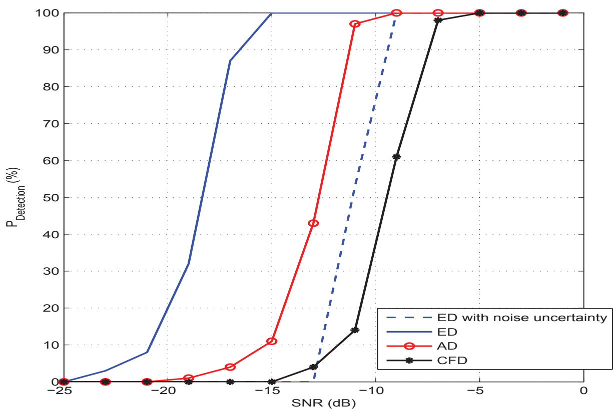


Fig. 1. Probability of detection ($P_D$) vs. Signal to Noise Ratio (SNR) for a $P_F = 10^{-3}$, $1ms$ sensing period, and 0.25dB noise uncertainty for the ED.

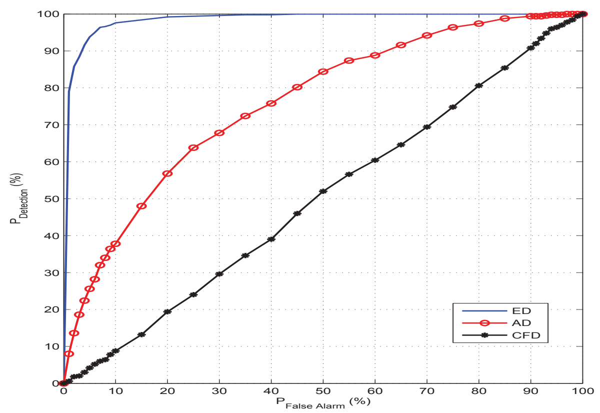


Fig. 2. Receiver Operating Characteristic (ROC) curve at SNR=-18dB and a sensing period of 5ms

the higher the achieved $P_D$, since the detector has enough time to estimate the signal's desired features and this improves the accuracy of the signal detection.

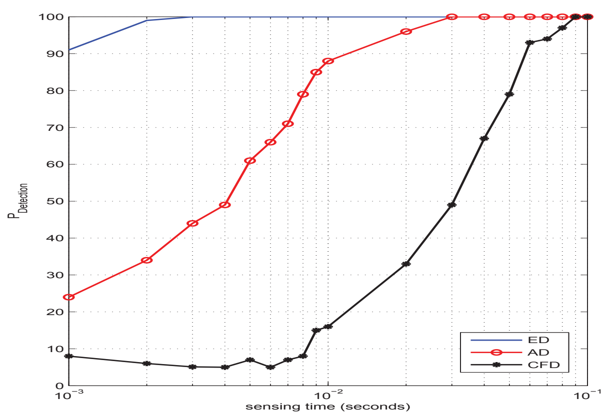


Fig. 3. Probability of detection ($P_D$) vs. Sensing period (in seconds) for a $P_F = 5\%$, SNR=-15dB, and a sensed WiFi signal.

### B. Addressing Energy Efficiency Tradeoffs

As stated in Sec. III the energy efficiency of the studied detectors is investigated based on their complexity and the corresponding energy consumption during the sensing period. In this purpose, a meaningful metric to assess the detectors complexity would be the CPU processing time that is required to complete the signal sensing process. Clearly, the higher the used CPU time the higher the complexity of the sensing algorithm and the more energy consumption is required.

Fig. 4, compares the CPU processing time as a function of the sensing period required by the ED, AD, and CFD. While the ED and the AD have almost a similar complexity with overlapping CPU time curves, as expected from Table I, the CFD has a much higher complexity and use a longer CPU time before reaching a sensing decision.

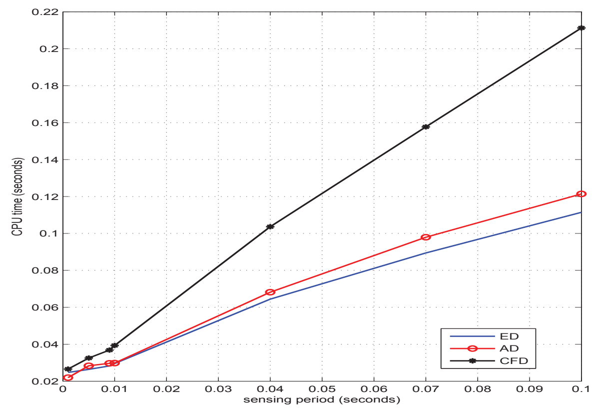


Fig. 4. Sensing period (seconds) vs. CPU time for a $P_F = 5\%$, a SNR=-15dB, and a sensed WiFi signal.

Fig. 5 shows the energy efficiency of the studied detectors expressed in Joules per computational operation as a function of the sensing time. From Fig. 5 we observe that the energy consumption characteristics of the ED, AD, and CFD follow closely their complexity trend in Fig. 4.

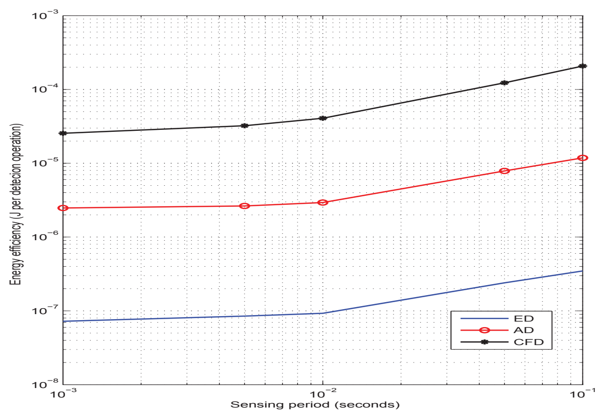


Fig. 5. Energy efficiency at SNR=-15dB and a $P_F = 5\%$

Finally, Figs. 1, 2, and 3 show that the detection performance (i.e, $P_D$) is highly dependent or constrained by allowed sensing period. So the longer the sensing period the better and higher $P_D$ gets but also means a higher energy consumption. This clearly highlight the need to address possible tradeoffs between the sensing period and energy consumption and the accepted $P_D$ for the different sensing algorithms. The first tradeoff is *Detection performance versus Sensing period*. From Figs. 4 and 5, it is clear that a possible compromise on the detection performance is to be considered in order to reduce the sensing period. This leads to the second tradeoff *Sensing period versus Energy Consumption* that also indicates the need to either accept a higher energy consumption or a lower energy consumption. In summary, the tradeoffs would depend on the sensing application, sensing device capabilities (e.g., battery-life), and the detectors sensing features described in Table III.

| Criterion/Detector | ED | AD | CFD |
|---|---|---|---|
| Probability of Detection | **** | *** | *** |
| False alarm control | *** | ***** | ***** |
| Complexity | ***** | ***** | ** |
| Assumption on PU signals | ***** | *** | **** |
| Effect of noise variance uncertainty | * | ***** | ***** |
| Distinguish between PU signals | * | *** | ***** |

TABLE III
SUMMARIZING SENSING TECHNIQUES PROPERTIES [6]

## V. CONCLUSIONS AND FUTURE WORK

This paper investigates the energy efficiency of three classical sensing algorithms and their suitability for implementation in battery-limited cognitive radio terminals, that require opportunistic access to available WiFi spectrum in multi-band LTE-A and WiFi systems. The study is focused on analyzing the sensing complexity and energy consumption of the WiFi spectrum sensing process in order to highlight the possible tradeoffs between the detection complexity, energy consumption, and detection performance of the sensing algorithms. The obtained results show that the autocorrelation detectors offer the best detection performance at a relatively low complexity and energy consumption levels when compared to the more complex cyclic feature detectors and the more noise sensitive energy detectors. This makes the autocorrelation detectors suitable candidates for implementation in battery-constraint cognitive radio terminals operating in future multi-band and multi-standard networks.

In future work we will investigate the energy consumption of the feature detection algorithms during the more complex signal classification step that is required to avoid interference between licensed WiFi users and opportunistic users offloaded from the LTE-A networks.


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