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This is a postprint version of the following published document:

Urquiza Villalonga, D.A.; Torres Gómez, J.; Fernández-Getino García, M.J. Optimal sensing policy for energy harvesting cognitive radio systems, in *IEEE transactions on wireless communications, 19(6), June 2020, Pp. 3826-3838*

DOI: https://doi.org/10.1109/TWC.2020.2978818

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Optimal sensing policy for energy harvesting cognitive radio systems

David Alejandro Urquiza Villalonga, Jorge Torres Gómez
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Abstract—**Energy harvesting (EH) emerges as a novel technology to promote green energy policies. Based on Cognitive Radio (CR) paradigm, nodes are designed to operate with harvested energy from radio frequency signals. CR-EH systems state several strategies based on sensing and access policies to maximize throughput and protect primary users from interference, simultaneously. However, reported solutions do not consider to maximize detection performance to detect spectrum holes which represent a major drawback whenever available energy is not efficiently used. In this concern, this paper addresses optimal sensing policies based on energy harvesting schemes to maximize probability of detection of available spectrum. These novel policies may be incorporated to previous reported solutions to maximize performance. Optimal processing scheduling schemes are proposed for offline and online scenarios based on convex optimization theory, Dynamic Programming (DP) algorithm and heuristic solutions (Constant Power and Greedy policies). Performance of proposed policies are validated by simulations for common detection techniques such as Matched Filter (MF), Quadrature Matched Filter (QMF) and Energy Detector (ED). As a result, it is shown that the best detection scheme theoretically addressed by MF, does not always perform better than the poorest detection scheme, given by the ED, in an energy harvesting scenario.**

Index Terms—**Energy harvesting, cognitive radio, optimal processing scheduling, offline power allocation policies, online power allocation policies.**

I. INTRODUCTION

COGNITIVE radio systems with energy harvesting capabilities (CR-EH) are designed to develop communication nodes to operate with spectral and energy efficient conceptions. In this concern, green cognitive networks capable of managing the use of spectrum, as well as energy, are currently available based on Green Communication paradigm [1].

Manuscript received August 18, 2019; revised December 23, 2019; accepted February 24, 2020. This work has received funding from the European Union (EU) Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie ETN TeamUp5G, grant agreement No. 813391. Also, this work has been supported in part by the Spanish National Project TERESA-ADA, funded by (MINECO/AEI/FEDER, UE) under grant TEC2017-90093-C3-2-R. The associate editor coordinating the review of this article and approving it for publication was H. Suraweera. (Corresponding author: Jorge Torres Gómez.)

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Digital Object Identifier 10.1109/TWC.2020.2978818

In CR-EH systems, energy may be harvested from multiple ambient sources (e.g., solar, wind, thermal, vibration). However, CR-EH nodes are mainly designed to harvest energy from radio frequency (RF) signals [1] [2]. Ambient radio signals are also energy sources provided wireless signals carry information and energy simultaneously [3]. In this direction, several solutions based on simultaneous wireless information and power transfer (SWIPT) algorithms are proposed to harvest energy from interference signals [4], [5], and from self-interference in full duplex communication channels [6] as well.

Primary problem in CR-EH is regarded to how Secondary Users (SUs) efficiently use harvested energy over time to maximize data throughput while keeping Primary Users (PUs) protected from interference. In this case, CR-EH primary problem is addressed through different solutions according to overlay [2], [7]–[13], underlay [14] or hybrid overlay-underlay dynamic spectrum access [15]. Through spectrum sensing (SS) operations, according to spectrum overlay model, SUs get opportunistic access to idle spectrum licensed by PUs to maximize data throughput. Additionally, to avoid interference to PUs, while the usability of the PU channel is properly guaranteed, two main detection performance parameters must be satisfied; the probabilities of detection (P_d) and false alarm (P_{fa}) [16]. These values are defined by IEEE 802.22 standard for cognitive wireless regional area networks (WRANs), where value of P_d must be superior to 0.9 and P_{fa} must be lower than 0.1 to have proper performance when detecting signals of interest (SoI) [17]. On the other hand, in underlay model, SU do not perform SS. In this case, SU develops a power allocation policy to maximize throughput but also to maintain interference levels on the PU under a given threshold [14]. Current research addresses overlay dynamic spectrum access problem through the proposal of optimal formulations to maximize detection performance.

A. Literature Survey

CR-EH problem for overlay dynamic spectrum access has been extensively investigated and several strategies, based on sensing and access policies, have been designed to maximize throughput in overlay model and simultaneously satisfy detection performance parameters according to standard 802.22 with energy restrictions [2], [7]–[13]. These strategies are usually based on a Markov decision process (MDP) to model randomness of energy harvesting profile as well as channel condition and the behavior of PUs. Based on available energy and probabilistic knowledge of PU activity, sensing policies determine the schedule of SUs in an energy efficient manner.

By this schedule, SUs sense the channel or remains idle conserving residual energy for future events. On the other hand, based on available energy and Channel State Information (CSI), access policies decide whether SUs occupy the channels or not.

Solution in [7] derives optimal distribution of energy values for SS and transmission operations in the time domain. This optimal distribution of energy values is formulated to maximize throughput based on MDP according to Bellman equation. A similar approach is proposed in [15] for a hybrid overlay-underlay dynamic spectrum access. In addition, in [2] authors propose an optimal harvesting-access policy to maximize the long-term achievable throughput. This proposed policy specifies the allocated time duration to harvest energy and power levels to be used in transmission based on CSI. Several relevant solutions are also focused in a single-user multi-channel scenario [8], [9]. In [8] a channel selection scheme based on the PU traffic characteristics as well as CSI to maximize energy efficiency criteria is proposed. Then, in [9] a channel selection criterion is developed based on probabilistic knowledge of PU occupancy, CSI and the available energy in SU's battery to maximize throughput of the SU.

Additional strategies for SS techniques to maximize achievable throughput are based on collision probability metrics [10]–[12]. Authors in [10] derive the optimal detection threshold for an energy detector technique that maximizes the expected total throughput subject to energy causality and collision constraints. Then, in [11] an upper bound on the achievable throughput based on energy arrival rate is described. Furthermore, authors in [12] propose an optimal access policy to achieve the upper bound of the throughput derived in [11]. In [13] an overlay dynamic spectrum access is studied while maintaining a quality of service (QoS) constraint on PU in terms of a given collision probability.

B. Motivation

Although solutions in [2], [7]–[13] and [15] are derived to maximize throughput, while maintaining PU protected from interference based on a given value of P_d or probability of collision, the efficient use of available energy to implement SS operations is not considered. The assumed constant sensing power value to obtain a fixed detection performance represents a major drawback as long as the dynamics of harvested energy values during the processing time-interval is not examined. In addition, reported sensing policies are only based on Energy Detector scheme and do not consider any other SS techniques. These drawbacks will in turn drive to reduced processing capabilities during a given detection time-interval.

In contrast, we may provide further system throughput when detection performance is maximized based on available harvested energy values. Maximizing P_d with the available energy implies throughput improvements provided the probability of collisions will be reduced. Therefore, if an optimal sensing policy, to dynamically schedule SS operations according to harvesting process, is incorporated to the SS stage of the reported solutions, then detection performance will be maximized and throughput will be improved. The development of an optimal energy allocation policy to schedule SS operations, then to maximize detection performance, represents a current open problem which demands further research [18].

To the best of our knowledge, optimal energy allocation policies are only reported in offline and online settings for transmitting information over communication channels [1] [19]–[41]. This without any optimal use of harvested energy for SS operations. Similar to optimal energy allocation policies to transmit information, a new policy may be derived to detect SoI from PU but to maximize detection performance.

Furthermore, selection criteria regarding the best SS technique to efficiently use available energy and to achieve the highest detection performance are not reported in scientific literature. Therefore, a comparison between performance of common reported SS techniques (e.g., Matched Filter (MF), Quadrature Matched Filter (QMF) and Energy Detector (ED)) must be conducted.

C. Contributions

In this paper, we propose an optimal sensing and scheduling policy to maximize detection probability P_d, subject to an established P_{fa}, signal-to-noise-ratio (η) value and energy constraints, when energy from wireless sources is harvested. This paper is divided in two parts. First part assumes prior knowledge regarding energy harvesting times as well as harvested energy amounts to develop an offline scheduling policy. The second part only assumes causal knowledge regarding energy harvesting rate, which is more realistic in practice.

Main contributions of this paper are detailed as follows:

1) Based on the increasing monotone relation between P_d and total number of processed samples (N), we demonstrate that for a constant value of P_{fa} and η, maximizing P_d is equivalent to maximizing N for the same energy constrains.
2) We design an energetic model to compute energy consumption required to detect SoI. We assume that energy consumption only depends on the processing of received samples to compute the test statistic. We derive an expression to relate energy consumption with N and the technology dependent parameters of the processing unit.
3) We derive a closed-form expression to establish the objective function to maximize N based on a dynamic adjustment of processing power and subject to the available harvested energy. Provided the objective function satisfies a concave relation between N and the processing power, we solve this optimization problem based on the underlying theory for transmission-scenario in [21].
4) We provide solutions to the optimization problem considering the offline and online scenarios. In particular, for online scenario we first derive Dynamic Programming (DP) algorithm, which offers the online optimal solution. However, DP demands high computational costs, which is not suitable in practice. For that reason, we propose two heuristic solutions: Constant Power and Greedy policies.
5) Finally, we provide proper comparison metrics based on detection performance criteria with common SS techniques (MF, QMF and ED) using the proposed offline

and online policies. We illustrate the selection of proper SS technique that achieves the highest P_d given a value of P_{fa} and η.

Presented results exhibit that the best detection scheme theoretically addressed by MF, does not always perform better than the poorest detection scheme given by the ED in an energy harvesting scenario. The proper selection of the detection scheme will be also dependent on the dynamic of harvested energy. This paper analyzes a scenario composed by a PU-SU pair. However, results here demonstrated are discussed to be extended to multi-channel settings and cooperative green cognitive networks.

D. Paper organization

This paper is organized as follows. The system model and problem formulation for offline and online scenarios are presented in Section II. In Section III the problem of maximizing P_d is considered in an offline setting. In Section III-A an energetic model to compute energy consumption required to detect SoI is designed. Then, in Section III-B the proposed offline processing policy is developed based on convex optimization algorithm. Section IV considers the optimization problem in an online setting. Optimal processing policy given by DP algorithm and less complex policies such as Constant Power and Greedy policies are developed. A case of study considering main SS techniques such as MF, QMF and ED, and assuming ARM Cortex-A7 as processor unit is presented in Section V to illustrate the operation of proposed policies in offline and online scenarios. Then, in Section V-D the behavior of the policy and practical scenarios for implementation are discussed. Simulations results are obtained in Section VI to validate policies performance. Finally, Section VII concludes the paper and the further remarks regarding to future work.

II. System model and Problem formulation

We consider a single CR scenario, compounded by only a pair of SU and PU. SU has not fixed power supplies, instead it is equipped with an EH device. Dynamic spectrum access is performed according to spectrum overlay model reference. Hence, in order to avoid collisions with PU, SU senses the activity of primary channel before transmission.

The sensing node of SU is modeled as a processing unit to compute a test statistic from primary received signal then to decide between two possible hypothesis: idle or busy primary channel. This is known as binary hypothesis testing problem, where $\mathcal{H}_1$ is the hypothesis that PU is active (received signal is compounded by information and additive noise), while $\mathcal{H}_0$ means the spectrum is idle (received signal is only compounded by noise).

Provided a detection scheme, P_d is related to three main quantities: the total number of processed samples used to detect SoI given by N (proportional to sensing time T_S), P_{fa} and η values. Therefore, given a detection technique, sensing performance is described by:

$$P_d = f(N, \eta, P_{fa}), \tag{1}$$

where $f(\cdot)$ is a function related to a given sensing technique. For instance, in case of common detection schemes such as MF, QMF and ED, P_d values in (1) are given as [42]:

$$P_d = Q\left(Q^{-1}(P_{fa}) - \sqrt{N\cdot\eta}\right), \tag{2}$$

$$P_d = Q_{\chi_2^2(N\cdot\eta)}\left(2\ln\frac{1}{P_{fa}}\right), \tag{3}$$

$$P_d \approx Q\left(\frac{Q^{-1}(P_{fa}) - \sqrt{\frac{N}{2}}\cdot\eta}{\eta+1}\right), \tag{4}$$

respectively, where $Q(x)$ is the complementary distribution of a standard Gaussian random variable and $Q_{\chi_2^2(\lambda)}(x)$ is the complementary distribution of a noncentral chi-squared random variable with two degrees of freedom and noncentrality parameter λ. Equations above illustrate that P_d is an increasing monotone function related to variable N.

Processing unit of SU is powered by an energy harvester circuit. Energy harvesting process is modeled as energy packets arriving at discrete time slots of index i, $i = \{1, 2, ..., M\}$, according to the vector $\mathbf{E} = [E_1, E_2 ..., E_M]$ at time vector $\mathbf{s} = [s_1, s_2, ..., s_M]$ [20]. Then, collected energy is stored in an infinite-sized battery and finally is used to process SoI. We consider that there is no energy loss in storing and retrieving energy from the battery. Additionally, the operation of the sensing node is constrained by energy causality (i.e., energy consumption by SS operations has to be less or equal than harvested energy) described by:

$$E_s(t) \le \sum_{i:s_i<t} E_i, \quad 0 < t \le T_p, \tag{5}$$

where $E_s(t)$ represents energy consumption over time in SS operations and $\sum_{i:s_i<t} E_i$ represents the cumulative harvested energy until time instant t. We also assume a temporal constraint T_p to complete the processing of received signals. This constraint is related to the required time for detecting SoI.

We assume that energy consumption E_s only depends on processing unit operations to compute the test statistic. We do not consider the energy consumption of RF circuit to receive signal samples. Analogue to [21], where bits to be transmitted are available in a transmission buffer, we also consider that received signal samples are available in memory. Then we assume that the processing unit has always samples to be processed in order to determine the maximum number of processed samples. According to [43], energy consumption of CMOS processing unit is expressed as:

$$E_s = N_{clk} V_{cc}^2 C, \tag{6}$$

where V_{cc} is the supply voltage, C is the average switched capacitance per clock cycle and N_{clk} is the total number of clock cycles required for the given task. Then, to implement detection of SoI, N_{clk} value will be dependent on the complexity of SS technique and the number of processed samples N. Thus, energy consumption of processing unit over time is modeled by a function that depends on N, V_{cc}, technology depending constant of the processing unit (C) and the implemented sensing technique as:

$$E_s(t) = F_e(N, V_{cc}, C), \tag{7}$$

where $F_e(\cdot)$ is an energy consumption function related to the implemented SS technique.

The increase in the total number of processed samples implies that detection performance will improve based on the monotonically increasing relation between P_d and N in (1). However, according to (7), energy consumption values will be also greater as a consequence of the higher N. That is, detection performance is improved at the cost of incrementing energy consumption values. In this work, we propose an optimal balance of this trade-off, considering the dynamics of harvested energy to maximize P_d.

Based on the linear relation between energy consumption over time and power consumption $p(t)$ given by $E_s(t) = \int_0^{T_p} p(t)\, dt$, above trade-off may be stated in terms of power instead of energy. This is a more tractable representation because it is expressed in terms of instantaneous values of power consumption that can be dynamically modified in actual processors. Similar to [19]–[41], we assume that processing unit can adaptively change its processing power for SS operations according to harvested energy. Then, it is possible to propose a power allocation policy to dynamically adjust digital signal processing operations in an interval T_p. By this way, processing rate can be adjusted to harvesting rate by optimally selecting processing power vector $\mathbf{p} = [p_1, p_2, ..., p_K]$ and its corresponding processing duration $\mathbf{l} = [l_1, l_2, ..., l_K]$. Here, we assume a time-index k, $k = \{1, 2, ..., K\}$, to denote the time instants when the processing power changes. The processing power may not change at every energy harvesting time instant and then index k does not necessarily match with i. In this direction, optimal scheduling policy objective is to find vectors $\mathbf{p}$ and $\mathbf{l}$ given $\mathbf{E}$ and $\mathbf{s}$ to maximize total number of processed samples.

Additionally, to select the SS technique to achieve the best detection performance based on its energetic model is still to be analyzed. For instance, coherent SS techniques such as MF require to process less samples to achieve the same P_d than non-coherent techniques such as ED. However, MF demands more energy cost operations per given sample than ED. In this case, ED may process more samples than MF, then to achieve better performance.

This paper proposes optimal energy management policy for offline and online scenarios. Both scenarios are implemented by two stages: first a processing power allocation policy for executing the highest number of SS operations with the harvested energy is developed. Then, we select the SS technique that achieves the highest P_d provided P_{fa} and η values.

A. Offline problem formulation

We first study an offline scenario with full knowledge of harvested energy amounts $\mathbf{E}$ and harvesting times $\mathbf{s}$. We consider that there is E_0 amount of energy stored in an infinite-sized battery at initial time t_0. We also assume that the processing unit may change dynamically its processing power K times in an interval T_p according to the obtained power vector $\mathbf{p}$ with corresponding processing duration $\mathbf{l}$.

Based on the optimization problem stated in [21], this to maximize total number of transmitted bits by a deadline T, we present a new optimization problem to find the optimal power allocation policy for SS. By considering simultaneously the two goals: maximize probability of detection and the efficient use of harvested energy the optimization problem is formulated as follows:

$$\begin{aligned} \max_{\mathbf{p},\mathbf{l}} \quad & P_d(N, \eta, P_{fa}) \\ s.t. \quad & P_{fa} = A \\ & \eta = B \\ & E_s(t) \le \sum_{i:s_i<t} E_i \quad 0 < t \le T_p, \end{aligned} \tag{8}$$

where A and B represent positive-real valued constants, T_p is the maximum processing time, $\sum_{i:s_i<t} E_i$ is the cumulative harvested energy and the energy consumed up to time t is given by $E_s(t) = p_1 \cdot t$ if $t \le l_1$. Otherwise, energy consumed is given by [20]:

$$E_s(t) = \sum_{k=1}^{\bar{k}} p_k \cdot l_k + p_{\bar{k}+1}\left(t - \sum_{k=1}^{\bar{k}} l_k\right), \tag{9}$$

where $\bar{k} = \max\{k : \sum_{n=1}^{k} l_n \le t\}$.

The optimization problem in (8) proposes to maximize P_d subject to a given value of P_{fa} and η [42] and satisfying energy causality constraints. However, a more tractable approach may be derived based on the monotone relation between N and P_d. Therefore, the larger the value of N for a fixed value of P_{fa} and η, the better the obtained P_d. Thus, maximizing P_d is equivalent to maximizing N provided certain P_{fa} and η values and same energy causality constraints. To this end, maximizing P_d in (8) may be derived by maximizing N as follows:

$$\begin{aligned} \max_{\mathbf{p},\mathbf{l}} \quad & N \\ s.t. \quad & E_s(t) \le \sum_{i:s_i<t} E_i \quad 0 < t \le T_p, \end{aligned} \tag{10}$$

given a SS technique. Then, the maximum number of processed samples (N_{max}) given an energy harvesting profile is obtained by solving the optimization problem in (10). Provided that N does not depend on P_{fa} and η, then formulation in (10) does not consider these quantities. Values of P_{fa} and η will be considered to compute P_d after evaluating N_{max} in equations (2), (3) and (4). Then, the SS technique that maximizes P_d is selected. This procedure is detailed in subsequent sections for offline and online scenarios.

B. Online problem formulation

Here, we consider an online scenario where processing unit has only a causal knowledge of harvesting rate, i.e. past realizations of harvesting process and the statistical behavior of harvesting rate random variable are available.

We model harvested energy $\mathbf{E} = [E_1, E_2, ..., E_M]$ by a first-order stationary Markov model over time slots defined by vector $\mathbf{l} = [l_1, l_2, ..., l_M]$ as in [1], [26], [30], and [39]. Several models are reported in scientific literature to describe the energy harvesting process including: Bernoulli, uniform, Poisson, and exponential processes [1]. However, these models do not consider the temporal correlation properties of energy harvesting process as examined in [1]. On the other hand, the use of the Markov model, similarly to reports in [1], [26], [30], and [39] to describe the energy harvesting process, will provide a more realistic scenario to study the proper use of arriving energy packets in the context of energy harvesting applications.

Based on the online formulation, b_i denotes the available energy in battery at the beginning of slot i and evolves according to:

$$b_{i+1} = (b_i - p_i \cdot l_i)_+ + E_i, \tag{11}$$

where $(\cdot)_+ = \max\{0, \cdot\}$ and $\mathbf{p} = [p_1, p_2, ..., p_M]$ is the processing power in ith slot. Here we assume the same index i, $i = \{1, 2, ..., M\}$, to denote the instants of energy harvesting and processing power variations. This assumption is based on the fact that in online case, at the beginning of each time-slot, a processing power value is selected. Therefore, unlike offline scenario, here both indices for energy harvesting and processing power match.

According to (11), processing power p_i in time slot i modifies the battery state to next slot and consequently it influences the future decisions on the use of available energy. The balance, between the current consumed energy and the remaining for the future use, represents a trade-off to have an overall optimum performance. Online problem formulation is to find optimal processing power value $\mathbf{p}^* = [p_1^*, p_2^*, ..., p_M^*]$ at the beginning of each time slot based on the statistical description of future energy arrivals to maximize detection performance. Similar to offline scenario, online optimization problem will maximize expected detection performance $\mathbb{E}[P_d]$ by maximizing the total number of expected processed samples $\mathbb{E}[N]$ with same energy constraints than in (10).

III. Optimal offline processing policy

Based on the optimization problem in (10) variable N is related to the processing capacity to detect SoI, while $E_s(t)$ is constrained by energy harvesting rate values. Then, consumed energy $E_s(t)$ is related to processed samples N according to (7). In this case, an energetic model must be derived to compute energy consumption to process N samples given a processing unit and a detection technique. By using this model, values of N may be timely modified based on energy collected and execution speed of the processor. The optimal processing policy to be derived modifies the processing power $\mathbf{p}^*$ during time-intervals $\mathbf{l}^*$ by controlling the frequency of the processor.

A. Energetic model

Proposed energetic model describes the total energetic cost to process SoI associated to arithmetic operators (adders, multipliers, dividers) and memory accesses (read/write) needed by a given SS technique to compute the test statistic. Analytically, the energetic model is formulated by the additive contribution of each operation as $E_s = E_{add}N_{add} + E_{mul}N_{mul} + E_{div}N_{div} + E_{mem}N_{mem}$, where N_{add}, N_{mul}, N_{div} and N_{mem} are the total number of adders, multipliers, dividers and memory accesses used to implement a given detection technique, respectively, and E_{add}, E_{mul}, E_{div} and E_{mem} are their corresponding associated energetic costs. In order to simplify the analysis, the energetic model is computed based on the cost of an adder operator as follows:

$$E_s = E_{add}\left(N_{add} + \alpha N_{mul} + \beta N_{div} + \gamma N_{mem}\right), \tag{12}$$

where α, β and γ are processor technology depending constants to relate the energetic cost of an adder to the energetic cost of a multiplier, a divider and memory access instructions, respectively.

On the other hand, dynamic energy consumption per instruction in general purpose CMOS processors can be modeled as in equation (6). Thus, the energetic model in (12) is related to the total number of clock cycles as $\alpha = E_{mul}/E_{add} = N_{clk_{mul}}/N_{clk_{add}}$, $\beta = E_{div}/E_{add} = N_{clk_{div}}/N_{clk_{add}}$ and $\gamma = E_{mem}/E_{add}$.

Provided that the same detection process is applied to each received sample, then total number of operations after N received samples will be the addition of performed operations for each specific sample. Therefore, values of N_{add}, N_{mul}, N_{div} and N_{mem} in (12) will depend linearly on the total number of samples N used to compute the test statistic of the given SS technique. In this case, provided that (12) represents also a linear relation on N, the energetic model may be simplified as follows:

$$E_s = E_{add}\left(\theta N + \vartheta\right), \tag{13}$$

where θ and ϑ are parameters depending on computational complexity of each detection technique and processor technology.

B. Offline processing policy

The optimization problem in (10) states to maximize the number of processed samples of the received signals. This problem is similar to the proposed in [20] when the total number of processed samples N is interpreted in a similar fashion to the total number of transmitted bits. Thus, similar to [20], we select processing power consumption p as the optimization variable to be dynamically modulated to maximize N.

According to the proposed energetic model in (13), by clearing variable N we obtain:

$$N = \frac{E_s}{E_{add}} \cdot \mu + \upsilon, \tag{14}$$

where we use $\mu = \theta^{-1}$ and $\upsilon = -\vartheta \cdot \theta^{-1}$ for convenience. This equation describes the total number of processed samples characterized by constants E_{add}, μ and υ where E_s represents the processing energy consumption.

Based on (14), a practical description of the processing policy is derived when N is related to power consumption

p instead of E_s, similar to [20]. Then, we maximize N by adjusting the time varying processing rate and power judiciously in response to harvested energy. To represent N in terms of p instead of E_s we consider the relation in [43] for the dynamic energy consumption per instruction. Then, energy consumption of an adder operation can be expressed as:

$$E_{add} = CV_{cc}^2 N_{clk_{add}}. \tag{15}$$

The expression in (15) may be developed in terms of p by using equations:

$$p = CV_{cc}^2 f_{clk}, \tag{16}$$

and:

$$V_{cc} = \delta \cdot f_{clk}, \tag{17}$$

where f_{clk} is the clock frequency and δ is a technology depending constant [44]. Proposed processing policy utilizes Dynamic Voltage and Frequency Scaling (DVFS) technique to obtain the optimal relation between V_{cc} and f_{clk} to have control on consumed power. By using DVFS technique f_{clk} can be adjusted dynamically during processing operations [45]. By replacing (17) in (16) and clearing f_{clk} yields:

$$f_{clk} = \sqrt[3]{p} \cdot \xi, \tag{18}$$

where $\xi = \sqrt[3]{\frac{1}{C \cdot \delta^2}}$ is also a technology depending constant. Finally, by replacing (18) in (17) and then in (15) we obtain:

$$E_{add} = C(\delta \sqrt[3]{p} \cdot \xi)^2 N_{clk_{add}}. \tag{19}$$

By using this expression and considering $E = p \cdot t$ after the proper substitutions in (14), then the objective function to solve problem in (10) is formulated by:

$$N = \frac{t \cdot \sqrt[3]{p}}{N_{clk_{add}}} \cdot \xi\mu + \upsilon. \tag{20}$$

This expression in terms of p represents the objective function to solve the problem formulated in (10). Main idea is to modify the value of p to maximize N accordingly, subject to EH constraints.

By this way, the optimization problem in (10) can be expressed as:

$$\begin{aligned} \max_{\mathbf{p},\mathbf{l}} \quad & N = \sum_{k=1}^{K} \frac{l_k \cdot \sqrt[3]{p_k}}{N_{clk_{add}}} \cdot \xi\mu + \upsilon \\ s.t \quad & E(t) \leq \sum_{i:s_i<t} E_i \qquad 0 < t < T_p. \end{aligned} \tag{21}$$

The objective function in (21) represents a concave function in p. This function may be used to establish an offline processing optimal policy to detect SoI. In this case, lemmas obtained in [20] for the optimal transmission policy might be applied to this processing scenario in (21) using the concave property of the objective function as follows:

Lemma 1 *Under the optimal policy, the processing powers increase monotonically, i.e,* $p_1^* \leq p_2^* \leq \ldots \leq p_K^*$.

Lemma 2 *Under the optimal policy, the processing powers remain constant between energy harvests, i.e., the processing powers only potentially change when new energy arrives.*

Lemma 3 *Under the optimal policy, whenever the processing powers change, the energy consumed up to that instant equals the energy harvested up to that instant.*

In addition, by using [20], a fourth lemma is included to the structure of the optimal processing policy.

Lemma 4 *Under the optimal policy based on Lemmas 1 to 3, all harvested energy has to be consumed in a maximum processing time* T_p.

Lemmas 1, 2 and 3 are proven in [20] by using properties of concave function defined by Jensen's inequality [46]. The proof of Lemma 4 is given in Appendix A. Based on the four lemmas above Theorem proposed in [20] may be extrapolated to optimal processing policy as follows:

Theorem 1: *For a given maximum processing time* T_p, *consider a processing policy with consumption power vector* $\boldsymbol{p}^* = [p_1^*, p_2^*, \ldots, p_K^*]$ *and corresponding duration vector* $\boldsymbol{l}^* = [l_1^*, l_2^*, \ldots, l_K^*]$. *This policy is optimal if and only if it has the structure:* $\sum_{k=1}^{K} l_k^* = T_p$ *and for* $k = \{1, 2, \ldots, K\}$, $i_k = \arg\min_{i:s_i \leq T_p, s_i > s_{i_{k-1}}} \left\{ \frac{\sum_{n=i_{k-1}}^{i-1} E_n}{s_i - s_{i_{k-1}}} \right\}$, $p_k^* = \frac{\sum_{n=i_{k-1}}^{i_k-1} E_n}{s_{i_k} - s_{i_{k-1}}}$, $l_k^* = s_{i_k} - s_{i_{k-1}}$, *where* i_k *is the index of the energy arrival slot when the processing power* p_k^* *switches to* p_{k+1}^*, *i.e., at* $t = s_{i_k}$ *the rate of energy consumption changes. Then, the maximum number of processed samples is:*

$$N_{max} = \sum_{k=1}^{K} \frac{l_k^* \cdot \sqrt[3]{p_k^*}}{N_{clk_{add}}} \cdot \xi\mu + \upsilon, \tag{22}$$

where $\xi = \sqrt[3]{\frac{1}{C \cdot \delta^2}}$ *is a technology depending constant,* μ *and* υ *are parameters depending on computational complexity of each detection technique and processor technology.* The proof of Theorem 1 is given in Appendix B.

Based on Lemmas 1, 2, 3 and 4, Theorem 1 states the optimal structure to compute the optimal processing power vector $\mathbf{p}^*$ and its time-duration $\mathbf{l}^*$. We can note that optimal processing policy leads to the tightest piecewise linear energy consumption that never exceeds the energy harvesting curve and spend all collected energy in the maximum processing time T_p. Therefore, offline processing policy is stated by applying Theorem 1 to maximize the total number of processed samples N. This is based on the available harvested energy and a given SS technique according to (10). Then, P_d is calculated given N_{max} and established values of P_{fa} and η for each SS scheme. The highest P_d defines the SS technique to be chosen according to the optimization problem in (8).

IV. Online processing policies

According to (11) online optimal processing power allocation policy has to balance present and future energy consumption to maximize a given reward. To this end, we derive an online policy that utilizes the statistic of the harvesting process to optimally adjust processing power vector $\mathbf{p}^*$ maximizing the expected value of N over a finite horizon of M slots. We assume that processing power decisions are restricted to a discrete set U ($p_i^* \in U$). The derived policy will be feasible if the energy causality constraint is satisfied, i.e. $p_i^* \cdot l_i \leq b_i$.

The objective function in (20), derived for the offline scenario, will be used as well to define the cost function $N_i(p_i^*)$ of the current online problem. Let $\mathbf{p}^* = [p_i^*, p_{i+1}^*, ..., p_M^*]$ be the optimal policy that maximizes the expected value of processed samples $\mathbb{E}[N_i^*(b_i, E_{i-1})]$ from ith slot till the deadline according to state vector (b_i, E_{i-1}). Then, based on the DP principles described in [47] the following DP algorithm to solve the online problem is derived:

$$N_M^*(b_M) = \max_{p_M \in U: 0 \leq p_M \cdot l_M \leq b_M} N_M(p_M) \tag{23}$$

where $N_i(p_i^*) = \frac{l_i \cdot \sqrt[3]{p_i^*}}{N_{clk_{add}}} \cdot \xi\mu + \upsilon$, then

$$N_i^*(b_i, E_{i-1}) = \max_{p_i^* \in U: 0 \leq p_i^* \cdot l_i \leq b_i} N_i(p_i^*) + \mathbb{E}[N_{i+1}^*(b_{i+1}, \tilde{E}_i)] \tag{24}$$

where $\tilde{E}_i$ denotes the harvested energy on current slot given the harvested energy E_{i-1} on past slot modeled by first-order stationary Markov model. In addition $b_{i+1} = (b_i - p_i^* \cdot l_i)_+ + \tilde{E}_i$ is the energy available in the battery in the next slot. DP algorithm proposes to solve optimization problem recursively starting from last slot M and proceeds backward to slot i.

The online solution based on DP offers the optimal results, but demands higher computational cost, which may not be suitable for practical scenarios. An alternative solution is to compute DP algorithm in offline manner, then to store results in a lookup table to future use on online processing for real time implementation [26]. However, changes on harvesting rate will produce regular updates of this lookup table, which also demands higher computational costs.

In addition to DP, less complex solutions have been derived given by Constant Power and Greedy policies [26], [30], [48]. Constant Power policy processes samples with constant power equal to the time average energy harvest rate ($\mathbb{E}[E]$) as long as there is sufficient energy on battery. If battery is out of energy then processing is stopped until next energy arrival. Then, assuming a discrete set of processing power U, Constant Power policy processes with the maximum power in the set U lower than $\mathbb{E}[E]$ whenever there is enough energy for processing. On the other hand, Greedy Policy establishes to use all the available harvested energy by the processing unit on each slot. These policies offer sub-optimal solutions, however they are rather simple to implement and do not require an extensive statistical knowledge of harvesting process. Constant policy only needs the average value of harvesting rate and Greedy Policy needs to sense battery state to have the available amount of collected energy.

Similar to offline scenario, online policy first proposes to apply processing power allocation policy (optimal policy based on DP algorithm or heuristics policies such as Constant or Greedy) to compute total number of samples from the received signal utilizing different SS techniques. Then, the SS technique that achieves the highest P_d is selected.

V. Case of Study

By considering three main detection techniques: Matched Filter (MF), Quadrature Matched Filter (QMF) and Energy Detector (ED), the offline and online processing policies are illustrated by obtaining total of processed samples and related probability of detection by using ARM Cortex-A7 processor [49]. Table I summarizes the computational complexity of these SS techniques to compute the test statistic considering the simplest detection scenario: a single tone $s[n] = \cos(2\pi f_0 n + \varphi_L)$, where f_0 represents its frequency and φ_L represents a given phase [42]. In case of MF, a phase recovery system was considered as described in [50].

TABLE I
Computational cost for a variety of sensing techniques.

Detection Technique	Adders	Multipliers	Dividers	Memory Accesses
MF	$3N-3$	$7N-2$	-	$4N-2$
QMF	$2N-1$	$2N+2$	2	-
ED	$N-1$	N	1	-

According to (12) and Table I, energy consumption relations of these detectors are computed as $E_{MF} = E_{add}(3N - 3 + \alpha(7N-2) + \gamma(4N-2))$, $E_{QMF} = E_{add}(2N-1+\alpha(2N+2)+2\beta)$ and $E_{ED} = E_{add}(N - 1 + \alpha N + \beta)$, respectively. To illustrate, in case of MF technique, clearing N in $E_{MF} = E_{add}(3N-3+\alpha(7N-2)+\gamma(4N-2))$, we obtain:

$$N_{MF} = \frac{E_{MF}}{E_{add}} \cdot \frac{1}{3+7\alpha+4\gamma} + \frac{3+2\alpha+2\gamma}{3+7\alpha+4\gamma}, \tag{25}$$

where $\mu = \dfrac{1}{3+7\alpha+4\gamma}$ and $\upsilon = \dfrac{3+2\alpha+2\gamma}{3+7\alpha+4\gamma}$ based on direct comparison with (14). Then, substituting μ and υ in (22) we finally obtain:

$$N_{MF} = \sum_{i=1}^{M} \frac{l_i \cdot \sqrt[3]{p_i} \cdot \xi}{N_{clk_{add}}} \cdot \frac{1}{3+7\alpha+4\gamma} + \frac{3+2\alpha+2\gamma}{3+7\alpha+4\gamma}. \tag{26}$$

A similar procedure may be applied to obtain objective functions for QMF and ED as follows:

$$N_{QMF} = \sum_{i=1}^{M} \frac{l_i \cdot \sqrt[3]{p_i} \cdot \xi}{N_{clk_{add}}} \cdot \frac{1}{2+2\alpha} + \frac{1-2(\alpha+\beta)}{2+2\alpha}, \tag{27}$$

$$N_{ED} = \sum_{i=1}^{M} \frac{l_i \cdot \sqrt[3]{p_i} \cdot \xi}{N_{clk_{add}}} \cdot \frac{1}{\alpha+1} + \frac{1-\beta}{\alpha+1}. \tag{28}$$

Proposed sensing policies are described by simulations in MatLab using ARM Cortex-A7 processor to run sensing node operations. According to several measurements reported in [49] for float arithmetic instructions, values of $E_{add} = 0.157$ nJ for 500 MHz, $\alpha = 1$, $\beta = 5$, $N_{clk_{add}} = 4$, $\gamma = 0.8$ and $\xi = 2.62 \cdot 10^9$ are established. In terms of frequency scaling, this processor operates in a clock frequency range between 500 MHz and 1.2 GHz with discrete frequency steps of 100 MHz.

A. Offline processing policy

We consider for offline scenario an initial energy amount given by $E_0 = 144$ nJ and a harvested energy vector $\mathbf{E} = [240, 148, 600]$ nJ, collected at time vector

$\mathbf{s}$ = [200, 400, 600] μs and maximum processing time T_p = 1 ms. These values are properly selected to illustrate performance of processing policy in a commercial processor. Vector $\mathbf{E}$ and $\mathbf{s}$ are computed taking into account the common power harvested values reported in [2], [8]–[10], [20] and depicted in Fig. 1 by using the solid line. Through optimal offline processing policy in Theorem 1, we obtain the optimal processing power vector $\mathbf{p}^* = [7.2, 9.7, 15]$ mW with time-duration $\mathbf{l}^* = [200, 400, 400]$ μs by conforming a monotonically increasing sequence (Lemma 1) as depicted in Fig. 1. Additionally, optimal policy employs all harvested energy at time T_p (Lemma 4) and power consumption only potentially changes at harvesting instances (Lemma 2) when energy consumption curve intercepts to the energy harvesting curve (Lemma 3).

The optimal power vector may be achieved on a processor unit by dynamically modifying the processing frequency according to (18). Corresponding frequency values required to achieve vector $\mathbf{p}^*$ are given by $f_{clk} = [506, 559, 646]$ MHz. However, these frequency values are not available for ARM Cortex-A7 processor. Therefore, optimal processing policy is not technologically possible to achieve with the selected processor. Instead, a suboptimal policy is developed by using available frequency values in ARM Cortex-A7 processor nearest to the optimal ones. Selected frequency vector is $f_{clk} = [500, 700]$ MHz which implies a suboptimal processing power vector $\mathbf{p}' = [6.9, 19]$ mW with time duration $\mathbf{l}' = [600, 376]$ μs. The suboptimal policy is depicted by the dashed line in Fig. 1, where Theorem 1 is not fulfilled.

To illustrate efficiency of proposed method we compare the total number of processed samples by using the optimal and suboptimal policies. By evaluating optimal power vector in (26), (27) and (28), we obtain the maximum number of processed samples for MF, QMF and ED, respectively. Obtained results show that $N_{MF} = 11053$, $N_{QMF} = 36471$ and $N_{ED} = 72946$ samples based on harvested energy values. However, by developing the suboptimal policy, as depicted in dashed line in Fig. 1, we obtain that MF reduces its processing capacity to $N_{MF} = 10670$ samples, QMF to $N_{QMF} = 35207$ samples and ED to $N_{ED} = 70418$ samples. We remark that ED obtains the larger total number of processed samples, provided this is the less complex technique.

Then, we study policy performance regarding to P_d when signal detection is operating under low SNR regime ($\eta = -20$ dB) and low P_{fa} values ($P_{fa} = 10^{-8}$). The computed amount of processed samples N for each SS technique is substituted by N_{MF}, N_{QMF} and N_{ED} into equations (2), (3) and (4), respectively. The obtained P_d values are illustrated in Table II where QMF is the detection scheme recommended to maximize detection performance. This particular case illustrates that the best detector scheme, theoretically addressed by MF, does not perform better than QMF when energy causality restrictions are established. This concern is further discussed on next Sections V-D and VI.

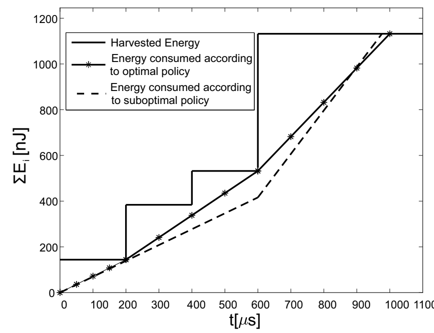


Fig. 1. Processing curve according to optimal and suboptimal policies.

TABLE II
PROBABILITY OF DETECTION ACHIEVED WITH OPTIMAL AND SUBOPTIMAL POLICY CONSIDERING $\eta = -20$ DB.

Detection Technique	Optimal Policy	Suboptimal Policy
P_{MF}	0.999999525486607	0.999998808732362
P_{QMF}	0.999999999999999	0.999999999999991
P_{ED}	1.23e-04	1.08e-04

B. Online processing policy

Current section analyzes online processing policies performance (DP, Constant Power and Greedy policies) by comparing average processed samples over 10^4 random realizations of energy harvesting profile generated with first-order Markov model. We consider a Markov model with two states ($h_0 = 0$ and $h_1 = 200$ nJ). We assume transition probabilities $q_{00} = 0.8$, $q_{01} = 0.2$, $q_{10} = 0.5$, $q_{11} = 0.5$ to simulate burst arrival case similar to [30]. Processing power decisions are restricted to a discrete set of $U = [6.9, 12, 19, 28.4, 40.4, 55.5, 73.8, 95.9]$ mW derived from equation (18) according to permissible frequency range of ARM Cortex-A7 processor when $\xi = 2.62 \cdot 10^9$. Processing time ($T_p = 1$ ms) is slotted into 100 slots with 10 μs of interval duration.

Table III shows averaged processed samples achieved for different online policies and spectrum sensing techniques during the whole processing interval T_p. Based on results illustrated in Table III we note that the highest amount of processed samples is obtained by applying DP.

Table IV illustrates P_d values achieved based on online policies in case of several SS techniques considering a low SNR value ($\eta = -20$ dB). We note that Constant Power achieves higher performance than Greedy policy. This is an expected result provided Constant Power is based on first order statistic of energy harvesting rate and Greedy is an even simple policy without any knowledge of harvesting rate.

Similar to the offline case, although ED processes the biggest amount of samples, achieves the poorest detection performance, instead. On the other hand, QMF stays as the detector that achieves the highest P_d. In this case QMF balances better required amount of samples to obtain higher values of P_d and energy consumption per processed samples. Further remarks are considered in Section VI to illustrate the better selection of SS techniques.

TABLE III
AVERAGED PROCESSED SAMPLES ACHIEVED FOR DIFFERENT ONLINE POLICIES AND SPECTRUM SENSING TECHNIQUES.

Detection Technique	**Dynamic Programming**	**Constant Power Policy**	**Greedy Policy**
N_{MF}	9577	7130	4047
N_{QMF}	31601	23287	13374
N_{ED}	63222	47123	26752

TABLE IV
PROBABILITY OF DETECTION FOR DIFFERENT ONLINE POLICIES AND SPECTRUM SENSING TECHNIQUES CONSIDERING $\eta = -20$ DB.

Detection Technique	**Dynamic Programming**	**Constant Power Policy**	**Greedy Policy**
$P_d(MF)$	0.99998	0.997	0.773
$P_d(QMF)$	0.999999999	0.999999999	0.99999998
$P_d(ED)$	7.35-05	2.71e-05	5.14e-06

C. Detection performance of wideband signals

Above subsections illustrate the performance of the proposed offline and online policies on the detection of single tone signals. In addition, to consider the case of wideband communications with multi-tone signals, then MF and QMF are not recommended SS techniques due to their high implementation-complexity. MF and QMF demand to detect each orthogonal component of the received complex signals, therefore the basic structure for single tone detection must be replicated to detect each orthogonal component. On the contrary, ED is commonly presented as the employed method provided that the detection criteria only depends on the arrived signal energy, hence the less complex implementation. Therefore, for detecting wideband signals our policy follows the description above excepting for the use of the ED only.

In case of offline scenario, we compute the optimal processing power vector through Theorem 1 above. Then, we compute the maximum total number of processed samples for ED (N_{ED}) by equation (28). Finally, we obtain the maximum value of P_d for a given value of P_{fa} and η by using expression (4). In case of online scenario, we compute the maximum total number of processed samples through the optimal DP algorithm, or sub-optimal Constant or Greedy policies.

To illustrate, let us consider a received complex signal with $\eta = -12$ dB and $P_{fa} = 10^{-8}$. For offline scenario we assume the same energy harvesting values used in Section V-A. In this case, we obtain a maximum detection performance given by $P_d \approx 1$ when evaluating N_{ED}, η and P_{fa} in (4). On the other hand, for online scenario using the same energy distribution than in Section V-B for DP algorithm, Constant and Greedy policies, we obtain values of $P_d \approx 1$, $P_d = 0.9999$ and $P_d = 0.9435$, respectively.

D. Concluding remarks

The implementation of the proposed policy presented above is divided into two major steps. A first step computes the optimal energy values to be used for offline and online scenarios. A second step evaluates the best SS technique (MF, QMF or ED) to have the highest performance in terms of probability of detection subject to a given false alarm condition as illustrated in Tables II and IV for offline and online policies, respectively. The developed method was theoretically addressed by the offline scenario to derive the optimum settings for maximum performance. In this case, a complete description of the arriving energy values is known apriori. However, in a practical context, the receiver operates in a realtime manner, where a current decision must be taken without the prior knowledge of future energy arrival values. In this direction, the online scheme establishes optimal (DP) and suboptimal (Constant Power and Greedy policies) settings to have the best affordable performance.

Although the presented method is illustrated through one pair of PU-SU only, it is also applicable to a multi-channel setting [8], [9]. In this scenario, our policy may be incorporated in a straightforward way to the reported multi-channel solutions to guarantee optimum SoI detection performance. Once the SU decided which channels will be sensed, our policy will provide the optimum detection structure to maximize P_d.

In addition, proposed solution may be easily extended to a cooperative environment, where SUs have the opportunity to operate and share sensing results in an energy-efficient manner [51], [52]. Proposed method may be implemented on each SU to achieve the best local performance when each PU channel is sensed with the harvested energy values. Through this approach, each SU will operate with optimal performance. On the other hand, a new problem formulation may be defined based on a similar objective function but in a global manner; i.e. to consider the contribution of the several SUs to a global probability of detection. In this direction, further investigation plans envisage addressing new formulations to include the mechanisms of cooperative environments.

VI. SIMULATION RESULTS

Simulation results are derived for offline and online scenarios by obtaining curves for P_d vs SNR. We assume same values of constants ξ, μ, υ and $N_{clk_{add}}$ that we have already considered in Section V. However, we obtain these results independently of frequency values available in actual processors to illustrate performance of the proposed policy. In addition, low energy harvesting rate is considered to show policy performance under critical scenarios.

A. Offline processing policy

We consider for offline scenario, an initial energy amount on battery $E_0 = 70$ nJ and a harvested energy vector given by $E = [40, 130, 80]$ nJ, collected at time vector $s = [200, 400, 600]$ μs and maximum processing time $T_p = 800$ μs as depicted in Fig. 2 by using the solid line.

By using the optimal structure given in Theorem 1, we obtain the optimal offline processing power vector $\mathbf{p} = [275, 525]$ μW with time duration $\mathbf{l} = [400, 400]$ μs as depicted in Fig. 2. Then, in order to illustrate the efficiency of the proposed method, a suboptimal policy is developed by the dashed line in Fig. 2, where Theorem 1 is not fulfilled.

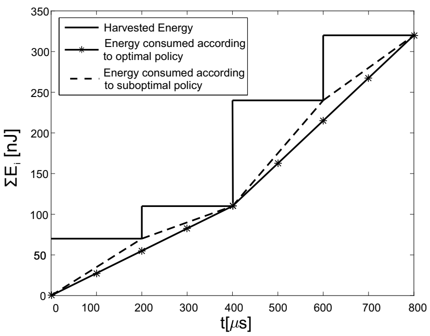
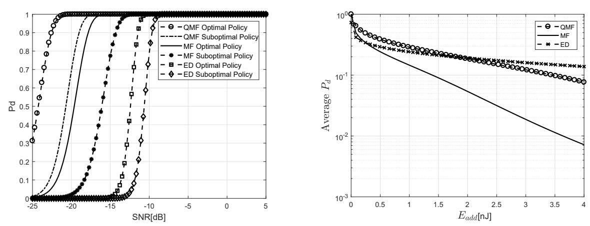


Fig. 2. Processing curve according to optimal and suboptimal policies.



(a) (b)

Fig. 3. Detection performance of the offline processing policy for P_{fa} = 10^{-8}. (a) Probability of detection for different SS techniques over SNR range [-25 5] dB. (b) Performance of different SS techniques for several values of energy consumption on adder operators averaging over SNR range [-25 5] dB.

Performance of optimal and suboptimal policies are described in Fig. 3(a) by obtaining curves of P_d vs SNR by each SS technique. Parameters selected for simulations are P_{fa} = 10^{-8} and SNR range [-25 5] dB according to requirements of common applications such as Digital Television systems [53]. Fig. 3(a) exhibits that proposed optimal processing policy always obtain improved P_d related to the suboptimal policy considered in Fig. 2. In addition, on this scenario QMF results with the highest values of P_d. In this case, the best balance between complexity and performance is provided by the QMF filter, which represents the best option to implement the detection process in comparison to the theoretical optimal MF and the less complex ED scheme.

To analyze the influence of energetic cost on the optimal performance, Fig. 3(b) illustrates average P_d related to a variety of SNR values vs energetic cost of adding operations E_{add}. These results are obtained by using the energetic model described in Section III-A and considering that all harvested energy, given by E = 320 nJ, is spent in SS operations. The obtained curves are derived by evaluating E_s = 320 nJ into equation (14) with the proper μ and υ variables for each SS technique. Then N is computed for several values of E_{add}. Finally, performance metric is obtained as the mean value of P_d, computed by expressions (2) to (4), over the SNR range [-25 5] dB when P_{fa} = 10^{-8}.

Fig. 3(b) shows that QMF performs better except on interval E_{add} > 2 nJ where ED obtains the best P_d values. Additionally, although MF is theoretically the best detector scheme, under higher values of E_{add} superior to 0.245 nJ, the MF detector performs worst than QMF and ED. These results, illustrate the performance of each SS technique for several processor technologies. We remark that QMF does not always perform better than the other SS techniques for higher power consumption processors. Therefore, the proper detection method for a given value of P_{fa} is then based on SNR, energy harvesting profile and processor power consumption.

Based on Fig. 3(b) the best detector scheme to apply when the device is high power consumer is the less complex scheme (given by the ED). This is mainly due to its lower complexity, therefore lower energy consumption, which in turns allows to process much more received samples. On the other hand, when the device has less power consumption, then it is preferable to implement a complex scheme to improve detection performance. In general, to obtain higher detection performance, the selected scheme must be of reduced complexity whenever the device has higher power consumption and viceversa.

B. Online processing policy

In case that causal knowledge of harvesting profile is available, online policies may be developed. Energy harvesting profile is generated with first-order Markov model with two states (h_0 = 0 and h_1 = 6 nJ). We assume transition probabilities q_{00} = 0.8, q_{01} = 0.2, q_{10} = 0.5 and q_{11} = 0.5 to simulate burst arrival case as already presented in Section V. Processing power decisions are restricted to a discrete set of U = $[50, 65, 72, 102, 130, 180, 200]$ μW. Processing time is slotted into 100 slots with 10 μs of interval duration. Achieved processed samples are averaged over 10^4 random realizations, then these values are divided by total number of slots. Fig 4 shows average processed samples per slot achieved with DP, Constant Power and Greedy policy by using common SS techniques.

We note that highest amount of samples is always obtained through optimal online policy given by DP algorithm. We also remark that Constant Power has superior performance than Greedy policy. Constant Power performance increases as total number of slots increases provided that mean value of harvesting rate becomes better estimated for higher number of processing slots. Thus, Constant Power is the proper online policy to apply for large values of total number of slots provided the balance between simplicity of implementation and performance. Additionally, Fig 4 shows that ED is the SS technique that achieved the highest amount of processed samples, provided it is the less computational complex technique.

Fig. 5(a) illustrates curves of P_d vs SNR by each SS technique by using values of P_{fa} = 10^{-8} and SNR range [-25 5] dB. Similar to offline scenario, we note that QMF presents the best performance for each online policy in comparison to another results from MF and ED. This is because QMF balances the trade-off between energy consumption per processed samples and the required number of processed samples to obtain a given value of P_d.

Similarly to Fig 3(b) for offline scenario, Fig 5(b) illustrates average P_d vs energetic cost related to adding operations obtained for Constant Power policy. These curves show that

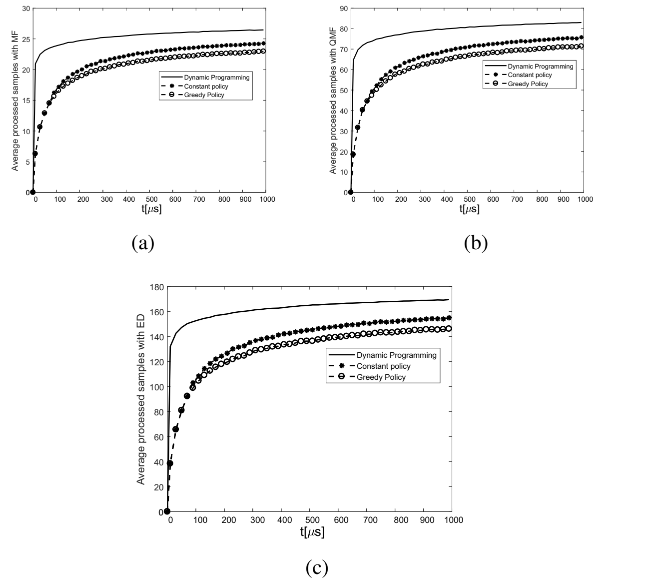


Fig. 4. Average processed samples achieved for different online policies by using: (a) MF; (b) QMF;(c) ED.

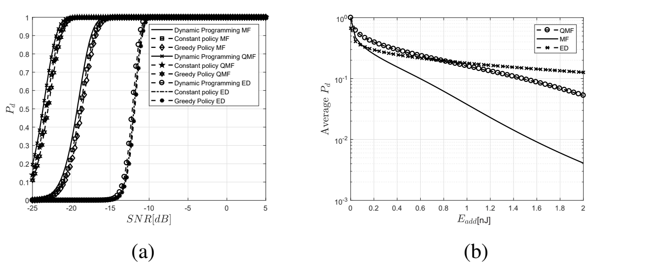


Fig. 5. Detection performance of the online processing policy for $P_{fa} = 10^{-8}$. (a) Probability of detection achieved for different SS techniques over SNR range [-25 5] dB. (b) Performance of different sensing techniques for several values of energy consumption on adder operators obtained for Constant Power policy and averaging over SNR range [-25 5] dB.

QMF does not always present the best results for higher power consumption processors. For instance, values of E_{add} superior to 0.817 nJ implies that ED is the detection scheme that achieves the highest P_d. In addition, similar to the case of offline scenario, the best detection scheme for high power consumption devices will be given by the less complex scheme and viceversa.

C. Discussion on performance

Reported CR-EH policies [2], [10] and [11] employ a constant sensing power during the whole sensing time, which is identified as the major drawback as long as the dynamics of energy harvesting values during the sensing interval is not considered. Above references report similar constant sensing power value of 110 mW in 2 ms time-length interval to achieve a fixed $P_d = 0.9$. This implies an energy consumption value of 220 μJ. By applying ED technique, a $P_{fa} = 0.0011$ is obtained for $\eta = -10$ dB in case of [2], while [10] and [11] report values of $\eta = -15$ dB and $P_{fa} = 0.4630$. However, our offline proposed policy, that employs a lower energy consumption (320 nJ) than in above references in a time-interval of 0.8 ms, obtains an even improved P_d nearly unity value $P_d \approx 1$ when $\eta = -10$ dB and a lower $P_{fa} = 10^{-8}$ as depicted in Fig 3(a). On the other hand, proposed online polices with ED achieve, in 1 ms time-interval, a similar value of $P_d \approx 1$ for same conditions with also a reduced energy consumption value compared to previous references as illustrated in Fig 5(a). Through these comparisons it is pointed out that our policy employs energy more efficiently and therefore obtains higher detection performance. Moreover, the consequence of our higher performance, at the end, will be an increased throughput, compared to previous works.

VII. CONCLUSIONS

In this paper a spectrum sensing policy for offline processing was derived to maximize the probability of detection in a CR system subject to false alarm probability, energy and temporal restrictions on several signal-to-noise ratio values. The proposed policy has two major contributions: provides the optimal processing strategy to maximize processed samples of the received signal and establishes the detection technique with highest energy efficiency. Additionally, optimal online processing policy based on Dynamic Programming is also developed. Two online heuristic policies: Constant Power and Greedy policy are investigated to reduce computational complexity of Dynamic Programming algorithm. Constant Power policy presents a recommended balance between simple implementation and high performance. Future work will be conducted on different directions: to include energetic costs related to acquiring samples in offline policy formulation, to develop a new heuristic policy for online scenarios, and further studies to establish offline and online processing policies in a cooperative cognitive radio scenario.

APPENDIX A
PROOF OF LEMMA 4

Assume that there exist two policies A and B that share the same structure over the duration $[0\ s_{i_{K-1}})$. Policy A will process samples with optimal processing power p_K^* and duration l_K^* until maximum processing time T_p, as suggested in Lemma 4. Then, policy B uses processing power p'_K and duration $l'_K < l_K^*$, which means that the processing time period ends before T_p. Based on Lemma 3, energy consumption up to time instant $s_{i_{K-1}}$ will be equal to the harvested energy value. In addition, Lemma 4 considers that there is no remanent energy at the end of processing time period to maximize N, that is $p_K^* \cdot l_K^* = p'_K \cdot l'_K$. Thus, based on the objective function in (20), we have to proof that the total number of processed samples N with policy A is higher than with policy B, that is: $\frac{l_K^* \cdot \sqrt[3]{p_K^*}}{N_{clk_{add}}} \cdot \xi\mu + \upsilon > \frac{l'_K \cdot \sqrt[3]{p'_K}}{N_{clk_{add}}} \cdot \xi\mu + \upsilon$. After simplifying common terms, this inequality could be rewritten as $\frac{l_K^* \cdot p_K^*}{\sqrt[3]{p_K^{*2}}} > \frac{l'_K \cdot p'_K}{\sqrt[3]{p_K'^2}}$, where the inequality holds based on the fact that the numerator terms are equal in both sides whereas the denominator terms accomplish with the inequality $p'_K > p_K^*$.

Appendix B
Proof of Theorem 1

The optimality of Theorem 1 may be proved by establishing the necessariness and the sufficiency of the described structure. To prove the necessariness, p_k^* must follow the structure given on Lemmas 1 to 4 and we prove this through contradiction similar to [20]. We consider that the optimal policy that satisfies Lemmas 1 to 4, do not follow the statement in Theorem 1. To this end, we assume that there is another policy $\mathbf{p}'$ with same structure than $\mathbf{p}^*$ until time instant $s_{i_{k-1}}$ but with less consumed power $p_k' < p_k^*$ right after $s_{i_{k-1}}$. Then, provided that consumed energy up to $s_{i_{k-1}}$ is equal to the harvested energy, there is not any available energy at $s_{i_{k-1}}$. In addition, $\sum_{n=i_{k-1}}^{i'-1} E_n$ is the available energy up to time $s_{i'}$, which is the next time instant where p_k' changes. If we consider that $s_{i'} < s_{i_k}$, then $p_k^*(s_{i'} - s_{i_{k-1}}) > \sum_{n=i_{k-1}}^{i'-1} E_n$. As a consequence, energy causality constraint is not satisfied and this energy allocation is unfeasible under this policy. On the other hand, if we assume that $s_{i'} > s_{i_k}$, then $p_k^*(s_{i_k} - s_{i_{k-1}}) + p_{k+1}^*(s_{i'} - s_{i_k}) = p_k'(s_{i'} - s_{i_{k-1}})$ provided both policies consume all the harvested energy at time instant $s_{i'}$. Since we assume $p_k' < p_k^*$, then $p_{k+1}^* < p_k' < p_k^*$ is also satisfied. Therefore, Lemma 1 is not satisfied and this policy can not be optimal.

Then we consider a processing power policy $\mathbf{p}^*$ with time duration vector $\mathbf{l}^*$ that satisfies the structure given by Theorem 1 to prove the sufficient condition of optimality. We prove this through contradiction assuming there is another policy $\mathbf{p}'$ and time duration vector $\mathbf{l}'$ by which the total number of processed samples N' is higher. Considering the same structure for the new policy as $\mathbf{p}^*$ until time instant $s_{i_{k-1}}$ and same deadline T_p, then $p_k' > p_k^*$ for two possible cases: $l_k' > l_k^*$ and $l_k' < l_k^*$. In addition, based on Lemma 3 then $\sum_{n=i_{k-1}}^{i_k} E_n = p_k^* l_k^*$. Considering the case $l_k' > l_k^*$, then $\sum_{n=i_{k-1}}^{i_k} E_n < p_k' l_k'$ provided $p_k' > p_k^*$, therefore the energy causality constraint is not satisfied. On the other hand, assuming the second possibility $l_k' < l_k^*$ then $p_k^* < p_k' < p_{k+1}'$ (based on Lemma 1) and energy causality constraint is also not satisfied $\left(\sum_{n=i_{k-1}}^{i_k} E_n < p_k' l_k' + p_{k+1}' l_{k+1}'\right)$. Thus, the new assumed policy $\mathbf{p}'$ with time duration $\mathbf{l}'$ is infeasible and not optimal. Summarizing, the policy described by Theorem 1 is optimal if and only if it has the given structure.

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