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Periodic Spectrum Sensing with Non-Continuous Primary User Transmissions

Andrea Mariani, *Member, IEEE*, Sithamparanathan Kandeepan, *Senior Member, IEEE*, and Andrea Giorgetti, *Senior Member, IEEE*

***Abstract*—In this paper we present a thorough study of spectrum sensing performance in cognitive radio (CR) scenarios where the primary user (PU) transmission is not continuous. In particular, we consider a sensing scheme in which the spectrum is monitored periodically for a fraction of time. In such a situation, sensing is affected by common detection impairments, including noise and fading, as well as by the PU temporal behavior. It is thus necessary to properly design periodic sensing parameters to balance between sensing overhead and detection performance. In this context, we derive a comprehensive analytical framework which accounts for detector performance, presence of noise and fading, PU temporal statistics and periodic sensing. The analysis allows to express the detection and false alarm probabilities in closed-forms to capture an explicit relationship between the PU temporal statistic and periodic sensing parameters. Our results show that the temporal behavior of the PU have a significant impact on the detection performance, and therefore a proper design of the sensing parameters is important. Based on our analysis we propose useful strategies to design effective periodic sensing.**

***Index Terms*—Cognitive radio, detection, periodic sensing, spectral occupancy, spectrum sensing.**

I. Introduction

THE SPECTRUM is a limited resource, and the ever growing demand for frequency bands has brought about the problems related to its shortage. Recent studies have emphasized that the real problem does not lie in the scarcity of resources available, but rather in the fact that they are poorly managed [1]. These considerations have lead to the development and evolution of the concept of cognitive radio (CR), further supported by the radio regulatory bodies around the world [1]–[3]. A CR device, by intelligently sensing and learning from the radio environment, uses spectrum opportunities as a secondary user (SU) whilst giving higher priority to the primary users (PUs) of the spectrum.

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Spectrum sensing is one of the key functionalities for opportunistic spectrum access, extensively studied in the recent literature [3]–[12]. Many spectrum sensing algorithms have been proposed, starting from most simple approaches, such as the energy detector (ED), that estimates the received signal energy and compares it to a decision threshold [1], [4], [5]. The unique impairment of the ED is that it requires the estimation of noise power level (see [5] for further details). If some features of the PU signal to be detected are known, they can be used for detection purposes, implementing algorithms such as correlation-based detection or cyclostationary detectors [1]. Other algorithms exploit diversity strategies, such as multiple antennas or cooperation among different nodes. In this context, the most popular approaches are based on the observation of the eigenvalues of the sample covariance matrix [6], [7]. For a more complete overview on spectrum sensing algorithms refer to [8] and [3, Chapter 1].

Considering the spectral occupancy in the time domain, there are mainly two scenarios that may be considered. The first one is in presence of continuous PU transmissions, such as television broadcasting in TV white spaces, or non continuous transmissions with high occupancy rates [32]. In these contexts the SU typically senses the spectrum in order to discover spectrum opportunities in the space and frequency domains. A different situation occurs in presence of non-continuous PU transmissions with a low occupancy rate such as wireless microphones, voice-based services in cellular systems, or packet-based wireless communications. In these cases, the variability of spectrum occupancy in time motivates the search for temporal spectrum holes [13]–[15]. To cope with non-continuous transmissions, periodic spectrum sensing has been proposed and investigated in specific contexts. Spectrum occupancy estimation in time-domain has been first analyzed in [16] using an asymptotical approach. The sensing requirements and the detection performance with periodic frequency scanning have been derived in [17], and in [18] the authors study scheduling for periodic sensing and the differences between the energy and feature based techniques. In [19] periodic sensing has been proposed in the practical context of the IEEE 802.22 standard with $1\,\mathrm{ms}$ sensing duration every $40\,\mathrm{ms}$. In [15] the problem of temporal spectrum holes discovery has been studied addressing the problem of learning the PU channel usage pattern, but assuming a sensing process with zero error probability. However, a comprehensive and systematic analysis of periodic sensing has not been addressed thoroughly.

In this paper, we formulate a general framework for temporal spectrum sensing, including PU non-continuous transmis-

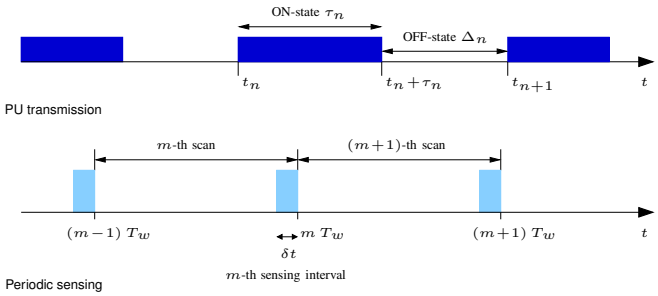

Fig. 1. Primary user temporal behavior and periodic spectrum sensing by the CR.

sions, periodic sensing, noise, and fading. In particular, the contributions of the paper are as follows.

- We provide general expressions of the temporal detection and false alarm probabilities that capture the explicit relationship between detector performance, noise effect, fading impact, PU temporal statistic and periodic sensing parameters.
- The analysis extends previously proposed studies, providing a formulation that can be applied to different detection algorithms and different PU temporal statistics.
- To investigate different scenarios, we derive the performance of three sensing tasks corresponding to the detection of a specific PU transmission, the detection of the PU using a single observation, and using multiple scans.
- The case in which sensing is based on ED and the PU is characterized by exponential inter-arrival and hold-time distributions is discussed in detail providing closed-form expressions for the probabilities of temporal detection and false alarm.

Our results show that the temporal statistic of the PU has a significant impact on the detection performance, and therefore a proper design of periodic sensing parameters is crucial. Finally, based on our analysis, we propose useful strategies to design effective periodic sensing in the CR context.

The rest of the paper is organized as follows. In Section II we present the temporal sensing framework providing general forms of the detection metrics. In Section III we analyze the case in which ED is adopted in presence of a PU with exponential distributed arrival time. In Sections IV and V we analyze periodic sensing based on the temporal statistic of the PU for constant and random hold-time cases, while in Section VI we present the design strategies, based on the periodic sensing framework proposed, and some numerical results. Finally, in Section VII we draw some concluding remarks.

II. Temporal Sensing Framework

In this section, we present the system model considered for the analysis of periodic sensing in the presence of non-continuous PU transmissions, and the definition of the detection metrics adopted. The PU temporal behavior is statistically modeled as a stationary ON-OFF random process with two states, where the ON state represents the PU transmission and the OFF state represents the PU inactivity. The ON and OFF period durations are denoted with τ_n and Δ_n, respectively, with $n \in \mathbb{N}$. Fig. 1 depicts an example of temporal scenario with non-continuous PU transmission, where the SU asynchronously observes the channel within *sensing intervals* of duration δt. We refer to the period between the ending of two consecutive sensing intervals, with duration T_w, as the *sensing scan*.

A. Periodic Spectrum Sensing

The temporal spectrum sensing performance can be studied starting from the definition of three temporal sensing tasks (TSTs):

- TST-nm: detect the nth PU transmission within the mth sensing scan;
- TST-S: detect any PU transmission within a single scan;
- TST-M: detect any PU transmission using multiple scans.

The first TST can be adopted for the design of the periodic sensing parameters, and for quantifying the impact of periodic sensing in terms of latency of the detection process, as described in Section VI. Moreover, the TST-nm represents an elementary task useful for the study of the latter two. The TST-S aims at quantifying the overall sensing capability to detect a PU within a single sensing scan. On the basis of this single observation the SU decides which behavior to adopt, such as, e.g., whether to transmit, and how to plan future actions, such as sensing intervals scheduling.[1] Another relevant scenario is represented by the situation in which the SU is interested in knowing if a PU is present to avoid using the channel for a relatively long period (band dropping) [1]. The SU performs sensing in different channels allocating different sensing periods within the same scan in time-division, but instead of making a decision at the end of each sensing interval, consecutive M scans can be monitored and a unique decision is made at the end. This situation is represented by TST-M, where an higher detection probability is expected and specific design rules are presented in the next sections. Note that TST-S and TST-M can be also combined in such a way that a first decision on whether to use a channel or not can be performed with TST-M and then, on a scan-by-scan basis, the selected channel can be monitored with TST-S. We remark that TST-S and TST-M directly provide a decision on the occupancy state of the channel, while TST-nm is useful for the analysis of periodic sensing and to derive a design strategy that accounts for detection latency.

Considering the presence of non-continuous PU transmissions, the sensing process is affected by the fact that PU transmissions are not always overlapped with the sensing intervals. Thus, for studying this temporal sensing problem, it is useful to define two events, $\mathcal{S}$ and $\mathcal{T}$, associated to a PU transmission:[2]

[1] Within the paper, we do not make assumptions on the SU behavior outside the sensing intervals. The time between two sensing intervals could be used, e.g., for transmitting SU data when the channel has been declared free, or, alternatively, to sense other channels.

[2] In the following, we use the notations $\overline{\mathcal{S}}$ and $\overline{\mathcal{T}}$ to denote the corresponding complementary events.

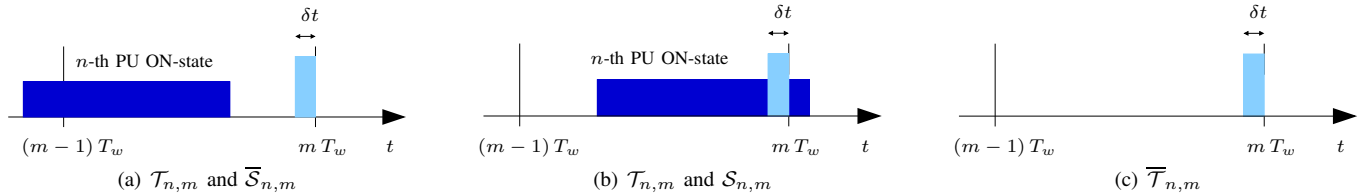

Fig. 2. Temporal events related to the temporal sensing tasks.

- $\mathcal{S}$: the PU transmission is overlapped with a sensing interval;
- $\mathcal{T}$: the PU transmission is in a scan period.

In particular, with reference to the TSTs defined above, we adopt the notation:

- $\mathcal{S}_{n,m}$ and $\mathcal{T}_{n,m}$, for the TST-nm, to indicate the presence of the nth PU transmission within the mth sensing interval, and the presence of the nth PU transmission within the mth sensing scan, respectively;
- $\mathcal{S}_m$ and $\mathcal{T}_m$, for the TST-S, to indicate the presence of at least one PU transmission within the mth sensing interval, and the presence of at least one PU transmission within the mth sensing scan, respectively;
- $\mathcal{S}_M$ and $\mathcal{T}_M$, for the TST-M, to indicate the presence of at least one PU transmission within M sensing intervals, and the presence of at least one PU transmission within M sensing scans, respectively.

Throughout the paper we use the notation $\mathcal{S}$ and $\mathcal{T}$ to indicate either $\mathcal{S}_{n,m}$ and $\mathcal{T}_{n,m}$, or $\mathcal{S}_m$ and $\mathcal{T}_m$, or $\mathcal{S}_M$ and $\mathcal{T}_M$, to maintain a general approach and avoid repetitions, and we specialize the analysis using the specific symbols, when necessary. A graphical representation of the possible events for TST-nm is provided in Fig. 2.

In analyzing the periodic sensing it is useful to consider two situations: a *transient phase* and a *steady-state regime*. The transient phase occurs when the SU starts monitoring the channel and consists in a situation in which the detection performance strongly depends on the sensing interval index m, while in the steady-state regime the detection performance is constant in time.

B. Detection Metrics

In this section, we discuss temporal sensing in a general framework, defining proper performance metrics. In the following sections, we explicitly calculate the detection performance in a specific case.

Signal detection is affected by noise, channel impairments and also by the non-continuous transmission of the PU. It is thus useful to separate their effects to better understand their impact on detection performance and to derive a general framework which accounts for PU temporal behavior and periodic sensing parameters. In light of this approach, we define two metrics namely, temporal sensing probability and temporal detection probability.

Let us define the *temporal sensing probability* as $P_{\text{TS}} = \mathbb{P}\{\mathcal{S}|\mathcal{T}\}$, which can be rewritten, using Bayes' theorem, as $P_{\text{TS}} = \mathbb{P}\{\mathcal{S}\cap\mathcal{T}\}/\mathbb{P}\{\mathcal{T}\}$. Given that $\mathcal{S}\subset\mathcal{T}$, such probability can be expressed as [20]

$$P_{\text{TS}} = \frac{\mathbb{P}\{\mathcal{S}\}}{\mathbb{P}\{\mathcal{T}\}}. \tag{1}$$

As can be seen, P_{TS} only accounts for periodic sensing and non-continuous transmission of the PU, not including the detection process in the presence of noise and channel impairments.[3]

In the presence of noise, considering a general detector characterized by a decision statistic Λ and a threshold ξ, the detection of a PU may occur in two cases: either because there is an overlap between the PU transmission and the sensing period with a correct detection (i.e., the event $\Lambda > \xi|\mathcal{S}$) or because there is a false alarm with no overlap between the PU transmission and the sensing period (i.e., the event $\Lambda > \xi|\overline{\mathcal{S}}$). Accordingly, we define the *temporal detection probability* as

$$\begin{aligned} P_{\text{TD}} &= \mathbb{P}\{\Lambda > \xi|\mathcal{T}\} = \\ &\quad \mathbb{P}\{\Lambda > \xi|\mathcal{S}\}\,\mathbb{P}\{\mathcal{S}|\mathcal{T}\} + \mathbb{P}\left\{\Lambda > \xi|\overline{\mathcal{S}}\right\}\mathbb{P}\left\{\overline{\mathcal{S}}|\mathcal{T}\right\} \\ &= P_{\text{D}}\,\mathbb{P}\{\mathcal{S}\}/\mathbb{P}\{\mathcal{T}\} + P_{\text{FA}}\left(1-\mathbb{P}\{\mathcal{S}\}/\mathbb{P}\{\mathcal{T}\}\right) \quad \text{(2a)} \\ &= P_{\text{D}}\,P_{\text{TS}} + P_{\text{FA}}\left(1-P_{\text{TS}}\right) \quad \text{(2b)} \end{aligned}$$

where $\mathbb{P}\{\Lambda > \xi|\mathcal{S}\}$ and $\mathbb{P}\left\{\Lambda > \xi|\overline{\mathcal{S}}\right\}$ are, respectively, the conventional probability of detection and probability of false alarm of the specific detector considered.[4] The above definition of temporal detection incorporates both periodic sensing and detection, and is by no means in conflict to the usual definition of detection probability, where the event $\overline{\mathcal{T}}$ corresponds to the null hypothesis and $\mathcal{T}$ to the alternative hypothesis [29]. Note that this is the main difference between simple detection and temporal detection; the former wants to infer the occupancy state in the observed interval given that there is a transmission in that interval, while the latter wants to infer the occupancy state accounting for the non-continuous nature of PU transmissions within a sensing scan.

If the PU transmission is continuous, then $P_{\text{TS}} = 1$ and P_{TD} reduces to the detection probability, i.e., $P_{\text{TD}} = P_{\text{D}}$.[5] On the other hand, when the detection probability is $P_{\text{D}} = 1$ and the false alarm probability is $P_{\text{FA}} = 0$ (a condition that can be approached for high signal-to-noise ratios (SNRs)) P_{TD} in (2) reduces to P_{TS}. Hence, temporal sensing probability can be interpreted as an asymptotic performance in the high

[3]Such metric can be interpreted as the overlap probability among the sensing periods and the PU transmissions.

[4]Also note that the events $\mathcal{S}$ and $\overline{\mathcal{S}}$ are often denoted as $\mathcal{H}_1$ and $\mathcal{H}_0$, respectively.

[5]This fact implies that the sensing scan duration, T_w, does no longer play any role, and periodic sensing looses its significance.

SNR regime. This fact is intuitive, since when noise can be neglected, the performance depends only on the PU temporal behavior and periodic sensing parameters. Also note that in (2) noise and temporal overlap are clearly separated. This aspect is useful to understand temporal sensing dependence on PU temporal behavior and to design periodic sensing parameters, as discussed in the next sections.

Since $\overline{\mathcal{T}} \subset \overline{\mathcal{S}}$, the probability of false alarm in the presence of non-continuous PU transmission can be written as

$$P_{\text{FA}} = \mathbb{P}\left\{\Lambda > \xi | \overline{\mathcal{T}}\right\} = \mathbb{P}\left\{\Lambda > \xi | \overline{\mathcal{S}}\right\} \tag{3}$$

which corresponds to the usual definition.

The detection probability over M scans depends on how we combine the information collected from the M sensing intervals. There are several data fusion strategies that can be used, generally classified as *hard fusion* schemes, that combine the results of hypothesis tests applied to each sensing interval, and *soft fusion* techniques, that combine the observations of different sensing intervals and use a global detection test.

Considering hard combining strategies, we adopt the OR rule, in which the CR decides for the presence of the PU if it is detected in any of the M sensing intervals.[6] The probability of detecting at least one transmission, given that at least one has occurred in the M scans, can be written as

$$P_{\text{TD}}^{\text{FU}} = \mathbb{P}\left\{ \left(\bigcup_{m \in \Omega_M} \{\Lambda_m > \xi\} \right) \neq \emptyset \,\middle|\, \mathcal{T}_M \right\} \tag{4}$$

where Λ_m is the test statistic in the mth sensing interval and Ω_M is set of the indexes of M consecutive sensing periods. Such expression can be simplified assuming the independence among different sensing periods, which is verified in particular when τ is small with respect to T_w.[7] Due to the independence assumption, $P_{\text{TD}}^{\text{FU}}$ can be expressed as

$$P_{\text{TD}}^{\text{FU}} = 1 - \prod_{m \in \Omega_M} \left(1 - \mathbb{P}\left\{\Lambda_m > \xi | \mathcal{T}_M\right\}\right) \tag{5}$$

where the inner term $\mathbb{P}\left\{\Lambda_m > \xi | \mathcal{T}_M\right\}$ can be expanded similarly to (2) as

$$\mathbb{P}\left\{\Lambda_m > \xi | \mathcal{T}_M\right\} = P_{\text{D}}\, \mathbb{P}\left\{\mathcal{S}_m | \mathcal{T}_M\right\} + P_{\text{FA}}\left(1 - \mathbb{P}\left\{\mathcal{S}_m | \mathcal{T}_M\right\}\right). \tag{6}$$

Now, let us denote with $P_{\text{S}}(m) = \mathbb{P}\left\{\mathcal{S}_m\right\}$ the probability of an overlap between a PU transmission and the mth sensing interval, and with $P_{\text{T}}^{\text{M}} = \mathbb{P}\left\{\mathcal{T}_M\right\}$ the probability of at least one transmission within the M scans. Considering that $\mathcal{S}_m \subset \mathcal{T}_M$, $\mathbb{P}\left\{\mathcal{S}_m | \mathcal{T}_M\right\} = \mathbb{P}\left\{\mathcal{S}_m\right\} / \mathbb{P}\left\{\mathcal{T}_M\right\}$ and the temporal detection probability (5) can be finally written in closed-form as

$$P_{\text{TD}}^{\text{FU}} = 1 - \prod_{m \in \Omega_M} \left(1 - P_{\text{D}} \frac{P_{\text{S}}(m)}{P_{\text{T}}^{\text{M}}} - P_{\text{FA}}\left(1 - \frac{P_{\text{S}}(m)}{P_{\text{T}}^{\text{M}}}\right)\right). \tag{7}$$

[6]We choose the OR rule because it is the most conservative from the PU protection perspective [1].

[7]As shown in Section VI, such approximation gives very good results compared with simulations.

Considering the high SNR regime, the temporal sensing probability can be derived from (7) as

$$P_{\text{TS}}^{\text{FU}} = \mathbb{P}\left\{\mathcal{S}_M | \mathcal{T}_M\right\} = 1 - \prod_{m \in \Omega_M} \left(1 - \frac{P_{\text{S}}(m)}{P_{\text{T}}^{\text{M}}}\right). \tag{8}$$

According to (3), the false alarm probability is not affected by the PU temporal behavior, hence considering the OR-based fusion rule we have

$$P_{\text{FA}}^{\text{FU}} = 1 - \left(1 - P_{\text{FA}}\right)^M. \tag{9}$$

Considering the soft fusion schemes, the hypothesis test Λ_{SF} for the TST-M depends on the number of overlaps between the PU transmissions and the sensing intervals, denoted in the following as K. Thus the temporal detection probability for Λ_{SF} can be expressed as

$$P_{\text{TD}}^{\text{FU}} = \mathbb{P}\left\{\Lambda_{\text{SF}} > \xi | \mathcal{T}\right\} = \sum_{k=0}^{M} p_k\, \mathbb{P}\left\{\Lambda_{\text{SF}} > \xi | K = k\right\} \tag{10}$$

where ξ is the decision threshold and $p_k = \mathbb{P}\left\{K = k\right\}$, as explained in Section III-B, is related to the temporal sensing probability. In fact, in the high SNR regime, Λ_{SF} is above the threshold when $K > 0$, and thus from (10) we obtain the corresponding temporal sensing probability $P_{\text{TS}}^{\text{FU}} = \sum_{k=1}^{M} p_k$. The false alarm probability for the soft fusion schemes is given by $P_{\text{FA}}^{\text{FU}} = \mathbb{P}\left\{\Lambda_{\text{SF}} > \xi | \overline{\mathcal{T}}\right\}$. In the next section, we discuss in detail the case where soft fusion is performed by equal gain combining (EGC) with energy detection.

III. Temporal Detection Probability with Noise, Fading and Non-continuous PU Transmission

The temporal sensing framework described in the previous section can be used in different practical case studies, by defining the PU ON-OFF statistics, the detector adopted and the fading model. Note that these aspects have different effects on the temporal detection metric. The PU temporal behavior, indeed, affects the temporal sensing probabilities (P_{TS}, $\mathbb{P}\left\{\mathcal{S}\right\}$, and $\mathbb{P}\left\{\mathcal{T}\right\}$), while the choice of the detector used and the fading model impacts P_{D} and P_{FA}. In this section, we consider the case study in which ED is adopted in presence of a PU with exponential arrival time.

Let us model the OFF-periods duration Δ_n as exponentially distributed random variables (r.v.s) with mean $\mathbb{E}\left\{\Delta_n\right\} = \bar{\Delta} = 1/\lambda$, where λ is the vacancy rate. For the ON-periods we analyze two situations: 1) the constant hold-time case where the occupancy times τ_n are deterministic and equal, i.e., $\tau_n = \tau$; and 2) the random hold-time case where the occupancy times τ_n are exponentially distributed r.v.s with mean $\mathbb{E}\left\{\tau_n\right\} = \bar{\tau} = 1/\mu$, where μ is the occupancy rate. Such statistical description has been widely adopted to model spectrum holes such as in [15], [20]–[27], also confirmed by spectrum occupancy measurements in [27] and by monitored HSDPA traffic in [28].

Although the temporal sensing analysis can consider, in principle, any type of detection technique, we focus our attention on the ED-based spectrum sensing. This choice is motivated by the fact that ED is the reference detector adopted in CR literature due to its simplicity and the fact that it does

not require a priori knowledge of the PU signal characteristics [1], [4], [5].

After bandpass filtering over a bandwidth W, the received signal $r(t)$, observed for δt seconds, is down converted and sampled at frequency W, obtaining $N_{\rm s} = \delta t\, W$ complex samples $\{y_j\}_{j=0}^{N_{\rm s}-1}$.[8] Hence, in the following we analyze the discrete time detection problem

$$\begin{array}{ll} \overline{\mathcal{S}}: & y_j = n_j \\ \mathcal{S}: & y_j = x_j + n_j \end{array} \tag{11}$$

with $j = 0, \ldots, N_{\rm s} - 1$, where $\{x_j\}_{j=0}^{N_{\rm s}-1}$ are the signal samples and $\{n_j\}_{j=0}^{N_{\rm s}-1}$ is a set of independent, identically distributed (i.i.d.) circularly symmetric complex Gaussian r.v.s with zero mean and variance $2\sigma^2$, representing the additive white Gaussian noise (AWGN). The test statistic for the ED is given by [4]

$$\Lambda = \frac{1}{2\sigma^2 N_{\rm s}} \sum_{j=0}^{N_{\rm s}-1} |y_j|^2 \underset{\overline{\mathcal{S}}}{\overset{\mathcal{S}}{\gtrless}} \xi \tag{12}$$

where the SNR in the hypothesis $\mathcal{S}$ is defined as $\rho = 1/\left(2\sigma^2 N_{\rm s}\right) \sum_{j=0}^{N_{\rm s}-1} |x_j|^2$, and ξ is the decision threshold.

Considering the AWGN scenario, it is well known that the test statistic (12) follows a chi squared distribution with $2\,N_{\rm s}$ degrees of freedom and thus we have [4][9]

$$P_{\rm D}(\rho) = \mathbb{P}\left\{\Lambda > \xi | \mathcal{S}\right\} = \mathcal{Q}_{N_{\rm s}}\left(\sqrt{2N_{\rm s}\,\rho}, \sqrt{2N_{\rm s}\xi}\right) \tag{13}$$

$$P_{\rm FA} = \mathbb{P}\left\{\Lambda > \xi | \overline{\mathcal{S}}\right\} = \widetilde{\Gamma}\left(N_{\rm s}, N_{\rm s}\xi\right) \tag{14}$$

where $\mathcal{Q}_\alpha(a,b) = \int_b^\infty u^\alpha \exp(-(u^2 + a^2)/2)\mathcal{I}_{\alpha-1}(au)/a^{\alpha-1} du$ is the generalised Marcum Q function with $\mathcal{I}_{\alpha-1}(\cdot)$ being the modified Bessel function of first kind with order $\alpha - 1$, and $\widetilde{\Gamma}(a,z) \triangleq \frac{1}{\Gamma(a)} \int_z^\infty x^{a-1} \exp\left(-x\right) dx$ is the regularized upper incomplete Gamma function with $\Gamma\left(\cdot\right)$ the Gamma function. When the PU signal is subject to slow fading, the SNR can be modelled by its probability density function (p.d.f.) $f_\rho(\cdot|\overline{\rho})$ with mean value $\overline{\rho} = \mathbb{E}\left\{\rho\right\}$. Therefore, the average detection probability can be computed as[10]

$$\widetilde{P}_{\rm D}(\overline{\rho}) = \int_0^\infty P_{\rm D}(h)\, f_\rho(h|\overline{\rho})\, dh. \tag{15}$$

In Section VI we consider the Rayleigh fading case where the corresponding detection probability can be found in closed-form in [36, eq. (9)]. Similar expressions for Rice and Nakagami fading can be found in [36].

[8]Without loss of generality we consider $\delta t\, W$ integer [4].

[9]Because of the PU temporal behavior, the hypothesis $\mathcal{S}$ does not necessarily imply that the PU transmission is completely overlapped with the sensing interval. Thus, in general, the energy captured by the ED is a r.v. that depends on the amount of temporal overlap [32], [33]. However, since our interest is in finding temporal spectrum holes with good temporal resolution, it is reasonable to consider δt sufficiently small with respect to the PU transmission duration. In this case, partial overlap can be neglected and the analysis can be simplified considering, either total overlap or no overlap, respectively. This approximation leads to a tractable performance analysis that matches very well with numerical results.

[10]The same approach can also be considered to account for shadow fading.

TABLE I
EVALUATION OF $P_{\rm TD}$ FOR TST-nm BASED ON (2a).

	TST-nm	
	const. τ	random τ
$\mathbb{P}\left\{\mathcal{S}\right\}$	(23)	(38)
$\mathbb{P}\left\{\mathcal{T}\right\}$	(24)	(39)
$P_{\rm D}$	(13) or (15)	
$P_{\rm FA}$	(14)	

TABLE II
EVALUATION OF $P_{\rm TD}$ FOR TST-S BASED ON (2a).

	TST-S	
	const. τ	random τ
$\mathbb{P}\left\{\mathcal{S}\right\}$	(26), (29)	(40), (42)
$\mathbb{P}\left\{\mathcal{T}\right\}$	(27), (28), (30)	(41), (28), (43)
$P_{\rm D}$	(13) or (15)	
$P_{\rm FA}$	(14)	

A. Temporal Detection over a Single Scan

The temporal detection probability for the sensing tasks TST-nm and TST-S can be derived from (2a) inserting the expressions of the probability of detection corresponding to the AWGN or fading scenario, i.e. (13) or (15), respectively, and the specific probabilities $\mathbb{P}\left\{\mathcal{S}\right\}$ and $\mathbb{P}\left\{\mathcal{T}\right\}$ related to the TST studied and the PU transmission statistic. Closed-form expressions of $\mathbb{P}\left\{\mathcal{S}_{n,m}\right\}$ and $\mathbb{P}\left\{\mathcal{T}_{n,m}\right\}$ for TST-nm and expressions for $\mathbb{P}\left\{\mathcal{S}_m\right\}$ and $\mathbb{P}\left\{\mathcal{T}_m\right\}$ for TST-S, are given in Section IV and V for the constant and random ON-period duration cases, respectively, considering both the transient phase and the steady-state regime. Tables I and II summarize the proper equations to be adopted in (2a) for the evaluation of the temporal detection probability.

B. Temporal Detection over Multiple Scans

In this section, we describe the temporal detection probability for the TST-M case, considering the OR rule for hard fusion and the EGC for soft fusion.

When the OR rule is applied, the temporal detection probability can be computed from (7) using the proper $P_{\rm D}$ (corresponding to the AWGN or fading case) and the closed-form expressions of $P_{\rm S}(m)$ and $P_{\rm T}^{\rm M}$ that are presented in Section IV and V for the constant and random ON-period duration case, respectively.[11] For convenience, in Table III we recap the equations to be adopted for TST-M with the OR rule.

For the soft fusion with EGC, we proceed, similarly to (11), denoting the received samples in the mth sensing slot as $y_{j,m} = x_{j,m} + n_{j,m}$, described by a complex Gaussian r.v. with mean $x_{j,m}$ and variance $2\sigma^2$. Note that in the $\overline{\mathcal{S}}$ hypothesis, i.e., when the PU transmission is not overlapped with the sensing interval, we have $x_{j,m} = 0$ and thus $y_{j,m}$ has zero mean. With EGC, the decision statistic $\Lambda_{\rm SF}$ is given by

$$\Lambda_{\rm EGC} = \sum_{m \in \Omega_m} \sum_{j=1}^{N_s} \frac{1}{2\sigma^2\, N_s} \left|y_{j,m}\right|^2. \tag{16}$$

[11]Note that, adopting (15) in (7), we are implicitly assuming that the channel fading is constant among the different scans.

TABLE III
EVALUATION OF $P_{\text{TD}}^{\text{FU}}$ FOR THE OR FUSION RULE WITH ED, BASED ON (7).

	TST-M for ED-OR	
	const. τ	random τ
$\mathbb{P}\{\mathcal{S}\}$	(26), (29)	(40), (42)
$\mathbb{P}\{\mathcal{T}\}$	(31), (33), (32)	(44), (33), (45)
P_{D}	(13) or (15)	
P_{FA}	(14)	

TABLE IV
EVALUATION OF $P_{\text{TD}}^{\text{FU}}$ FOR THE EGC FUSION RULE WITH ED, BASED ON (10).

	TST-M for ED-EGC	
	const. τ	random τ
$\mathbb{P}\{\mathcal{S}\}$	(29)	(42)
$\mathbb{P}\{\mathcal{T}\}$	(33), (32)	(33), (45)
$\mathbb{P}\{\Lambda_{\text{SF}} > \xi \vert K = k\}$	(17)	

Note that (16) is chi squared distributed with $2\,N_s\,M$ degrees of freedom and non centrality parameter $\lambda_{\text{EGC}} = K\rho$.[12] Thus for the ED-EGC strategy in AWGN the probability $\mathbb{P}\{\Lambda_{\text{SF}} > \xi | K = k\}$ in (10) becomes

$$\mathbb{P}\{\Lambda_{\text{EGC}} > \xi | K = k\} = \mathcal{Q}_{N_{\text{s}}\,M}\left(\sqrt{2N_{\text{s}}\,K\,\rho}, \sqrt{2N_{\text{s}}\xi}\right) \quad (17)$$

where ξ is the decision threshold. Note that, in the steady-state regime, the probability of overlap among PU transmissions and sensing intervals is constant $\forall m \in \Omega_{\text{M}}$, and thus K follows a binomial distribution. Therefore, we have $p_k = \binom{M}{k} p^k (1-p)^{M-k}$ with $p = P_{\text{S}}/P_{\text{T}}^{\text{M}}$, where the equations for P_{S} and P_{T}^{M} can be obtained from Table IV. In case in which fading is considered, the average probability of detection can be computed, similarly to (15), averaging (17) with respect to the p.d.f. of ρ. When the PU is inactive, Λ_{EGC} is a central chi squared distributed r.v. with $2\,N_s\,M$ degrees of freedom, and therefore the probability of false alarm can be written as

$$P_{\text{FA}}^{\text{FU}} = \widetilde{\Gamma}\left(MN_{\text{s}}, MN_{\text{s}}\xi\right). \quad (18)$$

IV. TEMPORAL SENSING PROBABILITY WITH RANDOM ARRIVAL AND CONSTANT HOLD-TIME

In the previous section we derived the temporal detection probabilities for TST-mn, TST-S, and TST-M. All the closed-form expressions obtained require the evaluation of the temporal sensing probabilities which depend on the PU temporal behavior and periodic sensing parameters. In this section, we calculate such probabilities when the PU has a temporal behavior characterized by a constant hold-time τ.

In this case, the nth transmission from the PU occurs at time t_n given by

$$t_n = t_0 + \sum_{i=1}^{n} \Delta_i + (n-1)\tau, \qquad n \in \mathbb{N} \quad (19)$$

where t_0 is an arbitrary time instant when the CR node starts to sense the spectrum, and assumed to be zero hereafter, without loss of generality. Since Δ_i are exponentially i.i.d. with parameter λ, the term $G_n = \sum_{i=1}^{n} \Delta_i$ follows an Erlang distribution, denoted hereafter as $G_n \sim \text{Erlang}(n, \lambda)$, with p.d.f. [30]

$$f_{G_n}(x) = \frac{\lambda^n x^{n-1} \exp(-\lambda x)}{\Gamma(n)}\, u(x) \quad (20)$$

where $u(x)$ is the unit step function, and the gamma function with integer parameter is $\Gamma(n) = (n-1)!$. The start time for the nth transmission is then given by $t_n = G_n + (n-1)\tau$, and the corresponding p.d.f. is $f_{t_n}(x) = f_{G_n}(x - (n-1)\tau)$, i.e.,

$$f_{t_n}(x) = \frac{\lambda^n (x-(n-1)\tau)^{n-1}}{\Gamma(n)}\, e^{-\lambda(x-(n-1)\tau)}\, u(x-(n-1)\tau). \quad (21)$$

From (21) the cumulative distribution function (c.d.f.) of t_n is given by

$$F_{t_n}(x) = \bar{\gamma}(n, \lambda(x - (n-1)\tau)) \quad (22)$$

where $\bar{\gamma}(a, z) \triangleq \gamma(a, z)\, u(z)$, and $\gamma(a, z) = \frac{1}{\Gamma(a)} \int_0^z t^{a-1} \exp(-t) dt$ is the incomplete gamma function.

A. Probability of Sensing the nth Transmission During the mth Scan

With a constant ON-period duration τ, the SU senses the PU in the mth scan if a PU transmission time falls within the interval $[mT_w - \delta t - \tau,\ mT_w)$. Hence, the probability corresponding to the event $\mathcal{S}_{n,m}$ is $P_{\text{S}}^{(n)}(m) = \mathbb{P}\{\mathcal{S}_{n,m}\} = \mathbb{P}\{mT_w - \delta t - \tau \le t_n < mT_w\}$, and can be expressed in closed-form by (22) as

$$\begin{aligned} P_{\text{S}}^{(n)}(m) = {} & \bar{\gamma}(n, \lambda(mT_w - (n-1)\tau)) \\ & - \bar{\gamma}(n, \lambda(mT_w - \delta t - n\tau)). \end{aligned} \quad (23)$$

Similarly to (23), the probability that the nth PU transmission occurs within the mth scan (the event $\mathcal{T}_{n,m}$) can be written as

$$\begin{aligned} P_{\text{T}}^{(n)}(m) = \mathbb{P}\{\mathcal{T}_{n,m}\} = {} & \bar{\gamma}(n, \lambda(mT_w - (n-1)\tau)) \\ & - \bar{\gamma}(n, \lambda((m-1)T_w - n\tau)). \end{aligned} \quad (24)$$

Note that $P_{\text{S}}^{(n)}(m)$ in (23) and $P_{\text{T}}^{(n)}(m)$ in (24) are zero when $n \ge n_{\text{max}}$, where $n_{\text{max}} = \lfloor\ mT_w/\tau\ - 1\ \rfloor$ is the maximum number of possible PU transmissions up to the mth scan.[13] According to Section II-B, the temporal sensing probability $P_{\text{TS}}^{(n)}(m) = \mathbb{P}\{\mathcal{S}_{n,m}\}/\mathbb{P}\{\mathcal{T}_{n,m}\}$ can be written in closed-form as

$$P_{\text{TS}}^{(n)}(m) = \frac{\bar{\gamma}(n, \lambda(mT_w - (n-1)\tau)) - \bar{\gamma}(n, \lambda(mT_w - \delta t - n\tau))}{\bar{\gamma}(n, \lambda(mT_w - (n-1)\tau)) - \bar{\gamma}(n, \lambda((m-1)T_w - n\tau))}. \quad (25)$$

From the above equation we observe that for continuous sensing, i.e., as δt approaches T_w, the temporal sensing probability becomes one, as expected.

[12] Here we assume that the SNR, ρ, is constant in the different sensing intervals.

[13] $\lfloor x \rfloor$ stands for the largest integer not greater than x.

B. Probability of Sensing the PU During a Single Scan

1) Transient phase: The probability $P_{\mathrm{S}}(m) = \mathbb{P}\{\mathcal{S}_m\} = \mathbb{P}\{\exists t_n \in [mT_w - \delta t - \tau, mT_w]\}$ is derived in Appendix-A, and can be expressed in closed form as

$$P_{\mathrm{S}}(m) = 1 - \sum_{n=0}^{n_{\max}} \frac{\lambda^n (mT_w - \delta t - n\tau)^n}{n!} e^{-\lambda(mT_w - n\tau)}. \tag{26}$$

For the derivation of $P_{\mathrm{T}}(m) = \mathbb{P}\{\mathcal{T}_m\} = \mathbb{P}\{\exists t_n \in [(m-1)T_w - \tau, mT_w]\}$, for $m > 1$, we can adopt the same approach, that leads to the expression

$$P_{\mathrm{T}}(m) = 1 - \sum_{n=0}^{n_{\max}} \frac{\lambda^n ((m-1)T_w - n\tau)^n}{n!} e^{-\lambda(mT_w - n\tau)} \tag{27}$$

while for $m = 1$ it is simply

$$P_{\mathrm{T}}(1) = \mathbb{P}\{0 \le t_1 \le T_w\} = \bar{\gamma}(1, \lambda T_w). \tag{28}$$

2) Steady-state regime: In the steady-state scenario, the probability to capture any PU transmission in a sensing interval, P_{S}, can be derived considering that it can be written as the sum of two terms: the first one is the probability of having a transmission within the sensing interval conditioned to the absence of a transmission at the beginning of the sensing interval, and the second is the probability of having a transmission present at the beginning of the sensing interval. Hence,[14]

$$P_{\mathrm{S}} = 1 - e^{-\lambda\delta t} \frac{\lambda^{-1}}{\lambda^{-1} + \tau} = 1 - \frac{e^{-\lambda\delta t}}{1 + \lambda\tau}. \tag{29}$$

With the same approach, the probability to have any PU transmission in a scan is

$$P_{\mathrm{T}} = 1 - \frac{e^{-\lambda T_w}}{1 + \lambda\tau}. \tag{30}$$

In Fig. 3 an example of $P_S(m)$ as a function of m is reported. As we can see, (26) matches the simulations and, after the transient phase, it converges to (29).

C. Temporal Sensing Probability over Multiple Scans

In Section III-B, we derived the temporal detection probability over multiple scans considering independence between sensing performed in the M sensing intervals. Considering the OR fusion rule, to apply (8) it is necessary to adopt (26) in the transient phase, and to adopt (29) for the steady-state regime. Denoting with $m_{\min}$ and $m_{\max}$ the minimum and the maximum indexes in Ω_M, respectively, the probability that a transmission occurs within M scans can be written using the results obtained in Appendix-A, and is given by

$$\begin{aligned} P_{\mathrm{T}}^{\mathrm{M}} &= \mathbb{P}\{\mathcal{T}_M\} = \mathbb{P}\{\exists t_n \in [(m_{\min} - 1)T_w - \tau, m_{\max} T_w]\} \\ &= 1 - \sum_{n=0}^{n_{\max}} \frac{\lambda^n ((m_{\min} - 1)T_w - n\tau)^n}{n!} e^{-\lambda(m_{\max} T_w - n\tau)} \end{aligned} \tag{31}$$

[14]Note that in the steady-state regime the temporal sensing probabilities are independent on the particular sensing interval considered, and thus the index m is omitted.

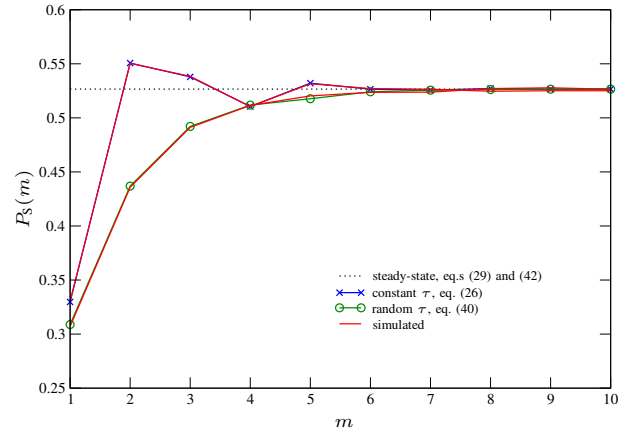

Fig. 3. Temporal sensing probability $P_{\mathrm{S}}(m)$ as a function of m for $T_w = 0.5\,\mathrm{s}$, $\delta t = 0.2\,\mathrm{s}$, $\lambda = 0.8\,\mathrm{s}^{-1}$ and $\tau = \bar{\tau} = 1\,\mathrm{s}$. Comparison between simulations and the closed-form expressions (26) and (40) is also given.

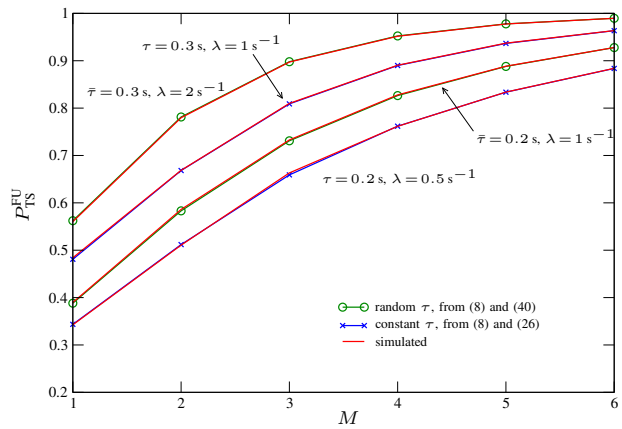

Fig. 4. Temporal sensing probability for multiple scans, with the OR rule, as a function of the number of scans considered, M, with $\delta t = 0.1\,\mathrm{s}$, $T_w = 1\,\mathrm{s}$. Comparison between simulations and the closed-form expressions (8) with (26) and (40) is also given.

for the transient phase, and by

$$P_{\mathrm{T}}^{\mathrm{M}} = 1 - \frac{e^{-\lambda M T_w}}{1 + \lambda\tau} \tag{32}$$

for the steady-state regime. If we consider the first M sensing periods, (31) reduces to

$$P_{\mathrm{T}}^{\mathrm{M}} = \bar{\gamma}(1, \lambda M T_w). \tag{33}$$

To prove the validity of the derived temporal sensing probability, in Fig. 4 we compare theoretical curves obtained from (8) with (26) and simulations. As can be seen, despite the approximations introduced, the theoretical probabilities match very well the simulated curves.

Considering the EGC rule, assuming the steady-state regime, $P_{\mathrm{TD}}^{\mathrm{FU}}$ is given in (10), where p is computed using (29) for P_{S} and (32) or (33) for $P_{\mathrm{T}}^{\mathrm{M}}$, and the conditional probability is given by (17).

V. Temporal Sensing Probability with Random Arrival and Random hold-time

In this section we derive the temporal sensing probabilities for the three TSTs considering an exponentially distributed

ON-period duration. In this case, the nth PU transmission occurs at time t_n given by

$$t_n = \sum_{i=1}^{n} \Delta_i + \sum_{i=1}^{n-1} \tau_i = G_n + H_n, \quad n \in \mathbb{N} \tag{34}$$

where $H_n = \sum_{i=1}^{n-1} \tau_i \sim \text{Erlang}(n-1, \mu)$. Hence, t_n is the sum of two Erlang distributed r.v.s with parameters λ and μ, respectively.

Using the results derived in [35], the complementary c.d.f. of t_n can be expressed as a linear combination of incomplete gamma functions as

$$\begin{aligned} Q_{t_n}(x) &= 1 - F_{t_n}(x) \\ &= \sum_{p=1}^{n} c_{1p}\, \bar{\Gamma}\left(n-p+1, \lambda x\right) + \sum_{q=1}^{n-1} c_{2q}\, \bar{\Gamma}\left(n-q, \mu x\right) \end{aligned} \tag{35}$$

where $\bar{\Gamma}(a,b) = 1 - \bar{\gamma}(a,b)$ is the normalised upper incomplete Gamma function, and

$$c_{1p} = (-1)^{p-1} \frac{\lambda^{p-1}\mu^{n-1}}{(\mu-\lambda)^{n+p-2}} \binom{n+p-3}{p-1} \tag{36}$$

$$c_{2q} = (-1)^{q-1} \frac{\lambda^{n}\mu^{q-1}}{(\lambda-\mu)^{n+q-1}} \binom{n+q-2}{q-1}. \tag{37}$$

A. Probability of Sensing the nth Transmission During the mth Scan

The probability that the nth transmission falls into the mth sensing interval can be computed as $P_{\text{S}}^{(n)}(m) = \mathbb{E}_{\tau}\{\mathbb{P}\left\{(mT_w - \delta t - \tau) \leq t_n < mT_w\right\}\}$. From (35) and the integral expressions derived in Appendix-B, we can express $P_{\text{S}}^{(n)}(m)$ in closed-form as in (38).

Similarly to (38), the probability $P_{\text{T}}^{(n)}(m)$ can be expressed as in (39). From (38) and (39) we obtain the temporal sensing probability $P_{\text{TS}}^{(n)}(m)$ which can be used in (2a) to calculate $P_{\text{TD}}^{(n)}(m)$.

B. Probability of Sensing the PU During a Single Scan

1) Transient phase: Similarly to (26) and (27), the probabilities $P_{\text{S}}(m)$ and $P_{\text{T}}(m)$ can be derived, as detailed in Appendix-A, as

$$\begin{aligned} P_{\text{S}}(m) =& 1 - e^{-\lambda m T_w} \\ &- \sum_{n=0}^{\infty} \mathbb{P}\left\{t_{n+1} > mT_w, t_n < mT_w - \delta t - \tau\right\} \end{aligned} \tag{40}$$

$$\begin{aligned} P_{\text{T}}(m) =& 1 - e^{-\lambda m T_w} \\ &- \sum_{n=0}^{\infty} \mathbb{P}\left\{t_{n+1} > mT_w, t_n < (m-1)T_w - \tau\right\} \end{aligned} \tag{41}$$

that can be expressed in closed-form using (52) and (60). In practice, the infinite summations in (40) and (41) can be truncated to a finite number n^*_{max}, considering that, as numerical simulations confirm, the arguments rapidly vanish with n. Note that, for the $m = 1$ case, $P_{\text{T}}(m)$ is given by (28).

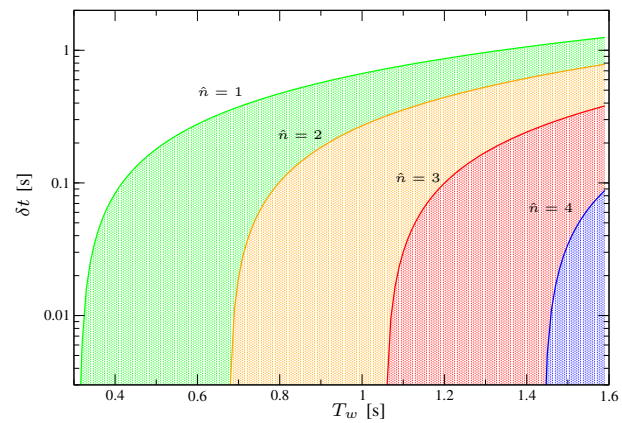

Fig. 5. Minimum sensing duration δt as a function of T_w for detecting the nth transmission with $P_{\text{TS}}^{\text{DES}} = 0.95$. The shaded areas below the curves indicate the regions where detection requirement, $P_{\text{TS}} > P_{\text{TS}}^{\text{DES}}$, is not satisfied.

2) Steady-state regime: In the steady-state scenario, it is possible to derive the sensing probability, P_{S}, and the transmission probability, P_{T}, following the same approach presented in Section IV-B, which leads to[15]

$$P_{\text{S}} = 1 - \frac{e^{-\lambda \delta t}}{1 + \lambda \bar{\tau}} \tag{42}$$

$$P_{\text{T}} = 1 - \frac{e^{-\lambda T_w}}{1 + \lambda \bar{\tau}}. \tag{43}$$

In Fig. 3 we can see an example of $P_S(m)$ as a function of m. The figure confirms also that (40) matches the simulated curve and that after the transient phase it converges to (42).

C. Probability of Detection over Multiple Scans

To apply (8) it is necessary to adopt (40) to derive the performance in the transient phase, or (42) for the steady-state regime. Considering the generic set Ω_M, similarly to (31) and (41), the probability $\mathbb{P}\left\{\mathcal{T}_M\right\}$ is given by

$$\begin{aligned} P_{\text{T}}^{\text{M}} =& 1 - e^{-\lambda m_{\text{max}} T_w} \\ &- \sum_{n=0}^{\infty} \mathbb{P}\left\{t_{n+1} > m_{\text{max}} T_w, t_n < (m_{\text{min}} - 1)T_w - \tau\right\} \end{aligned} \tag{44}$$

while considering the first M sensing periods it is given by (33).

In the steady-state regime, $\mathbb{P}\left\{\mathcal{T}_M\right\}$ can be easily expressed as

$$P_{\text{T}}^{\text{M}} = 1 - \frac{e^{-\lambda M T_w}}{1 + \lambda \bar{\tau}}. \tag{45}$$

Note that if we consider the first M scans, $\mathbb{P}\left\{\mathcal{T}_M\right\}$ is given by (33).

Considering the EGC rule, assuming the steady-state regime, $P_{\text{TD}}^{\text{FU}}$ is given in (10), where p is computed using (42) for P_{S} and (45) or (33) for P_{T}^{M}, and the conditional probability is given by (17).

[15]Note that in the steady-state regime, the two probabilities (42) and (43) have the same form as (29) and (30) where now $\bar{\tau}$ appears in place of τ.

$$
\begin{aligned}
P_{\mathrm{S}}^{(n)}(m) &= \int_0^\infty Q_{t_n}(mT_w - \delta t - \tau)\frac{1}{\bar{\tau}}\exp\left(-\frac{\tau}{\bar{\tau}}\right)d\tau - Q_{t_n}(mT_w) \\
&= \sum_{p=1}^{n} c_{1p}\Bigg(\bar{\gamma}\left(n-p+1, \lambda m T_w\right) - \bar{\gamma}\left(n-p+1, \lambda(mT_w - \delta t)\right) \\
&\quad + \gamma\left(n-p+1, \lambda(mT_w - \delta t)\left(1-\frac{\mu}{\lambda}\right)\right)\left(\frac{\lambda}{\lambda-\mu}\right)^{n-p+1}\exp(-\mu(mT_w - \delta t))\Bigg) \\
&\quad + \sum_{q=1}^{n-1} c_{2q}\Bigg(\bar{\gamma}\left(n-q, \mu m T_w\right) - \bar{\gamma}\left(n-q, \mu(mT_w - \delta t)\right) \\
&\quad + \frac{(\mu(mT_w - \delta t))^{n-q}}{(n-q)!}\exp(-\mu(mT_w - \delta t))\Bigg).
\end{aligned} \tag{38}
$$

$$
\begin{aligned}
P_{\mathrm{T}}^{(n)}(m) &= \int_0^\infty Q_{t_n}((m-1)T_w - \tau)\frac{1}{\bar{\tau}}\exp\left(-\frac{\tau}{\bar{\tau}}\right)d\tau - Q_{t_n}(mT_w) \\
&= \sum_{p=1}^{n} c_{1p}\Bigg(\bar{\gamma}\left(n-p+1, \lambda m T_w\right) - \bar{\gamma}\left(n-p+1, \lambda((m-1)T_w)\right) \\
&\quad + \gamma\left(n-p+1, \lambda((m-1)T_w)\left(1-\frac{\mu}{\lambda}\right)\right)\left(\frac{\lambda}{\lambda-\mu}\right)^{n-p+1}\exp(-\mu((m-1)T_w))\Bigg) \\
&\quad + \sum_{q=1}^{n-1} c_{2q}\Bigg(\bar{\gamma}\left(n-q, \mu m T_w\right) - \bar{\gamma}\left(n-q, \mu((m-1)T_w)\right) \\
&\quad + \frac{(\mu((m-1)T_w))^{n-q}}{(n-q)!}\exp(-\mu((m-1)T_w))\Bigg).
\end{aligned} \tag{39}
$$

VI. Design Strategies and Results

In this section we present some design strategies for periodic sensing based on the derived temporal detection framework. We start addressing the design of the sensing duration δt and the sensing period T_w. We then derive the complementary receiver operating characteristic (C-ROC) curves, and finally we provide a case study for periodic sensing in which the PU is represented by a Wi-Fi system.

A. Minimum Sensing Time to Guarantee a given Temporal Detection Probability

Considering a PU adopting a packet-based transmission, from the regulatory point of view as well as from the PU perspective, it is important to quantify or control how many PU packets are interfered by the SU. For instance, assume that the PU may tolerate $\hat{n}-1$ undetected transmissions, and that for $n \geq \hat{n}$ all transmissions are interfered with a probability which cannot exceed $P_{\mathrm{I}}^{\max}$, named maximum probability of interference. A simple metric for quantifying the maximum interference to the PU is the missed detection probability, i.e. $P_{\mathrm{I}}^{\max} = 1 - P_{\mathrm{TD}}^{\mathrm{DES}}$ where $P_{\mathrm{TD}}^{\mathrm{DES}}$ is the minimum desired probability of detection.[16] Then, considering $m=1$, and, for instance, a PU with fixed packet duration, we are interested in designing the minimum sensing duration δt. If, for example, we consider the situation in which the SNR is high, the temporal detection probability reduces to the temporal sensing probability ($P_{\mathrm{TD}} \approx P_{\mathrm{TS}}$), hence from (25) it is possible to derive the following inequality

$$
\frac{\bar{\gamma}(\hat{n}, \lambda(T_w - \delta t - \hat{n}\tau))}{\bar{\gamma}(\hat{n}, \lambda(T_w - (\hat{n}-1)\tau))} \leq 1 - P_{\mathrm{TD}}^{\mathrm{DES}} \tag{46}
$$

which can be inverted to derive[17]

$$
\begin{aligned}
\delta t \geq\ & T_w - \hat{n}\tau \\
& + \frac{1}{\lambda}\bar{\gamma}^{-1}\left(\hat{n}, \left(1 - P_{\mathrm{TD}}^{\mathrm{DES}}\right)\bar{\gamma}(\hat{n}, \lambda(T_w - (\hat{n}-1)\tau))\right).
\end{aligned} \tag{47}
$$

The expression (47) allows the design of δt, given the PU transmission parameters, λ, τ, and the scanning period T_w to guarantee $P_{\mathrm{TD}}^{\mathrm{DES}}$. As an example, in Fig. 5 we show the minimum δt required to satisfy $P_{\mathrm{TD}}^{\mathrm{DES}} = 0.95$ as a function of T_w for different values of $\tilde{n}$. The shaded areas denote the regions where the interference probability constraint is not satisfied. Note that Fig. 5 can be also used for the design of the sensing scan duration T_w, chosen a particular value of δt. Similar design strategies can be derived for the random hold-time case and/or considering the presence of noise through the corresponding expressions for P_{TD}.

[16] Note that the probability of missed detection is a worst case probability of interference, derived assuming that the SU transmit whenever it declares the channel free.

[17] If $\bar{\gamma}(a, z) = w$, then the inverse lower incomplete gamma function is defined as $z = \bar{\gamma}^{-1}(a, w)$. Note that this inverse expression can be easily computed using standard mathematical software.

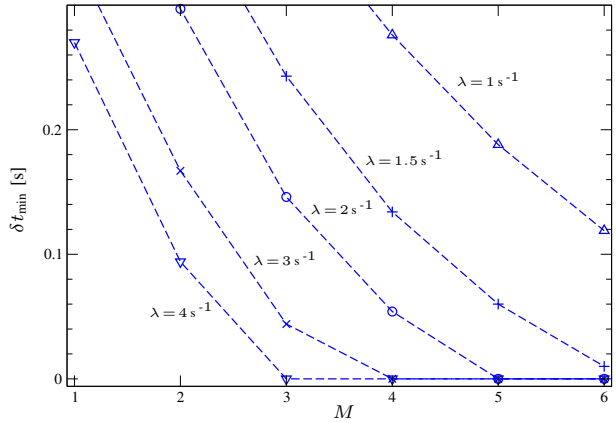

Fig. 6. Minimum sensing duration δt required to reach a target $P_{\mathrm{TD}}^{\mathrm{DES}} = 0.9$ with $\tau = 0.3\,\mathrm{s}$ and $T_w = 1\,\mathrm{s}$ for different values of λ.

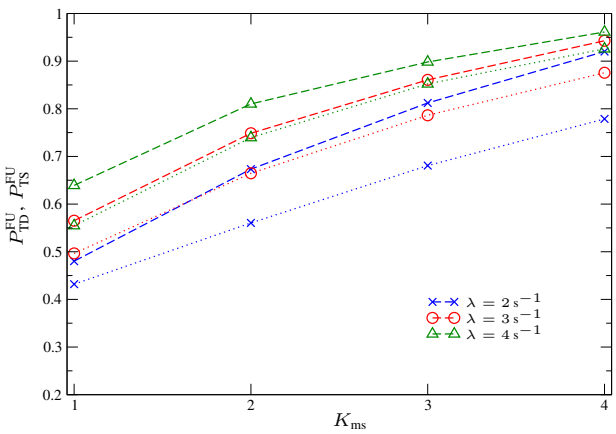

Fig. 7. $P_{\mathrm{TD}}^{\mathrm{FU}}$ (dotted lines) and $P_{\mathrm{TS}}^{\mathrm{FU}}$ (dashed lines) as a function of the number of mini-slots K_{ms} with constant and random PU hold-time $\tau = \bar{\tau} = 0.2\,\mathrm{s}$, sensing period $T_w = 1\,\mathrm{s}$, sensing duration $\delta t = 0.1\,\mathrm{s}$, and $N_{\mathrm{s}} = 84$. For $P_{\mathrm{TD}}^{\mathrm{FU}}$ an ED in the presence of AWGN with $\rho = 15\,\mathrm{dB}$, and with a decision threshold set to guarantee a $P_{\mathrm{FA}}^{\mathrm{FU}} = 0.1$, is considered.

The design of the sensing time required can be also performed when multiple scans are considered. In this case, by using equation (7), the minimum sensing interval duration, $\delta t_{\min}$, can be found as

$$\delta t_{\min} = \min\left\{\delta t | P_{\mathrm{TD}}^{\mathrm{FU}} \geq P_{\mathrm{TD}}^{\mathrm{DES}}\right\}. \tag{48}$$

For example, considering the OR fusion rule, in Fig. 6 we show the minimum $\delta t_{\min}$ as a function of the number of scans M with $P_{\mathrm{TD}}^{\mathrm{DES}} = 0.9$, $\tau = 0.3\,\mathrm{s}$ and $T_w = 1\,\mathrm{s}$, for different values of λ, when τ is constant and $\rho \to \infty$. As can be seen, an increase of λ, corresponding to a decrease of the OFF-period duration, requires shorter sensing durations to guarantee the same performance.

B. Periodic Sensing by means of Mini-slots

Assuming that the time dedicated to sensing for each scan is d, an interesting aspect to investigate if it is better to adopt a single sensing interval of duration $\delta t = d$ or to divide it into K_{ms} shorter periods, called *mini-slots*, equally spaced in the scan period by $(T_w - d)/K_{\mathrm{ms}}$ and each with a sensing window of duration $\delta t = d/K_{\mathrm{ms}}$. In Fig. 7 we show the $P_{\mathrm{TS}}^{\mathrm{FU}}$ relative to K_{ms} mini-slots when the OR rule is applied, for different values of λ, whit random τ. It is clear that the adoption of multiple shorter sensing windows within a scan period provides an higher sensing probability. In the noisy case we plot $P_{\mathrm{TD}}^{\mathrm{FU}}$ which confirms the same behavior. This fact is explained by the ability of mini-slots to counteract the effect of non-continuous PU transmission, increasing the chance to have an overlap between a PU transmission and the sensing period.

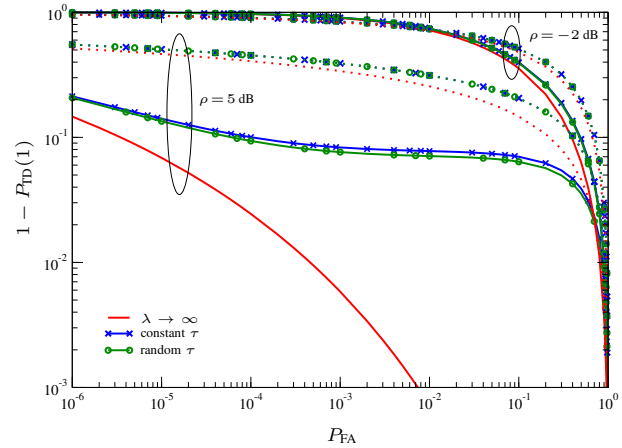

Fig. 8. Complementary ROC curves for various SNRs ρ in AWGN (continuous lines) and Rayleigh fading (dotted lines) scenarios, with $T_w = 1\,\mathrm{s}$, $\delta t = 0.1\,\mathrm{s}$, $\bar{\tau} = \tau = 0.2\,\mathrm{s}$, $N_{\mathrm{s}} = 10$ and $\lambda = 8\,\mathrm{s}^{-1}$.

C. Receiver Operating Characteristics for Periodic Sensing

In this section, we show some examples of ROC for temporal detection. We choose in particular to adopt the C-ROC curves to highlight the probability $1 - P_{\mathrm{TD}}$ which, as discussed above, can be interpreted as a probability of interfering the PU. Fig. 8 depicts the C-ROC curves varying the SNR for AWGN and Rayleigh fading scenarios. From the figure we observe that for high values of ρ the PU temporal behavior dominates the detection performance, which is poor compared to the scenario with a continuous PU transmission (i.e. $\lambda \to \infty$). This confirms that the performance of periodic sensing are severely degraded by the PU temporal behavior. For low SNR, instead, the dependence on λ is smaller, and thus the noise is the dominant effect in the detection performance. Also note that the presence of Rayleigh fading results in a strong decrease in the detection probability. In this case the effects of fading is dominant with respect to the PU temporal behavior. Fig. 9 shows the C-ROC curves for multiple scans based on the OR rule, corresponding to equation (7) and (9), and the EGC approach described by (17). As expected, the detection performance improves with increasing M. Note, in particular, that soft fusion EGC always provides better performance with respect to the hard fusion based on the OR rule, especially for low P_{FA}. This result suggests that soft fusion strategies should be preferred to hard fusion approaches.

In all cases, and for the parameters considered, the performance with random and constant hold-time, with $\tau = \bar{\tau}$, are very similar, indicating a small dependence of the hold-time statistic on the SU detection performance.

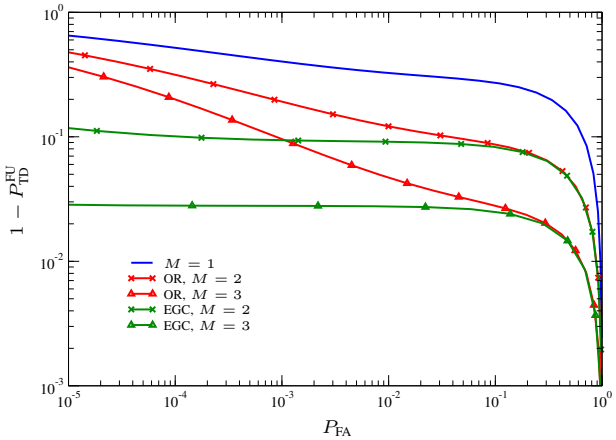

Fig. 9. Complementary ROC curves for the TST-M, considering ED with OR and EGC combining. An AWGN scenario with $\tau = 0.2\,\text{s}$, $\lambda = 5\,\text{s}^{-1}$, $\delta t = 0.1\,\text{s}$, $T_w = 1\,\text{s}$, and $N_\text{s} = 10$, and $\rho = 3\,\text{dB}$ have been considered.

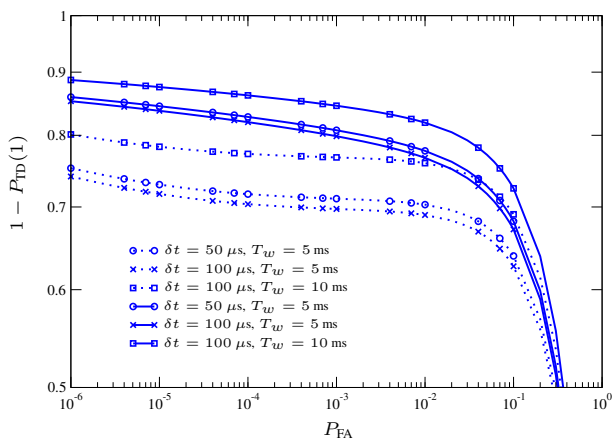

Fig. 10. Complementary ROC curves in AWGN (continuous lines) and Rayleigh fading (dotted lines) scenarios, with $\bar{\tau} = 1\,\text{ms}$, $\bar{\Delta} = 1/\lambda = 4.2\,\text{ms}$, $N_\text{s} = 10$, and $\rho = 5\,\text{dB}$. The PU parameters adopted are typical for Wi-Fi signals.

D. Case study: detection of a Wi-Fi signal

As a case study we propose the analysis of periodic sensing of a Wi-Fi signal considering the TST-S for the first sensing scan for different choices of δt and T_w. In order to consider a realistic scenario, we adopt the measured parameter values presented in [13], [14]. In Fig. 10 we show the C-ROC for the AWGN and Rayleigh fading cases, considering $\tau = \bar{\tau} = 1\,\text{ms}$ and $\bar{\Delta} = 4.2\,\text{ms}$, typical of a VoIP application [13]. In [14] it has been shown that the statistic of the idle time noticeably depends on the amount of traffic, which also impacts the temporal detection probability. In Fig. 11 we show the detection performance considering $\bar{\Delta} = 2.45$, 4.2 and 10 ms, which corresponds to the traffic scenarios with 100, 75 and 25 pkts/s [14].

A second aspect investigated is the evaluation of the latency of periodic sensing, defined as the minimum number of PU transmissions for which the probability of interference is below $P_\text{I}^{\max}$. This number, denoted with $\widetilde{n}$, is given by

$$\widetilde{n} \triangleq \arg\min_n \left\{ P_\text{I} = 1 - \frac{P_\text{S}^{(n)}(1)}{P_\text{T}^{(n)}(1)} \,\middle|\, P_\text{I} \leq P_\text{I}^{\max} \right\}. \tag{49}$$

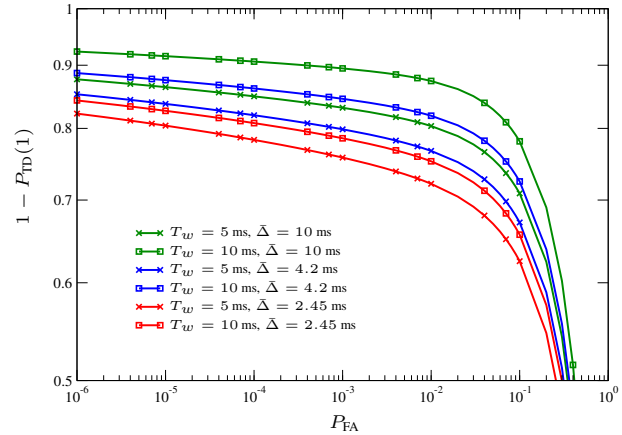

Fig. 11. Complementary ROC curves Rayleigh fading scenarios, with $\delta t = 100\,\mu\text{s}$, $\bar{\tau} = 1\,\text{ms}$, $N_\text{s} = 10$, and $\rho = 5\,\text{dB}$. The PU parameters adopted are typical for Wi-Fi signals and VoIP-like traffic.

TABLE V
EXAMPLES OF $\widetilde{n}$ AND R FOR THE WI-FI SIGNAL DETECTION CONSIDERED IN FIG. 10. $P_\text{TD}^\text{DES} = 0.9$ AND $P_\text{FA}^\text{DES} = 0.1$.

	$\delta t = 50\,\mu\text{s}$ $T_w = 5\,\text{ms}$	$\delta t = 100\,\mu\text{s}$ $T_w = 5\,\text{ms}$	$\delta t = 100\,\mu\text{s}$ $T_w = 10\,\text{ms}$
$\widetilde{n}$	4	4	8
R	0.696	0.676	0.752

Note that when $n < \widetilde{n}$, the constraint on P_I is not guaranteed, and thus the sensing process requires at least $\widetilde{n}$ transmissions to provide the required performance, i.e., $P_\text{TD} > P_\text{TD}^\text{DES}$.

Finally, it is interesting to calculate simple metrics for quantifying the impact of periodic sensing on the performance of the SU, such as, for example, the maximum SU rate. We adopt, in particular, the maximum normalised achievable throughput, considered in [20], [37], [38], defined as $R = \frac{T_w - \delta t}{T_w} P_\text{TX}$, where P_TX is the maximum SU transmission probability. In accordance with [37], we assume that the SU successfully transmits every time the sensing task decides for the absence of the PU, and thus we have

$$R = \frac{T_w - \delta t}{T_w} \left(1 - P_\text{TD}\right). \tag{50}$$

In Table V we report some numerical examples of $\widetilde{n}$ and R, corresponding to the scenario considered in Fig. 10. As can be seen, an increase in T_w from 5 ms to 10 ms corresponds to an increase in the latency and in the maximum SU rate. These results reveal the trade-off between the PU protection and the SU throughput.

VII. CONCLUSIONS

In this paper we presented a general analytical framework for the study of the detection performance in CR contexts, taking into account, in particular, the presence of non-continuous PU transmissions and the adoption of periodic spectrum sensing. The analysis allows to study the sensing task in its entirety, but at the same time is able to separate the effects of detection impairments, such as noise, fading, and non-continuous PU transmissions, and to show their respective impact on the overall performance. Numerical results prove that the PU temporal behavior has a very strong impact on detection

performance. Moreover, the relationship among arrival rate, occupancy duration, sensing period and sensing duration are revealed. The analysis is general enough to describe several practical scenarios considering both scan-by-scan sensing as well as sensing based on multiple scans. As a case study, the energy detector was chosen to derive numerical results. Based on the analysis developed, we then proposed some design strategies to set up periodic sensing parameters in different scenarios.

APPENDIX A

Constant τ case: computation of $\mathbb{P}\{\exists\, t_n \in [a,b]\}$

With the notation $\mathbb{P}\{\exists\, t_n \in [a,b]\}$ we indicate the probability that at least one transmission, represented by its starting time t_n, $\forall n \in \mathbb{N}$, falls in the interval (a,b). This probability is computed in this section considering that t_n is distributed as in (21), where a and b are constants. Note that, given the definition in (19), we can write

$$\begin{aligned}\mathbb{P}\{\exists\, t_n \in [a,b]\} &= 1-\mathbb{P}\{\nexists\, t_n \in [a,b]\}\\ &= 1-\mathbb{P}\left\{t_1 > b \text{ or } \bigcup_{n=1}^{n_{\max}}\{t_{n+1} > b, t_n < a\}\right\}\\ &= 1-\mathbb{P}\{t_1 > b\}-\sum_{n=1}^{n_{\max}}\mathbb{P}\{t_{n+1} > b, t_n < a\}\end{aligned} \tag{51}$$

where the last equality is given by the union of mutually exclusive events and $n_{\max} = \lfloor b/\tau - 1\rfloor$. Considering that $t_{n+1} = t_n + \Delta_{n+1} + \tau$, we have $\mathbb{P}\{t_{n+1} > b, t_n < a\} = \mathbb{P}\{\Delta_{n+1} > b-\tau-t_n, t_n < a\}$, and, given that t_n and Δ_{n+1} are independent r.v.s, we can write

$$\begin{aligned}&\mathbb{P}\{\Delta_{n+1} > b-\tau-t_n, t_n < a\}\\ &= \int_{t_n<a}\mathbb{P}\{\Delta_{n+1} > b-\tau-t\}\, f_{t_n}(t)dt\\ &= \int_{t_n<a} e^{-\lambda(b-\tau-t)} f_{t_n}(t)dt\\ &= \frac{\lambda^n\,(a-(n-1)\tau)^n}{n!}e^{-\lambda(b-n\tau)}.\end{aligned} \tag{52}$$

Considering that

$$\mathbb{P}\{t_1 > b\} = \exp(-\lambda b) \tag{53}$$

we can express (51) as

$$\mathbb{P}\{\exists t_n \in [a,b]\} = 1-\sum_{n=0}^{n_{\max}}\frac{\lambda^n\,(a-(n-1)\tau)^n}{n!}\,e^{-\lambda(b-n\tau)}. \tag{54}$$

Random τ case: computation of $\mathbb{P}\{\exists\, t_n \in [a-\tau,b]\}$.

For the random hold time τ case, in this section we compute the probability $\mathbb{P}\{\exists\, t_n \in [a-\tau,b]\}$ where a and b are constants, and t_n is defined in (34). Following the same approach used in (51) we can write

$$\begin{aligned}\mathbb{P}\{\exists\, t_n \in [a-\tau,b]\} =& 1-\mathbb{P}\{t_1 > b\}\\ &-\sum_{n=1}^{\infty}\mathbb{P}\{t_{n+1} > b, t_n < a-\tau\}.\end{aligned} \tag{55}$$

Defining $\theta_n = t_n + \tau$ we obtain $\mathbb{P}\{t_{n+1} > b, t_n < a-\tau\} = \mathbb{P}\{\theta_n + \Delta_{n+1} > b, \theta_n < a\}$ and thus, given that θ_n and Δ_{n+1} are independent r.v.s, we can write

$$\begin{aligned}&\mathbb{P}\{t_{n+1} > b, t_n < a-\tau\}\\ &= \mathbb{P}\{\Delta_{n+1} > b-\theta_n, \theta_n < a\}\\ &= \int_{\xi<a}\mathbb{P}\{\Delta_{n+1} > b-x\}\, f_{\theta_n}(x)dx\\ &= \int_{\xi<a} e^{-\lambda(b-x)} f_{\theta_n}(x)dx.\end{aligned} \tag{56}$$

The p.d.f. of θ_n can be obtained from the complementary c.d.f. expression given in [35] as

$$\begin{aligned}f_{\theta_n}(x) =& \sum_{i=1}^{n}\widetilde{c}_{1i}\,\frac{x^{n-i}\,e^{-\lambda x}}{\Gamma(n-i+1)}u(x)\\ &+\sum_{j=1}^{n}\widetilde{c}_{2j}\,\frac{x^{n-j}\,e^{-\mu x}}{\Gamma(n-j+1)}u(x)\end{aligned} \tag{57}$$

$$\widetilde{c}_{1i} = (-1)^{i-1}\binom{i+n-2}{i-1}\frac{\lambda^n\mu^n}{(\mu-\lambda)^{n+i-1}} \tag{58}$$

$$\widetilde{c}_{2j} = (-1)^{j-1}\binom{j+n-2}{j-1}\frac{\lambda^n\mu^n}{(\lambda-\mu)^{n+j-1}} \tag{59}$$

and therefore we derive

$$\begin{aligned}\mathbb{P}\{t_{n+1} > b, t_n < a-\tau\} =& e^{-\lambda b}\sum_{i=1}^{n}\widetilde{c}_{1i}\,\frac{a^{n-i+1}}{(n-i+1)!}\\ &+\widetilde{c}_{2i}\,\frac{\bar{\gamma}(n-i+1,(\mu-\lambda)a)}{(\mu-\lambda)^{n-i+1}}.\end{aligned} \tag{60}$$

The probability $\mathbb{P}\{\exists t_n \in [a-\tau,b]\}$ can be thus computed using (55) using (53) and (60).

APPENDIX B

In this section we provide the solutions of two integral forms useful for computation of the probabilities in Section V. We consider in particular integrals in the form $\int_0^\infty \bar{\gamma}(n, a+b\tau)f_\tau(\tau)d\tau$ with $n \in \mathbb{N}$, $a,b,\mu \in \mathbb{R}$, $a,b,\mu > 0$ and $b > \mu$. Considering the case in which $f_\tau(\tau) = \mu\exp(-\mu\tau)$, for $\tau \geq 0$ and zero otherwise, solving by parts we obtain

$$\begin{aligned}&\int_0^\infty \bar{\gamma}(n, a-b\tau)\,\mu\,\exp(-\mu\tau)d\tau\\ &= \frac{\mu}{b}\exp\left(-\frac{\mu}{b}a\right)\int_0^a \bar{\gamma}(n,x)\,\exp\left(\frac{\mu}{b}x\right)dx\\ &= \bar{\gamma}(n,a)-\gamma\left(n, a\left(1-\frac{\mu}{b}\right)\right)\left(\frac{b}{b-\mu}\right)^n\exp\left(-\frac{\mu}{b}a\right).\end{aligned} \tag{61}$$

Considering the case in which $f_\tau(\tau) = b\exp(-b\tau)$, for $\tau \geq 0$ and zero otherwise, we get the form

$$\begin{aligned}&\int_0^\infty \bar{\gamma}(n, a-b\tau)\,b\,\exp(-b\tau)d\tau\\ &= \exp(-a)\int_0^a \bar{\gamma}(n,x)\,\exp(x)\,dx\\ &= \bar{\gamma}(n,a)-\frac{a^n}{n!}\,\exp(-a).\end{aligned} \tag{62}$$

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