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Evaluation of Adaptive MAC-Layer Sensing in Realistic Spectrum Occupancy Scenarios

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***Abstract*—Spectrum scarcity has been discussed as a possible road block that may slow down the growth of wireless communications. Dynamic Spectrum Access (DSA) has been proposed as a possible solution. In this paper, we study the impact of the spectrum occupancy statistics on the MAC-layer sensing performance. Namely, we consider the duty cycle and the distributions of the lengths of time periods during which a channel is busy or idle (ON- and OFF-periods). We use spectrum occupancy data extracted from extensive measurements and generated from accurate models that we previously fitted to our measured traces. We show that if the ON- and OFF-period durations tend to be longer adaptive algorithms that exploit knowledge on these distributions will achieve significant performance gains. If the lengths are shorter the enhancements will be limited. Additionally, also the benefit from investigating more channels changes with the spectrum occupancy statistics. Under more rapidly changing conditions, adding resources for sensing yields more improvements compared to scenarios with longer ON- and OFF-periods.**

I. Introduction

Dynamic Spectrum Access (DSA) has become an intensely studied proposal to mitigate spectrum scarcity [1], [2]. Two types of nodes are commonly assumed to coexist in DSA scenarios. The Primary Users (PUs) hold the license to access a spectrum band and Secondary Users (SUs) opportunistically access the band if left vacant by the PUs [3]. The SUs have to search for free spectrum bands before starting their communication in order to prevent any harmful interference to the primary system. Often, spectrum sensing has been proposed as flexible solution [4], [5] that does not require any access to external databases or cooperation from the PU. Here, we focus on the scenario in which each SU has only one radio interface available and secondary communication has to be stopped for spectrum sensing. Thus, shortening the sensing time by lowering the number of channels to sense improves the performance of the secondary system.

We study the problem of how many and which particular channels should be selected for detailed sensing, also known as MAC-layer sensing [6] or adaptive spectrum sensing [7], [8]. If the selected channels are free with high probability the total number of sensed channels can be reduced and the sensing time will also be decreased. The SU may also sense further channels in order to increase the probability to detect sufficient amount of free spectrum. We investigate the described problem using realistic spectrum models [9] extracted from our extensive spectrum occupancy measurements [10]. We confirm that exploiting knowledge of PU activity can significantly increase spectrum sensing efficiency. However, when considering more realistic statistics for the PU activity the performance gain achievable by advanced algorithms is limited due to too frequent occupancy state transitions in the examined channels. In these scenarios it turns out to be enough to exploit only duty cycle information.

We also investigate the trade-off between the bandwidth selected for sensing and the amount of detected idle spectrum. We show that there are in essence two major cases to consider. Either the advanced sensing algorithms improve the sensing efficiency significantly but adding more resources does not help much, or the more intelligent algorithms fail to improve the system but sensing further channels enhances the performance considerably. The former situation will occur if the durations of active PU periods and free spectrum tend to be longer. The latter scenarios will happen if occupancy state transitions occur quickly one after another.

The remainder of the paper is structured as follows. We start with a short review of our spectrum measurements and the developed spectrum model in Section II and Section III, respectively. We continue in Section IV with the concept of adaptive spectrum sensing. In Section V we formulate the underlying optimization problem and present simulation results using our realistic spectrum model in Section VI. Finally, we conclude the paper in Section VII.

II. Spectrum Measurements

The work presented in this paper is based on spectrum occupancy data collected throughout an extensive measurement campaign. In the following, we shortly point out the key characteristics of the measurement setup and of the locations that are relevant for the latter sections. A more complete description of the performed measurement campaigns is available in [10], [11]. Additionally, most of the measurement data is publicly available for download from [12].

The measurement setup was based on a high-performance spectrum analyser and wideband antennas. The spectrum analyser was deployed in a weather-proof and shielded box in different indoor and outdoor locations in Germany and the Netherlands. We concentrate in this paper on data gathered in a quite calm radio environment collected on a third floor balcony in a residential area of Aachen, Germany, and results collected at a more exposed rooftop location in Maastricht, the Netherlands. In the following, we refer to these two data sets and corresponding spectrum occupancy models by AB and NE, respectively.

We covered very wide spectrum bands of 1.5 GHz bandwidth in single sweeps and chose a resolution bandwidth of 200 kHz. The measured channels were not aligned to any specific technology such as the Global System for Mobile communications (GSM). We differentiate between measurement channels and technology channels, the latter covering a technology-specific bandwidth, e.g., 200 kHz for GSM or 5 MHz for UMTS (Universal Mobile Telecommunications System). The rate of the conducted measurements was approximately one sweep per 1.8 s preventing the reconstruction of any signal characteristics or fine-grained MAC patterns such as the GSM time slot structure. Significantly faster sensing rates are less probable also for practical systems since SUs with a single transceiver would have to stop data communication for every sensing step. Individual measurements lasted up to two weeks and also the shortest traces cover more than one week.

III. Spectrum Model

Using the gathered measurement data we developed an accurate spectrum model in [9]. We focused on the binary spectrum occupancy state that we extracted from our data by application of a fixed energy detection threshold[1]. The basis for modelling were representative fractions of the time series collected at each measurement channel. Each of these selected subtraces covers a time period of 12 h and consists of slightly more than 24 000 samples.

We have identified several key characteristics of spectrum occupancy in the time and frequency domains. In the time domain, the activity of the PU is essential because more frequent transitions between the busy and the idle state reduce the attractiveness of the channel for secondary access. Thus, the distributions of what we refer to as the durations of the PU's ON- and OFF-periods, are important for the SU. These have often been assumed [6], [15], [16] or measured [17], [18] to be geometric.

For some of our traces we could confirm the assumption of geometric distributions. However, for other cases, we successfully fitted log-normal distributions to the ON- and OFF-period durations distributions. These occurred often in channels with low traffic load, that are especially attractive for secondary use. For most traces, we confirmed that subsequent ON- and OFF-period lengths are not correlated. However, we also introduced a technique in order to reproduce the rare correlation patterns for simulated data in [19].

In the frequency domain, the spectrum occupancy is clustered and channels with similar characteristics occur in *groups*. In order to reproduce such correlation in the frequency domain we defined spectrum occupancy archetypes and all channels in a group belong to the same type. Each archetype is characterized by its probability of occurrence and the parameters of the distributions of the ON- and OFF-period durations. Finally, we fitted a log-normal distribution also to the distribution of the numbers of channels per group.

We applied a divide-and-conquer methodology during the whole modelling process in order to separate the investigation of the time- and the frequency-domain and to keep the model complexity at a reasonable level. Thus, the binary state over time is modelled separately for each channel. Only the parameters of the distributions of the lengths of the ON- and OFF-periods may be correlated if two channels form part of the same group of channels.

IV. Adaptive Spectrum Sensing

The goal of spectrum sensing is to find idle spectrum that can be exploited by SUs. In order to enable detection of weak PU signals the secondary data communication has to be stopped during sensing. In the single receiver scenario, time spent for sensing cannot be used for transmission of user data anymore. Consequently, any efficient spectrum sensing system should reduce the sensing time to the minimum possible.

In addition to the signal processing algorithm applied for sensing [4], [5] the question arises, which and how many channels should be sensed. This process is referred to as MAC-layer sensing or adaptive spectrum sensing and is independent of the physical layer sensing algorithm. We assume the time spent for sensing a single channel to be a given system constant and deal only with the problem of selecting how many and which channels should be sensed.

The efficiency of a MAC-layer sensing algorithm can be measured by the probability that a channel selected for sensing will in fact be idle. If we improve this probability we can lower the number of sensed channels and can shorten the time spent for each sensing step. We refer to this probability as $p_{\text{algorithm}}(\mathsf{idle}, s)$, where s denotes the index of the sensed frequency channel. Two major approaches have been applied previously. Either, the algorithms try to exploit deterministic PU behaviour or they evaluate the statistics of the occupancy for each channel over time.

The results presented in [20]–[22] all belong to the first group. Some of these approaches require a very high sensing rate in order to successfully identify a deterministic pattern such as the GSM time slot structure as used in [20]. We believe that SUs will rarely sense with sufficiently fast sensing rates without accepting the additional costs for a second radio interface [23]. When assuming a lower sensing rate as emulated in our measurements the potential for identifying deterministic behaviour is significantly lower. We detected almost no periodic behaviour in our data [7], [8] although several wireless communication signals possess such characteristics. However, we were able to extract deterministic patterns with more complex entropy metrics [24], [25], but it is unlikely that such complex algorithms will be deployed in SU devices at least initially.

[1] We used the energy detection threshold $\delta_P = -107\,\mathrm{dBm}/200\,\mathrm{kHz}$ as initially proposed in the IEEE 802.22 standardization process for detection of wireless microphones [13]. Due to regulatory decisions of the American regulator FCC (Federal Communications Commission) these thresholds have been changed recently [14].

Therefore, we will focus on the purely statistical approach in the following. It has also been studied previously in, e.g., [6], [16], [26]. However, all of the reported results have been based on artificial spectrum data and it is not clear if similar gains can be achieved in more realistic scenarios.

V. Renewal Theory based Problem Formulation

We use a renewal theory based approach to formulate the underlying optimization problem [27]. Renewal theory has previously been applied to the problem of MAC-layer sensing in [6], [28]. It has also been extended as basis for evaluation of proactive channel access [29], [30].

Due to the swept operation of the spectrum analyser in our measurements we applied a slotted time structure during the modelling work. We assume that the SU has knowledge on the occupancy state of each channel during a previous time slot. Additionally, we start with the case of exponentially distributed ON- and OFF-period durations. Let us denote the parameters of both distributions by λ_{ON} and λ_{OFF}, respectively. The duty cycle of the channel in the exponential case can be computed as $DC_{\text{exp}} = \frac{\lambda_{\mathsf{OFF}}}{\lambda_{\mathsf{ON}}+\lambda_{\mathsf{OFF}}}$.

It has been shown in [6], [28] that we can describe the probability to be in the ON- or OFF-state in the upcoming time slot using the equations

$$\begin{aligned} p_{\mathsf{OFF,OFF}}(\Delta t) &= (1 - DC_{\text{exp}}) + DC_{\text{exp}} e^{-(\lambda_{\mathsf{ON}}+\lambda_{\mathsf{OFF}})\Delta t}, \\ p_{\mathsf{ON,OFF}}(\Delta t) &= DC_{\text{exp}} - DC_{\text{exp}} e^{-(\lambda_{\mathsf{ON}}+\lambda_{\mathsf{OFF}})\Delta t}, \\ p_{\mathsf{OFF,ON}}(\Delta t) &= (1 - DC_{\text{exp}}) - (1 - DC_{\text{exp}}) e^{-(\lambda_{\mathsf{ON}}+\lambda_{\mathsf{OFF}})\Delta t}, \\ p_{\mathsf{ON,ON}}(\Delta t) &= DC_{\text{exp}} + (1 - DC_{\text{exp}}) e^{-(\lambda_{\mathsf{ON}}+\lambda_{\mathsf{OFF}})\Delta t}, \end{aligned} \tag{1}$$

where $p_{\mathsf{ON,OFF}}(\Delta t)$ describes the probability to switch from the OFF-state to the ON-state. The other transition probabilities are defined accordingly. The time elapsed since the known state Δt is given as a multiple of the duration of a single time slot T_{sl}.

The set of equations (1) show that the impact of the distributions of the ON- and OFF-period lengths decreases with the time elapsed since the studied channel has been last time sensed. The probabilities depend more and more on DC_{exp}, and we have

$$\begin{aligned} \lim_{\Delta t\to\infty} p_{\mathsf{OFF,OFF}}(\Delta t) = \lim_{\Delta t\to\infty} p_{\mathsf{OFF,ON}}(\Delta t) &= 1 - DC_{\text{exp}}, \\ \lim_{\Delta t\to\infty} p_{\mathsf{ON,ON}}(\Delta t) = \lim_{\Delta t\to\infty} p_{\mathsf{ON,OFF}}(\Delta t) &= DC_{\text{exp}}. \end{aligned} \tag{2}$$

We matched geometric as well as log-normal distributions to our measurement traces. The geometric distribution is the discrete analogue to the exponential distribution. If X is an exponentially distributed random variable with parameter λ, $Y = \lfloor X \rfloor$ will be a geometrically distributed random variable with parameter $q = 1 - e^{\lambda}$, where the floor function $\lfloor \cdot \rfloor$ gives the largest integer not greater than the argument. However, the case of the log-normal distribution cannot be derived in closed form and we numerically determined the state transition probabilities from our measurements.

A. Probability of Finding Idle Spectrum

After we have discussed the probabilities per channel to be in the ON- and OFF-state we shall now study the probability to find a specific amount of spectrum idle. We start with the probability that the whole sensed spectrum is idle. The sensed spectrum may either be consecutive spectrum, indicated by $\Theta = 1$, or built up from non-continuous collection of spectrum bands, corresponding to the case $\Theta = 0$.

We compare four algorithms for selecting which channels should be sensed. Each of them is in charge of selecting K_s out of the K_a channels, that comprise the whole considered spectrum band. The outcome of each algorithm is the vector $\mathbf{s}$ of length K_s that lists the indices $s_i \in [1, K_a]$ of all channels that have been chosen for sensing.

1) Reference case: The reference case selects the channels for sensing randomly and does not rely on any spectrum occupancy information. We start with the consecutive case, $\Theta = 1$,

$$\begin{aligned} s_1 &\leftarrow U_{\text{int}}\big([1, K_a - K_s + 1]\big), \\ \forall i \in [2, K_s] : s_i &\leftarrow s_{i-1} + 1, \end{aligned} \tag{3}$$

where s_1 is the index of the first sensed channel. The variable s_i gives the index of the i-th channel selected for sensing. The term $U_{\text{int}}([\cdot,\cdot])$ gives a uniformly distributed random variate from a discrete distribution over the provided range. We continue with the non-consecutive case, $\Theta = 0$, for which we have

$$\begin{aligned} s_1 &\leftarrow U_{\text{int}}\big([1, K_a]\big), \\ \forall i \in [2, K_s] : s_i &\leftarrow U_{\text{int}}\big([1, K_a] \setminus [s_1, \dots, s_{i-1}]\big). \end{aligned} \tag{4}$$

Due to the random channel selection the probability of finding the whole sensed spectrum vacant solely depends on the average DC and the number of sensed channels K_s by

$$p_{\text{ref}}(\mathsf{idle}, \mathbf{s}) = \big(1 - \mathbb{E}(DC)\big)^{K_s}, \tag{5}$$

where $\mathbb{E}(\cdot)$ signifies the expectation and $p_{\text{ref}}(\mathsf{idle}, \mathbf{s})$ is the probability for the reference scheme that all K_s channels listed by the vector $\mathbf{s}$ are free.

2) DC-based sensing: The second algorithm relies on information giving the duty cycle per channel. All duty cycles are assumed to be constant throughout the examined time span and are known a priori. We first consider the consecutive case, $\Theta = 1$, for which we obtain

$$\begin{aligned} s_1 \leftarrow f, \text{ such that } &\prod_{k=f}^{f+K_s-1} DC(k) \\ &\equiv \min_{j\in[1,K_a-K_s+1]} \prod_{k=j}^{j+K_s-1} DC(k), \\ \forall i \in [2, K_s] : s_i &\leftarrow s_{i-1} + 1, \end{aligned} \tag{6}$$

where f is a frequency index identifying a specific channel and $DC(k)$ is the duty cycle of channel k. For the non-consecutive case, $\Theta = 0$, we get

$$s_1 \leftarrow f, \text{ such that } DC(f) \equiv \min_{k\in[1,K_a]} DC(k),$$
$$\forall i \in [2, K_s] : s_i \leftarrow f, \text{ such that } DC(f) \equiv \min_{k\in[1,K_a]\setminus[s_1,\ldots,s_{i-1}]} DC(k). \tag{7}$$

The algorithm selects the channel with the least DC first and continues to select the channels in increasing order of the DCs. The probability to find all investigated channels free for the DC-based sensing is given by

$$p_{\mathrm{DC}}(\mathsf{idle}, \mathsf{s}) = \prod_{i=1}^{K_s}(1 - DC(s_i)). \tag{8}$$

3) Ideal distribution-based sensing: The third and the fourth algorithm exploit knowledge on the distributions of the durations of ON- and OFF-periods. Thus, these rely on the equations given in (1) or the numerically computed probabilities in the log-normal case.

For the third algorithm we assume the ideal case, in which the SU knows the occupancy state for all channels in the previous time slot. Let us denote a busy state of channel f in time slot t by $\Omega(t, f) = 1$ and an idle state by $\Omega(t, f) = 0$, respectively. We set the previous time slot to start at time t_0 and the elapsed time is exactly one time slot of duration T_{sl}.

As above we differentiate between the consecutive case, $\Theta = 1$, for which

$$\begin{aligned} s_1 \leftarrow f, \text{ such that } &\prod_{k=f}^{f+K_s-1} \big[\Omega(t_0, k)p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}}) \\ &+ \big(1 - \Omega(t_0, k)\big)p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}})\big] \\ \equiv \max_{j\in[1,K_a-K_s+1]} &\prod_{k=j}^{j+K_s-1} \big[\Omega(t_0, k)p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}}) \\ &+ \big(1 - \Omega(t_0, k)\big)p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}})\big], \\ \forall i \in [2, K_s] : s_i \leftarrow s_{i-1} + 1,& \end{aligned} \tag{9}$$

and the non-consecutive case, $\Theta = 0$. For the latter case

$$\begin{aligned} s_1 \leftarrow f, \text{ such that } &\big[\Omega(t_0, f)p_{\mathsf{OFF,ON}}(f, T_{\mathrm{sl}}) \\ &+ \big(1 - \Omega(t_0, f)\big)p_{\mathsf{OFF,OFF}}(f, T_{\mathrm{sl}})\big] \\ \equiv \max_{k\in[1,K_a]} &\big[\Omega(t_0, k)p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}}) \\ &+ \big(1 - \Omega(t_0, k)\big)p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}})\big], \\ \forall i \in [2, K_s] : s_i \leftarrow f, \text{ such that } &\big[\Omega(t_0, f)p_{\mathsf{OFF,ON}}(f, T_{\mathrm{sl}}) \\ &+ \big(1 - \Omega(t_0, f)\big)p_{\mathsf{OFF,OFF}}(f, T_{\mathrm{sl}})\big] \\ \equiv \max_{k\in[1,K_a]\setminus[s_1,\ldots,s_{i-1}]} &\big[\Omega(t_0, k)p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}}) \\ &+ \big(1 - \Omega(t_0, k)\big)p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}})\big], \end{aligned} \tag{10}$$

where $p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}})$ is the state transition probability from the ON- to the OFF-state for channel k. The probability $p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}})$ is defined accordingly. The probability to find only idle channels with the ideal distribution-based sensing is

$$p_{\mathrm{distI}}(\mathsf{idle}, \mathsf{s}) = \prod_{i=1}^{K_s}\big[\Omega(t_0, s_i)p_{\mathsf{OFF,ON}}(s_i, T_{\mathrm{sl}}) + \big(1 - \Omega(t_0, s_i)\big)p_{\mathsf{OFF,OFF}}(s_i, T_{\mathrm{sl}})\big]. \tag{11}$$

4) Realistic distribution-based sensing: The fourth algorithm is the realistic version of the third. The SU will not have access to all occupancy states in the previous time slot. Instead, we assume that the state for each channel may have been measured more than a single time slot ago. We describe the additional time duration by the vector $\mathbf{T}$ and its elements T_f. If the frequency with index f has been sensed during the previous time slot $T_f = 0$.

Following the definitions for the third algorithm we get for the consecutive case, $\Theta = 1$,

$$\begin{aligned} s_1 \leftarrow f, \text{ such that } &\prod_{k=f}^{f+K_s-1} \big[\Omega(t_0 - T_k, k)p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}} + T_k) \\ &+ \big(1 - \Omega(t_0 - T_k, k)\big)p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}} + T_k)\big] \\ \equiv \max_{j\in[1,K_a-K_s+1]} &\prod_{k=j}^{j+K_s-1} \big[\Omega(t_0 - T_k, k)p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}} + T_k) \\ &+ \big(1 - \Omega(t_0 - T_k, k)\big)p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}} + T_k)\big], \\ \forall i \in [2, K_s] : s_i \leftarrow s_{i-1} + 1,& \end{aligned} \tag{12}$$

and for the non-consecutive case, $\Theta = 0$, that

$$\begin{aligned} s_1 \leftarrow f, \text{ such that } &\big[\Omega(t_0 - T_f, f)p_{\mathsf{OFF,ON}}(f, T_{\mathrm{sl}} + T_f) \\ &+ \big(1 - \Omega(t_0 - T_f, f)\big)p_{\mathsf{OFF,OFF}}(f, T_{\mathrm{sl}} + T_f)\big] \\ \equiv \max_{k\in[1,K_a]} &\big[\Omega(t_0 - T_k, k)p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}} + T_k) \\ &+ \big(1 - \Omega(t_0 - T_k, k)\big)p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}} + T_k)\big], \\ \forall i \in [2, K_s] : s_i \leftarrow f, \text{ such that } &\big[\Omega(t_0 - T_f, f)p_{\mathsf{OFF,ON}}(f, T_{\mathrm{sl}} + T_f) \\ &+ \big(1 - \Omega(t_0 - T_f, f)\big)p_{\mathsf{OFF,OFF}}(f, T_{\mathrm{sl}} + T_f)\big] \\ \equiv \max_{k\in[1,K_a]\setminus[s_1,\ldots,s_{i-1}]} &\big[\Omega(t_0 - T_k, k)p_{\mathsf{OFF,ON}}(k, T_{\mathrm{sl}} + T_k) \\ &+ \big(1 - \Omega(t_0 - T_k, k)\big)p_{\mathsf{OFF,OFF}}(k, T_{\mathrm{sl}} + T_k)\big]. \end{aligned} \tag{13}$$

Finally, the probability to find all sensed channels idle for the realistic case is

$$p_{\mathrm{distR}}(\mathsf{idle}, \mathsf{s}) = \prod_{i=1}^{K_s}\big[\Omega(t_0 - T_{s_i}, s_i)p_{\mathsf{OFF,ON}}(s_i, T_{\mathrm{sl}} + T_{s_i}) + \big(1 - \Omega(t_0 - T_{s_i}, s_i)\big)p_{\mathsf{OFF,OFF}}(s_i, T_{\mathrm{sl}} + T_{s_i})\big]. \tag{14}$$

B. Trade-off between Sensed Bandwidth and Detected Idle Spectrum

The above results describe only the probability that all sensed channels are idle. Usually, not all channels will be vacant and more channels have to be sensed in order to ensure that enough spectrum opportunities, also known as

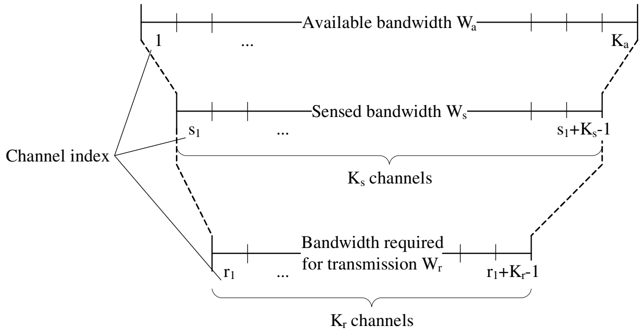


Figure 1. The relations between the available, the sensed, and the required bandwidth and the corresponding channel indices.

white spaces, are found. We extend our approach as shown in Figure 1. Until now each sensing algorithm was in charge of selecting K_s channels out of the available K_a channels and the goal was that all of them are free. Now, we focus on the case of consecutive spectrum, $\Theta = 1$, and expect only a subset of the sensed channels to be free, the required K_r channels with indices $r_i \in [s_1, s_1 + K_s - 1]$. We call them *required* as we assume that the SU has specific QoS (Quality of Service) requirements that can only be fulfilled with sufficient spectrum.

If the spectrum sensing does not detect enough white space the secondary QoS will drop to unacceptable state. We refer to this scenario as the SU being in *outage* [8]. However, depending on the running applications the SU may accept intermediate outage in order to save resources that would otherwise have to be spent for extended sensing[2]. We describe such differences by another given requirement of a maximum outage probability $p_{\text{out, max}}$. A delay-tolerant application has a higher $p_{\text{out, max}}$ than a delay-sensitive application.

Let us define the probability of outage achieved by a specific sensing algorithm for a given number of required channels K_r as

$$p_{\text{out}}(K_r) = 1 - p_{\text{algorithm}}(\mathsf{idle}, \mathsf{s}, K_r). \tag{15}$$

Obviously, the sensing process could simply examine all K_a channels and would always accomplish the minimum possible $p_{\text{out}}(K_r)$. However, we want to minimize the amount of resources spent for sensing. We are interested in an optimal number of sensed channels $\hat{K}_s$ given by the optimization problem

$$\begin{aligned} \hat{K}_s = & \min_{K_s \in [1, K_a]} K_s, \\ & \text{such that } \exists W_r \in [W_s^{(K_s)}(s_1), \ldots, W_s^{(K_s)}(s_{K_a - K_s + 1})], \\ & \quad \text{which satisfies } p_{out}(K_r) \le p_{\text{out, max}}, \end{aligned} \tag{16}$$

where W_r is the complete required bandwidth comprising K_r channels and $W_s^{(K_s)}(s_i)$ is the sensed bandwidth covering K_s channels starting at channel index s_i.

If we have determined the minimum number of channels to sense we have to select the first channel index. Since we assume consecutive channels it will be sufficient to select the optimal first index $\hat{s}_1$ and the number of channels to sense $\hat{K}_s$. We formulate a second optimization problem as

$$\hat{s}_1 = \max_{s_1 \in [1, K_a - \hat{K}_s + 1]} p_{\text{algorithm}}(\mathsf{idle}, \mathsf{s}, K_r). \tag{17}$$

The optimization problem in (16) essentially requires an efficient way to compute the probability $p_{\text{algorithm}}(\mathsf{idle}, \mathsf{s}, K_r)$ due to its relation to $p_{\text{out}}(K_r)$ as given in (15).

The sought probability $p_{\text{algorithm}}(\mathsf{idle}, \mathsf{s}, K_r)$ can also be seen as the probability that at least one of the subbands $S^{(K_r)}(k)$ is completely idle. Each subband $S^{(K_r)}(k)$ comprises K_r channels and starts at index $k \in [s_1, s_1 + K_s - K_r - 1]$. When considering the positions of all subbands in the spectrum we get

$$\begin{aligned} & p_{\text{algorithm}}(\mathsf{idle}, \mathsf{s}, K_r) \\ & \quad = p_{\text{algorithm}}\Big(\mathsf{idle}, W_r \in \bigcup_{k=s_1}^{s_1+K_s-K_r} S^{(K_r)}(k)\Big). \end{aligned} \tag{18}$$

Evaluating (18) is challenging for large $K_s - K_r$ and requires simplifications in more complex scenarios. The separate events are not mutually exclusive because the subbands $S^{(K_r)}(k)$ are partially overlapping. For instance, $S^{(K_r)}(1)$ and $S^{(K_r)}(2)$ share all channel indices but one. We have considered such relations and have introduced an appropriate heuristic in [8]. The underlying idea is that the behaviour over time for each channel is generated independently in our model. Based on this fact we can identify those subbands that contribute most to the idle probability and neglect the impact of the other subbands.

Using the approximation we can compute the outage probability for a given number of sensed channels and determine the minimum required K_s for a given $p_{\text{out, max}}$. However, we do not have a solution for the second optimization problem given in (17), yet.

We compare the following three heuristics [8] for selecting $\hat{s}_1$:

1) Reference strategy: The reference strategy randomly selects $\hat{s}_1 = U_{\text{int}}\big([1, K_a - K_s + 1]\big)$. It is the only strategy we shall consider that does not rely on any spectrum occupancy statistics. We name this case the $RandS1$-result.

2) Best-requested bandwidth strategy: The second strategy selects the subband $S^{(K_r)}(x)$ that maximizes $p_{\text{algorithm}}\big(\mathsf{idle}, S^{(K_r)}(x)\big)$ based on the specified adaptive sensing algorithm. Afterwards, the sensed bandwidth is extended around the K_r channels until K_s indices have been selected for sensing. If $S^{(K_r)}(x)$ is located close to the border of the considered spectrum band we extend the sensed bandwidth to the border of the band and add all further channels on the other side. The number of required channels K_r is given by the application and does not change throughout system operation. Therefore, the outage probability $p_{\text{out}}(K_r)$ monotonically decreases with respect to the number of sensed channels K_s.

[2]We consider only outage events caused by insufficient amount of detected idle spectrum. Additional outage situations may occur if transmissions fail due to, e.g., channel fading.

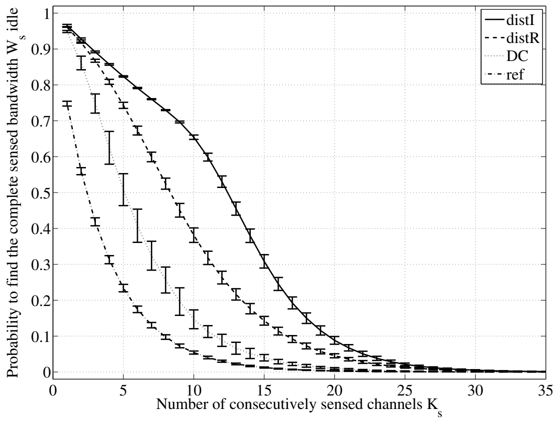


Figure 2. The probability to find all sensed channels idle plotted over the number of consecutively sensed channels and evaluated for all four different sensing algorithms. The ON- and OFF-period durations were geometrically distributed for all channels with a uniformly distributed DC over all channels.

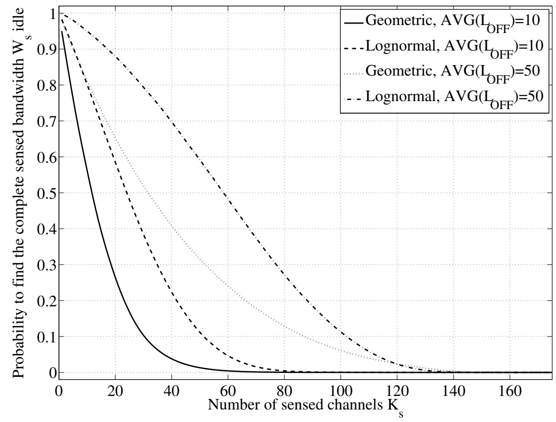


Figure 3. The probability to find all sensed channels idle plotted over the number of non-consecutively sensed channels and evaluated for four different distribution parameter sets for the ON- and OFF-period durations. The DC was uniformly distributed over all channels.

We refer to this strategy as the $BestReq$-strategy.

3) Best-sensed bandwidth strategy: Instead of extending the sensed bandwidth around a subband of K_r channels, the third strategy selects K_s channels from the beginning. It chooses the subband that maximizes $p_{\text{algorithm}}\big(\mathsf{idle}, S^{(K_s)}(x)\big)$ using the specified adaptive sensing algorithm. Which subband maximizes $p_{\text{algorithm}}\big(\mathsf{idle}, S^{(K_s)}(x)\big)$ obviously changes with increasing K_s. Hence, $p_{\text{out}}(K_r)$ does not automatically monotonically decrease when more channels are sensed. We call this approach the $BestSens$-strategy.

VI. Results

Now, after we have provided the formulation of the studied problem, we shall discuss simulation results. We use artificial spectrum data generated using simple as well as our more realistic spectrum models. Additionally, we consider binary spectrum occupancy data that we extracted from our raw measurement traces by applying energy detection. In the case of artificially generated spectrum data we averaged the results over ten simulation runs.

A. Probability of Finding Idle Spectrum

We follow a similar split as in Section V and start with the probability that the whole sensed spectrum is idle. Figure 2 shows $p_{\text{algorithm}}(\mathsf{idle}, \mathsf{s})$ for all four sensing algorithms and an increasing number of consecutively sensed channels. The DC across all channels has been taken as being uniformly distributed, that is, $DC_f = U([0.05, 0.45])$, where $U([\cdot,\cdot])$ gives a uniformly distributed random variate from a continuous distribution over the provided range. The ON- and OFF-period durations have been geometrically distributed[3], $q_{\mathsf{OFF}} = 0.04$ and q_{ON} has been adapted to match the computed DC_f per channel. We have simulated 200 channels for 25 000 time slots.

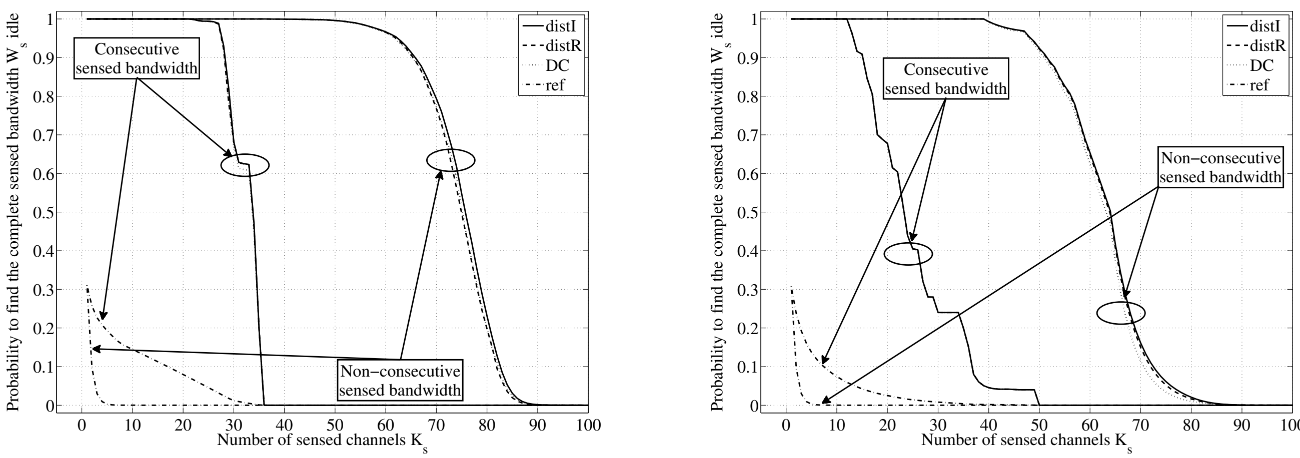
The performance of the algorithms that exploit statistics of the PU activity is clearly superior compared to the reference scheme. Also, using the information on the ON- and OFF-period length distributions improves the performance significantly. The standard deviation is higher in the case of the DC-based sensing because it always selects the same channels independently of their previous occupancy states.

For the non-consecutive case we focus on the $distR$-scheme because it is the most advanced but still realistic approach. Figure 3 shows that the distribution parameters have significant impact on $p_{\text{distR}}(\mathsf{idle}, \mathsf{s})$. The average duty cycle has been same for all four cases, only the length of the ON- and OFF-period durations have been sampled from different distributions. We configured the distributions to result either in an average OFF-period duration of $\overline{L}_{\mathsf{OFF}} = 10$ time slots or $\overline{L}_{\mathsf{OFF}} = 50$ time slots. The distribution parameters[4] were $q_{\mathsf{OFF}} = 0.10$, $\mu_{\mathsf{ON}} = 1.00$, $\sigma_{\mathsf{ON}} = 0.64$, and $\mu_{\mathsf{OFF}} = 1.00$ for the shorter ON- and OFF-period length scenario. In the other situation, the parameters were $q_{\mathsf{OFF}} = 0.02$, $\mu_{\mathsf{ON}} = 1.00$, $\sigma_{\mathsf{ON}} = 1.90$, and $\mu_{\mathsf{OFF}} = 2.00$. The remaining settings q_{ON} and σ_{OFF} have been set based on the computed DC_f per channel.

The probability $p_{\text{distR}}(\mathsf{idle}, \mathsf{s})$ will be higher if the ON- and OFF-periods are longer. When comparing the two different distributions the log-normal case results in an increased probability for very long OFF-period durations. The sensing-based algorithm successfully selects these channels for sensing and improves the sensing efficiency. This example proves the importance of the ON- and OFF-period durations distributions for spectrum sensing. Additionally, it also shows the implications of the assumption that ON- and OFF-period lengths are geometrically distributed that we validated only for a subset

[3]The Probability Mass Function (PMF) of the geometric distribution is given by $f(n;q) = (1-q)^{n-1} \cdot q, n \geq 0, q \in (0,1]$.

[4]The Probability Density Function (PDF) of the log-normal distribution is defined as $f(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\log(x)-\mu)^2}{2\sigma^2}}, \mu \in \mathbb{R}, \sigma \in \mathbb{R}^+$. The continuous samples were rounded to the next discrete integer value while not considering zero-samples.



(a) Measured traces.

(b) Time-frequency model.

Figure 4. The probability to find all sensed channels idle plotted over the number of sensed channels and evaluated for all four different sensing algorithms. Both cases, consecutive as well as non-consecutive bandwidth, are shown. The spectrum occupancy data was either taken from the measured traces or generated using our time-frequency model. In both cases, we selected the location AB and GSM1800 DL as wireless technology.

of our measurement results.

In the next step, we consider spectrum data generated using our spectrum model and binary occupancy data extracted from our raw measurement data. We use the GSM1800 DL (downlink) band as first scenario. Figure 4 shows the results for the consecutive and the non-consecutive cases.

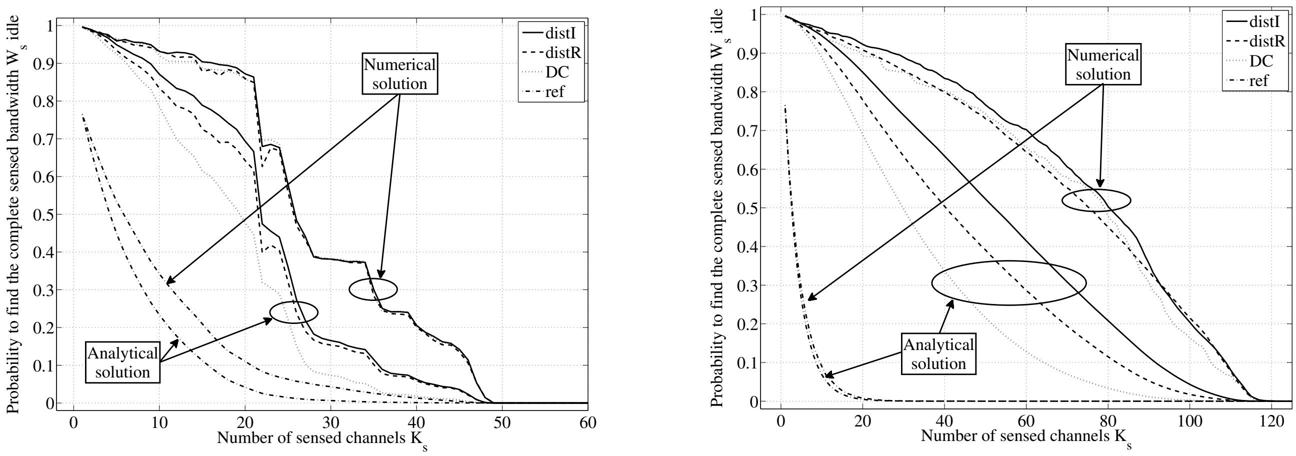
The reference scheme gives surprising results. Counterintuitively, the probability is higher for the consecutive sensing scheme. In the studied band, only few subbands have high probability to be free. In the non-consecutive case, only a limited set of additional channel combinations results in high idle probabilities. At the same time, the total number of channel sets considerably increases and the probability to select an idle combination decreases. The probability can be seen as ratio between the number of subbands that are free with high probability and the total number of subbands. Both, the number of subbands giving high probabilities and the toal number of subbands are higher in the non-consecutive case due to the more flexible channel selection. However, since only a very small number of subbands gives high idle probabilities and most of them are consecutive ones, the increase in the total number of subbands is significantly higher. The final result is a lower ratio and a lower probability to find the complete sensed subband free. This result is also reproduced when using data generated from the time-frequency spectrum model.

The algorithms that consider knowledge on the occupancy statistics are significantly better for measured and generated data. However, only marginal improvement can be achieved when using not only information on the DC but also on the distributions of the ON- and OFF-period durations. Several characteristics of the spectrum use in the studied scenario can be identified as underlying reasons. First, intermediate DC-values occur less often but these channels usually have more complex occupancy patterns that can be exploited by the distribution-based sensing schemes. Second, the spectrum archetypes that have been fitted to log-normal distributions are less probable in this case. As we have seen above, geometric distributions tend to produce shorter ON- and OFF-period lengths strictly limiting the potential for improved MAC-layer sensing. We have evaluated further spectrum bands allocated to other technologies that yield similar results.

The partially steep steps in the probability curves are caused by the correlations in the frequency domain. Adjacent channels show similar occupancy statistics and the smart sensing algorithms focus their activity around those bands. If the consecutively sensed bandwidth is further extended around a subband of low DC some channels with high DC are added before the next subband with low DC is reached. These channels with higher DC cause the steep drop of the combined probability to find the whole sensed band vacant. The steps do not occur in the non-consecutive scenario because the channels with higher DC are not chosen for sensing.

The above results have been computed using the problem formulation introduced in Section V. The state transition probabilities have been determined on a per channel basis and the probability to find the whole band idle can be computed using the described algorithms. When using the binary occupancy information extracted from the raw measurement data we can also investigate the probability that the channels selected for sensing are in fact idle because we have the occupancy information available for the next time slot. We refer to this evaluation as the *numerical* method compared to the *analytical* method that only relies on estimation techniques for the extraction of the state transition probabilities.

When comparing both approaches we can study the impact of one assumption that we took during the model development.



(a) Consecutively sensed bandwidth.

(b) Non-consecutively sensed bandwidth.

Figure 5. The probability to find all sensed channels idle plotted over the number of sensed channels and evaluated for all four different sensing algorithms. Both cases, consecutive as well as non-consecutive bandwidth, are shown. The spectrum measurement data was taken at AB and in the GSM900 UL band.

Following several other authors, e.g., [6], [16], [26], we modelled each channel independently. We described correlations in the frequency domain only by using similar parameters for the ON- and OFF-period distributions but generate the occupancy over time for each channel separately. This assumption is essential for the formulation derived in Section V and our measurement data enables us to examine its wider validity.

Figure 5 compares the analytical and the numerical approach for both consecutively and non-consecutively sensed spectrum. Due to the model properties the results for both approaches are same for spectrum data generated from the time-frequency model. For the measured data the results clearly differ.

The effect can be explained best using the reference case. The results for the non-consecutive results are close but the curves for the consecutive sensing differ. The occupancy over time develops similarly for adjacent channels allowing for increased idle probabilities for consecutive channels. The probability to find a single channel idle is the same for both approaches.

The found correlations also cause differences for the smart sensing algorithms. Here, also the results for the non-consecutive sensing differ because the algorithms successfully focus the sensing on few channels that seem to be correlated with higher probability.

Our spectrum model does not reproduce these correlations. This disadvantage of the model has been accepted during the model development in order to accomplish the decomposition of the modelling of time- and frequency-domain. Nevertheless, the introduced spectrum model is to the best of our knowledge the most accurate spectrum model available from the literature. In light of these results investigating integrated time-frequency-spectrum models that reproduce the determined correlation characteristics is certainly well motivated. Such a model would also enable the description of spectrum bands that are not dominantly used by a specific technology with a fixed channel bandwidth [9]. Reasons for the correlations maybe transmissions of signalling information in similar time patterns across multiple channels or the fact that sometimes technology-specific channels and measurement channels were not aligned although both are of the same bandwidth.

B. Trade-off between Sensed Bandwidth and Detected Idle Spectrum

As said above a SU will most probably sense more channels than required for the ongoing communication. Some channels may be busy and few vacant channels will be needed as quickly available backup if the PU returns. We shall now study the trade-off between the number of sensed channels and the amount of detected white spaces.

We start with the question of how to select the first channel to be sensed and compare the three different strategies introduced in Section V-B. Figure 6 shows the outage probability for an increasing number of sensed channels and requested number of channels $K_r = 4$. We focused on the $distR$-sensing algorithm. However, the smart sensing algorithm does not improve the performance for the $RandS1$-strategy because the first sensed channel is randomly selected.

As expected sensing further channels improves $p_{\text{out}}(K_r)$. The advantage is higher for the random scheme that is still constantly outperformed by both adaptive strategies. The performance gain with increased number of sensed channels is smaller for longer ON- and OFF-period durations. At the same time, the advantage of the adaptive sensing algorithm is larger for this case as we have also seen above. We get two different effects that both may improve the sensing efficiency. If the ON- and OFF-period lengths tend to be longer applying smart sensing algorithms significantly improves the spectrum

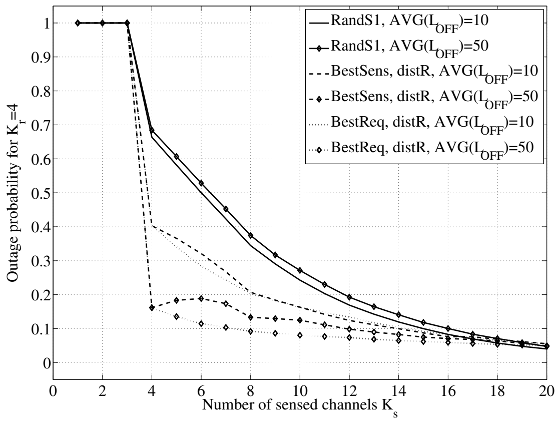


Figure 6. Comparison of different strategies to select $\hat{s}_1$ based on two different spectrum scenarios. The durations of the ON- and OFF-periods have been generated using the same parameters as used for Figure 3. We simulated 20 channels and 12 000 time slots.

sensing but increasing the number of sensed channels results only in small performance gains. In the opposite situation with shorter ON- and OFF-periods, the improvements achieved by the better algorithms are limited but extending the amount of sensed spectrum helps more.

The above results are due to two ways how the ON- and OFF-period durations impact sensing performance. First, if the occupancy state of a channel changes more quickly knowing the duration distributions does not help that much because the estimates of an idle channel will only be valid for a limited amount of time. Second, estimations of a busy channel will also be valid for shorter time periods making it worthwhile to check the same channel again after shorter time. The first fact is directly connected to the above result that sensing improvements achieved by the adaptive algorithms are larger for the log-normal distribution. The second fact explains why we can gain more by sensing further channels if ON- and OFF-periods tend to be shorter. Since channel states change more often there are more candidate channels that may have recently switched from busy to idle state and that should be sensed again.

For both scenarios shown in Figure 6 the $BestReq$-strategy is consistently better than the $BestSens$-strategy. Additionally, as explained above, its performance monotonically improves with the number of sensed channels. For the $BestSens$-strategy that is not always the case.

Figure 7 shows this difference more clearly because it is based on a scenario with more diverse duty cycles. Again, the adaptive schemes are better than the reference scheme. The $BestReq$-scheme performs well and the small non-monotonic steps in the curve are due to the fact that the results have been achieved using the numerical approach. For the data generated from the time-frequency spectrum model, the shape of the $BestSens$-strategy is an example for the more fluctuating performance. Although the $BestSens$-strategy performs best for few numbers of sensed channels we conclude that the $BestReq$-strategy is preferable. It ensures good and stable performance.

In the measurement case, the outage probability accomplished by the adaptive schemes quickly drops to ≈ 0.03 but does almost not improve further. The studied spectrum band includes a subband with low duty cycles on which both approaches focus the sensing. Since all surrounding channels have considerably higher duty cycles the outage probability can hardly be improved further.

We average the results over ten simulation runs and there is no comparably clear maximum performance threshold in the case of generated spectrum data. Additionally, the standard deviation of the results is very large for intermediate numbers of sensed channels and cannot be reasonably visualized. However, since our model accurately reproduces the clustering of channels with similar characteristics in the frequency domain such variations across different simulation runs are to be expected.

Finally, we compare the different sensing algorithms when combined with the selected $BestReq$-strategy. Figure 8 shows two pairs of results for measured and generated spectrum data. In all four graphs the reference scheme is the worst and exploiting knowledge on spectrum occupancy statistics proves to be useful in all considered scenarios. Similarly as discussed above, more drastic changes occur in the scenarios using measured data. However, the results for the time-frequency model graphs are similar confirming that our model reproduces most of the important characteristics.

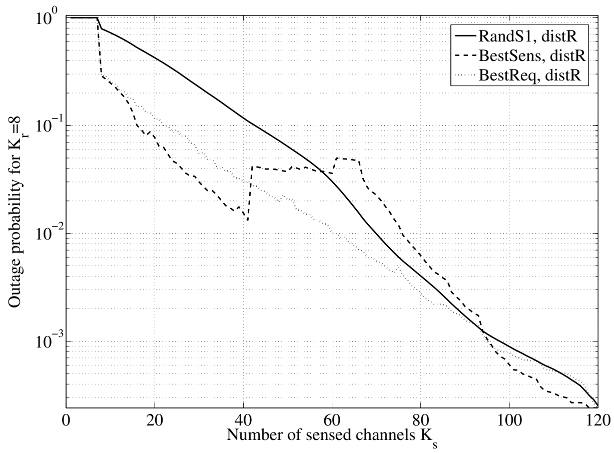
For the NE-results, almost negligible performance gain can be achieved when using distribution-based instead of DC-based sensing. Relying only on DC-information would be sufficient. In the case of the calmer radio environment at AB, at least $\approx 10\,\%$ gain in the outage probability or the same probability but approximately ten sensed channels less can be accomplished.

The impact of the spectrum occupancy statistics is essential for the performance of the sensing algorithm. More advanced algorithms often do not further improve the performance due to too rapid changes in the occupancy. In these cases, using the simpler DC-based approach is sufficient.

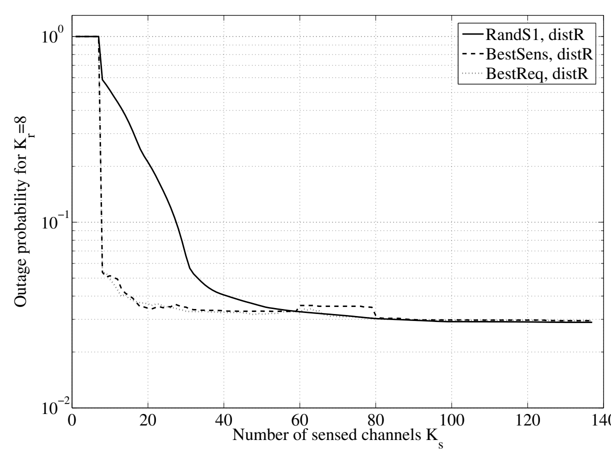
VII. Conclusions

In this paper, we compared the performance of four MAC-layer sensing algorithms that use different amounts of information on the spectrum occupancy statistics. All adaptive schemes have clearly outperformed the random selection of channels for sensing and relying on the DC on a per channel resolution is always worthwhile.

The consideration of more detailed knowledge on the distributions of ON- and OFF-period durations does sometimes not improve the sensing efficiency significantly. In this context, the distribution types and the average durations of the ON- and OFF-periods are important. If these tend to be longer sensing algorithms that exploit them can considerably increase the probability to successfully detect the required amount of white



(a) Time-frequency model: AB, GSM900 UL.



(b) Measurement data: AB, GSM900 UL.

Figure 7. The probability $p_{\text{out}}(K_r = 8)$ to be in outage when increasing the number of channels in the sensed bandwidth W_s for all three strategies to select $\hat{s}_1$. The spectrum occupancy has either been generated using the time-frequency model or extracted from the measurement data. In the former case, the model parameters have been adapted in order to fit to a specific measurement scenario. The results have been computed using the numerical approach. For the time-frequency model simulation, we used 120 channels and 25 000 time slots and averaged the results over ten simulations runs. The considered GSM900 UL band was covered by 137 measurement channels in Germany and we used measurement traces of 24 121 samples.

spaces. In the case of shorter ON- and OFF-period durations, the advanced algorithms result only in limited improvements but adding further resources for sensing decreases the outage probability. Sensing larger number of channels is more useful in this case.

The whole study has shown the impact of the spectrum occupancy statistics. Simple models may often be required in order to keep the formulation analytically tractable but the second step of using more accurate models should also be taken. The detailed model parameters published in [9] enable such studies. Additionally, we have recently made available extensive parts of our raw spectrum measurement traces for public download [12].

In this paper we focused on studying the impact of different spectrum occupancy scenarios on the performance of few MAC-layer sensing schemes. A more thorough comparison of the discussed algorithms with solutions proposed in the literature is an important topic for future work. Another one is the development of appropriate protocols to control adaptive sensing schemes across a network. All nodes must not transmit in the band to be sensed and local decisions on the channels selected for sensing have to be exchanged and synchronized across the network.

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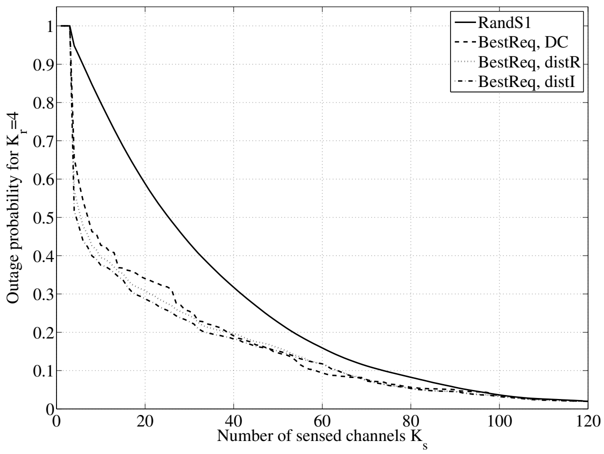
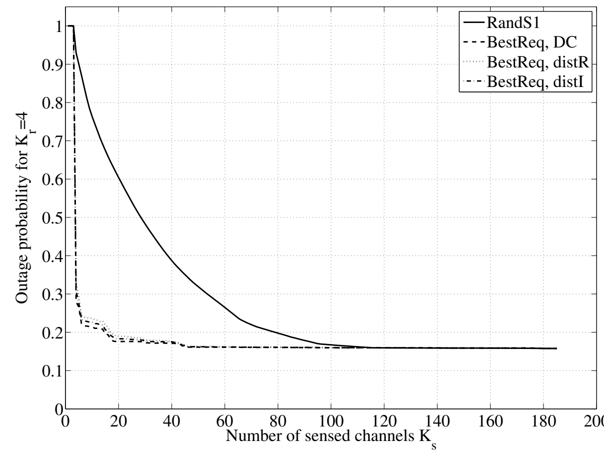
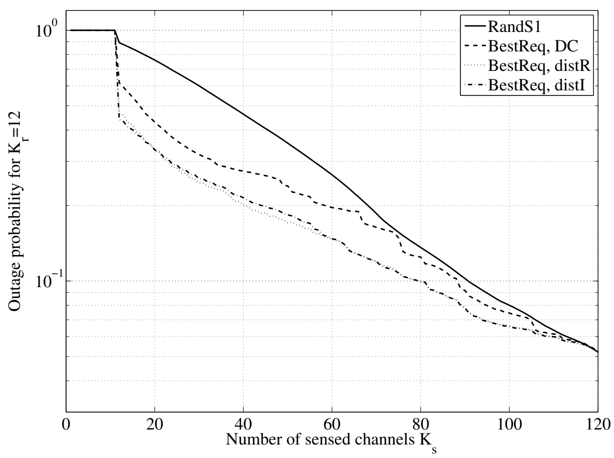


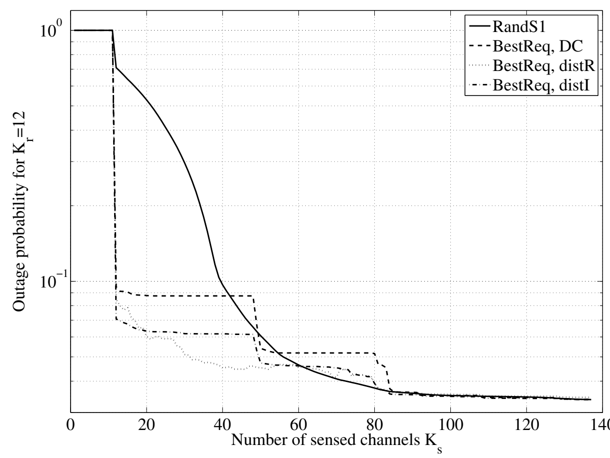
(a) Time-frequency model: NE, GSM900 UL.



(b) Measurement data: NE, GSM900 UL.



(c) Time-frequency model: AB, GSM900 UL.



(d) Measurement data: AB, GSM900 UL.

Figure 8. The probability $p_{\text{out}}(K_r)$ to be in outage when increasing the number of sensed channels, K_s, for all four sensing algorithms. The spectrum occupancy has either been generated using the time-frequency model or extracted from the measurement data. In the former case, the model parameters have been adapted in order to fit to a specific measurement scenario. The results have been computed using the numerical approach. For the data based on the measurement location AB, we used the same simulation parameters as given for Figure 7. For the NE case, we also generated occupancy for 120 channels and $25\,000$ time slots when using the time-frequency model. The considered GSM900 UL band comprised 187 measurement channels in the Netherlands and the selected measurement traces consisted of $24\,123$ samples. We ran 10 simulations for both time-frequency models.

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