Spectrum Usage in Cognitive Radio Networks: From Field Measurements to Empirical Models**

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SUMMARY Cognitive Radio (CR) is aimed at increasing the efficiency of spectrum utilization by allowing unlicensed users to access, in an opportunistic and non-interfering manner, some licensed bands temporarily and/or spatially unoccupied by the licensed users. The analysis of CR systems usually requires the spectral activity of the licensed system to be represented and characterized in a simple and tractable, yet accurate manner, which is accomplished by means of spectrum models. In order to guarantee the realism and accuracy of such models, the use of empirical spectrum occupancy data is essential. In this context, this paper explains the complete process of spectrum modeling, from the realization of field measurements to the obtainment of the final validated model, and highlights the main relevant aspects to be taken into account when developing spectrum usage models for their application in the context of the CR technology.

key words: cognitive radio, dynamic spectrum access, spectrum usage, spectrum measurements, spectrum models

1. Introduction

Spectrum underexploitation has been demonstrated by many spectrum measurement campaigns all over the world [1]–[14]. The Dynamic Spectrum Access (DSA) principle [15]–[19], based on the Cognitive Radio (CR) paradigm [20]–[24], has emerged as a promising solution to conciliate the conflicts between spectrum demand growth and spectrum underutilization without changes to legacy systems.

The underlying idea of DSA/CR is to allow unlicensed users to access, in an opportunistic and non-interfering manner, some licensed bands not used by licensed users during certain time periods and/or over certain areas. The operation principle is to identify temporal and/or spatial spectrum gaps not occupied by licensed (primary) user transmissions, referred to as *spectrum holes* or *white spaces* [25], place unlicensed (secondary) transmissions within such spaces and vacate the channel as soon as primary users return. Secondary transmissions are allowed following this operation principle provided no harmful interference is caused to the primary system. Based on DSA/CR, new and legacy radio communication systems can coexist in the same spectrum, thus leading to a more efficient exploitation thereof.

Owing to the opportunistic nature of DSA/CR, the behavior and performance of a secondary network depends on the spectrum occupancy patterns of the primary system[***]. A realistic and accurate modeling of such patterns becomes therefore essential and extremely useful in the domain of DSA/CR research [26]. Spectrum usage models can find many interesting applications in analytical studies, the design and dimensioning of DSA/CR networks, the implementation of new simulation tools and the development of more efficient DSA/CR techniques. However, the practical utility of such models depends on their degree of realism and accuracy. In order to be realistic and accurate, spectrum models need to be developed and validated based on empirical measurement data from real systems. However, the complete process from the realization of field measurements to the final validated model is not straightforward and requires many problematic aspects to be carefully taken into account. In this context, this paper addresses the problem of modeling spectrum usage patterns of real wireless systems in the context of DSA/CR. In particular, this paper provides a detailed step-by-step description of the complete process that starts with the realization of field measurements and ends up with a validated spectrum model. Based on the experience gained from past spectrum modeling works, several observations, guidelines and recommendations are provided in order to assist researchers in developing realistic and accurate spectrum occupancy models for their application in the analysis and development of the DSA/CR technology.

2. Field measurements

The first step in the development of realistic and accurate spectrum occupancy models is the obtainment of spectrum occupancy data from real systems. A possible way to obtain spectrum data is to monitor internally the traffic of a wireless network and its transmitters. While this option provides exact information on spectrum occupancy, it requires access to hardware in the system of interest, which is normally constrained to a commercial wireless operator. A more practical

***Spectrum occupancy patterns cannot be inferred from traffic generation models. The varying data rates of wireless links, the occurrence of errors requiring packet retransmissions and the use of radio resource management procedures (e.g., channel selection or admission control) result in unpredictable spectrum occupancy sequences for a certain traffic generation sequence. Therefore, traffic generation models are not convenient in the study of DSA/CR systems and spectrum occupancy models become necessary.

alternative for researchers is to obtain spectrum occupancy data by directly performing empirical measurements of the spectrum band(s) of interest and inferring the occupancy patterns from the captured samples. This is the approach considered in this paper, which involves designing and implementing an appropriate spectrum measurement platform, conducting field measurements and post-processing the captured data to extract the information of interest. The main drawback of this approach is that the presence of the radio propagation channel and its degrading effects cannot be avoided, which may potentially lead to measurement errors (e.g., a busy channel may be observed as idle as a result of a deep signal fade). However, accurate and reliable results can be obtained if appropriate methodological considerations are taken into account. An in-depth discussion of these methodological aspects is provided in [27]. This section summarizes the most relevant aspects. Further particular considerations are discussed in Sections 4.2, 5.2 and 6.2.

2.1 Measurement platform

Depending on the particular requirements of the study, different measurement configurations have been used in past spectrum measurements, ranging from simple setups with a single antenna connected to a measurement unit [28] to more sophisticated specific-purpose designs [1], [3]. Different configurations between both extreme points may determine various trade-offs between complexity and measurement capabilities. Figure 1 shows an example of a measurement design providing a balanced trade-off, based on a spectrum analyzer with some external devices to improve the detection capability and provide more accurate results.

When covering a small frequency range or a specific licensed band, a single antenna may suffice. However, several antennas may be required in broadband measurements. An attractive option is to use discone-type antennas, which provide an exceptionally wideband coverage and therefore allow a wide frequency range to be covered with a low number of antennas. The example shown in Figure 1 covers the frequency range up to 7 GHz with only two antennas.

The use of two or more antennas requires a switch in order to select the desired antenna (depending on the spectrum band of interest) as well as appropriate filters in order to remove undesired signal components from each antenna branch. The example shown in Figure 1 makes use of low/high-pass filters to remove out-of-band components, which may create harmonics or intermodulation products and thus lead to inaccurate measurements. In addition to these filters, a band-stop filter may be necessary to remove overloading FM signals that may lead to problems of saturation or dynamic range (especially when performing measurements in urban environments, where high-power FM broadcast stations may be near the measurement location).

An important aspect of the measurement platform is its sensitivity, which needs to be good enough to enable a reliable detection of any signal present in the measured bands. A convenient practice is to place a low-noise pre-amplifier
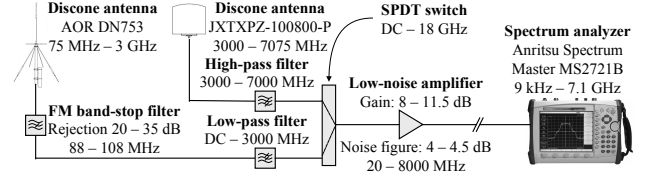

Fig. 1   Example of a balanced spectrum measurement platform [29].

right after the antenna system, as shown in Figure 1, in order to lower the system's noise figure and improve the overall sensitivity. However, the gain of this amplifier needs to be selected carefully since a high gain will improve the sensitivity but also will reduce the dynamic range of measurable signals, which may be an important aspect to take into account as well. The example of Figure 1 shows some typical values for the current state-of-the-art technology.

Finally, a spectrum analyzer or a similar measurement device is needed to record the spectral activity, which may be controlled by a computer running a tailored software.

2.2 Measurement configuration

There are several dimensions that a spectrum measurement strategy should clearly specify [30]: *time* (sampling rate and measurement period), *frequency* (frequency span/band and frequency points to be measured within the selected frequency span/band), *location* (measurement site selection), *direction* (use of omni-directional or directive antennas, and the antenna pointing angle in the latter case) and *polarization* (receiving antenna polarization). The particular configuration of the parameters for each of these dimensions determines the way the spectrum occupancy patterns are observed by the measurement platform and therefore plays a key role in the reliability and accuracy of the obtained spectrum occupancy data and the resulting spectrum models. The impact of these parameters and their configuration on the resulting spectrum models is discussed later on.

2.3 Data post-processing

Depending on the employed measurement device, the captured spectrum occupancy data can be composed of signal samples (amplitude or I/Q components) or power samples. From the point of view of DSA/CR, the relevant aspect is not the signal amplitude/power itself but the instantaneous states of the channel (i.e., busy or idle). Therefore, the first step in the processing of the captured data is to determine which samples correspond to busy/idle channels. The instantaneous occupancy state of the spectrum is the basic information to be used as input when modeling spectrum use.

To determine when a channel is used by a licensed user, different signal detection methods (referred to as *spectrum sensing* techniques in the context of DSA/CR) have been proposed in the existing literature [31]–[33], which provide different trade-offs between required sensing (observation) time, complexity and detection capabilities. The
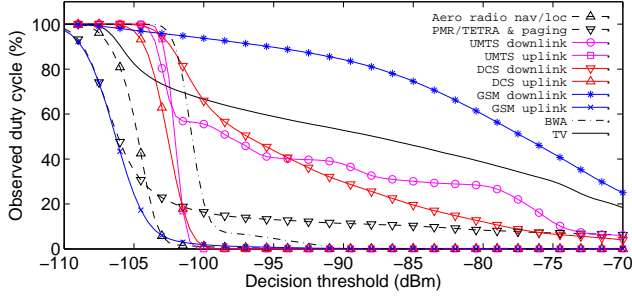
Fig. 2 Observed duty cycle as a function of the decision threshold for: TV (470-862 MHz), BWA (3400-3600 MHz), GSM uplink (880-915 MHz) and downlink (925-960 MHz), DCS 1800 uplink (1710-1785 MHz) and downlink (1805-1880 MHz), UMTS uplink (1920-1980 MHz) and downlink (2110-2170 MHz), PMR/TETRA and paging (406.1-470 MHz), and aeronautical radio navigation and location (960-1350 MHz) [27].

practical applicability of each method depends on how much information is available about the licensed signal to be detected. When no detailed information is available, the energy detection method [34] can be used. Energy detection compares the received signal energy in a certain channel or frequency band to a predefined decision threshold. If the signal is above the threshold, the channel/band is declared to be busy. Otherwise the channel/band is supposed to be idle. The decision threshold is a critical parameter in data post-processing since its value impacts severely the observed spectrum occupancy. As shown in Figure 2, the spectrum occupancy observed for various systems (expressed in terms of the duty cycle) may exhibit significant variations depending on the selected decision threshold (in some cases, with changes from 100% to 0% for a variation of 5 dB or less). While the real duty cycle of a channel is constant, the value observed by the measurement platform may vary significantly depending on the selected decision threshold. This highlights the importance of using an adequate criterion to select the decision threshold of energy detection. Several methods to set the decision threshold can be employed, which are described and analyzed in detail in [27].

3. Spectrum occupancy modeling

Once the busy/idle information has been extracted from the captured measurement data, it can be used for the development of spectrum occupancy models. Models can be elaborated based on the captured data following an empirical approach or a theoretical approach. In the empirical approach, the measurement data is examined and analyzed in order to extract the information relevant to the parameter(s) to be modeled (e.g., duration of idle periods). An appropriate model is then found by comparing this information to various candidate models, assessing the accuracy of each option and selecting the most convenient modeling alternative (e.g., the distribution that best fits the duration of the observed idle periods). In the theoretical approach, the spectrum model is developed based solely on theoretical reasoning and the empirical data is used to validate the final

theoretical result. The most convenient modeling approach depends on the parameter(s) to be modeled and the spectrum occupancy data available, which requires an individual analysis for each particular modeling problem.

When developing a spectrum model it is important to bear in mind that the model needs not only to capture and reproduce accurately the relevant properties of the spectrum occupancy but also be simple enough to be applicable in analytical studies, simulation tools, etc. This trade-off between accuracy and simplicity may require sometimes to favor one of these compromised aspects, depending on the particular purpose the model is developed for.

There are various aspects that a spectrum occupancy model needs to define and specify in a clear manner:

- *What parameter(s) or aspect(s) of spectrum usage are modeled?* The model can be developed to capture and reproduce the statistical properties of parameters such as the duration of the busy/idle periods of the licensed channels, the time evolution of the channel load, the number of free channels in a spectrum band at any time instant, etc. Spectrum occupancy models can be aimed at characterizing the properties of a single parameter or may involve simultaneously two or more parameters.
- *How are such parameter(s) or aspect(s) of spectrum usage modeled?* The most convenient modeling approach depends on the particular parameter(s) of interest. Some examples of modeling tools include (but are not limited to) Markov chains and processes, probabilistic/stochastic formulations, time series, curve fitting techniques, etc. Several modeling tools may sometimes be combined in a particular modeling approach.
- *What information is provided by the model?* The information provided by the model will usually be the same information provided by the modeled parameter, but it can also be some kind of more elaborated information obtained from the model itself. For example, in the case of modeling the duration of busy/idle periods, the model may provide the statistical distribution of the period durations, which can be used to provide other information such as the minimum and mean period duration or the probability that a particular period duration is observed in the channel.

The following sections provide a more detailed discussion on how these questions are answered by some spectrum occupancy models for the time, frequency and space dimensions [35]. Moreover, the impact that the measurement configuration employed in the field measurements may have on the final spectrum model is also discussed.

4. Time-dimension modeling

4.1 Models

The spectrum occupancy pattern of a licensed channel in the time domain can be characterized in terms of three main aspects, namely the channel occupancy level (channel load),
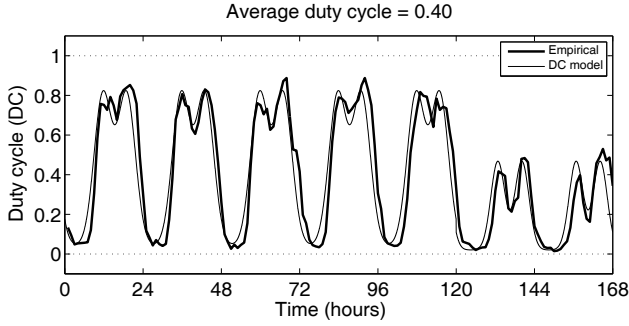
Fig. 3 Empirical duty cycle time evolution and corresponding deterministic model for a cellular mobile communication system [38].

the durations of the busy/idle periods and the correlation structures of the period durations. These three aspects are discussed in more detail in the following.

The channel occupancy level or channel load is a relevant parameter because it determines the amount of spectrum opportunities that a DSA/CR system can expect to find in a channel. The channel occupancy level can be characterized in terms of the duty cycle, which represents the fraction or percentage of time (or samples) that the channel is busy[†]. While the average value of this parameter is relevant, its temporal variation pattern also represents an interesting aspect to analyze. In some channels, the load variation pattern is characterized by a predominantly deterministic component arising from social behavior and common habits. A clear example of this is the case of cellular mobile communication systems [36]. In such a case, the modeling of the duty cycle variation by means of time series analysis and Auto-Regressive Integrated Moving Average (ARIMA) models has been proposed [37]. However, a deterministic modeling approach by means of tailored mathematical functions can be simpler (the computation of the duty cycle value at a particular time instant is direct and does not require the computation of past values at previous time instants as it is the case of time series) and can provide satisfactory results as well (see Figure 3) [38]. In some other channels, the load variation pattern is characterized by a highly random component resulting from a significant number of random factors such as the number of incoming and outgoing users, resource management policies, social behavior of users, external events and so forth, which may lead to highly unpredictable variations (e.g., see [39]). In such a case, a stochastic modeling becomes a more convenient approach [38].

While the duty cycle is a relevant parameter of the spectrum occupancy pattern of a channel in the time domain, a more complete and realistic modeling requires not only the duty cycle but also the durations of busy and idle periods to be taken into account. A popular channel model in DSA/CR research is the well-known two-state Continuous-

Time Markov Chain (CTMC) model (with two states used to represent the busy and idle states of the channel) where the *state holding times* or *sojourn times* (i.e., the period durations) are modeled as exponentially distributed random variables. Although the CTMC model has been widely used in the existing literature, several studies based on empirical measurements [40]–[44] have demonstrated that period durations are not exponentially distributed in real systems. More concretely, it has been found that the period durations are more adequately described by means of generalized Pareto [40], a mixture of uniform and generalized Pareto [41], [42], hyper-Erlang [41], [42], generalized Pareto and hyper-exponential [43] as well as geometric and log-normal [44] distributions. A detailed study on the best-fitting distribution for various radio technologies can be found in [45]. Based on the conclusions from empirical modeling works, a more appropriate model is therefore the Continuous-Time Semi-Markov Chain (CTSMC) model, where the state holding times can follow any arbitrary distribution.

The CTSMC channel model is able to capture and reproduce the mean channel occupancy (duty cycle) and the statistical distributions of busy and idle periods observed in real channels. However, some studies [44] have indicated that in some cases the lengths of busy and idle periods can be correlated, a feature that the CTSMC model cannot reproduce. Two different correlation metrics can be distinguished. The first metric is the correlation between the durations of periods of different type (i.e., busy and idle periods). The correlation coefficients between busy and idle periods have been shown to take negative values [46], meaning that when the duration of a busy period increases, then the duration of the next idle period tends to decrease and vice versa. The second metric is the correlation between the sequence of periods of the same type (either busy or idle) of a channel and a shifted version of itself (i.e., the autocorrelation), which has experimentally been observed to exhibit two different behaviors, namely one periodic and another non-periodic, for which appropriate mathematical functions have been proven to be a convenient modeling approach [46]. Other studies have suggested the possibility of modeling correlation properties by means of aggregated ON/OFF processes [47]. This approach, however, is very difficult to configure and apply in practice. The reason is that the resulting correlation depends on the number of aggregated processes and their underlying distributions, but there is no straightforward way to determine the relation between the number of processes to aggregate (and their parameters) and the resulting level of correlation. A more convenient and effective approach is the set of models developed in [46].

4.2 Impact of the measurement configuration

There are two main parameters of the measurement configuration that can affect the resulting time-dimension models, namely the measurement period (i.e., time interval during which the occupancy of a channel/band is observed) and the sampling rate (i.e., the rate at which samples are captured).

[†]The term *channel* is used in this work to refer to a primary radio channel, which represents the minimum bandwidth unit the primary system can use for transmission. Thus, the whole bandwidth of a channel is used by the primary system when it is busy.

The required measurement period is determined by the number of samples required to obtain a statistically reliable estimation of the parameter(s) to be modeled. However, in some cases it can also be determined by the spectrum occupancy pattern itself. For example, it has been shown that mobile communication systems exhibit a periodic duty cycle pattern that is repeated on a daily basis [36], [38]. This means that an appropriate modeling of the duty cycle pattern in this type of systems requires a minimum measurement period of 24 hours. Moreover, the daily pattern can be different between weekdays and weekends [38]. If this aspect needs to be modeled, then a measurement period of at least 7 days is required to appreciate not only the differences between days and nights but also between weekdays and weekends.

The sampling rate of the measurement platform determines the accuracy to which the duration of the busy/idle periods can be estimated. The minimum duration of a busy/idle period is given by the duration of a time-slot in the radio technology under study. When an accurate model down to the slot level is required, the employed sampling period needs to be shorter than this minimum period duration (i.e., shorter than the duration of one time-slot). A sampling period larger than the minimum period duration (which may occur when employing low time-resolution devices such as spectrum analyzers) may lead to an undersampling of the spectrum occupancy pattern. As a result, some channel state changes may be misdetected between consecutive channel observations. The binary busy/idle occupancy pattern observed in such a case, although inaccurate, is still interesting and useful in the development of spectrum models for DSA/CR. The main reason is that such binary pattern can be thought of as the occupancy perception of a DSA/CR user that periodically senses the channel and observes its state at discrete time instants. Since the behavior of a DSA/CR system is driven by the channel occupancy pattern as perceived by the sensing nodes, the modeling of such observed pattern is interesting and useful in the study of DSA/CR systems. On the other hand, short idle periods resulting from bursty data transmissions are difficult to exploit for secondary usage in practice (the time-slot duration for many radio technologies is in the order of milliseconds or microseconds), which from a practical point of view is equivalent to a busy channel state. Exploitable idle periods normally arise when there is no primary user making use of the channel, which can be detected with a low sampling rate. Therefore, while high sampling rates lead to a more accurate observation of the real channel occupancy pattern, low sampling rates resulting from the use of low time-resolution devices such as spectrum analyzers may not necessarily be inappropriate.

5. Frequency-dimension modeling

5.1 Models

The spectrum occupancy pattern of a licensed band in the frequency domain can be characterized in terms of various parameters. Some examples of relevant parameters in the
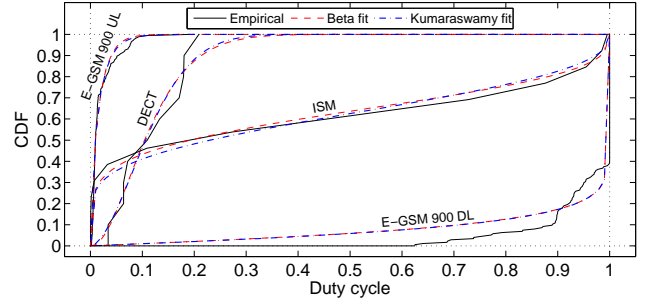
Fig. 4 Empirical duty cycle distributions for various radio technologies and the corresponding beta and Kumaraswamy fits [49].

frequency domain include the statistical distribution of the duty cycle values for channels within the same band, the clustering of the duty cycle over frequency and the number of free channels within the band at a given time instant.

The duty cycle values for individual channels within the same spectrum band have been shown to follow a beta distribution [48], [49]. The Kumaraswamy distribution, which closely resembles the beta distribution, can also be used as an appropriate model [49] (see Figure 4). The beta distribution can be found in many popular software simulation packages. However, it may present some difficulties in analytical studies due to the complex expression of its density and distribution functions. The Kumaraswamy distribution is similar to the beta distribution but easier to use in analytical studies due to its simpler form. While the former may be more appropriate for simulations, the latter may be more convenient for analytical studies.

The analysis of empirical measurement data also indicates that channels with similar load levels (duty cycle values) are not found alone but in groups (clusters) of a certain size (i.e., the duty cycle is clustered in the frequency domain) [44], [49]. This aspect can be modeled by defining a set of duty cycle archetypes (i.e., ranges of duty cycle values). Based on this definition, a cluster can then be thought of as a group of channels that belong to the same duty cycle archetype (i.e., whose duty cycle values are all comprised within the same interval). This is illustrated in the lower graph of Figure 5 by showing each cluster and the corresponding duty cycle archetype in a different color. Following this approach, the cluster size (i.e., the number of channels in a cluster) can then be modeled as a random variable with a lognormal [44] or geometric [44], [49] distribution.

Another aspect that could be analyzed and modeled in the frequency domain is the fragmentation of the spectrum holes, which can be described in terms of the contiguous free bandwidths that can be found in the band. However, this parameter may not be of special interest due to the introduction of multi-carrier modulation techniques such as Orthogonal Frequency-Division Multiplexing (OFDM). OFDM has gained popularity in the context of DSA/CR, among other reasons, due to its capability to exploit non-contiguous spectrum holes by notching the parts of the carriers overlapping with busy licensed channels [50], [51]. As
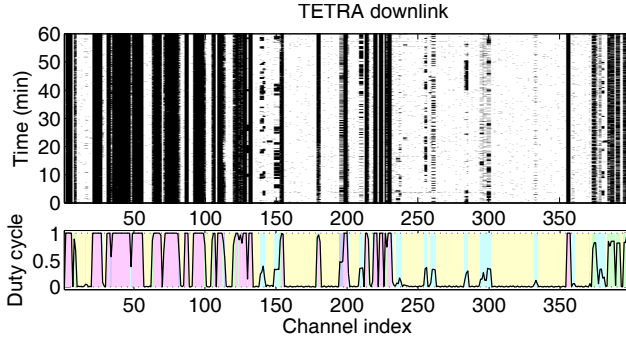
Fig. 5 Duty cycle clustering example for TETRA downlink band [49].

a result, from the point of view of DSA/CR, the contiguous free bandwidth of a spectrum band is not as relevant as the total amount of aggregated free bandwidth (contiguous and non-contiguous) available at any moment. Assuming that the channels of the spectrum band have the same radio bandwidth, the problem reduces to characterizing the total number of free channels available (i.e., not being used by the primary system) at any time instant, which can be modeled as a random variable with a certain distribution. The work reported in [52] concluded that the Camp-Paulson distribution can be employed to describe the total number of free channels in a band, while a discretized version of the log-normal distribution was found in [53] to be an adequate model for the number of occupied channels.

5.2 Impact of the measurement configuration

From the point of view of the measurement configuration, the main parameters to be taken into account when developing frequency-dimension models are the frequency span (i.e., bandwidth over which the measurement is performed), the frequency points to be measured within the selected frequency span and the resolution bandwidth.

The frequency span needs to be wide enough to enable the simultaneous observation of the occupancy state of all the channels within the band under study. If only a subset of channels is observed, the obtained statistics may be biased and not representative of the real occupancy statistics of the considered band. However, it is important to take into account that there is a trade-off between the bandwidth observed in the frequency domain and the time resolution in the time domain. Some measurement devices such as spectrum analyzers can enable very wide measurement bandwidths but at the expense of a lower time resolution. On the other hand, some other measurement devices capable to capture samples of the signal amplitude at a high rate may provide limited bandwidth capabilities. Therefore, it is important to select an appropriate device and configuration in accordance with the needs of the model to be developed.

Another important aspect in the frequency dimension is the particular frequency points measured within the band under study. The data provided by measurement devices correspond to samples taken at particular frequency points.

It is important that the distance between two consecutive frequency points (referred to as *frequency bin*) is lower than the radio bandwidth of the measured channels. This requirement is necessary to guarantee that there is at least one measured frequency point within each radio channel of the band under study (ideally, several frequency points per channel). As demonstrated in [27], the channel occupancy estimation is reasonably accurate as long as the frequency bin size remains acceptably narrower than the channel bandwidth.

Measurement devices perform measurements by consecutively tuning a narrow-band filter at each of the configured frequency points. The bandwidth of this filter, which is configurable, is referred to as *resolution bandwidth* and determines the ability to resolve signals in frequency. If the selected resolution bandwidth is too wide, the measurement at a particular frequency point may be affected by signal components from more than one channel, thus leading to the observation of incorrect occupancy patterns. Therefore, the resolution bandwidth needs to be appreciably narrower than the bandwidth of the measured channels in order to provide reliable and accurate measurement data for the development of spectrum models in the frequency dimension.

6. Space-dimension modeling

6.1 Models

Spatial models are aimed at describing how the spectrum occupancy perceived by DSA/CR users depends on the user location. An important characteristic property of spatial models is that they intend to reproduce the properties of the secondary receiver's perception, as opposed to time/frequency models where the target is to reproduce the properties of the primary transmitter's spectrum occupancy pattern.

The spectrum occupancy perception of a DSA/CR user in the spatial domain can be characterized in various ways. A simple modeling approach is to determine the average power received from a certain transmitter in a particular set of locations of interest, which can be obtained by means of path loss models. Assuming that DSA/CR users make a decision on the spectrum occupancy state based on energy detection, the predicted power levels are then compared to a properly set decision threshold in order to determine if the DSA/CR user observes the sensed spectrum as busy or idle at the considered locations (see Figure 6). This binary busy/idle modeling approach can be complemented with spatial statistics by fitting an analytic semivariogram model to the predicted power levels, which permits reproducing some statistical properties (e.g., spatial correlations) of the powers observed over a certain region [54]. The main attractiveness of binary busy/idle modeling approaches is their simplicity. However, this kind of methods results in an oversimplified characterization of the perceived occupancy where the spectrum at a given location is observed by DSA/CR users either as always busy or always idle. In practice, radio propagation phenomena such as slow (shadowing) fading and fast (multipath) fading may lead to
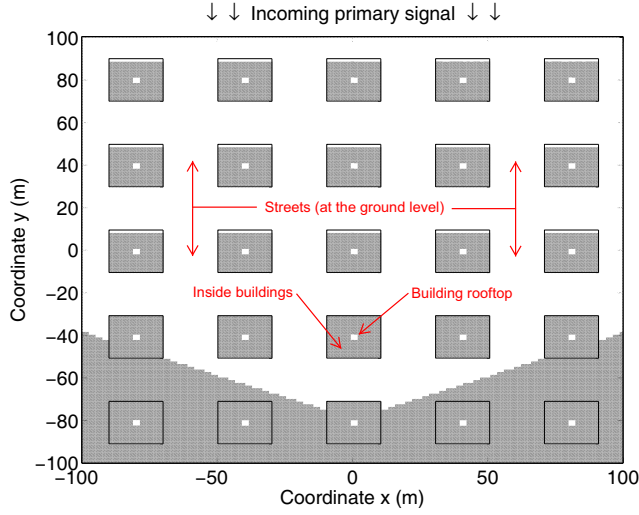
Fig. 6 Binary characterization of spatial spectrum occupancy perception in urban environment in terms of busy/idle (white/gray) observations [55]. Only path loss is considered (no shadowing, no multipath fading).
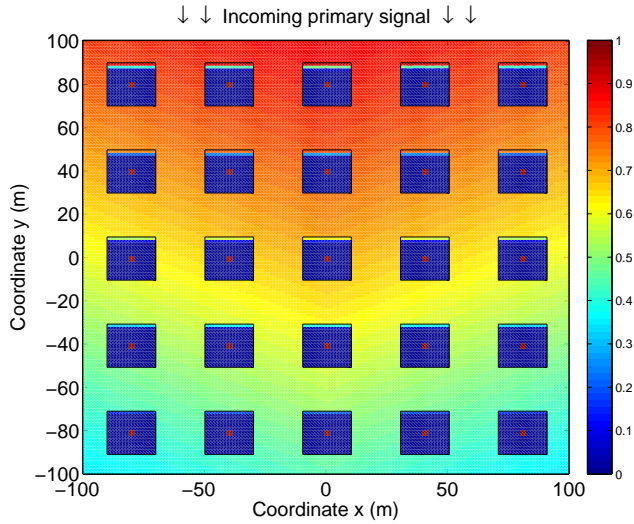
Fig. 7 Probabilistic characterization of spatial spectrum occupancy perception in urban environment in terms of busy observation probability [55]. Path loss is considered in the radio propagation model, shadowing and multipath fading are implicitly considered in the duty cycle model [56].

momentary signal fades, which in turn may result in signal misdetections (i.e., the DSA/CR user observes the spectrum as idle when it is actually busy). Therefore, the probability that the spectrum is observed as busy constitutes a more appropriate parameter to characterize the spectrum occupancy perceived at various locations. In [55], the power levels predicted by the propagation (path loss) model are not compared to a threshold but mapped (by means of a duty cycle model [56] that implicitly accounts for shadowing and multipath fading) to the probability that the spectrum is perceived as busy by DSA/CR users (see Figure 7). This approach is more complex but provides a more realistic characterization of spectrum occupancy in the spatial domain.

6.2 Impact of the measurement configuration

Some important spatial aspects of the measurements affecting the resulting space-dimension models are the selected measurement location, direction and polarization.

As shown in [57], the considered measurement location can have a significant impact on the perceived (and hence modeled) spectrum occupancy, depending on the receiving conditions and level of radio propagation blocking. Measurements performed in high points, such as building rooftops, can benefit from direct line-of-sight conditions, thus providing accurate information about the actual spectral occupancy pattern of a primary transmitter. Other measurement locations, such as indoor environments, streets and open areas can provide information on the spectrum occupancy perceived at other locations of practical interest.

The direction of a measurement also plays a key role in the observed spectrum occupancy. Omnidirectional antennas can be used in studies where the aspect of interest is the spectrum occupancy pattern of a channel or band but the particular transmitter(s) making use of the spectrum is not a relevant aspect. In studies where the aspect of interest is the spectrum occupancy pattern of a particular transmitter, the direction of the incoming signal needs to be resolved, which can be accomplished by means of directive antennas or multiple antenna arrays along with beam forming techniques.

The signal polarization is another important aspect to consider. In some cases, the presence of high-power transmitters can be detected with an orthogonal polarization but when the received signal level is low this may not be the case. Therefore, the polarization of the employed antenna should match the polarization of the transmitter under study.

In any case, it is not worthless to mention here that the measurement platform does not necessarily have to employ the same antenna type as that of the assumed secondary system. If the objective is to model the real occupancy pattern of the primary transmitter, then any antenna type can be employed as long as the resulting sensitivity is enough to determine reliably when the transmitter is actually active or inactive. However, if the objective is to model the occupancy pattern as perceived by the secondary system, then same antenna type should be used in order to reproduce the same perception of the secondary system.

7. Conclusions

Spectrum occupancy models can find many applications in DSA/CR. However, the utility of such models depends on their realism and accuracy. To guarantee an acceptable level of realism and accuracy, the use of empirical measurement data is essential in the development and validation of spectrum occupancy models. This paper has presented the complete process of spectrum occupancy modeling, from the realization of measurements to the obtainment of models, highlighting the most relevant aspects to take into account when developing spectrum usage models for DSA/CR. In

particular, this paper has reviewed the main aspects in the design and implementation of a spectrum measurement platform, the selected measurement configuration and the employed data post-processing methods. The main aspects to be considered in the development of spectrum occupancy models have been pointed out and illustrated with some selected examples from the existing literature.

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