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COGNITIVE RADIO SYSTEMS EVALUATION

Measurement, modeling, and emulation approach

Deepaknath Tandur, Jonathan Duplicy, Kamran Arshad, David Depierre, Klaus Moessner, Janne Lehtomäki, Keith Briggs, Luis Gonçalves, and Atílio Gameiro

A vertically integrated approach is presented to evaluate the performance of cognitive radio (CR) systems. The approach consists of three pillars: measurement, modeling, and emulation (MME). This integrated approach enables the reproduction of the radio environment in laboratory conditions and aims to guarantee the same performance results as one would obtain in the field. This article provides a detailed explanation for each pillar along with state-of-the-art overviews. Finally, a test bed based on the MME approach is presented.

MME Approach

In today's wireless industry, it is generally accepted that the spectrum scarcity faced by the operators can be significantly alleviated by employing CR technology [1]. However, CR technology is still not mature, and it creates many challenges that have so far prevented its wide commercial deployment. Thus, it is critical that all stakeholders interested in CR, such as operators, device manufacturers, and regulators, have a clear understanding of the limitations and possibilities of this technology. An accurate characterization of the radio environment is therefore an essential task, as it will aid in understanding CR limitations.

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In this article, we propose a new approach to bring realism into the technology assessment. The MME approach of the radio environment is shown in Figure 1. In general, the radio frequency (RF) scene is first measured over a range of frequencies, time instants, and locations. The data collected can then be converted to a mathematical model, which can further be emulated in a controlled environment either in software or hardware. It should be noted that, besides this sequence (Flow 1), it is possible that models are built from the scratch and then confirmed or fine-tuned through measurements, before being finally emulated (Flow 2). Finally, it is also possible that the modeling block is completely bypassed (Flow 3). The last sequence is called the deterministic case, where the measurement is immediately followed by emulation of the measured signals.

The timescale and target of Flows 1 and 2 are different from the one from Flow 3. In the first two cases, a system-level evaluation is targeted, and its aim is to evaluate the capacity of CR systems or the macrospectrum occupancy

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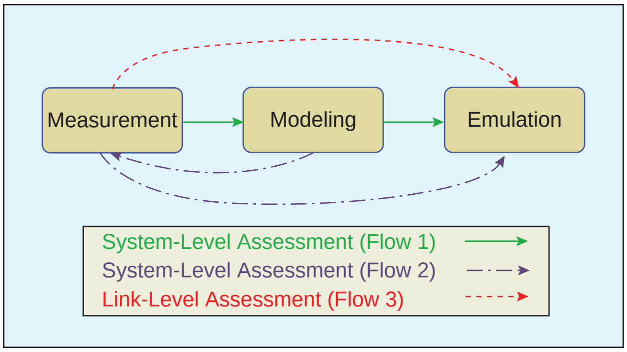

FIGURE 1 MME-integrated approach.

pattern. In particular, this methodology should assist designers in evaluating the potential of CR system in various bands and locations. This activity will require measurements over multiple periods and may involve days or weeks. In the last case (Flow 3), a link-level evaluation is targeted. Typically, short radio scenes are captured and then directly replayed in the laboratory to evaluate CR-sensing algorithms. The timescale in this case can be considered to be in the order of a fraction of seconds. The MME-integrated approach brings the real-world environment to the laboratory and aims to offer fully trustable results to the various CR stakeholders.

MME: Measurement

Since the CR concept emerged in 1999 [1], numerous measurement campaigns have been performed in diverse locations and for different scenarios. The measurements have typically covered a wide range of frequencies, from a few tens of megahertz to a few gigahertz. Table 1 summarizes some of the recent campaigns. The main conclusions are always consistent. They show a low usage of the overall spectrum with vacant spectrum bands, spatially and temporally. This implies that CR technology has the potential to significantly improve the spectrum usage by exploiting these spectrum holes.

The most commonly used measurement method is the energy/power detection scheme. In [6], it was shown that, depending on the selected parameter such as the frequency span, measurement period, location, and antenna polarization, the measurements results can lead to a different conclusion about spectrum occupancy. However, the most significant parameter is the decision threshold, which may have a huge impact on perceived spectrum occupancy.

Figure 2 shows an example of a measurement result that compares the sensitivity of the signal occupancy in percentage to the decision threshold variation for the industrial, scientific, and medical (ISM) band in 2.4–2.4835-GHz frequency. The results are obtained at 2:00 p.m. and 8:00 a.m. for an entire week, with the outcome for Wednesday afternoon at 2.00 p.m. highlighted. These measurements were done at the University of Oulu in downtown Oulu, Finland, in June 2011. The setup consisted of an ISM-band antenna, ISM-band filter, a low-noise amplifier (LNA), and Agilent N6841A RF sensor. Frequency bin separation was set to 109.375 kHz. The figure shows that the average occupancy is typically low. Similar low-occupancy results for ISM bands have also been reported in [3] and [7]. Figure 2 also shows a different occupancy result as the threshold is varied. Thus, if the selected threshold is too high, it will lead to an underestimation on the spectrum occupancy, and if it is too low, it will lead to an overestimation. The selection of the correct threshold value is therefore an important criterion. There are classically three ways to select a threshold [6].

- *Maximum Noise Criterion*: This takes the maximum recorded noise level as the threshold. Its main drawback is that it may underestimate the occupancy because of weak signal samples lying below the maximum noise level.
- *Probability of False Alarm (PFA)*: The threshold is selected such that only a fraction of the noise samples are above the threshold. The PFA is classically set to 1%, which is considered to be the best tradeoff.
- *m-dB Criterion*: This adds *m* dB to the average noise floor.

The criterion for threshold selection is dependent on the application use case. However, the selected threshold value should result in the most accurate picture of the occupancy scenario.

In Figure 3, we compare the occupancy result based on power measurements, with the access point (AP) logs taken from the public access network OULU (panOULU). This figure has been obtained after a one-week measurement in the Tellus library at the University of Oulu in

TABLE 1 ***Characteristics of some recent measurement campaigns for spectrum usage evaluation.***

Location	***Instigator***	***Type***	***Frequency Range***	***Reference***
Denver, San Diego, Los Angeles	National Telecommunications and Information Administration	Outdoor	108 MHz–19.7 GHz	[2]
Singapore	Institute for Infocomm Research	Outdoor	80 MHz–5.85 GHz	[3]
Auckland, New Zealand	University of Auckland	Indoor/outdoor	806 MHz–2.75 GHz	[4]
Aachen, Germany	Rheinisch-Westfaelische Technische Hochschule Aachen University	Indoor/outdoor	20 MHz–6 GHz	[5]

January 2011. The power measurement results were obtained by a fast Fourier transform (FFT)-based spectrum analyzer that performs at least 200 measurements per second for a 156-kHz frequency bin separation in 2.4–2.5-GHz ISM band. The threshold is set to 20 dB above the noise floor, which is approximately −95 dBm in this case. The high threshold value is selected so as to avoid any false alarm due to internal noise of the receiver. In the figure, the log-based traffic information has been scaled and shifted up according to a regression analysis. The comparison is made for only one wireless LAN (WLAN) channel with a closeby AP. The figure shows that there is a good agreement with the actual WLAN activity logs. The slight deviation from the logs may be due to non-panOULU WLAN traffic, nontraffic beacon signals, and other interferences.

Similar occupancy results for global system for mobile communication (GSM) carriers for one working day were obtained at the University of Aveiro campus in Portugal [8]. Figure 4 shows the variation of the spectrum occupancy of a single 200-kHz GSM 1800 channel consisting of eight time-division multiple access (TDMA) slots. The measurement period is set equal to the GSM frame duration of 4.62 ms. The measurement here is continuous compared with the typically discontinuous wideband (WB) measurements undertaken in Table 1. In the result, a channel is considered occupied if at least one of the eight time slots in the frame is used. From the figure, we see that, during the business hours, the occupancy is at most 70%, whereas during the night hours, there is considerably more availability of the spectrum.

So far, we have considered only the spectrum occupancy criterion, but for certain radio access technologies, the spectral resource is used even when no user is actually transmitting, for example, in downlink code-division multiple access (CDMA) systems. Even with GSM systems, a huge difference exists between spectrum occupancy and real traffic occupancy. This can be due to two factors:

- an increase in number of frequency channels used as broadcast channels (BCHs)
- an increase in occupancy due to frequency-hopping functionality.

Thus, the concept of traffic occupancy gives a much better image of how spectral resources are actually used. In the GSM case, it can be defined as the average occupancy over the TDMA time slots on each of the traffic channels (TCHs), which can be potentially used by the user equipment (UE). To this end, a measurement campaign was undertaken by Thales Communications and Security in a business area in the suburbs of Paris in February 2011. The campaign was conducted to quantify the difference that exists between the spectrum and traffic occupancies on GSM 900 bands. On each of the 124 channels of the band, a detection algorithm was implemented to detect and decode the BCHs and detect the TCHs and estimate their time-slot occupancy.

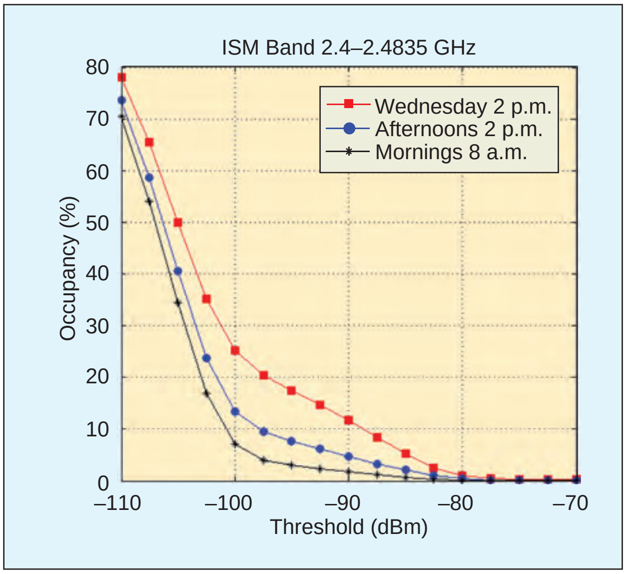

FIGURE 2 Impact of the decision threshold on the spectrum occupancy of ISM band.

Figure 5 illustrates the evolution of both occupancies during 24 h for France Telecom (FT) Orange network operator. This figure emphasizes the existing difference between the spectrum occupancy and its actual usage on GSM bands. One can observe that the spectrum occupancy is much higher than the traffic occupancy. The results highlight that there is much more potential opportunity in the available spectrum space, which can be exploited by the CR system.

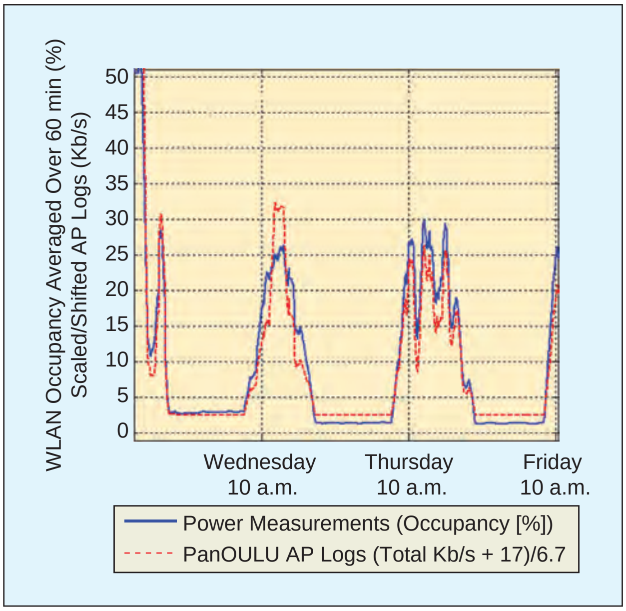

FIGURE 3 Power measurement versus AP logs (time series) with a sliding window of 60 min.

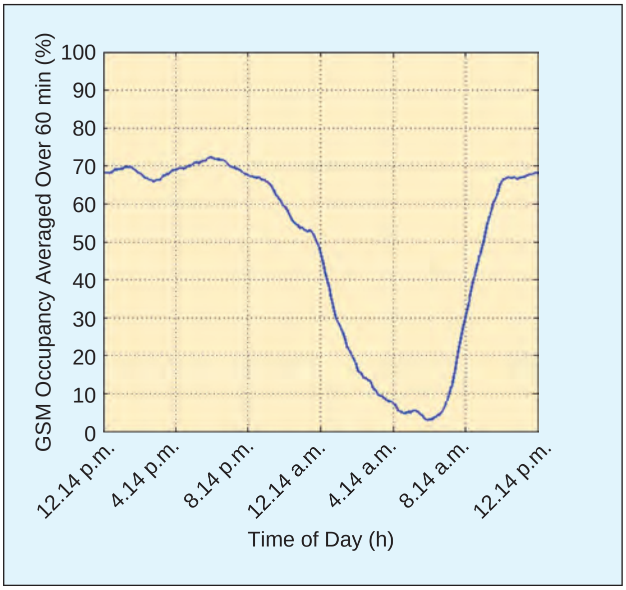

FIGURE 4 A single 200-kHz GSM 1800 channel occupancy measured over a single day at Aveiro, Portugal, with a sliding window of 60 min.

It should be noted that Figures 3–5 provide the measurement results for a 60-min window period and mainly emphasize on system-level evaluation. The results from these measurements are first fed to the modeling block, and then based on statistical studies, the emulation block plays the radio scene to evaluate the capacity of CR systems. This corresponds to Flow 1 within the MME framework.

Similarly, shorter measurement periods in the order of fraction of seconds or minutes can also be estimated. In this case, short radio scenes are captured and then directly fed to the emulation block to evaluate the CR sensing algorithms. This corresponds to Flow 3 within the MME framework. The aim here is to evaluate and validate the link-level evaluation of the CR system. We may now consider the second item that is the modeling block in our three-pillar process.

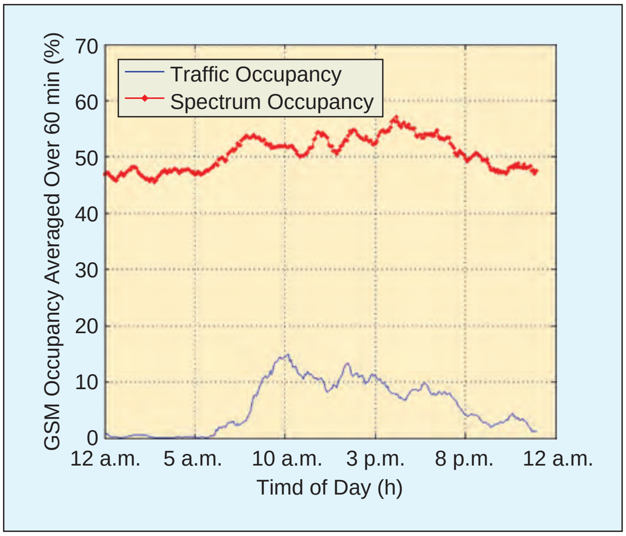

FIGURE 5 Spectrum and traffic occupancies during a single day for a French operator at Colombes, Paris, with a sliding window of 60 min.

MME: Modeling

To enable spectrum-sharing techniques based on CR technology, it is also crucial to understand and model incumbent user behavior. Therefore, we provide an overview of modeling task within the MME framework. The approach is divided into statistical modeling and database modeling. While the statistical approach models the dynamic behavior of the incumbents, the database approach focuses on the static environment, such as the television white space (TVWS) bands.

Statistical Modeling

The measurement results shown in the previous section cannot be extended directly to other locations, spectrum bands, and time intervals, and this is because of variations in the incumbent usage pattern; hence, in theory, separate measurements are needed at each time and place. To provide a representative usage of an incumbent, a statistical-based modeling approach can be considered as an attractive solution. Here, the first- and second-order statistical parameters are employed on the measurement results to develop the spectrum occupancy model of the incumbent users. Then the radio scene corresponding to this occupancy model is finally played by the emulator for the system-level evaluation. It should be noted that, within the MME framework, this corresponds to Flow 1.

A quick survey of literature shows that the statistical modeling is a very active area in research. The different approaches that have been considered for modeling the incumbent usage pattern in time, frequency, and space domain are discussed below.

In the time domain, spectrum occupancy models are widely based on discrete- or continuous-time Markov chain (CTMC) schemes. The basic principle of Markov chain is that the spectrum usage in each channel can be modeled by two states, with one state indicating that the channel is occupied and therefore not available to the opportunistic user while the other state indicates that the channel is free and available to the opportunistic users. In CTMC model, the channel remains in one state for a random period of time. This state-holding time can be modeled based on empirical results as a generalized Pareto, or as geometric or log-normal distributions [9]. In real systems (e.g., cellular systems), occupancy of a channel is a consequence of a large number of random factors such as traffic load, resource management policies, specific location, mobile operator packages, and so on; as a result, channel usage is itself a complex stochastic process and still an open research question. Recently, Wang and Salous [10] analyzed the spectrum occupancy in GSM bands by applying time-series models. To analyze the data, an autoregressive integrated moving average (ARIMA) model was fitted to the data in GSM bands in Durham, United Kingdom [10]. A time-varying spectrum occupancy model was also proposed in [11]. Here, the statistical spectrum occupancy model is based on a combination of several probability density functions (PDFs).

In the frequency domain, the statistical distribution of channel occupancy is shown to follow a beta distribution [12]. The use of Poisson and Poisson-normal distributions for the characterization of channel occupancy has also been presented in [13]. In the spatial domain, the models characterize the spectrum occupancy patterns at different locations. Spatial distribution of the power spectral density of incumbent user signal has been studied in [14] using random field theory. Most recently, a more sophisticated approach to model spectrum occupancy in a realistic urban environment (at a ground level, inside buildings, and on rooftops) was presented in [15].

Based on the incumbent user's channel access dynamics for specific location and time, it is also possible to derive statistical information, such as the total number of spectrum opportunities in terms of the probability of each channel being free. In previous work [16], the exact and approximate probability distributions for the total number of free channels not being used by the incumbent users was derived. Figure 6 compares the exact and the various approximate probability distribution functions in a scenario when the channels are most likely occupied by the incumbent users. It is seen from Figure 6 that Camp–Paulson approximation provides the most accurate curve.

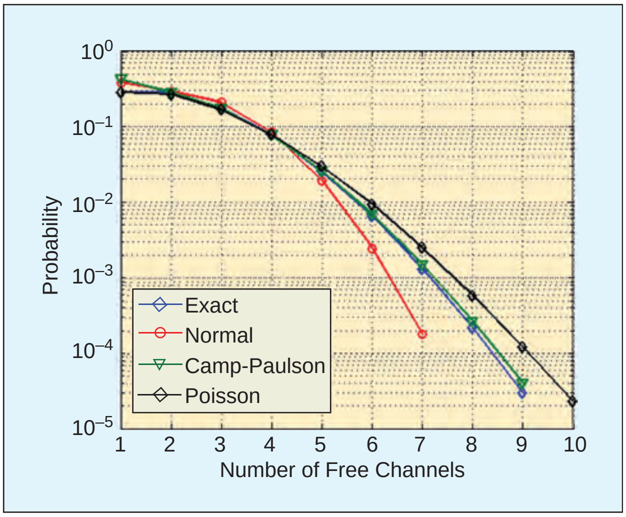

FIGURE 6 Probability distribution function of total number of opportunities.

Database Modeling

In static radio environments, CR systems are envisaged to have access to a database of incumbent spectrum occupancy to minimize the risk of interference and reduce the sensing requirements. In TVWS bands, such a database will contain signal strength information from TV transmitters as well as wireless microphone data. The computation of such a database is a large computational task. It needs two main inputs:

- The first input is a list of TV transmitter data, which is usually provided by national regulators.
- The second input is the terrain data required by propagation models. The propagation models used are often of the irregular terrain Longley–Rice type, which include empirical models of diffraction effects over hills.

Additionally, a protocol is required for remote communication with the database; various proposals are currently being evaluated. Security will be a basic requirement here. Upon receipt of a query, the database will provide a channel (or channels) and an allowed power level and register the channel as in use at the specified locations and for the specified period. In the United Kingdom, the Ofcom regulator has published consultation documents on design issues [17]. Such databases are starting to be offered as a commercial service [18]. Figures 7 and 8 show the typical database computation outputs for the United Kingdom. Figure 7 shows a square of size 6° longitude and 6° latitude covering most of England, with spectral colors indicating minimum channel occupancy (dark blue) to maximum (red). It will be seen that there is considerable spatial variation, proving that the database does provide useful information.

From the database, statistical summary information may also be computed. The most useful is population-density weighted so that we gain estimates of the distribution of the amount of free spectrum per user. Figure 8 shows a typical cumulative distribution computed this way for the whole of the United Kingdom. It will be seen that 50% of the population has six channels available, i.e., 48 MHz.

Within the MME framework, the database computations derived from TV transmitter and propagation data can eventually be fed to the measurement block (Flow 2) for further verification and refinement of the model. Once the verification is complete, the computed data can then be fed to the emulation block.

MME: Emulation

Emulation is the third pillar of the MME-integrated approach. It is worth noting that this test bed can be implemented either in hardware or software. It is the core of the proposed CR test bed shown in Figure 9. The emulator consists of a WB signal generator that stimulates the sensing engine of a CR device with a set of waveforms derived from the measurement-modeling (MM) stages of the MME approach. As discussed in the "MME Approach" section, the emulation involves two cases with different time scales: deterministic and model based.

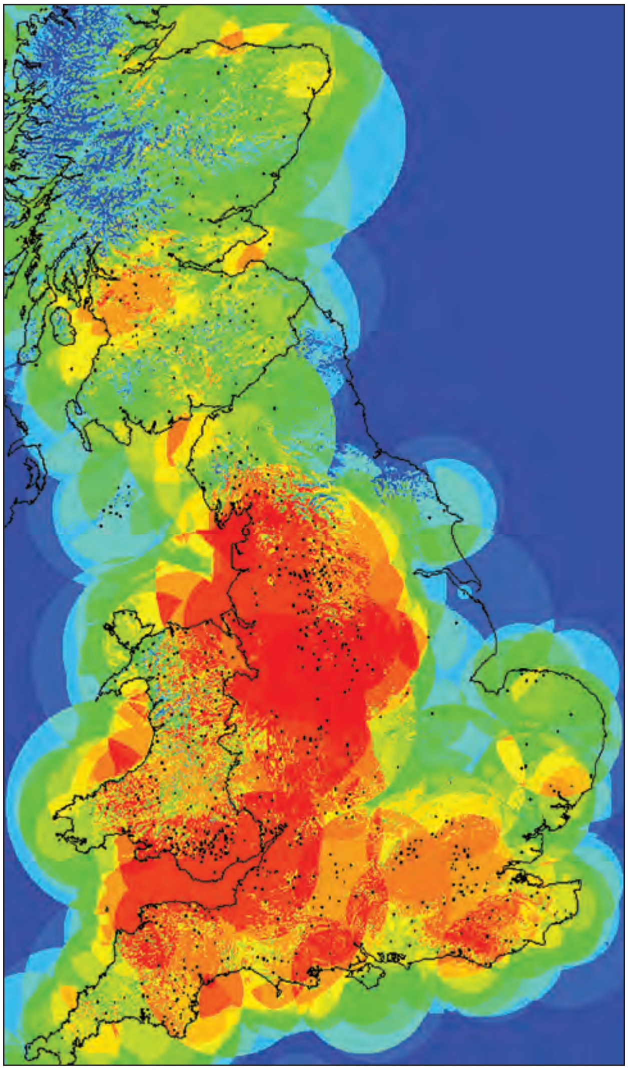

FIGURE 7 The TV band occupancy density for United Kingdom. (Image courtesy of BT Innovate & Design.)

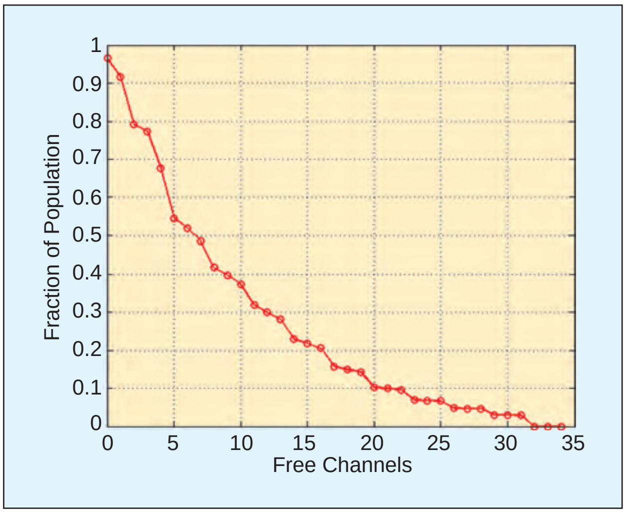

FIGURE 8 The TV band white space availability for the whole of the United Kingdom.

In the first deterministic case, the modeling block is skipped and the recorded sequences obtained from the measurement campaign are directly replayed on the emulator without any changes. The incumbent usage pattern (on/off) is emulated without the need for any channel emulation. This emulation scenario serves the link-level performance evaluation and, in particular, the sensing engine performance study.

In the second model-based case, both statistical and database approaches are considered. Here, the incumbent usage pattern emulation is combined with the channel emulation to accurately reproduce the actual RF scene. This emulation scenario serves the system-level performance evaluation.

Figure 9 shows that, in the test bed, the sensing estimates of the CR device can be compared with the source to evaluate the performance of the sensing engine. Metrics such as probabilities of detection, false alarm, or the detection speed can be evaluated in this manner. On the other hand, the CR device can also make decisions about the available opportunities based on the sensing engine outputs. In this case, the transmitter of the CR device (secondary) can start transmitting on the available spectrum holes. The output of the secondary transmitter is then added to the stimulus signal and later fed to CR device receiver as well as the incumbent systems receiver. Through bit error rate (BER) measurements (as an example), both the quality of the secondary transmission and its impact on the incumbent systems can be evaluated. As depicted in the figure, a CR test bed can also include channel emulation blocks. Adding these blocks between the receivers and the modeled (or emulated) transmit sources will enable the inclusion of fading and Doppler effects in the radio scene. A true radio scene experienced by the mobile device is then emulated; hence, both the static and the vehicular cases are appropriately tested.

The emulator should have the following three properties.

- *Controllability*: The user should be able to precisely control the emulation scenario.
- *Repeatability*: The user should be able to repeat any desired sequence of events in the emulation scenario.
- *Representability*: The emulated RF scene should represent as well as possible the real environment that the CR system will experience. This is guaranteed through the MME vertical approach.

Besides the above desirable properties, the emulator should also provide a deep enough memory for the deterministic-case emulation, whereas a WB system is typically required for both deterministic as well as model-based cases.

Conclusions

We have presented an integrated vertical approach involving MME. This approach enables the reproduction of the

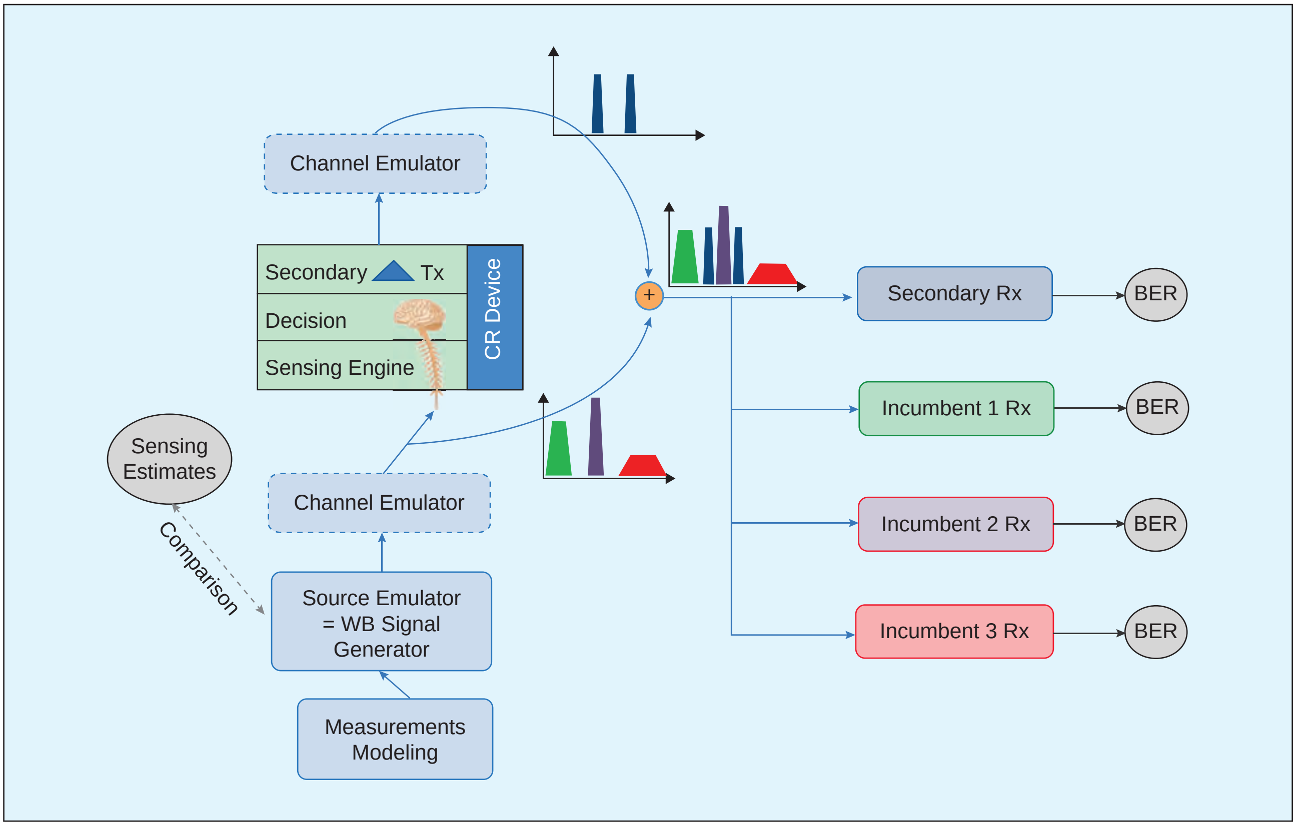

FIGURE 9 MME-based CR test bed.

radio environment in laboratory conditions and offers fully trustworthy results to the various CR stakeholders.

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VT

THE SPECTRUM SCARCITY FACED BY THE OPERATORS CAN BE SIGNIFICANTLY ALLEVIATED BY EMPLOYING CR TECHNOLOGY.

THE MOST COMMONLY USED MEASUREMENT METHOD IS THE ENERGY/POWER DETECTION SCHEME.

THE CRITERION FOR THRESHOLD SELECTION IS DEPENDENT ON THE APPLICATION USE CASE.

IT IS CRITICAL THAT ALL STAKEHOLDERS INTERESTED IN CR, SUCH AS OPERATORS, DEVICE MANUFACTURERS, AND REGULATORS, HAVE A CLEAR UNDERSTANDING OF THE LIMITATIONS AND POSSIBILITIES OF THIS TECHNOLOGY.

IT IS ALSO CRUCIAL TO UNDERSTAND AND MODEL INCUMBENT USER BEHAVIOR.

IN STATIC RADIO ENVIRONMENTS, CR SYSTEMS ARE ENVISAGED TO HAVE ACCESS TO A DATABASE OF INCUMBENT SPECTRUM OCCUPANCY TO MINIMIZE THE RISK OF INTERFERENCE AND REDUCE THE SENSING REQUIREMENTS.

EMULATION IS THE THIRD PILLAR OF THE MME-INTEGRATED APPROACH.

THE EMULATOR SHOULD HAVE THE FOLLOWING THREE PROPERTIES: CONTROLLABILITY, REPEATABILITY, AND REPRESENTABILITY.

THE APPROACH CONSISTS OF THREE PILLARS: MEASUREMENT, MODELING, AND EMULATION.