Lessons Learned from Long-Term and Imperfect Sensing in 2.4 GHz Unlicensed Band

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Abstract. Accuracy of spectrum sensing affects the decision making operation of cognitive radio. In order to achieve meaningful results, in related experimental and simulation work, realistic wireless environment representation is a necessity. Existing spectrum occupancy models range from simple additive white Gaussian noise to elaborate, based on large scale wireless spectrum measurements, but universal models are not available. Creating such a model for unlicensed bands would be particularly difficult, if not impossible, because of its unpredictability and inherent dynamics. On the other hand, our experience shows that using real-life, relatively low-resolution, data collected using inexpensive spectrum analyzer provides insight consistent with observations made with more sophisticated setups, preserves more nuances than simple models, and could be a viable alternative to spectrum occupancy modeling.

Keywords: Cognitive radio · Wireless environment model · WiSpy
Long-term measurement

1 Introduction

Spectrum sensing is a fundamental element of cognitive radio operation and it is very sensitive to the "garbage in, garbage out" principle. In other words, having a good representation of wireless environment is key to meaningful cognitive radio experiment. For that purpose, researchers frequently need to resort to using synthetic environments for that purpose, usually in the form of spectrum occupancy models. However, models have their limitations and "do not necessarily reflect real-world scenarios in most of the cases" [1]. And while the model catalog has became fairly extensive over the years, many of them are only applicable to a specific spatio-temporal situations. Also, it is uncertain "whether a general, if not universal, model exists that can unify most existing models" [2].

One of the directions communication networks (including cognitive radio) are heading towards is heterogeneity, where long- and short-range activities need to co-exist. Many measurement campaigns, with equipment frequently placed on the rooftops of high-rise buildings [3], may be incapable of capturing certain short-range radio activities, especially at the street level or indoors, and fail to capture potentially important subtleties. At the same time still need more insight and understanding of

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complex wireless environments and the more nuances we capture the better representations of wireless environment we can create.

All the above arguments ring particularly true when one considers unlicensed bands, which are particularly challenging from the perspective of cognitive radio development. Diversity of technologies involved (both long- and short-range), and inapplicability of primary/secondary user scenario in many cases, increase complexity. So does mobility.

In order to better understand the nature and spatio-temporal dynamics of unlicensed band environment a more comprehensive, dedicated and multi-point measurement campaign would be more useful. However, as survey [2] shows, unlicensed bands (i.e. 2.4 GHz and 5 GHz) are usually only a part of much wider spectrum being monitored and less frequently considered on its own. Equipment, know-how, and logistical complications can make such large-scale, multi-point measurements cost-prohibitive.

If measurement quality requirements were to be relaxed, an affordable and easy-to-use spectrum analyzer such as WiSpy [4] could potentially offer a viable solution to that problem. This work presents an overview of findings based on relatively long-term 2.4 GHz band measurements performed using this device. One of the goals was to discover what kind of information can be extracted from data collected with limited precision. Another one was to use statistics of collected data to build a simple AWGN (additive white Gaussian noise) model and evaluate its deficiencies in comparison to the real-life traces.

This work is divided into following sections. Section 2 introduces related work and Sect. 3 provides necessarily preliminaries. Followed by Sect. 4, where our findings are presented and Sect. 5 where we state our conclusions.

2 Related Work

WiSpy users used to submit their own spectrum environment recordings to the Metageek (WiSpy creators) website, but these were usually very short-term, meant to illustrate particular local findings. We are not aware of other work based on long-term WiSpy measurements. On the other hand, environmental studies dedicated exclusively to 2.4 GHz band exists, such as [5], and others are a part of wide-band project (as the ongoing one at IIT [3]). Chen [2] provides an extensive survey of such campaigns and studies.

Still, Lopez-Benitez [6] argues that obtaining “reliable and accurate real-time information on spectrum occupancy” by cognitive radios needs to be addressed more. In his work he outlines current challenges and points out practical limitations. Performance under imperfect sensing performance is a particularly important aspect which our work can help address. Other aspects would be: finite sensing period and limited number of observations. Studies on effects of quality of sensed information on performance are also important to other areas, such as radio environment map construction [7] or cognitive radio network modeling and simulation. In fact, development of our agent-based simulation framework [8] sparked the initial interest in spectrum occupancy models.

We discovered that spectrum models range from fairly simple, such as AWGN, to complex, multi-parameter ones and are used to provide either as representations of the environment or for prediction purposes. In his survey, Chen [2] distinguishes between parameter (power, occupancy, duty cycle) statistics models, parameter cumulative distribution and probability density functions, Markov chain and linear regression models. In this work, only AWGN model is employed.

3 Preliminaries

Data collection setup comprised of a Windows PC (running Chanalyzer 2.1 software) and WiSpy 2.4× spectrum analyzer. WiSpy 2.4× [4] is a portable USB (v1.1 or better) spectrum analyzer operating in 2.4 GHz band. Chanalyzer [4] is a spectrum monitoring software designed to work with WiSpy devices. Version 2.1, which was used for data collection, is discontinued, but still available for download at [9] (Table 1).

Table 1. WiSpy 2.4× technical specifications.

Parameter	Value(s)
Frequency range	2.400 to 2.495 GHz
Amplitude resolution	0.5 dBm
Resolution bandwidth	(2.4 GHz) 58.036 to 812.500 kHz
Sweep time	(2.4 GHz) 507 ms

Time-frequency measurements were conducted indoors at the Illinois Institute of Technology for approximately three months (Dataset A, see Table 2 for details). Due to time and computing power constraints some experiments were conducted using a smaller dataset B, a subset of dataset A.

Table 2. Dataset details.

Parameter	Value(s)
Start time	A and B: Tue, 19 Jan 2010 12:52:56 GMT
End time	A: Thu, 22 Apr 2010 17:51:34 GMT
	B: Mon, 25 Jan 2010 08:12:15 GMT
Measured quantity	Power [dBm]
Size	A: 256 frequencies × 22 757 357 data points
	B: 256 frequencies × 1 415 486 data points
Frequency range	2.400 to 2.495 GHz
Resolution bandwidth	373.26 kHz

For each frequency/real-life data trace we created an AWGN synthetic trace, where signal is modeled using normal distribution with real-data mean and variance of a given frequency with addition of zero-mean noise.

4 Observations and Results

4.1 Overview (Dataset B)

Figure 1 shows a min/mean/max signal power as a function of frequency plot based on data from dataset B. Activity on WiFi channels 1, 6 and 11 appears to be the most prominent on the mean power plot, with visible, characteristic profile.

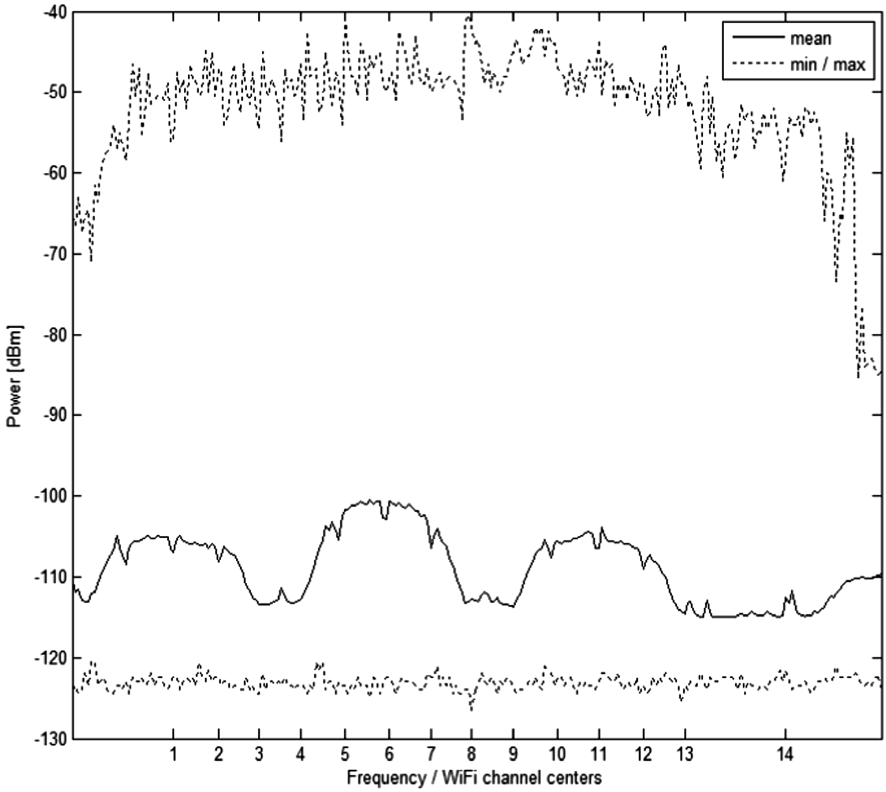

Fig. 1. Basic statistics of wireless environment (based on dataset B).

4.2 Temporal Trends (Dataset A)

Figure 2 shows time series plots for one week of measurements of WiFi channels 1, 6, 11 (center frequencies) utilization. Temporal patterns are evident: more transmission in

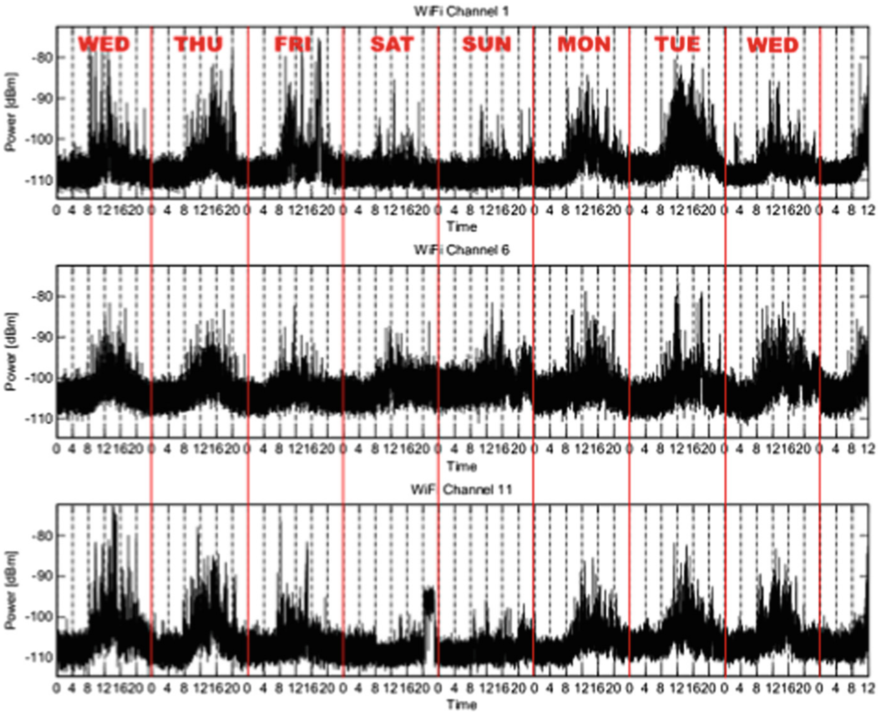

Fig. 2. One week of WiFi channel 1, 6, 11 (center frequencies).

the afternoons and on weekdays, and lower activity on weekends - in this case following typical campus network usage by IIT community.

Next plot (Fig. 3) shows daily relative frequency of signal power value occurrence (ratio of number of times when particular value was observed to total number of observations; based on three months of measurements) for WiFi channel 6 for different days of week. Extracted patterns suggest that examined spectrum frequency range is utilized in a similar way on every day of the week.

In similar fashion, but at a different time scale, Fig. 4 shows hourly relative frequency of signal power value for the same channel for Mondays (other days of the week have comparable characteristics). Higher afternoon activity as seen on Fig. 2 is again evident.

It is worth mentioning that information shown on Fig. 4 could be considered as a simple internal cognitive radio model of daily spectrum utilization for a given channel that can be easily generated from datasets like the ones used in this study.

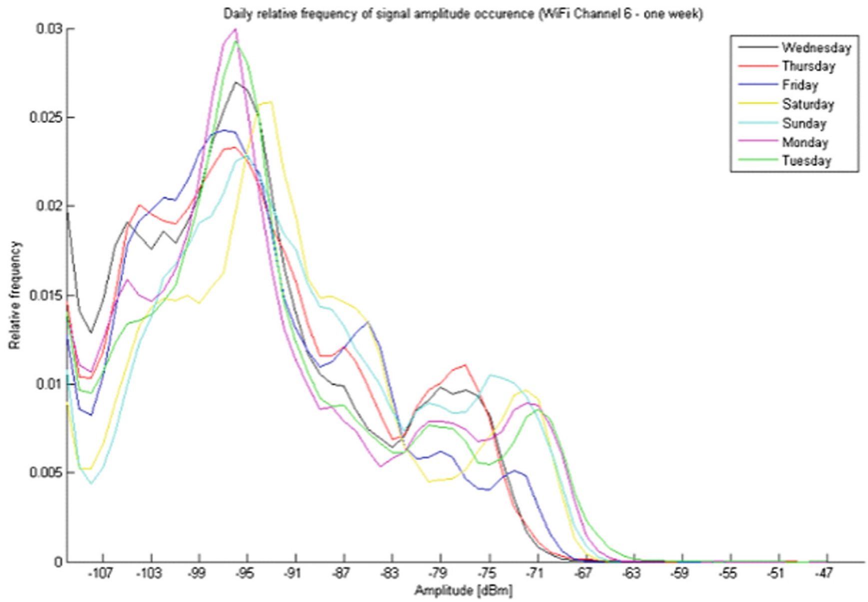

Fig. 3. Daily relative frequencies of signal power occurrence on WiFi channel 6 center frequency.

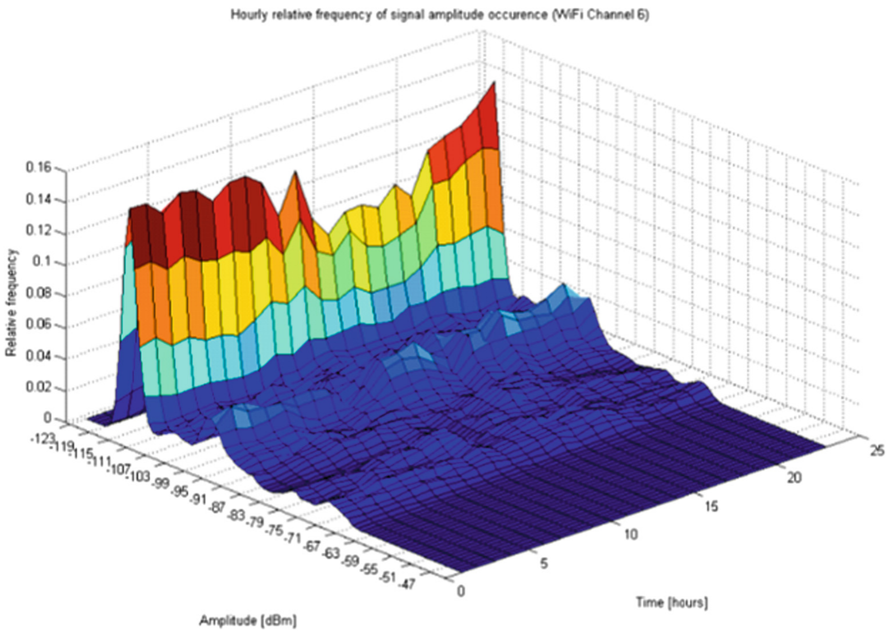

Fig. 4. Hourly relative frequencies of signal power occurrence on WiFi channel 6 center frequency - Mondays.

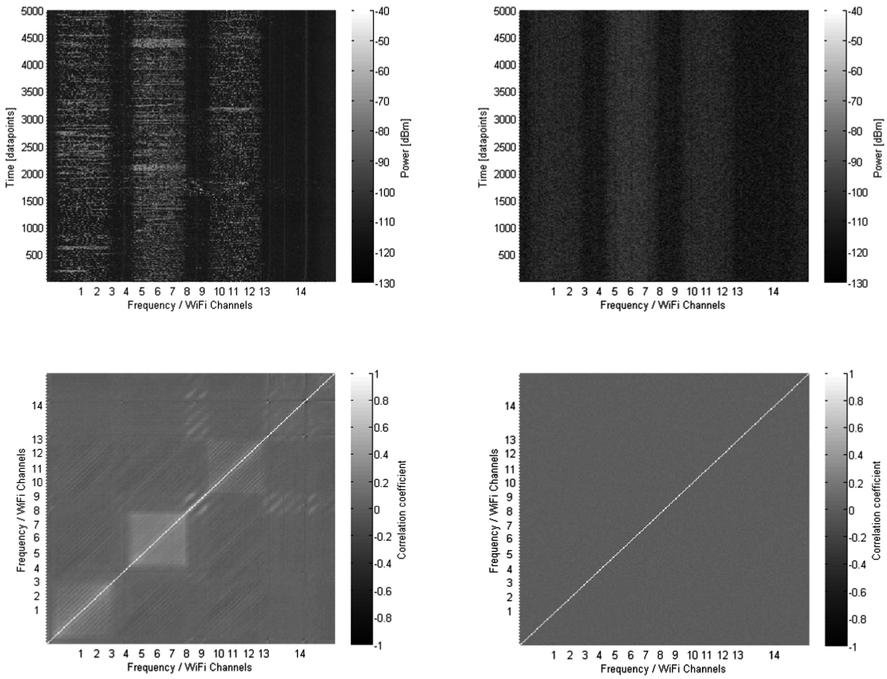

Fig. 5. Real (left) vs. synthetic (right) data: (top) waterfall fall plots, (bottom) visualization of frequency correlation coefficient matrix.

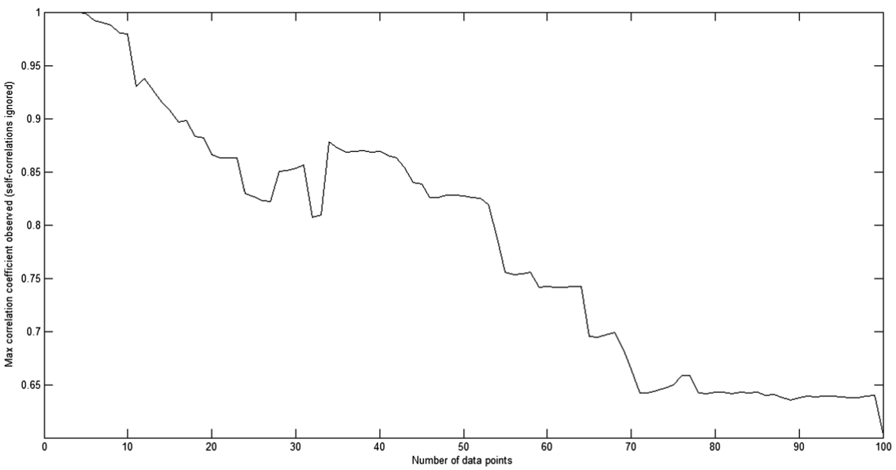

Fig. 6. Maximum correlation coefficient (between frequencies in time).

4.3 Real vs. Synthetic Data. Correlations (Dataset B)

Waterfall plots (see top section of Fig. 5) depict how details and dynamics of real-life data are lost when using a corresponding AWGN model. Bottom section of the same figure presents visualization of correlation coefficient matrices (correlation measured between traces of two frequencies). In case of real-life data correlations correspond to WiFi channels spanning over 22 MHz of bandwidth. Synthetic data does not preserve that effect.

Interestingly, maximum values of correlation coefficient remain quite high over time for real-life data (see Fig. 6) suggesting relationships between activities on certain frequencies. Corresponding effect can be observed on Fig. 7 below, where correlation coefficients are computed based on 1415486 data points per frequency (more than six days). Long-term patterns corresponding to WiFi channel 1, 6 and 11 activity emerge, which could be used by cognitive radio device to learn what kind of users are present technology-wise. As before, synthetic data does not preserve this information.

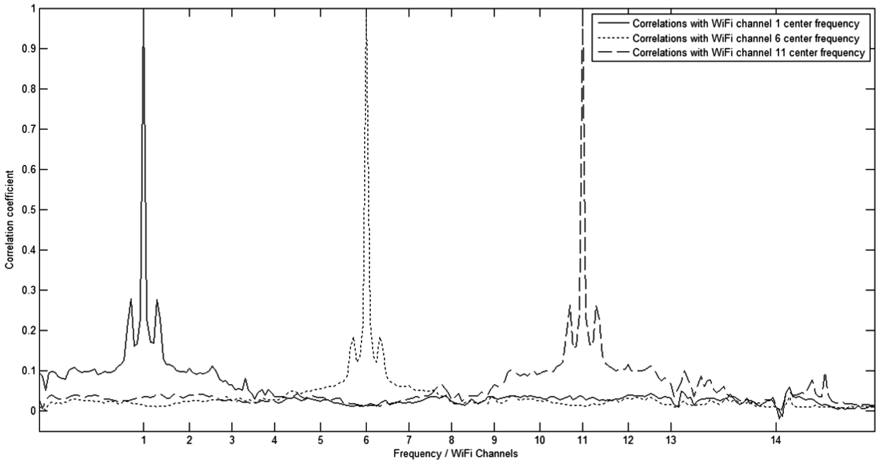

Fig. 7. Real-life data: correlations with WiFi 1, 6 and 11 channels across entire measured frequency range.

Figures 8 and 9 are plots representing duty cycle as a function of frequency and detection threshold for both real-life and synthetic data. Results are fairly comparable, which suggests that AWGN models should not be immediately dismissed in case of duty cycle-related experiments. What is interesting is the fact (see Fig. 9) that mean duty cycle (averaged over all measured frequencies) remains lower than 20% (real-life data) for detection thresholds greater than −110 dBm (and approximately −85 dBm for maximum duty cycle). 20% average spectrum utilization is consistent with results obtained through other measurement campaigns, e.g., underutilization.

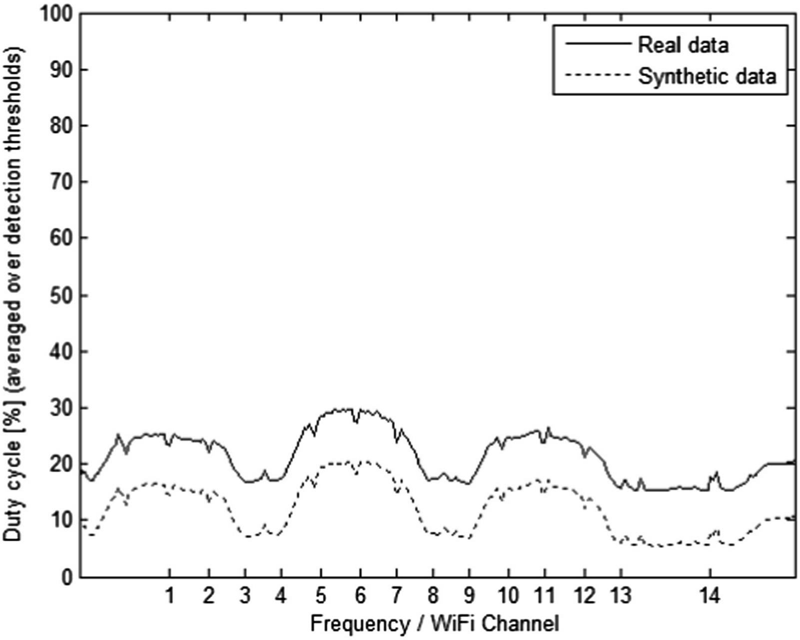

Fig. 8. Mean duty cycle (averaged over all detection thresholds).

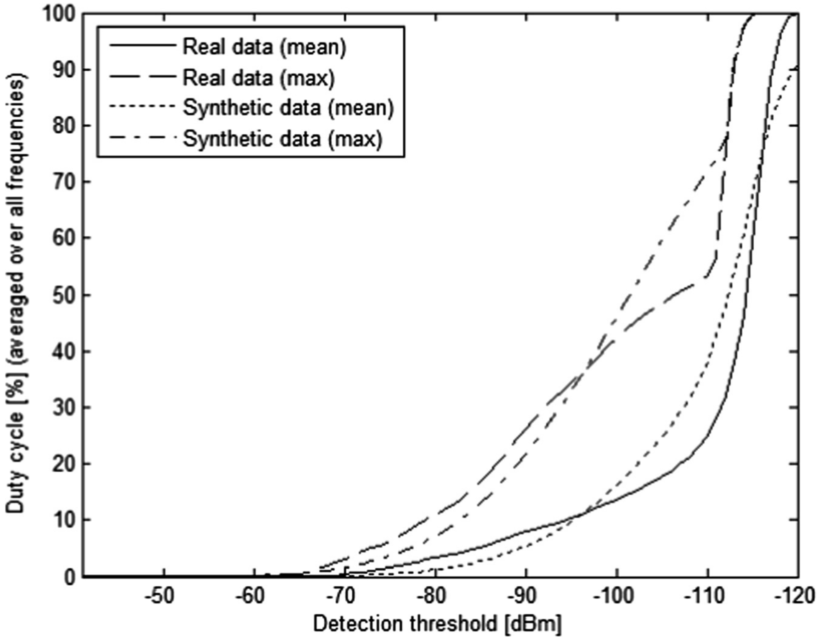

Fig. 9. Mean and maximum duty cycle (averaged over all frequencies).

5 Conclusions

Despite using a simple and relatively imprecise spectrum analyzer, collected long-term data was rich enough to notice wireless environment characteristics observed during elaborate long-term measurement campaigns, e.g. weekly and daily trends, underutilization, etc. Also, it has shown correlations between activities on different frequencies (WiFi channels in this case, but we observed the same effect in different datasets as well) that remains present over a long period of time. It could possibly be used to help identify networks with the most prominent presence within the environment. On the other hand, corresponding measurement-based AWGN models that we created failed to capture both temporal trends and correlations between individual frequencies. Information that could be used, as it was shown, to create internal models of expected daily unlicensed band activity, was not preserved in AWGN models which makes them inadequate for experimenting with certain aspects of cognitive radio development (i.e. learning, decision-making, etc.).

Robust wireless spectrum environment/occupancy models are not easy to develop and no universal model has been presented yet. Unlicensed bands, because of their complexity and dynamics, are especially challenging in this regard. Oversimplification, as we have shown, is likely to remove interesting subtleties that could be important to the overall cognitive radio behavior. While simple models remain valuable in some circumstances (e.g. when all relevant information is preserved and the model matches the experiment well), real data is richer and preserves nuances better. Given how easy it is to collect, manipulate and share WiSpy data, a publicly available repository of datasets would be an alternative to a collection of models which are likely to not be generic enough because of their spatio-temporal idiosyncrasies.

Finally, using WiSpy (or similar device) offers an additional benefit of working with data of similar quality to future consumer-end devices built with low-cost components; imprecise data adds realism in such context.

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