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# Improving Spectrum Sensing as a Method for White Space Identification through Design Principles

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Received 15 March 2016;

Accepted 6 June 2016

## Abstract

Spectrum sensing's inability to provide maximum protection to primary users operating in television white spaces summarizes the technical challenges associated with it. Building upon "WhiteNet", a white space network management platform for campus connectivity, this paper proposes design principles that can be incorporated in a white space identification system based on a cooperative spectrum sensing model that both minimizes the probability of causing interference to primary users due to false negatives and reduces false positives thereby increasing the amount of white spaces identified. Real-world indoor measurements of a TV transmitter signal were used to evaluate the proposed principles. The results reveal the relevance of using these design principles in white space networking using the emerging *White-Fi* protocol.

**Keywords:** White-Fi, cooperative spectrum sensing, detection threshold, spectrum sensing principles.

## 1 Introduction

So far, geo-location and spectrum sensing are two main approaches that have been proposed and accepted as possible methods of accessing unused spectrum

*Journal of ICT, Vol. 3, 177–200.*

doi: 10.13052/jicts2245-800X.331

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in the TV frequency band (television white spaces) for secondary use. Geo-location database approach guarantees more protection from interference to spectrum incumbents or primary users than the spectrum sensing approach. It is therefore not surprising that geo-location database approach is the preferred method of access in the US and Europe [1] at the moment. Protocols that have been developed so far for television white space (TVWS) access both in the US and Europe by telecommunications regulatory authorities there support the use of geo-location database. Example of such protocols include Protocol to Access White Space (PAWS) [2] by the Internet Engineering Task Force (IETF), the IEEE 802.11af standard [3] and the IEEE 802.22 standard [4]. However, the use of a geo-location database has been questioned as the best approach to accessing TV white spaces (TVWSs) [5] in some regions of Africa due to its limitations and the abundance of TVWSs that nullify the need for stringent constraints on primary user (PU) protection. Therefore, in such regions, spectrum sensing is expected to play a key role as an alternative method of accessing TVWSs.

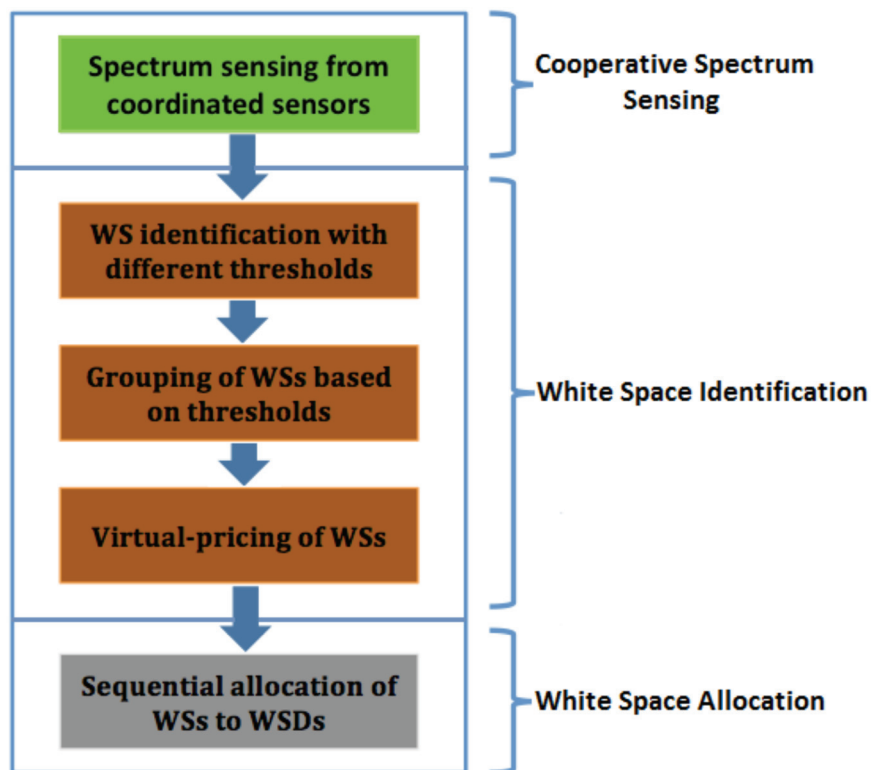
Technical challenges of accessing TVWSs through spectrum sensing without causing interference to PUs have not been solved completely. Spectrum sensing is still haunted by spectrum sensing problems such as fading, shadowing, noise uncertainty just to mention a few. The Federal Communications Commission (FCC) may have been influenced by these spectrum sensing problems to remove the mandatory requirement that WS devices should include sensing technology to detect the signals of TV stations and low-power auxiliary service stations (wireless microphones) in its second Memorandum Opinion and Order (MO&O) [6], which determines the final rules for the use of WS devices (WSDs) in TVWS. However, the FCC continue to believe that spectrum sensing will continue to develop and improve and anticipate that some form of spectrum sensing may very well be included in television band devices (TVBDs) on a voluntary basis [1]. With this view in mind, this paper proposes some design principles for improvement on spectrum sensing as a method for TVWS access.

New design principles that can be incorporated in a WS identification system based on cooperative spectrum sensing model to further minimize probability of causing interference to the PUs are being proposed in this paper. The proposed principles minimize probability of interference to PUs that may come due to false negatives. The proposed principles also reduce false positives in addition to reducing the probability of interference due to false negatives. The proposed principles include: i) use of multi-detection threshold values to identify WSs; ii) group WSs based on the threshold used;

iii) deployment of virtual WSs pricing and iv) sequential access of WSs by WSDs based on threshold groups and virtual WSs pricing. These principles add an additional layer of interference protection to PUs after the cooperative spectrum sensing layer. The block diagram depicting the hierarchical flow of how the principles work is depicted in Figure 1.

The main contributions of the paper are as follows:

- We propose three new principles that minimize further the probability of interference to incumbents by WS devices in a cooperative spectrum sensing model for identifying WSs. The principles have been evaluated through experimentation with real TV transmitter-allocation scheme and the results show better performance in both the number of white spaces identified and interference protection to PUs than any of the existing proposed spectrum sensing principles for either indoor or outdoor environment.



**Figure 1** Hierarchical flow of how the principles work.

- Out of the three spectrum sensing WS identification principles being proposed in this paper, we follow them up with another proposal to allocate the WSs identified to WS devices using sequential allocation.
- We propose the first design step of *WhiteNet*, a WS network management platform for university campus networking that uses the proposed principles to boost the current capacity of Wi-Fi networks with bandwidth acquired through safe secondary access to WS frequencies.

The rest of the paper is structured as follows: Section 2 gives a background to some of the challenges of spectrum sensing as a method for identifying TVWSs; Section 3 introduces the principles and discusses how they foster protection of PUs; Section 4 discusses some major existing principles that can be included in a spectrum sensing-based WS identification system; Section 5 discusses how the proposed principles can be implemented; Section 6 is a discussion of the experimental evaluation of the principles and Section 7 concludes the paper.

## 2 Challenges of Spectrum Sensing Explained

There are several spectrum-sensing methodologies available but the most commonly used in WS identification is the energy detector-based sensing. Energy detector-based sensing works by measuring the energy contained in a spectrum band and comparing it with a set threshold value [7, 8]. If the energy level is above the threshold value, then the signal is considered present otherwise the spectrum band is considered vacant. This technique reigns superior over the other spectrum sensing techniques because of several factors: i) it is simple as it has low computational and implementation complexities [8, 9], ii) it has good performance [10–12] and iii) it is more generic as receivers do not need any knowledge on the PUs' signals [7, 8].

Much as the energy detector-based sensing has these advantages over the other spectrum-sensing methodologies, it has some inherent challenges that make it less desirable as a means of accessing TVWSs, which can be summed up into inability to provide maximum protection to PUs from interference. One of its major challenge in relation to identifying TVWSs is that there is no standardized way of selecting the signal detection threshold that gives optimal performance, i.e., simultaneously giving low false positives and low false negatives. As a result, it is extremely difficult to come up with a single detection threshold that simultaneously give low false positives and low false negatives. The value chosen as the detection threshold has a major impact

on the performance of the spectrum sensing equipment. If the value is too high, the technique fails to detect the presence of a TV signal in a channel thereby causing harmful interference, and if the value is too low, it gives false detection when there is actually no TV signal in the channel.

Another challenge of this technique is that it suffers from multi-path fading or shadowing that results into the *hidden user problem* [9]. In this scenario, a WS device is unable to detect the presence of a PU service in a channel due to obstacles that block the PU's signal path as it propagates through the wireless medium. This leads to misinterpretation of measured data by the WS device where it thinks the channel is available and start to transmit, causing interference to the PU.

### **3 Proposed Principles**

Design paradigm underlying any suggested model based on spectrum sensing aims at eliminating the technical challenges of spectrum sensing. This section discusses the proposed principles that are being incorporated in the cooperative spectrum sensing-based WS identification component of *WhiteNet*; a white space networking platform under development at the University of the Western Cape (UWC) in South Africa with the expectation of resolving some of the technical challenges associated with this method of identifying WSs.

#### **3.1 Use of Multi-Detection Thresholds**

Deciding on the threshold to be used in spectrum sensing is a challenging issue that has been at the heart of debates concerning an absolute value to be used. The sensitivity threshold of  $-114$  dBm for Advanced Television Systems Committee (ATSC) TV signal detection as mandated by the FCC is too conservative as shown by several measurement studies [13–16].  $-114$  dBm is said to be conservative because it leads to significant loss of WSs [16], i.e., leads to too many false positives. For example, [13] found no TVWSs in all the locations where the studies were done in China when a sensing sensitivity threshold of  $-114$  dBm was used. However, relying on the analog terrestrial television (ATT) database as ground-truth data for the ATT channel occupancy situation in Beijing, setting the sensitivity threshold to  $-97$  dBm was enough to find WS ATT channels in indoor scenarios. On the other hand, different signal detection thresholds have been used by different studies. These studies have claimed that their thresholds led to low false positives and/or low false negatives. Therefore, to compromise the two extremes, *many false negatives*

*or many false positives*, the likely results when a single threshold is used, we are proposing to use more than one threshold value, which seem to be logical. The threshold values can range from  $-114$  dBm to a value that is dependent on a country's TV transmitter allocation scheme for transmitting sites. The FCC's mandated detection threshold of  $-114$  dBm is being proposed as the start threshold because it is conservative and also able to find WSs in some environments.

### **3.2 Group WSs Based on Thresholds Used**

Instead of putting the WSs identified in one pool as is in the case where one threshold value is used, we are proposing to put them in different groups based on the thresholds values used. Assume that probability of interference to incumbents due to false negative has not been eliminated completely after cooperative spectrum sensing and use of more than one threshold principle has been applied, grouping of WSs based on the thresholds used to identify them and sequential allocation of the groups that starts with the group of WSs identified with the lowest threshold provides some level of protection to incumbents from interference due to false negative. Groups of WSs identified with lower threshold values are safer in terms of causing interference to incumbents than those WSs identified with higher threshold values; lower threshold values are conservative than higher threshold values. Assuming that at each point in time when there is a demand for WS use from WSDs, the demand is met well before using WSs identified with higher threshold values, then the proposed approach minimizes chances of interference to PUs than using random or haphazard allocation of WSs identified with a single threshold value. This assumption seem to be logical because the demand for WS use comes from local Wi-Fi devices where the demand is normally not expected to be higher than the number of WSs that may exist at a location.

### **3.3 Virtual Pricing of White Spaces**

Up to this level, channels within any WS group as in WS groups discussed in Subsection 3.2 can only be randomly allocated to WSDs as they have not been ranked in any way in terms of probability of causing interference to incumbents. Even though one threshold is used to identify WS channels within a group, the WS channels have different probabilities of causing interference to incumbents if allocated to WSDs because of their differences in energy levels or signal strengths recorded in each channel. Consequently,

random allocation of WS channels within a group is also not safe as some channels may have higher probabilities of causing interference than others. A common quantity to all WS channels within a group, for example, their energy levels/signal strengths, can be used to rank or virtual-price them in terms of probability of causing interference to the incumbents. Once they are ranked or virtual-priced, they can be sequentially allocated to WSDs. Those WS channels with higher energy levels/stronger signal strengths are virtual-priced higher than WS channels with lower energy levels/weaker signal strengths. The allocation starts with the WS channel virtual-priced lowest, i.e., one with the lowest probability of causing interference to the incumbents. It is logical to expect a channel which is not WS but has been identified as WS to have higher energy level/stronger signal strength than a channel which is actually WS on the ground; the signal measured in a channel that is not WS is a resultant signal from the incumbent's broadcast signal plus some channel interference while that from a channel that is actually WS on the ground, the measured signal is only from channel interference. So channels that are not WSs on the ground but have been identified as WSs are expected to have higher virtual-prices than those that are actually WSs on the ground. With this approach to virtual price the WS channels within a group and sequentially allocating them to WS devices, channels with missed detection can never be allocated to any WS device unless all the channels that are actually WSs in a particular WS channel group are exhausted.

## **4 Existing Spectrum Sensing Design Methods**

This section discusses existing spectrum sensing design methods that this work considers relevant to the implementation of a spectrum sensing-based WS identification system.

### **4.1 Cooperative Spectrum Sensing**

Cooperation among sensing equipment is vital for the optimal performance of spectrum sensing when used as a method of identifying TVWSs because a network of spectrum sensors that share sensing information obtained from their individual locations with each other has a better chance of detecting the PU compared to local spectrum sensing [9] by a single spectrum sensor. Cooperative spectrum sensing is proposed in the literature as the solution to the

*hidden user problem* [14, 15, 17–19] that may arise due to multi-path fading or shadowing. As mentioned in the introduction, our proposed principles rely on the results generated from cooperative spectrum sensing model as the first step to minimizing chances of interference to PUs that may arise due to multi-path fading or shadowing. If a *hidden user problem* still exists after cooperative spectrum sensing, then the proposed principles help to protect it further from interference.

## 4.2 Channel-Clustering and Location-Clustering

In their experiment, Ying et al. [20] observed that there is strong correlation in signal strength across multiple indoor locations from a single channel and that there is also strong correlations in multiple channels in their signal strengths and white space availability patterns across all locations. The observations suggest that it is possible to focus on monitoring representative channels at representative indoor locations and infer the availability of other channels at other locations by exploiting the location and channel correlations [20]. In order to do that, both channels and locations need to be clustered. Clustering both the channels and locations helps to avoid random placement of the energy detectors, which may result into waste of energy detectors, i.e., many unnecessary detectors deployed or not guarantee coverage, i.e., insufficient detectors deployed. Once the channel clustering and location clustering is done, the algorithm proposed in [20] can be used to determine placement positions for the energy detectors. Implementing the clustering principle on both channels and locations means WSs are calculated according to location clusters. Therefore, secondary users are required to be equipped with a geographical positioning system (GPS) to enable them identify their positions before sending a request for white space use. For detailed discussion of these principles and how they can be implemented, consult [20].

## 5 Algorithm Implementation

The proposed principles and the existing methods that have been discussed are not environment specific, i.e., they are general principles and methods that can be implemented in a spectrum sensing-based WS identification system meant for outdoor or indoor environment. This section shows how the proposed principles can be implemented algorithmically.



## 5.1 WS Identification Using Multi-Thresholds and Grouping of the WSs

The method for computing TVWSs using different signal detection thresholds and grouping of the WSs identified is presented in Algorithm 1. The algorithm also shows how cooperative spectrum sensing is implemented with the two principles.

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### Algorithm 1: Identify white space channels using different thresholds

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**input** : Two-dimensional matrix  $st$  of size  $m$  by  $n$  of signal strength values, set  $CH = \{ch(1), ch(2), ch(3), \dots, ch(m)\}$  of channels.  $\{m$  is the number of channels under consideration;  $n$  is the number of sensors deployed}

**output**:  $SC = \{SC(1), SC(2), SC(3), \dots, SC(x)\}$ , where  $x$  is less than or equal to number of threshold values,  $SS = \{SS(1), SS(2), SS(3), \dots, SS(x)\}$ .  $\{SC$  is a set of sets of white space channels;  $SS$  is a corresponding set of sets of signal strength values of the white space channels}

```

1 initialize  $t \leftarrow startThreshold, x \leftarrow 1;$ 
2 repeat
3   for  $i \leftarrow 1$  to  $m$  do
4     if  $SC$  is not empty then
5       | check if  $ch(i)$  is in any of  $SC$  subsets;
6     end
7     if  $ch(i)$  is not found in any  $SC$  subsets or  $SC$  is empty then
8       |  $strongestSignal \leftarrow 0;$ 
9       | for  $j \leftarrow 1$  to  $n$  do
10        | if  $st[i][j] > strongestSignal$  then
11        | |  $strongestSignal \leftarrow st[i][j];$ 
12        | end
13      | end
14      |  $rss(i) \leftarrow strongestSignal - t // rss(i)$  is representative
15      | relative signal strength for channel  $i$ 
16      | if  $rss(i) \leq 0$  then
17      | | add  $ch(i)$  to  $SC(x);$ 
18      | | add  $st[i][j]$  to  $SS(x)$ 
19      | end
20    | end
21    | if  $WS(x)$  is not empty then
22    | | add  $SC(x)$  to  $SC;$ 
23    | | add  $SS(x)$  to  $SS;$ 
24    | end
25    |  $t \leftarrow t + increment, x \leftarrow x + 1$ 
26  until  $t$  is equal to  $endThreshold;$ 
27  return  $SC, SS$ 

```

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The inputs to the algorithm are signal strength values of all the channels from the frequency spectrum sensors deployed and the channels under consideration. The algorithm first checks if a channel under consideration is an already identified WS using any of the previously used threshold values if any. This is done in lines 4 to 6. This helps to make sure that each channel is not identified as WS more than once as the threshold values keep changing. Once the algorithm finds that a channel is not an already WS channel, it then compares the signal strength values for that channel from all the sensors deployed from line 9 to 13 to find the representative signal strength value, which is the strongest signal measured in that channel from all the sensors deployed. The strongest signal is used to calculate the relative signal strength for that channel by subtracting the current threshold from it in line 14. Then the algorithm checks if the channel is WS by checking if its relative signal strength is less than or equal to zero in line 15. If it is found to be WS, it is added to the set of WSs for that detection threshold in line 16. The process is repeated for all the channels using the current threshold value (*lines 3 to 20*). Once all the channels are considered using the current threshold value, the next threshold value is considered (*line 24*) and the process is repeated from the beginning (*from line 2*). This process is repeated until all the threshold values have been considered. The output from this algorithm is the set of sets of WS channels  $SC$  identified using different thresholds and the set of sets of signal strength values  $SS$  corresponding to the set of sets of all WS channels  $SC$ .

## 5.2 Compute Virtual Prices of WS Channels

Once WSs channels have been identified using the different threshold values and put into groups based on the thresholds, Algorithm 2 follows to compute their virtual prices based on signal strength recorded in each channel.

The input to the algorithm is  $SS$ , the output from Algorithm 1. The algorithm first searches through the set of signal strength values  $SS(i)$  to find the strongest signal in that set in lines 2 to 7. Then algorithm calculates the virtual price of each WS channel by dividing its absolute signal strength with the absolute strongest signal in lines 9 to 12. The process is repeated for each WS channel group  $SS(i)$  using the strongest signal in that group and the signal strengths of WS channels in the group until all WS channel groups are considered. The output of the algorithm is the set of sets of virtual prices  $VP$  corresponding to the set of sets  $SS$  of signal strength values for the WS channels.

**Algorithm 2:** Compute virtual prices of white space channels identified

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input :  $SS = \{SS(1), SS(2), SS(3), \dots, SS(x)\}$ .
output:  $VP = \{VP(1), VP(2), VP(3), \dots, VP(x)\}$ . {VP is a corresponding set of
sets of virtual prices of white space channels}

1 initialize  $j \leftarrow 1, strongestSignal \leftarrow 0$ ;
2 for  $i \leftarrow 1$  to  $x$  do
3   while  $SS(i)$  has elements do
4     if  $strongestSignal < ss(i)(j)$  then
5        $strongestSignal \leftarrow ss(i)(j)$ ;
6        $j \leftarrow j + 1$ ;
7     end
8   end
9   for  $a \leftarrow 1$  to  $(j - 1)$  do
10     $vp(i)(a) = |ss(i)(a)| / |strongestSignal|$ ;
11    add  $vp(i)(a)$  to  $VP(i)$ ;
12  end
13  initialize  $j \leftarrow 1$ 
14 end
15 return  $VP$ ;

```

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### 5.3 Implementation of Proposed Principles

As mentioned in Section 3, the proposed principles have been incorporated in the cooperative spectrum sensing-based WS identification component of a white space networking platform under development at UWC in South Africa. As an example of how the principles can be implemented, the identification component of the platform is explained briefly. It consists of a central database where Algorithm 1 and Algorithm 2 are implemented. The database is connected to a number of spectrum sensors through some intermediate processing units like Raspberry Pi, which send summarised sensing information, e.g., signal strength recorded in each channel, to the database. Using the summarised sensing information recorded from each spectrum sensor, the database compute the available WSs and virtual-price by running Algorithm 1 and Algorithm 2 respectively. The database compute the WSs based on the detection thresholds hard-coded into Algorithm 1.

## 6 Experimental Evaluation

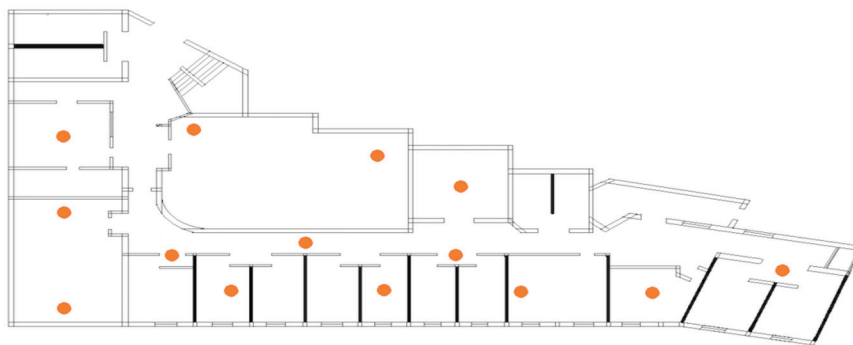
To have a better understanding of how the principles can work in real spectrum sensing-based WS identification system and evaluate their performance, we conducted short time indoor measurements at the University of the Western

Cape in Cape Town, South Africa in the ultra-high frequency (UHF) band used for TV broadcasting and used the measurement data in the spectrum sensing-based WS identification component of *WhiteNet*. The Department of Computer Science, occupying the ground floor of Mathematical Sciences Building, was used as the experimental site. It has a floor area of approximately 560 m<sup>2</sup>. The layout of the ground floor of the building and the measurement points are shown in Figure 2. The environment for the measurement locations was regarded as the same since all the locations were on the same floor of the building and the locations covered a small area. We assumed that the spectrum sensors detected similar signal strengths from all the locations such that the same WS channels were identified from each location. That simplified the experiment since WSs did not have to be calculated based on location.

The hand-held RF Explorer model WSUB1G was used in the measurement process, which has a measurement frequency range of 240 MHz to 960 MHz. The complete technical specification of the model can be found in [21]. The model was fitted with a Nagoya NA-773 wideband telescopic antenna with vertical polarization, which has wide band measurement capability. The RF Explorer was connected to an Android phone installed with an android code that starts to measure signals as soon as the RF Explorer is connected using an OTG cable.

### 6.1 Detection Thresholds Used

No WSs were detected when  $-114$  dBm was used. Therefore, different threshold values were tried by incrementing the  $-114$  dBm sequentially with  $0.5$  dBm each time. The first WS was detected with  $-103$  dBm threshold and it



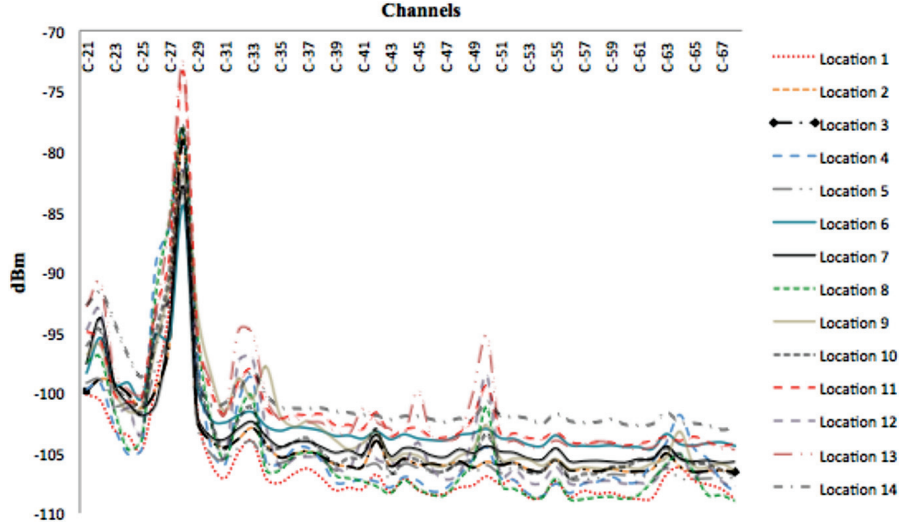
**Figure 2** Layout of the building and measurement points.

was taken as the start threshold. For the final detection threshold, an adequate criterion had to be used to select it to ensure maximum protection of PUs. We looked at the Draft Terrestrial Broadcasting Plan 2013 document [22] from the Independent Communications Authority of South Africa (ICASA) to see how the UHF TV channels are arranged in the band. According to the document, UHF ATT frequency band (470 MHz and 854 MHz) contains 48 channels of each 8 MHz bandwidth. The 48 channels are arranged into 12 groups of 4 channels each, which mean that 4 channels are available for assignments at any transmitting site on a national basis. In areas of great demand, 7 to 11 channels are assigned to a particular area by either combining lattice node points or using both VHF and UHF channels. The measurement site is a typical urban area, and as such, we considered it an area of great demand. This was confirmed when we examined the Tygerberg transmitting site in [22], which is the closest ATT transmitting site to UWC. There are 6 UHF channels being used by different TV stations at the site with the first TV station broadcasting from channel 22. A close examination of how these channels are allocated in the band shows that each allocated channel is spaced by at least 4 channels before the next allocated channel. We believe this allocation scheme was done to reduce interference between the allocated channels. Based on this allocation scheme, we concluded that at least the first 24 channels could not be detected as WSs at the measurement site. That was achieved with the maximum detection threshold of  $-102$  dBm, and was considered the end detection threshold. Since small variations in threshold values have a very big impact on the amount of white spaces found [23], our detection thresholds were spaced by an absolute value of  $0.5$  dBm difference, resulting into the following detection thresholds;  $-103$  dBm,  $-102.5$  dBm and  $-102$  dBm.

## **6.2 Measurement Results**

Since we were interested with the temporal distribution of WSs, the signal measurements were taken for only *120 seconds* at each location. The *120 seconds* included the signal amplitude stability time. Observation of the data showed that after about *90 seconds* into the measurement, the signal amplitude stabilised to within  $\pm 5$  dBm. Therefore, only the data recorded in the last *30 seconds* of the measurement at each location was used for calculating the average received signal strength, which was regarded as the temporal signal strength for that channel at that location.

Figure 3 shows the temporal signal strengths recorded in each channel from the *14* locations. The standard deviation of the signal strength for each



**Figure 3** Signal strengths recorded from all locations.

channel recorded from the 14 locations is shown in Table 1. It is easy to see from the table that the standard deviation of the signals for most of the channels was below 2 dBm. The largest standard deviation was 3.8 dBm from channel 27. The small standard deviations signify that the signals collected in a particular channel from the 14 locations varied very little from one location to another. The results confirm the validity of our assumption that the spectrum sensors detect similar signal strengths for each channel under consideration from the locations.

The temporal signal strength recorded in each channel from each of the 14 locations was fed into the Algorithm 1 to calculate the WSs. Table 2 shows the WS channels that were found with the three thresholds. The relative spectrum occupancy for all the channels for each of the three threshold is shown from Figure 4 to Figure 6. The relative spectrum occupancy for each channel was defined by the following three equations:

$$O_{RS}(i) = 100 * R_{SS}(i, T_j) / M(i, T_j) \quad (1)$$

$$R_{SS}(i, T_j) = SS(i) - T_j \quad (2)$$

$$M(i, T_j) = \max(R_{SS}(i, T_j)) \quad (3)$$

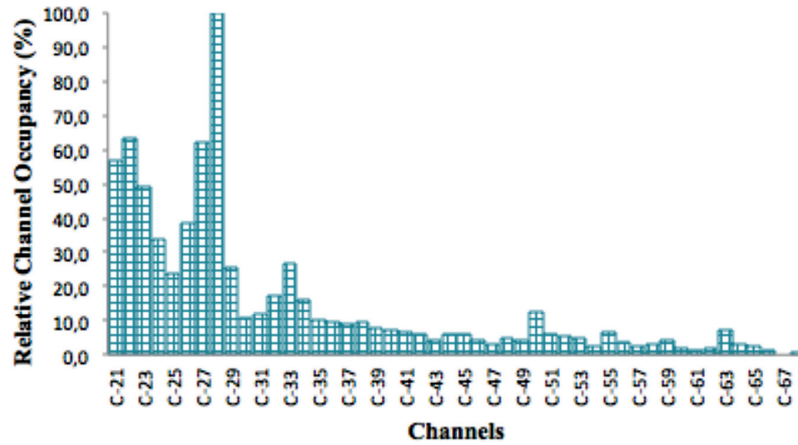
where  $O_{RS}(i)$  is the relative spectrum occupancy in channel  $i$ ,  $R_{SS}$  is the relative signal strength collected in channel  $i$  using threshold  $T_j$ ,  $SS(i)$  is the representative signal strength in channel  $i$ , which is equal to the strongest signal

**Table 1** Standard deviation of signal strengths collected from the 14 measurement locations (+/- dBm)

Channel	21	22	23	24	25	26	27	28	29	30	31	32
STDEV	2.6	3.0	2.2	2.2	1.8	3.4	<b>3.8</b>	3.4	3.2	2.2	1.9	2.9
Channel	33	34	35	36	37	38	39	40	41	42	43	44
STDEV	2.7	2.7	2.0	1.6	1.5	1.7	1.9	1.9	2.0	2.0	1.9	1.6
Channel	45	46	47	48	49	50	51	52	53	54	55	56
STDEV	2.3	1.9	1.8	1.7	2.1	3.3	1.7	1.7	1.9	1.9	1.7	1.9
Channel	57	58	59	60	61	62	63	64	65	66	67	68
STDEV	1.7	1.8	1.7	1.7	1.7	1.6	1.4	1.5	1.4	1.5	1.6	1.8

**Table 2** White spaces identified with different thresholds

Threshold (dBm)	No. of WSs Identified	Channel (s)
-103	1	67
-102.5	8	54, 57, 60, 61, 62, 65, 66, 68
-102	11	43, 46, 47, 48, 49, 52, 53, 56, 58, 59, 64



**Figure 4** Spectrum occupancy with -103 dBm threshold.

measured in channel  $i$  out of the 14 locations and  $M(i, T_j)$  is the maximum relative signal strength in the band collected in channel  $i$  using threshold  $T_j$ .

The WS channels groups and the corresponding signal strengths of WS channels groups were fed into Algorithm 2 to calculate their virtual prices, which are shown in Table 3.

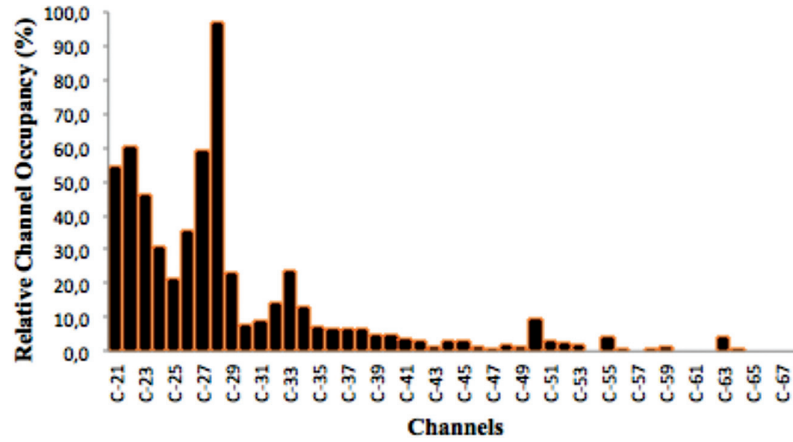


Figure 5 Spectrum occupancy with  $-102.5$  dBm threshold.

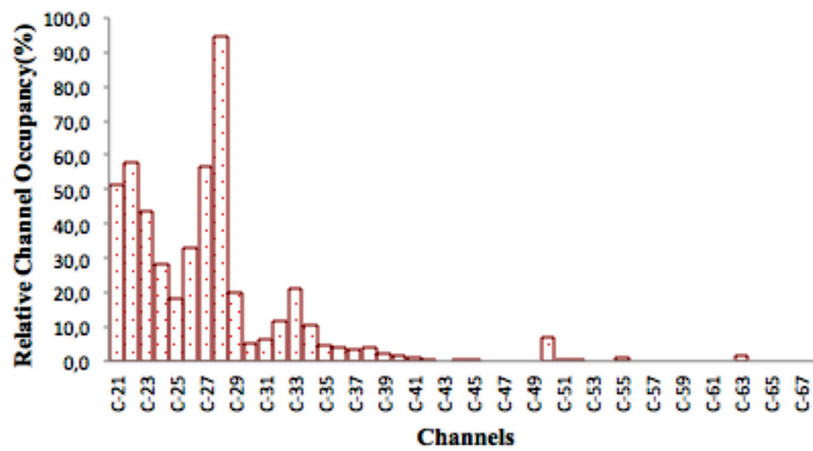


Figure 6 Spectrum occupancy with  $-102$  dBm threshold.

Table 3 Prices for white space channels

WS Channel Group	WS Channels with Their Prices
$-103$ dBm	67:1.000
$-102.5$ dBm	54:0.997, 57:0.996, 60:0.998, 61:0.998, 62:0.997, 65:0.997, 66:0.998, 68:1.000
$-102$ dBm	43:0.998, 46:0.997, 47:1.000, 48:0.996, 49:0.998, 52:0.995, 53:0.996, 56:0.999, 58:1.000, 59:0.997, 64:1.000



**Table 4** Statistical analysis of current and proposed methods based on thresholds used

Method Type	Threshold(s)	Allocation Type	No. of WSSs Generated	Interference Probability
Current Methods	103 or	random	1	0
	102.5 or	random	9	0
	102	random	20	> 0
Proposed Methods	103, 102.5, 102	sequential	20	0

### 6.3 Simple Evaluation of Proposed Design Principles Against Existing Proposals

Based on the thresholds used and the WSSs generated, an evaluation is made between the current spectrum sensing methods for identification and allocation of the WSSs to WSDs and our proposed methods for identification and allocation of WS to WSDs based on the number of WSSs identified and the probability of causing interference to incumbents. Table 4 shows the results of the evaluation. The following assumptions are made:

- Some thresholds are conservative leading to identification of channels which are indeed WSSs on the ground while other thresholds are not conservative leading to identification of some channels which are not WSSs on the ground, and these channels only appear in the last group, i.e., 102 dB threshold.
- Demand for WS use is local and the actual WSSs available at a location are enough to met the local demand.

### 6.4 Discussion

The grouping of WS channels as show in Table 2 helps to start allocating them to WSDs with the safest group, which is the one detected with  $-103$  dBm in this case. The least safest group of WSSs out of the three groups is the one identified with  $-102$  dBm threshold. WSSs in this group are allocated only if the demand for WS use is not met after using the WSSs in the first two groups. If there are any missed detections from some channels in the group and the demand for WS use is met before using the channels in that group, then the PUs in those channels are protected from interference. It is different if the WS channels are identified using one threshold and they are also allocated randomly to WSDs as it can be seen from Table 4. Note that the number of WSSs identified using one threshold is always less than or equal to the number of WSSs identified using more than one threshold. For example, the current methods can use either of the three thresholds;  $-103$  dBm or  $-102.5$  dBm or

$-102$  dBm. If  $-103$  dBm is used, only 1 WS is found and if  $-102.5$  dBm is used, only 9 WSs are found and if  $-102$  dBm is used, 20 WSs. As seen from the table, when the number of WSs identified with one threshold is equal to the number of WSs identified with more than one threshold, the probability of causing interference to incumbents is greater than zero with the current methods. This is so because channels which are not WSs but have been identified so, can be allocated to a WS device because of the random allocation used by current methods although there are still some channel, which are actually WSs on the ground that have not been allocated.

An additional layer of security is provided within a group of WSs if the channels are virtual-priced based on the signal strengths in the channels. Channels with stronger signals are priced higher than channels with weaker signals as shown in Table 3 because channels with stronger signals are the ones that are more likely to have PUs in them than channels with weaker signals. For example, looking at WS channel group identified with  $-102$  dBm in Table 3, allocating the cheapest channels such as 52, 53, 48 first to WS devices adds some protection to the expensive channels such as 47, 58 and 64, which are the most likely channels to result into false negatives in that group. In this case, allocating the channels sequentially based on the lowest prices, starting with channel 52, provides some level of protection to the expensive channels such as channel 47 or channel 58 if there was missed detection in them.

## 7 Conclusion and Future Work

In this paper, we proposed three design principles that have been included in a spectrum sensing-based white space identification system to reduce further chances of interference to PUs due to false negatives after cooperative spectrum sensing. The principles were experimented in the white space network platform for campus connectivity at the University of the Western Cape in South Africa using real measurement data in the UHF band used for ATT broadcasting. The results show that the application of the principles can reduce the probability of interference to PUs to some extent.

As a first design step of *WhiteNet*; a white space network management platform for campus networking, spectrum sensing design principles have been proposed and implemented using real TV-transmitter signal measurements. For the proposed principles to work efficiently, they require redesigning existing network management techniques to manage white spaces. Cost-based traffic engineering techniques such as proposed in [24, 25] will also need to be redesigned as PU protection mechanisms using cost metrics to reflect the

white space availability under primary and secondary usage. The integration of parallel path models [26, 27] in white space bonding deployments and the use of white space for long distance wireless deployments [28, 29] are other avenues for future work. The design of market pricing mechanisms to protect PUs while managing white spaces to meet quality of service (QoS) agreements between the offered traffic and the available spectrum is another avenue for future research. The design of low cost white space gateway devices building around the emerging Raspberry pi hardware and the flexibility and robustness principles proposed in [30, 31] is another direction for future research.

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