# WHITENET: A WHITE SPACE NETWORK FOR CAMPUS CONNECTIVITY USING SPECTRUM SENSING DESIGN PRINCIPLES

Hope Mauwa, Antoine Bagula

University of the western Cape ISAT Laboratory, Department of CS Bellville, 7535, South Africa mhope@uwc.ac.za, bbagula@uwc.ac.za

### ABSTRACT

To this day, the technical challenges of accessing TV white spaces through spectrum sensing can be summed up into its inability to provide maximum protection to primary users from interference. Yet, off-the-shelf spectrum sensing devices, which are emerging on the market at low cost, and the low computation and implementation complexities of the sensing technique, make them more and more attractive to the developing world. Building upon "WhiteNet", a white space network management platform for campus connectivity, this paper proposes design principles that can be incorporated in a spectrum sensing-based white space identification system to minimise probability of causing interference to primary users. The principles are designed around the cooperative spectrum sensing model to further reduce chances of interference to primary users. Evaluation of the principles was done using real-world indoor measurements and based on a real TV transmitter-allocation at the University of the Western Cape in Cape Town, South Africa. The results reveal the relevance of using these design principles in white space networking using the emerging White-Fi protocol to boost the capacity of current Wi-Fi campus networks.

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

## 1. INTRODUCTION

It has been widely recognized that in many regions of the developing world, poor Internet access in universities and research institutions is one of the causes of the scientific divide between developed and developing countries. In many of these regions, Wi-Fi has played a key role to connect campus communities by enabling inter-campus connectivity and access to the Internet but at lower access bandwidth compared to research institutions of the developed world. The transition from analog to digital television is a great opportunity to address this bandwidth issue in campus networks by using emerging protocols such as IEEE 802.11af, also referred

Marco Zennaro

International Centre for Theoretical Physics T / ICT4D Laboratory Strada Costiera 11, Trieste, Italy mzennaro@ictp.it

to as *White-Fi* or *Super Wi-Fi* [1] to boost the current capacity of Wi-Fi networks with bandwidth acquired through secondary access to white space (WS) frequency. However, technologies and protocols have yet to mature to provide the proper WS equipment at affordable prices and WS identification, quantification and allocation techniques have yet to improved and move from the research boundaries to the implementation arena.

Two main approaches of accessing unused spectrum in the TV frequency band (white spaces) for secondary use have been suggested in the literature; geo-location database and spectrum sensing. At the moment, there is a trend towards the use of only geo-location database approach in the US and Europe [2] as it guarantees high protection of the spectrum incumbents from the interference. The trend is supported by the development of the protocols such as Protocol to Access White Space (PAWS) [3] by the Internet Engineering Task Force (IETF), the IEEE 802.11af standard [4] and the IEEE 802.22 standard [5] to access spectrum database. However, in some regions of Africa, the use of a geo-location database has been questioned as the best approach to accessing TV white spaces (TVWSs) [6] due to its limitations and the abundance of TVWSs that nullify the need for stringent constraints on primary user protection. In such regions, therefore, spectrum sensing is expected to play a key role as an alternative method of accessing TVWSs.

To this day, technical challenges of accessing TVWSs through spectrum sensing without causing interference to primary users have not been solved completely. In this paper, some design principles are being proposed that can be incorporated into a spectrum sensing-based WS identification system to minimise probability of causing interference to the primary users. These principles are designed around the concept of cooperative spectrum sensing. The proposed principles are: i) the use of different threshold values and ii) the deployment of virtual WSs pricing. These principles add an additional layer of protection to primary users after the cooperative spectrum sensing layer. The block diagram depicting the hierarchical flow of how the principles work is depicted in *Figure 1*.

The rest of the paper is structured as follows: Section 2 gives a background to some of the challenges of spectrum sensing

Paper accepted for presentation at "Trust in the Information Society" ITU Kaleidoscope Conference, Barcelona, Spain, 9-11 December 2015, http://itu.int/go/K-2015.



Figure 1. Hierarchical flow of how the principles work

as a method for identifying TVWSs; Section 3 introduces the principles and discusses how they foster protection of primary users; 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. BACKGROUND INFORMATION

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 [9, 8], ii) it has good performance [10, 11, 12] and iii) it is more generic as receivers do not need any knowledge on the primary users' 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 primary users 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. 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 a 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 primary user service in a channel due to obstacles that block the primary user'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 primary user.

#### 3. PROPOSED PRINCIPLES

Design paradigm underlying any suggested model based on spectrum sensing aims at eliminating its technical challenges. This section discusses the proposed principles that are being incorporated in the 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. Using more than one detection threshold

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. To get around this problem, we are proposing to use more than one threshold value to compromise the two extremes, *many false negatives or many false positives*, the likely results when a single threshold is used.

Measurement studies have shown that the sensitivity threshold of  $-114 \ dBm$  for Advanced Television Systems Committee (ATSC) TV signal detection as mandated by the Federal Communications Commission (FCC) is too conservative [13, 14, 15, 16].  $-114 \ dBm$  is said to be conservative because it leads to significant loss of WSs [16]. Some studies have confirmed that, 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, relaying 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 to find WS. Therefore, using more than one threshold in the range from  $-114 \ dBm$  to a value that is dependent on a country's TV broadcasting allocation scheme for transmitting sites seems to be a logical solution and is being proposed here. 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 although it ends up with no WSs in others. Identifying WSs in this way helps to group WSs based on the threshold values used to detect them. If there is a request for WS use from WS devices, allocation starts with WSs detected with the lowest detection threshold and if they are not enough to satisfy the demand, then the next slot of WSs identified using the next higher detection threshold is used and so on. Based on the assumption that at each point in time, the demand for white space use from white space devices is satisfied well before using white

spaces identified with higher threshold values, the approach of identifying WSs using different thresholds and starting the allocation with WSs identified with the lowest thresholds minimizes the chances of interference to primary users due to false negatives than using random or haphazard allocation of WSs identified with a single threshold. WSs identified with higher thresholds are the most likely thresholds that may result into interference. The approach also solved the problem of resulting with either *too many false negatives* or *too many false positives* when one threshold is used to identify the TVWSs.

### 3.2. Virtual pricing of white spaces

Another principle being proposed in this work to minimize interference to primary users from WS devices is to virtualprice WS channels within each group based on some common quantity associated with all WSs. For example, a virtual price can be given to each WS channel based on the signal strength detected in each channel with the highest price given to a channel with strongest signal and the lowest price given to a channel with the weakest signal within each group. As mentioned in subsection 3.1, the groups of WSs are based on the signal detection thresholds used to identify them. When WS devices submit requests for WS use, the cheapest WS channels within each group are allocated first. In this way, the probability of a WS device causing interference to primary incumbents if there is any false negative within the group is minimized since channels that may result into false negatives have stronger signals than channels that are actually WSs, and as such, their virtual prices are higher than the channels that are actually WSs. Consequently, they cannot be allocated to any WS device unless all the channels that are actually WSs in that 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 white spaces because a network of spectrum sensors sharing sensing information obtained from their individual locations with each other has a better chance of detecting the primary user compared to local spectrum sensing [9] by a single spectrum sensor. It is due to this reason why cooperation between sensing equipment is proposed in the literature as the solution to the *hidden user problem* [14, 15, 17, 18, 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 as the first step to minimising chances of interference to primary users. If there is a *hidden user problem* after cooperative spectrum sensing, then the proposed principles help to protect further that *hidden user* from interference.

#### 4.2. Channel-clustering and location-clustering

As mentioned in [20] and [21], a spectrum sensing-based WS identification system must also take spectrum sensor cost as a major consideration in the design of the system as they can be expensive. To avoid random placement of the energy detectors, which could result into either waste of energy detectors, i.e., many unnecessary detectors deployed or not guarantee coverage, i.e., insufficient detectors deployed [20], it is vital to perform channel-clustering and location-clustering as proposed in [20]. 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 these principles means WSs are calculated according to location clusters. Therefore, secondary users are required to 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 in this paper are not environment specific. 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 different thresholds

The method for computing TVWSs using different signal detection thresholds is presented in Algorithm 1. The algorithm shows how cooperative spectrum sensing is implemented with the principle of varying the detection threshold. 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 it is found that a channel is not an already WS channel, the algorithm 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.

Algorithm 1: Identify white space channels using different thresholds

input : Two-dimensional matrix st of size m by n of signal strength values, set  $CH = \{ch(1), ch(2), ch(3), ..., ch(m)\}$  of channels. {m is the number of channels under consideration; n is the number of sensors deployed} output:  $SC = \{SC(1), SC(2), SC(3), ..., SC(x)\}$ , where x is less than or equal to number of threshold values,  $SS = \{SS(1), SS(2), SS(3), ..., SS(x)\}$ .  $\{SC$  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}

 $\textbf{1} \textit{ initialize } t \leftarrow startThreshold, x \leftarrow 1;$ 

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

### 5.2. Compute virtual prices of WS channels

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

Algorithm 2:	Compute	virtual	prices	of	white	space	chan-
nels identified							

input :  $SS = \{SS(1), SS(2), SS(3), ..., SS(x)\}.$ output:  $VP = \{VP(1), VP(2), VP(3), ..., VP(x)\}$ .  $\{VP$ is a corresponding set of sets of virtual prices of white space channels} 1 *initialize*  $j \leftarrow 1$ ,  $strongestSignal \leftarrow 0$ ; for  $i \leftarrow 1$  to x do 2 while SS(i) has elements do 3 if strongestSignal < ss(i)(j) then 4  $strongestSignal \leftarrow ss(i)(j);$ 5 6  $j \leftarrow j + 1;$ 7 end 8 end for  $a \leftarrow 1$  to (j-1) do vp(i)(a) = |ss(i)(a)|/|strongestSignal|;10 add vp(i)(a) to VP(i); 11 12 end *initialize*  $j \leftarrow 1$ 13 14 end 15 return VP;

The input to the algorithm is SS, the output from *Algorithm I*. 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.

#### 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  $m^2$ . The layout of the ground floor of the building and the measurement points are shown in *Figure 2*. The environment for the measurement locations



Figure 2. Layout of the building and measurement points

was regarded 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 [22]. 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 to measure spectrum on the go 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 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 primary users. We looked at the Draft Terrestrial Broadcasting Plan 2013 from the Independent Communications Authority of South Africa (ICASA) [23] to see how the UHF TV channels are arranged in the band. According to ICASA [23], 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 [23]. 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 [23], 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 coming from other transmitters from the same transmitting site. 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 [24], 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 sec*onds 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 +/-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 where the measurements were taken. The standard deviation of the signal strength for each 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 channels 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 the WS channels that were



Figure 3. Signal strengths recorded from all locations

Channel	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
STDEV	2.6	3.0	2.2	2.2	1.8	3.4	3.8	3.4	3.2	2.2	1.9	2.9	2.7	2.7	2.0	1,6
Channel	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52
STDEV	1.5	1.7	1.9	1.9	2.0	2.0	1.9	1.6	2.3	1.9	1.8	1.7	2.1	3.3	1.7	1.7
Channel	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68
STDEV	1.9	1.9	1.7	1.9	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 1. Standard deviation of signal strengths collected from the 14 measurement locations (+/- dBm)

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	12	43, 46, 47, 48, 49, 52, 53, 56, 57, 58, 59, 64			



Figure 4. Spectrum occupancy with -103 dBm threshold

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:

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

$$R_{SS}(i,T_i) = SS(i) - T_i \tag{2}$$

$$M(i, T_i) = max(R_{SS}(i, T_i))$$
(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 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

#### 6.3. Discussion

The grouping of WS channels as show in Table 2 helps to start allocating them to WS devices with the *safest* group, which is the one detected with  $-103 \ dBm$  in this case. The least safe group of WSs out of the three groups is the one detected with  $-102 \ dBm$  threshold. WSs in this group is allocated only if the demand for WS use is not satisfied after

 Table 3. Prices for white space channels

WS Channel	WS Channels With Their Prices						
Group							
-103 dBm	67:1.000						
	54:0.997, 57:0.996, 60:0.998,						
-102.5 dBm	61:0.998, 62:0.997, 65:0.997,						
	66:0.998, 68:1.000						
	43:0.998, 46:0.997, 47:1.000,						
102 dBm	48:0996, 49:0.998, 52:0.995,						
-102 uDiii	53:0.996, 56:0.999, 58:1.000,						
	59:0.997, 64:1.000						

using the WSs in the first two groups. If there are any false negatives in that group and the demand for WS use is met, then the primary users in those channels are protected from interference, as the channels are not allocated for secondary usage by WS devices. It is different if the WS channels are detected using one threshold and they are also allocated randomly to WS devices.

An additional layer of security is provided within a group of WSs if the channels are priced based on the signal strengths in the channels. Channels with stronger signals are priced higher than channels with weaker signals within each group as shown in Table 2 because channels with stronger signals are the ones that are more likely to have primary users in them than channels with weaker signals. For example, WS channel group detected with -102 dBm in Table 2, 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, protects primary users that may be broadcasting in the expensive channels such as channel 47 or channel 58.

## 7. CONCLUSION AND FUTURE WORK

In this paper, we proposed two design principles that have been included in a spectrum sensing-based white space identification system to reduce further chances of interference to primary users due to false negatives after cooperative spectrum sensing has been done. The principles were experimented in the white space network (WhiteNet) 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 primary users to some extent.

Spectrum sensing principles have been proposed and implemented as a first design step of WhiteNet; a white space network management platform for campus networking. For our proposed principles to work efficiently, they will require redesigning existing network management techniques to manage white spaces. Cost-based traffic engineering techniques such as proposed in [25, 26] will also be redesigned as primary user protection mechanisms using cost metrics to reflect the white space availability under primary and secondary usage. The integration of parallel path models [27, 28] in white space bonding deployments and the use of white space for long distance wireless deployments [29, 30] are other avenues for future work. The design of market pricing mechanisms to protect primary users 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 [31, 32] is another direction

for future research.

## REFERENCES

- IEEE WG802.11 Wireless LAN Working Group, "IEEE Standard 802.11af-2013," IEEE, http://standards.ieee.org/findstds/standard/802.11af-2013.html, 2013.
- [2] V. Gonçalves and S. Pollin, "The value of sensing for TV white spaces," in *New Frontiers in Dynamic Spectrum Access Networks (DySPAN)*, 2011 IEEE Symposium on. IEEE, 2011, pp. 231–241.
- [3] L. Zhu, V. Chen, J. Malyar, S. Das, and P. McCann, "Protocol to access white-space (paws) databases," 2015.
- [4] IEEE Standards Association, 802.11af IEEE Standard for Information technology - Telecommunications and information exchange between systems - Local and metropolitan area networks - Specific requirements - Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications Amendment 5: Television White Spaces (TVWS), IEEE, http://standards.ieee.org/getieee802/download/802.11af-2013.pdf, 2013.
- [5] IEEE Standards Association, 802.22-2011 -IEEE Standard for Information technology– Local and metropolitan area networks– Specific requirements– Part 22: Cognitive Wireless RAN Medium Access Control (MAC) and Physical Layer (PHY) specifications: Policies and procedures for operation in the TV Bands, IEEE, http://standards.ieee.org/getieee802/download/802.22-2011.pdf, 2011.
- [6] E. Pietrosemoli and M. Zennaro, *TV White Spaces*. *A pragmatic approach*, vol. 1, chapter 4, pp. 35–40, ISTB, December 2013.
- [7] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proceedings of the IEEE*, vol. 55, no. 4, pp. 523–531, 1967.
- [8] M. A. Abdulsattar and Z. A. Hussein, "Energy Detector with Baseband Sampling for Cognitive Radio: Real-Time Implementation," *Wireless Engineering and Technology*, vol. 3, no. 04, pp. 229, 2012.
- [9] T. Yücek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *Communications Surveys & Tutorials, IEEE*, vol. 11, no. 1, pp. 116–130, 2009.
- [10] P. Lingeswari, K. J. Prasanna Venkatesan, and V. Vijayarangan, "Legacy User Detection in OFDM based Cognitive Radio," in *International Conference on Recent Trends in Computational Methods, Communication and Controls (ICON3C 2012),*

http://research.ijcaonline.org/icon3c/number7/icon3c1053.[28] ICASA, Draft Terestrial Broadcasting Frequency Plan 2012.

- [11] N. Yadav and S. Rathi, "A comprehensive study of spectrum sensing techniques in cognitive radio," International Journal of Advances in Engineering & Technology, vol. 1, no. 3, pp. 85, 2011.
- [12] Z. Sun, Design and Implementation of Sequence Detection Algorithms for Dynamic Spectrum Access Networks, Ph.D. thesis, University of Notre Dame, 2010.
- [13] L. Yin, K. Wu, S. Yin, J. Li, S. Li, and L. M. Ni, "Digital dividend capacity in China: A developing country's case study," in Dynamic Spectrum Access Networks (DYSPAN), 2012 IEEE International Symposium on. October 2012, pp. 121-130, IEEE.
- [14] T. Zhang, N. Leng, and S. Banerjee, "A vehiclebased measurement framework for enhancing whitespace spectrum databases," in Proceedings of the 20th annual international conference on Mobile computing and networking. September 2014, pp. 17-28, ACM.
- [15] G. Naik, S. Singhal, A. Kumar, and A. Karandikar, "Quantitative assessment of TV white space in India," in Communications (NCC), 2014 Twentieth National Conference on. February 2014, pp. 1-6, IEEE.
- [16] S. M. Mishra and A. Sahai, "How much white space has the FCC opened up?," IEEE Communication Letters, 2010.
- [17] Y. Zeng, Y. C. Liang, A. T. Hoang, and R. Zhang, "A review on spectrum sensing for cognitive radio: challenges and solutions," EURASIP Journal on Advances in Signal Processing, vol. 2010, pp. 2, 2010.
- [18] P. G. Scholar, "An overview of cognitive radio architecture," Journal of Theoretical and Applied Information Technology, vol. 41, no. 1, 2012.
- [19] J. Milanović, S. Rimac-Drlje, and I. Majerski, "Radio wave propagation mechanisms and empirical models for fixed wireless access systems," Tehnički vjesnik: znanstveno-stručni časopis tehničkih fakulteta Sveučilišta u Osijeku, vol. 17, no. 1, pp. 43–52, 2010.
- [20] X. Ying, J. Zhang, L. Yan, G. Zhang, M. Chen, and R. Chandra, "Exploring indoor white spaces in metropolises," in Proceedings of the 19th annual international conference on Mobile computing & networking. 2013, pp. 255-266, ACM.
- [21] D. Liu, Z. Wu, F. Wu, Y. Zhang, and G. Chen, "FI-WEX: Compressive Sensing Based Cost-Efficient Indoor White Space Exploration," 2015.
- [22] Nuts About Nets, http://rfexplorer.com/ combo-specs/, RF Explorer: Handheld Spectrum Analyser. RF Explorer Combo Devices Specification Chart.

- 2013. Independent Communications Authority of South Africa (ICASA), April 2013.
- [24] M. Lopez-Benitez and F. Casadevall, "Spectrum usage in cognitive radio networks: from field measurements to empirical models," IEICE Transactions on Communications, vol. 97, no. 2, pp. 242-250, 2014.
- [25] A. B. Bagula, "Hybrid routing in next generation IP networks," Computer Communications, vol. 29, no. 7, pp. 879-892, 2006.
- [26] A. B. Bagula, "On Achieveing Bandwidth-aware LSP//spl lambda/SP Multiplexing/Separation in Multilayer Networks," Selected Areas in Communications, IEEE Journal on, vol. 25, no. 5, pp. 987-1000, 2007.
- [27] A. B. Bagula and A. E. Krzesinski, "Traffic engineering label switched paths in IP networks using a pre-planned flow optimization model," in Modeling, Analysis and Simulation of Computer and Telecommunication Systems, 2001. Proceedings. Ninth International Symposium on. IEEE, 2001, pp. 70-77.
- [28] A. B. Bagula, "Modelling and implementation of QoS in wireless sensor networks: a multiconstrained traffic engineering model," EURASIP Journal on Wireless Communications and Networking, vol. 2010, pp. 1, 2010.
- [29] M. Zennaro, A. Bagula, D. Gascon, and A. B. Noveleta, "Planning and deploying long distance wireless sensor networks: The integration of simulation and experimentation," in Ad-Hoc, Mobile and Wireless Networks, pp. 191-204. Springer, 2010.
- [30] M. Zennaro, A. Bagula, D. Gascon, and A.B. Noveleta, "Long distance wireless sensor networks: simulation vs reality," in Proceedings of the 4th ACM Workshop on Networked Systems for Developing Regions. ACM, 2010, p. 12.
- [31] M. Zennaro and A. B. Bagula, "Design of a flexible and robust gateway to collect sensor data in intermittent power environments," International Journal of Sensor Networks, vol. 8, no. 3-4, pp. 172-181, 2010.
- [32] A. Arcia-Moret, E. Pietrosemoli, and M. Zennaro, "Whisppi: White space monitoring with raspberry pi," in Global Information Infrastructure Symposium, 2013. IEEE, 2013, pp. 1-6.