Cooperative Spectrum Sensing Algorithms in WBAN

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Master of Science Thesis

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Abstract

Wireless Body Area Network (WBAN) is used for communication among sensor nodes operating on, in or around the human body in order to monitor vital body parameters and movements. A typical sensor node in WBAN should ensure accurate sensing of the signal from the body, carry out low-level processing of the sensor signal, and wirelessly transmit the processed signal to a local processing unit. One of the main limitations of the WBAN radio receiver at Imec-Holst Centre, is its poor performance in the presence of excessive interference in the unlicensed 2.4 GHz Industrial Scientific and Medical (ISM) band. Several WLAN, bluetooth and Zigbee devices are expected to operate in the same band, causing interference to the WBAN system. The ability to tolerate the presence of unacceptable interferences in this band is crucial in order to minimize the energy consumption of the WBAN system. By designing suitable spectrum sensing algorithms using network cooperation, all the available spectral holes (white spaces) in this band can be obtained accurately and efficiently, thereby improving interference tolerance level of the WBAN system.

This thesis work focuses on developing energy detection based cooperative spectrum sensing algorithms, that would enhance the interference tolerance capability of WBAN system in the unlicensed 2.4 GHz ISM band. The available spectral holes in this band are expected to be accurately and efficiently obtained by introducing adaptive scheduling techniques in these spectrum sensing algorithms. The challenge lies in designing these algorithms when considering multiple interferer's in the unlicensed 2.4 GHz ISM band, since numerous devices of different applications are expected to be operating in close proximity, using the same band. The proposed algorithms are investigated and compared with respect to various sensing parameters including accuracy, efficiency, energy and complexity.

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Chapter 1

Introduction

1-1 Introduction and Motivation

The rapid advancement in physiological sensors and ultra-low power wireless communication has enabled a new generation of Wireless Sensor Networks (WSN). These wireless sensor networks are utilized to monitor health, crops, traffic etc, where crucial and sensitive information can be obtained and handled on a real time basis. Wireless Body Area Network (WBAN) is an interdisciplinary area within WSN, in which wireless sensors are used to monitor, collect and transmit vital signs and other medical information [1]. Here, a number of intelligent and comfortable physiological sensors can be integrated into wearable wireless body area networks, which can be used for personalized, predictive, preventive and participatory health care. The sensor information in these WBAN radio's will be transmitted wirelessly to an external processing unit. This unit instantly transmits all information to the backbone, in real time, to the doctors throughout the world. In case of emergencies, the physicians can immediately attend to the patients or inform them by sending appropriate messages or alarms. The concept of WBAN technology is presented in Figure 1-1.

The WBAN technology is still in its early stage and it is being widely researched. At present there are several research challenges associated with this technology. The precision with which the information is transmitted between the devices in WBAN is limited. In other words, the wireless communication among these devices needs to be improved, by avoiding any interference that is affecting the system. WBAN primarily utilizes standards such as IEEE 802.15.4 Zigbee and Bluetooth that operate in the unlicensed 2.4 GHz Industrial, Scientific and Medical (ISM) band [2]. Numerous devices are expected to operate in this band and thus the impact of interference becomes very severe when the radios of different applications are located in close proximity [3], [4]. To ensure seamless wireless communication of data among the devices in the network, suitable methods have to be adopted to avoid any interference present in the 2.4 GHz ISM band.

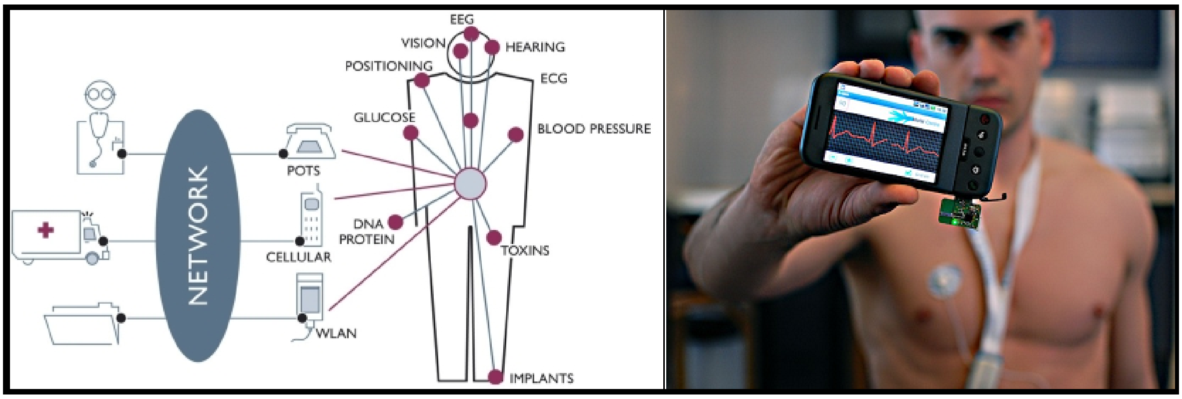

Figure 1-1: WBAN technology [5]

WBAN technology emerges from the existing sensor network technology. The WBAN devices can vary greatly in terms of data rate and power consumption, as shown in Figure 1-2. Another important concern associated with WBAN technology is the total energy consumption of the sensors. From [6] and [7], it can be concluded that the wireless communication module is often the major power consumer in the sensor node of WBAN. Hence it is evident that efficient wireless communication must be accomplished, in order to avoid unnecessary energy expenditure required for any retransmissions caused due to the presence of interference.

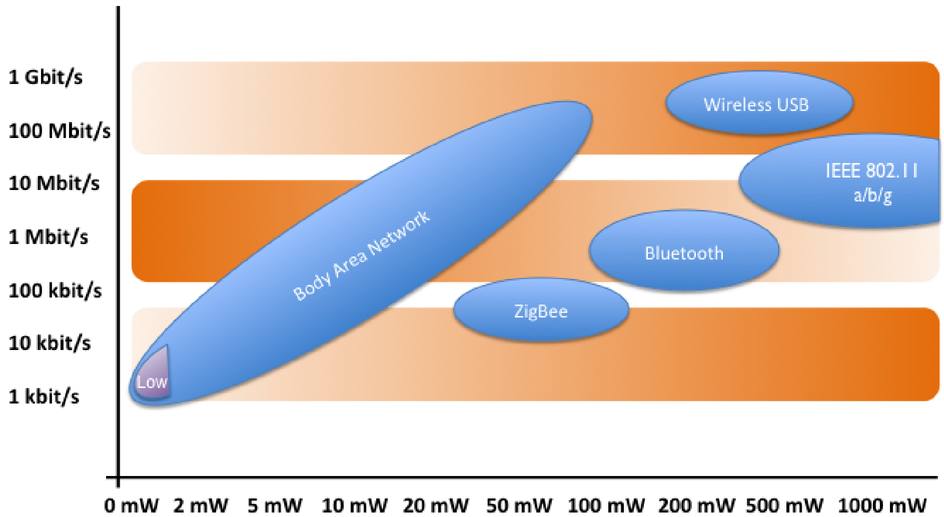

Figure 1-2: Data rate versus Power consumption for various standards in the 2.4 GHz ISM band

Spectrum Sensing (SS) is a key feature of Cognitive Radio (CR) technology that can be utilized to improve the spectrum utilization, by opportunistically identifying the available spectral holes in the licensed/unlicensed frequency band. By performing SS operation in the 2.4 GHz ISM band, an energy efficient wireless communication can be easily achieved in WBAN. Further in a WBAN with many devices, Cooperative Sensing (CS) can also be adopted to improve the robustness against interference. [8].

1-2 Problem Formulation

Imec-Holst Centre has developed an Ultra-Low Power (ULP) WBAN radio that operates on the principle of super-regeneration [1], [9]. Super-Regenerative Receiver (SRR) is a potential candidate to achieve ULP wireless communication in WBAN. Although this WBAN radio at Imec has a simple architecture with an embedded envelope detector, its performance is severely degraded in the presence of excessive interference. The ability to tolerate the presence of these unacceptable interferences in the 2.4 GHz ISM band is crucial to minimize the energy consumption of the system.

Cognitive Radios (CR) have been proposed as a possible solution to improve spectrum utilization. It enables efficient spectrum usage by reliably and autonomously identifying spectrum holes (white spaces) via opportunistic sensing of the licensed/unlicensed frequency band. In this thesis, the WBAN is considered to be a Cognitive Radio Network (CRN). The individual WBAN radios behave as the Secondary User's (SU) sensing the 2.4 GHz ISM band for spectral holes. The various other devices operating in the vicinity of WBAN radio's, using the same 2.4 GHz ISM band, are considered to be Primary User's (PU) or interferers of WBAN system. The SU's should be aware of the environment and capable of sensing it. They should learn to utilize the spectrum adaptively and efficiently without allowing any of the PU's to affect its performance. The SU's should be capable of dynamically utilizing the spectrum hole across time, frequency and space, and vacate the frequency band on sensing the presence of PU activity, as shown in Figure 1-3. In order to achieve this, there is a need to develop various spectral hole search algorithms that would help the WBAN radio's (SU's) to sense and identify the spectrum holes efficiently amidst the presence of multiple interferer's in the 2.4 GHz ISM band.

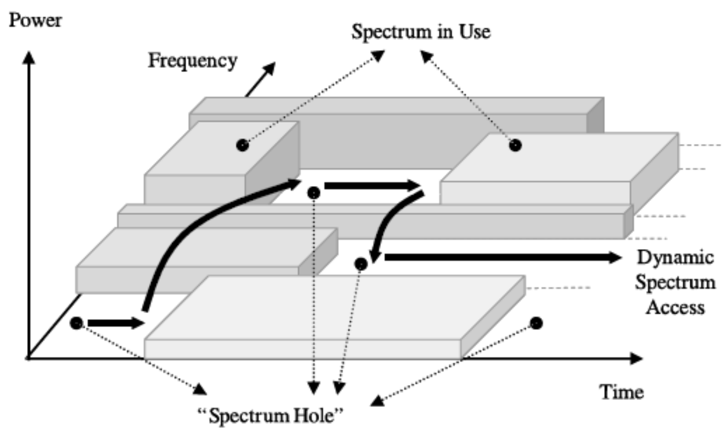

Figure 1-3: Concept of Spectral hole

As mentioned in the previous section, numerous devices are expected to be operating in the 2.4 ISM band, at any given time. Thus there is a need to search for spectral holes, amidst many PU interferer's in the ISM band. In this thesis, the target is to develop several spectral hole search algorithms, that would satisfy the following criteria,

- Improve the certainty of the spectral holes detected
- Efficiently obtain all the available spectral holes in the spectrum
- Should possess low sensing complexity and sensing energy

In order to satisfy the above criteria, cooperative spectrum sensing is introduced [8]. A centralized CS model is adopted, where a central identity called the Fusion Center (FC) (or a remote device) controls the entire operation of the spectrum sensing process in the WBAN. Thus, through these novel cooperative spectrum sensing algorithms, we aim to achieve an improved spectral utilization in WBAN.

1-3 Literature Survey

The key challenge of spectrum sensing is the detection of PU signals accurately and efficiently, in the presence of noise and interference. Each of the SU's sensing performance can be improved by enhancing the radio's Radio Frequency (RF) front-end sensitivity, exploiting digital signal processing gain, and using network cooperation where SU's share their spectrum sensing information. Spectrum sensing is often addressed as a cross layer design problem in the context of communication networks [10]. On the one hand, the Physical Layer (PHY) sensing focuses on efficiently detecting the signals of the PU's to identify whether the PU's are present or not. This PHY layer sensing takes place locally in each SU. Some PHY layer sensing methods have been studied in [11], including Energy Detection (ED), matched filter and feature detection. Figure 1-4 shows the classification of the PHY layer sensing techniques. In this thesis, a non-coherent, narrowband ED based sensing technique is opted due to following reasons [12],

- It is most simple among all the other sensing techniques
- Low computational and implementation costs
- Ability to work irrespective of the knowledge of the actual received signal.

Further, from [6] and [7], it is clear that the ULP BAN radio at Imec consists of an embedded envelope detector. Even though, the detection performance of ED is subject to the uncertainty in the noise power, it is chosen due to its simplicity and its ability to meet the energy requirement of Imec's ULP BAN radio. Therefore, only ED based SS algorithms are dealt with,in this thesis.

On the other hand, the Medium Access Layer (MAC) layer sensing which plays an important role in cognitive radio networks, determines, when and which SU should sense which channels, to obtain good sensing performances such as sensing accuracy, efficiency etc. As mentioned in the previous section, WBAN utilizes wireless standards such as Zigbee and Bluetooth, that operate in the unlicensed ISM 2.4 GHz band. Numerous devices are expected to be occupying this spectrum bandwidth, thereby causing an interference to the signals being transmitted among devices in the WBAN.

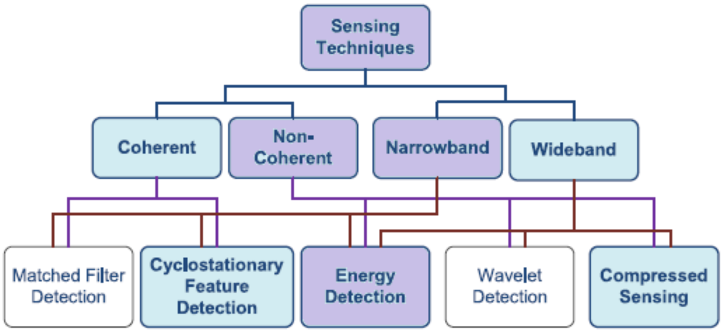

Figure 1-4: Classification of Sensing Techniques [8]

The most common interference in this band would be the IEEE 802.11 Wireless Local Area Network (WLAN), Zigbee or Bluetooth devices operating within the vicinity of SU's. Hence there is a need to avoid more than one interferer in WBAN.

Most of the previous literatures on spectrum sensing have targeted the single channel scenario [13] [14]. Recently, a multichannel scenario for spectrum sensing has been considered in [15] [16] [17]. In [16] and [17], multichannel joint energy detection and sequential detection were designed respectively, to optimize throughput performance. Here multiple detectors, each assigned with a single channel, simultaneously observe multiple channels. This however becomes highly infeasible for CR to implement a large number of detectors and to operate them simultaneously. Further in [15], only a single available channel is assumed. However this may not be the case always in CRN. In [18], a multichannel sensing scheme has been proposed to quickly and accurately locate a single spectral hole. Here the algorithms were developed based on the sequential application of Sequential Probability Ratio Test (SPRT) and energy detection to the candidate channels. Unlike the previous works, in this thesis we are considering detection of multiple spectral holes in a multichannel system, thereby increasing the spectral efficiency. Furthermore sensing parameters such as accuracy, efficiency and energy are also taken into account while designing algorithms.

In this thesis, a centralized CS model has been adopted, as mentioned in Section 1-1. From [8], it is evident that distributive cooperative model require large amount of computations. In [19], a novel adaptive sensing schedule scheme has been proposed in a collaborative network for fast discovery of spectrum holes. Here in this thesis, we propose a novel adaptive scheduling scheme that is based on the sensed data of SU's. Unlike [19], here the main goal is to achieve all the available spectral holes in the ISM band. By developing CS algorithms along with adaptive scheduling of the sensed data, between the SU's and the FC in the network, an enhanced system performance is expected to be achieved.

1-4 Thesis Outline

Chapter 2: Introduction to Spectrum Sensing in WBAN

This chapter provides an overview of the system model that is adopted in this thesis. The considered spectrum sensing scenario is explained in detail. Then the centralized cooperative spectrum sensing scheme that is adopted is analyzed. Further, the concept of scheduling in the cooperative network is also introduced. The threshold deduced for the WBAN radio at Imec, is also presented. Finally the performance parameters pertaining to the spectrum sensing algorithms are also described clearly.

Chapter 3: Spectrum Sensing Algorithms

This chapter initially introduces the design criteria, necessary assumptions and definition of terms pertaining to the spectrum sensing algorithms that are being proposed. A novel generic Basic Sequential Search (BSS) that accounts for two narrowband interferers (PU's) in the 2.4 GHz ISM band is proposed. Using BSS as the basis algorithm, we propose another algorithm called the Improved Sequential Search (ISS) where several novel scheduling techniques are introduced and discussed. These scheduling algorithms are focused on improving either sensing accuracy or sensing efficiency of CR system. Non-cooperative as well as cooperative scenarios are considered while dealing with both BSS and ISS algorithms. Finally a novel generic cooperative Parallel-Sequential Search (PSS) algorithm is proposed which exploits the spatio-temporal diversity to optimize sensing accuracy, sensing efficiency and also the sensing energy. An example scenario is provided for each of the algorithms.

Chapter 4: Performance Analysis and Comparison of Algorithms

This chapter initially describes the simulation setup utilized, to evaluate the performances of the algorithms explained in Chapter 3. A detailed analysis of the sensing performance parameters, including accuracy, efficiency, complexity and energy are performed for individual algorithms. Both non-cooperative and CS schemes are exploited and analyzed in each of the algorithms. Then a comparative study of all the three algorithms in the cooperative scenario is done. Further, the measurement setup to validate the simulation results is presented and the sensing accuracy of all the three algorithms, with both measured and simulated spectrum are plotted.

Chapter 5: Summary, Conclusion and Future Work

All the contributions in this thesis are summarized and the possible directions for future work are highlighted in this chapter.

Chapter 2

Introduction to Spectrum Sensing in WBAN

2-1 Introduction

In a WBAN, the sensor nodes monitoring vital body parameters and movements, operate on, in or around the human body. A typical sensor node in WBAN should ensure accurate sensing of the signal from the body, carry out low-level processing, and support flawless wireless transmission to a local processing unit [9]. Further, WBAN primarily utilizes standards such as IEEE 802.15.4 (Zigbee) and Bluetooth that operate in the unlicensed 2.4 GHz ISM band [2]. Numerous devices are expected to operate in this band and thus the impact of interference becomes very severe when radios of different applications are located in close proximity [3] [4]. Hence there is a need to utilize the spectrum efficiently. Cognitive radio has been proposed as a suitable solution to improve the spectrum utilization. By performing spectrum sensing, the excess interference can be avoided and thus flawless wireless communication can be achieved in WBAN.

This chapter provides an overview of the system model that is adopted in this thesis. The considered spectrum sensing scenario is explained in detail. Then the centralized cooperative spectrum sensing scheme that is adopted is analyzed. Further, the concept of scheduling in the cooperative network is also introduced. The threshold deduced for the WBAN radio at Imec, is also presented. Finally the performance parameters pertaining to the spectrum sensing algorithms are also described clearly.

2-2 System Model

2-2-1 Block diagram

The system model considered in this thesis is illustrated via block diagram as shown in Figure 2-1.

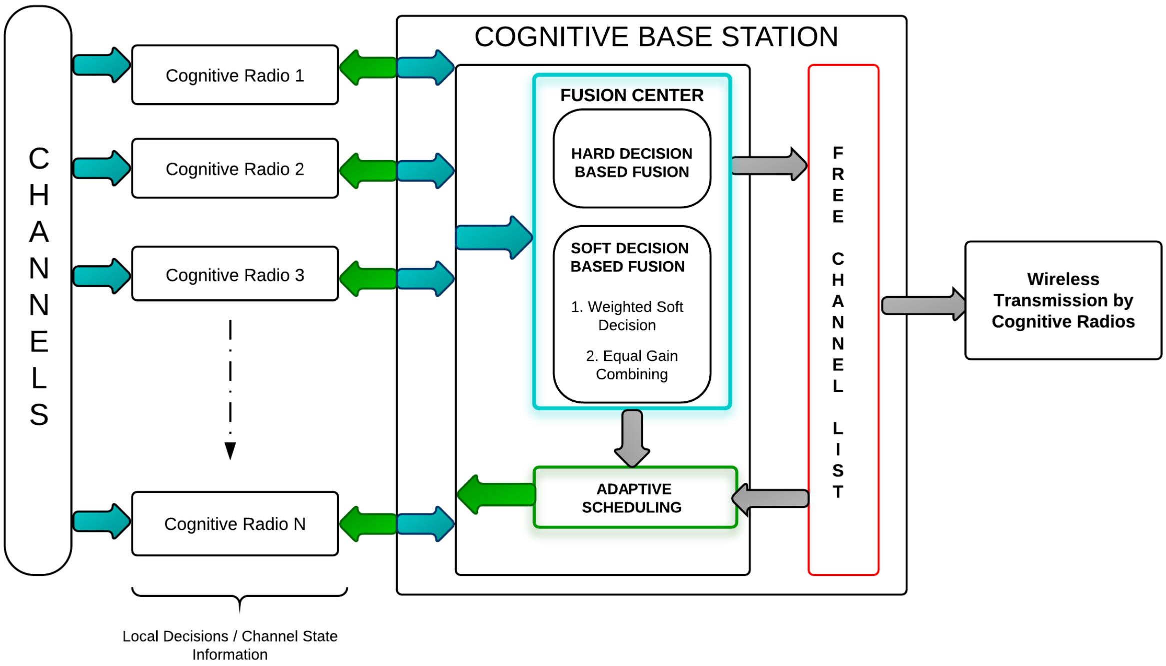

Figure 2-1: System Model

As seen, a CRN has been adopted in the WBAN system. In this thesis, the chosen spectrum (2.4 GHz ISM band) containing multiple interferer's that are considered as Primary User's (PU), are sensed by the BAN radios that are considered as Secondary User's (SU). The PU's in the chosen band include IEEE802.11 WLAN, IEEE802.15.4 Zigbee, etc. All the SU's are considered to be located fairly close to one another and are dependent on a synchronized clock. The sensed data at each SU, consists of local decisions (busy/idle state) and/or channel state information (received signal power). This sensed information is forwarded to the cognitive base station (CBS) which consists of three modules; fusion centre (FC), scheduling module and available/free channel list. The FC synchronously receives the sensed data from all the SU's and determines the states of channels via either hard/soft decisions, which will be explained in Chapter 3. Then the idle channels are added to the free channel list and the remaining busy channels are ignored. The scheduling module makes use of the obtained idle channels and other parameters that are decided prior to sensing operation, in order to adaptively schedule some/all of the SU's to sense appropriate channels. The scheduling operation will be dealt with in detail, in Chapter 3 of this thesis.

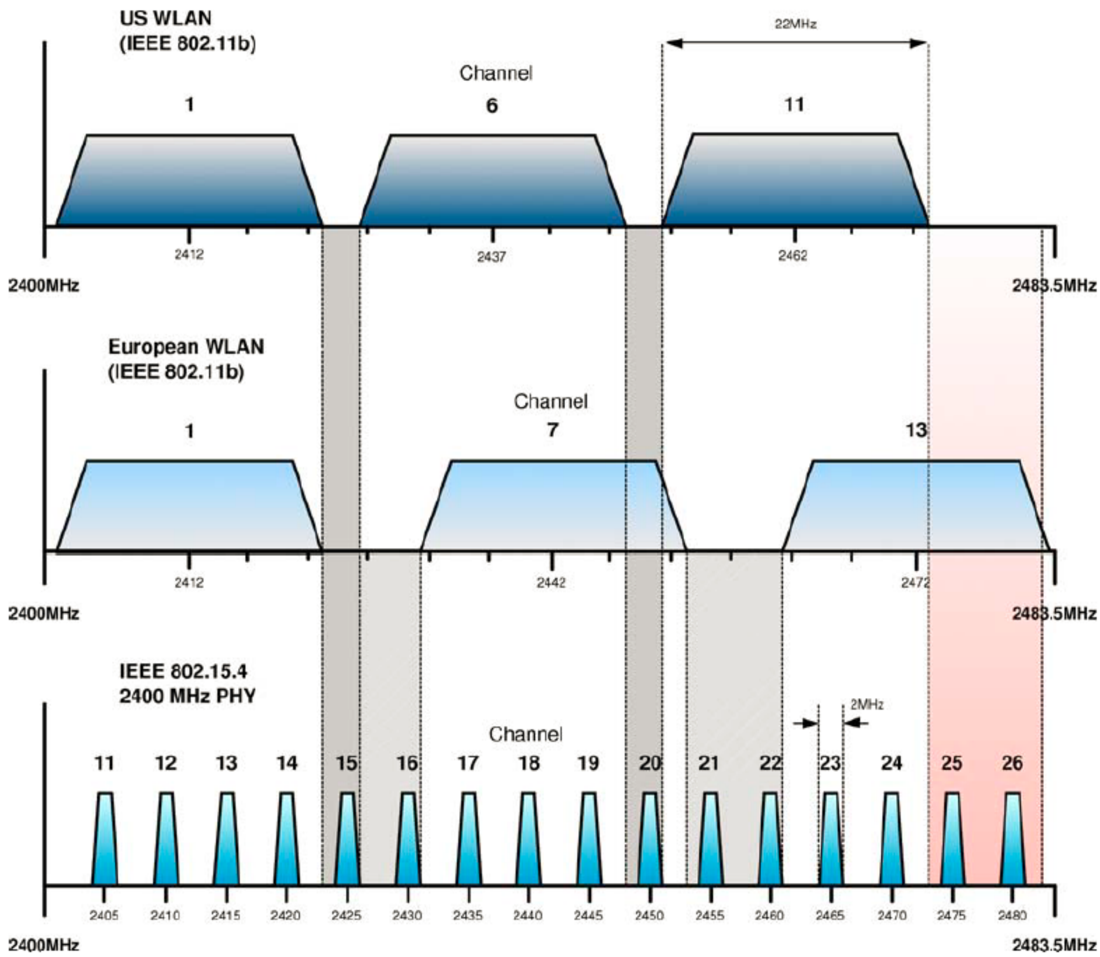

Figure 2-2: Example scenario with multiple PU (WLAN and Zigbee) interferer channels in 2.4 GHz ISM band [20]

2-2-2 Spectrum sensing scenario

2-2-2-1 Detection Technique

An ED based spectrum sensing is performed to detect the state of the PU. As mentioned in Section 1-3, ED based SS is the simplest technique, that does not require any prior information of the nature of PU signals. The total power consumption of the WBAN radio is expected to be maintained at a minimal level, when ED based sensing is chosen.

2-2-2-2 Interferer's in the 2.4 GHz ISM band

The chosen 2.4 GHz ISM band may contain more than one active PU, at any given time. Figure 2-2 illustrates an example scenario with both IEEE802.11 WLAN and IEEE802.15.4 Zigbee channels in the 2.4 GHz ISM band. Clearly, there are many overlapped Zigbee and WLAN channels indicating that both the interferer's must be accounted for, while performing spectrum sensing. This thesis focusses on developing spectrum sensing algorithms that considers any two interferer signals in the ISM band. The number of PU channels sensed is limited to two in this thesis work, as the computational complexity of the system will increase when considering algorithms dealing with higher number of PU interferers.

2-2-2-3 Cooperative Sensing Model

Cooperative spectrum sensing (CS) scheme is introduced in order to enhance the performance of the sensing operation. In other words, the ability to obtain maximum number of idle channels accurately, is expected to be achieved via CS scheme. A well designed cooperation technique for CS can tremendously improve the overall sensing performance. Here in this thesis, a centralized cooperative sensing model is adopted as shown in Figure 2-3. The central role is played by the FC, which controls the processes taking place within the network [8].

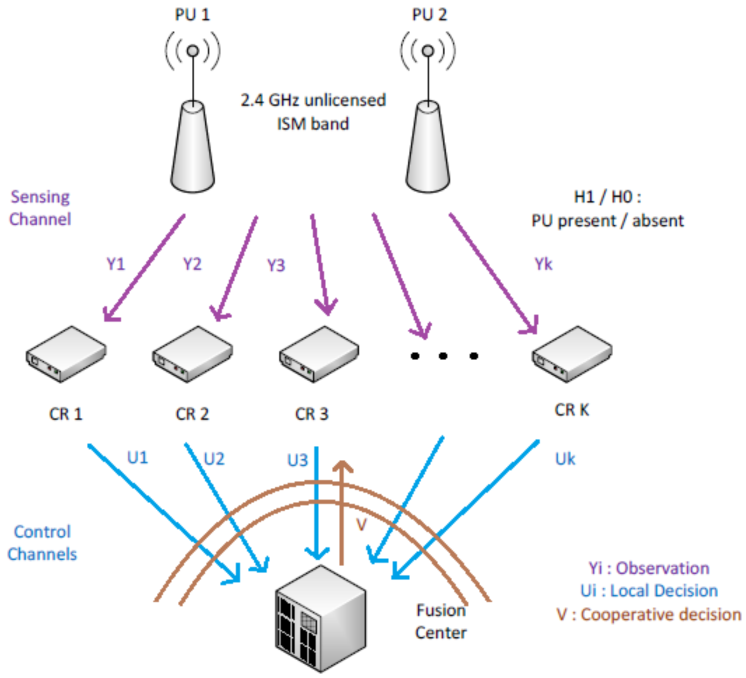

Figure 2-3: Centralized cooperative sensing model with parallel data fusion

There are three processes related to the centralized CS scheme, as described below:

1. Initially, the FC decides an individual channel or a portion of the chosen frequency band to be sensed. It then notifies all the cooperating SU's to perform local sensing operation.
2. All the cooperating SU's performs local sensing and reports the sensed data to the FC via dedicated control channels.
3. The sensed information from all the cooperating SU's are suitably combined at the FC, via a process called parallel data fusion. Using this combined data,

decisions regarding the presence of PU's are taken and adaptive scheduling of the cooperative SU's are performed for further sensing. The scheduling operation is performed to overcome any uncertainties in the decisions taken at the FC.

Several data fusion techniques are utilized in this thesis. They include Weighted Soft Decision (WSD) or otherwise known as Weighted Combining (WC) [21], [22] and Equal Gain Combining (EGC). These techniques are discussed below:

Weighted Soft Decision - In this combining scheme, weights are assigned to all the branches between the SU's and the FC before combining. These weights are decided based on two different criteria namely:

1. *Received Signal Strength (RSS)* - The RSS of each channel in each SU are used to designate priorities to the weights assigned to every branch between SU's and FC. The weight of a branch is determined by the ratio between the channel RSS in one SU and the total sum of the channel RSS's of all the SU's in the network.
2. *Signal to Noise Ratio (SNR)* - If the received SNR is known at the receiver, the branch with higher SNR can be assigned with a higher priority compared to others. The process of assigning weights based on SNR is similar to the one explained in the RSS method described above.

After assigning the weights, all the weighted sensed data in all the branches, are summed together. It is to be noted that the threshold at the FC must be adjusted accordingly to the weights assigned to all the branches. The process of assigning weights to each SU branch and determining the threshold at the FC are clearly explained in Section 4-3-2.

Equal Gain Combining - In this combining scheme, the received signal strength of a channel in all SU's are assigned with equal unit weights, and then the average received signal strength is estimated for all the branches. Here the threshold at the FC remains the same, as the threshold used at each SU.

2-2-2-4 Scheduling Operation

In practice, the spectrum sensing may cause negative effect on the performance of the CR network, as all CR communications has to be postponed during channel sensing [23]. Further, the spectrum sensing algorithms may not yield all the spectral holes during its search. This is because of various channel impairments and/or system constraints, that causes uncertainties in the decision making process of the spectral holes in both SU and FC. Therefore by introducing adaptive scheduling algorithms, these drawbacks could be overcome. These scheduling algorithms are designed to re-sense the spectrum or channels that are more prone to be idle. In this thesis, the scheduling operation takes place at FC and depends on the sensed data of the spectral hole search algorithms. The FC controls either some, or all of the SU's in the network to sense specific channels, or portions of the spectrum. Several scheduling algorithms are proposed and discussed in detail, in Chapter 3.

2-2-3 WBAN radio transceiver threshold

Imec's WBAN radio transceiver has a well-established receiver sensitivity level. It has been concluded from [9] that, with a receiver sensitivity level of -75 dBm, more than 95% reliability could be acquired. Further in [24], the spectrum sensing results of the WBAN radio at Imec indicate that a false alarm probability of less than 1% is achieved for the sensitivity level of -75 dBm. According to the above mentioned literature, this sensitivity level is suitable for most WBAN applications. The threshold for WBAN radio transceiver is established based on the following system constraints [9]:

- Bit Error Rate (BER) < 0.001
- Minimum received signal power of -71.5 dBm
- Signal to Interference Ratio (SIR) of 7 dB is added to the received signal level to nullify any presence of frequency offsets between the WBAN radio link and the interferer's channel frequency
- A value of $10\log_{10}(S^{2/3})$ must be added to the received signal, to account for the change in processing gain caused due to averaging of S samples at the energy detector of the WBAN radio. A value of 9 dB (sample size = 22) is considered approximately
- Minimum operating Signal to Noise Ratio (SNR) region for the WBAN radio is 11 dB

Based on the above system constraints, the threshold λ_b was calculated as shown in equation 2-1.

$$\lambda_b(dBm) = -71.5 - 7 - 9$$

$$\lambda_b = -87.5dBm \tag{2-1}$$

2-2-4 Channel Conditions

In this thesis, a Gaussian channel has been considered for simplicity, while evaluating the algorithms. The spectrum sensing operation performed at the receiver can be considered as binary hypothesis testing problem. The received signal statistic is given by the following expression,

$$x(t) = \begin{cases} n(t) & \text{,under } H_0, \\ s(t) + n(t) & \text{,under } H_1. \end{cases} \tag{2-2}$$

where *x(t)* is the signal received by a single SU. H_0 is the null hypothesis which represents the inactive state of the PU. H_1 is the alternative hypothesis, which indicates that the PU is active. A complex Additive White Gaussian Noise (AWGN) represented by *n(t)* constitutes the H_0 hypothesis, indicating the absence of the PU interfering signal and *s(t)* is the PU signal with a constant amplitude 'A'. An energy detector (ED) is employed in each SU (WBAN radio) to determine the state of the PU. The ED output statistic in each SU is given as,

$$R = \frac{1}{S} \sum_{i=1}^{S} |x(i)|^2 \tag{2-3}$$

Where S is the number of samples. In Section 4-2-1, the energy detector's distribution statistic has been derived for simulation purposes.

2-2-5 Performance Parameters

The spectral hole search algorithms that are designed in this thesis can be evaluated using the following performance parameters as listed below,

1. ***Sensing Efficiency* -** Sensing efficiency refers to the ability of an algorithm to find the maximum number of available spectral holes within one sensing period.
2. ***Sensing Energy* -** In this thesis, the overall sensing energy is expressed by the total number of computations performed during a sensing period. This will be discussed in detail in Section 4-3-1.
3. ***Sensing Complexity* -** Sensing complexity is very much related to the sensing energy. The complexity of any spectral hole search algorithm is measured by the number of sensing slots utilized per sensing period.
4. ***Sensing Accuracy* -** Sensing accuracy refers to the certainty with which the spectral holes are detected. Since efficient spectral hole detection is the major concern in this thesis, the spectral hole search algorithms are evaluated based on the following criteria,

Probability of Missed Idle Channels It is defined as the probability that the available idle channels are determined to be busy. Mathematically, probability of missed idle channels, denoted by P_{mis} is expressed as:

$$P_{mis} = p(R > \lambda_b | H_0) \tag{2-4}$$

Probability of False Alarm of Busy Channels It is defined as the probability that the actual busy channels are determined to be idle. Mathematically, it can be expressed as:

$$P_{false} = p(R < \lambda_b | H_1) \tag{2-5}$$

Probability of Total Sensing Error It is defined as the sum of P_{mis} and P_{false}:

$$P_{error} = P_{mis} + P_{false} \tag{2-6}$$

A detailed analysis of the performance of various spectral hole search algorithms are provided in Chapter 4.

Chapter 3

Spectrum Sensing Algorithms

3-1 Introduction

This chapter initially introduces the design criteria, necessary assumptions and definition of terms, pertaining to the spectrum sensing algorithms that are being developed. A generic basic sequential search (BSS) that accounts for any two narrowband interferers (PU's) in the 2.4 GHz ISM band, is proposed. Using BSS as the basis algorithm, we propose another algorithm called the improved sequential search (ISS) where several novel scheduling techniques are introduced and discussed. These scheduling algorithms are focused on improving either sensing accuracy or sensing efficiency of system. Non-cooperative as well as cooperative scenarios are considered while dealing with both BSS and ISS algorithms. Finally a generic cooperative parallel-sequential search (PSS) algorithm is proposed which exploits the spatio-temporal diversity to optimize sensing accuracy, sensing efficiency and also the sensing energy. An example scenario is provided along with each of the generic algorithms discussed in this chapter.

3-2 Algorithm Design Criteria

As mentioned in Section 2-2-2-2, only 2 PU interferer sources are considered for the design of the spectrum sensing algorithms. The following design criteria are considered:

- ***Interferer_1*** - PU interferer **with larger channel bandwidth** (e.g. WLAN)
- ***Interferer_2*** - PU interferer with smaller channel bandwidth (e.g. Zigbee)
- ***N1*** - Total number of non-overlapping Interferer_1 channels in the ISM band
- ***N2*** - Total number of non-overlapping Interferer_2 channels in the ISM band
- ***N*** - Total number of SU's in the WBAN.

3-3 Assumptions

The following assumptions are made while designing the algorithms:

- Always N2 > N1.
- Spectrum sensing is performed in *slots*. The spectrum sensing operation is performed with 2 MHz frequency channel resolution and thus each slot contains information of 2 MHz of channel bandwidth. In a non-cooperative scenario, each sensing slot contains the local decision of the sensed channel in each SU. This is the same with hard decision based cooperative sensing scenario. However in a soft decision based cooperative scenario, each slot contains channel state information such as RSS, that is utilized at the FC for final decisions. In this thesis, one sensing period is assumed to consist of "N1+N2" slots.
- In a soft decision based cooperative scenario the channel state information including RSS, channel state etc., are sent from each SU to the FC in slots, via control channels.
- The scheduling period at the FC, is much lesser than the sensing period.
- Both Interferer_1 and interferer_2 channels are sensed for spectral holes. However only Interferer_2 channels are utilized for transmission while the PU is idle in the CRN. This assumption is valid for Imec's WBAN radio receiver, due to its limited frequency selectivity [9].
- The scheduling and the sensing operations within the CRN are assumed to be dependent on a synchronized clock, controlled by the FC.

3-4 Definition of Terms

It is crucial to understand the terms and concepts that are used to design the algorithms, before interpreting its operation. The following are the list of terms along with its definitions:

- ***Portion*** - The chosen spectrum (2.4 GHz ISM band) of bandwidth 'B' Hz is split into 'N1' sub-bands of varying sizes, as shown in Figure 3-1. These are defined as portions. Each portion contains one Interferer_1 channel and many Interferer_2 channels. Spectrum sensing is performed sequentially one portion after another. The portion size depends on the following:
  - Choice of Interferer_1
  - Interferer_1 channel spacing
  - Spectrum bandwidth (2.4 GHz ISM band)

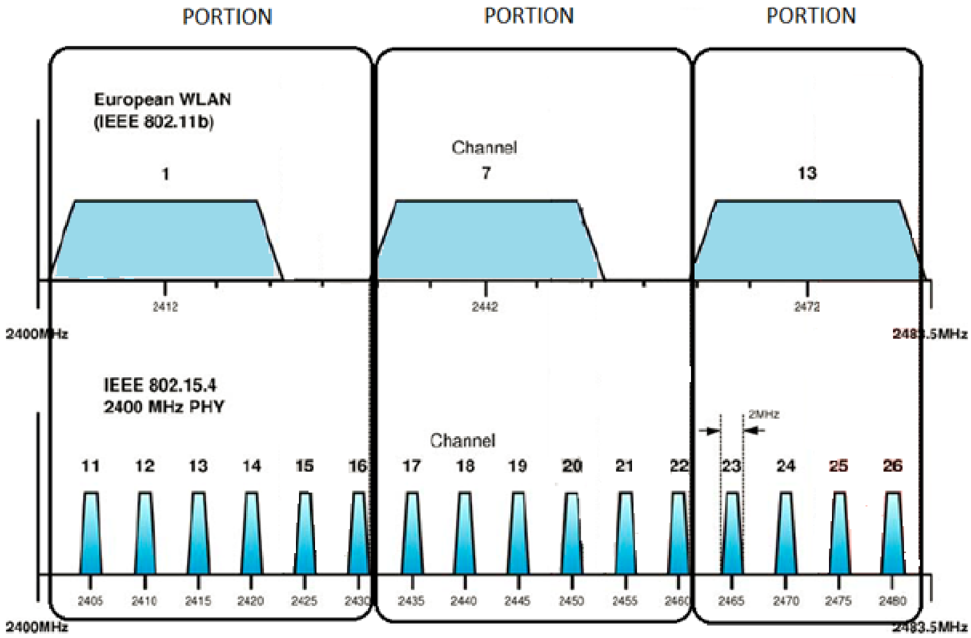

Figure 3-1: Understanding PORTIONS with IEEE802.11b European WLAN and IEEE802.15.4 Zigbee in 2.4 GHz ISM band

- ***Hard Decision*** - This term pertains only to the cooperative spectrum sensing scenario, where each SU takes local decisions of the PU's channel state (either busy/ idle) and then forwards it to the FC, where they will be combined further. Most common means of performing hard decision are by employing 'OR' and 'AND' rules [25]. Under 'OR' condition, atleast one of the SU's involved in the sensing decides the presence of the PU. Whereas 'AND' condition decides the presence of PU when all the SU's detects the PU signal. Here in this thesis, the 'AND' rule has been adopted in order to improve the accuracy of the obtained spectral holes.

- ***Soft Decision*** - This term pertains only to the cooperative spectrum sensing scenario, where all the SU's simply forward the all channel state information to the FC. In this soft decision method, weights are assigned to each branch between the SU and the FC, before combining at the FC. Suitable combining schemes can be adopted to improve the decisions at the FC. The combining operation usually involves averaging all the weighted branch values. In [26], some of the common soft combination schemes in CRN are explained. Even though soft decision schemes leads to large overhead, it achieves better performance than hard decision scheme [27].

3-5 Algorithm 1 - Basic Sequential Search (BSS)

3-5-1 Introduction

BSS is a simple sequential search technique, that forms the basis for the remaining algorithms that are explained in this thesis. In BSS, the chosen spectrum (2.4 GHz ISM band) is split into 'N1' portions as illustrated in Figure 3-1. These portions are predetermined before executing this algorithm. The generic BSS algorithm can be executed in each SU or at the FC, depending on the considered sensing scenario.

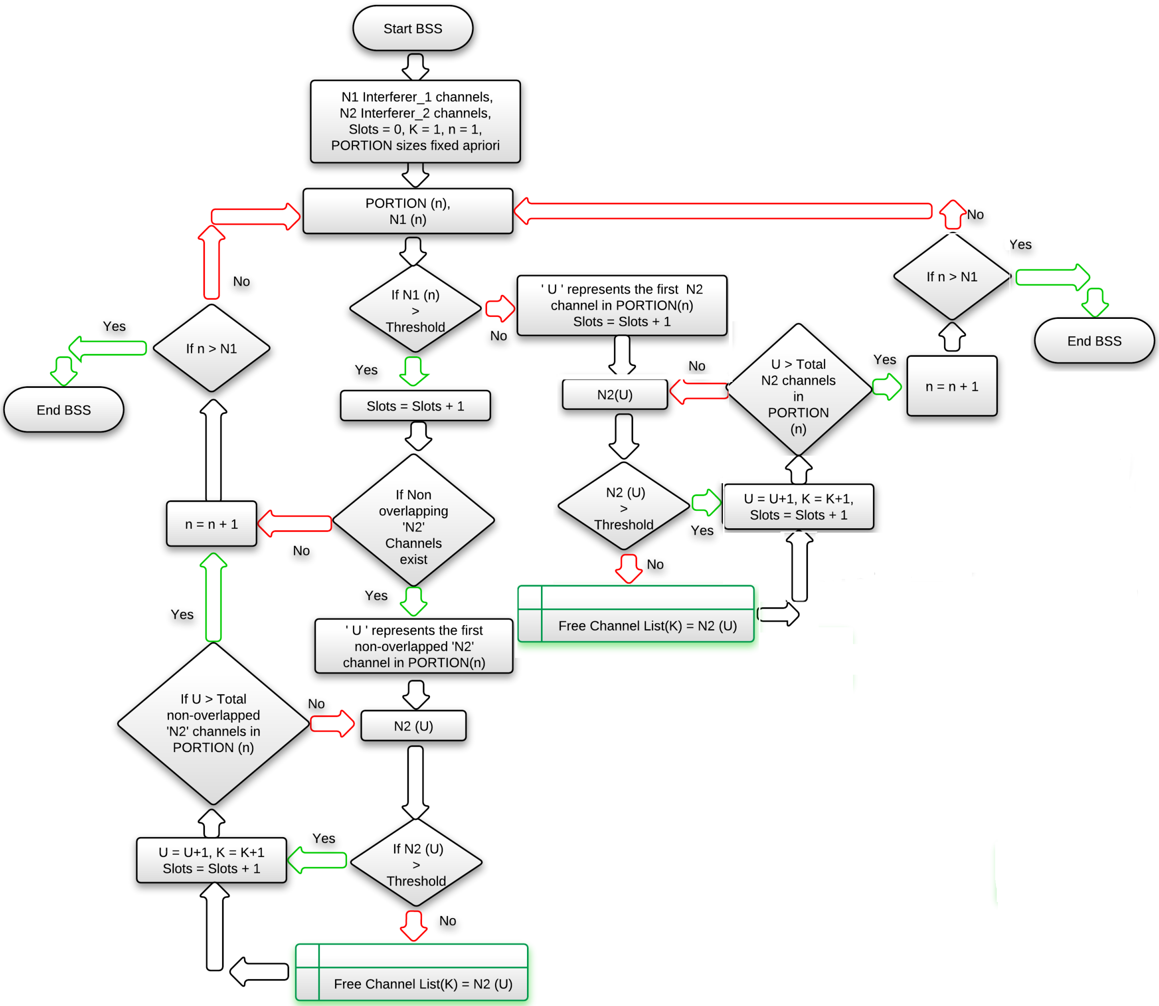

Figure 3-2: Flowchart for generic Basic Sequential Search (BSS) algorithm

3-5-2 Operation of generic BSS algorithm

In Figure 3-2, the operation of the generic BSS algorithm is illustrated through a flowchart. 'N1' and 'N2' represents the Interferer's 1 and 2 respectively. 'n' corresponds to the interferer's individual channels in the ISM band. 'Slots' indicate the actual sensing slots within each SU. The 'Threshold' denotes the optimal threshold that has been deduced in equation 2-1. 'Free Channel' is the list that contains any detected idle Interferer_2 channels of the ISM band.

```
Data: BSS always starts with the first portion in the spectrum
input  : Pre-determined choice of portion sizes, Any two Interferer's
output: Free channel list
Step 1 - Consider the portion of the spectrum
Step 2 - Sense Interferer_1 channel within the portion
if busy then
    if non-overlapping Interferer_2 channels exists then
        sense all non-overlapping Interferer_2 channels within the portion
        store idle channels in free channel list and drop the busy channels
        else
            if next portion exists then
                jump to next portion and return to step 1
                else
                    jump to step 3
                end
            end
        end
    end
    else
        sense all the Interferer_2 channels within the portion
        store idle channels in free channel list and drop the busy channels
    end
    if next portion exists then
        jump to next portion and return to the step 1
        else
            jump to step 3
        end
    end
end
Step 3 - End the BSS algorithm
```

Figure 3-3: Pseudocode of Basic Sequential Search

The pseudo-code for the BSS algorithm is provided in Figure 3-3. When the BSS algorithm begins, the first Interferer_1 channel is sensed. Depending on whether this Interferer_1 channel is busy or idle, the Interferer_2 channels that are non-overlapping with the Interferer_1 channel or all the Interferer_2 channels in the same portion are sensed respectively. This process repeats itself until all the portions in the 2.4 GHz

ISM band are covered. It can be noticed from Figure 3-1 that the portion size varies according to the choice of the Interferer_1. There may be occasions where, within a portion, there may not be any Interferer_2 channels that are non-overlapped with the Interferer_1 channel. In such cases, it simply jumps to the next portion if there exists any. During the execution of the BSS, the idle Interferer_2 channels are stored within the "Free Channel list".

3-5-3 Example scenario for BSS

The BSS operation has been explained for an example scenario, with IEEE802.11b WLAN and IEEE802.15.4 Zigbee interferers, as illustrated in Figure 3-4.

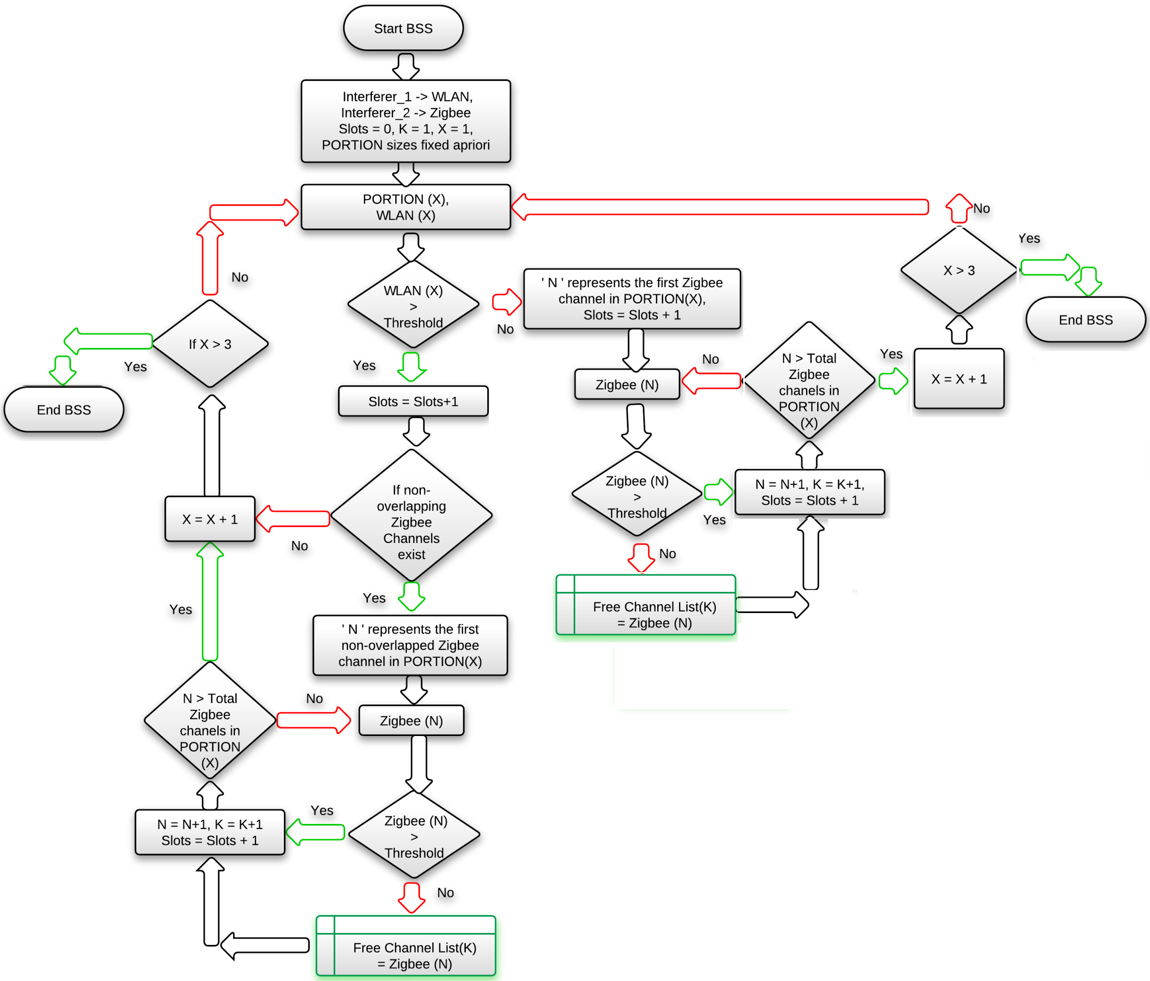

Figure 3-4: BSS - Example scenario with IEEE802.11b WLAN and IEEE802.15.4 Zigbee interferers

In this scenario the algorithm design criteria are given by the following:

1. Interferer_1 is chosen as the device operating under IEEE802.11b WLAN standard

2. Interferer_2 is chosen as the device operating under IEEE802.15.4 Zigbee standard
3. N1 = 3 channels
4. N2 = 16 channels

Here the BSS operation begins by sensing the WLAN channel in the first portion. Following this, depending on whether the WLAN channel is busy or idle, the Zigbee channels that is non-overlapping with the WLAN channel or all the Zigbee channels in the same portion are sensed, respectively. The BSS ends after three portions. With reference to Figure 3-1, it can observed that one of the portions do not contain any Zigbee channels that is non-overlapped with WLAN channel.

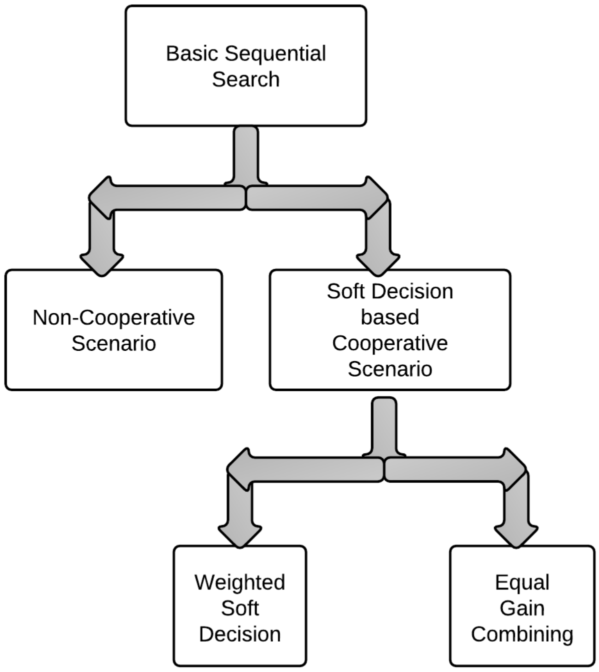

Figure 3-5: Sensing Scenarios for Basic Sequential Search

BSS algorithm is executed under two different scenarios in this thesis, as shown in Figure 3-5.

1. *Non-cooperative :* Here the BSS is executed in each SU, where the local decisions regarding the channel states of the PU's are made. Thus with 'N' SU's in the network, the algorithm is performed 'N' times during the sensing stage. There is no FC employed in this scenario and hence no collaboration of the sensed channels.
2. *Cooperative :* Here the BSS is executed once in each SU and once in the FC. Further soft decision based fusion scheme is preferred over hard decision based fusion scheme due to its improved performance [27]. Hence for a generic case with 'N' SU's in the system, the BSS is performed 'N+1' times in total.

3-5-4 Limitations of BSS

The BSS algorithm utilizes a maximum of "N1+N2" sensing slots per sensing period. Thus the total number of slots utilized will match the total number of channels sensed by the SU. There are several limitations associated with BSS, are described below:

- *Reliability* : In a highly crowded spectrum with atleast one active Interferer_1 channel, the BSS algorithm execution will end sooner than the fixed sensing period ('N1+N2' slots). In such cases, there will be under utilized slots during that sensing period. These remaining slots could be used to improve the sensing performance in terms of efficiency and accuracy.
- *Sensing Overhead* : In BSS, a soft decision based CS scheme is adopted that aims at achieving very high sensing performance. However, with soft decision based decision fusion, the overhead increases drastically, compared to hard decision based fusion method [28].

3-6 Algorithm 2 - Improved Sequential Search (ISS)

3-6-1 Introduction and Motivation

ISS is an extension of the BSS algorithm. Here, a scheduling algorithm is executed at the end of BSS, to enhance the sensing performance in terms of accuracy or efficiency. With regards to BSS, it is imperative to know that the number of sensing slots utilized, after each BSS execution, is inversely proportional to the percentage occupancy of the interferer's (PU's) in the spectrum. In particular, it depends on the percentage of active Interferer_1 channels, since they occupy the majority of the spectrum, as shown in Figure 3-1. Hence the ISS algorithm is valid only when the spectrum has atleast one active Interferer_1 channel at any given time.

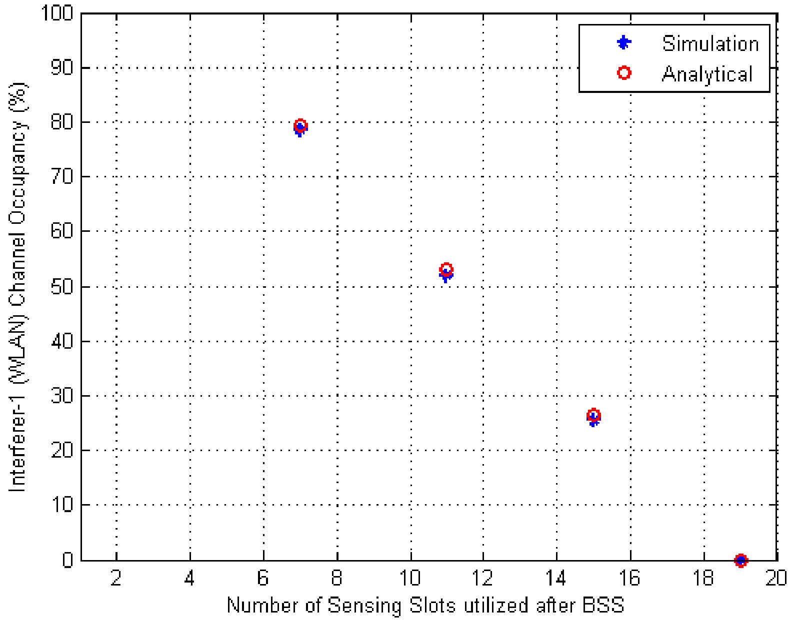

Figure 3-6: Effect of WLAN occupancy on number of sensing slots utilized after BSS in 2.4 GHz ISM band

The effect of Interferer_1 (IEEE 802.11 WLAN) channel occupancy, on the number of sensing slots utilized per BSS execution in the 2.4GHz ISM band, is illustrated via an example in Figure 3-6. By increasing the number of busy WLAN channels from 0 (indicating all are free) to 3 (indicating all are busy/active), it can be observed that there is a decrease in the number of sensing slots used. Clearly this implies that in a highly crowded spectrum, there are sensing slots that will remain unused as explained in Section 3-5-4. Hence, by efficiently exploiting these slots after the end of each BSS, the sensing performance in terms of accuracy and efficiency can be improved.

3-6-2 Operation of ISS algorithms

Here in ISS algorithm, the *free channel list* obtained at the end of each BSS is utilized to develop various scheduling algorithms. These scheduling algorithms control the Interferer_2 channels that needs to be sensed again by the SU's in the network. The ISS algorithm can be executed based on the several criteria and scenarios, as shown in Figure 3-7,

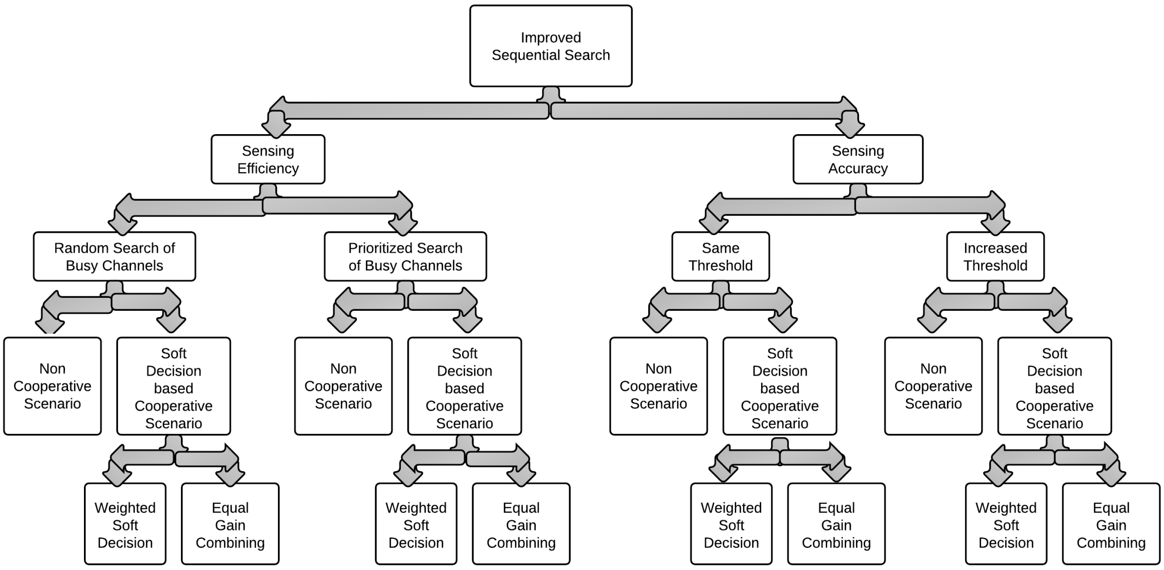

Figure 3-7: ISS - Scheduling criteria and sensing scenarios

ISS is primarily categorized based on the targeted sensing performance criteria. They include:

1. *Improving Sensing Accuracy* - reconfirming the idle state of the obtained free channel list after BSS

2. *Improving Sensing Efficiency* - finding maximum number of idle channels available in the spectrum

3-6-2-1 Improving Sensing Accuracy

Sensing accuracy, as defined in Section 2-2-5 refers to the certainty with which the idle channels are detected such that any existing interfering signal (PU) can be avoided. The improvement in the sensing accuracy can be achieved via the following two techniques:

1. The obtained free channel list is sensed again with the same threshold.

2. The obtained free channel list is sensed again with an increased threshold.

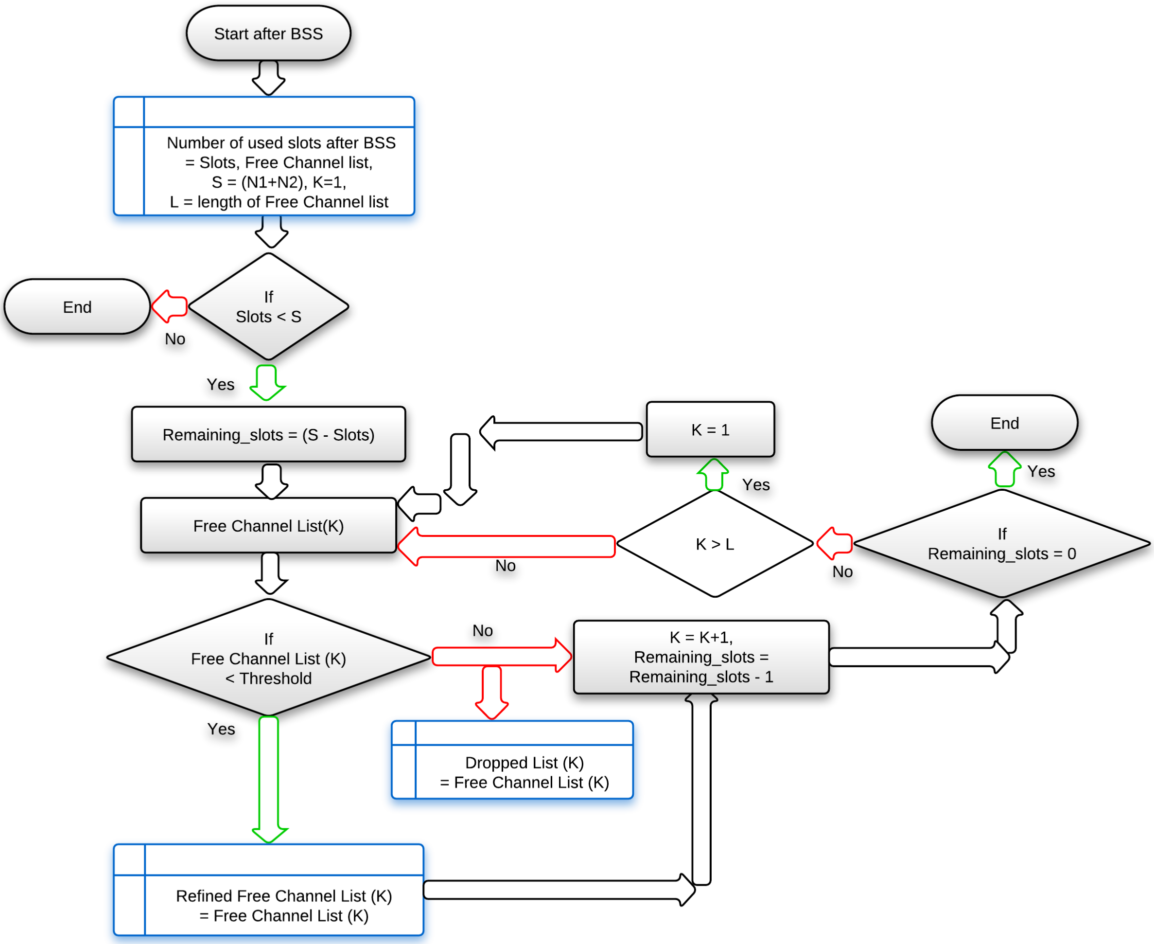

Figure 3-8: ISS scheduling algorithm with same threshold

Figure 3-8 provides the flowchart to improve the sensing accuracy by utilizing the same threshold. At the end of the BSS, the number of unused sensing slots are noted. These slots are completely utilized to sense the free channels that were obtained at the end of BSS. Any falsely detected idle channels (busy channels) are dropped and the confirmed idle channels are stored in the *refined channel list*. Similarly, by increasing the threshold level by a suitable value, the chances of deciding the actual idle channels in the spectrum is expected to be improved. This increased threshold accounts for any noise that incorrectly indicates the idle channels to be busy and it is determined by trial and error method.

3-6-2-2 Improving Sensing Efficiency

Sensing efficiency on the other hand refers to the number of available spectral holes discovered per sensing period. The primary concern is to find the maximum number of free channels existing in the spectrum. The following scheduling methods are considered to improve the sensing efficiency.

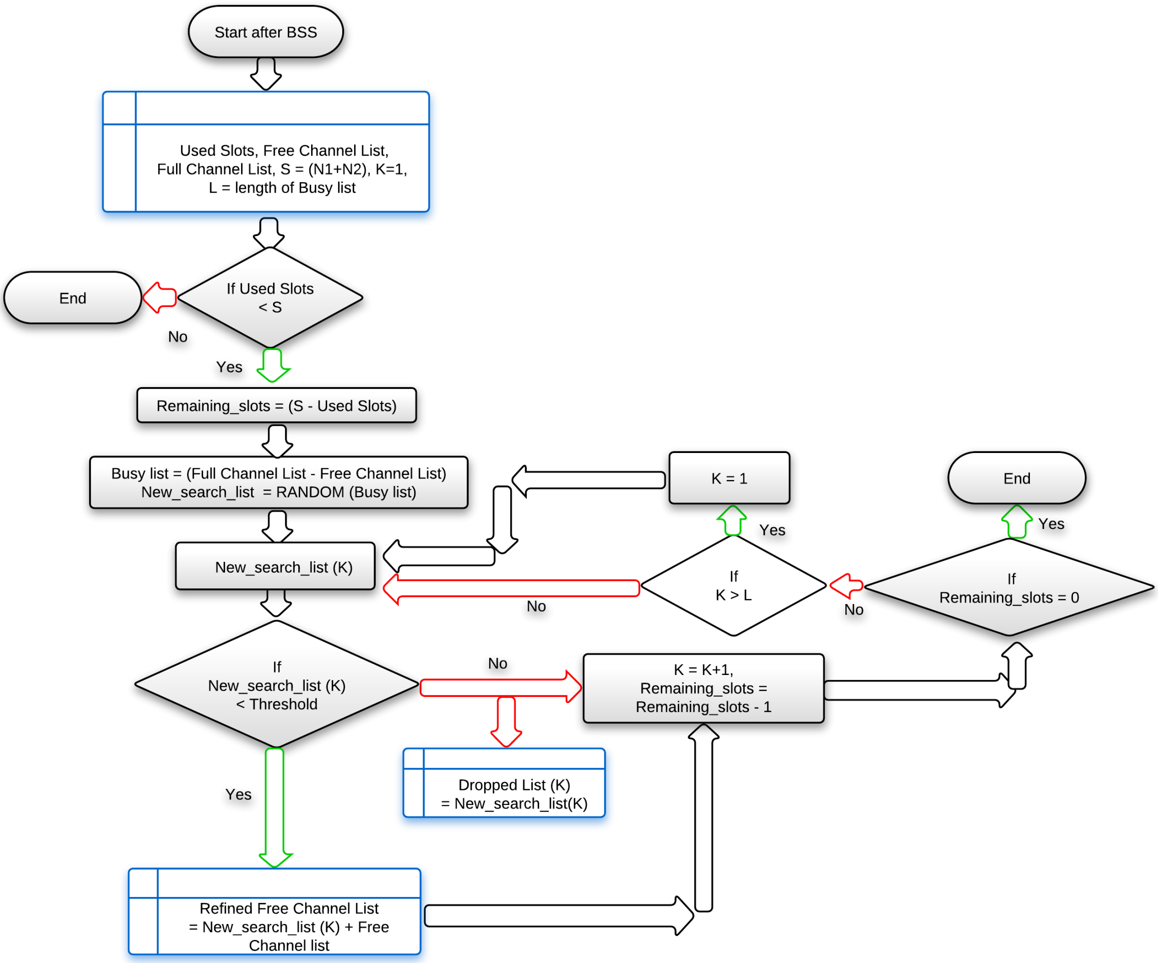

Figure 3-9: ISS scheduling algorithm with random channel search

1. The remaining Interferer_2 busy channels are sensed in a random order
2. The remaining Interferer_2 busy channels are sensed after locating the region of the spectrum that is more prone to idle channels

Figure 3-9 illustrates the scheduling algorithm in which the remaining busy Interferer_2 channels in the spectrum are acquired after BSS. These busy channels are then sensed in a completely random order. There is another method to improve the sensing efficiency. By identifying the regions of the spectrum that is more prone to idle channels, priorities are assigned to those regions. Then the busy channels in the region with highest priority are sensed first sequentially. The regions that entirely contain either idle or busy channels are skipped from being sensed, due to the fact that the entire region is most likely idle or busy respectively. The sensing operation is performed with decreasing priority until the total number of slots used, reaches 'N1+N2'.

ISS is executed under different scenarios, as seen in Figure 3-7. They are non-cooperative and cooperative sensing scenarios.

1. *Non-cooperative scenario :* Here the obtained free channel list at the end of the BSS is utilized locally in each SU to develop the scheduling algorithms. The scheduling operation decides the set of interferer_2 channels that needs to be sensed again by the same SU.

2. *Cooperative scenario :* Here only a soft decision based cooperative scenario is considered in which all the 'N1+N2' channel state information from each SU are forwarded to the common FC where they are all combined. After combining, BSS is performed at the FC and the obtained free channel list is used to schedule all the SU's to sense simultaneously, the decided interferer_2 channels again. It should be noted that a hard decision based fusion scheme is not opted in this algorithm (refer Section 2-2-5).

All these scenarios and scheduling criteria are simulated and the results are discussed in Chapter 4 of this thesis.

3-6-3 Limitations of ISS

Although the ISS algorithm overcomes the issues of the BSS algorithm, it still has certain limitations of its own. They are as follows:

1. *Balance between Sensing Accuracy and Efficiency* : Here in the ISS, we considered several scheduling algorithms that enhances the sensing efficiency and accuracy independent of one another. Sensing accuracy and efficiency are two opposite aspects that reflect the performance of spectrum sensing [29]. Since both these parameters are important for the overall sensing performance, the trade-off between them should be dealt with suitably.

2. *Sensing Energy* : So far in this section, we have dealt with algorithms and scenario's that enhance the sensing accuracy and efficiency of the system. However, an important criterion that has not been considered so far, is the *sensing energy*. Sensing energy is an essential concern in the ULP WBAN radio. Imec's ULP WBAN radio design is described clearly in [9], from which it can be concluded that the transmitter block of the WBAN radio transceiver consumes the most amount of power. Since the target is to minimize the overall power consumption of the transceiver block, there is a need to perform energy efficient spectrum sensing in order to avoid unnecessary re-transmissions due to interferences.

3. *Sensing Overhead* : Here, due to the use of soft decision based CS scheme, the sensing overhead increases drastically [28].

3-7 Algorithm 3 - Parallel-Sequential Search (PSS)

3-7-1 Introduction and Motivation

Parallel-Sequential Search (PSS) is an algorithm that is designed to overcome all the drawbacks of the previous algorithms. By exploiting spatio-temporal diversity, the PSS technique is expected to optimize the sensing accuracy, efficiency and energy.

In [29], several different cooperation mechanisms, including sequential, full-parallel, semi-parallel cooperative sensing schemes have been analyzed and compared. The obtained results indicate that parallel cooperation strategy achieves more robust performance with regards to sensing accuracy and efficiency, compared to existing and traditional sequential cooperative spectrum sensing in cognitive radio networks. In this thesis however, via this PSS algorithm the over-all sensing performance is expected to be optimized.

3-7-2 Definitions of Terms in PSS

Figure 3-11 provides the block diagram of this PSS algorithm, to help understand the various terms pertaining to it. The terms and its definitions are provided below:

- ***Block*** : The entire 2.4 GHz ISM band is divided into a number of sub-bands called blocks. Unlike in BSS, where the portion sizes could vary, here all the blocks are of equal size. The total number of blocks matches the total N1 interferer channels. An example scenario with WLAN and Zigbee interferers, is provided in Figure 3-10, demonstrating the concept of equal sized blocks. The total number of blocks is equal to 3 (N1 = 3, WLAN Channels). Each block has a total bandwidth of 27 MHz. Here in this algorithm, the spectrum sensing operation takes place in blocks.
- ***Cycle*** : Time taken by each and every SU in CRN to sense a single block of the spectrum. In order to understand this concept, two scenarios are provided. When N (refer Section 3-2) equals N1, each SU in the CRN would have sensed a unique block in one cycle and the spectrum would have been sensed once completely, within (1/N1)th fraction of the total sensing time. For N greater than N1 however, the spectrum would have been sensed completely, more than once, within (1/N1)th fraction of the total sensing time. The concept of cycle can be better understood from Figure 3-11. After one cycle, the entire spectrum would have been sensed completely.
- ***Group (G)*** : A group contains N1 SU's and 'N1-1' cycles. After each cycle, the blocks will be sensed in a cyclic fashion as shown in Figure 3-11. This repeats for a total of 'N1-1' cycles after which the sensed results (local decisions) are forwarded to the FC for further decisions and scheduling. The total number of groups can be generalized to a lower bound value of the ratio between N and N1. Mathematically it is expressed as:

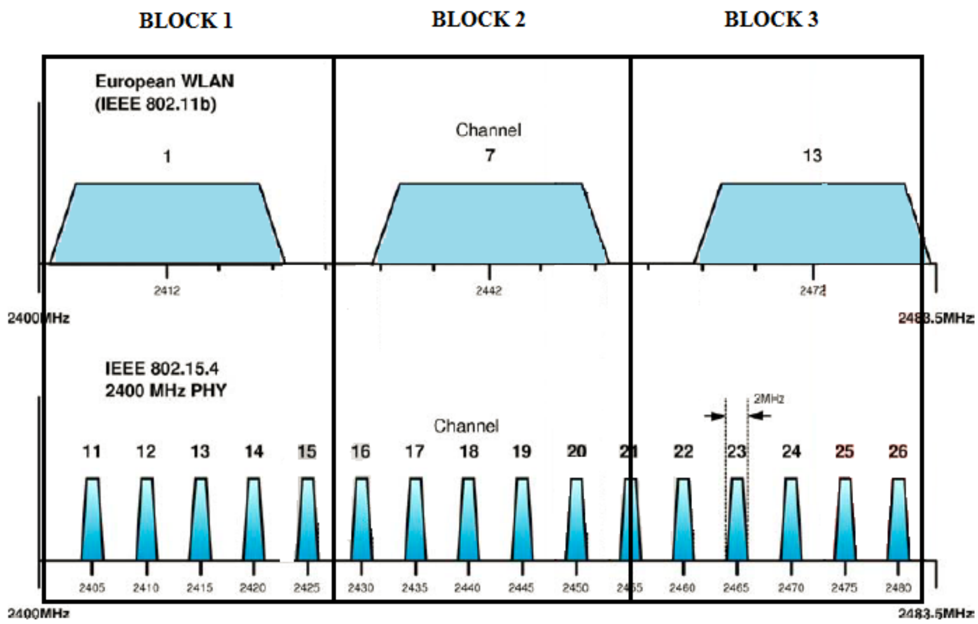

Figure 3-10: Example - Understanding blocks with WLAN and Zigbee Interferers in 2.4 Ghz ISM band

$$G = \lfloor N/N1 \rfloor \tag{3-1}$$

- ***SubGroup (SG)*** : A subgroup consists of set of blocks that are sensed in a specific order by a single SU in 'N1-1' cycles. As seen in Figure 3-11, there are a total of N1 subgroups within a group and each subgroup within a group consists of unique order of blocks. When N is equal to N1, the number of subgroups will be equal to N1. However, when N is greater than N1, the order of subgroups repeats itself in every group. The remaining number of SU's in ratio (N/N1), are assigned to the subgroups of the same order as in every group. Mathematically, the number of subgroups required for the remaining SU's is given by the expression

$$SG = N - (N1 * \lfloor N/N1 \rfloor) \tag{3-2}$$

- ***Total Sensing Time*** : It is the time taken to complete N1 cycles as shown in Figure 3-12

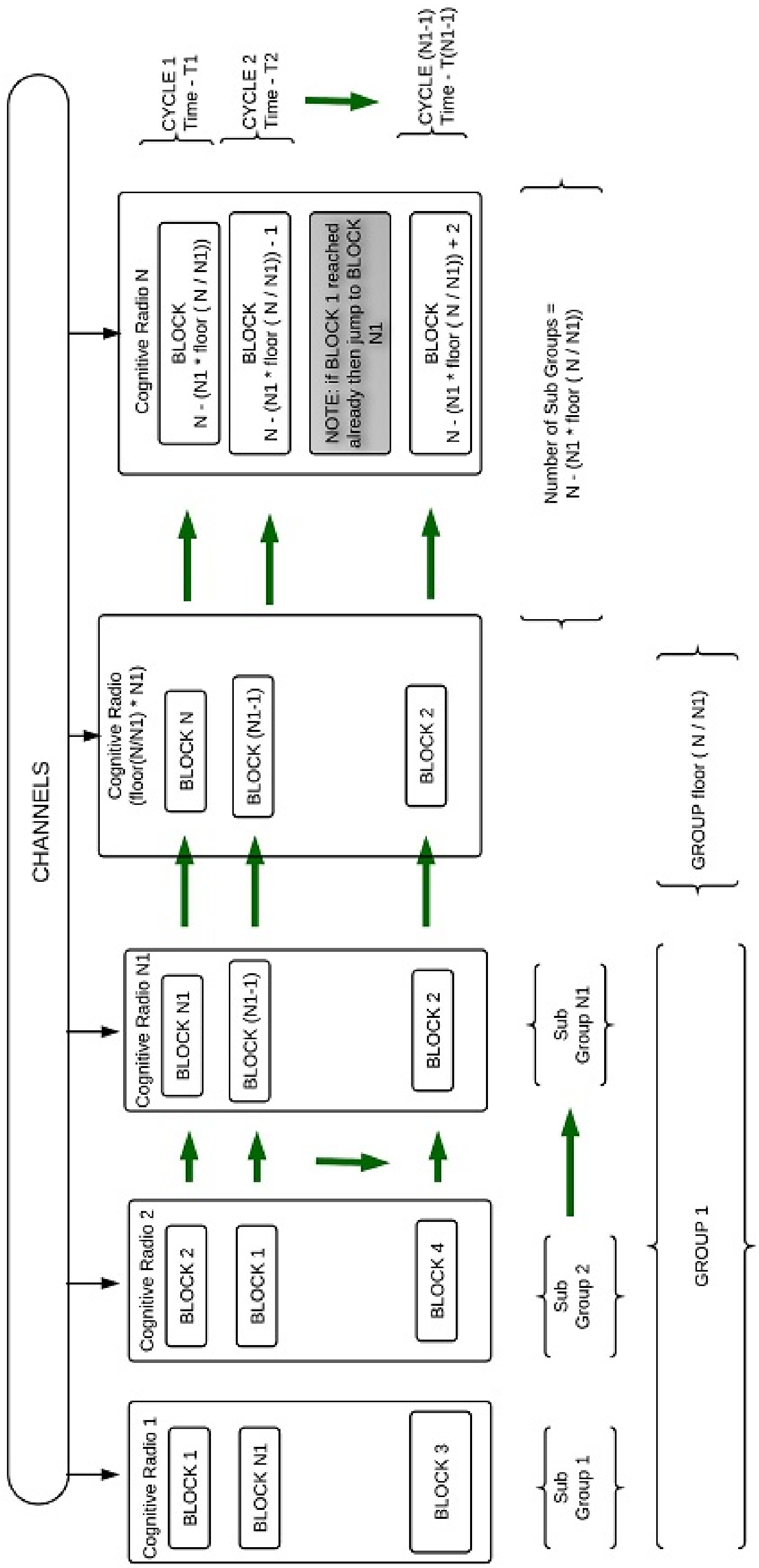

Figure 3-11: Block diagram to understand the terms used in PSS algorithm

3-7-3 Operation of PSS algorithm

Figure 3-12 provides an overview of the entire PSS algorithm. Similar to BSS, a sequential search technique is adopted in PSS. However the sequential search is performed parallely via blocks in each cycle. A total of N1 cycles represents one sensing period. 'N1-1' sensing cycles are performed initially, before the scheduling operation begins. During these 'N1-1' cycles, each SU in the network would have sensed 'N1-1' unique blocks of the spectrum at different time periods and in an unique order. Moreover, since all the SU's are assumed to be at a certain distance from one another (refer Section 2-2-1), spatio-temporal diversity is exploited in PSS.

The effect of spatio-temporal diversity on the detection capabilities of CR networks is studied clearly for both fixed and variable relay (SU) schemes in [30]. It is shown in [30] that multiple relay (SU) scheme exploits spatio-temporal diversity to minimize the average PU detection time, thereby minimizing the sensing energy. Using this as a motivation, here in this thesis PSS algorithm is designed to improve the overall sensing performance in terms of sensing energy, accuracy and efficiency.

After 'N1-1' cycles, a hard decision based fusion is performed at the FC. Here in PSS, a hard decision based fusion scheme is opted over soft decision based scheme due to large overhead involved in soft decision scheme, that increases the energy consumption. Since our primary focus is to minimize the energy consumption, hard decision based fusion is preferred. It is evident that, the FC will contain complete knowledge of the spectrum, even though each SU in the network has only partial information of the spectrum occupancy. The choice of performing the scheduling operation at the FC and the sensing of N1th cycle depends on the following criterion:

Energy Saving Criteria - By assigning a desired number of idle channels, prior to the execution of PSS, the sensing energy can be expected to be minimized. This desired number of idle channels could be chosen approximately, either from a rough knowledge of the number of devices operating in the vicinity or by allowing a single SU to perform BSS. This process can be repeated at regular intervals to adjust the desired number of idle channels. If the number of obtained idle channels after 'N1-1' cycles, falls close to this predetermined number, then the scheduling and the sensing operation of the SU's in the N1th cycle is avoided, thereby minimizing the sensing energy. In this case, the spectrum sensing period is reduced by a fraction of ($\frac{T_N}{T_1+T_2+...+T_N}$), as shown in Figure 3-12. Since all the sensed blocks are of the same size and all the sensing operations are synchronized, we have ($T_1 = T_2 = ... = T_N$). However, if the scheduling is performed and the sensing operation takes place in the N1th cycle, if the obtained idle channels does not lie close to this predetermined number.

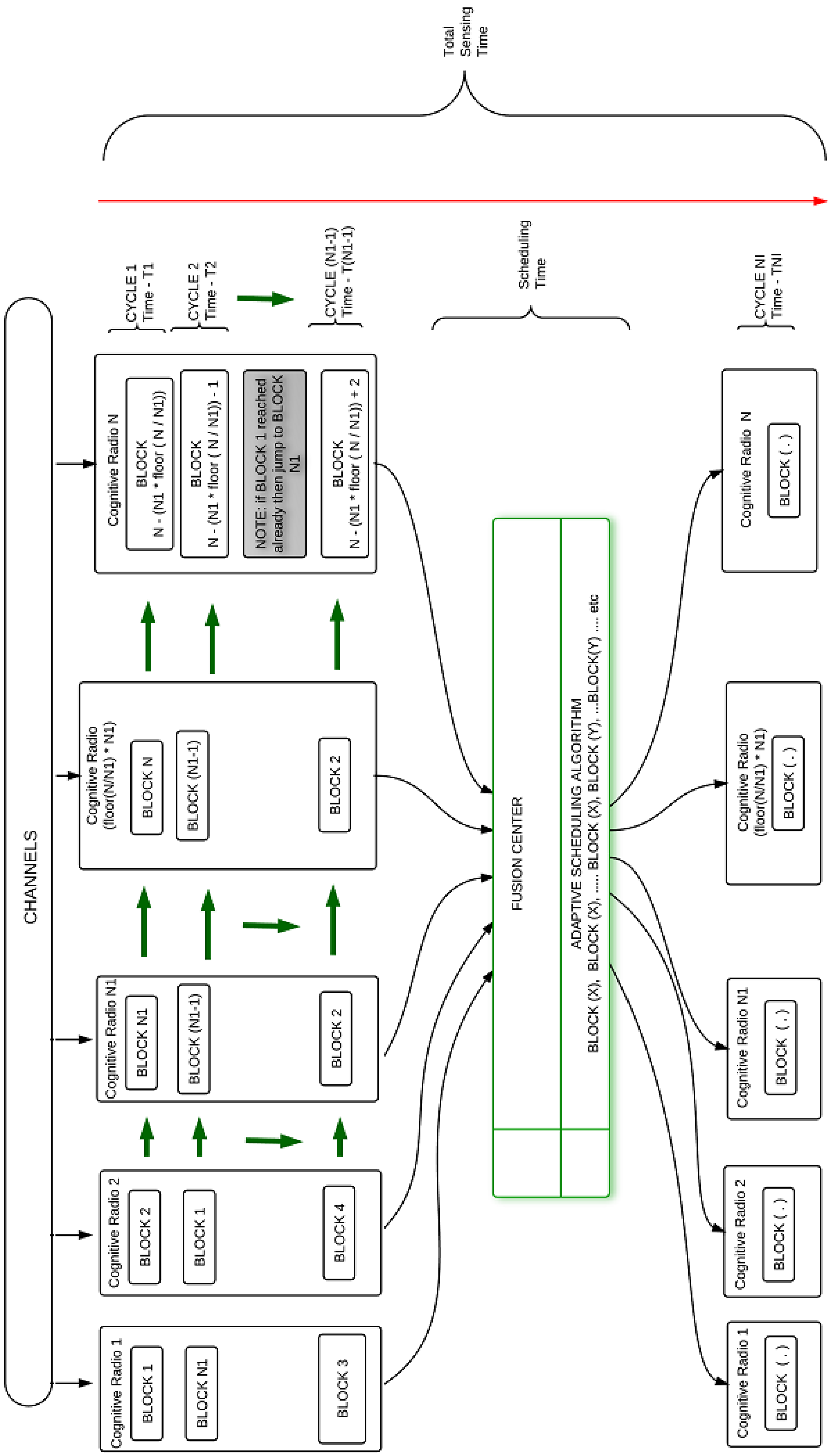

Figure 3-12: Generic PSS algorithm for 'N > N1' and 'N1,N >=3'

3-7-3-1 Scheduling operation in PSS

After "N1-1" cycles, if the energy saving criteria is not met, then the scheduling algorithm is run at the FC, for further sensing. In this scheduling operation, priorities are set based on the subsequent paradigm:

1. Number of acquired Common Free Channels (CFC) in each block, sensed by different SU's in every cycle
2. The list of SU's that sensed a corresponding block, along with the knowledge of the number of idle channels in a particular block sensed by each SU

The scheduling operation can be better understood from an example scenario with N = N1 = 3, shown in Figure 3-13. After 'N1-1' (i.e. two) cycles, the CFC among each of the blocks sensed in both the cycles, are considered. Further, the list of SU's that sensed a corresponding block, along with the knowledge of the number of idle channels in a particular block sensed by each SU, is noted. As described earlier, scheduling is performed by assigning priorities. Two different priorities are introduced in this algorithm:

1. ***Primary priority*** - Primary priorities are assigned to the blocks depending on the number of CFC in each block. A higher priority is set to a block containing lower number of CFC, thus aiming to improve the sensing efficiency. Correspondingly, a lower priority is set to a block containing higher number of CFC. Further, no priority is assigned to the blocks that contain either all busy or all idle channels, as it indicates that the entire block has a very high probability of being either busy or idle respectively.
2. ***Secondary priority*** - Secondary priorities are assigned to the SU's. Considering the blocks that have been assigned with primary priorities, the corresponding SU's that sensed each of these blocks are assigned with secondary priorities. The main criteria to assign secondary priority is the number of idle channels in a prioritized block, sensed by various SU's. In particular, the SU that has sensed a higher number of free channels in the block, indicates that it is comparatively more reliable than other SU's that sensed lower number of idle channels in the same block, in other cycles. By assigning this priority, the sensing accuracy and reliability can be achieved. The sensing accuracy is achieved by sensing the most reliable block again, so that the idle channels in that block of spectrum will be confirmed.

Once the primary and secondary priorities are set, the highest priority block is scheduled to be sensed by a large number of SU's, including the SU's that have been assigned with the secondary priorities. A lower priority block is scheduled to be sensed by comparatively smaller number of SU's with lesser secondary priorities and the least priority block is sensed by a very minimal number of SU's with least or no secondary

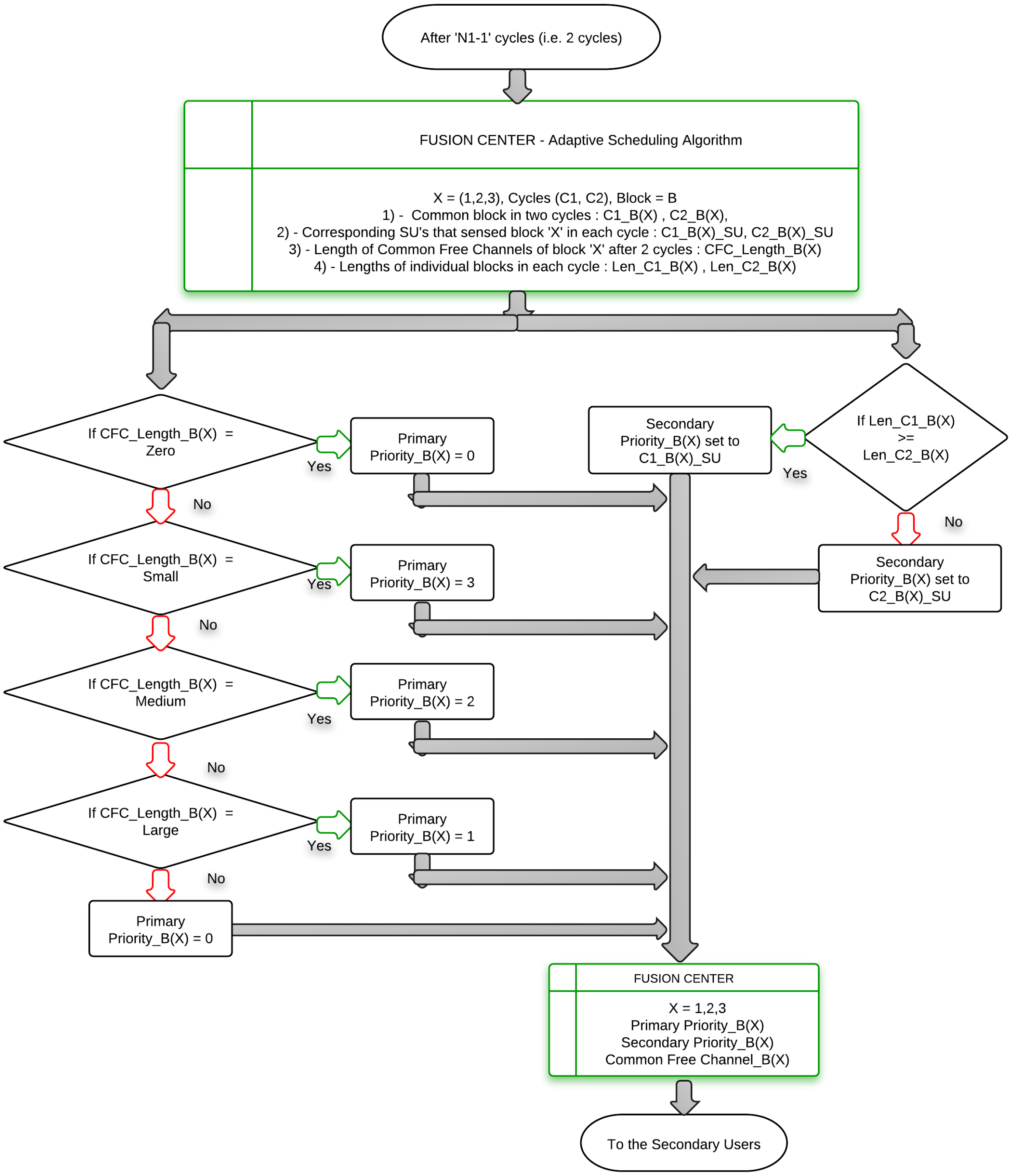

Figure 3-13: Example : PSS scheduling algorithm when 'N = N1 = 3'

priority. In addition to all this, we can minimize the sensing energy of few SU's. This can be achieved when the least reliable SU's are not utilized for sensing in the $N1^{th}$ cycle. In the end, after the execution of all the cycles, the sum of CFC of each block are stored in a list, that could be utilized by the SU's for future transmissions.

Through these priorities, we achieve both sensing accuracy and efficiency while reducing the sensing energy. If '$B_{Priotiry}$' represents the priority of a block and 'N_{SU}' represents the number of SU's sensing the prioritized block, then the relation between them is given by

$$B_{Priotiry} \propto N_{SU} \tag{3-3}$$

It is clear from Figure 3-13, that there must be atleast 2 sensing cycles in order to perform the scheduling algorithm in PSS. Since the scheduling criteria is dependent on the CFC's of atleast two sensing cycles, PSS algorithm will be valid only if the following conditions are met:

1. N and N1 must be greater than or equal to 3 (N,N1 >= 3)
2. N must be greater than or equal to N1 (N >= N1)

3-7-4 Example scenario for PSS

So far the operation of the PSS algorithm has been explained for a generic case. An example scenario is presented for PSS with the following design criteria:

1. Number of CR's, N=4
2. Interferer_1 is chosen to be a device operating in IEEE802.11 WLAN standard, therefore N1=3
3. Interferer_2 is chosen to be a device operating in IEEE802.15.4 Zigbee standard, therefore N2=16

Clearly, the PSS algorithm is valid since it meets the conditions mentioned in the previous section. In this scenario, the 2.4 GHz ISM band is split into three blocks of equal size as shown in Figure 3-10. From Figure 3-14, it is evident that there are 4 CR's, parallely sensing 3 blocks in every cycle. Here 3 CR's form a group. The number of groups here can be found using equation 3-1. It is calculated as shown below

$$\begin{aligned} G &= \lfloor 4/3 \rfloor \\ G &= 1 \end{aligned} \tag{3-4}$$

Hence each CR within this group senses a unique block, in each cycle. Hence there are 3 subgroups within this group. Each subgroup contains unique order of blocks (for example, CR-1 has a subgroup with blocks 1 and 2, CR-2 with blocks 2 and 3, etc). The fourth CR senses the set of blocks pertaining to subgroup 1.

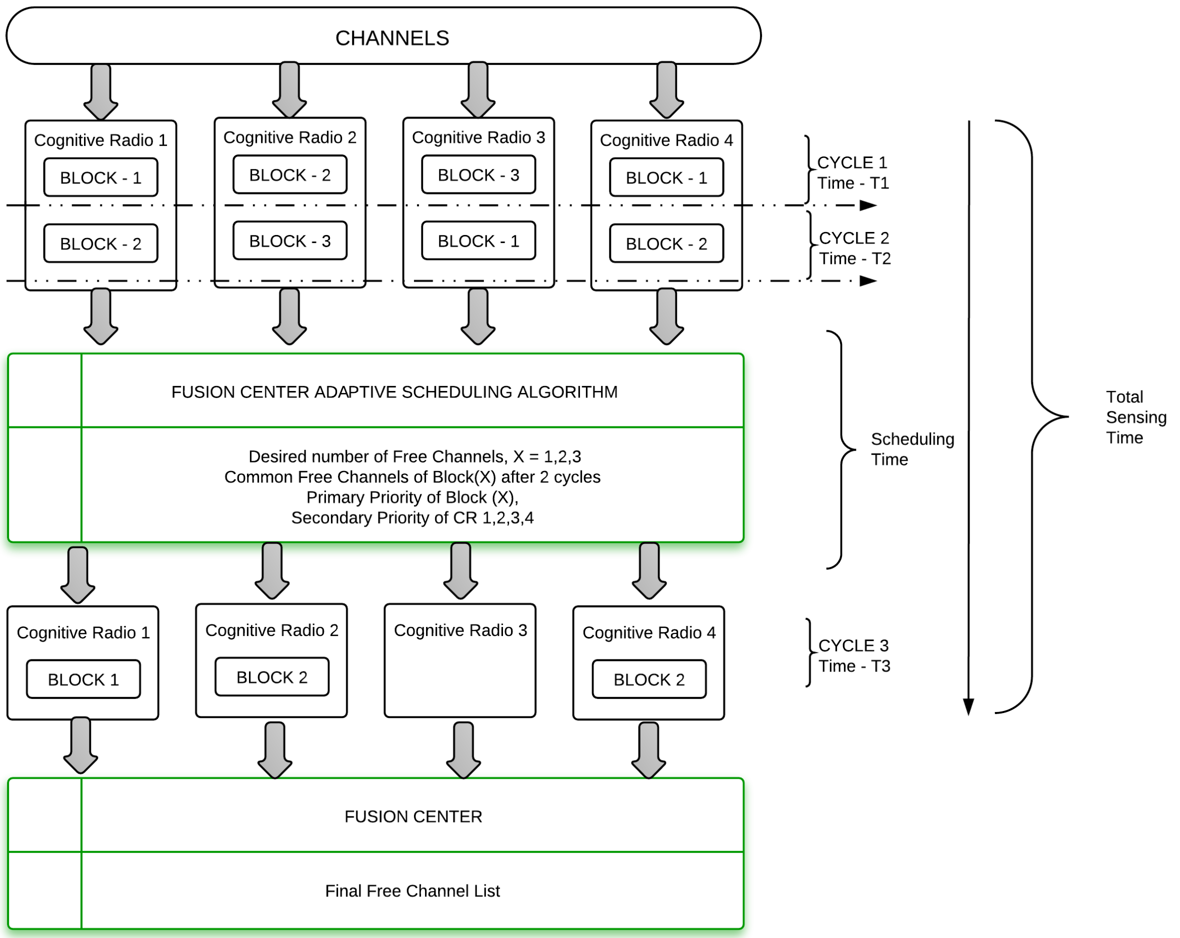

Figure 3-14: Example Scenario of PSS algorithm with N=4,N1=3

This can be concluded using equation 3-2 as shown below

$$SG = 4 - (3 * \lfloor 4/3 \rfloor)$$
$$SG = 1 \tag{3-5}$$

After 2 cycles (i.e. 'N1-1' cycles), the sensed data from all CR's are forwarded to the common FC. The common free channels (CFC) of each block sensed by all the CR's in both the cycles, are noted. Primary priorities are set to all the blocks and the secondary priorities are set to the SU's according to the rules described in Section 3-7-3-1.

Cycle 3 is performed if the desired number of free channels is not achieved. The above condition is checked by comparing the sum of CFC of all the blocks, with the desired number of idle channels that is decided apriori. Here in Figure 3-14, cycle 3 is performed, assuming that the desired number of free channels is not achieved.

The following scenario's are considered during the scheduling process:

- Block 2 has the highest and Block 3 has the lowest primary priority

- Block 2 has been sensed by CR-1, CR-2 and CR-4 prior to scheduling and thus secondary priorities are set to one of these CR's with respect to block 2. Both CR-2 and CR-4 have been assigned with higher secondary priorities among the three CR's.
- Similarly, block 1 is considered to have the second highest primary priority. Among those CR's that sensed block 1, CR-1 is assumed to be assigned with the highest secondary priority.
- Block 3 has the least priority and hence it has not been assigned to any of the CR's.
- CR-3 does not sense any block in the 3rd cycle as it is the least reliable among all the CR's.

Finally after all 3 cycles, the sum of CFC of all the blocks are stored in the free channel list.

3-7-5 Limitations of PSS

1. *Sensing Accuracy* - Since only hard decision based fusion is considered here in PSS, the sensing accuracy would not be as good as expected.
2. *Hardware constraints* - A minimum of 3 SU's in the network is necessary for the PSS algorithm to be valid.

3-8 Summary of Spectrum Sensing Algorithms

To overcome the effects of any two interferers in the 2.4 GHz ISM band, several novel cooperative spectrum sensing algorithms along with adaptive scheduling techniques have been discussed in detail in this chapter. This chapter can be summarized as follows:

- Imec's WBAN radio transceiver performs poorly in the presence of excessive interference in the 2.4 GHz ISM band. Thus a multichannel interferer system consisting of 2 PU interferer's is considered in this thesis.
- Due to the excessive power consumption of the transmitter front end of the WBAN radio transceiver at Imec, the spectral sensing algorithms are aimed at improving the overall sensing performance in terms of sensing accuracy, efficiency and energy. Through this the energy consumption of the entire WBAN system can be minimized.
- In Basic Sequential Search (BSS) algorithm, sequential sensing of any two narrowband interferer's in the 2.4 GHz ISM band is performed. A novel concept of sequential sensing via portions is proposed here. BSS forms the basis for both ISS and PSS algorithms.

- In Improved Sequential Search (ISS) method, several novel adaptive scheduling algorithms have been discussed in detail. ISS technique is useful only in a crowded spectrum with atleast one active Interferer_1 channel. Through ISS, the sensing accuracy and efficiency are expected to be achieved, independent of one another.
- Parallel-Sequential Search (PSS) is a novel algorithm that aims at overcoming all the drawbacks of both ISS and BSS. By adopting spatio-temporal diversity and adaptive scheduling algorithms, the overall sensing performance is expected to be optimized.
- Both Non-cooperative and Cooperative scenarios are considered in all the above algorithms and the performance plots are discussed in detail in Chapter 4 of this thesis.

Chapter 4

Performance Analysis and Comparison of Algorithms

4-1 Introduction

This chapter initially describes the simulation setup utilized, to evaluate the performances of the algorithms explained in Chapter 3. A detailed analysis of the sensing performance parameters, including accuracy, efficiency, complexity and energy are performed for individual algorithms. Both non-cooperative and CS schemes are exploited and analyzed in each of the algorithms. Then a comparative study of all the three algorithms in the cooperative scenario is done. Further, the measurement setup to validate the simulation results is presented and the sensing accuracy of all the three algorithms, with both measured and simulated spectrum are plotted.

4-2 Simulation Setup

The evaluation framework for the simulations of all three algorithms have been implemented in Matlab. Table 4-1 provides the list of parameters that are considered, for the simulations of all the algorithms. Devices utilizing IEEE802.11b European WLAN and IEEE802.15.4 Zigbee are considered to be the PU interferers. Three SU's (WBAN radios) are considered to be cooperating in the network. From both Figure 3-1 and Table 4-1, it is clear that a total of 19 channels (3 WLAN + 16 Zigbee) are being sensed. Therefore a sum of 19 sensing slots are assumed to comprise of one sensing period in all the proposed algorithms. The WBAN radio at Imec-Holst Centre supports OOK modulation. A total of 5 Zigbee channels and 1 WLAN channel are considered to be idle. Thus, the remaining 11 Zigbee Channels and 2 WLAN channels are considered to be busy. The spectral hole search operation is performed via slots, each with a frequency resolution of 2 MHz.

Nr.	PARAMETER	DESCRIPTION
1	Channel	AWGN
2	Detection Technique	Energy Detection
3	Threshold	λ_b = *-87.5 dBm*
4	Monte Carlo runs	5000
5	Samples	22
6	Operating SNR region	11 (dB)
7	Modulation	OOK
8	Number of Secondary Users	3
9	Primary User 1 or Interferer_1	IEEE802.11b WLAN device
10	Primary User 2 or Interferer_2	IEEE802.15.4 Zigbee device
11	Frequency resolution per sensing slot	2 MHz
12	Nr. of WLAN Channels	3
13	Nr. of Zigbee Channels	16
14	Nr. of idle Zigbee channels	5
15	Nr. of busy Zigbee channels	11
16	Nr. of idle WLAN channels	1
17	Nr. of busy WLAN channels	2
18	Nr. of sensing slots per sensing period	19
19	Max nr. of sensed channels per sensing period	19
20	Nr. of channels utilized for transmission	16 Zigbee channels

Table 4-1: Common Simulation Parameters for BSS, ISS and PSS

Further, Table 4-2 lists the common performance parameters that are related to all the algorithms. Each of the performance parameters in all the three algorithms will be analyzed and compared with one another, later in this Chapter.

4-2-1 Energy detector distribution statistic

As mentioned in Section 2-2-4, a Gaussian channel model is considered in this thesis, for simplicity. Let *s(t)* denote the transmitted PU signal of constant amplitude A, acting as an interfering source. *n(t)* is the complex additive white Gaussian noise (AWGN) with zero mean and noise variance σ_v^2 , given by $N(0,\sigma_v^2)$. Then the average received SNR at the WBAN radio receiver front end is defined as,

Nr.	PARAMETER	DESCRIPTION
1	Total Sensing Error	$P_{mis,mac} + P_{false,mac}$
2	Sensing Accuracy	Total Sensing Error
3	Sensing Efficiency	Nr. of Idle Zigbee Channels obtained in one execution
4	Sensing Complexity	Nr. of slots used in one sensing period
5	Sensing Energy	Total number of hypothesis testing operations in one execution

Table 4-2: Common Performance Parameters for BSS, ISS and PSS

$$\gamma = \frac{A^2}{\sigma_v^2} \tag{4-1}$$

The spectrum sensing operation performed at the receiver can be considered as binary hypothesis testing problem. The received signal statistic is given by the following expression,

$$x(t) = \begin{cases} n(t) & \text{,under } H_0, \\ s(t) + n(t) & \text{,under } H_1. \end{cases} \tag{4-2}$$

where *x(t)* is the signal received by a single SU. H_0 is the null hypothesis, which represents the inactive state of the PU. H_1 is the alternative hypothesis, which indicates that the PU is active. An energy detector is employed in each SU to determine the state of the PU. The ED output statistic in each SU is given as,

$$R = \frac{1}{S}\sum_{i=1}^{S} |x(i)|^2 \tag{4-3}$$

Where R represents one observation of a narrowband channel in the 2.4 GHz ISM band, in each SU. S is the number of averaged samples. Although R follows a chi-square distribution, using central limit theorem, it can be considered to be asymptotically normally distributed if S is sufficiently large (S >= 20) [19]. The ED output for both the hypotheses can be expressed as,

$$R_{H_0} = |n|^2 \tag{4-4}$$

$$R_{H_1} = |A + n|^2 \tag{4-5}$$

where R_{H_0} and R_{H_1} represents the observation of the ED under H_0 and H_1, respectively. In order to model the statistic for R, we require the mean and variance for both the hypotheses. Let us first consider the null hypothesis H_0 from equation 4-2. The expected value (mean) and the variance of the ED output statistic R, $E(R_{H_0})$ and $Var(R_{H_0})$ respectively, can be calculated using probability theory. It is given by,

$$E(R_{H_0}) = \sigma_v^2 \tag{4-6}$$

$$Var(R_{H_0}) = \frac{1}{S} \times (2\sigma_v^4) \tag{4-7}$$

Now let us consider the alternate hypothesis H_1 as given in equation 4-2. Here, the ED output is of the form,

$$\begin{aligned} R_{H_1} &= |A + n|^2 \\ &= A^2 + n^2 + 2An \end{aligned} \tag{4-8}$$

Now, the mean and the variance of the ED output statistic R, obtained after solving and simplifying using probability theory, are given by,

$$E(R_{H_1}) = A^2 + \sigma_v^2 \tag{4-9}$$

$$Var(R_{H_1}) = \frac{1}{S} \times (2\sigma_v^4 - 4A^2\sigma_v^2) \tag{4-10}$$

From equations 4-6,4-7,4-9 and 4-10, the statistic of R can be modelled as follows:

$$R \sim \begin{cases} N(\sigma_v^2, \frac{2\sigma_v^4}{S}) & \text{,under } H_0, \\ N((A^2+\sigma_v^2), \frac{2\sigma_v^4+4A^2\sigma_v^2}{S}) & \text{,under } H_1. \end{cases} \tag{4-11}$$

Equation 4-11 represents the distribution statistic of an ED output for a Gaussian channel model. Clearly, R has a dependency on the signal amplitude A, the unknown noise power σ_v^2 at the receiver, and the number of samples S. For a sample size of S> 20, R follows a Gaussian distribution [19]. Figure 4-1 shows the simulated spectrum in Matlab, using the above simulation parameters and the derived distribution statistic given in equation 4-11.

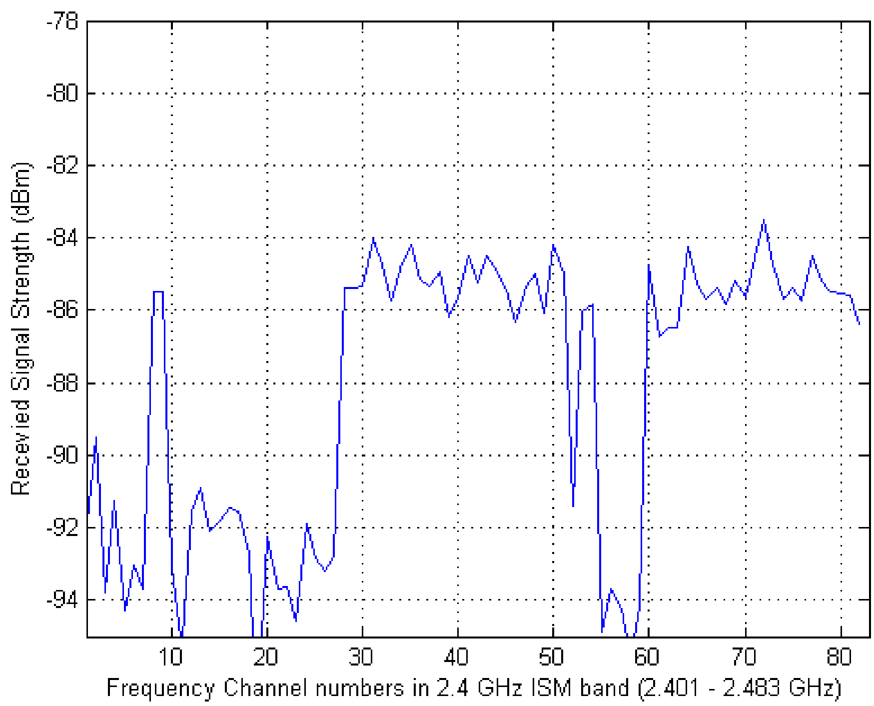

Figure 4-1: Simulated spectrum based on considered simulation parameters in Table 4-1

4-3 Performance Evaluation of Spectrum Sensing Algorithms

In this section, we present the simulation results of all the three algorithms. The various spectrum sensing parameters that are mentioned in Table 4-2 are analyzed for each algorithm.

4-3-1 Performance parameters

Before presenting the results, it is crucial to understand clearly each of the sensing parameters with respect to these simulation scenario.

Sensing accuracy - is evaluated in terms of total sensing error. From Table 4-2 we have,

$$TotalSensingError = P_{mis} + P_{false} \tag{4-12}$$

Now, the total sensing error is evaluated with respect to the total number of channels utilized for transmission. From Table 4-1, it is clear that only 16 Zigbee channels are utilized for transmission, when the PU's are idle. Further, 5 Zigbee channels are set to be idle. From equation 2-4, we have the maximum probability of missed idle channels, $P_{mis,max}$ given by,

$$\begin{aligned} P_{mis,max} &= \frac{5}{16} \\ &= 0.3125 \end{aligned} \tag{4-13}$$

Similarly, 11 Zigbee channels are set to be busy. From equation 2-5, we have the maximum probability of false alarm of busy channels, $P_{false,max}$ given by,

$$\begin{aligned} P_{false,max} &= \frac{11}{16} \\ &= 0.6875 \end{aligned} \tag{4-14}$$

Sensing efficiency - refers to the total number of available idle Zigbee (Interferer_2) channels obtained after a sensing period. The sensing efficiency is highest, if all the available idle channels in the spectrum are obtained, and vice versa. In the simulation environment explained in this thesis, there are a total of 5 idle Zigbee channels.

Sensing complexity - is evaluated by determining the total number of slots utilized per sensing period. A larger number of slots utilized in an algorithm indicates that the algorithm has a higher sensing complexity, and vice versa. Here in this simulation environment, we have a total of 19 sensing slots per SU, as given in Table 4-1.

Sensing energy - indicates the total number of computations involved in a single execution of an algorithm. In this thesis, the computations mainly refer to hypothesis testing operation during the execution of the algorithm. Since the hypothesis testing operation is assumed to consume most of the energy compared to other operations such as scheduling, storing, etc., it determines the energy consumption. A brief study of the sensing energy is made for each of the algorithms. It is to be noted that the sensing energy and complexity are directly related to one another. From Section 3-3, it is clear that there are a total of "N1+N2" slots in one sensing period. Further, each slot indicates one hypothesis testing operation, since each slot contains the sensed result of a single channel. Thus the total number of slots utilized, matches the total number of hypothesis testing operations performed in an algorithm. Hence we can conclude,

$$SensingEnergy \propto SensingComplexity \tag{4-15}$$

4-3-2 Sensing Scenarios

The performance evaluation of all the algorithms are done under the following scenarios,

1. ***Non-Cooperative*** **-** Algorithm is evaluated in each SU
2. ***Cooperative*** **-** Algorithm is evaluated at the common FC, after suitable fusion methods have been adopted (refer Section 2-2-2-3). For simulation purposes, 3 SU's have been considered to cooperate in the network

In order to compare both the scenarios mentioned above, the received SNR has been fixed at a constant value in any two out of three SU's in the simulations. Further all the data fusion schemes are exploited. In order to understand the concept of assigning weights to all the SU branches in the CS scheme, all the fusion methods are re-addressed here in detail,

1. ***Weighted Soft Decision*** - This technique has the following criteria namely,
   - Received Signal Strength (RSS) - The RSS of each channel in all the SU's, are used to designate priorities to every branch between the SU's and FC. The weights are determined based on the following relation,

$$W_{i,RSS} = \frac{A_i^2}{\sum_{i=1}^{N}(A_i^2)} \tag{4-16}$$

Where i $= (1, ..., N)$, represents the branch between ith SU and the FC. W$_{i,RSS}$ represents the weights assigned to the ith branch. A$_i^2$ represents the received signal strength (RSS) of a channel in the ith branch. Here, higher the RSS in a SU, larger the weight assigned to that branch and vice versa.

- Signal to Noise Ratio (SNR)-Similar to the process explained in RSS above, the weights here, are assigned based on the following expression,

$$W_{i,SNR} = \frac{SNR_i}{\sum_{i=1}^{N}(SNR_i)} \tag{4-17}$$

  Where W$_{i,SNR}$ represents the weights assigned to the ith branch. Here, higher the received SNR at a SU, larger the weight assigned to that branch and vice versa.

Here in this WSD based combining methods, the threshold at the FC is affected by the total sum of weights of all the branches. It can be expressed as,

$$\lambda_{b,FC,WSD} = \sum_{i=1}^{N} W_i \times \lambda_b \tag{4-18}$$

2. ***Equal Gain Combining*** - Here, each branch is assigned with unit weight. The threshold at the FC is given by,

$$\lambda_{b,FC,EGC} = \lambda_b \tag{4-19}$$

4-3-3 Basic Sequential Search (BSS)

4-3-3-1 Sensing Accuracy

Figure 4-2 shows the performance of BSS algorithm in terms of total sensing error, under both cooperative and non-cooperative scenarios. All the combining methods have been studied in the cooperative case, while fixing any two of the three SU's received SNR at 3 dB.

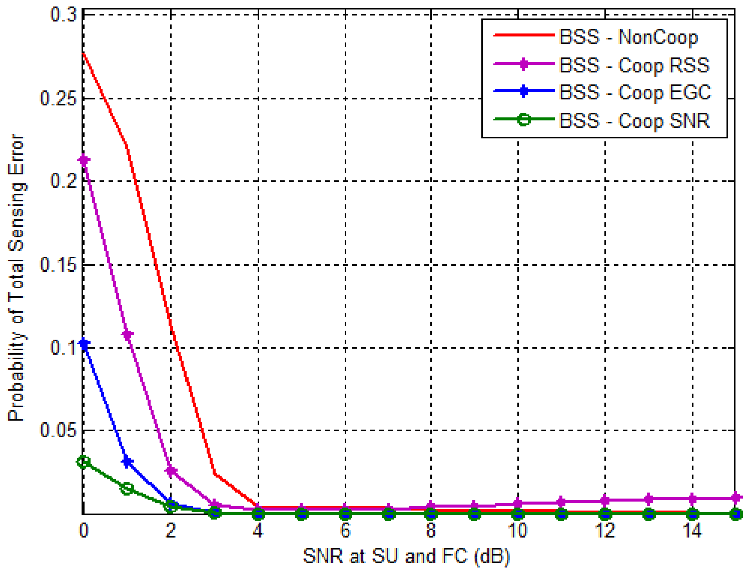

Figure 4-2: BSS - Sensing Accuracy at a single SU and at FC when SNR of any two SU's are fixed at 3 dB

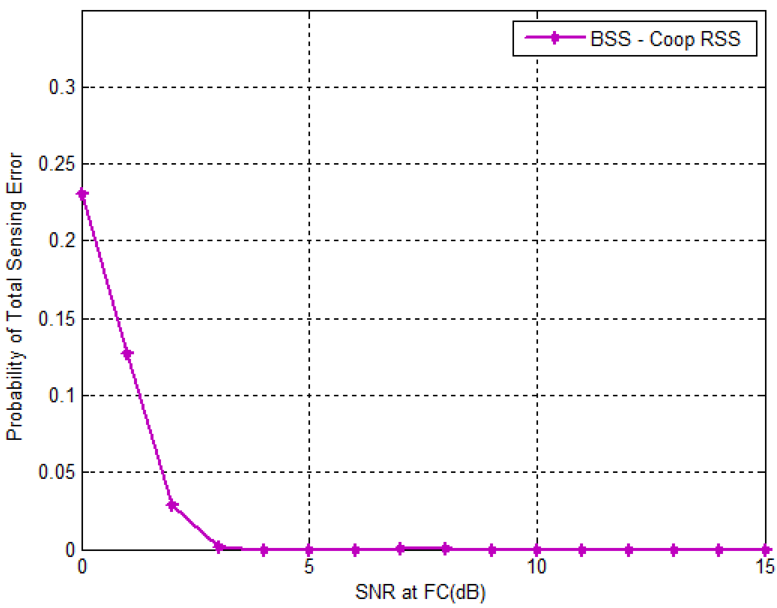

Figure 4-3: BSS - Sensing Accuracy at FC when SNR of any two SU's are fixed at 9 dB

It is clear that at low SNR regions, the CS scenario outperforms the non-cooperative sensing scenario. In particular, the SNR based fusion method provides robust performance with a sensing error probability of less than 4%. Further, at the operating region of the WBAN radio of about 11dB, both CS and non-cooperative sensing schemes achieve a sensing error probability of less than 0.8%. It can be noticed that with RSS based fusion method, the performance degrades slightly at high SNR values. This is primarily due to the fact that, two out of the three SU's received SNR have been fixed at a constant low value of 3dB, and hence there is a degradation. This degradation will be overcome when the two SU's are fixed (operating) at higher SNR values as shown in Figure 4-3.

4-3-3-2 Sensing Efficiency

The ability of the BSS to detect all the available idle Zigbee channels in the 2.4 GHz ISM band, is studied under both cooperative and non-cooperative scenarios, for varying SNR values as shown in Figure 4-4.

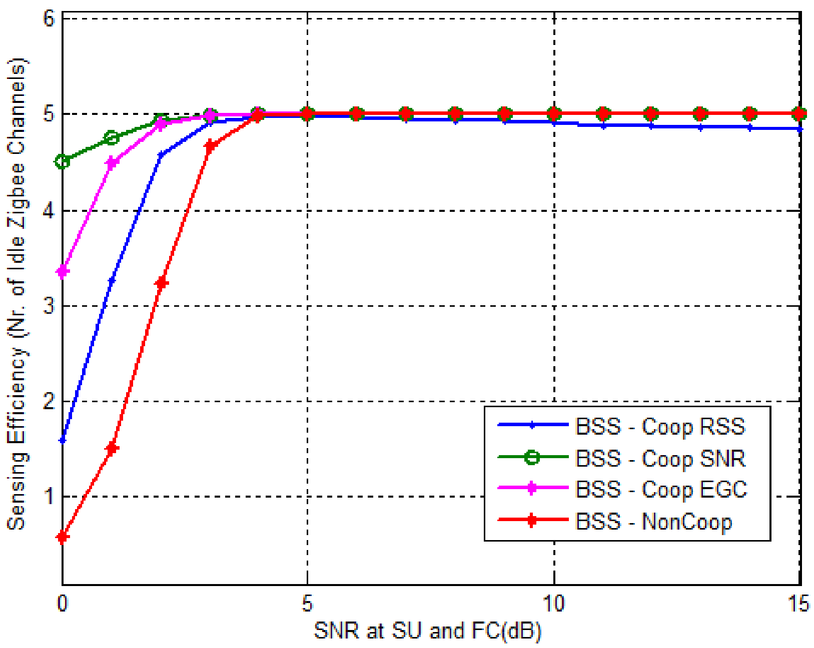

Figure 4-4: BSS - Sensing Efficiency at a SU and at FC when SNR of any two SU's are fixed at 3 dB

Here again the SNR based fusion method, under CS scenario outperforms all the other techniques, by a significant amount. As the SNR increases, almost all these scenario's achieve the optimal value. In other words, all the 5 available idle Zigbee channels are acquired efficiently. With RSS based fusion method, a more robust performance can be observed at high SNR regions when the two SU's received SNR is fixed at a higher value, similar to the plot shown in Figure 4-3.

4-3-3-3 Sensing Complexity

Figure 4-5 shows the comparison of overall sensing complexity of BSS under different sensing scenarios. From Table 4-1 and the pseudo-code given in Figure 3-3, it is clear that the BSS under high SNR regions in this simulation, utilizes a total of 11 sensing slots, thus indicating a maximum complexity value of 11 in the Figure 4-5. A non-cooperative method achieves a lower complexity at low SNR values. However all the methods have the same level of complexity at the operating SNR region of Imec's WBAN radio.

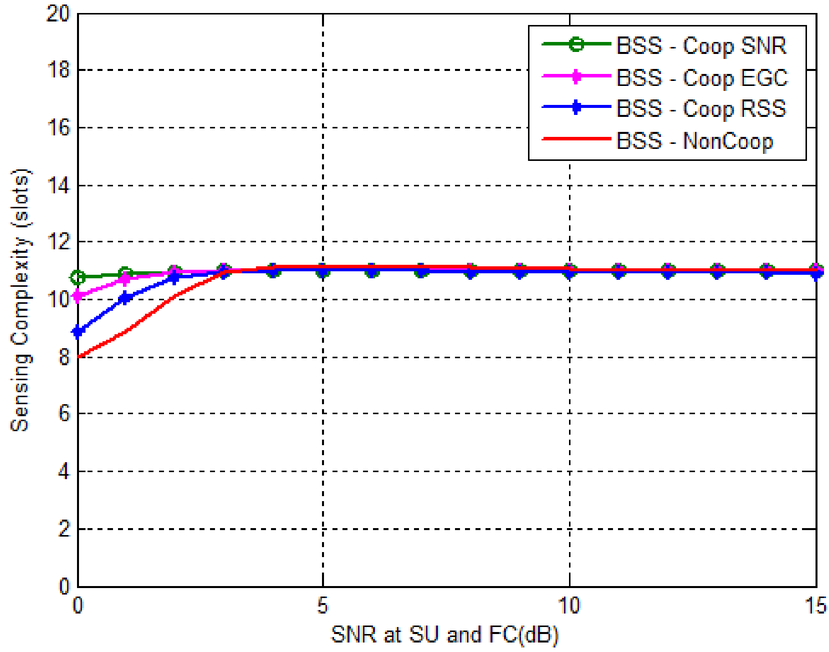

Figure 4-5: BSS - Sensing Complexity at SU and FC when received SNR of any two SU's are fixed at 3 dB

4-3-3-4 Sensing Energy

From Figure 4-5, it is clear that, in a single SU, the BSS performs a total of 11 hypothesis testing operations, one for each sensed channel, at a SNR value of say 11 dB. In other words, 11 sensing slots are utilized. Since the maximum number of hypothesis testing operations that can be performed by BSS during a single execution is 19, the percentage of energy consumed by the BSS algorithm at a SU and FC, at 11 dB, is given by,

$$\begin{aligned} Energy_{(BSS,11dB)} &\approx (\frac{11}{19})\% \\ &\approx 57.9\% \end{aligned} \tag{4-20}$$

Similarly from Figure 4-5, we can observe that at low SNR regions of say 2 dB, an average of 10.78 slots are used in the RSS based fusion method under CS scenario. Thus, the percentage energy consumption is lowered, given by,

$$
\begin{aligned}
Energy_{(BSS,2dB)} &\approx (\frac{10.78}{19})\% \\
&\approx 56.73\% \qquad (4\text{-}21)
\end{aligned}
$$

However it is clear that in a CS scenario with 3 SU's, the energy consumption per SU remains close to 58%. Further, in a CS scenario with 3 SU's , the total energy consumption is multiplied by three fold.

4-3-4 Improved Sequential Search

From Figure 3-7, it is seen that ISS exploits several scheduling algorithm criteria that aims at improving either sensing accuracy or efficiency, independent of one another. The following sections clearly provides a detailed study of these scheduling criteria under both cooperative and non-cooperative scenarios. Further, several data fusion methods are also exploited in the CS scenario.

4-3-4-1 Sensing Accuracy

The total sensing error probability for all the scheduling criteria of ISS in a non-cooperative scenario is compared as shown in Figure 4-6.

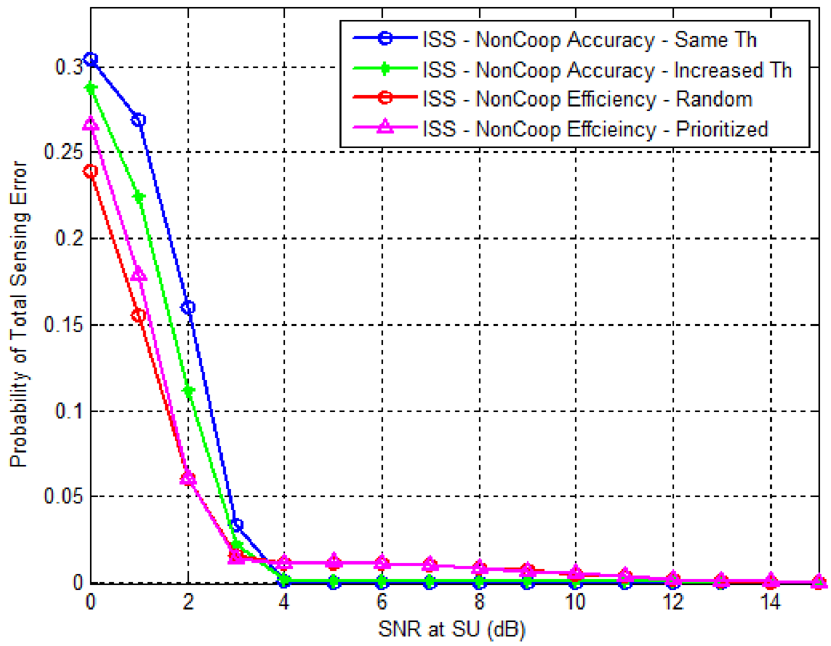

Figure 4-6: ISS - Sensing Accuracy at SU for all scheduling criteria

It is seen that the accuracy based scheduling criteria of ISS provides a robust performance at higher SNR values (say around 8dB). However at a lower SNR region (say 2dB), the efficiency based scheduling criteria outperforms the other. In a CS scenario, the various data fusion methods are studied for all the scheduling criteria of ISS, as shown in Figures 4-7, 4-8 and 4-9.

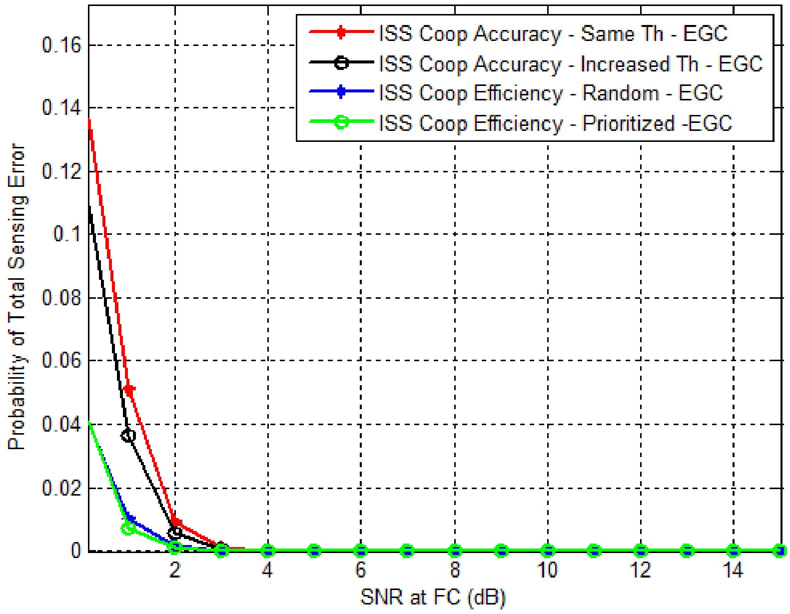

Figure 4-7: ISS - Sensing Accuracy at FC for all scheduling criteria based on EGC method

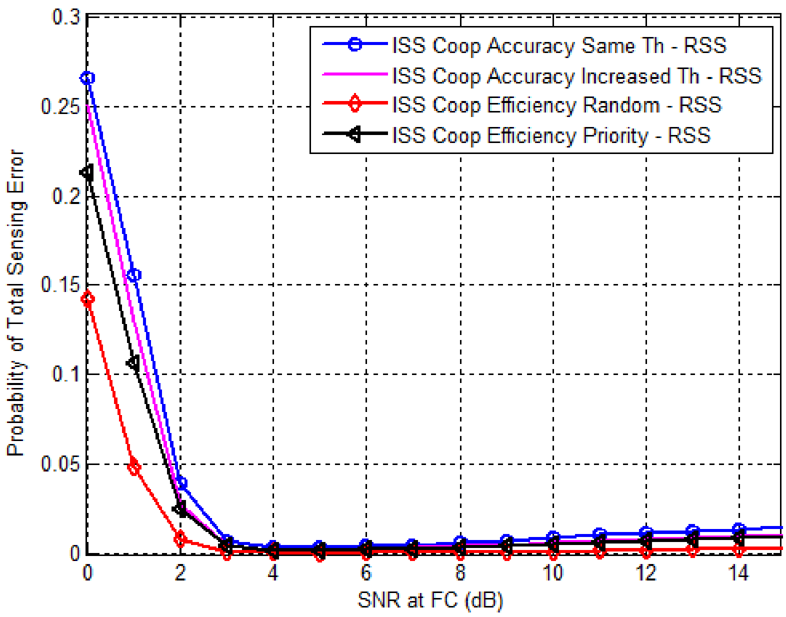

Figure 4-8: ISS - Sensing Accuracy at FC for all scheduling criteria based on RSS method

From Figures 4-7, 4-8 and 4-9, it is clear that the performance of the ISS algorithm under efficiency based scheduling criteria is most robust. In particular, the random search method under the efficiency based scheduling criteria of ISS, provides the most robust sensing performance, especially with the SNR and EGC based fusion methods. At low SNR regions, sensing error probability of less than 1% and 4% is achieved via SNR and EGC based fusion method, respectively.

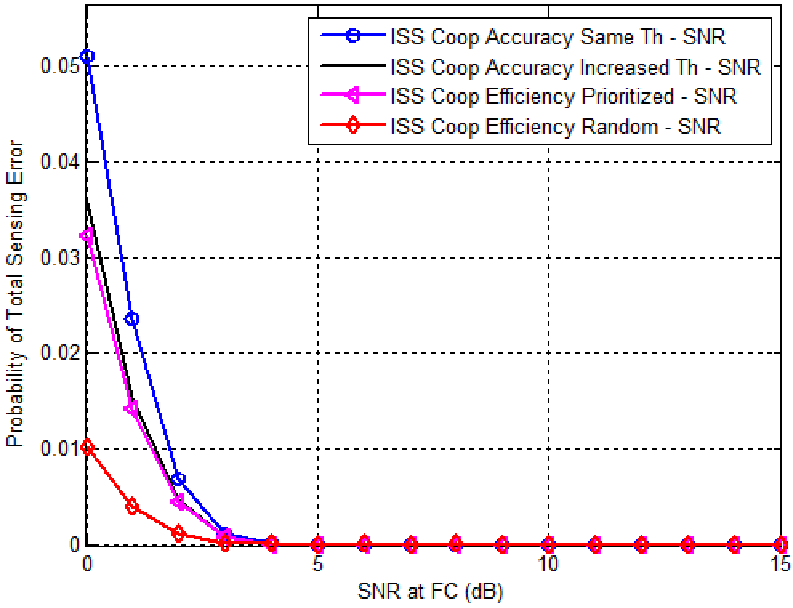

Figure 4-9: ISS - Sensing Accuracy at FC for all scheduling criteria based on SNR method

A comparison between CS and non-cooperative scenario is provided for the random search technique of the ISS, in Figure 4-10.

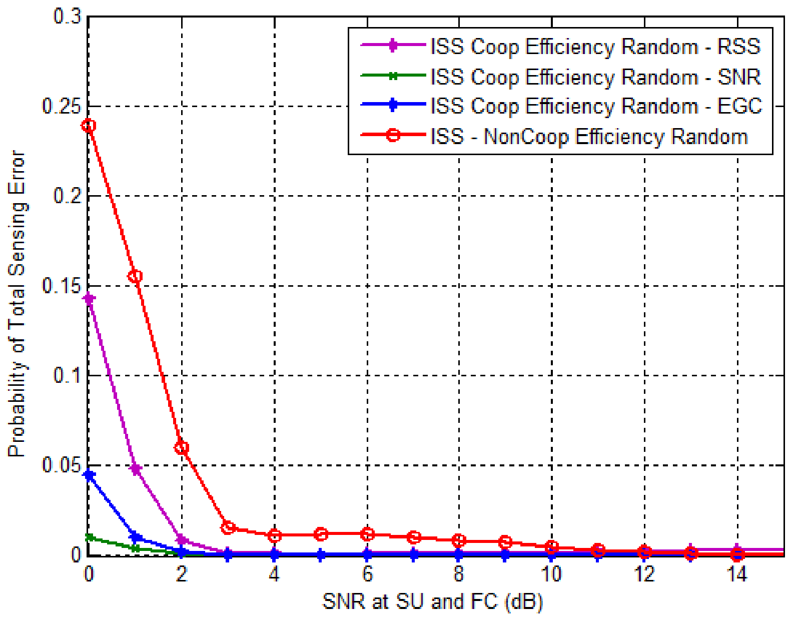

Figure 4-10: ISS - Sensing Accuracy at a SU and FC for Random search method under efficiency based scheduling criteria of ISS

As expected, the CS scenario with both SNR and EGC based fusion methods outperforms the non-cooperative scenario. From all the plots in this section, it can be concluded that, among the various scheduling criteria of ISS, random search method in efficiency based scheduling criteria, under CS scenario proves to be the more robust technique.

4-3-4-2 Sensing Efficiency

Figures 4-11 and 4-12 help determine the scheduling criteria of ISS, that provides the highest sensing efficiency. The sensing efficiency in a non-cooperative sensing scenario, for all the scheduling criteria of ISS, is provided in Figure 4-11. Similarly in Figure 4-12, the sensing efficiency in a CS scenario with the SNR based fusion method for all the scheduling criteria of ISS is shown.

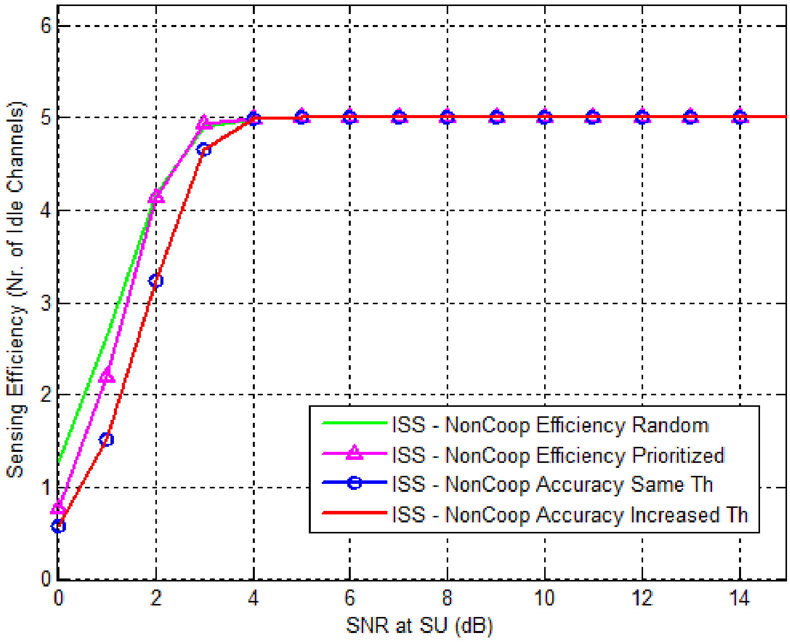

Figure 4-11: ISS - Sensing Efficiency at SU for all scheduling criteria

It is evident that the random search method in efficiency based scheduling criteria of ISS, achieves the highest efficiency at low SNR regions in both CS and non-cooperative scenarios. However all the scheduling criteria performs the same at high SNR regions. A comparison between CS and non-cooperative sensing scenarios is provided for random search method in efficiency based scheduling criteria in ISS, in Figure 4-13. All the fusion methods are also exploited, as shown.

Clearly, the SNR based CS scenario achieves the highest sensing efficiency, among all the fusion methods. In the lower SNR regions, a significant improvement in the efficiency is seen between the CS and the non-cooperative sensing scenario.

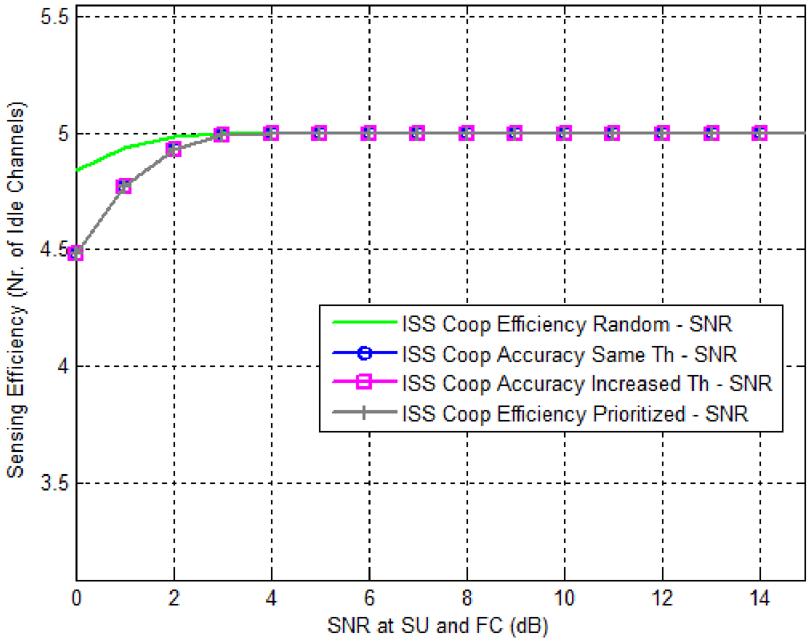

Figure 4-12: ISS - Sensing Efficiency at FC for all scheduling criteria under SNR based fusion method

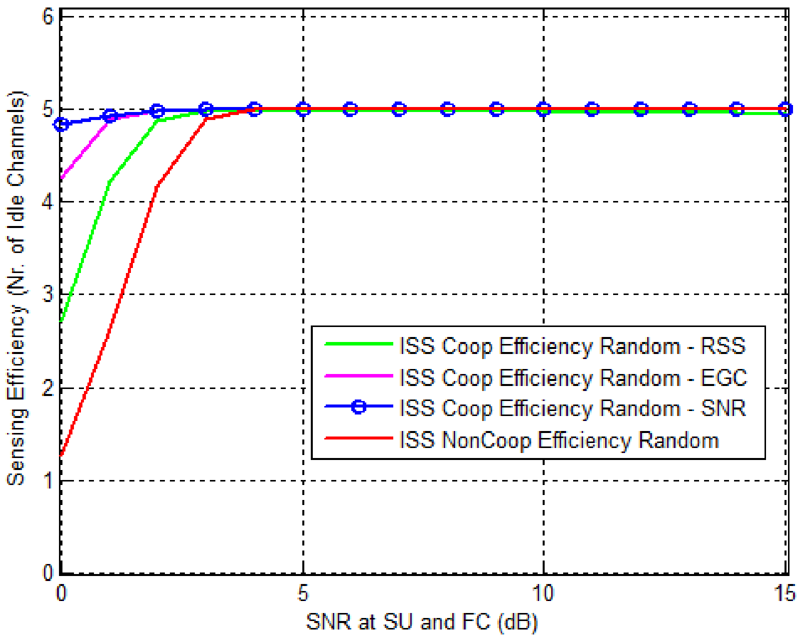

Figure 4-13: ISS - Sensing Efficiency at a SU and FC for Random search method in efficiency based scheduling criteria of ISS, and for all fusion methods

4-3-4-3 Sensing Complexity

The main motivation behind developing ISS algorithms, is to make efficient use of all the remaining slots, after the execution of BSS algorithm. Hence it is clear that the sensing complexity of all the scheduling criteria within ISS will be maximum, with a value of 19 (slots). This is evident for both the CS and non-cooperative sensing scenarios, as shown in Figure's 4-14 and 4-15 respectively. An example of SNR based fusion method has been chosen to show the sensing complexity for the CS scenario.

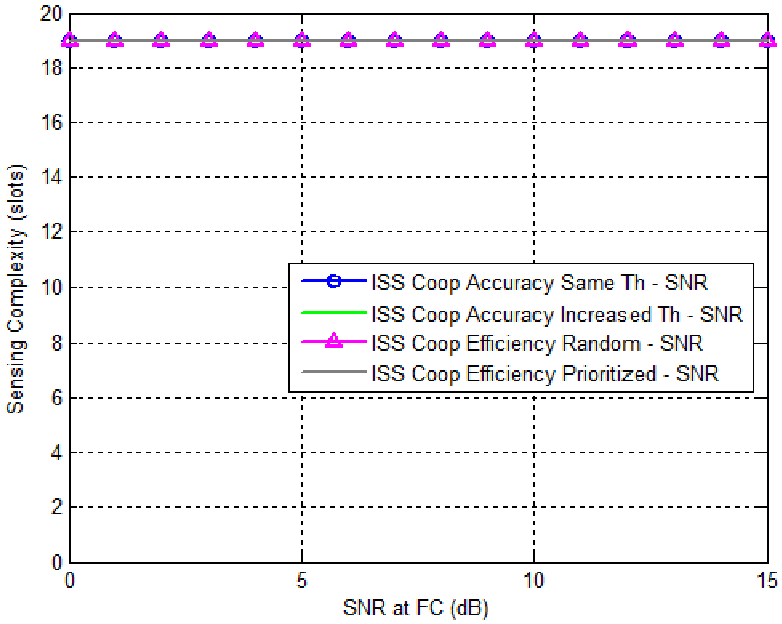

Figure 4-14: ISS - Sensing Complexity at FC for all scheduling criteria of ISS, SNR based fusion method

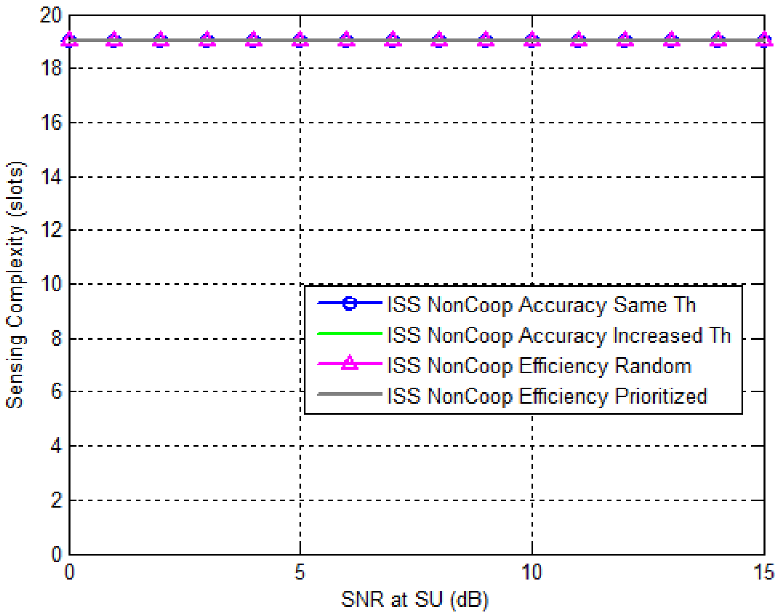

Figure 4-15: ISS - Sensing Complexity at SU all scheduling criteria of ISS

The sensing complexity remains maximum for all received SNR values, under both CS and non-cooperative sensing scenarios as seen in the figures.

4-3-4-4 Sensing Energy

The sensing energy is evaluated for the ISS, after considering the simulation parameters given in Table 4-1. From Figure's 4-14 and 4-15, it is clear that the ISS always utilizes 19 slots during the entire operation , thus performing 19 hypothesis testing operations, one for each slot (channel). Since the maximum number of hypothesis testing operations that can be performed during a single execution is 19, the percentage of energy consumed by ISS at a SU or at FC, is always $Energy_{ISS} = 100\%$. However it is clear that in a CS scenario with 3 SU's, the total energy consumption is increased by three fold, one for each SU.

4-3-5 Parallel-Sequential Search

As mentioned in Section 3.7, the PSS algorithm aims at bringing a balance between the sensing accuracy and efficiency, while also minimizing the total sensing energy. The various performance results of PSS algorithm are discussed in the following sections. In the simulation scenario provided in Table 4-1, we have N = 3 and N1 = 3.

4-3-5-1 Sensing Accuracy

Figure 4-16 shows the total sensing error probability of the PSS algorithm, for varying received SNR values. It is clear from the plot that the PSS algorithm at high SNR regions introduces atleast 1% of sensing error.

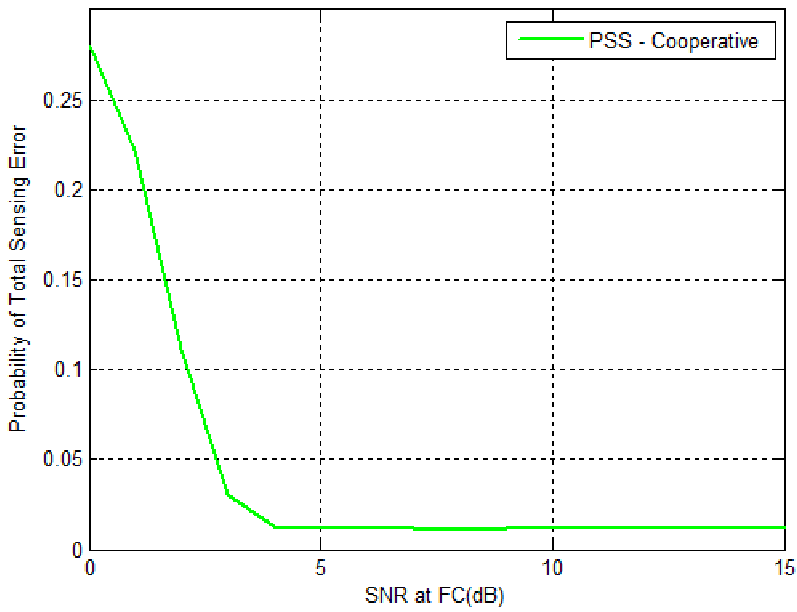

Figure 4-16: PSS - Sensing Accuracy at FC

4-3-5-2 Sensing Efficiency

The sensing efficiency of the PSS algorithm is presented in Figure 4-17. PSS achieves a very good efficiency even at low SNR regions.

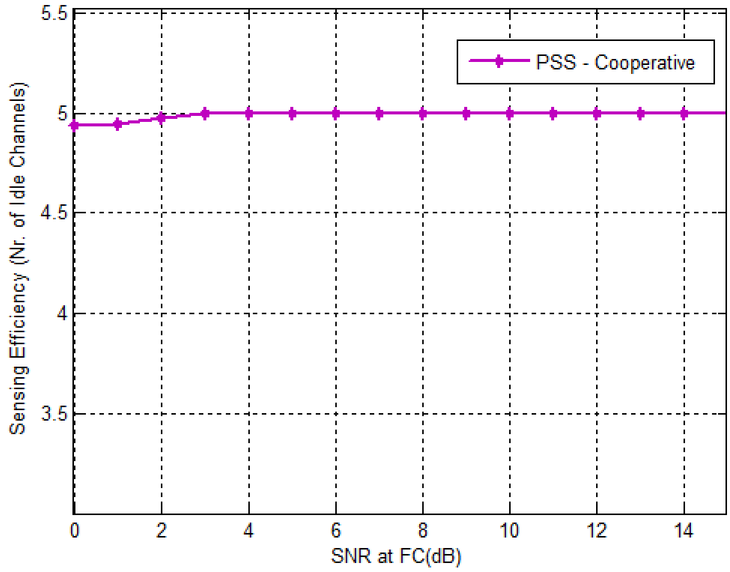

Figure 4-17: PSS - Sensing Efficiency at FC

4-3-5-3 Sensing Complexity

Figure 4-18 shows the variation of sensing complexity of the PSS algorithm, when the energy criteria is met.

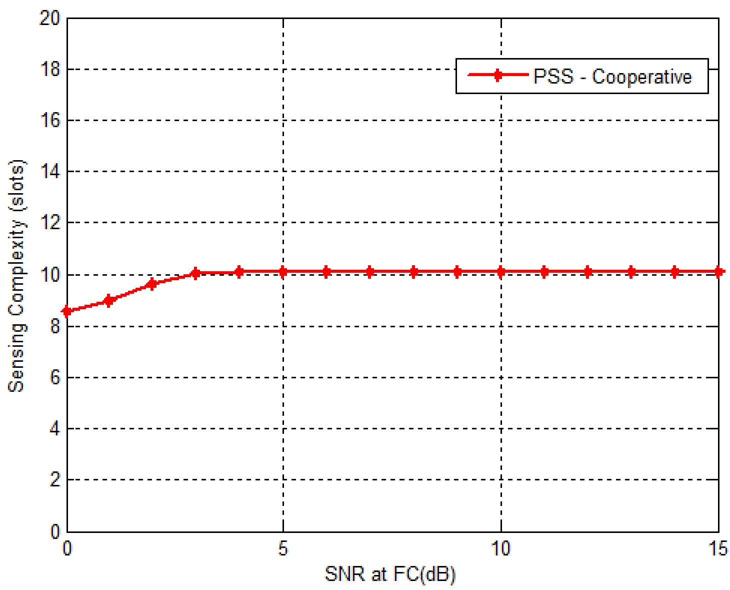

Figure 4-18: PSS - Sensing Complexity at FC after one cycle

In this simulation, the sensing period is reduced by $(\frac{1}{3})^{rd}$ of the total sensing period, since all the blocks are of equal size.

4-3-5-4 Sensing Energy

Here in the PSS algorithm simulation, we consider 3 SU's in the CRN as mentioned in Table 4-1. The percentage energy consumed by PSS, can be evaluated after considering the energy saving criteria, explained in Section 3-7-3. Since at the end of one cycle the entire spectrum is sensed using 19 slots, the number of slots used in one cycle should give the total energy consumed. From Figure 4-18, it is clear that at high SNR value (say 11 dB), a maximum of only 10 slots are utilized. Hence the percentage energy consumed by PSS at 11 dB, is given by,

$$\begin{aligned} Energy\_PSS, 11dB &\approx (\frac{10}{19})\% \\ &\approx 52.5\% \end{aligned} \tag{4-22}$$

However, at low SNR values (say 2 dB), 9.62 slots are used approximately. Thus, the percentage energy consumed by PSS at 2 dB, is given by,

$$\begin{aligned} Energy\_PSS, 2dB &\approx (\frac{9.62}{19})\% \\ &\approx 50.6\% \end{aligned} \tag{4-23}$$

4-4 Comparative Analysis of Algorithms

4-4-1 Sensing Accuracy

Figure 4-19 shows the comparison of all the algorithms in the CS scenario, with respect to the total sensing error probability.

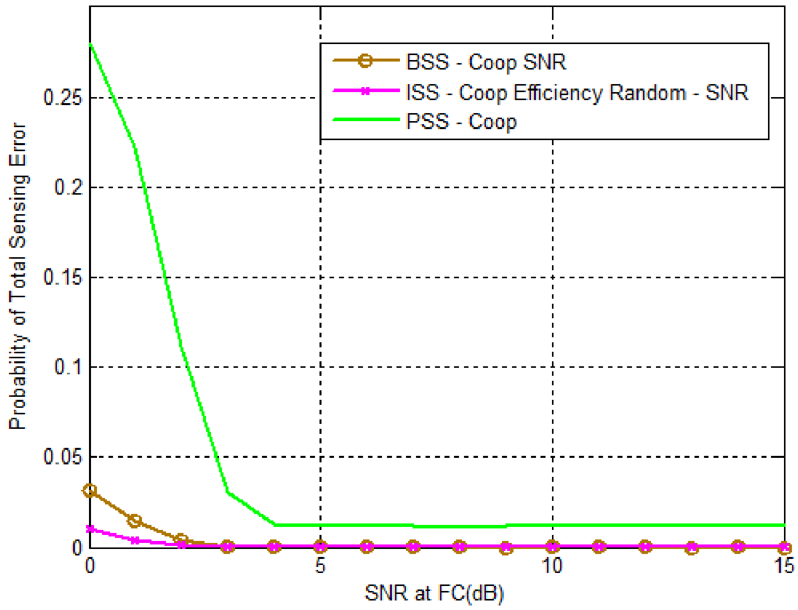

Figure 4-19: Sensing Accuracy : Comparison of best case scenario of BSS and ISS versus PSS

Here the techniques that provide the best performances in CS scenario of both ISS and BSS are compared with PSS algorithm. It is clear that random search method in efficiency based scheduling criteria of ISS algorithm, provides the highest performance. Further, PSS has the worst performance. This can be justified from the fact that in both ISS and BSS algorithms, soft decision based data fusion method was adopted. However in PSS, hard decision based CS was chosen, in order to meet the energy saving criteria. Even though the spatio-temporal diversity technique adopted in PSS should improve the accuracy, it can be noticed that only $(\frac{2}{3})^{rd}$ of the total sensing energy is spent for the sensing operation. Thus it is evident that there is a trade-off between the sensing energy and accuracy.

Figure 4-20 shows the comparison of all the algorithms in terms of sensing accuracy. However, here the techniques that provide the worst performance in CS scenario of both BSS and ISS algorithms are compared with the PSS algorithm. It is evident that, in the high SNR regions of say 11 dB, all the three algorithms provide similar error performance,with a maximum of 1% sensing error probability.

4-4-2 Sensing Efficiency

Figure 4-21 shows the comparison of all three algorithms with respect to sensing efficiency.

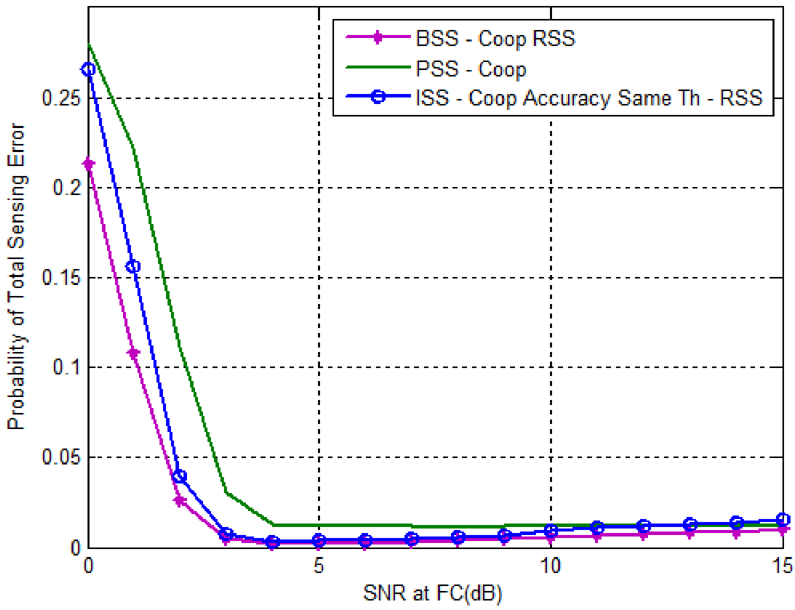

Figure 4-20: Sensing Accuracy : Comparison of worst case scenario of BSS and ISS versus PSS

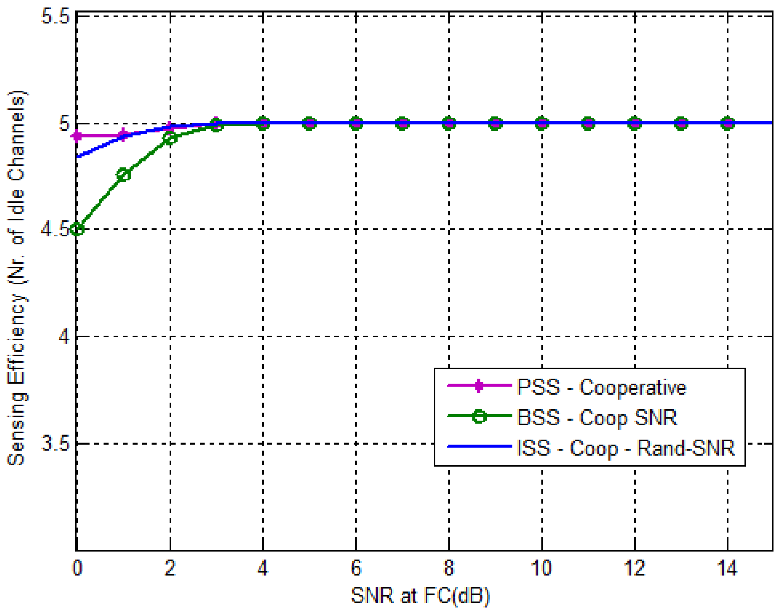

Figure 4-21: Sensing Efficiency - Comparison of best case scenario of BSS and ISS versus PSS

Here the techniques that provide the best performance in the CS scenario of both BSS and ISS algorithms are compared with the PSS algorithm. It is evident that at low SNR regions, the PSS outperforms BSS by a significant amount. However both ISS and PSS algorithms have similar performances even at low SNR regions.

Similarly a comparison between the three algorithms in the worst case scenario, is shown in Figure 4-22. Here, the techniques that provide the worst performance in the CS scenario of both BSS and ISS algorithms are compared against the PSS algorithm. Clearly PSS provides more robust sensing efficiency at low SNR regions. Even at high

SNR regions (say around 11 dB), PSS has a very small improvement of 0.1% over BSS and ISS.

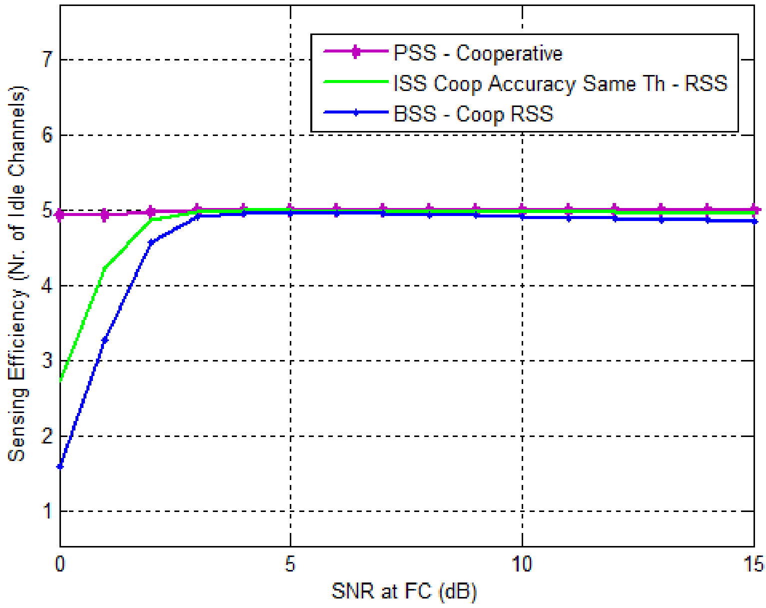

Figure 4-22: Sensing Efficiency - Comparison of worst case scenario of BSS and ISS versus PSS

4-4-3 Sensing Complexity

Figure's 4-23 and 4-24 provide the comparison of the three algorithms with respect to the sensing complexity, when considering the best and the worst case, respectively. From both the figures, it is clear that PSS algorithm has the least complexity compared to the other two algorithms.

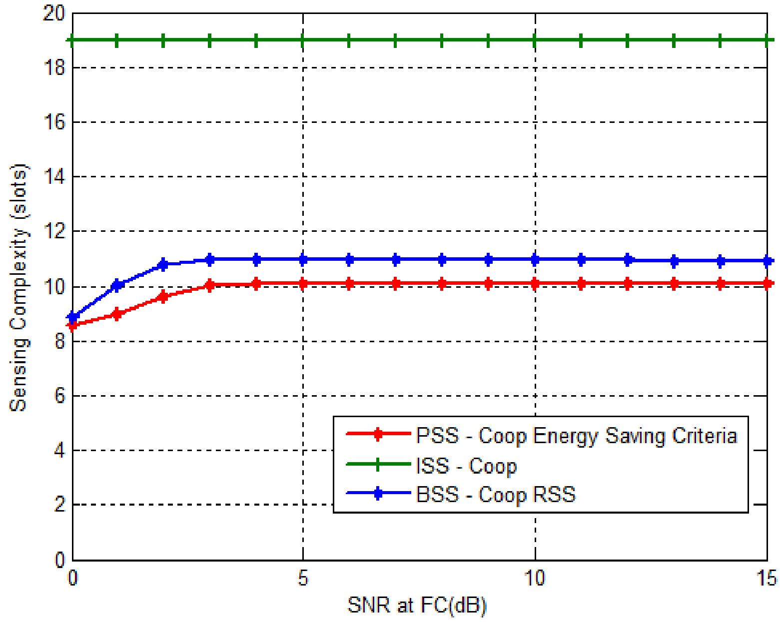

Figure 4-23: Sensing Complexity - Comparison of best case scenario of BSS and ISS versus PSS

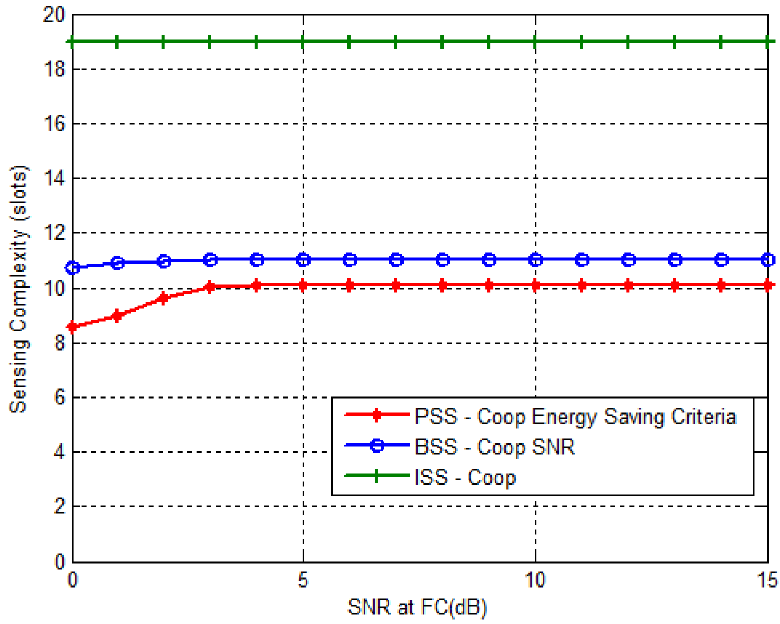

Figure 4-24: Sensing Complexity - Comparison of worst case scenario of BSS and ISS versus PSS

4-4-4 Sensing Energy

Considering the simulation parameters given in Table 4-1, an analysis is made with respect to the sensing energy consumption for all the algorithms discussed in this thesis. Figure 4-25 shows the sensing energy analysis and comparison for the best case scenario under the CS scheme of both BSS and ISS versus PSS. Also two different SNR regions are considered in order to have a better understanding of the analysis.

ALGORITHM	SENSING TECHNIQUE	PERCENTAGE ENERGY CONSUMPTION	
		SNR region (11 dB)	SNR region (2 dB)
BSS	RSS based fusion	57.89 %	56.73 %
ISS	All scheduling type	100 %	100 %
PSS	Energy saving criteria	52.63 %	50.63 %

Figure 4-25: Sensing energy analysis for best performance techniques of BSS and ISS versus PSS

Figure 4-26 shows the sensing energy analysis and comparison for the worst case scenario under the CS scheme of both BSS and ISS algorithms versus PSS algorithm.

ALGORITHM	SENSING TECHNIQUE	PERCENTAGE ENERGY CONSUMPTION	
		SNR region (11 dB)	SNR region (2 dB)
BSS	SNR based fusion	57.89 %	57.68 %
ISS	All scheduling type	100 %	100 %
PSS	Energy saving criteria	52.63 %	50.63 %

Figure 4-26: Sensing energy analysis for worst performance techniques of BSS and ISS versus PSS

Clearly, PSS algorithm is more robust with respect to the sensing energy consumption. ISS algorithm has the worst performance with a total energy consumption of 100%.

4-5 Validation of Spectrum Sensing Algorithms

The various algorithms proposed in this thesis are validated by acquiring real time measurements using Imec's lab equipment's. The setup used to obtain the spectrum measurements is explained in the following sections. An equivalent simulation scenario has been created to compare the results of the three algorithms in terms of sensing accuracy.

4-5-1 Measurement Setup

Figure 4-27 shows the setup that was used to obtain the real time spectral measurements.

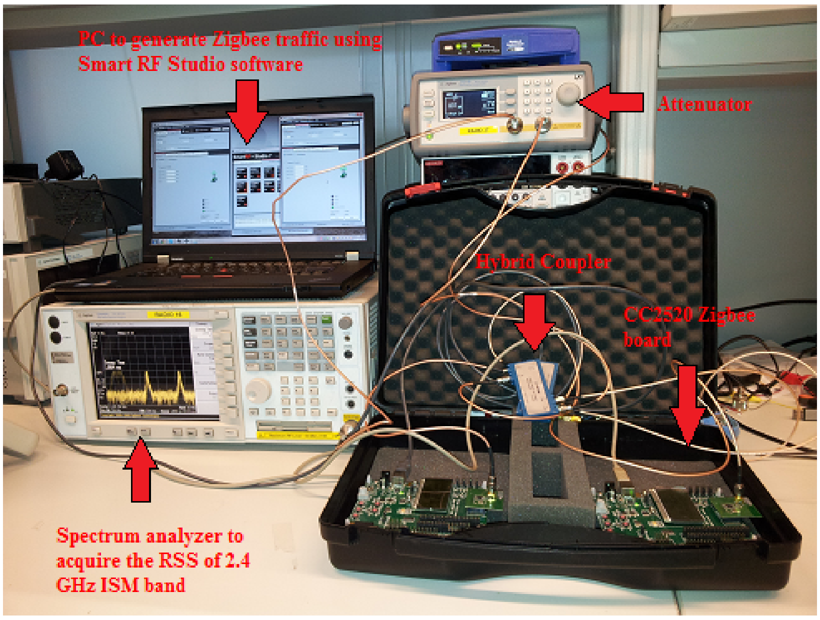

Figure 4-27: Measurement Setup for the validation of BSS, ISS and PSS algorithms

The setup consists of the following components,

1. *PC / Laptop* - To generate the Zigbee traffic and interface it to the CC2520 evaluation board.
2. *CC2520 Evaluation Module Kit* - Used to transmit Zigbee traffic.
3. *Hybrid Coupler* - To combine two Zigbee traffic sources transmitted by the CC2520 boards.
4. *Attenuator* - To control the observed RSS to study the variation of sensing performance.
5. *Spectrum Analyzer* - To acquire the RSS of 2.4 GHz ISM band.

Nr.	PARAMETER	DESCRIPTION
1	Primary User 1 or Interferer_1	IEEE802.11b WLAN
2	Primary User 2 or Interferer_2	IEEE802.15.4 Zigbee
3	Number of Secondary Users	3
4	Nr. of idle Zigbee channels	14
5	Nr. of busy Zigbee channels	2
6	Nr. of idle WLAN channels	3
7	Nr. of busy WLAN channels	0

Table 4-3: Common simulation parameters for validation of BSS, ISS and PSS algorithms

The measurement setup includes two CC2520 RF boards interfaced with the laptop that generates continuous Zigbee traffic using the Smart RF Studio software. This software enables to control the nature of the traffic along with the choice of the channel. The generated traffic from the two CC2520 boards are coupled using a hybrid coupler and is further passed through an attenuator via optical cables. The main role of the attenuator is to control the transmitted signal strength, in order to vary the received SNR to study the variations of the sensing accuracy of the three algorithms. The attenuator output is connected to the spectrum analyzer, where the spectrum is acquired for the above mentioned parameters in Table 4-3. The acquired spectral information is fed into the algorithms proposed in this thesis. The sensing accuracy of both non-cooperative and cooperative schemes are evaluated.

An equivalent Matlab simulation scenario is created matching the parameters provided in Table 4-3. A comparison between the two are made and the results are plotted in the following section.

4-5-2 Performance Results

Figure 4-28 shows the sensing error probability comparison between the non-cooperative and cooperative scenarios, when BSS algorithm is executed with the measured RSS values. As expected, the CS scheme outperforms the non-cooperative scheme.

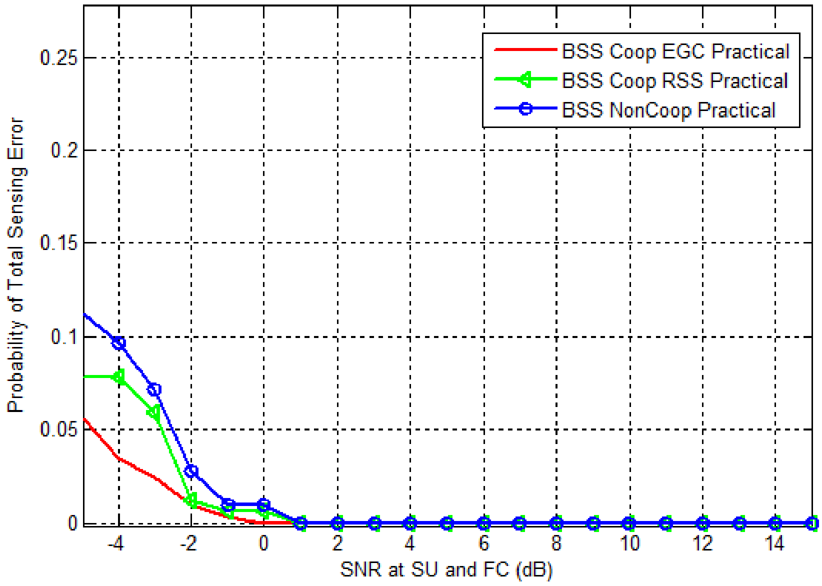

Figure 4-28: BSS - Measurement - Sensing accuracy at SU and at FC when any 2 SU's received SNR are fixed at -1dB

Figure 4-29 provides a comparison between the simulation and measurement results, when BSS is executed at the SU (non-cooperative scenario).

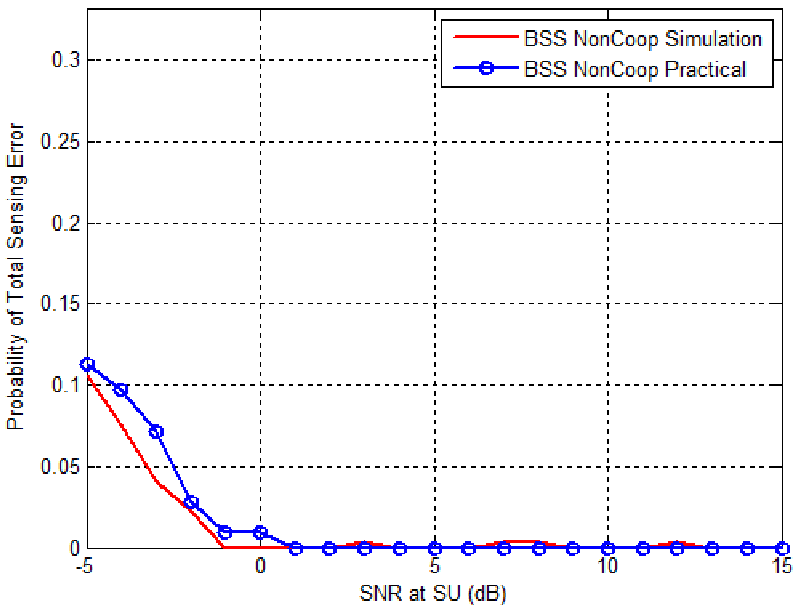

Figure 4-29: BSS - Sensing accuracy comparison between simulation and measurement at SU

Figure's 4-30 and 4-31 show an example scenario where the comparison between the simulation and measurement results are shown, when BSS is executed in a cooperative scenario, under both EGC and RSS based fusion methods, respectively.

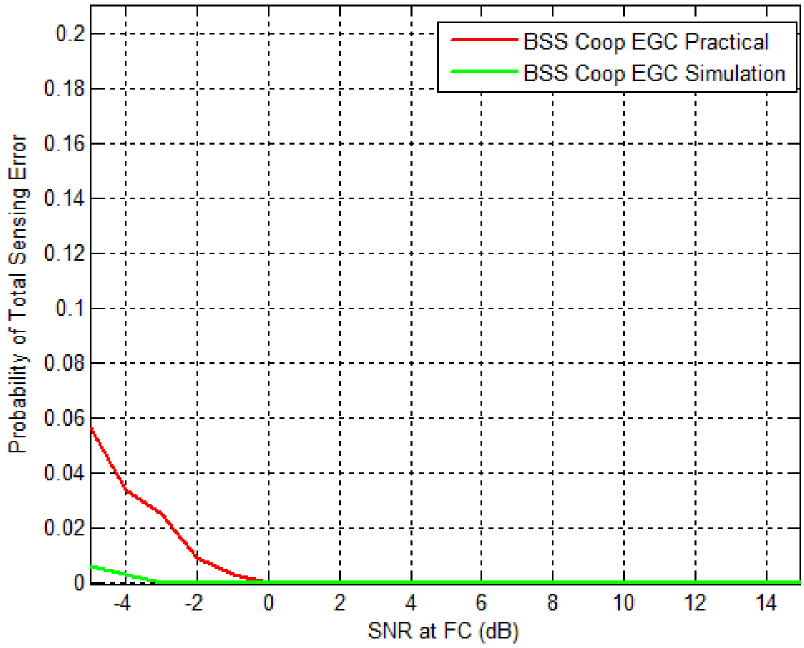

Figure 4-30: BSS - Sensing accuracy comparison between simulation and measurement at FC with EGC based fusion method

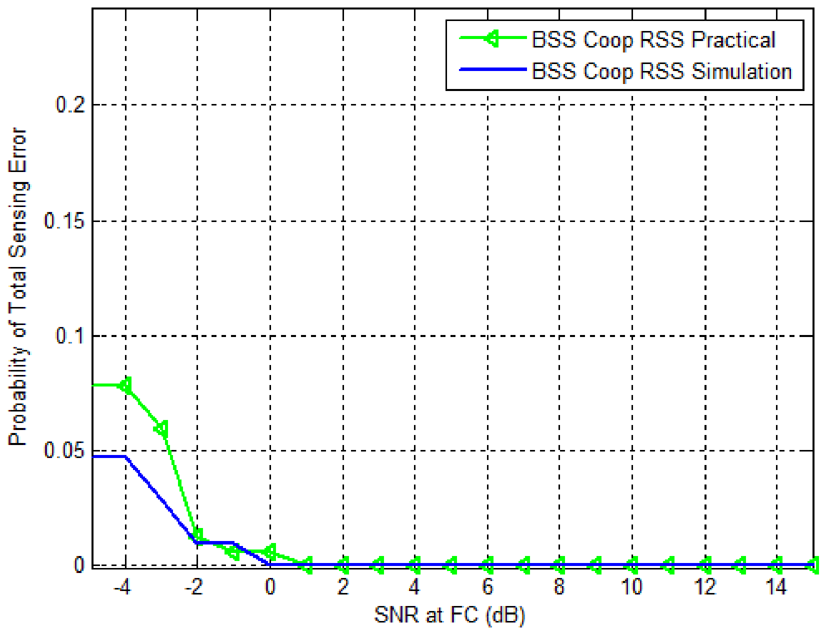

Figure 4-31: BSS - Sensing accuracy comparison between simulation and measurement at FC with RSS based fusion method

Clearly, both the simulation and practical performance results of BSS algorithm are more or less matching each other.

Similar results are observed for the ISS algorithm as well. Figure 4-32 shows the performance of ISS algorithm with the measured spectrum results. Both non-cooperative and CS schemes are compared.

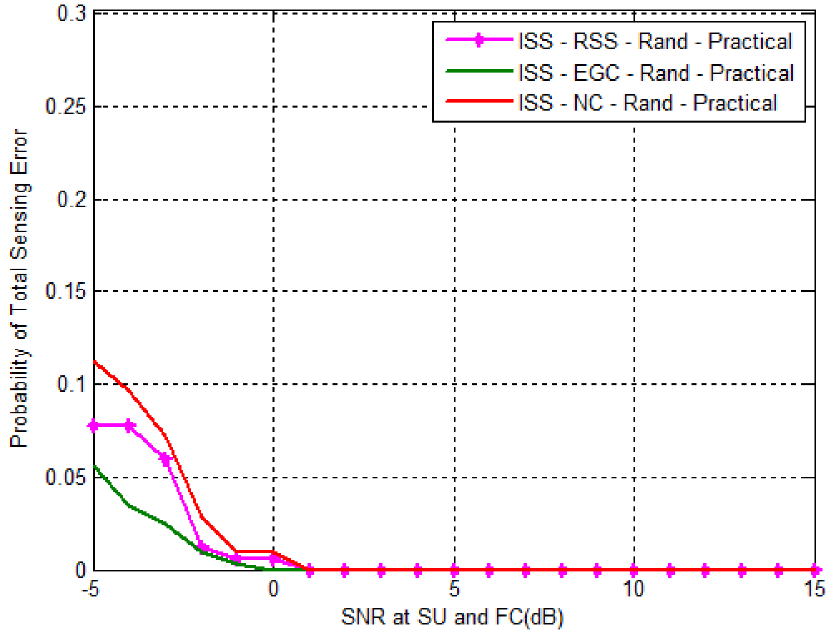

Figure 4-32: ISS - Sensing accuracy at SU and FC with the measured spectrum under random search method based efficiency scheduling criteria (2 out of 3 SU's SNR fixed at -1dB)

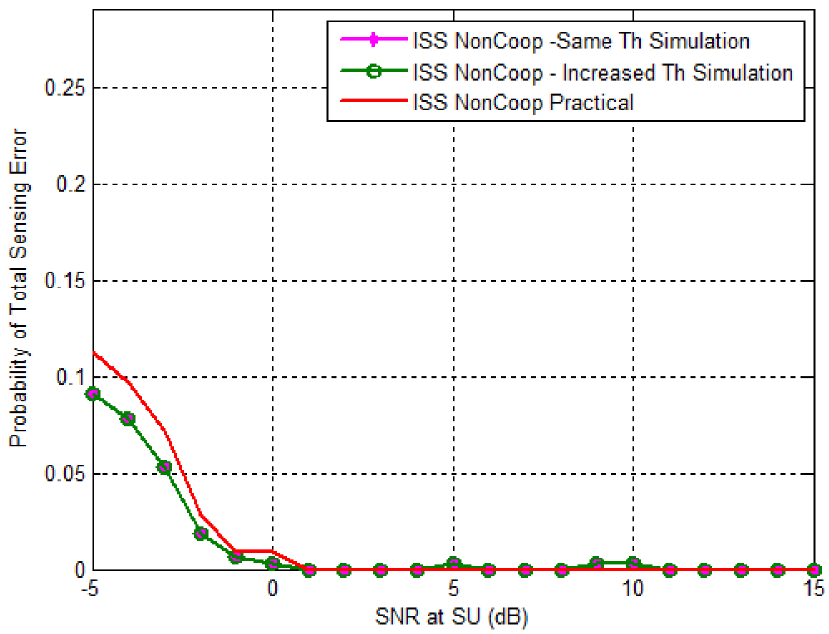

Figure 4-33: ISS - Sensing accuracy comparison between simulation and measurement results in the non-cooperative scenario

Figure 4-33, indicates the comparison between the simulation and measurement results when ISS algorithm is executed. Clearly both of the performances match very well.

A comparison is made for a cooperative scenario when ISS is executed in both simulated and measured spectrum, as shown in Figure 4-34.

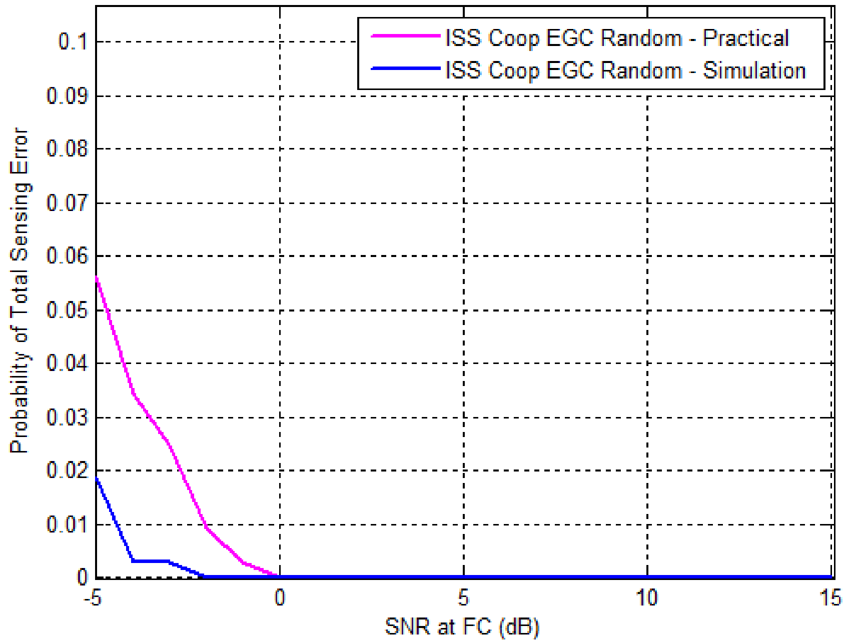

Figure 4-34: ISS - Sensing accuracy comparison between simulation and measurement results in the cooperative scenario under EGC based fusion method

PSS algorithm is also executed and validated with both simulated and measured spectrum as shown in Figure 4-35.

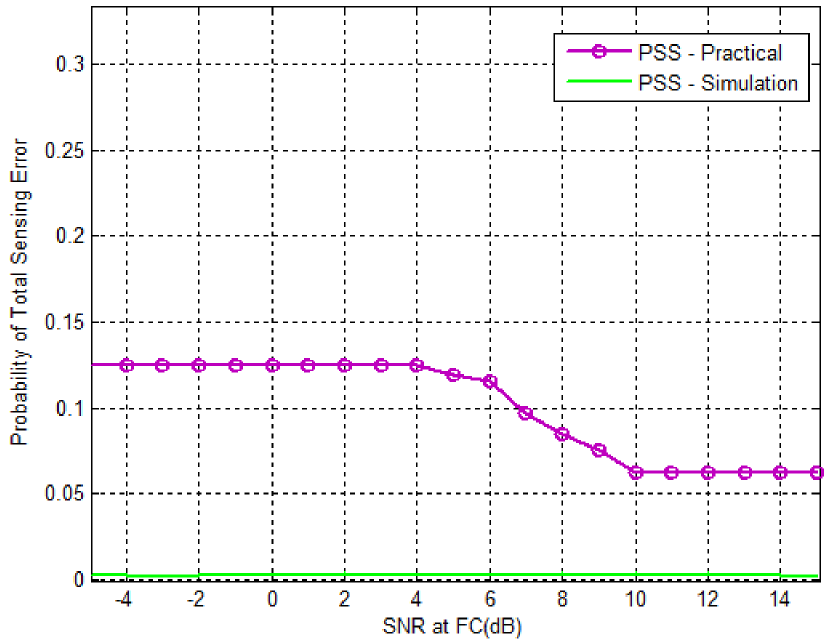

Figure 4-35: PSS - Sensing accuracy comparison between simulation and measurement results

Chapter 5

Summary, Conclusion and Future Work

5-1 Summary and Conclusions

In this thesis, several spectrum sensing algorithms were proposed for WBAN, in order to overcome the presence of excessive interference in the unlicensed 2.4 GHz ISM band. Any two narrowband interferer's within this band are considered for the design of these algorithms. A centralized cooperative sensing model has been adopted to enhance the overall sensing performance in terms of accuracy, efficiency and energy. The main contributions of this thesis are,

- Energy detection (ED) based cooperative spectrum sensing (CS) algorithms, adopting a simple sequential channel search technique.
- Basic Sequential Search (BSS) algorithm designed to sense any two PU's in the 2.4 GHz ISM band. BSS forms the basis for both ISS and PSS algorithms.
- Improved Sequential Search (ISS) algorithms introducing several scheduling techniques to improve either sensing accuracy or sensing efficiency.
- Parallel-Sequential Search (PSS) algorithm adopting spatio-temporal diversity to enhance both sensing accuracy and efficiency. Through the proposed energy saving criteria, the overall sensing energy has also been minimized.
- Performance evaluation and comparison of BSS, ISS and PSS algorithms in terms of sensing accuracy, efficiency, complexity and energy. Both non-cooperative and CS schemes have been explored, in order to understand the benefits of CS sensing. Several data fusion techniques have also been studied in the CS scheme.
- Validation of simulation results with real time measurement of spectrum in the 2.4 GHz ISM band.

The overall comparison of BSS, ISS and PSS algorithms under a CS scenario are summarized in Figure 5-1. We have the following conclusions,

- The cooperative sensing (CS) scenario proves to be more robust than the non-cooperative scenario, in terms of sensing performance. Although, with CS scenario, one must account for large sensing overhead. This trade-off must be appropriately balanced, while dealing with energy aware systems such as WBAN.
- Parallel-Sequential Search (PSS) algorithm proves to be the better choice in terms of sensing complexity, efficiency and energy. PSS algorithm consumes about 5.26% less energy than BSS algorithm and about 47.37% less energy than ISS algorithm, for the considered simulation scenario. The sensing complexity and energy in PSS generally depends on the spectrum occupancy of the PU's. In a crowded spectrum, PSS would consume less energy and vice versa. When we consider the total energy consumed during the execution of PSS, a small fraction of about ($\frac{1}{N1}$) is reduced, if the energy saving criteria is met. As the number of SU's increase in the network, the total energy saved will higher when compared to BSS and ISS. The concept of spatio-temporal diversity enables this algorithm to achieve higher sensing efficiency than other algorithms. On the other hand, sensing accuracy of PSS is comparatively lower than BSS and ISS. PSS introduces approximately 2% of total sensing error at the operating region (11 dB) of Imec's WBAN radio. The trade-off between the sensing energy and accuracy can be clearly argued. The sensing overhead involved is much lower than BSS and ISS, due to the hard decision based fusion method that is adopted in PSS. This decision fusion method is an added reason for the lower sensing accuracy of PSS. PSS algorithm can only be adopted when there are atleast 3 SU's in the network. This is an added constraint in situations where only two SU's are available.
- With Basic Sequential Search (BSS), we can observe that both complexity and the energy consumption are on moderate level, for the considered simulation scenario. Both these parameters are related and depend on the nature of the spectrum occupancy, in the 2.4 GHz ISM band. In a highly crowded spectrum, BSS has lower sensing energy and complexity, and vice versa. No scheduling algorithms are involved with BSS, thus making it more simpler than PSS and ISS algorithms. BSS achieves a very high sensing accuracy under all the soft decision based fusion methods, indicating that it is reliable, when the number of SU's in the network is less.
- Improved Sequential Search (ISS) algorithm proves to be the least suitable among all the algorithms. Since all the slots within a sensing period are utilized, the sensing complexity is always maximum. It is observed that under SNR based fusion method along with random search technique of efficiency based scheduling criteria, a very high sensing efficiency, that is close to that of PSS is obtained. The same method improves the sensing accuracy as well, indicating that the random search technique in efficiency based scheduling criteria is the more suitable choice among the 4 techniques proposed. It should be noted that with ISS, the sensing overhead increases drastically in the soft decision based cooperative scenario.

PARAMETERS	**BSS**	**ISS**	**PSS**
Sensing Scenario's Possible	Non-Cooperative, Cooperative	Non-Cooperative, Cooperative	Cooperative
Decision Fusion Technique(s)	Only Soft Decision : SNR, RSS, EGC	Only Soft Decision : SNR, RSS, EGC	Only Hard Decision
Scheduling	NO	YES	YES
Sensing Overhead in CRN with 3 SU's	***Moderate***	***High***	***Small***
Sensing Accuracy @ operating region of BAN radio (11 dB), when the received SNR of any two SU's are fixed at 3 dB	Best Case Scenario: ***SNR based Fusion*** ***High***	Best Case Scenario: ***SNR based Fusion & Random search method in Efficiency based Scheduling Criteria*** ***High***	***Low***
	Worst Case Scenario: ***RSS based Fusion*** ***High***	Worst Case Scenario: ***RSS based Fusion & Accuracy based Scheduling Criteria with Same Threshold*** ***Moderate***	***Low***
Sensing Efficiency @ operating region of BAN radio (11 dB), when the received SNR of any two SU's are fixed at 3 dB	Best Case Scenario: ***SNR based Fusion*** ***High***	Best Case Scenario: ***SNR based Fusion & Random search method in Efficiency based Scheduling Criteria*** ***High***	***High***
	Worst Case Scenario: ***RSS based Fusion*** ***Low***	Worst Case Scenario: ***RSS based Fusion & Accuracy based Scheduling Criteria with Same Threshold*** ***Moderate***	***High***
Sensing Complexity @ operating region of BAN radio (11 dB), when the received SNR of any two SU's are fixed at 3 dB	Best Case Scenario: ***RSS based Fusion*** ***Moderate***	Best Case Scenario: ***All Fusion methods & All Scheduling Criteria*** ***High***	***Low***
	Worst Case Scenario: ***SNR based Fusion*** ***Moderate***	Worst Case Scenario: ***All Fusion methods & All Scheduling Criteria*** ***High***	***Low***
Sensing Energy @ operating region of BAN radio (11 dB), when the received SNR of any two SU's are fixed at 3 dB	Best Case Scenario: ***Moderate***	Best Case Scenario: ***High***	***Low***
	Worst Case Scenario: ***Moderate***	Worst Case Scenario: ***High***	***Low***

Figure 5-1: Summary of evaluation of BSS, ISS and PSS algorithms

5-2 Furure Scope

- In this thesis, we have dealt with algorithms that sense any 2 PU's in the 2.4 GHz ISM band. However, it can be extended to sense more than 2 narrowband PU's. By accounting for more PU's, the sensing complexity will be increased by the total number of non-overlapping channels in each of the considered PU. It given by the relation,

$$SensingComplexity = N1 + N2 + ... + N_n \tag{5-1}$$

  Where 'n' represents the nth PU and 'N$_n$' represents the total number of non-overlapping channels of the nth PU in the 2.4 GHz ISM band.

- In this thesis, only the Interferer_2 channels are utilized for transmission due to the WBAN radio's limited frequency selectivity. However, if the selectivity of the radio is improved, then both Interferer_1 and 2 channels can be utilized.
- We have considered a Gaussian channel model. It is difficult to obtain the closed form expression for the corresponding threshold of the ED. Hence a theoretical study on the evaluation of the ED threshold can be performed. Further, Rayleigh and/or Rician channel models can also be considered for the evaluation of the receiver's ED threshold.
- Through location aware cognitive radios, priorities can be assigned to each of the SU in the network, thereby aiming to improve the sensing accuracy and efficiency. The SU's closer to the PU interferers can have a higher priority (or higher reliability factor) and vice versa. However, one must account for the energy consumption method, since each CR has to be aware of its surroundings either constantly or at regular intervals.
- A decentralized cooperative sensing model can be explored, where there is no FC. Each of the SU can communicate among themselves and arrive at a unified decision on the presence or absence of PU's, as shown in Figure 5-2.

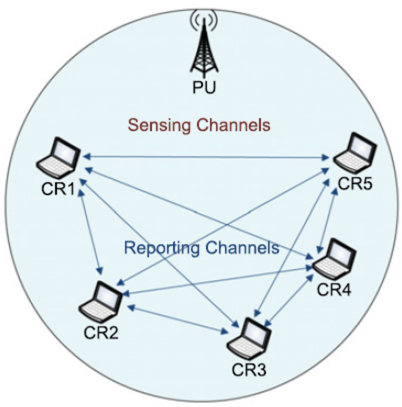

Figure 5-2: A decentralized cooperative sensing model [6]

Publications

1. (Pre-study)
   Kalyanasundaram, P.; Li Huang; Imamura, K.; Dolmans, G.; , "Autonomous operation of super-regenerative receiver in BAN," *Medical Information and Communication Technology (ISMICT), 2012 6th International Symposium* on , vol., no., pp.1-4, 25-29 March 2012

2. Kalyanasundaram, P, Li Huang, Dolmans, G and E. Onur. Cooperative spectrum sensing algorithms along with adaptive scheduling in WBAN. To be submitted to PIMRC 2013

3. Kalyanasundaram, P, Li Huang, Dolmans, G and E. Onur. Energy efficient cooperative spectrum sensing algorithm for wireless sensors. To be submitted to SPAWC 2013

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Glossary

List of Acronyms

CRN Cognitive Radio Network

SS Spectrum Sensing

CR Cognitive Radio

ISM Industrial Scientific and Medical

SU Secondary User

PU Primary User

FC Fusion Center

CS Cooperative Sensing

CBS Cognitive Base Station

WC Weighted Combining

SRR Super-Regenerative Receiver

SPRT Sequential Probability Ratio Test

BSS Basic Sequential Search

ISS Improved Sequential Search

PSS Parallel-Sequential Search

MAC Medium Access Control

PHY Physical Layer

ED Energy Detector

ULP Ultra-Low Power

SIR Signal to Interference Ratio

CFC Common Free Channels

SNR Signal to Noise Ratio

RSS Received Signal Strength

EGC Equal Gain Combining

RF Radio Frequency

WBAN Wireless Body Area Network

WLAN Wireless Local Area Network

WSN Wireless Sensor Network