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Author(s)	Hossain, Mohammad Amzad
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Enhancing Spectrum Sensing Performance for the Cognitive Radio Based Internet of Things

PhD Dissertation

Mohammad Amzad Hossain

School of Computer Science
College of Science and Engineering
National University of Ireland Galway, Galway, Ireland

Dr. Enda Barrett (Supervisor)
Dr. Michael Schukat (Co-supervisor)
Prof. Dr. David Grace (External Examiner)
Dr. Finlay Smith (Internal Examiner)

Abstract

In cognitive radio based internet of things (CR-IoT) networks spectrum sensing and decision making processes to determine whether the primary user (PU) signal is present or absent in the network are very important and vital issues to the utilisation of the idle licensed spectrum. Spectrum sensing is at the heart of CR-IoT networks to minimize the interference between the PU signal and the CR-IoT user signal. Within that context, this thesis makes the following contributions:

Firstly, I proposed the concept of multiple reporting channels (MRC) for cluster-based cooperative spectrum sensing (CSS) for CR-IoT networks to better utilize the reporting time slot by extending the sensing time of CR-IoT users. A multiple reporting channels concept is proposed based on frequency division multiple access to enhance the spectrum sensing performance and reduce the reporting time delay of all cluster heads (CHs). This approach significantly enhances the sensing time for all CR-IoT users than the non-sequential as well as minimize the reporting time delay of all CHs than sequential single channel reporting approach. These two features of our proposed approach increase the decision accuracy of the fusion centre (FC) more than the conventional approach. Simulation results prove that my proposed approach significantly enhances the sensing accuracy and mitigate the reporting time delay of CH compared to the conventional approach.

Secondly, I proposed a novel energy efficient sequential energy detection (ED) spectrum sensing technique which enhances the sensing duration of each unlicensed CR-IoT user by utilizing the reporting time slot when compared to the non-sequential conventional ED spectrum sensing scheme. In addition, each unlicensed CR-IoT user calculates the weight factor based on the Kullback Leibler divergence (KLD) score, which enhances the detection performance and sum rate. The simulation results indicate that the my proposed sequential ED spectrum sensing scheme achieves a better sensing gain, an increased sum rate, an enhanced energy and spectral efficiency when compared to the non-sequential conventional ED spectrum sensing scheme with interference constraints.

Thirdly, I introduced a novel multi-user multiple-input and multiple-output (MU-MIMO) antennas aided cluster based cooperative spectrum sensing (CB-CSS) scheme for cognitive radio based internet of vehicles (CR-IoV) networks. In this proposed scheme, each CR embedded vehicles (CRV) sends sensing data to the cluster head

which makes a cluster decision by using the soft data fusion rule like the equal gain combining (EGC) fusion rule and the maximal ratio combining (MRC) fusion rule; whereas the FC makes a final global decision by using the K-out-of-N rule to identify the presence of the PU signal. Simulation results show that the proposed MU-MIMO antennas aided CB-CSS scheme achieves a better sensing gain, enhanced the sum rate and lower global error probability when compared to both the conventional single-input and single-output (SISO) antenna based CSS and non-cooperative spectrum sensing (NCSS) schemes. In addition, the proposed scheme achieves a lower traffic overhead when compared to the MU-MIMO based CSS scheme without the cluster.

Finally, I introduced a machine learning (ML)-based secure cooperative spectrum sensing techniques for CR-IoT networks. In the proposed scheme, we use the Support Vector Machines (SVM), K-Nearest Neighbors (KNN) and Naive Bayes (NB) machine learning algorithms to classify the legitimate CR-IoT users and three types of malicious users (MUs), such as (i) Always Low Energy Malicious Users (ALEMUs), (i) Always High Energy Malicious Users (AHEMUs), and (i) Random Energy Malicious Users (REMUs). In this thesis, I use majority fusion rule at the intelligent fusion centre (IFC) on the sensing results of legitimate CR-IoT users to make the global decision about presence or absence of the primary user (PU) in the networks. My proposed scheme is significantly improved the sensing performance of knowing the activity of PUs for three kinds of malicious users (i.e., ALEMUs, AHEMUs, and REMUs) cases than the conventional(without security technique) scheme. In addition, it decreases the global error probability at the IFC over the conventional scheme.

Statement of Originality

I declare that the research described in this thesis is original work, which I undertook at the National University of Ireland Galway (NUIG), Galway, Ireland during the years 2017-2021. This work has not previously been presented for an award at this or any other university.

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Nomenclature

ADC	Analog-to-digital converter
ACI	Adjacent channel interference
AF	Amplify-forward
AIC	Akaike's information criteria
BPSK	Binary phase shift keying
CAV	Covariance absolute value
CB-CSS	Cluster based cooperative spectrum sensing
CCI	Co-channel interference
CCRRN	Cluster-based cognitive radio relay network
CCRN	Cluster-based cooperative cognitive radio network
CIoV	Cognitive internet of vehicles
CH	Cluster head
CLT	Central limit theorem
CR	Cognitive radio
CR-IoT	Cognitive radio-Internet of things
CR-IoV	Cognitive radio-Internet of vehicles
CRN	Cognitive radio network
CRV	Cognitive radio enable vehicle
CSCG	Circularly symmetric complex Gaussian
CSS	Cooperative spectrum sensing
DABFS	Direction aware best forwarder selection
FCM	Fuzzy C-Means
ED	Energy detection
EE	Energy efficiency
EGC	Equal gain combination
EVD	Eigenvalue based detection
FC	Fusion centre
FCC	Federal communication commission
GSM	Global system for mobile communications
HDF	Hard decision fusion
IoT	Internet of things
ISI	Inter symbol interference

ITS	Intelligent transportation system
KLD	Kullback-Leibler divergence
M2M	Machine-to-machine
MIMO	Multiple-input and multiple-output
MISO	Multiple-input and single-output
MRC	Maximal ratio combination
MU	Multi-user
MUs	Malicious users
MU-MIMO	Multi-user multiple-input and multiple-output
NCSS	Non-cooperative spectrum sensing
PSD	Power spectral density
PDF	Probability distribution function
PU	Primary user
QoS	Quality of service
QPSK	Quadrature Phase Shift Keying
ROC	Receiver operating characteristic
Rx	Receiver
SE	Spectral efficiency
SINR	Signal-to-interference plus noise
SISO	Single-input and single-output
SNR	Signal-to-noise ratio
SU	Secondary user
SVM	Support vector machine
TDMA	Time division multiplexing access
Tx	Transmitter
VANETs	Vehicular ad hoc networks
V2I	Vehicle to roadside infrastructure
V2V	Vehicle to vehicle
V2X	Vehicle to anything
WSN	Wireless sensor network
HD	Half duplex
FD	Full duplex
LTE	Long term evolution

Chapter 1

Introduction

1.1 Motivation

The growing interest and demand for wireless applications has led to the ongoing development and expansion of wireless communication technologies. This continued improvement and development of these technologies has facilitated areas such as military communications, data communication, video conferencing, healthcare services, financial transactions, social interactions, education, mobile communications, Internet of Things (IoT) devices, device-to-device communications and intelligent transportation systems. The increase in the volume of wireless communications creates a growing demand for radio spectrum. However, the radio spectrum is a limited resource. Due to the limitation of spectrum resources, academic researchers, network operators, regulators, and manufacturers are working together to improve spectrum utilization. At present, the radio spectrum is allocated for various services on a dedicated basis. This means that specific frequency bands are assigned to a specific service or wireless user. This fixed radio spectrum access policy allows systems to operate at a sufficient transmit power without interference with other communication systems within the specific geographical and frequency areas of each authorized system. As a result, each wireless system can provide their services covering a larger area with the required quality. Nevertheless, due to the high demand for radio spectrum from various wireless services, it is becoming increasingly difficult to integrate new systems into the limited radio spectrum. In the current fixed spectrum allocation policy, the utilization of the radio spectrum varies significantly with time, geographic region, frequency band, and the number of users. In this context, several researchers have found that the allocated fixed spectrum bands are not fully utilized by licensed users [Pandit & Singh 13, Moon 17, Si *et al.* 19]. In this context, the utilization of the allocated licensed spectrum for the Trans-European Trunked Radio (TETRA) frequency band, the Code-Division Multiple Access (CDMA) frequency band, the Television (TV) frequency band, the System for Mobile Communication 1800 (GSM 1800) frequency band, the Extended GSM frequency band, the Universal Mobile Telecommunication System (UMTS) frequency band, and the Industrial, Scientific & Medical (ISM) frequency band are 37.5%, 50.7%, 20.4%, 21.8%, 51.9%, 3.8%, and 1% utilised respectively [Bhagate & Patil 17, Valenta *et al.* 09]. This non-utilisation of the radio spectrum has led to the need for greater flexibility in spectrum management and the utilisation of unused spectrum. These unused spectrum bands are called white space [Nekovee 09], which provides a great opportunity for wireless communication to overcome spectral deficiencies. Spectrum utilisation can be increased by allowing unlicensed users to use unused parts of the spectrum owned by licensed users. Therefore, new technology is needed to use this unused radio spectrum.

Internet of Things (IoT) is a data communication technology that connects various communication devices and methods to exchange data. It is a fast-growing technology that allows all connected devices to continuously capture and exchange data over the internet in order to enhance their value and services. IoT devices are called smart devices because they can automatically connect to other devices to perform data processing and exchange. Academics and regulatory bodies have provided different definitions of IoT. Some of the known definitions of IoT are given below:

According to the European Research Cluster [Van Kranenburg 08]:

—*"A dynamic global network infrastructure with self-configuring capabilities based on standard and inter-operable communication protocols where physical and virtual things have identities, physical attributes, and virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network."*

According to Haller et al. [Haller *et al.* 08]:

—*"A world where physical objects are seamlessly integrated into the information network, and where the physical objects can become active participants in business processes. Services are available to interact with these 'smart objects' over the Internet, query their state and any information associated with them, taking into account security and privacy issues."*

Figure 1.1 shows the application areas of IoT. However, there are many issues that slow down the growth of IoT networks. Connecting a large number of heterogeneous wireless devices for data transmission, requires a lot of radio spectrum. In addition, higher implementation costs are required if large amounts of radio spectrum are to be purchased under the fixed spectrum allocation policy.

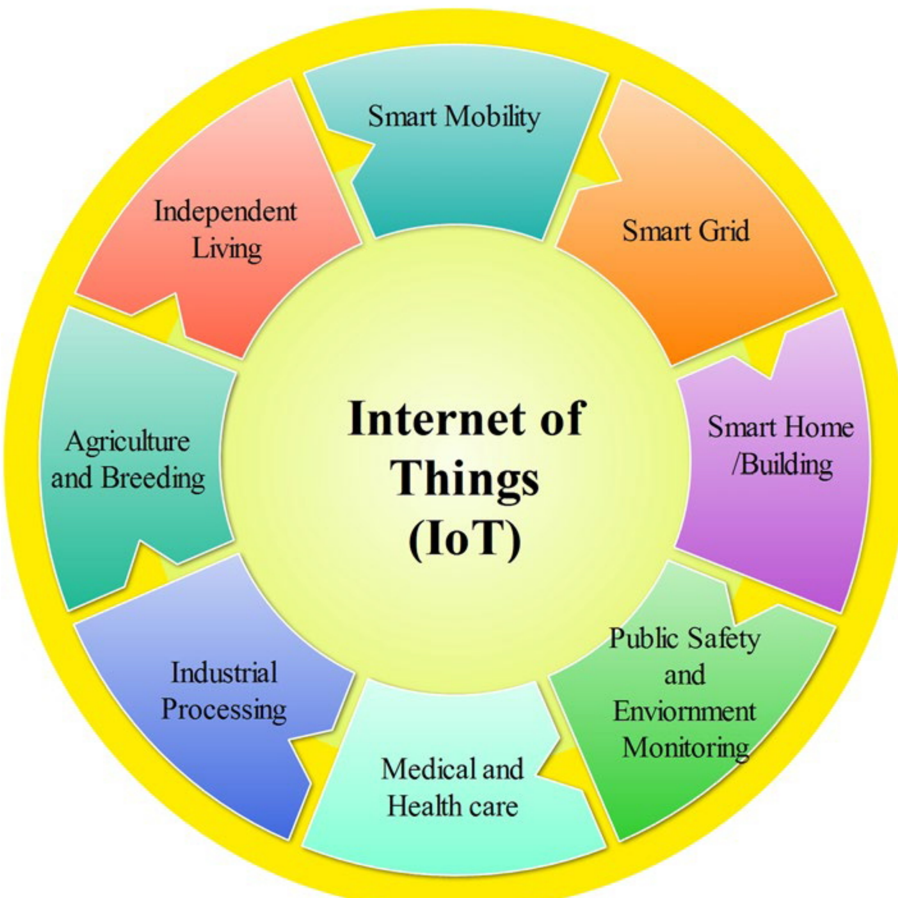

Figure 1.1: Applications area of IoT [Khanna & Kaur 20]

To meet the future radio spectrum demand, the cognitive radio (CR) is considered as an effective and revolutionary wireless communication technology to enhance radio spectrum utilization. Cognitive radio is a novel concept that mitigates the spectrum shortage problem by allowing a cognitive radio embedded unlicensed user (i.e., secondary user) to access the unused licensed user's (i.e., primary user) spectrum without interfering with each other. CR enables the secondary user to utilize the unused licensed-spectrum, referred to as a spectrum hole or white space. If a primary user starts to use this band, then the secondary user should seamlessly move to another spectrum hole to avoid interfering with the primary user. Figure 1.2 shows the opportunistic access of unused licensed spectrum (white space) by a CR user (i.e., secondary user).

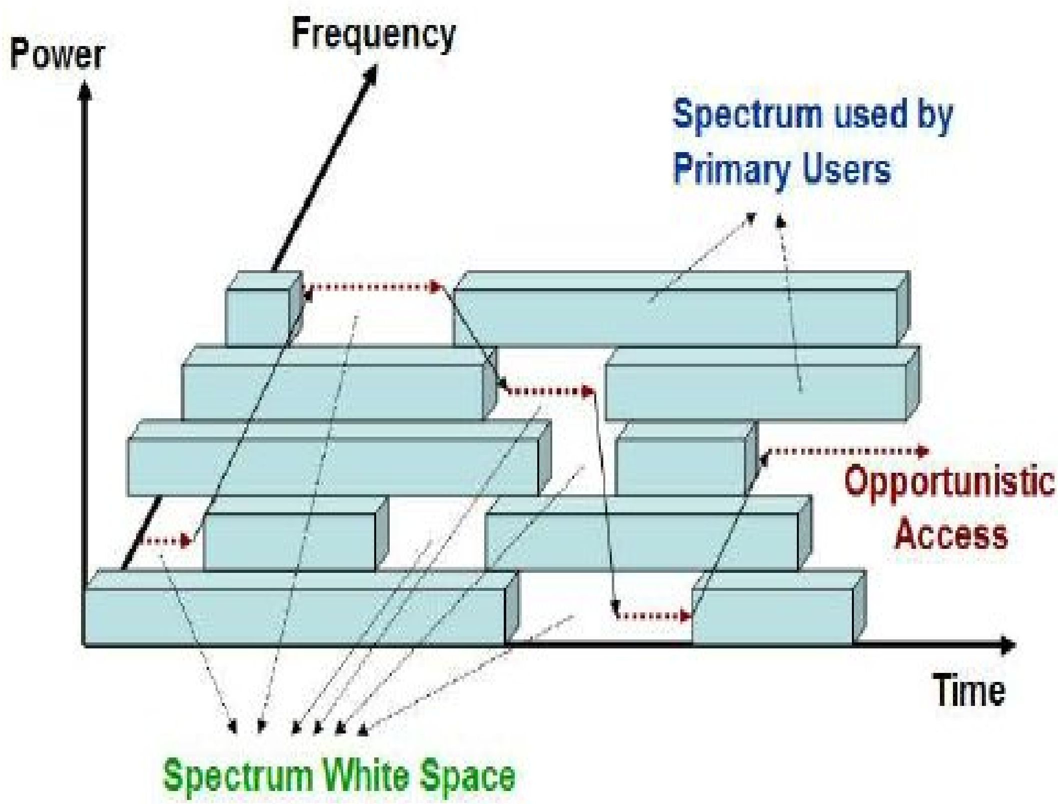

Figure 1.2: Opportunistic access of unused licensed spectrum (white space) by a CR user [Meghanathan 13]

There are several benefits to sharing this radio spectrum. For instance, the same radio frequency band can be used by more than one wireless communication system. Furthermore, a radio spectrum sharing opportunity can make it easier for operators to access spectrum and implement their own wireless infrastructure in which it is needed.

Cognitive Radio-enabled Internet of Things (CR-IoT) is an emerging field that is considered a future technology which can handle the increasing demands of radio spectrum for various IoT applications. CR-IoT mitigates the radio spectrum scarcity problem of large numbers of IoT devices by allowing cognitive radio embedded IoT user access to the licensed user spectrum in convenient conditions. However, there are several challenges that abate the outgrowth of CR-IoT networks such as lack of licensed spectrum detection accuracy, a low throughput, an inefficient energy consumption, and a higher global error probability. Therefore, this thesis is essentially concentrated to address the above challenges.

1.2 Research Questions

To overcome the technical challenges of CR-IoT networks, I conducted my research based on the following research questions:

- **RQ1**: How to increase the spectrum sensing gain and reduce reporting delays of cluster based CR-IoT networks?
- **RQ2**: How can the energy and spectral efficiency for CR-IoT networks be enhanced?
- **RQ3**: How to increase the spectrum sensing gain and system sum rate as well as reduce the global decision error of cluster based Cognitive Radio-Internet of Vehicles (CR-IoV) networks?
- **RQ4**: How can we detect a malicious secondary user in CR-IoT networks to enhance the security and sensing performance?

1.3 Contributions

The major technical contributions of this thesis can be summarized as follows:

- Firstly, I propose a sequential multiple reporting channels approach for cluster-based cooperative CR-IoT networks to enhance the sensing time for CR-IoT users and minimize the reporting time delay of cluster heads (CHs), compared to the non-sequential conventional approach. The sensing performance and reporting time delay of the proposed approach is analysed based on the longest sensing time duration by using the "K-out-of-N" rule. Using simulation, I show that my proposed approach achieves better sensing performance for CR-IoT users and reduces the reporting time delay of CHs compared to the conventional approach.

- Secondly, I propose a novel energy efficient sequential energy detection (ED) spectrum sensing scheme to extend the sensing time of each unlicensed CR-IoT user by utilizing the reporting time slot of a previously unlicensed CR-IoT user, which enhances the detection performance. Also, each unlicensed CR-IoT user calculates the weight factor based on the Kullback Leibler divergence (KLD) score to overcome the interference problem. The effectiveness of the proposed scheme is verified by comparing the numerical performance, e.g., the sensing performance and sum rate with the conventional non-sequential ED spectrum sensing scheme with and without interference constraints. Based on the sensing performance and sum rate, the spectral efficiency and the energy efficiency are analyzed for the proposed novel sequential ED spectrum sensing scheme. Simulation results reveal that the proposed sequential ED spectrum sensing scheme enhances the sensing performance, the sum rate, the spectral efficiency and the energy efficiency when compared to the conventional non-sequential ED scheme with interference constraints.

- Thirdly, I propose a multi-user, multiple-input and multiple-output (MU-MIMO) antenna aided cluster based cooperative spectrum sensing (CB-CSS) scheme for cognitive radio based internet of vehicle (CR-IoV) networks where each cognitive radio vehicle (CRV) is assumed to be equipped with MIMO antennas. Simulation results are presented to demonstrate that the proposed scheme achieves an improved detection gain and enhanced sum rate when compared to other conventional schemes like the non-cooperative spectrum sensing (NCSS) and the single input and single output (SISO) antenna based CSS. Moreover, the proposed scheme obtains a lower global error probability and traffic overhead at the FC as compared with conventional schemes.

- Finally, I propose a machine learning(ML)-based secure CSS technique for CR-IoT networks. In the proposed scheme, we use Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Naive Bayes (NB) machine learning algorithms to classify the legitimate CR-IoT users and three types of malicious users (MUs) (i.e., (i) Always Low Energy Malicious Users (ALEMUs), (i) Always High Energy Malicious Users (AHEMUs), and (i) Random Energy Malicious Users (REMUs)). In this thesis, I use a majority fusion rule at the intelligent fusion centre (IFC) on the sensing results of legitimate CR-IoT users to make the global decision about the presence or absence of the PU in the networks. Simulation results show that the the trained SVM, KNN, and NB classifiers obtain 100%, 99.4% and, 97.5% detection accuracy of legitimate CR-IoT and MUs, respectively. Therefore, my proposed ML-based secure CSS scheme with majority fusion rule achieves a better sensing gain and lower global error probability compared to the conventional majority fusion rule scheme in the CR-IoT networks.

1.4 Publications

The publications list of this thesis is given below:

1.4.1 Journal Papers

1. **Mohammad Amzad Hossain**, Michael Schukat and Enda Barrett. Machine Learning Based Secure Cooperative Spectrum Sensing for Cognitive Radio based IoT Networks. *Physical Communication (Submitted, November 2021)*

2. **Mohammad Amzad Hossain**, Michael Schukat and Enda Barrett. Performance Analysis of MU-MIMO Based Cooperative Spectrum Sensing for Cognitive Radio Enable IoV. *Computer Networks (Submitted, May 2021)*

3. **Mohammad Amzad Hossain**, Michael Schukat and Enda Barrett. Enhancing the Spectrum Sensing Performance of Cluster-Based Cooperative Cognitive Radio Networks via Sequential Multiple Reporting Channels. *Wireless Personal Communications Journal, Vol. 116, No. 3, pp. 2411–2433 (2020)*

1.4.2 Conference Proceedings

1. **Mohammad Amzad Hossain**, Michael Schukat and Enda Barrett. MU-MIMO Based Cognitive Radio in Internet of Vehicles (IoV) for Enhanced Spectrum Sensing Accuracy and Sum Rate. *IEEE 93rd Vehicular Technology Conference (IEEE VTC2021-Spring), Helsinki, Finland.*

2. **Mohammad Amzad Hossain**, Michael Schukat and Enda Barrett. A Reliable Energy and Spectral Efficient Spectrum Sensing Approach for Cognitive Radio Based IoT Networks. *IEEE 11th Annual Computing and Communication Workshop and Conference (IEEE CCWC-2021), pp. 1569-1576, Nevada, USA.*

3. **Mohammad Amzad Hossain**, Michael Schukat and Enda Barrett. Enhancing the Spectrum Utilization in Cellular Mobile Networks by Using Cognitive Radio Technology.*30th IEEE Irish Signals and Systems Conference (IEEE ISSC 2019), Maynooth, Ireland.*

4. Md. Sipon Miah, **Mohammad Amzad Hossain**, Michael Schukat and Enda Barrett. MISO Antenna for Sensor-aided Cognitive Radio Networks: Sensing and Throughput Analysis. *7th International Conference on Advanced Technologies (ICAT 2018), Antalya, Turkey.*

1.5 Thesis Overview

This section provides an overview of each chapter within this thesis. The chapters of this thesis are organised as follows:

- Chapter 2 (Background and Literature Survey) describes the general system model and background information on the technologies that are discussed within the thesis. An overview of cooperative spectrum sensing along with a literature review are also given in this chapter.

- Chapter 3 (Cluster Based CSS for CR Enabled IoT Networks) describes the conventional non-sequential approach and the proposed sequential multiple reporting channels approach in the cluster based CSS for CR-IoT networks. I also describe the sensing performance and reporting time delay for the conventional and proposed approach. I compare the sensing performance and the delay in reporting of my proposed approach with the conventional approach.

- Chapter 4 (Energy & Spectral Efficiency Analysis for CR-IoT) presents a novel energy efficient sequential ED spectrum sensing technique and the conventional energy detection spectrum sensing technique. We discuss the characteristics of two scenarios for the proposed and conventional technique, such as (i) scenario I (no interference between the PU and the CR-IoT user) and (ii) scenario II (where there is interference between the PU and the CR-IoT user). The effectiveness of the proposed scheme is verified by comparing the numerical performance, e.g., the sensing performance, sum rate, the spectral efficiency and the energy efficiency with the conventional non-sequential ED spectrum sensing scheme with and without interference constraints.

- Chapter 5 (MU-MIMO Based CSS for CR Enabled IoV) describes the proposed MU-MIMO antenna aided CB-CSS scheme for CR-IoV networks as well as the conventional SISO antenna based NCSS and CSS schemes. The performance of the proposed scheme is compared with the conventional SISO antenna based NCSS and CSS schemes by using the MATLAB simulation environment.

- Chapter 6 (Machine Learning Based Secure CSS for CR-IoT Networks) introduces a machine learning-based secure CSS techniques for CR-IoT networks. In the proposed scheme, I use SVM, KNN, and NB machine learning algorithms to classify the legitimate CR-IoT users and three types of MUs (i.e., ALEMUs, AHEMUs, and REMUs). I use majority fusion rule at the IFC on the sensing results of legitimate CR-IoT users to make the final global decision about the existence of the PU in the networks. The performance of the proposed ML-based secure CSS with majority fusion rule scheme is compared to the conventional majority fusion rule scheme.

- Chapter 7 (Conclusions, Implementation Challenges and Future Work) presents the summary of this dissertation, implementation challenges and possible future directions for the CR-IoT networks.

1.6 Summary

In this chapter, I have described motivating scenarios for this thesis. I have also presented the main contributions, the publications, and an overview of the thesis.

Chapter 2

Background and Literature Survey

In this chapter, the basic concepts and literature review related to this thesis are described. In particular, it describes the relevant technologies, methods and performance evaluation metrics.

2.1 The Concept of the Internet of Things

In its general sense, the IoT is the concept of interconnecting the virtual world of smart devices with the real world of physical artifacts [Mattern & Floerkemeier 10]. IoT integrates different devices and communication technologies to share information through the internet in order to facilitate our lives [Kumar *et al.* 19]. IoT will be an essential framework for data communication in the future as it allows the connection of new devices and services to join and leave the network spontaneously. All devices will be connected and able to communicate with each other, while their large data volume will require more radio bandwidth for transmission. This later aspect will lead to the radio spectrum deficit challenge. It is estimated that by 2025, the number of connected IoT devices reach over 30 billion [Kamel *et al.* 21]. According to the International Data Corporation (IDC), there will be 55.7 billion connected devices worldwide by 2025, with 75% of them connected to an IoT platform. According to the IDC, data generated by connected IoT devices will total 73.1 zettabytes by 2025. The majority of this data is generated by security and video surveillance, but industrial IoT applications will also consume a significant portion of it [Tsai *et al.* 21]. This unprecedented growth in the number of devices connected to the Internet will lead to a huge demand for radio bandwidth for reliable wireless connections.

The fundamental characteristics of the IoT are given as follows [SECTOR & ITU 12, Vermesan *et al.* 14]:

- Interconnectivity: With regard to the IoT, anything can be interconnected with the global information and communication infrastructure for data transmission.
- Things-Related Services: IoT is capable of providing services within the constraints of devices, such as privacy protection and semantic consistency between physical devices and their associated virtual entities. In order to provide related services within the constraints of the devices, both the technologies in the physical world and information world will change.
- Heterogeneity: The devices in the IoT are heterogeneous as they are often based on different hardware platforms and networks. They can interact with other devices or application platforms through different network infrastructure.
- Dynamic Changes: The state of devices change dynamically, e.g., sleeping and waking up, connected and/or disconnected as well as the context of devices including location and speed. Moreover, the number of devices in the networks can change dynamically.
- Enormous Scale: The number of devices that need to be managed and that communicate with each other will be at least an order of magnitude larger than the devices connected to the current Internet. The ratio of communication triggered by devices as compared to communication triggered by humans will noticeably shift towards device-triggered communication. Even more critical will be the management of the data generated and their interpretation for application purposes. This relates to the semantics of data, as well as efficient data handling.

In recent years, IoT systems have been used in a wide range of applications [Khanna &

Kaur 20, Trayush *et al.* 21, Yang 19, Devi & Rukmini 16, Karmakar *et al.* 19, Prathibha *et al.* 17, Pătru *et al.* 16]:

- Industrial systems use IoT systems to monitor both the industrial processes themselves – the quality of the product – and the state of the equipment.
- Smart buildings use IoT systems to identify the locations of people as well as the state of the building. That data can be used to control heating/ventilation/air conditioning systems and lighting systems to reduce operating costs.
- Smart cities use IoT systems to monitor pedestrian and vehicular traffic and may integrate data from smart buildings.
- Vehicles use IoT systems to monitor the state of the vehicle and provide improved dynamics, reduced fuel consumption, lower emissions, reduction in traffic congestion and accidents.
- Healthcare systems use IoT services. IoT systems creates new value propositions for patient care through real-time health observations and access to patient health records. This data is extremely valuable for healthcare stakeholders looking to improve patient health and experiences while also lowering costs and improving healthcare operations.
- IoT technology enhances the controlling and servicing ability of the power industry. IoT applications in smart grid (IoT-SG) have numerous benefits, including cost savings, time savings, and improved grid equipment intelligence.
- Smart agriculture relies heavily on IoT. Smart farming is a relatively new concept, where IoT sensors provide real-time information about the state of the farm
- IoT home automation is the ability to control domestic appliances by electronically controlled, internet-connected systems. It may entail pre-programming complex heating and lighting systems as well as alarms and home security controls, all of which are linked by a central hub and controlled remotely via a mobile app.

Although there are numerous research challenges inside of the IoT network, this thesis focuses on addressing the issues of spectrum scarcity, low data throughput, data transmission delay, inefficient energy consumption, and the resulting higher global error probability.

2.2 Radio Spectrum Overview

Radio frequency (RF) radiation is a subset of electromagnetic radiation that carries radio waves with a wavelength of 100km to 1mm, operating in a frequency range of 3 KHz to 300 GHz, respectively [Group & *et al.* 13]. Radio frequency bands are classified by the International Telecommunications Union (ITU) together with their mode of propagation and uses. As shown in Table 2, these radio frequencies support a wide range of radio communication systems [Sabri *et al.* 15, Sibomana 16]. The propagation characteristics and the amount of information carried by signals are the key factors of the radio spectrum. In general, if higher frequencies are used to transmit signals, the signals travel long distances in free space and provide greater bandwidth [Marcus 13]. Each frequency band of the radio spectrum can be used by different licensed and unlicensed users for their services. It is essential to manage the use of radio spectrum nationally and internationally to avoid interfering with each other. In general, the radio spectrum is controlled by national, regional, and international organizations that are usually referred to as radio spectrum regulators. As examples, at international level, the ITU regulates the allocation of radio spectrum. At regional level, the European Conference of Postal and Telecommunications Administrations (CEPT) provides detailed guidance on radio frequency allocation, licensing and technical criteria to national regulatory authorities among European countries.

Table 2.1: Radio frequency spectrum and some of its applications

Band Name	Frequency Range	Wavelength Range	Primary Uses/Applications
Very Low Frequency (VLF)	3-30 kHz	33-10 km	Navigation, communication, standard frequency, and time
Low Frequency (LF)	30-300 kHz	10-1 km	Maritime and broadcasting
Medium Frequency (MF)	300-3000 kHz	1000-100 m	AM radio, aeronautical, international distress, and maritime/land mobile
High Frequency (HF)	3-30 MHz	100-10 m	Short wave broadcasting, Amateur radio, Maritime, Remote control
Very High Frequency (VHF)	30-300 MHz	10-1 m	Analog TV, Remote control, Aeronautic, FM radio, Digital audio broadcasting
Ultra High Frequency (UHF)	300-3000 MHz	1000-100 mm	GSM, WCDMA, LTE, WiMAX, UWB, WiFi, Bluetooth, Wireless sensors, Analog TV, Digital TV
Super High Frequency (SHF)	3-30 GHz	100-10 mm	Space communications, TV, radar, broadcasting
Extremely High Frequency (EHF)	30-300 GHz	10-1 mm	Space communication, Radar satellite broadcast

At national level, National Regulatory Authorities (NRAs) are responsible for allocating the radio spectrum [Massaro 17]. A radio spectrum regulatory organization is responsible for controlling the radio spectrum by allocating and assigning radio spectrum to several licensed and unlicensed users. The technical purpose of spectrum management is to enhance the utilization of radio spectrum while avoiding both interference and unnecessarily large gaps or guard bands between adjacent bands. The radio spectrum is a vital and finite resource for wireless communication systems, but its demand is limitless [Anupama *et al.* 19]. The demand for radio spectrum around the world is increasing year by year. This is due to an increase in the number of wireless devices as well as new applications such as streaming video, IoT applications, machine-to-machine communication, wireless surveillance.

Several studies have been mentioned that the radio spectrum is significantly underutilized over a period of time in many geographic regions [Xue *et al.* 13, Chiang *et al.* 07, Erpek *et al.* 07, Subramaniam *et al.* 15]. In particular, the spectrum usage reports have mentioned that the average spectrum occupancy in many cities was estimated to be less than 25%. With a limited radio spectrum, the use of radio spectrum for a large number of wireless communication services needs to be increased. In this context, cognitive radio provides a promising concept for the efficient and full use of radio spectrum [Elhachmi & Guennoun 16]. Cognitive radio-based networks have attracted increased attention and extensive research in order to address the issue of spectrum scarcity in next-generation wireless communication systems.

2.3 Basics of Cognitive Radio Networks

The CRN is an emerging wireless communication concept to enhance spectrum utilization by allowing SUs to opportunistically access the unused licensed spectrum band when the PU is absent in the network. To avoid the harmful interference between the PU and the SU, the SU relinquishes the spectrum when the PU returns to the network.

2.3.1 Cognitive Radio Definition

The concept of cognitive radio technology was proposed by J. Mitola in 1999 [Mitola & Maguire 99]. Academics and regulatory bodies have provided different definitions of CR. Some of the known definitions of CR are given below:

Joe Mitola definition [Mitola & Maguire 99]:

—*"A really smart radio that would be self-, RF- and user-aware, and that would include language technology and machine vision along with a lot of high-fidelity knowledge of the radio environment."*

Simon Haykin definition [Haykin 05]:

—*"Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind: (i) highly reliable communications whenever and wherever needed; (ii) efficient utilization of the radio spectrum."*

ITU-R definition [Filin *et al.* 11]:

—*"Cognitive radio system (CRS): A radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives; and to learn from the results obtained."*

FCC definition [Commission & *et al.* 03]:

—*"A radio or system that senses, and is aware of its operational environment and can dynamically and autonomously adjust its radio operating parameters accordingly."*

SDR definition [Group & *et al.* 06]:

—*"Cognitive Radio (design paradigm-1): An approach to wireless engineering wherein* *the radio, radio network, or wireless system is endowed with awareness, reason, and agency to intelligently adapt operational aspects of the radio, radio network, or wireless system"*

In general, CR nodes/users can sense their operating environment and adapt their implementation to achieve the best performance.

The advantages of CR [Joshi & Bagwari 19] are as follows:

- Relieve spectrum scarcity by broadcasting on unused spectrum and avoid interference with the primary license holder,
- Avoid radio jamming and interference based on the selected spectrum sensing approach,
- Support switching to a power saving protocol,
- Improve communication quality by using higher bandwidth services, and
- Improve the overall quality of service (QoS), since network availability, suitability and reliability will be enhanced.

2.3.2 Cognitive Radio Characteristics and Functions

The two main characteristics of cognitive radio are [Kaur *et al.* 15, Sandeep 17]:

Cognitive capability: Cognitive capability is the ability of the cognitive radio to sense the real time information from its radio environment. The cognitive radio uses three sophisticated techniques such as spectrum sensing, spectrum analysis, and spectrum decision to capture the real time information about the radio environment. This characteristic is very important to avoid interference to other users. Through this capability, the cognitive radio can detect the unused spectrum at a specific time and location and more suitable radio channels and appropriate operating parameters can be selected.

Reconfigurability: The ability of cognitive radio to adjust operating parameters for data transmission without modifying the hardware components is referred to as reconfigurability. Cognitive radio can transmit and receive on different frequencies due to its special hardware design and can adapt with different transmission access technologies [Kaur *et al.* 15]. The cognitive radio, through its cognitive capability and reconfigurability, enables the use of temporarily unused spectrum, also known as a spectrum hole or white space. If a licensed user returns to use this band, the cognitive radio user switches to another spectrum hole to avoid interfering with the licensed users [Lee 09]. The CR networks face some critical challenges because of the coexistence of primary networks and the different QoS requirements. Therefore, CR networks require complex spectrum management functions to overcome the following critical challenges:

Interference Avoidance: The cognitive radio user should avoid interference with the primary users.

QoS Awareness: The CR networks need to identify an appropriate spectrum band to ensure the required QoS.

Uninterrupted communication: The CR networks should provide seamless connectivity for the CR users, regardless of the presence of the primary users in the network. To address these challenges, CR networks require spectrum-aware operations, which form a cognitive cycle. Figure 2.1 shows the cognitive cycle which consists of four spectrum management functions: spectrum sensing, spectrum decision,

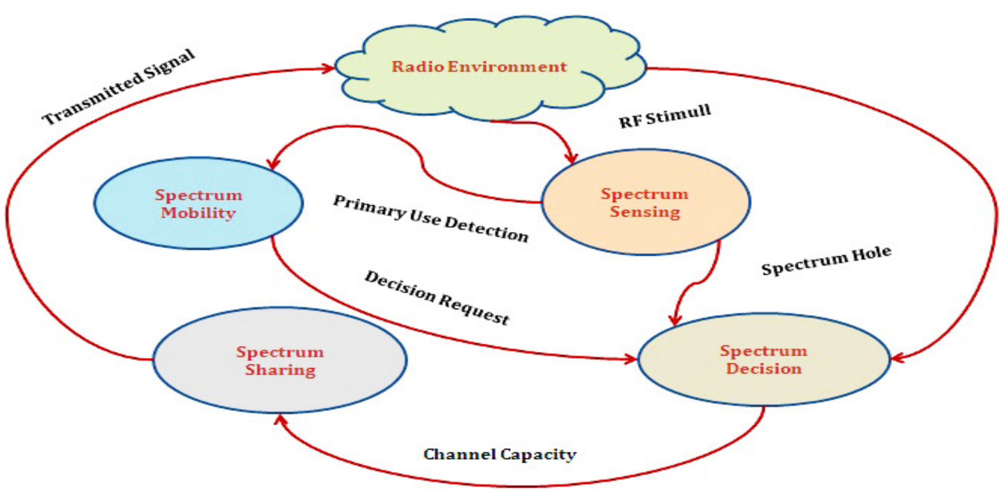

Figure 2.1: Cognitive work cycle of Cognitive Radio [Leena & Hiremath 21]

spectrum sharing, and spectrum mobility. The following are the main features of spectrum management functions [Akyildiz *et al.* 08]:

Spectrum Sensing: The spectrum sensing function enables CR users to detect the unused spectrum band and share the information to their neighbors in the case of a cooperative distributed network or central node in the case of an infrastructure based network. This function monitors the spectrum band to sense the spectrum hole of the primary network by using spectrum sensing techniques.

Spectrum Decision: This function selects the best available spectrum band to be used by cognitive users among available spectrum bands based on a channel's characteristics such as data rate, error rate, primary user's statistics and cognitive users QoS requirements.

Spectrum Sharing: The spectrum sharing function of cognitive radio networks allows CR users to share the spectrum bands of the licensed spectrum. Due to the shared nature of wireless transmission, radio channels are shared amongst CR users during wireless communication. For efficient channel utilization and fair allocation of network resources among cognitive users spectrum sharing functionality is integrated in spectrum management functions.

Spectrum Mobility: CR users are considered as visitors to the licensed spectrum. When a primary user returns to the network then the CR user vacates the channel and finds a new unused channel to continue the transmission or wait for the primary user to vacate the same band. To ensure reliable end-to-end communication, cognitive users must inform the source node's application of network changes and reduce the sending rate until the connection is reestablished. This function of CR is referred to as the spectrum mobility. A new type of hand-off arises due to the primary users activities. Spectrum hand-off occurs: when the primary user returns, when the cognitive user loses its connection due to the mobility of intermediate users involved in communication, and when the current spectrum band can not fulfill the required QoS [Yadav & Misra 14].

2.3.3 Cognitive Radio Based Internet of Things

The advancement in technology has caused an explosion in the number of objects connected to the IoT. IoT is a system of interconnected digital objects that provide devices with the ability to transmit data over the Internet without human-to-human or human-to-computer interaction [Tarek *et al.* 20, Qureshi *et al.* 17]. The IoT concept has expanded so quickly that it touches most of our daily life. Currently, IoT applications can be found in all aspects of our daily lives [Yu & Zikria 20]. Therefore, with the unprecedented growth in the number of digital objects connected to the IoT, more and more challenges are emerging every day. In the last few years, many new terms have been added to IoT, such as, but not limited to, smart health, smart cities, smart homes, smart transportation, smart agriculture, and smart industry. This growth has forced businesses to adopt different strategies to cope with this exponential growth and the challenges associated with them, such as allocating sufficient spectrum bands in IoT applications [Awin *et al.* 19b].

However, as it is growing rapidly, a vast amount of data needs to be sent over the radio spectrum band, which is extremely limited [Zhang *et al.* 20]. Spectrum deficiency not only depends on channel availability but also depends on the spectrum utilization and the used technologies. The radio spectrum becomes inadequate due to the conventional fixed spectrum allocation policy in this radio spectrum [Tarek *et al.* 20]. To overcome this crisis, cognitive radio technology is consolidated with IoT to create the Cognitive Radio based Internet of Things (CR-IoT) that can search for the available licensed spectrum and use it for data transmission [Leena & Hiremath 21, Nathani *et al.* 21]. By using cognitive capabilities, a CR-IoT user can avoid collision amongst the network elements to ensure better connectivity, accessibility, scalability, and reliability of the CR-IoT network. Currently, the research on CR-IoT is at its early stage. The usage of a CR-IoT smart network will be an efficient and economical solution to the IoT spectrum scarcity problem. CR-IoT smart networks have to perform several functions as follows [Khan *et al.* 17]:

- Capture the interference free channels without the presence of a PU.
- Estimate the QoS of the detected free communication channels.

- Provide continuous data communication when any IoT object changes its operating communication channel, either for the arrival of a PU or its movement.

- Finally, licensed spectrum usage can be increased by regulating the licensed spectrum access for a large number of IoT objects with minimal interference to PUs.

Figure 2.2 shows the IoT reference model, which was introduced by ITU-T [SECTOR & ITU 12, Vermesan *et al.* 14, Bhajantri & *et al.* 20]. It is composed of four layers as well as management capabilities and security capabilities which are associated with the four layers. The description of each layer is presented below:

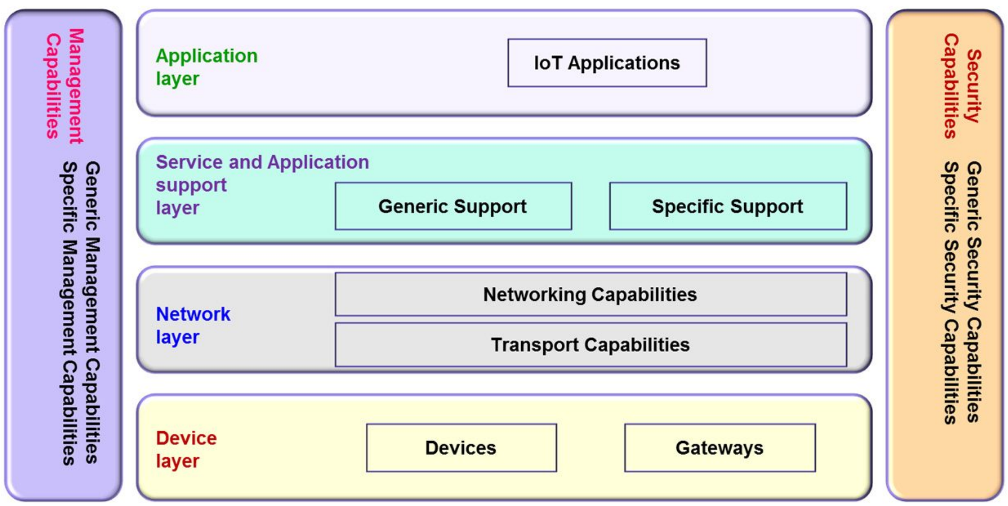

Figure 2.2: ITU-T reference model for IoT

- **Application Layer:** The application layer contains the IoT applications.

- **Service Support and Application Support Layer:** This layer consists of the following two capability groupings:

  - Generic Support Capabilities: The generic support capabilities are common capabilities which can be used by different IoT applications, such as data processing or data storage.

  - Specific Support Capabilities: The specific support capabilities are particular capabilities which cater for the requirements of diversified applications. In fact, they may consist of various detailed capability groupings, in order to provide different support functions to different IoT applications.

- **Network Layer:** Network layer consists of the following two types of capabilities:

  - Networking Capabilities: Networking capabilities provide relevant control functions of network connectivity, such as access and transport resource control functions, mobility management or authentication, authorization and accounting (AAA)
  - Transport Capabilities: Transport capabilities focus on providing connectivity for the transport of IoT services and application specific data information, as well as the transport of IoT-related control and management information.

- **Device Layer:** Device layer capabilities can be logically categorized into two kinds of capabilities:

  - Device Capabilities: The device capabilities include but are not limited to:

    (a) Direct interaction with the communication network: Devices are able to gather and upload information directly (i.e., without using gateway capabilities) to the communication network and can directly receive information (e.g., commands) from the communication network.

    (b) Indirect interaction with the communication network: Devices are able to gather and upload information to the communication network indirectly, i.e., through gateway capabilities. On the other side, devices can indirectly receive information (e.g., commands) from the communication network.

    Ad-hoc networking: Devices may be able to construct networks in an ad-hoc manner in some scenarios which need increased scalability and quick deployment.

    (c) Sleeping and waking-up: Device capabilities may support sleeping and waking-up mechanisms to save energy.
  - Gateway Capabilities: The gateway capabilities include but are not limited to:

    (a) Multiple interfaces support: At the device layer, the gateway capabilities support devices connected through different kinds of wired or wireless technologies, such as a controller area network (CAN) bus, ZigBee, Bluetooth or Wi-Fi. At the network layer, the gateway capabilities may communicate through various technologies, such as the public switched telephone network (PSTN), second generation or third generation (2G or 3G) networks, long-term evolution networks (LTE), Ethernet or digital subscriber lines (DSL).

(b) Protocol conversion: There are two scenarios where gateway capabilities are needed. One scenario is when communications at the device layer use different device layer protocols, e.g., ZigBee technology protocols and Bluetooth technology protocols, the other one is when communications involving both the device layer and network layer use different protocols e.g., a ZigBee technology protocol at the device layer and a 3G technology protocol at the network layer.

- **Management Capabilities:** In a similar way to traditional communication networks, IoT management capabilities cover the traditional fault, configuration, accounting, performance and security (FCAPS) classes, i.e., fault management, configuration management, accounting management, performance management and security management. The IoT management capabilities can be categorized into generic management capabilities and specific management capabilities

  – Generic Management Capabilities: Essential generic management capabilities in the IoT include:

    (a) Device management, such as remote device activation and de-activation, diagnostics, firmware and/or software updating, device working status management.

    (b) Local network topology management.

    (c) Traffic and congestion management, such as the detection of network overflow conditions and the implementation of resource reservation for time-critical and/or life-critical data flows.

  – Specific Management Capabilities: Specific management capabilities are closely coupled with application-specific requirements, e.g., smart grid power transmission line monitoring requirements.

- **Security Capabilities:** There are two kinds of security capabilities: generic security capabilities and specific security capabilities.
    - Generic Security Capabilities: Generic security capabilities are independent of applications. They include:

      (a) At the application layer: authorization, authentication, application data confidentiality and integrity protection, privacy protection, security audit and anti-virus.

      (b) At the network layer: authorization, authentication, use data and signalling data confidentiality, and signalling integrity protection.

      (c) At the device layer: authentication, authorization, device integrity validation, access control, data confidentiality, and integrity protection.
    - Specific Security Capabilities: Specific security capabilities are closely coupled with application-specific requirements, e.g., mobile payment, security requirements.

2.4 Idle Licensed Spectrum Identification Techniques for CRN

Idle licensed spectrum identification techniques can be broadly classified into two main categories:

(a) Spectrum database technique

(b) Spectrum sensing technique

2.4.1 Spectrum Database Technique

Recent rulings by the Federal Communications Commission (FCC) mandating the creation of spectrum databases [Commission & *et al.* 11] have reduced the erstwhile complete dependence on spectrum sensing alone to infer the primary user activity in the licensed bands. In a spectrum database, TV stations and other primary users update their next week's use of the licensed radio spectrum in a database that the

FCC maintains. The advantages of this method are that the cognitive radio devices can seek information about free spectrum from this database, so they do not have to rely on complex, time-consuming and expensive spectrum sensing techniques.

The drawback of this method is that it is difficult for the database to update dynamic spectrum activity in real-time. As a result, CR devices may miss out on opportunities to access unused spectrum. To support the growing number of devices that use the radio frequency spectrum, a spectrum sensing technique is useful. It ensures that devices can quickly and accurately detect unused spectrum and so improve QoS.

2.4.2 Spectrum Sensing Techniques for CRN

Spectrum sensing plays a vital role in CR-IoT networks. Spectrum sensing enables CR-IoT users to estimate the radio channel parameters such as transmission channel characteristics, interference level, noise level, spectrum availability, power availability, etc [Mehta 09]. The cognitive radio users or CR-IoT users use the spectrum sensing technique to continuously sense the licensed spectrum for detecting the presence or absence of the licensed users or PUs in the networks. If the primary user is absent for a particular time on specific radio spectrum, the CR-IoT user can use that radio spectrum for transmission until the primary user reappears in the network. Once the PU reappears, the CR-IoT user should give up that spectrum for the PU and then shift to another unused spectrum. This implies that the CR-IoT users should continuously sense the entire spectrum for an opportunity to use a channel that is not being used by the licensed user. This technique of continuously monitoring the spectrum is called spectrum sensing.

Spectrum sensing techniques can be broadly classified into three main categories [Suseela & Sivakumar 15, Tan & Jing 21, Hossain *et al.* 21a]:

(i) Non-cooperative spectrum sensing (NCSS)

(ii) Cooperative spectrum sensing (CSS)

(iii) Cluster based cooperative spectrum sensing (CCSS)

2.4.2.1 Non Cooperative Spectrum Sensing

In NCSS, each CR-IoT user decides about the presence or absence of a PU signal in the network only on the basis of their own sensing data. The fundamental features of wireless radio channels such as noise uncertainty, multi-path fading, and shadowing, limit the performance of NCSS. The NCSS technique is not able to overcome the hidden terminal problem which arises at a particular geographical location due to noise uncertainty, multi-path fading, and the shadow effect. This problem causes serious interference between the CR-IoT user and the primary user because the CR-IoT user cannot reliably detect the primary user's signal and tries to use the radio channel when the PU signal is present in this particular channel. As a result, the sensing performance is degraded [Hossain *et al.* 21b].

2.4.2.2 Cooperative Spectrum Sensing

To overcome the weaknesses of the NCSS technique, cooperative spectrum sensing has been proposed [Tan & Jing 21, Ernesto *et al.* 20, Yu *et al.* 21] where multiple CR-IoT users cooperate and integrate their sensing data to enhance sensing outcomes. A CSS scheme can significantly decrease the probabilities of missed-detection, false alarm, and sensing time by taking advantage of cooperative sensing of multiuser. Cooperative sensing involves three main steps, namely, local sensing, reporting, and data fusion. Furthermore, based on how cooperating CR-IoT users share the sensing information in the network, CSS can be categorized into three main types [Akyildiz *et al.* 11]: (a) centralized CSS, (b) distributed CSS, and (c) relay-based CSS.

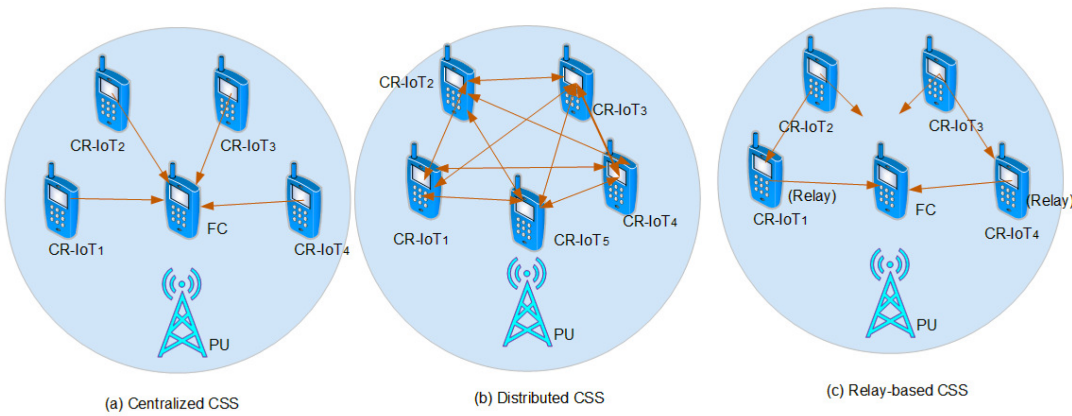

Figure 2.3: Classification of cooperative sensing: (a) centralized CSS, (b) distributed CSS, (c) Relay-based CSS

These three types of cooperative spectrum sensing are illustrated in Figure 2.3.

(a) Centralized CSS: In centralized CSS [Akyildiz *et al.* 11], a central node called a fusion center (FC), controls the three-step process of cooperative sensing. First, the FC selects a specific frequency band for sensing and instructs all cooperating CR-IoT users to individually perform local spectrum sensing. Second, all cooperating CR-IoT users report their local sensing results to the FC through the reporting channel. Then the FC integrates the received local sensing data, determines the presence or absence of PUs by using some fusion rules, and diffuses back the decision to the CR-IoT users. Figure 2.3 (a) illustrates cooperation in a centralized manner.

(b) Distributed CSS: Unlike centralized cooperative sensing, distributed CSS [Li *et al.* 16] does not rely on a FC for making the cooperative decision. In this case, each CR-IoT user shares the local sensing information with other CR-IoT users within their sensing area, combines its data with the received sensing data, and decides whether or not the PU is present by using a local threshold. However, the distributed algorithm for CSS may involve several iterations to converge to a unified cooperative decision on the presence or absence of PUs. Figure 2.3 (b) illustrates the cooperation in the distributed manner.

(c) Relay-based CSS: In the relay-assisted case [Hussain & Fernando 13], if both the sensing and reporting channels are not perfect, relay-assisted cooperative sensing can be used to improve CSS performance. For example, a CR-IoT user observing a weak sensing channel and a strong reporting channel can be assisted with another CR-IoT user with a strong sensing channel and a weak reporting channel. The relay-assisted CSS can be implemented in a distributed scheme resulting in multiple hops to reach the intended SU receiving node. Figure 2.3 (c) illustrates the cooperation in the relay-based manner.

However, the challenges of cooperative sensing include developing efficient information sharing algorithms, sensing time, reporting delay and noisy reporting channels [Zou *et al.* 11, Akyildiz *et al.* 11].

2.4.2.3 Cluster Based Cooperative Spectrum Sensing

In cluster-based cooperative spectrum sensing, CR-IoT users with a similar location are grouped into a cluster using some distributed clustering algorithm [Younis & Fahmy 04]. Then, the most favorable user is selected according to the largest instantaneous reporting channel's gain, namely, cluster head (CH). In each cluster, the CR-IoT users start to forward the sensing result of the received PU's signal to the CH, and then the CH collects the sensing results from the cluster members and makes the cluster decision about the presence or absence of the PU. Thereafter, all CHs send cluster decisions to the FC during their allocated reporting time slots. Afterwards, the FC combines the received clustering decision to make the final decision about the presence or absence of the PU and then broadcasts it back to all CHs and the CHs send it to their cluster members [Van & Koo 09, Sun *et al.* 07]. Figure 2.4 illustrates the cluster based cooperative spectrum sensing technique.

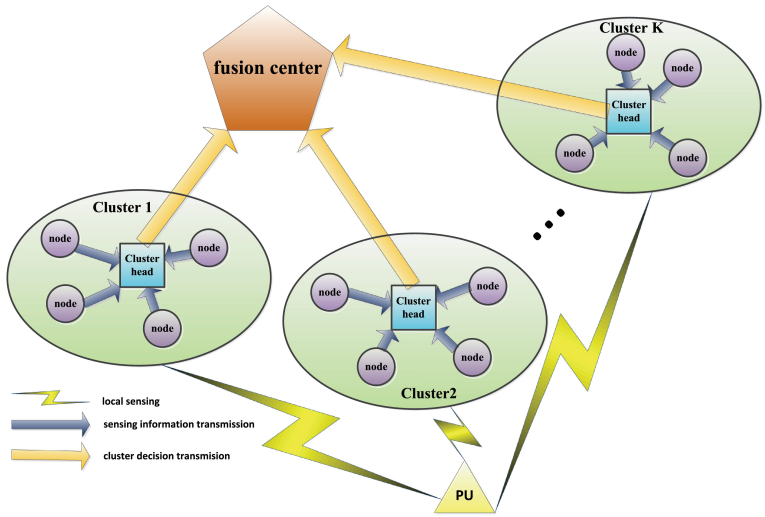

Figure 2.4: Cluster based cooperative spectrum sensing [Liu *et al.* 19a]

2.5 Types of Primary Signal Detection Methods

Regardless of the cooperation spectrum sensing techniques, the process of cooperative spectrum sensing starts with local spectrum sensing (i.e., primary signal detection) at each cooperating CR-IoT user. Basically, the CR-IoT user uses the local spectrum sensing method to detect the primary signal. Primary signal detection methods are crucial in cooperative sensing in the sense that how primary signals are detected, sampled, and processed is strongly related to how CR-IoT users cooperate with each other. The spectrum sensing method is one of the most important fundamental elements of CR-IoT networks. It enables a CR-IoT user to have information about its environment and spectrum availability [Develi & *et al.* 20]. The most widely used spectrum sensing methods are matched filter detection [Claudino & Abrao 17, Zhang *et al.* 14, Salama *et al.* 18, Alnwaimi & Boujemaa 19], cyclostationary based detection [Sherbin & Sindhu 19, Yang *et al.* 15, Bollig *et al.* 17], Eigenvalue based detection [Zeng & Liang 09, Ali *et al.* 16, Zhao *et al.* 20, Miah *et al.* 20], and energy detection [Hossain *et al.* 21c, Hossain *et al.* 19, Plata & Reátiga 12a, Miah *et al.* 18a, Miah *et al.* 20].

2.5.1 Matched Filter Detection

Matched filter detection is a process for detecting a known piece of signal that is embedded in noise. The filter will maximize the signal to noise ratio (SNR) of the signal being detected with respect to the noise [Bancroft 02]. For the matched filter based detection, PU signal features such as operating frequency, bandwidth, modulation type, the pulse shape, and packet format are required at the CR-IoT user. If the CR-IoT user has a prior knowledge of the PU signal information, matched filter detection is known as the optimal detection technique [Yucek & Arslan 09]. This method has the advantage of low detection time and high processing gain. Depending on this prior knowledge requirement, CR-IoT users should be equipped with timing and carrier synchronization devices. Unfortunately, these requirements of the matched filter systems cause an increase in implementation complexity. Additionally, it is hard for the CR-IoT user to obtain complete signal information of the PU signal. Another drawback of matched filtering is large power consumption for the detection process [Arjoune & Kaabouch 19a].

2.5.2 Cyclostationary Feature Detection

In wireless transmission systems, the transmitted signal is associated with some cyclostationary characteristics such as modulation type, carrier frequency, and symbol duration [Qu 19]. If the statistical characteristics of the signal are changed cyclically according to time it is called a cyclostationary process. The cyclostationary feature detection is implemented based on the cyclostationary characteristics of the modulated signal [Noguet *et al.* 10]. The unique set of features of a particular radio signal can be identified based on conducting cyclostationary analysis of the CR-IoT user. These cyclostationary features can be recognized by analyzing the cyclic auto-correlation function of the received PU signals by using the following equation [Sibomana 16]:

$$R_y(\tau) = E[y(n)y^*(n-\tau)exp^{-j2\pi\delta n}] \tag{2.1}$$

where $E[]$ represents auto-correlation function, $y(n)$ is a received PU signal, and δ is the cyclic frequency. Furthermore, τ is the lag value associated with the auto-correlation function and $*$ denotes the complex conjugate. It gives excellent information of signal characteristics even at very low SNR due to its robustness to noise and also realizes the modulation scheme used for transmitting the signal [Sherbin & Sindhu 19]. In addition, it can differentiate the primary signals from the noise or other interfering signals with different cyclic frequency. However, the cyclostationary feature detection requires prior knowledge of the PU signal characteristics. Also, it has high computational complexity and demands long sensing times. In addition, long sensing times reduce the overall throughput of CR-IoT system.

2.5.3 Eigenvalue Based Detection

Spectrum sensing of primary users under very low SNR and noise uncertainty is crucial for CR systems. Eigenvalue based spectrum sensing can make detection by catching correlation features in space and time domains, which can not only reduce the effect of noise uncertainty, but also achieve high detection probability under very low SNR values [Ali *et al.* 16]. Hence, the eigenvalue based detection is always a hot topic in the spectrum sensing area. However, one pressing disadvantage of eigenvalue-based spectrum sensing algorithms is their high computational complexity, which is due to the calculation of the covariance matrix and its eigenvalues [Dikmese *et al.* 13].

2.5.4 Energy Detection

The energy detector based spectrum detection is the easy way of spectrum sensing because of its low computational and implementation complexities, and it does not require prior knowledge of the PU signal [Yucek & Arslan 09]. Energy detection can be performed in either the time domain or the frequency domain. The energy detector provides high detection accuracy of the PU signal when the received SNR is sufficiently high. The presence of the PU signal is detected by comparing the output of the energy detector with a threshold which depends on the SNR. The signal is simply detected by comparing the output of the energy detector with a predefined threshold in order to identify the presence or absence of a PU signal. The PU signal sensing process at the CR-IoT transmitter using the energy detection is shown in Figure 2.5.

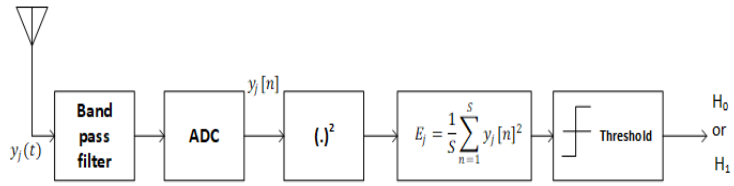

Figure 2.5: A block diagram of the energy detection method [Pandit & Singh 17, Xuping & Jianguo 07, Pandya *et al.* 15]

The received signal at the SU-Tx has the following form [Majumder 18]:

$$y(n) = h(n)x(n) + w(n) \tag{2.2}$$

where $x(n)$ denotes the signal to be detected, $h(n)$ is the antenna gain, $w(n)$ is the additive white Gaussian noise (AWGN), and n is the sample index. The signal detection is represented by binary hypothesis-testing as follows:

$$y(n)\,(l) = \begin{cases} w\,(n) & : H_0 \\ h\,(n)\,x\,(n) + w\,(n) & : H_1 \end{cases} \tag{2.3}$$

where H_1 and H_0 represent the hypotheses of the presence and absence of the PU in the network, respectively. The received PU signal energy is measured by the following equation [Plata & Reátiga 12b, Amin *et al.* 18].

$$E = \frac{1}{S}\sum_{n=1}^{S} y(n)^2 \tag{2.4}$$

where S denotes the number of samples of the digital signal. However, when the SNR values are low, the energy detection technique cannot provide a high level of performance. In addition, the energy detector cannot be used to detect spread spectrum signals.

2.6 Fusion Rules to Make the Global Decision

In cooperative sensing, fusion rules play a critical role for making a final global decision at the fusion center [Han *et al.* 13]. Fusion rules refer to the process of combining locally sensed data from individual CR-IoT users at the fusion center to make a final global decision about the presence or absence of the PU signal in the networks. Fusion rules can be classified into two categories such as [Yang *et al.* 19b]: (i) soft decision fusion (SDF) rule and (ii) hard decision fusion (HDF) rule.

2.6.1 Soft Decision Fusion Rule

In the case of SDF rule, CR-IoT users send their raw spectrum sensing data to the FC without any local process to make the global decision about the presence or the absence of the PU [Nallagonda *et al.* 13]. There are several soft fusion rules such as the equal gain combining (EGC) rule, maximal ratio combining (MRC) rule, and optimal soft combination rule, which can be used for the soft combining of local sensing data or test statistics. The soft fusion techniques provide better detection probability than hard fusion techniques [Gupta *et al.* 18]. Additionally, the CR-IoT users do not need the capability of complex signal processing in soft schemes [Atapattu *et al.* 11]. However, there is a significant difference in the cooperation overhead between SDF and HDF rule based detectors. The SDF rule requires a wide bandwidth of the control channel for sending sensing data to the FC [Khalid 14]. The two SDF rules are defined below:

- **Equal Gain Combination (EGC) Rule:** In [Khan *et al.* 20a, Nallagonda *et al.* 17, Awin *et al.* 19a], the authors applied the soft combination technique for CSS based on the EGC of the received signal energy. In the case of EGC, the fusion center equally combines all the sensing gains of the CR-IoT users. Finally, the FC makes the global decision by comparing the sum of the sensing gains y_i with a predefined threshold value δ as follows [Srinu *et al.* 10]:

$$GD(EGC) = \begin{cases} H_1, & if \sum_{i=1}^{N} |y_i|^2 > \delta \\ H_0, & \text{otherwise} \end{cases} \tag{2.5}$$

  where N is the number of CR-IoT users in the CR-IoT networks.

- **Maximal Ratio Combination (MRC) Rule:** In [Zarin *et al.* 12, Duong *et al.* 10, Khan *et al.* 20a, Kulkarni *et al.* 14], the authors applied the soft combination technique for CSS based on the MRC of the received signal energy. The MRC is the optimum diversity technique in the sense of maximizing the output SNR of the combiner [Soltanmohammadi 14]. The MRC rule makes the global spectrum sensing decision by comparing the weighted sum of the received energies of CR-IoT users with the decision threshold as follows:

$$GD(MRC) = \begin{cases} H_1, & if \sum_{i=1}^{N} |y_{i,j(k)}|^2 \times \frac{\gamma_i}{\sqrt{\sum_{i=1}^{S} \gamma_i^2}} > \delta \\ H_0, & \text{otherwise} \end{cases} \tag{2.6}$$

where γ_i is a signal-to-noise ratio.

2.6.2 Hard Decision Fusion Rule

In the HDF rule, each CR-IoT user makes a local decision and sends it to the FC which applies a hard decision fusion rule on the received binary data to make a final global decision about the presence or absence of the PU signal in the networks [Salout 17]. The main advantage of the HDF rule is the reduction of cooperation overhead. However, the CR-IoT users need the capability of complex signal processing in a hard combining scheme. The commonly used HDF rules are AND, OR, and majority voting rules which are special cases of the general "K-out-of-N" rule. Those hard decision fusion rules can be described as below [Arshad *et al.* 10, Khalid 14, Khan *et al.* 20a, Debnath *et al.* 20]:

- **OR Rule:** In this fusion rule, the FC decides on the presence of the primary user's signal if any of the CR-IoT users reports the detection of the primary user's signal in the network. Thus, this rule increases the PU protection but at the expense of inefficient spectrum utilization.

- **AND Rule:** In the AND fusion rule, if all CR-IoT users decide that there is a primary user's signal, then the final global decision at the FC declares that there is a primary user's signal. Thus, this rule increases spectrum utilization but at the risk of increasing the interference with the PU.

- **Majority Voting Rule:** In the majority voting fusion rule, also known as the half voting rule, if half, or more than half of the CR-IoT users decide that there is a primary user's signal, then the final global decision at the FC declares that there is a primary user's signal.

- **"K-out-of-N" rule:** The "K-out-of-N" rule means that if K or more out of N CR-IoT users individually identify the presence of primary user's signal, then the FC makes the global decision that the primary user is present in the network; otherwise, it makes the global decision that the primary user is absent in the network. The global decision making process at the FC using "K-out-of-N" rule is shown in Figure 2.6.

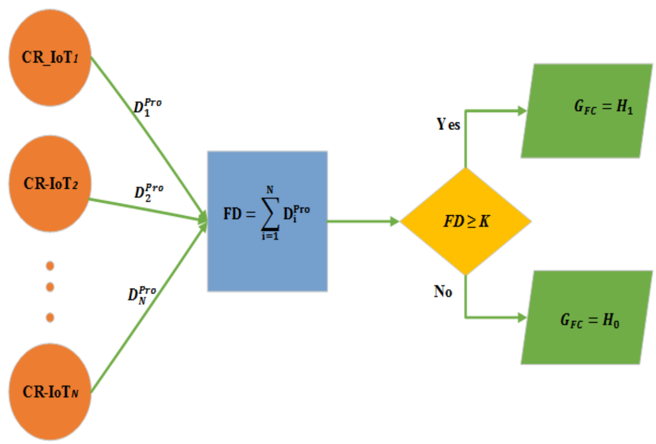

Figure 2.6: Block diagram of the global decision making process at the FC using "K-out-of-N" rule

We can summarise the global decision making process of the FC about the presence or absence of the licensed IoT user in the network as follows:

$$G_{FC} = \begin{cases} H_1, & if \sum_{i=1}^{N} D_i^{Pro} \geq K \\ \\ H_0, & Otherwise \end{cases} \tag{2.7}$$

where G_{FC} denotes the global decision of the FC. The value of K in the "K-out-of-N" rule is very crucial for the detection performance of the spectrum sensing techniques. The optimal value of K can be calculated as follows: [Zhang *et al.* 09]

$$K_{opt} = min\left(N, \left\lceil \frac{N}{1+\alpha} \right\rceil\right) \tag{2.8}$$

where $\alpha = \frac{ln\frac{P_f}{P_d}}{ln\frac{1-P_d}{1-P_f}}$, P_f indicates probability of false alarm, and P_d indicates probability of detection. If the primary user's location is on one side of the cluster or far away from all CR-IoT users, then the PU signal detection probability at the CR-IoT user is decreased due to the location of the PU. In this situation, the global decision accuracy is decreased if the FC uses the "K-out-of-N" fusion rule.

2.7 Applications and Standards of CRNs

The CR technology aims to maximize spectrum utilization by allowing unlicensed users to access unused radio spectrum resources held by the government and commercial users. Radio frequency bands assigned to PUs could be shared with CR-IoT users under certain negotiable conditions without requiring licensed users to release their own license. There are many emerging CR networks applications based on CR technologies.

2.7.1 Applications of CRNs

CR techniques can be applied in a wide range of communication systems [Nasser *et al.* 21]. In the following, we briefly discuss some examples of CRN applications.

- **Cellular Networks:** The introduction of smartphones, social networks, and growing media web sites has increased the wireless user load of current wireless cellular networks. The capacity of the cellular network is enhanced by integrating cognitive radio technology to handle the extra load of the user [Hamdouchi *et al.* 17]. By allowing cellular networks like Wideband Code Division Multiple Access (WCDMA) and LTE to dynamically access the TV bands, CT-IoT can facilitate cellular networks to meet bandwidth requirements. This can be implemented, for example, by using cognitive femtocells [Yau *et al.* 18, Sibomana 16] and licensed shared access (LSA) [Morgado 20, Sadreddini *et al.* 18].
- **Mesh Networks:** Wireless mesh networks are emerging as a cost-effective solution for providing broadband connectivity, i.e., for last-mile Internet access [Sibomana 16]. The challenge for conventional wireless mesh networks is that higher bandwidth is required to meet user needs as user density increases. Since CR technology eliminates the bandwidth shortages, cognitive mesh networks can be used to provide broadband access in dense urban areas. For example, the QoS

of wireless mesh networks can be enhanced by using cognitive radio technology [Yuan *et al.* 12].

- **Emergency Networks and Public Safety:** Natural disasters (e.g., hurricanes, earthquakes, etc.) are unplanned events that cause significant disruptions and can disable or damage existing communication infrastructure. For instance, some base stations (BSs) of cellular networks can fall and existing WLANs can be damaged, etc. Plus the increased traffic demand, hampers the recovery effort. Therefore, the receivers cannot receive or relay the information they need, victims cannot report their location or request help, and the overall response cannot be coordinated effectively [Ghafoor *et al.* 14]. Thus, an emergency network needs to be established. Quick repair of the communication networks in the critical first period after the disaster could provide a significant boost to the response. Since a CR can detect spectrum availability and reconfigure itself, CRNs can be used for such emergency networks [Wang & Liu 10]. Further, CRNs can facilitate interoperability between different communication systems through adapting the requirements and conditions of another network.

  The public safety communication networks known as Public Safety Broadband Network (PSBN) and Emerging Long-Term Evolution based broadband networks are operated over a 20MHz spectrum in the 700MHz spectrum band to meet the requirements of the first responders (law-enforcement, fire fighters, and emergency medical services) [Chaudhry & Hafez 19]. Unsurprisingly, a recent report has concluded that if the first responder's community is to become truly interoperable and to endorse some of the state-of-the art technologies in indoor navigation, telemedicine, multimedia broadcast, etc, then 20MHz will be insufficient [Alkheir & Mouftah 16]. As a matter of fact, the unpredictable nature of an emergency's (or a disaster's) time, location, and magnitude (scale), makes it safe to say that vast amounts of spectrum may be needed. However, because spectrum is a very precious and very limited resource, so permanently allocating a large amount of spectrum for first responders is impractical. A solution to this dilemma can be found in the concept of spectrum sharing, especially in the leading technology of Cognitive Radio (CR) [Pagotto *et al.* 13]. CR technology facilitates hierarchical coexistence in licensed spectrum bands based on interference avoidance or interference control paradigms. This technology is cast as a solution to the spectrum underutilization phenomenon resulting from the legacy spectrum licensing system based on command-and control [USFCCSPT]. Using this technology, license-exempt users, e.g., first responders, can intelligently access underutilized licensed spectrum bands. This underutilization occurs in both spatial dimension, i.e., location, and temporal dimension. Using this technology, first responders can stretch the capacity of the envisioned PSBN to meet their demand. In fact, CR technology can offer much more than just additional capacity. It can offer network resilience, flexible network topology, and security. However, interference mitigation/avoidance between PUs and CR-enabled first responders is clearly the most critical issue. There are more chances open for attackers in cognitive radio technology compare to traditional wireless networks. The data may be eavesdropped or altered without notice. The channel might be jammed or overused by the adversaries.

- **Wireless Health Care Networks:** A wireless medical body area network provides a wide range of health-care services such as telemedicine, wearable body sensors are being used increasingly. Numerous wireless sensor nodes are placed on patients in hospitals for vital signs such as temperature, pressure, blood oxygen, and electrocardiogram is of interest. Wireless health care applications have already been in use in some remote areas of developing countries, such as in Nepal and India [Mishra *et al.* 09]. The deployments of wireless platforms for health care service brings new challenges related to interference with neighboring medical devices and lack of radio bandwidth [Wang *et al.* 11]. The QoS may not be achieved to a satisfactory level if the operating spectrum band is crowded in telemedicine devices. The implementation of CR in wireless health care networks can be a solution to these challenges because of its capability to overcome the spectrum shortage problem by allowing secondary users access to licensed spectrum. The implementation of cognitive radio in wireless health care networks are discussed in reference [Wang *et al.* 11].

- **Military Communication Networks:** It is difficult to achieve reliable and secure communications in military communication networks. Also, a significant amount of bandwidth is required for the military because of communication between soldiers, armed vehicles, and other units in the battlefield amongst themselves as well as with the headquarters. However, the frequency bandwidth allocated for conventional military communications networks is not sufficient for these communications. The CRN is a key emerging technology for realizing such densely deployed networks to achieve both the bandwidth and reliability needs. In this respect, the defense advanced research project agency (DARPA) initiated the wireless network after next (WNaN) program with the main goal to create a flexible architecture for next generation military communications [Redi & Ramanathan 11, Fette 13]. The idea behind the WNaN program is to create a low-cost CR device capable of selecting unused licensed spectrum and supporting a wide range of military communication needs. In specific, the WNaN system has demonstrated CR functionality in real-world military experiments for up to 100 nodes [Redi & Ramanathan 11, Fette 13].

- **Home Appliances and Indoor Applications:** To achieve an adequate QoS, many potential and emerging indoor applications require a dense wireless sensor networks environment. Conventional wireless sensor networks experience significant challenges in achieving reliable communication because industrial, scientific and medical (ISM) bands in indoor areas are extremely crowded. [Zhou *et al.* 06]. Some examples of the indoor applications of wireless sensor networks are intelligent buildings, home monitoring systems, factory automation, personal entertainment, etc [Kumbhar 17]. Cognitive radio based wireless sensor networks can mitigate the challenges faced by conventional indoor wireless sensor applications.

- **Transportation and Vehicular Networks:** The Internet of Vehicles (IoV) embedded transportation systems are expected to play an important role in road safety and convenient driving. The US Federal Communication Commission (FCC) has already allocated 75 MHz of spectrum in the 5.9 GHz band for the implementation of transportation services [Gill *et al.* 20], a substantial increase in vehicle applications, particularly in urban environments, will lead to an overcrowding of band and spectrum shortage for vehicle communications. Cognitive radio technology based vehicular ad-hoc networks (CR-VANETs) are a promising solution to maximize the utilization of the available frequency bandwidth by allowing the CR embedded vehicles (CRV) as a secondary user to use the allocated licensed spectrum frequency bands, when they are temporally idle [Hossain *et al.* 21b].

2.7.2 Standards of CRNs

Standardization is at the core of the current and future success of cognitive radio. Regulatory organizations and standards groups are interested in studying the possibilities of allowing dynamic access of CR users in the licensed radio spectrum. For the purpose of enhancing spectrum utilization in TV bands, the FCC has allowed unlicensed users to dynamically access and operate within unused TV channels [Marcus 05]. Moreover, in the context of the Europe radio spectrum policy programme, two schemes for radio spectrum sharing, i.e., collective use of spectrum (CUS) and authorised shared access (ASA) have been set out to meet the growing demand for wireless applications and to enhance radio spectrum utilization [Group & *et al.* 11]. The IEEE 802.22 standard for cognitive wireless regional area networks (WRAN) has been defined to enable the wireless access in TV white spaces spectrum [Sherman *et al.* 08]. The CR users can operate in the TV broadcast bands between 54 MHz and 862 MHz without interfering with the existing broadcasters.

2.8 Performance Evaluation Metrics

The performance evaluation of cognitive radio systems may be described in terms of a number of metrics. In this section, we give a brief introduction of some performance metrics used in this thesis given as follows:

- **Spectrum Sensing Gain:** In cognitive radio networks, spectrum sensing gain is one of the most critical performance metrics. The concept of spectrum sensing gain can be determined in two ways (a) the slope of the probability of detection (p_d) versus the probability of false alarm (p_f) which calls the ROC curve [Miah *et al.* 18a]; and (b) the slope of probability of detection versus average SNR value curve [Shah & Koo 18a]. The sensing gain is very useful in the performance analysis of spectrum sensing in CR-IoT networks. If the spectrum sensing gain value is high, the CR-IoT user can use idle licensed spectrum bands without causing interference to primary users.

- **Throughput/Sum Rate:** The network throughput is defined as the ratio between the total transmitted data volume and the total total needed time [Elias & Fernández 21]. Moreover, the system sum rate is referred to as the transmission capacity of the CR-IoT network [Shalmashi *et al.* 16]. It is measured in unit of bit/second (bps) or Hz. We can calculate the average throughput/sum rate of the CR-IoT network by using the following equation [Verma & Singh 14, Miah *et al.* 20]:

$$R_T = W\left[C_0(1-P_f)P(H_0) + C_1(1-P_d)P(H_1)\right] \tag{2.9}$$

where $W = \frac{T-(\tau_s+\tau_r)}{T}$, $C_0 = \log_2(1+SNR_{CR-IoT})$ is the channel capacity between the transmitter and the receiver path of the CR-IoT users when the PU is absent in the CR-IoT networks, $C_1 = \log_2\left(1+\frac{SNR_{CR-IoT}}{1+SNR_{PU}}\right)$ is the channel capacity between the transmitter and the receiver path of the CR-IoT users when the PU is present in the CR-IoT networks, T denotes frame duration, τ_s and τ_r are the sensing time and reporting time for the CR-IoT user, respectively. In addition, $P(H_0)$ and $P(H_1)$ are the probability of absence and presence of the PU signal in the CR-IoT network, respectively. SNR_{CR-IoT} denotes the SNR values between the CR-IoT user transmitter and the CR-IoT user receiver link and SNR_{PU} denotes the SNR values between the PU transmitter and the CR-IoT user receiver link.

- **Energy Efficiency:** Energy efficiency (EE) is one of the most important performance metrics in CR-IoT networks [Tripathi & Prasad 13]. Energy efficiency is the ratio of the achievable sum rate of the system (bits/s) to the total power consumption (Joule) [Zhang *et al.* 16, Sudhamani & *et al.* 19], which is given as follows:

$$v_{EE} = \frac{R_T}{P} \tag{2.10}$$

where v_{EE} denotes the energy efficiency in bps/J and P denotes the total transmit power consumption in J.

- **Spectral Efficiency:** The spectral efficiency (SE) is the ratio of the achievable sum rate of the system (bits/s) to the channel bandwidth (Hz) [Haider *et al.* 15], which is given as follows:

$$v_{SE} = \frac{R_T}{W} \tag{2.11}$$

where v_{SE} is the spectral efficiency in bps/Hz and W is the channel bandwidth in Hz

- **Global Error Probability:** The global error probability is a very important performance metric for cooperative spectrum sensing based CR-IoT networks. The total probability of error in detecting the PU signal is calculated by using the global error probability measuring equation, which is given as follows [Liu *et al.* 13, Wan *et al.* 19a, Shah & Koo 18a]:

$$P_e = P(H_0)P_f + P(H_1)(1 - P_d) \tag{2.12}$$

where $P(H_0)$ and $P(H_1)$ represents the probability of the absence of the PU and the probability of the presence of the PU in the network, respectively. From Eq. (2.12), it is observed that the global error probability will be low if the detection probability (P_d) is high and the false alarm probability is low.

2.9 Summary

In this chapter, I have presented the background technologies I have considered in this thesis. Cognitive radio and IoT is the main area we have focused in this research.

Chapter 3

Cluster-Based CSS for CR Enabled IoT Networks

3.1 Introduction

In this chapter I propose an approach based on sequential multiple reporting channels for cluster based cooperative spectrum sensing (CSS) for CR-IoT networks to address the first research question — *"How to increase the spectrum sensing gain and reduce reporting delays of cluster based CR-IoT networks?"*. In this proposed approach each CR-IoT user achieves a longer sensing time slot to sense the PU signal by utilizing a reporting framework that uses the sequential approach in the CR-IoT networks. Nowadays different kinds of devices are connected in wireless networks [Gauniyal & Jain 19]. IoT is a unique framework for communication between a variety of heterogeneous networks. It can automatically connect and control different kinds of devices in the network available [Gu *et al.* 19a]. As the number of IoT devices increases exponentially, the availability of radio spectrum for IoT wireless networks becomes a significant issue due to the limited radio spectrum [Khan *et al.* 19b]. Cognitive radio is an emerging technology which aims to solve the spectrum scarcity problem in IoT networks [Miah *et al.* 18b, Aswathy *et al.* 19]. In a CR-IoT network, CR-IoT users exploit spectrum holes for communication through spectrum sensing. To allow for coexistence between the primary user (PU) and the CR-IoT user in the same network, interference prevention strategies must be included to avoid harmful interference between both users [Chauhan & Sanger 14, Amin *et al.* 18]. The performance efficiency of interference prevention strategies fully depends on spectrum sensing accuracy, whereby the CR-IoT user/device monitors the spectrum and uses it when the PUs are offline. However, when a PU comes back in to the network, the CR-IoT user must instantly vacate the allocated licensed spectrum immediately [Chaudhari 19].

To ensure interference free access of the PU spectrum by the CR-IoT user, it is required that the CR-IoT users accurately identify the unused PU spectrum [Wan *et al.* 19a]. Spectrum sensing time play an important role for the CR-IoT users to accurately identify an ideal spectrum gap and use the spectrum efficiently while avoiding interference with the PUs [Moon 17]. My proposed approach significantly enhances the sensing gain for all CR-IoT users compared to the non-sequential spectrum sensing approach, as well as minimizes the reporting time delay of all CHs compared to the sequential single channel reporting approach. These two features of my proposed approach enhance the decision accuracy of the fusion centre (FC) about the presence or the absence of the PU signal in CR-IoT networks. As a result, my approach significantly reduces the interference between the PU and the CR-IoT users.

The detection accuracy of the spectrum sensing method is dependent on various parameters such as received signal power, SNR, fading, shadowing, and noise power uncertainty. In general, spectrum sensing methods can be categorized into non-cooperative detection and cooperative detection. In a non-cooperative technique, the detection of the PU signal is based on the local observations of a single CR-IoT user [Kumar & Kumar 20]. In this approach, the spectrum sensing gain is compromised due to the hidden terminal problem, shadow effect and multi-path fading . In cooperative detection techniques, the spectrum sensing becomes useful as each individual CR-IoT device locally detects the PU signal and each CR-IoT user sends the detection results to the corresponding FC via the noise free or noise reporting channel between the CR-IoT users and the FC. After that, the FC applies a fusion rule on the received detection results from the CR-IoT users to make a global decision. Finally, the FC sends the global decision to the CR-IoT users of the CR-IoT networks [Zhang *et al.* 15]

3.1.1 Contributions

In this chapter, I make the following major contributions:

- I propose an sequential multiple reporting channels approach for cluster-based CSS in which each CR-IoT user achieves a longer sensing time slot to sense the PU signal by utilizing a reporting framework that uses the sequential approach in the CR-IoT networks.
- I evaluate the sensing performance of CHs and FC, based on the longest sensing time duration by using the "K-out-of-N" rule.
- I evaluate the global error probability of CHs and FC for the proposed approach and the non-sequential conventional approach.
- I compare the time delay for reporting of all CHs for my proposed sequential multiple reporting channel approach and conventional sequential single reporting channel approach.
- I show that my proposed approach achieves better sensing performance of CR-IoT users and reduce the global error of CHs and FC compared to the non-sequential conventional approach.

3.1.2 Publications

The work outlined in this chapter was published in:

Mohammad Amzad Hossain, Michael Schukat and Enda Barrett. Enhancing the Spectrum Sensing Performance of Cluster-Based Cooperative Cognitive Radio Networks via Sequential Multiple Reporting Channels. *Wireless Personal Communications Journal, Vol. 116, No. 3, pp. 2411–2433 (2020).*

3.1.3 Chapter Structure

The remainder of the chapter is organized as follows: The background of this chapter is summarised in Section 3.2. Section 3.3 describes the system model and energy detection technique. Section 3.4 describes the non-sequential conventional approach in cluster-based CR-IoT networks, where CR-IoT users are not utilising the reporting time slot for sensing purposes. Section 3.5 introduces the proposed sequential multiple reporting channels approach. Section 3.6 describes the mathematical model for performance analysis. In Section 3.7 I compare my proposed approach with other existing approaches. Finally, conclusions and future work are addressed in Section 3.8.

To make the article easier to read, all parameters with corresponding definitions are mentioned in Table 3.1.

Table 3.1: Main parameters

Parameters	Corresponding Definitions
H_0	The hypothesis which indicates the absence of the PU signal
H_1	The hypothesis which indicates the presence of the PU signal
U	The total number of CR-IoT users
N	The total number of clusters
M	The number of CR-IoT users in a every cluster
$x(t)$	Signal transmitted from PU
$w(t)$	The reporting channel noise
$h(t)$	The channel gain between the PU and the CR-IoT user
$y(t)$	The sensing signal received by the CR-IoT user
γ	The SNR at the CR-IoT user
E	The energy of the received signal
F_s	The sampling frequency
T_s	The sensing time slot
$T_{r,SU}$	The time duration for reporting of the CR-IoT user
$T_{r,ch}$	The time duration for reporting of the CH
$P_{f,k}^{con}$	Probability of false alarm for the conventional approach
$P_{d,k}^{con}$	Probability of detection for the conventional approach
$P_{f,k}^{prop}$	Probability of false alarm for the proposed approach
$P_{d,k}^{prop}$	Probability of detection for the proposed approach
λ_k^{con}	Decision threshold for the conventional approach
λ_k^{prop}	Decision threshold for the proposed approach
P_f^{FC}	The global probability of alarm at the FC
P_d^{FC}	The global probability of detection at the FC
T_d^{ch}	The reporting time delay of CH

3.2 Related Work

Cluster-based CR-IoT networks with parallel multiple reporting channels enhance the spectrum utilisation. There is a lot of research activity in the area of spectrum sensing for CR-IoT networks and several techniques have been proposed. In [Suseela & Sivakumar 15], NCSS for CR-IoT networks is analyzed. An analysis of CSS is presented in [Ahsant & Viswanathan 13, Akyildiz *et al.* 11]. In [Awe & Lambotharan 15] a multi-class support vector machine (SVM) classifier is proposed for spectrum sensing under various primary user conditions. In [Alhamad & Boujemaa 19] a multi-hop multi-branch spectrum sensing is proposed using two cooperation protocols that allowed any number of hops and branches to overcome the interference problem between PU and CR-IoT user signal. The advantages and limitations of both narrow-band as well as wide-band spectrum sensing approaches have also been studied in [Arjoune & Kaabouch 19b]. In [Prasad & Venkatesan 19] the authors introduce group based multi-channel synchronised spectrum sensing to sense multiple channels with minimum interference and without decreasing the precision of sensing for 5G networks. Dynamic dual threshold cooperative spectrum sensing has been considered in [Wan *et al.* 19b] to minimise the impact of noise uncertainty and enhance the accuracy of spectrum sensing. In [Shah & Koo 18b] the authors propose a k-nearest neighbor machine learning algorithm-based spectrum sensing technique for fading and nonfading channels. Deep learning based spectrum sensing methods have been investigated in [Yang *et al.* 19a].

Hesham et al. [Hesham *et al.* 12a] propose a sequential detection technique in the FC to obtain a reliable decision. This scheme considers only one reporting channel, which increases the reporting delay from CR-IoT user to cluster head and cluster head to fusion center. In [Hesham *et al.* 12b], the authors propose a sequential detection technique to achieve a reliable decision regarding PU activity. However, the sensing time of CR-IoT users is not utilised in the reporting framework. This paper considers only one reporting channel to reduce the number of reporting channels and distributed CR-IoT users in the CR-IoT networks; when the number of CR-IoT users is increased, this approach is not able to provide optimal performance. In [Fu *et al.* 17] the authors propose a cross-layer parallel cooperative spectrum sensing for heterogeneous channel for CR-IoT networks in order to obtain higher available throughput compared to the iterative Hungarian based method and the Greedy method. However, this method only focuses on the throughput without analysing the spectrum sensing performance. Nguyen-Thanh et al. [Nguyen-Thanh & Koo 13a] propose a cluster-based optimal selective CSS scheme with multiple reporting mechanisms for CR-IoT networks in order to reduce reporting time delays between clusters and the FC, which keeps a similar accuracy of spectrum sensing compared to the conventional CSS scheme. In this approach, each cluster uses individual sub-control channels to transfer the spectrum sensing data to the FC.

In [Nguyen-Thanh & Koo 13a], the authors propose a parallel reporting mechanism to reduce the decision-making time by the FC. However, in this paper, CR-IoT users are not utilising the reporting time slot for sensing purpose. Sipon et al. [Miah *et al.* 18a] propose a sequential approach for cluster-based cognitive radio relay networks (CCRRNs) with and without a relay. This approach considers only one noisy reporting channel. In this scheme the authors focus on enhancing the sensing time of CR-IoT users by utilising reporting time slots. However, this scheme considers only one reporting channel for all CR-IoT users and CHs which increases reporting delay. Moreover, the reporting delay is not analysed in this paper.

3.3 System Model

I consider a cluster-based cooperative spectrum sensing for CR-IoT networks with cooperative CR-IoT users (i.e., secondary users (SUs)), the number of CR-IoT users is denotes by U. All CR-IoT users access the same frequency band as a PU of the primary network without causing interference and with one FC, as shown in Figure 3.1.

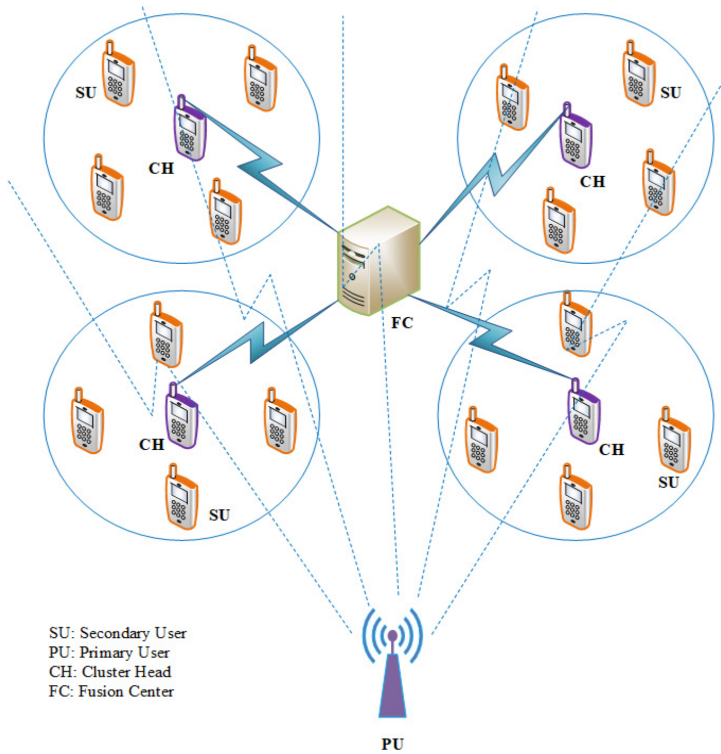

Figure 3.1: The proposed cluster-based CR-IoT networks model

In this network model the PU uses a time division multiplexing access (TDMA) technique to transmit the data to its receiver by using independent time slots. The CR-IoT users also use TDMA to transmit the data to its corresponding receiver by identifying the ideal time slot.

The cluster-based CR-IoT networks consists of N clusters with each cluster having the same number of CR-IoT users with one CH based on a Fuzzy C-Means (FCM) protocol and their geographical location (e.g. through a global positioning system (GPS)) [Hoang *et al.* 13, Yau *et al.* 14, Maity *et al.* 16, Chatterjee *et al.* 14]. In a cluster the CR-IoT users are located very close to each other. In physically small clusters (like 4 to 10 CR-IoT users per cluster), CR-IoT users can be better coordinated, so smaller cluster size increase the network performance. We consider that the FC uses the Fuzzy C-Means clustering protocol for creating cluster and selecting CHs. The Fuzzy C-Means is a centralized clustering algorithm. The working process of the FCM algorithm is divided into three steps [Bhatti *et al.* 16a] as follows: (i) cluster formation step, (ii) cluster head selection step and (iii) spectrum sensing step.

In cluster-based CR-IoT networks, initially each CR-IoT user sends a HELLO message to the FC with five parameters, such as geographical location of the CR-IoT user, distance between the CR-IoT user and the FC, SNR of the CR-IoT user, residual energy of the CR-IoT user, and identification number of the CR-IoT user. In the cluster formation step (i), the FC uses the FCM algorithm to calculate the centers of all clusters in the networks and selects the nearest CR-IoT users to the cluster centers to become cluster members of a cluster based on the geographical location of CR-IoT users. In the cluster head selection step (ii), the FC selects the CH for each cluster based on the location of CR-IoT users with respect to the FC, location of CR-IoT users within the cluster, residual energy level of CR-IoT users and SNR of the reporting channel of CR-IoT users. After selecting CHs the FC broadcasts a REPLY message. If the CR-IoT user identification number matches with the CH identification number of the REPLY message, then this CR-IoT user becomes a CH; otherwise the CR-IoT user becomes a specific cluster member. The CH makes a TDMA schedule of the reporting channel to allocate the time slot when cluster members can transmit their sensing information to the CH. In the spectrum sensing step (iii), CR-IoT users send their spectrum sensing results about the PU signal to the corresponding CH and then the CH makes the cluster decision based on the spectrum sensing results of cluster members, in order to reduce the reporting time delay and minimise the bandwidth usage. Then all CHs send their cluster decision to the FC at the same time by using a dedicated parallel reporting channel. Consequently, the FC applies a "K-out-of-N" rule on the received cluster head decisions for making a global decision. Finally, the FC sends the global decision to all CHs of the network. Subsequently, the CHs send this global decision to their corresponding cluster members.

The cluster formatting process is repeated in every PU signal sensing interval. Only at the first PU signal sensing interval, the FC selects the CH for each cluster. However, from the second PU signal sensing interval, the next CH of the cluster is selected by the current CH from cluster members based on the location of CR-IoT users with respect to the FC, location of CR-IoT users within the cluster, residual energy level of CR-IoT users and the SNR of the reporting channel of CR-IoT users [Hoang *et al.* 10a]. In cluster-based CR-IoT networks, each CR-IoT user continuously searches the PU signal in the network, which is the so called spectrum sensing process. This spectrum sensing process makes a decision between two conditions such as whether the PU signal is present or not in the network. This spectrum sensing process can be formulated by the following binary hypothesis testing [Singh *et al.* 11]:

$$\begin{cases} H_0 : y_j(t) = w_j(t) \\ H_1 : y_j(t) = h_j(t) * x(t) + w_j(t) \end{cases} \tag{3.1}$$

where hypothesis H_0 indicates the PU signal is absent and hypothesis H_1 indicates the PU signal is present in the network, $y_j(t)$ denotes the signal that is received by the jth CR-IoT user, here $j = 1, 2, 3, ..., U$, $h_j(t)$ represents the channel gain between the PU and the jth CR-IoT user, $x(t)$ is the binary phase shift keying (BPSK) modulated signal transmitted from the PU, and $w_j(t)$ is a circularly symmetric complex Gaussian (CSCG) noise signal. The CSCG noise with zero mean and variance $\sigma^2_{w,j}$ is denoted by $w_j(t) \sim \mathcal{CN}(0, \sigma^2_{w,j})$ [Zeng *et al.* 13]. This noise is characterised by the noise variance $\sigma^2_{w,j}$. The CR-IoT user transmits the sensing report to its corresponding CH through a noisy channel. The reporting signal received by the kth CH from the jth CR-IoT user can be given as follows:

$$r_k(t) = g_j(t) * y_j(t) + c_j(t) \tag{3.2}$$

where $g_j(t)$ represents the channel gain between the jth CR-IoT user and the kth CH and $c_j(t)$ represents the CSCG noise signal between the jth CR-IoT user and the kth CH, with $K = 1, 2, 3, ..., N$. The SNR at the kth CH can be given by [Shrestha *et al.* 16]: $\gamma_k = \frac{\sigma^2_{x,j}}{\sigma^2_{w,j}+\sigma^2_{c,j}}$. where γ_k is the SNR at the kth CH, $\sigma^2_{x,j}$ is the PU signal variance, $\sigma^2_{w,j}$ is the variance of the noise signal $w_j(t)$ and $\sigma^2_{c,j}$ is the variance of the noise signal $c_j(t)$.

3.3.1 Energy Detection Process

Spectrum sensing is the most important step in cluster-based CR-IoT networks because it is used to detect the presence of the PU signal in a licensed band. Interference is a very important issue for cognitive radio networks, and the spectrum sensing process is used to avoid the interference between the CR-IoT user signal and the PU signal [Pandit & Singh 17]. In this thesis, we consider the energy detection method to identify the presence or absence of the primary user signal in the network. It is an attractive spectrum sensing technique due to the fact it does not require any previous knowledge about the PU signal to identify the presence/absence of the PU signal in the a licensed spectrum [Xuping & Jianguo 07].

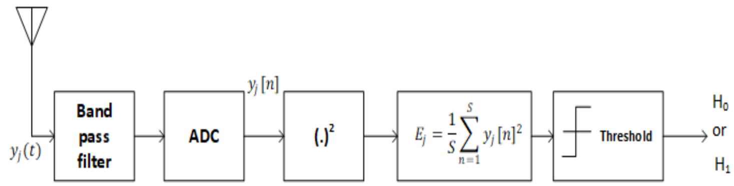

Figure 3.2: Architecture of the energy detection process [Pandit & Singh 17, Xuping & Jianguo 07, Pandya *et al.* 15]

In this thesis, I assume that all CR-IoT users in the cluster-based CR-IoT networks use the energy detection method to identify the presence or absence of a PU signal. Figure 3.2 displays the energy detection process at the CR-IoT user to obtain the energy level of the received PU signal [Pandya *et al.* 15]. Firstly the received signal is transmitted through a band-pass filter to get the desired signal, then this signal is transmitted through an analog-to-digital converter (ADC) to change the analog signal to the digital signal. Afterwards, the signal energy is measured by the following equation [Plata & Reátiga 12b, Amin *et al.* 18].

$$E_j = \frac{1}{S}\sum_{n=1}^{S} y_j[n]^2 \tag{3.3}$$

where S denotes the number of samples of the digital signal, which is defined as $S = 2F_sT_s$ in which F_s and T_s correspond to sampling frequency and the sensing time of the PU signal, respectively. $y_j[n]$ is a digitised sample of the received signal for the nth sample, and E_j denotes the measured energy of the received signal at the jth CR-IoT user for a specific sensing interval. Finally, this measured energy level is compared to the pre-defined threshold value to decide if a PU signal is present or not in the network.

3.4 Conventional Approach in Cluster-based CR-IoT networks

In the non-sequential conventional approach, the sensing time slot T_s^{con} for all CR-IoT users is fixed to detect the PU signal, as well as the reporting time slot T_r^{con} used to forward the sensing data to CHs. In this approach all CR-IoT users use separate reporting channels for sending their spectrum sensing results to CHs [Miah & Rahman 14]. The non-sequential conventional approach introduces two problems. Firstly when the number of CR-IoT users in the cluster-based CRNs is increased, it is not possible to provide separate reporting channels for all CR-IoT users at the same time, as the number of reporting channels is limited. Secondly CR-IoT users are not able to use the reporting time slot for sensing purposes, and all CR-IoT users transmit their sensing data to the CH in a non-sequential way. Figure 3.3 shows the frame architecture of the non-sequential conventional approach for cluster-based CR-IoT networks [Anaand & Charan 16].

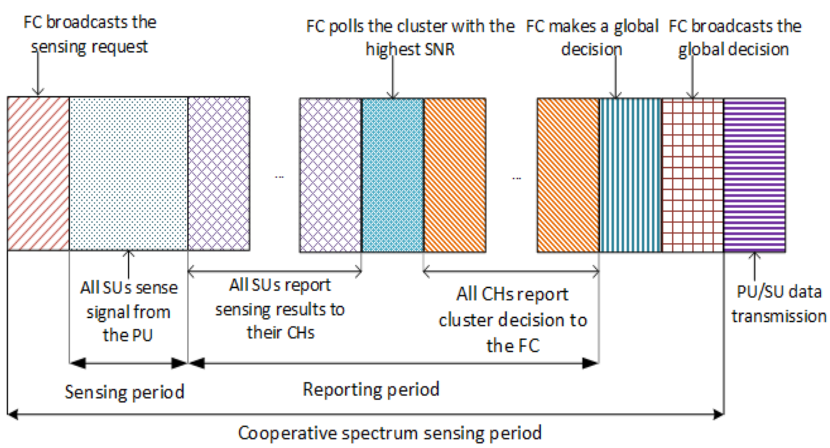

Figure 3.3: Frame architecture of the non-sequential conventional approach in the cluster-based CR-IoT networks [Miah *et al.* 18a]

Thus, this non-sequential conventional approach is not suitable for cluster-based CR-IoT networks with large numbers of CR-IoT users. This approach is not effective for spectrum sensing because spectrum sensing time slot T_s^{con} is small and fixed.

3.5 Proposed sequential multiple Peporting Channel Approach in Cluster-based CR-IoT networks

In the proposed sequential multiple reporting channel approach, one dedicated orthogonal reporting channel is assigned for each cluster. All CR-IoT users in the specific cluster use the same orthogonal reporting channel to forward the PU signal sensing result to the CH in a sequential way. In the proposed approach, the spectrum sensing time slot duration for each CR-IoT user is longer than the conventional non-sequential approach due to the reporting time slots of previous CR-IoT users being merged with the fixed sensing time slot of the CR-IoT user.

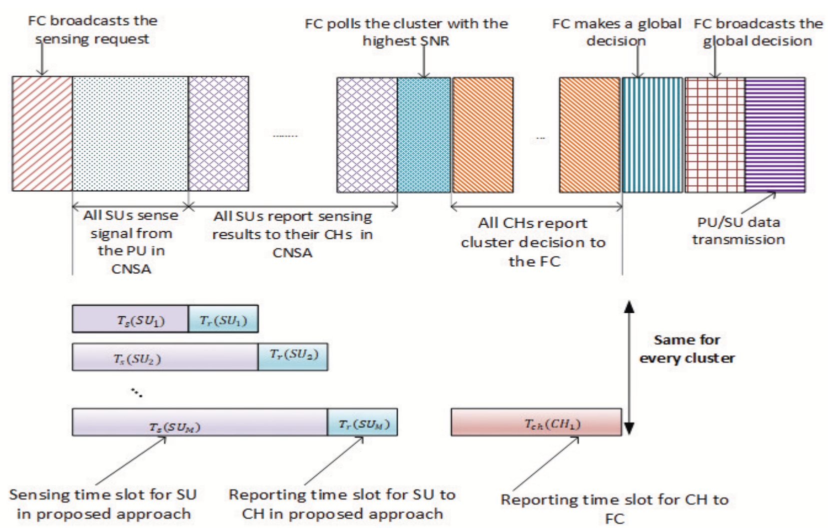

Figure 3.4: Frame structure of the proposed sequential approach to utilize the reporting time slot in cluster-based CR-IoT networks

In Figure 3.4, the sensing time for the 1st CR-IoT user in all clusters is fixed, but the sensing time for the 2nd CR-IoT user in all clusters is a combination of the allocated fixed sensing time slot and the rigid reporting time slot of the 1st CR-IoT user, while the sensing time for the 3rd CR-IoT user in every cluster is a combination of the allocated fixed sensing time slot and the rigid reporting time slots of the previous two CR-IoT users, and so on. In every cluster, the CR-IoT users forward their spectrum sensing results of the PU signal to the corresponding CH by using a single reporting channel in a sequential way, and then the CH collects the spectrum sensing results of the corresponding CR-IoT users, and makes the cluster decision. All CHs use a dedicated parallel reporting channel to forward the cluster result to the FC at the same time, which increases the global decision making efficiency of the FC. Afterwards, the FC makes a global decision on the basis of received CH decisions and then broadcasts this decision to every CHs. Finally, all CHs transmit this decision to their corresponding CR-IoT users.

3.5.1 Proposed Synchronisation Process for the System

In order to realize the benefits of CRs, spectrum awareness is a must. Typically, this is done by cooperative sensing in a sequential manner. Cognitive radio systems use time frame/slot structures for spectrum sensing and data transmission. This implies that all the clocks in a CR network are synchronized. Otherwise, time differences can cause CR-IoT users to sense the spectrum at different times. This may lead to incorrect sensing results. Therefore, time synchronization is a vital concern for any cognitive radio network to perform dynamic spectrum management for efficient operation [Ruttik *et al.* 07]. I consider the CR-Sync [Nieminen *et al.* 09] protocol for the synchronization of the spectrum sensing process among CR-IoT users. Before starting the synchronization process, the FC will initialize the synchronization process and eventually all CR-IoT users in the network synchronize to the time reference provided by the FC. It is also assumed that all CR-IoT users in the network have similar clocks, so that there is no need to compare clock attributes of different CR-IoT users.

3.6 Mathematical Model for Performance Analysis

In this section, I analyse the spectrum sensing performance and reporting time delay of the conventional and proposed approach, respectively.

3.6.1 Spectrum sensing analysis

When S is sufficiently large (e.g., $S > 250$) [Nguyen-Thanh & Koo 13b], then the received signal energy E_j at the jth CR-IoT user can be considered as a Gaussian random variable for both hypotheses H_0 and H_1. According to the central limit theorem, E_j can be expressed for both hypotheses as follows [Plata & Reátiga 12b]

$$E_j = \begin{cases} \mathcal{N}(S\sigma_{w,j}^2, & 2S\sigma_{w,j}^4) \\ \mathcal{N}(S(1+h^2\delta_j)\sigma_{w,j}^2, & 2S((1+h^2\delta_j)\sigma_{w,j}^2)^2) \end{cases} \tag{3.4}$$

where h is the antenna gain and $\delta_j = \frac{\sigma_{x,j}^2}{\sigma_{w,j}^2}$ is the SNR at the jth CR-IoT user.

In each cluster, CR-IoT users sequentially transmit their PU signal sensing results to their corresponding CH. Each CH uses the Equal Gain Combining (EGC) technique to compute the cluster decision statistic. For every cluster, the power level of the received PU signal at the CH is represented by the cluster decision statistic, which is expressed by the following equation [Hossain *et al.* 19]:

$$Z_k|_{k=1}^{N} = \sum_{i}^{M} \frac{1}{S} \sum_{n=1}^{S} r_{k,i}[n]^2 \tag{3.5}$$

where M is the number of CR-IoT users in a each cluster and $i = 1, 2, ..., M$. However, each CH makes the cluster decision about presence or absence of the PU signal in the network by comparing the cluster decision statistic with a pre-defined threshold λ. It is given for the kth CH as follows:

$$D_k^{ED} = \begin{cases} 1, & if Z_k \geqslant \lambda_k \quad (for \quad H_1) \\ 0, & if Z_k < \lambda_k \quad (for \quad H_0) \end{cases} \tag{3.6}$$

If $D_k^{ED} = 1$ that indicates the PU signal is present and $D_k^{ED} = 0$ that indicates the PU signal is absent in the networks.

3.6.1.1 The Conventional Approach

For the non-sequential conventional approach, I know that the sensing time slot for all CR-IoT users in the cluster-based CR-IoT networks is fixed and the same, which is denoted by T_s^{con}. According to [Arjoune *et al.* 18, Plata & Reátiga 12b], the detection performance of the non-sequential conventional approach can be evaluated through the probability of false alarm ($P_{f,k}^{con}$) and the probability of detection ($P_{d,k}^{con}$). At the kth CH, these probabilities are given as follows:

$$
\begin{aligned}
P_{f,k}^{con} &= Pr(D_k^{ED} = 0|H_0) \\
&= Q\left(\frac{\lambda_k^{con} - 2T_s^{con}F_s\sigma_{w+c}^2}{\sqrt{2*2T_s^{con}F_s\sigma_{w+c}^4}}\right)
\end{aligned}
\tag{3.7}
$$

$P_{f,k}^{con}$ refers to the number of times that a PU's signal is falsely detected by the sensing device over the total number of sensing trials. $P_{f,k}^{con}$ is the probability that a sensing device decides the PU's signal is present when it is absent in the CR-IoT networks.

$$
\begin{aligned}
P_{d,k}^{con} &= Pr(D_k^{ED} = 1|H_1) \\
&= Q\left(\frac{\lambda_k^{con} - 2T_s^{con}F_s(1+h^2\gamma_k)\sigma_{w+c}^2}{\sqrt{2*2T_s^{con}F_s((1+2h^2\gamma_k)\sigma_{w+c}^2)^2}}\right)
\end{aligned}
\tag{3.8}
$$

where $\sigma_{w+c}^2 = \sigma_{w,j}^2 + \sigma_{c,j}^2$, γ_k is the SNR at the kth CH, $N = 2T_s^{con}F_s$ and $Q(.)$ is a Q-function. The Q-function is the right-tail probability of a normalized Gaussian distribution, which is defined as [Bilim 19]

$$
Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} exp(-\frac{t^2}{2})dx \tag{3.9}
$$

$P_{d,k}^{con}$ refers to the numbers of times that the PU's signal is correctly detected by the sensing device over the total number of sensing trials. $P_{d,k}^{con}$ is the probability that a sensing device decides correctly the presence of the PU's signal in the CR-IoT networks.

According to [Sarker 15, Patil *et al.* 18], we can compute the threshold value λ_k^{con} from the probability of the false alarm $P_{f,k}^{con}$, which is obtained from Eq.(3.8) and given as:

$$
\lambda_k^{con} = [Q^{-1}(P_{f,k}^{con}) + \sqrt{T_s^{con}F_s}]2\sqrt{T_s^{con}F_s}\sigma_{w+c}^2 \tag{3.10}
$$

where $Q^{-1}(.)$ represents the inverse function of the Q-function.

3.6.1.2 The Proposed Approach

In my proposed sequential multiple reporting channel approach, every CR-IoT user in each cluster obtains the longest spectrum sensing time slot, except only the first CR-IoT user in each cluster. According to [Miah *et al.* 18a], in my proposed sequential multiple reporting channel approach for cluster-based CR-IoT networks, the sensing time slot duration for every CR-IoT user in each cluster is given as follows:

$$T_s^{prop} = T_s + (i-1)T_{r,CR-IoT} \tag{3.11}$$

where T_s^{prop} represents the extended time to sense the PU signal for every CR-IoT users at each cluster, T_s denotes the fixed sensing time duration for every CR-IoT user, and $T_{r,CR-IoT}$ represents the reporting time duration to report for every CR-IoT user.

I can calculate the probability of false alarms $P_{f,k}^{prop}$ and the probability of detection $P_{d,k}^{prop}$ of the kth CH for the sequential multiple reporting channel approach are given as [Arjoune *et al.* 18, Plata & Reátiga 12b]:

$$\begin{aligned} P_{f,k}^{prop} &= Pr[D_k^{ED} = 0|H_0] \\ &= Q\left(\frac{\lambda_k^{prop} - 2T_{s,k}^{prop}F_s\sigma_{w+c}^2}{\sqrt{2*2T_{s,k}^{prop}F_s\sigma_{w+c}^4}}\right) \end{aligned} \tag{3.12}$$

$$\begin{aligned} P_{d,k}^{prop} &= Pr(D_k^{ED} = 1|H_1) \\ &= Q\left(\frac{\lambda_k^{prop} - 2T_{s,k}^{prop}F_s(1+h^2\gamma_k)\sigma_{w+c}^2}{\sqrt{2*2T_{s,k}^{prop}F_s((1+2h^2\gamma_k)\sigma_{w+c}^2)^2}}\right) \end{aligned} \tag{3.13}$$

We can derive the equation for the decision threshold λ_k^{prop} at the CH from Eq.(3.12) for the proposed approach as follows [Sarker 15, Patil *et al.* 18]:

$$\lambda_k^{prop} = [Q^{-1}(P_{f,k}^{prop}) + \sqrt{T_s^{prop}F_s}]2\sqrt{T_s^{prop}F_s}\sigma_{w+c}^2 \tag{3.14}$$

The FC applies the “K-out-of-N” rule on all received CH results to make the global decision to declare that the PU signal is present or not in the cluster-based CR-IoT networks. This final decision is then broadcast to all CHs. Consequently, the CHs dispatch this global decision to their corresponding CR-IoT users. The FC declares that the PU signal is present if at least K out of N CHs report that the PU signal exist in the network. The "K-out-of-N" voting rule means that if K or more out of N CHs individually mention the presence of the PU signal, the FC makes the global decision that the PU is present in the cluster-based CR-IoT networks; otherwise, it makes the global decision that the PU is absent in the cluster-based CR-IoT networks. Let $Di = (0, 1)$ be the binary decision for the ith CH, where $Di = 0$ and $Di = 1$ indicate the absence and presence of the PU signal in the CR-IoT networks, respectively. According to the "K-out-of-N" rule, if at least K out of N CHs send the binary decision value $D = 1$, the FC makes the global decision that the PU signal is present, otherwise the PU is absent in the CR-IoT networks.

The global decision making process at the FC is shown in Figure 3.5.

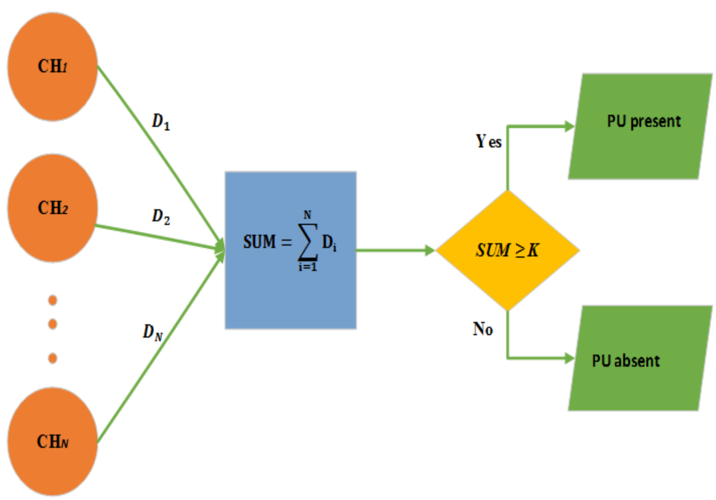

Figure 3.5: The global decision making process at the FC

The probability of false alarms and the probability of detection can be expressed by using the "K-out-of-N" rule are given as follows [Chilakala & Ram 18, Althunibat *et al.* 13]:

$$P_{f,FC} = \sum_{l=K}^{N} \binom{N}{l} P_f^l (1 - P_f)^{N-l} \tag{3.15}$$

$$P_{d,FC} = \sum_{l=K}^{N} \binom{N}{l} P_d^l (1 - P_d)^{N-l} \tag{3.16}$$

where N is the number of total clusters in the cluster-based CR-IoT networks and K

is the number of CHs that indicate that a PU signal is present ($N > K$).

3.6.2 Global Error Probability Analysis

I can calculate the global error probability P_e for the proposed hybrid spectrum sensing scheme at the FC as follows [Liu *et al.* 13, Wan *et al.* 19a]:

$$P_e = P(H_0)P_{f,FC} + P(H_1)(1 - P_{d,FC}) \tag{3.17}$$

where $P(H_0)$ and $P(H_1)$ represents the probability of the absence of the PU and the probability of the presence of the PU in the network, respectively.

3.6.3 Reporting Time Delay Analysis

In cluster-based CR-IoT networks, the reporting delay is a very important factor to make a global decision [Hu *et al.* 14]. In my proposed sequential multiple reporting channels approach, all CHs simultaneously send their local decision to the FC after an identical time period by using a separate reporting channel, as shown in Figure 3.4. In my proposed approach, we consider the sectoring based frequency reuse concept for minimising the extra bandwidth requirement for separate reporting channels for each CH [Sezginer & Sari 09, Ahmed *et al.* 14]. Sipon et al. [Miah *et al.* 18a] propose a signal reporting channel sequential approach for cluster-based CR-IoT networks in which the reporting time delay for a CH is not identical and not able to simultaneously send all CHs decisions to the FC. However, the single reporting channel sequential approach is not effective for cluster-based CR-IoT networks, because it is not able to send all CHs decisions to the FC at the same time; it also increases the delay among the CH decisions, which decreases the global decision making efficiency of the FC; however, cluster-based CR-IoT networks need to take decision as soon as possible.

Proposition 1. The reporting time delay of CHs for sequential single reporting channel approach are [Miah *et al.* 18a] given as follows:

$$\begin{aligned} T_{d,ch_1} &= (M+1)T_r \\ T_{d,ch_2} &= 2(M+1)T_r \\ T_{d,ch_3} &= 3(M+1)T_r \\ &\cdot \\ T_{d,ch_N} &= N(M+1)T_r \end{aligned} \tag{3.18}$$

where M indicates the number of CR-IoT users in a every cluster, T_r indicates the reporting time duration and N is a number of cluster in the network.

Proof: The reporting time delay of CHs for single reporting channel sequential approach are given as follows: The reporting time delay for first CH is:

$$\begin{aligned} T_{d,ch_1} &= MT_{r,SU} + T_{r,ch} \\ &= (M+1)T_r \end{aligned} \tag{3.19}$$

where $T_{r,SU} = T_{r,ch} = T_r$ and M is the number of SUs in a every cluster.
The reporting time delay for second CH is:

$$\begin{aligned} T_{d,ch_1} &= T_{d,ch_1} + MT_{r,SU} + T_{r,ch} \\ &= 2(M+1)T_r \end{aligned} \tag{3.20}$$

Similarly, the reporting time delay for the Nth cluster is:

$$T_{d,ch_N} = K(M+1)T_r \tag{3.21}$$

where N is a number of cluster in the network.

Proposition 2. The identical reporting time delay for every CH in our proposed sequential multiple reporting channel approach is given as follows:

$$T_{d,ch} = (M+1)T_r \tag{3.22}$$

Proof: The identical reporting time delay for every CHs in our proposed approach is given as follows:

$$\begin{aligned} T_{d,ch} &= MT_{r,SU} + T_{r,ch} \\ &= (M+1)T_r \end{aligned} \tag{3.23}$$

where $T_{r,SU} = T_{r,ch} = T_r$ and M is a number of SUs in a every cluster. Therefore, in my proposed sequential multiple reporting channel approach there is no time delay among CHs to forward local decisions to the FC.

3.7 Simulation Results and Discussion

Via simulation I verify the theoretical results and evaluate the performance of the proposed approaches. This is done through numerical simulations via Matlab (Matrix Laboratory). As one of the most widely used scientific experimental tools with powerful mathematics toolboxes and packages, Matlab is the pioneer on cognitive radio simulation because of it provides a realistic simulation environment for cognitive radio networks. As a result many researchers use Matlab to validate spectrum sensing and allocation schemes [Lin *et al.* 15]. The physical layer communications system is established by introducing a dynamic spectrum access scheme, which enhances the performance of the network capacity and throughput [Miah 20]. Matlab is ideal for cognitive radio networks physical layer simulation, because it is naturally deployed to process signals, build up transceiver model, and further to set up communication systems. To justify the feasibility and viability of energy detection, the PU signal is first generated with added noise. Using a proper radio propagation model, the received signal can be simulated on the secondary user side, and the energy detection technique is easily adopted by measuring received signal level.

In this section, I firstly assess the performance of our proposed sequential approach by spectrum sensing analysis, and secondly by reporting the time delay analysis based on the Monte-Carlo numerical simulation method. Monte-Carlo simulations were carried out using the simulation parameters listed in Table 3.2 below which are based on the rationale of the other researchers [Miah *et al.* 18a, Vishnu & Bhagyaveni 20, Miah *et al.* 20, Semba Yawada & Trung Dong 18].

Table 3.2: List of parameters for simulation

List of parameters	Values
Number of CR-IoT users in network, U	25
Number of CHs in network, N	5
Sample rate, F_s	400kHz
Time duration for sensing of the CR-IoT user, T_s	20ms
Time duration for reporting of the CR-IoT user, $T_{r,CR-IoT}$	10ms
Time duration for reporting of the CH, $T_{r,ch}$	10ms
Transmit signal of the PU, $x(t)$	BPSK
Noise for the transmit channel $w(t)$	CSCG
noise for reporting channel , $c(t)$	CSCG
Signal-to-noise ratio at the PU, SNR_{PU}	-14 dB

Figure 3.6 shows the sensing performance of CHs and FC by using receiver operating characteristic (ROC) curves for the non-sequential conventional and proposed sequential multiple reporting channels approach, respectively.

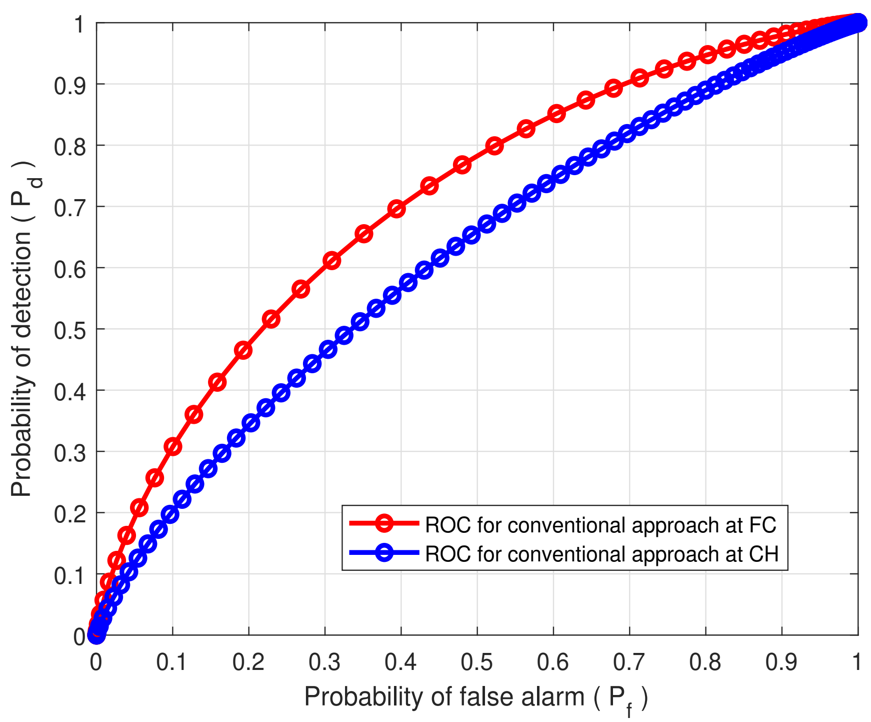

Figure 3.6: ROC curves for the FC and CH of the non-sequential conventional approach

In the non-sequential conventional approach the sensing performance is the same for the four CHs. Therefore, just one CH curve is shown in Figure 3.6. The sensing performance is not better, because the sensing time for CR-IoT users is small and fixed. Therefore the non-sequential conventional approach is not able to enhance the sensing gain of CR-IoT users.

Figure 3.7 shows the ROC curve for the proposed sequential multiple reporting channels approach. In this figure we show one CH and FC, because the remaining four CHs have the same ROC curve. In my proposed approach, sensing performance of the CH is better when compared to the non-sequential conventional approach.

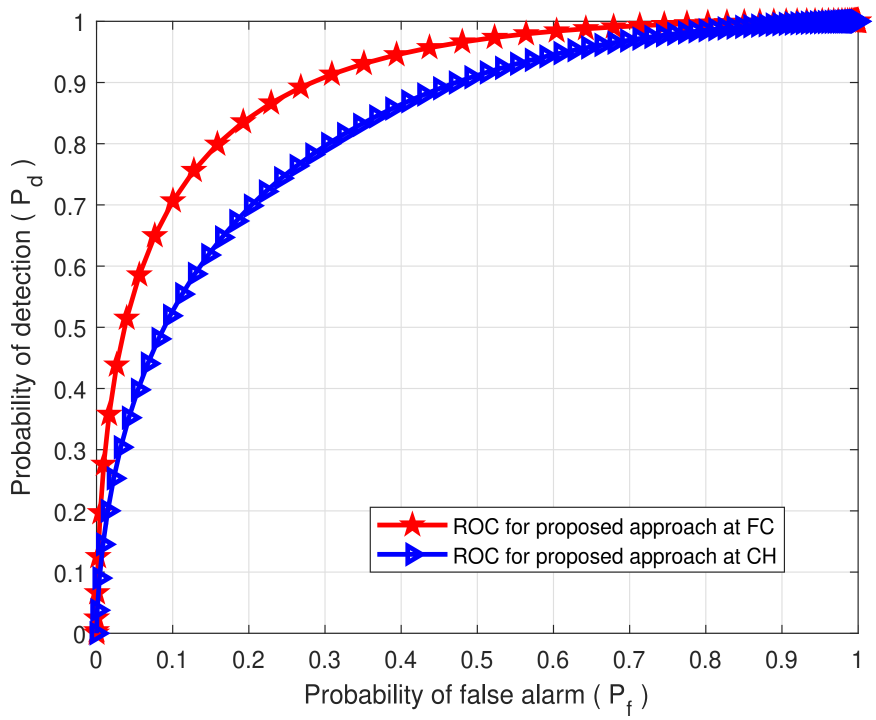

Figure 3.7: ROC curves for the FC and CH of the proposed approach

The reason for this is that the sensing gain is higher due to the longer sensing time according to Eq.(3.11) when compared to the non-sequential conventional approach. The sensing performance of the FC in our proposed approach is better than of the non-sequential conventional approach.

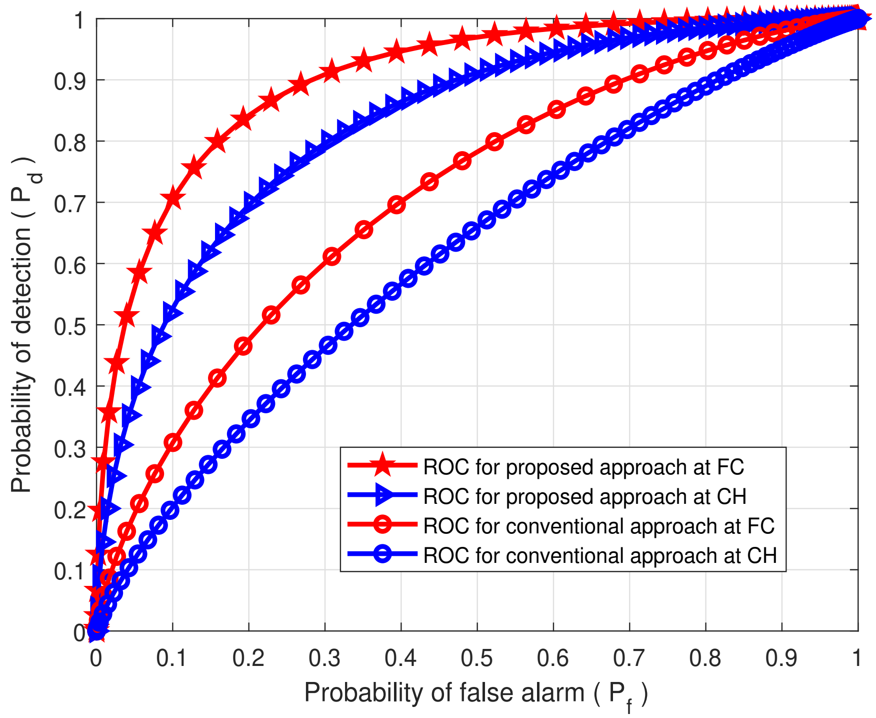

Figure 3.8: Performance comparison ROC curves at the CH and FC of the non-sequential conventional and proposed approach

In Figure 3.8, I compare the sensing performance of the CH and FC for the conventional approach and proposed approach. We can observe from Figure 3.8 that our proposed sequential multiple reporting approach shows better sensing performance than the non-sequential conventional approach for the CHs and FC. Also from Figure 3.8 it is observed that the probability of detection of the CH is 0.70 and 0.35 for proposed approach and conventional approach when probability of false alarm is 0.2. The sensing gain at the FC; the probability of detection of the FC is 0.84 and 0.48 for proposed approach and conventional approach when probability of false alarm is 0.2. This sequential multiple reporting channel approach enhances the PU signal detection gain over the non-sequential conventional approach. It can be observed that the probability of detection for the CHs and the FC in the proposed approach are 35% and 36% better than the non-sequential conventional approach, respectively. Therefore, my proposed approach is more applicable than the conventional approach to real system.

The spectrum sensing performance results of the CH and FC for conventional and proposed approaches are shown in Table 3.3.

Table 3.3: Sensing result of the CH and FC for conventional and proposed approaches

Categories	Measurement	Non-sequential approach	Proposed sequential approach	Figure
CH	P_d	0.35	0.70	3.8
	P_f	0.20	0.20	
FC	P_d	0.48	0.84	
	P_f	0.20	0.20	

In the reporting time delay analysis scenario, I consider three different CR-IoT user settings for every cluster. In the first setting, I consider four CHs in a network and four CR-IoT users in each cluster. Figure 3.9 shows the number of CR-IoT users versus

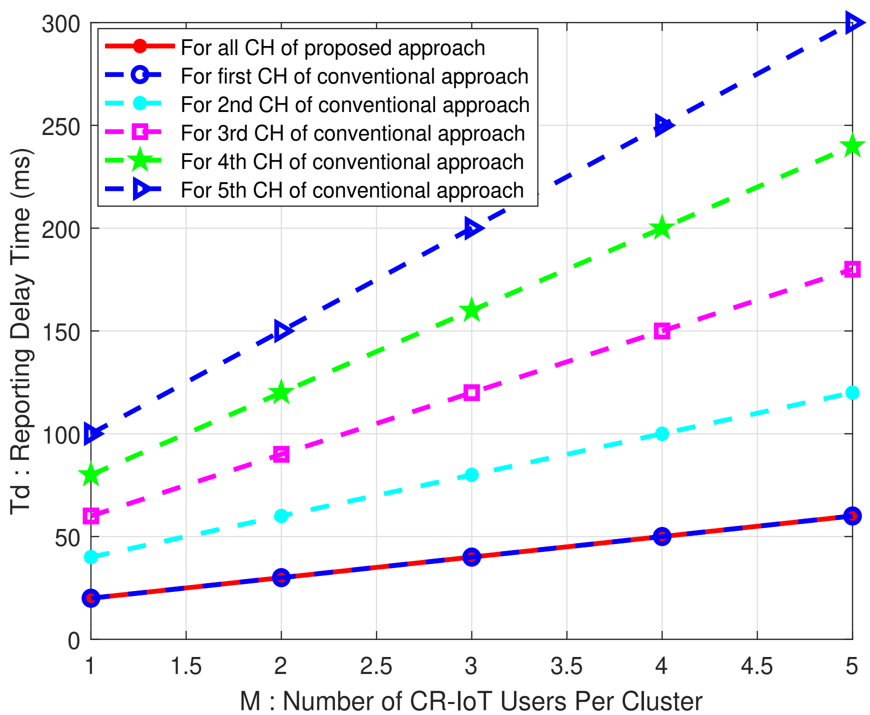

Figure 3.9: Number of CR-IoT users (M = 5) vs reporting time delay of CHs

the reporting time delay of CHs for the conventional sequential single reporting channel approach and proposed sequential multiple reporting channel approach. It can be seen that my proposed sequential multiple reporting channel approach shows the minimum and same reporting time delay for all CHs in the network, i.e., the reporting time delay for all CHs is 60 ms. Otherwise, when using the conventional sequential single reporting channel approach, it can be seen that the reporting time delay is longer and different for each CH in the networks, i.e., the reporting time delay for the first, second, third, fourth, and fifth CH are 60 ms, 120 ms, 180 ms, 240 ms, and 300 ms, respectively. From Figure 3.9, it is observed that the reporting time delay for the first CH using the conventional approach is the same as in my proposed approach, but the reporting time delay for the 2nd, 3rd, 4th, and 5th CHs is increased gradually.

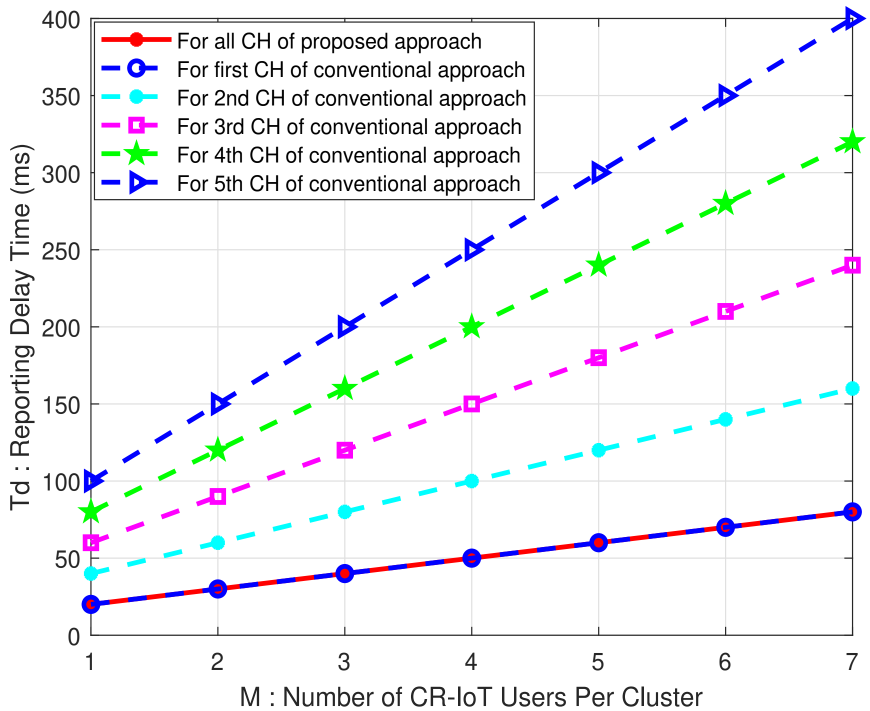

Figure 3.10: Number of CR-IoT users (M = 7) vs reporting time delay of CHs

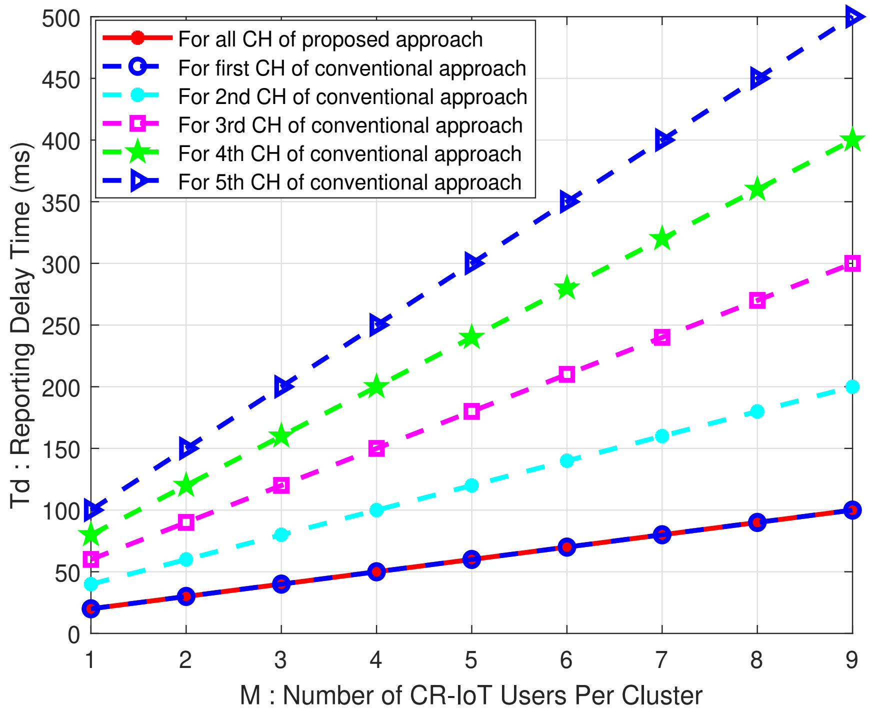

Figure 3.11: Number of CR-IoT users (M = 9) vs reporting time delay of CHs

In the second and third setting, I consider seven and nine CR-IoT users in every cluster, respectively. From Figure 3.10 and Figure 3.11, it is observed that, when CR-IoT user numbers increase in every cluster, the reporting time delay of CHs increase for both approaches. However, the reporting time delay for the proposed approach is smaller and the same for all CHs; otherwise the reporting time delay for the conventional approach is longer and different for each CH. The reporting time delay of CHs for three different numbers of CR-IoT users setting scenarios is given in Table 3.4. From my simulation results, it is observed that the proposed sequential multiple reporting channel approach achieves better sensing gain and minimum reporting time delay compared to the conventional sequential single reporting channel approach which is more applicable for the 5G networks.

Table 3.4: Reporting time delay of CHs vs different approaches

Number of SUs per cluster	Approach	Reporting time delay of the CHs (ms)					Figure
		CH1	CH2	CH3	CH4	CH5	
M = 5	Sequential single reporting channel approach	60	120	180	240	300	3.9
	Sequential multiple reporting channel approach	60	60	60	60	60	
M = 7	Sequential single reporting channel approach	80	160	240	320	400	3.10
	Sequential multiple reporting channel approach	80	80	80	80	80	
M = 9	Sequential single reporting channel approach	100	200	300	400	500	3.11
	Sequential multiple reporting channel approach	100	100	100	100	100	

3.8 Summary

Achieving a higher PU signal detection accuracy in a cluster-based CR-IoT networks depends on appropriate spectrum sensing and a minimum reporting time delay. In this chapter, we propose sequential multiple reporting channels for cluster-based CR-IoT networks to achieve a better sensing gain by utilising the reporting time slot of CR-IoT users. However, the proposed approach minimises the reporting time delay of CHs. Our proposed approach enhances the sensing gain of CR-IoT users by utilizing the reporting frameworks of CR-IoT users. With regard to the PU signal detection gain, simulation results have shown that the probability of detection for the CHs and the FC in the proposed approach are 35% and 36% better than the non-sequential conventional approach, respectively. Also, our proposed sequential multiple reporting channels approach for cluster-based CR-IoT networks minimises the reporting time delay of all CHs to transmit the sensing report to the FC than the conventional sequential single reporting channel approach by using parallel multiple reporting channels. Therefore, I conclude that my proposed sequential multiple reporting channels approach will be more applicable for wireless networking to overcome the issue of spectrum shortage.

Chapter 4

Energy & Spectral Efficiency Analysis for CR-IoT

4.1 Introduction

In the previous chapter I proposed a new approach for cluster-based cooperative spectrum sensing to increase the spectrum sensing gain and reduce reporting delays of cluster-based CR-IoT networks. It increases the spectrum sensing gain and reduces reporting delays for CR-IoT networks without interference between primary user and CR-IoT user. However, this approach is not capable of ensuring optimal spectrum detection performance in case of interference between the primary user and the CR-IoT user. Moreover, the sum rate, energy efficiency and spectral efficiency of CR-IoT networks has not been investigated under interference constrains. Therefore in this chapter I propose a novel energy efficient sequential energy detection (ED) for cluster based cooperative spectrum sensing (CSS) approach for CR-IoT networks to address the limitation of the previous chapter.

The Internet of Things is a fast-growing network technology that links a vast range of networking devices around the world to the internet and allows connectivity among devices. All devices can continuously capture and exchange data over the internet in order to enhance their value and services [Kim *et al.* 20]. However, there are many issues that slow down the growth of IoT networks, including the ever-growing bandwidth requirements to connect increasing numbers of communicating devices and applications. Also, it must maintain the security of a large number of heterogeneous devices and networks, while there is a high implementation cost and a lack of adequate available spectrum with a higher energy consumption than more general radio platforms [Awin *et al.* 19b]. Cognitive radio technology is an emerging technology to overcome the spectrum shortage problem by allowing the SU to access the licensed spectrum when it is not in use [Tsimba *et al.* 20]. In a CR-IoT network [Gu *et al.* 19b], each CR-IoT user is opportunistically using the unused licensed spectrum band when the licensed user, or PU is absent. By detecting the spectrum, CR-IoT users identify the spectrum gaps and select the channel that is most appropriate for communication. To avoid the harmful interference between primary user and the CR-IoT user, the CR-IoT user relinquishes the spectrum when the PU returns to the network [Mayekar *et al.* 15]. Spectrum sensing is the most critical step in the CR-IoT network to prevent harmful interference between the PU and the CR-IoT users [Hossain *et al.* 20].

The energy detection (ED) technique is one of the most common sensing techniques; it is simple, non-coherent, cost-effective, and does not require any prior knowledge of the PU signal [Kobeissi *et al.* 16]. Therefore, it is widely accepted as one of the most frequently used methods for spectrum detection in numerous sensing applications. However, the accuracy of the spectrum sensing is compromised due to fading, shadowing, uncertainty and the hidden terminal issue [Sun *et al.* 16]. In order to address the problems of ED-based spectrum sensing, a cooperative spectrum sensing technique was investigated [YILMAZEL & SEYMAN 18]. In [Rawat *et al.* 10], the detection performance of CSS have been analyzed under a situation in which malicious users transfer a wrong detection result to the FC, i.e. malware attacks. In [Ghamry & Shukry 20], the authors introduced the eigenvalue-based CSS scheme to enhance the spectrum detection performance under the effects of impulsive noise distributions. In [Awin *et al.* 18], the authors analysed the blind CSS methods for interweave CRN. In [Iqbal *et al.* 18] each CR-IoT user used the CSS technique to sense the PU signal, they are used noisy reporting channel to send the sensing results to the FC. In [Gul *et al.* 17], CR-IoT users make their own sensing results and send these results to the FC, and FC stores the information in a database. The FC determines the Kullback-Leibler divergence (KLD) score against each CR-IoT user and also makes the global decision about presence or absence of PU's signal. In [Vu-Van & Koo 12], the authors applied the KLD method to calculate the dissimilarity in the probability distribution functions by using the presence and absence hypotheses of the PU's signal. However, the present cooperative spectrum sensing techniques have been evaluated by using fixed sensing time slots for sensing purposes, which did not contribute to achieving a better sensing performance, an enhanced sum rate, an enhanced energy and spectrum efficiency. The authors proposed sub-optimal recursive search algorithm to maximize energy efficient licensed spectrum detection for a CRN by optimizing sensing and transmission time in [Awasthi *et al.* 19]. Its minimizes the interference between PU and cognitive user transmission. However, their paper considered only one PU and one SU; for the large number of SUs, this scheme is not capable of ensuring optimal spectrum detection performance.

In [Kishore *et al.* 20], the authors proposed the conventional collaborative compressive sensing (CCCS) approach for better energy efficiency spectrum sensing in CRNs. Their paper optimized the parameters value to enhance the energy efficiency of the CCCS scheme. The authors introduced the energy efficient spectrum sensing approach using Dempster–Shafer (D-S) theory in CR Sensor Networks (CRSNs) to maximize detection accuracy and minimize energy consumption in [Qiao *et al.* 18]. In [Ansere *et al.* 19], the authors proposed a two-way dynamic spectrum sensing scheme which the energy efficiency for data transmission in CR-IoT networks are maximized. Moreover, the proposed an energy efficient power assignment approach is to improve the spectrum detection performance and throughput. In [Eappen & Shankar 20], the authors proposed a hybrid PSO (Particle Swarm Optimization)-GSA (Gravitational Search Algorithm) which is maximized the energy efficiency of the spectrum detection by identifying the licensed spectrum, the power spectral density and the transmission power. In [Hossain *et al.* 20], the authors proposed a cluster-based sequential sensing scheme which extended the sensing time duration of each CR-IoT user. The authors analyzed only the probability of detection versus the probability of false alarm with different sensing time. However, they did not analyze the sum rate, energy efficiency and spectrum efficiency with interference constraints. We propose a novel sequential ED spectrum sensing technique to achieve better sensing gain and sum rate of the CR-IoT user as well as the energy and spectrum efficiency of the CR-IoT network under interference constraints.

4.1.1 Contributions

The main contributions of this chapter can be summarized as follows:

- I propose a sequential ED spectrum sensing scheme. The effectiveness of the proposed scheme is verified by comparing the numerical performance, e.g., the sensing performance and sum rate with the conventional non-sequential ED spectrum sensing scheme with and without interference constraints.
- Based on the sensing performance and sum rate, the spectral efficiency and the energy efficiency are analyzed for the proposed novel sequential ED spectrum sensing scheme.
- Finally, simulation results reveal that the proposed sequential ED spectrum sensing scheme enhances the sensing performance, the sum rate, the spectral efficiency and the energy efficiency when compared to the conventional non-sequential ED scheme with interference constraints.

4.1.2 Publications

The work outlined in this chapter was published in:

Mohammad Amzad Hossain, Michael Schukat and Enda Barrett. A Reliable Energy and Spectral Efficient Spectrum Sensing Approach for Cognitive Radio Based IoT Networks. IEEE 11th Annual Computing and Communication Workshop and Conference (IEEE CCWC-2021), pp. 1569-1576, Nevada, USA.

4.1.3 Chapter Structure

The rest of this chapter is organized as follows: In Section 4.2 describes the system model for two scenarios I and II. In Section 4.3, I describe the conventional non-sequential ED technique. In Section 4.4 I describe the proposed sequential ED scheme.

The simulation results and discussion are presented in Section 4.5. Finally, our summary and future work of this chapter are addressed in Section 4.6.

For ease of comparison, in Table 4.1, I list my generally used notations with description as follows:

Table 4.1: **List of notations**

Notation	**Description**
H_0	Hypothesis representing the PU's signal present
H_1	Hypothesis representing the PU's signal absent
M	Total number of the unlicensed CR-IoT users
N_s	Total number of samples during sensing time
f_s	Sampling frequency
τ_r	Duration of the fixed reporting time slot
T	Duration of a total frame
γ	SNR for scenario
τ_s/τ_s^m	Duration of a rigid sensing time/a flexible sensing time
$x(l)$	Signal transmitted by the PU at symbol time l
$y_i(l)$	Noise of the i^{th} CR-IoT user at symbol time l
$z_i^I(l)/z_i^{II}(l)$	Received signal by the i^{th} CR-IoT user for scenarios $I/\ II$
$h_i\,(l)$	Channel gain at symbol time l
SNR_{PU}	SNR of the PUs link
$SNR_{CR-IoT,i}$	SNR of the secondary link
$P_{f,i}^{Con}/P_{f,i}^{Pro}$	Probability of false alarm of the i^{th} CR-IoT user for conventional/proposed scheme
$P_{d,i}^{Con}/P_{d,i}^{Pro}$	Detection probability of the i^{th} CR-IoT user for conventional/proposed scheme
$\lambda_{i,ED}^{Con}/\lambda_{i,ED}^{Pro}$	Local decision threshold for i^{th} CR-IoT user with an ED method for conventional/proposed scheme
$P_{f,FC}^{Con}/P_{f,FC}^{Pro}$	Global probability of false alarm at the FC for conventional/proposed scheme
ω_i	Weight factor of the i^{th} CR-IoT user
$P_{d,FC}^{Con}/P_{d,FC}^{Pro}$	Global detection probability at the FC for conventional/proposed scheme
β^{Con}/β^{Pro}	Global decision threshold at the FC for conventional/proposed scheme
α	Primary activity factor
R^{Con}/R^{Pro}	Sum rate at the FC for conventional/proposed scheme
$V_{SE}^{Con}/V_{SE}^{Pro}$	Spectral efficiency at the FC for conventional /proposed scheme
$V_{EE}^{Con}/V_{EE}^{Pro}$	Energy efficiency at the FC for conventional /proposed scheme

4.2 System Model

Spectrum sensing is a fundamental and crucial function for CR-IoT networks to identify the available spectrum that is assigned for the PUs. In this chapter, I consider a primary network with a primary user and a cooperative spectrum sensing based CR-IoT network with cooperative CR-IoT users as well as one FC, where the transmitter (Tx) and the receiver (Rx) pairs are in close proximity to both networks as shown in Figure 4.1. The number of secondary users is denoted by M. Both networks are assumed to operate on the same frequency band.

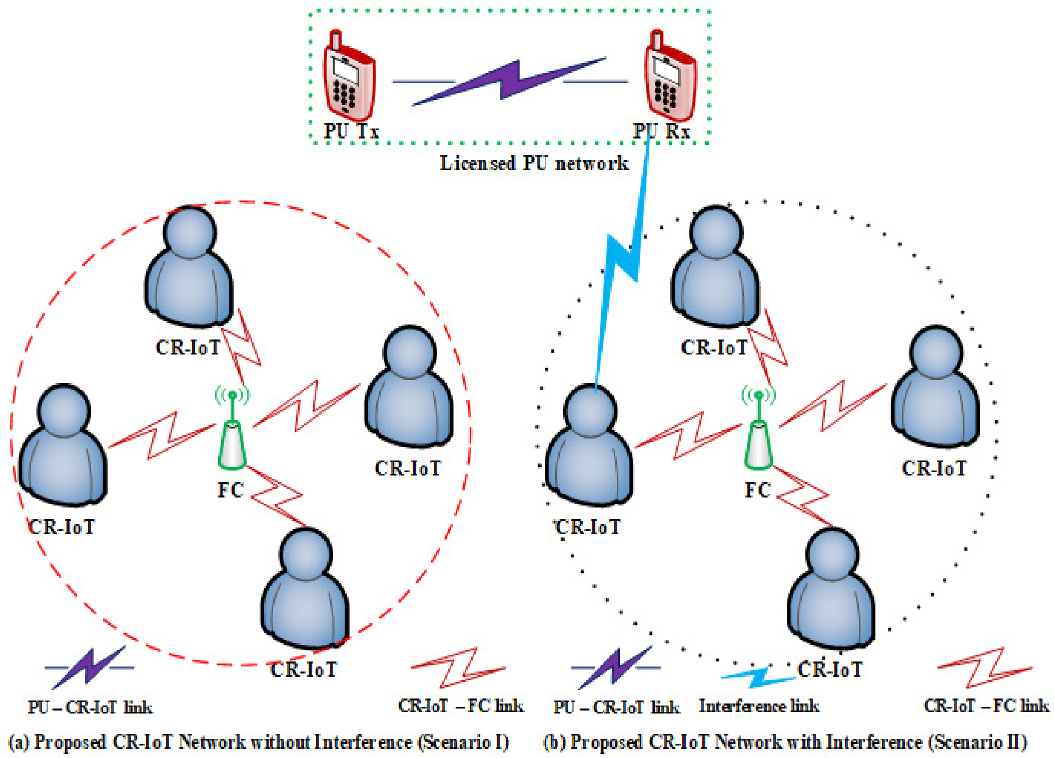

Figure 4.1: Proposed system model (a) Scenario I and (b) Scenario II.

Let H_1 and H_0 represent the hypotheses of the presence and absence of the PU in the network, respectively. In a binary hypothesis testing problem, we define the hypotheses representing the absence and presence of the PU's signal as follows:

$$\begin{cases} H_0: & \text{if the PU's signal is absent,} \\ H_1: & \text{if the PU's signal is present.} \end{cases} \tag{4.1}$$

I consider two scenarios when both networks operate on the same frequency band, (i) scenario I (no interference between the PU and the CR-IoT user) and (ii) scenario II (where there is interference between the PU and the CR-IoT user). In the following subsection, we discuss the characteristics of scenario I and scenario II, respectively.

4.2.1 Scenario I

The system model for the scenario I is shown in Figure 4.1 (a). The primary network consists of a transmitter and receiver for the primary user. In this scenario, the PU uses a time division multiplexing access (TDMA) technique to transfer data to its corresponding receiver using an independent time slot. The CR-IoT network consists of M unlicensed CR-IoT users and a FC. In Figure 4.1 (a), the CR-IoT user is denoted as an unlicensed user that opportunistically accesses the spectrum of the PU without causing interference. Each CR-IoT user reports their local sensing information about the PU channel to the FC. Then the FC collects sensing notifications of all individual CR-IoT users and generates a global decision to show the actual status of the PU spectrum.

For scenario I, the received signal of the i^{th} CR-IoT user for both binary hypotheses can be expressed as follows [Hossain *et al.* 20]:

$$z_i^I(l) = \begin{cases} y_i(l) & : H_0 \\ h_i(l)\,x(l) + y_i(l) & : H_1 \end{cases} \tag{4.2}$$

where $z_i^I(l)$ denotes the signal received by the i^{th} CR-IoT user in the l^{th} sample time for scenario I, and $h_i(l)$ is the channel gain between the i^{th} CR-IoT user and the PU transmitter for $i = 1, 2, \cdots, M$ and $l = 1, 2, \cdots, N_s$. It is assumed that the channel is static during each sensing period. Moreover, $x(l)$ is a signal transmitted from the PU, which is modulated by a binary phase shift keying (BPSK) with a power of p_x^2, and $y_i(l)$ is a circularly symmetric complex Gaussian noise at the i^{th} CR-IoT user with a variance of $\sigma_{y,i}^2$.

4.2.2 Scenario II

The system model for scenario II as shown in Figure 4.1 (b). In this scenario, the unlicensed CR-IoT users opportunistically use the unused licensed PU user spectrum bands causing interference. When the licensed user/PU comes back to the network and starts transmitting data by using the licensed spectrum band that is currently used by the CR-IoT user, the CR-IoT user makes the band free as soon as possible and switches to another free band. There is interference when the PU returns and takes over the spectrum used by the CR-IoT user, which is considered in this scenario. As a result, this interference is degraded the detection performance of the proposed ED method.

For scenario II, the received signal of the i^{th} CR-IoT user for both binary hypotheses can be expressed as follows [Ekti *et al.* 13]:

$$z_i^{II}(l) = \begin{cases} y_i(l) & : H_0 \\ h_i(l)\, x(l) + k_i(l) + y_i(l) & : H_1 \end{cases} \tag{4.3}$$

where $z_i^{II}(l)$ denotes the signal received by the i^{th} CR-IoT user in the l^{th} sample time and $k_i(l)$ is the interfering signal for $i = 1, 2, \cdots, M$ and $l = 1, 2, \cdots, N_s$ in the scenario II.

4.3 Conventional Non-Sequential ED Spectrum Sensing Scheme

In the conventional non-sequential ED spectrum sensing scheme the sensing time slots for all CR-IoT users are the same and fixed to sense the PU signal in the CR-IoT network. In this approach, all CR-IoT users use individual reporting channels to send their spectrum sensing reports to the FC. However, when the number of CR-IoT users in the CR-IoT network is increased in the conventional non-sequential ED sensing scheme, it is not feasible to assign independent reporting channels to all CR-IoT users at the same time, as the number of reporting channels is limited. Moreover, the CR-IoT users cannot utilize the reporting time slots for sensing purposes, therefore their detection performance and sum rate cannot be enhanced. Figure 4.2 shows the frame architecture of the conventional non-sequential ED spectrum sensing scheme.

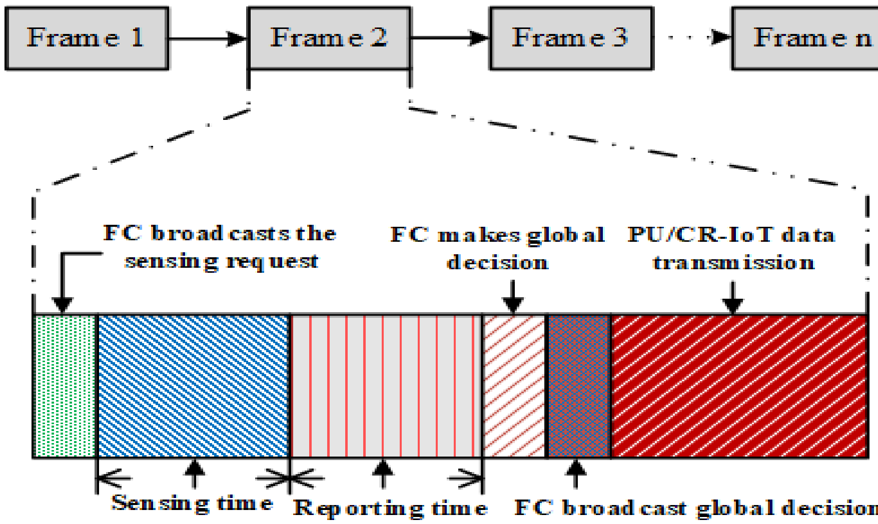

Figure 4.2: Frame structure of the the conventional non-sequential ED technique for scenario I and II [Wyglinski *et al.* 09]

The received signal energy for a given time period is measured and compared with the threshold [Wyglinski *et al.* 09, Alghorani *et al.* 15] as shown in Figure 4.3. For each CR-IoT user to obtain the decision statistics for the ED, the time-domain signal power occupying a particular frequency band is measured as follows. First, the received signal is passed through a band-pass filter to select the appropriate signal bandwidth, and the output of this filter is then transformed by an analog-to-digital converter (ADC).

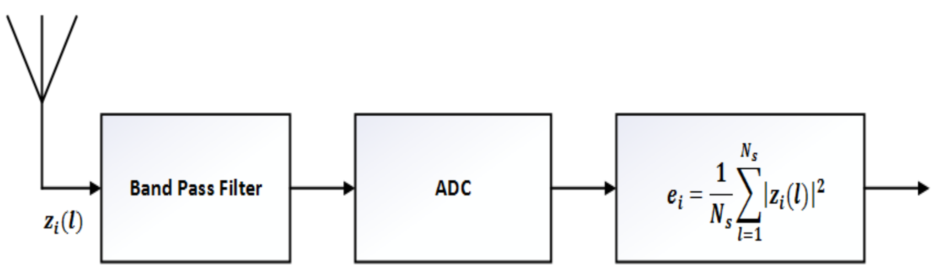

Figure 4.3: Block diagram of the conventional ED technique [Wyglinski *et al.* 09]

Here, the analog signal is sampled to obtain a discrete signal, which is individually averaged and squared for the conventional non-sequential ED technique to estimate its own received signal energy [Jan *et al.* 18].

In the conventional non-sequential ED technique for the scenario I and II, the measured energy at the i^{th} CR-IoT user for the fixed sensing time slot τ_s is expressed as follows:

$$e_i = \frac{1}{N_s} \sum_{l=1}^{N_s=2\tau_s f_s} |z_i(l)|^2, \tag{4.4}$$

where $z_i(l)$ is equal to $z_i^I(l)$ and $z_i^{II}(l)$ when I consider scenario I and scenario II respectively. N_s denotes the total number of signal samples used for sensing, which is defined as $N_s = 2\tau_s f_s$, where τ_s denotes the duration of the sensing time slot and f_s denotes the sampling frequency. Therefore, the duration of the rigid sensing time slot τ_s is commonly used by all CR-IoT users in a CR-IoT network for scenario I and scenario II.

In what follows, we analyse the spectrum sensing performance, the sum rate, the spectral efficiency and the energy efficiency of the conventional non-sequential ED spectrum sensing technique.

4.3.1 Analysis of Sensing Performance

Based on the central limit theorem (CLT), the distribution of the decision statistic e_i for the i^{th} CR-IoT user under both hypotheses can be expressed as follows:

$$e_i \sim \begin{cases} \aleph\left(\mu_{0,i}(H_0), \sigma_{0,i}^2(H_0)\right) \\ \aleph\left(\mu_{1,i}(H_1), \sigma_{1,i}^2(H_1)\right) \end{cases} \tag{4.5}$$

where $\mu_{0,i}(H_0) = 2\tau_s f_s \sigma_{z,i}^2$, $\sigma_{0,i}^2(H_0) = 2\tau_s f_s \sigma_{z,i}^4$, $\mu_{1,i}(H_1) = 4\tau_s f_s \left(1 + |h_i|^2\gamma_i\right)\sigma_{z,i}^2$, $\sigma_{1,i}^2(H_1) = 4\tau_s f_s \left(1 + 2|h_i|^2\gamma_i\right)\sigma_{z,i}^4$, and γ_i is SNR that is defined as $\gamma_i = \frac{p_x^2}{\sigma_{y,i}^2}$.

Based on Eq. (4.5), we can calculate the probability of a false alarm $p_{f,i}^{Con}$ and the probability of detection $p_{d,i}^{Con}$ for the i^{th} CR-IoT user by comparing e_i with a predefined local threshold $\lambda_{i,ED}^{Con}$ as follows:

$$\begin{aligned} p_{f,i}^{Con} = Pr\left[e_i \geq \lambda_{i,ED}^{Con} | H_0\right] &= Q\left(\frac{\lambda_{i,ED}^{Con} - \mu_{0,i}(H_0)}{\sigma_{0,i}(H_0)}\right) \\ &= Q\left(\frac{\lambda_{i,ED}^{Con}}{\sqrt{2\tau_s f_s}\sigma_{z,i}^2} - \sqrt{2\tau_s f_s}\right) \end{aligned} \tag{4.6}$$

and

$$\begin{aligned} p_{d,i}^{Con} &= Pr\left[e_i \geq \lambda_{i,ED}^{Con} | H_1\right] \\ &= Q\left(\frac{\lambda_{i,ED}^{Con} - \mu_{0,i}(H_1)}{\sigma_{0,i}(H_1)}\right) \\ &= Q\left(\frac{\lambda_{i,ED}^{Con}}{\sqrt{2\tau_s f_s (1 + 2|h_i|^2\gamma_i)\sigma_{z,i}^2}} - \frac{\sqrt{2\tau_s f_s}(1 + |h_i|^2\gamma_i)}{\sqrt{(1 + 2|h_i|^2\gamma_i)}}\right), \end{aligned} \tag{4.7}$$

where $Q(\Theta)$ denotes a Gaussian tail function that is defined as $Q(\Theta) = \frac{1}{\sqrt{2\pi}} \int_{\Theta}^{\infty} e^{-\frac{t^2}{2}} dt$.

The probability of a false alarm $p_{f,i}^{Con}$ is the probability that the CR-IoT user incorrectly declares that the PU exists although the PU is actually absent. In contrast, the probability of detection $p_{d,i}^{Con}$ denotes the probability that the CR-IoT user correctly declares that the PU is present.

All the CR-IoT users send their local decisions to the FC, where they are combined with the local results to obtain a global decision about the PU's occupancy of the spectrum [Miah *et al.* 17]. The sensing performance, i.e., $\left(p_{f,FC}^{Con}/p_{d,FC}^{Con}\right)$, of the global decision is given by

$$p_{f,FC}^{Con} = \begin{cases} 1, & if \sum_{i=1}^{M} p_{f,i} < \beta^{Con} \\ 0, & otherwise \end{cases} \tag{4.8}$$

and

$$p_{d,FC}^{Con} = \begin{cases} 1, & if \sum_{i=1}^{M} p_{d,i} \geq \beta^{Con} \\ 0, & otherwise \end{cases} \tag{4.9}$$

where β^{Con} denotes the global decision threshold at the FC.

4.3.2 Analysis of Sum Rate

Based on the global sensing performance $(p_{f,FC}^{Con}/p_{d,FC}^{Con})$, the sum rate R^{Con} can be calculated as follows [Verma & Singh 14]:

$$R^{Con} = \alpha p_{d,FC}^{Con} R_{PU}^{Con} + (1 - \alpha)\left(1 - p_{f,FC}^{Con}\right) R_{CR-IoT,i}^{Con} \tag{4.10}$$

where $\alpha \in [0, 1]$ denotes the primary activity factor, R_{PU}^{Con}, and $R_{CR-IoT,i}^{Con}$ are defined as follows:

$$R_{PU}^{Con} = W \log_2\left(1 + SNR_{PU}\right) \tag{4.11}$$

and

$$R_{CR-IoT}^{Con} = \frac{T - \tau_s - \tau_r}{T} \sum_{i=1}^{M} W \log_2 \left(1 + SNR_{CR-IoT,i}\right) \tag{4.12}$$

where W is the channel bandwidth in Hz and T denotes total frame duration in ms.

4.3.3 Analysis of Spectral and Energy Efficiency

In this section, I can calculate the spectral efficiency of the conventional non-sequential spectrum sensing scheme as follows:

$$v_{SE}^{Con} = \frac{R^{Con}}{W} \tag{4.13}$$

where v_{SE}^{Con} is the spectral efficiency (SE) in bps/Hz.

Also I can calculate the energy consumption of the conventional non-sequential spectrum sensing scheme as follows:

$$v_{EE}^{Con} = \frac{R^{Con}}{P} \tag{4.14}$$

where v_{EE}^{Con} denotes the energy efficiency (EE) in bps/J and P denotes the transmit power in J.

4.4 Proposed Sequential ED Spectrum Sensing Scheme

In the proposed sequential ED spectrum sensing scheme, a dedicated orthogonal reporting channel is assigned to each group of CR-IoT users. All CR-IoT users in a particular group use the same orthogonal signal reporting channel to send the sensing result of the PU signal to the FC in a sequential manner. In the proposed scheme, the spectrum sensing time slot duration for each CR-IoT user is extended as the reporting time slots of previous CR-IoT users are combined with the fixed sensing time slot of the CR-IoT user. Figure 4.4 shows the frame architecture of the sequential ED spectrum sensing scheme.

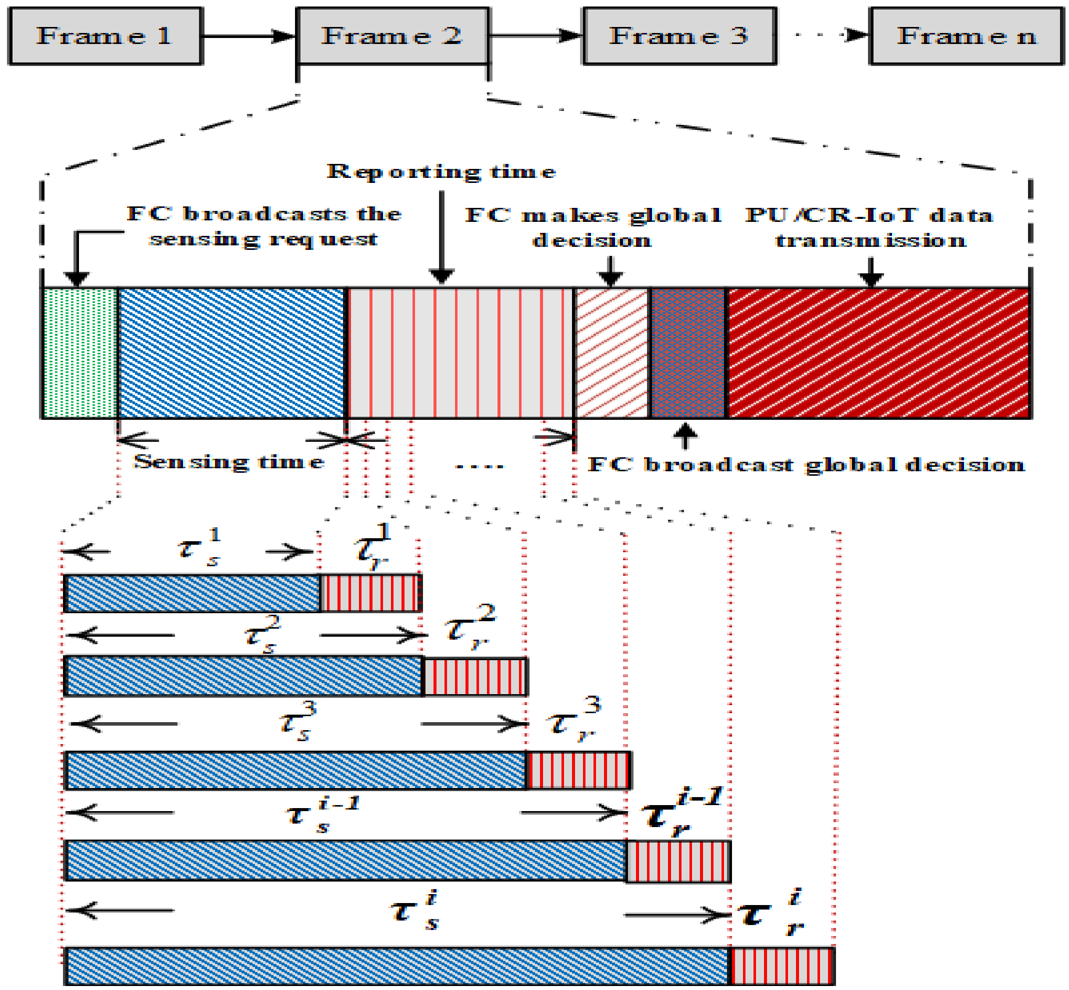

Figure 4.4: Frame structure of the proposed sequential ED spectrum sensing scheme, here utilizing the reporting framework

From Figure 4.4 I can see that the 2nd CR-IoT user can utilize the rigid reporting time slot of the 1st CR-IoT user, and the 3rd CR-IoT user can utilize the rigid reporting time slots of the previous 1st CR-IoT and 2nd CR-IoT user for sensing the PU signal, and so on. Therefore, all CR-IoT users can obtain a flexible sensing time slot except for the 1st CR-IoT user. Therefore, the CR-IoT users can utilize the reporting time slot for sensing purposes, therefore enhancing the detection performance and sum rate.

Now, I calculate the flexible sensing time slot of the proposed scheme as shown in Figure 4.4 as follows [Hossain *et al.* 20]:

$$\tau_s^m = \tau_s + (i-1)\tau_r \tag{4.15}$$

where τ_s^m is a flexible sensing time slot, τ_s is a rigid sensing time slot and τ_r is the common duration of the reporting time slot.

In the proposed ED technique for the scenario I and II, the measured energy at the i^{th} CR-IoT user for the flexible sensing time slot τ_s^m is expressed as follows:

$$e_i = \frac{1}{N_s^m} \sum_{l=1}^{N_s^m = 2\tau_s^m f_s} |z_i(l)|^2 , \tag{4.16}$$

where $z_i(l)$ is equal to $z_i^I(l)$ and $z_i^{II}(l)$ when we consider scenario I and scenario II respectively. N_s^m denotes the total number of signal samples used for sensing, which is defined as $N_s^m = 2\tau_s^m f_s$, where τ_s^m denotes the duration of the flexible sensing time slot and f_s denotes the sampling frequency. Therefore, the duration of the flexible sensing time slot τ_s^m is commonly used by all CR-IoT users in a CR-IoT network for scenario I and scenario II.

In this section, I analyse the weight factor, the spectrum sensing performance, the sum rate, the spectral efficiency and the energy efficiency for the proposed sequential ED spectrum sensing scheme.

4.4.1 Analysis of Weight Factor

Under the frame structure presented in Figure 4.4, all the CR-IoT users sense the PU's channel based on the flexible sensing time slot (τ_s^m) and the KLD score.

The KLD score is calculated based on the dissimilarity between two probability distribution functions, i.e.it measures the relative entropy between two probability density functions. If $a(y)$ and $b(y)$ are two probability density functions (PDF) then the relative entropy is defined as [Gul *et al.* 17, Vu-Van & Koo 12, Gul *et al.* 18, Miah *et al.* 20]:

$$KLD(a(y)||b(y)) = \int_{y \epsilon Y} a(y) log \left(\frac{a(y)}{b(y)} \right) dy \tag{4.17}$$

where Y is a finite set of probability space. The (4.17) can be rewritten for the functions $a(y)$ and $b(y)$ with the mean and variance (μ_a, σ_a) and (μ_b, σ_b) as follows [Gul *et al.*

18]:

$$\begin{aligned} KLD(a(y)||b(y)) &= KLD(\mu_a, \mu_b, \sigma_a, \sigma_b) \\ &= \frac{1}{2}\left[log\frac{\sigma_b^2}{\sigma_a^2} - 1 + \left(\frac{\sigma_a^2}{\sigma_b^2}\right) + \frac{(\mu_a - \mu_b)^2}{\sigma_b^2}\right] \end{aligned} \tag{4.18}$$

Now we can calculate the KLD score value of the received PU signal at the ith CR-IoT user for functions $a_i(H_1)$ and $b_i(H_0)$ with the means $(\mu_{1,i}, \mu_{0,i})$ and the variances $(\sigma_{1,i}^2, \sigma_{0,i}^2)$ under H_1 and H_0 as follows:

$$\begin{aligned} KLD[a_i(H_1)||b_i(H_0)] &= KLD\left(\mu_{0,i}, \sigma_{0,i}^2||\mu_{1,i}, \sigma_{1,i}^2, \right) \\ &= \frac{1}{2}\left[log\frac{\sigma_{0,i}^2}{\sigma_{1,i}^2} - 1 + \left(\frac{\sigma_{1,i}^2}{\sigma_{0,i}^2}\right) + \frac{(\mu_{1,i} - \mu_{0,i})^2}{\sigma_{0,i}^2}\right] \end{aligned} \tag{4.19}$$

where $a_i(H_1)$ denotes the PDF of the sensed information when the PU is present, and $b_i(H_0)$ represents the PDF of the sensed information when the PU is absent at the ith SU.

To this end, means are updated based on the flexible sensing time slot (τ_s^m) under two hypotheses as follows:

$$\begin{aligned} \bar{\mu}_{0,i} &= 2\tau_s^m f_s \sigma_{z,i}^2 \\ \bar{\mu}_{1,i} &= 4\tau_s^m f_s \left(1 + |h_i|^2 \bar{\gamma}_i\right) \sigma_{z,i}^2 \end{aligned} \tag{4.20}$$

where $\bar{\mu}_{0,i}$ and $\bar{\mu}_{1,i}$ are the updated mean values for the i^{th} CR-IoT user and are updated with the previous mean values $\mu_{0,i}$ and $\mu_{1,i}$ based on the flexible sensing time slot (τ_s^m) under both hypotheses. Moreover, $\bar{\gamma}_i$ is the signal-to-interference plus noise (SINR) which is defined as $\frac{p_x^2}{(\sigma_{y,i}^2 + \sigma_{I,i}^2)}$.

In the same manner, the variances are updated based on the flexible sensing time slot (τ_s^m) under two hypotheses as follows:

$$\begin{aligned} \bar{\sigma}_{0,i}^2 &= 2\tau_s^m f_s \sigma_{z,i}^4 \\ \bar{\sigma}_{1,i}^2 &= 4\tau_s^m f_s \left(1 + 2|h_i|^2 \bar{\gamma}_i\right) \sigma_{z,i}^4 \end{aligned} \tag{4.21}$$

where $\bar{\sigma}_{0,i}^2$ and $\bar{\sigma}_{1,i}^2$ are the updated variance values for the i^{th} CR-IoT user and are updated with the previous variance values $\sigma_{0,i}^2$ and $\sigma_{1,i}^2$ based on the flexible sensing time slot (τ_s^m) under two different hypotheses.

After calculating the updated means and variances, the i^{th} CR-IoT user obtains a weight factor (ω_i) based on the KLD score as follows:

$$\begin{aligned}\omega_i &= KLD\left(\bar{\mu}_{0,i}, \bar{\sigma}^2_{0,i} || \bar{\mu}_{1,i}, \bar{\sigma}^2_{1,i}\right)\\ &= \frac{1}{2}\left[\log\left(\frac{\bar{\sigma}^2_{0,i}}{\bar{\sigma}^2_{1,i}}\right) - 1 + \left(\frac{\bar{\sigma}^2_{1,i}}{\bar{\sigma}^2_{0,i}}\right) + \frac{\left(\bar{\mu}_{1,i} - \bar{\mu}_{0,i}\right)^2}{\bar{\sigma}^2_{0,i}}\right]\end{aligned} \tag{4.22}$$

4.4.2 Analysis of Sensing Performance

Based on Eq. (4.20) and Eq. (4.21), I can calculate the probability of a false alarm $p^{Pro}_{f,i}$ and the probability of detection $p^{Pro}_{d,i}$ for the i^{th} CR-IoT user by comparing e_i with a pre-defined local threshold $\lambda^{Pro}_{i,ED}$ as follows:

$$\begin{aligned}p^{Pro}_{f,i} = Pr\left[e_i \geq \lambda^{Pro}_{i,ED} | H_0\right] &= Q\left(\frac{\lambda^{Pro}_{i,ED} - \bar{\mu}_{0,i}(H_0)}{\bar{\sigma}_{0,i}(H_0)}\right)\\ &= Q\left(\frac{\lambda^{Pro}_{i,ED}}{\sqrt{2\tau^m_s f_s \sigma^2_{z,i}}} - \sqrt{2\tau^m_s f_s}\right)\end{aligned} \tag{4.23}$$

and

$$\begin{aligned}p^{Pro}_{d,i} &= Pr\left[e_i \geq \lambda^{Pro}_{i,ED} | H_1\right]\\ &= Q\left(\frac{\lambda^{Pro}_{i,ED} - \bar{\mu}_{0,i}(H_1)}{\bar{\sigma}_{0,i}(H_1)}\right)\\ &= Q\left(\frac{\lambda^{Pro}_{i,ED}}{\sqrt{2\tau^m_s f_s (1 + 2|h_i|^2\bar{\gamma}_i)\sigma^2_{z,i}}} - \frac{\sqrt{2\tau^m_s f_s}(1 + |h_i|^2\bar{\gamma}_i)}{\sqrt{(1 + 2|h_i|^2\bar{\gamma}_i)}}\right)\end{aligned} \tag{4.24}$$

The probability of a false alarm $p^{Pro}_{f,i}$ is the probability that the CR-IoT user incorrectly declares that the PU exists although the PU is actually absent for proposed scheme. In contrast, the probability of detection $p^{Pro}_{d,i}$ denotes the probability that the CR-IoT user correctly declares that the PU is present for proposed scheme.

All the cooperative CR-IoT users provide the information of their local decision statistics to the FC. The FC then collects the information and makes a global decision. We can then evaluate the sensing performance $(p^{Pro}_{f,FC}/p^{Pro}_{d,FC})$ based on both the weight factor (ω_i) and the local decision $(p^{Pro}_{f,i}/p^{Pro}_{d,i})$ of the i^{th} CR-IoT user as follows:

$$p^{Pro}_{f,FC} = \begin{cases} 1, & if \sum_{i=1}^{M} \omega_i p^{Pro}_{f,i} < \beta^{Pro} \\ 0, & otherwise \end{cases} \tag{4.25}$$

and

$$p_{d,FC}^{Pro} = \begin{cases} 1, & if \sum_{i=1}^{M} \omega_i p_{d,i}^{Pro} \geq \beta^{Pro} \\ 0, & otherwise \end{cases} \tag{4.26}$$

where β^{Pro} denotes the global decision threshold at the FC.

4.4.3 Analysis of the Sum Rate

Using the frame structure and sensing performance in the above subsection, I can analyze the sum rate using several assumptions. In the transmission slot, the CR-IoT transmitter sends data according to scheduling in a round-robin manner [Miah *et al.* 20].

In a non-false alarm event, i.e., the absence of the PU is accurately detected by the unlicensed CR-IoT user when the PU is absent, the unlicensed CR-IoT user can access the primary spectrum with probability $\left(1 - p_{f,FC}^{Pro}\right)$. In a detection event, the PU's transmission is not interfered by the CR-IoT users. Therefore, the sum rate of both the PU and the CR-IoT users with round-robin scheduling is expressed as follows:

$$R^{Pro} = \alpha p_{d,FC}^{Pro} R_{PU}^{Pro} + (1-\alpha)\left(1 - p_{f,FC}^{Pro}\right) R_{CR-IoT}^{Pro} \tag{4.27}$$

where R^{Pro} denotes the sum rate in b/s or Hz, R_{PU}^{Pro} denotes the channel capacity of the PU link, R_{CR-IoT}^{Pro} is the channel capacity of the CR-IoT link, and $\alpha \in [0,1]$ denotes the primary activity factor, which indicates the probability of the PU's transmission in a given frame. R_{PU}^{Pro} and R_{CR-IoT}^{Pro} are defined as follows:

$$R_{PU}^{Pro} = W \log_2\left(1 + \frac{SNR_{PU}}{W}\right) \tag{4.28}$$

and

$$R_{CR-IoT}^{Pro} = \frac{T - \tau_s^m - \tau_r}{T} \sum_{i=1}^{M} W \log_2\left(1 + \frac{SNR_{CR-IoT,i}}{W\left(1 + SNR_{PU}\right)}\right) \tag{4.29}$$

where SNR_{PU} and $SNR_{CR-IoT,i}$ denote the SNR of the PU transmitter and the CR-IoT user receiver link and the SNR of the CR-IoT user transmitter and the CR-IoT user receiver link, respectively, and T denotes the total frame length.

4.4.4 Analysis of Spectral and Energy Efficiency

In this section, I calculate the spectral efficiency of the proposed scheme as follows:

$$v_{SE}^{Pro} = \frac{R^{Pro}}{W} \tag{4.30}$$

where v_{SE}^{Pro} is the spectral efficiency (SE) in bps/Hz.

Also we calculate the energy consumption of the proposed scheme as follows:

$$v_{EE}^{Pro} = \frac{R^{Pro}}{P} \tag{4.31}$$

where v_{EE}^{Pro} denotes the energy efficiency (EE) in bps/J and P denotes the transmit power in J.

4.4.5 Total Time Analysis

In the proposed scheme, if we increase the number of CR-IoT users M, the total sensing and reporting time τ_t, consisting of the sensing time τ_s and reporting time τ_r, will be increased [Awin *et al.* 18]. The total time required by the proposed scheme can be calculated as follows:

$$\tau_t = \tau_s + \sum_{i=1}^{M} \tau_{r,i} = \tau_s + \sum_{i=1}^{M} \tau_{r,i} = \tau_s + M\tau_r \tag{4.32}$$

where $\tau_{r,i} = \tau_r$ denotes the reporting time for the i^{th} CR IoT user. The total time τ_t is dependent on the number of CR-IoT users M. As M increases, the cooperative sensing performance is improved but the time complexity of cooperation increases.

4.5 Simulation Results and Discussion

In this section, the simulation results and the related discussion are presented. To evaluate the performance of the proposed sequential ED spectrum sensing scheme, numerical evaluations were performed and compared with conventional non-sequential ED spectrum sensing schemes using the Monte Carlo method. The simulations have been executed using MATLAB 2016a, and the results are obtained from the average of 30,000–70,000 independent simulation runs based on the simulation parameters listed in Table 4.2 below, which are based on the rationale of the other researchers [Quach *et al.* 19, Bayat & Colak 21, Jiang *et al.* 12]. Note that I considered different SNR values and the number of CR-IoT users in Chapter 4 and Chapter 3 because in this chapter I consider interference condition and the CR-IoT network architecture without clusters. On the other hand, in chapter 3 I considered an interference-free and cluster-based CR-IoT network architecture.

Table 4.2: **Parameters used in simulations.**

Parameter	**Value**
The total number of CR-IoT users M	12
Sampling frequency f_s	300 kHz
Sensing time slot τ_s	[5, 10] ms
Reporting time slot τ_r	5 ms
PU's signal $x(l)$	BPSK
SNR_{PU}	10 dB
$SNR_{CR-IoT,i}$	7 dB
Global decision threshold β	3
Primary activity factor α	0.7

For scenario I, Figure 4.5 shows the receiver operating characteristic (ROC) curves of the cooperative sensing performance for the conventional ED and the proposed ED schemes under the varying sensing time slots τ_s for the CR-IoT users. For both schemes, the probability of detection of the FC increases with sensing time slots τ_s. In the conventional ED scheme, for the probability of false alarm is 0.20, the probability of detection at the FC is 0.60 and 0.64 when $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. In the proposed scheme, the probability of false alarm is 0.20, the probability of detection at the FC is 0.88 and 0.94 when $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively.

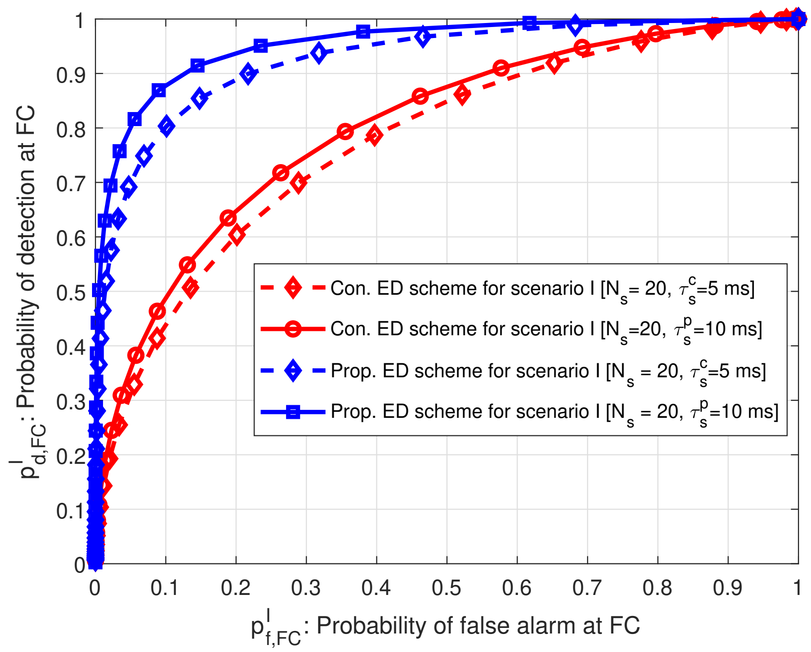

Figure 4.5: ROC curves at the FC of the proposed and conventional schemes for scenario *I*

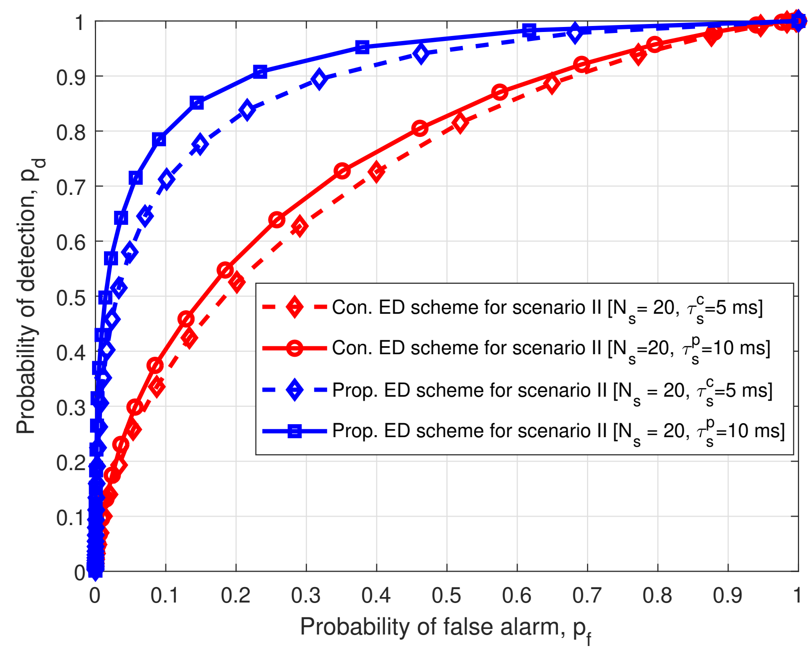

Figure 4.6: ROC curves at the FC of the proposed and conventional schemes for scenario *II*

For scenario II, Figure 4.6 shows the ROC curves of the cooperative sensing performance for the conventional ED and the proposed ED schemes under the varying sensing time slots τ_s. For both schemes, the probability of detection at the FC increases with sensing time slots τ_s. In the conventional ED scheme, for the probability of false alarm is 0.20, the probability of detection at the FC is 0.52 and 0.57 with $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively. In the proposed scheme, the probability of false alarm is 0.20, the probability of detection at the FC is 0.82 and 0.89 with $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively. In the comparison of the sensing performance at the FC as in Figure 4.5 and Figure 4.6, it is observed that the proposed ED scheme provides much better detection performance when compared to the conventional ED scheme for scenario I and scenario II. For the proposed ED and conventional ED schemes, in scenario II the detection performance is lower when compared to scenario I due to interference. The sensing performance of the ED technique mainly depends on the total number of samples, and the SNR value of the PU signal at the CR-IoT user. When interference occurs between the PU signal and the CR-IoT user signal, the signal path-loss increases and as a result decreases the total number of samples and SNR value of the PU signal at the CR-IoT user. Therefore, the presence of interference degrades the detection performance of the ED technique in CR-IoT networks.

Figure 4.7 shows the sum rates versus the probability of false alarm curves of the conventional and proposed ED techniques for scenario I. This figure is obtained by using sum-rate calculating Eq.4.27 and probability of false alarm values.

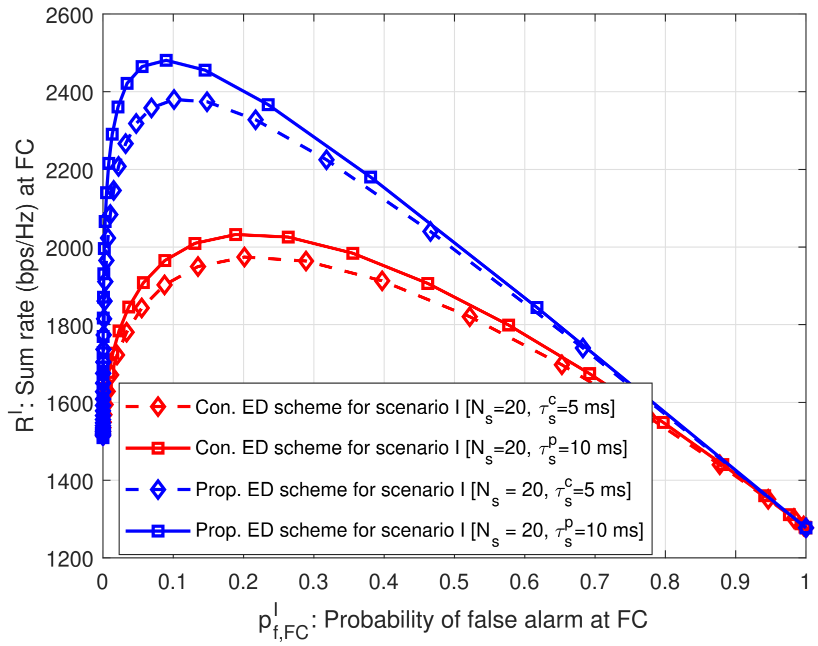

Figure 4.7: Sum rate curves versus probability of false alarm of a CR-IoT user for scenario I when $\alpha = 0.7$

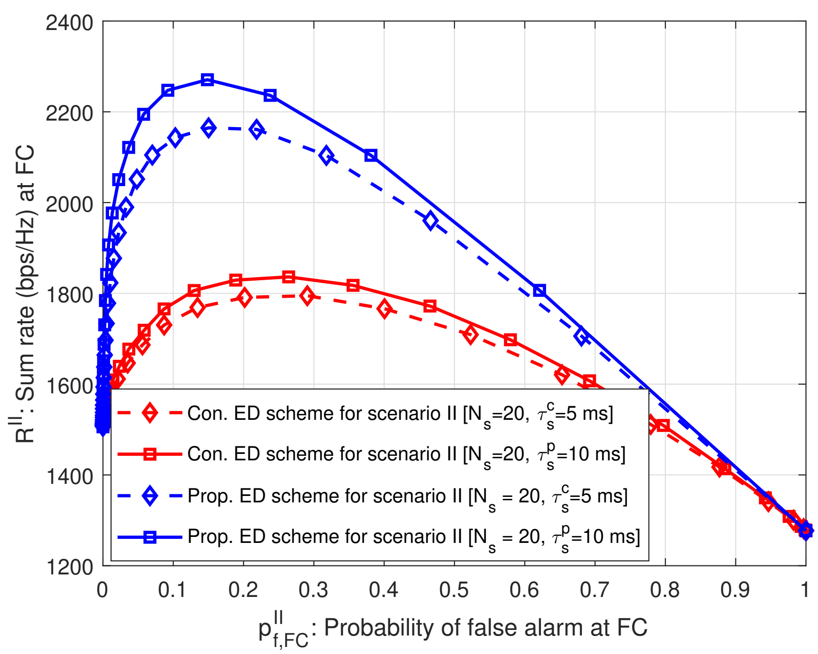

Figure 4.8: Sum rate curves versus probability of false alarm of a CR-IoT user for scenario II when $\alpha = 0.7$

The sum rate of the proposed ED technique is higher than that the conventional ED technique for the entire range of the probability of false alarm. At the probability of false alarm ($p^{I}_{f,FC} = 0.1$), the sum rate of the proposed ED technique is 2380 bps/Hz and 2460 bps/Hz for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively; whereas the sum rate of the conventional ED technique is 1920 bps/Hz and 1990 bps/Hz for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively. Figure 4.8 shows the sum rates versus the probability of false alarm curves for the conventional and proposed ED techniques for scenario II. For a probability of false alarm ($p^{II}_{f,FC} = 0.1$), the sum rate of the proposed ED technique is 2150 bps/Hz and 2260 bps/Hz for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively; whereas the sum rate of the conventional ED technique is 1740 bps/Hz and 1790 bps/Hz for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively. Therefore, we conclude that the sum rate of the proposed ED technique for scenario I and scenario II are better when compared to the conventional ED technique with the sensing time slot ($\tau_s = 5$ or 10) ms.

Figure 4.9 and Figure 4.10 show the spectral efficiency of the proposed ED scheme and the conventional ED scheme for scenario I and scenario II, respectively. From Figure 4.9, we can see that the spectral efficiency of the proposed scheme is better than the conventional scheme for scenario I. For example, at the probability of false alarm ($p^{I}_{f,FC} = 0.1$), the spectral efficiency of the proposed ED technique is 7.90 bps/Hz and 8.30 bps/Hz for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively; whereas the spectral efficiency of the conventional ED technique is 6.40 bps/Hz and 6.60 bps/Hz for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively. From Figure 4.10, it is observed that the spectral efficiency of the proposed scheme is better than the conventional scheme for scenario II. At the probability of false alarm ($p^{II}_{f,FC} = 0.1$), the spectral efficiency of the proposed ED technique is 7.15 bps/Hz and 7.50 bps/Hz for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively; whereas the spectral efficiency of the conventional ED technique is 5.75 bps/Hz and 5.90 bps/Hz for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10$ ms, respectively.

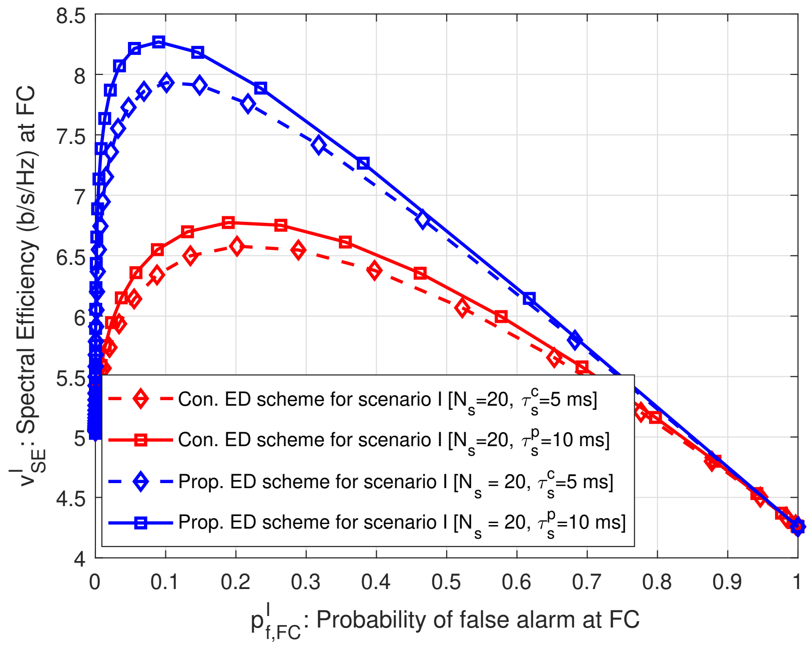

Figure 4.9: Spectral efficiency curves versus $p^I_{f,FC}$ at FC for scenario I

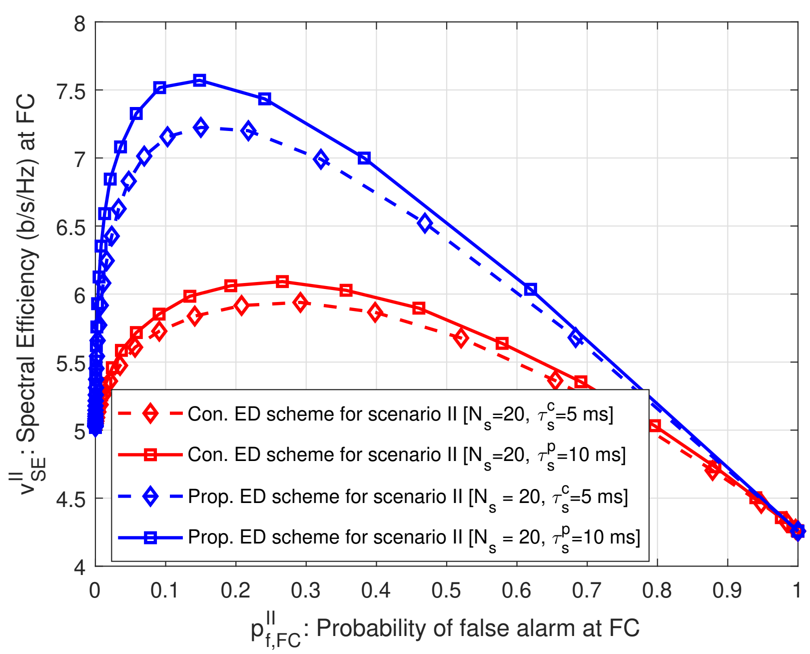

Figure 4.10: Spectral efficiency curves versus $p^{II}_{f,FC}$ at FC for scenario II

Figure 4.11 and Figure 4.12 shows the energy efficiency of the proposed ED scheme and the conventional ED scheme for scenario I and scenario II, respectively. From Figure 4.11, we can see that the energy efficiency of the proposed scheme is better than the conventional scheme for scenario I. For example, at the probability of false alarm ($p^I_{f,FC} = 0.1$), the energy efficiency of the proposed ED technique is 1.25 bps/J and 1.30 bps/J for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively; whereas the energy efficiency of the conventional ED technique is 1.01 bps/J and 1.04 bps/J for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. From Figure 4.12, it is observed that the energy efficiency of the proposed scheme is better than the conventional scheme for scenario II. At the probability of false alarm ($p^{II}_{f,FC} = 0.1$), the energy efficiency of the proposed ED technique is 1.13 bps/J and 1.18 bps/J for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively; whereas the energy efficiency of the conventional ED technique is 0.92 bps/J and 0.93 bps/J for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. Therefore, I conclude that the energy efficiency of the proposed scheme for scenario II is less than the proposed scheme for scenario I.

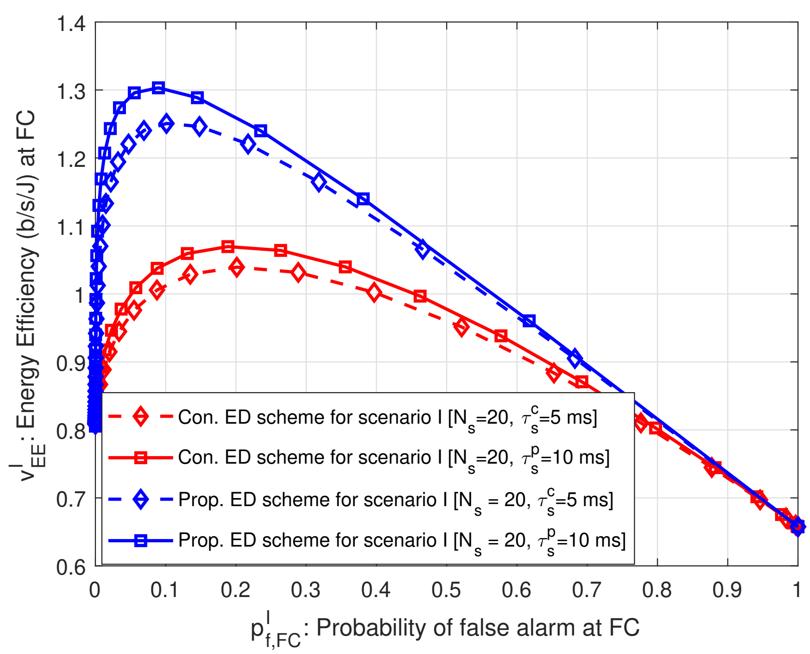

Figure 4.11: Energy consumption curves versus $p^I_{f,FC}$ at FC for scenario I

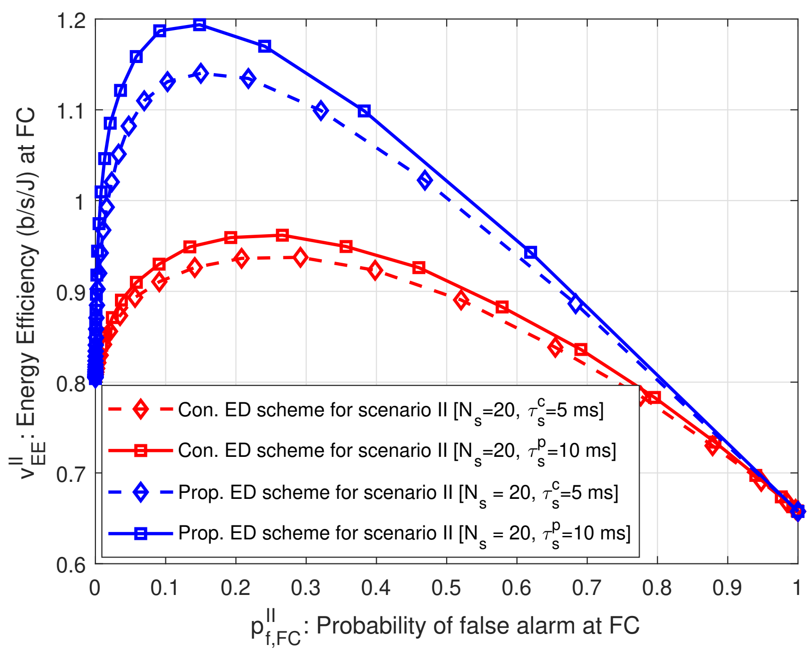

Figure 4.12: Energy consumption curves versus $p^I_{f,FC}$ at the FC for scenario II

4.6 Summary

In this chapter, I have proposed a novel ED technique that enhances the sensing performance, the sum rate, the energy and spectral efficiency for a CR-IoT network with interference constraints. In the sensing performance, for (i) scenario I, the probability of detection of the FC when using the proposed ED scheme is 46.66% and 44.61% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. For (ii) scenario II, the probability of detection of the FC when using the proposed ED scheme is 57.69% and 56.14% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. Also, with respect to sum rate, for (i) scenario I, the sum rate of the CR-IoT user when using the proposed ED scheme is 23.95% and 23.61% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. For (ii) scenario II, the sum rate of the CR-IoT user when using the proposed ED scheme is 23.56% and 26.25% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively.

With regard to the spectral efficiency in terms of bandwidth, for (i) scenario I, the spectral efficiency of the network when using the proposed ED scheme is 23.43% and 25.75% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. For (ii) scenario II, the spectral efficiency of the network when using the proposed ED scheme is 24.34% and 27.11% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. Moreover, with regard to the energy efficiency in terms of sum rate, for (i) scenario I, the energy efficiency of the proposed ED scheme is 23.76% and 25% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. For (ii) scenario II, the energy efficiency of the proposed ED scheme is 22.82% and 26.88% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. Therefore, I conclude that my proposed ED technique can be widely used for detecting the PU signal under interference constraints and with low SNR values, making it suitable for future CR-IoT networks, due to the fact that it enhances the sensing performance and sum rate of the CR-IoT user as well as maximising the spectral efficiency and the energy efficiency of the cognitive radio based IoT networks when compared to the conventional ED technique.

In my future work, the dynamic threshold of the proposed ED technique could be considered under a real time environment.

Chapter 5

MU-MIMO Based CSS for CR Enable IoV

5.1 Introduction

In the previous two chapters I consider a signal input and signal output (SISO) antenna-based CSS scheme for stationary CR-IoT users and primary users in CR-IoT networks. However, this SISO antenna-based CSS scheme is not capable of ensuring optimal spectrum detection gain, sum rate and the global error probability for mobile secondary user in cognitive radio-based Internet of Vehicles (IoV) networks. To address these problems, I propose the multiple user-multiple input multiple output (MU-MIMO) antenna aided cluster based cooperative spectrum sensing (CB-CSS) scheme for mobile CR embedded vehicles (CRV) in CR-IoV networks to achieve better sensing gain and sum rate as well as to reduce the global error probability and the traffic overhead.

The demand for access to the wireless radio spectrum has risen exponentially over the last few decades. This rise is attributed to a massive increase in the number of end users in areas like healthcare, industry, finance, security and the transportation systems [Khattab *et al.* 13, Sharma & Kaushik 19]. The IoV embedded intelligent transportation system (ITS) are expected to play an important role in road safety and convenient driving, because the vehicles will be able to share real-time data about their speed and location to roadside infrastructure and to other vehicles [Wootton *et* *al.* 95, Awin *et al.* 19b]. While the US Federal Communication Commission (FCC) has already allocated 75 MHz of spectrum in the 5.9 GHz band for the implementation of ITS services [Gill *et al.* 20], a substantial increase in vehicle applications, particularly in urban environments, will lead to an overcrowding of band and spectrum shortage for vehicle communications in vehicular ad-hoc networks (VANETs) [Pan *et al.* 12]. High-speed data communication is required for real time transmission in IoV networks [Li *et al.* 17]. However, data transmission speed depends on per channel bandwidth, and large channel bandwidth is required for high-speed data communication. In 4G networks, the per channel bandwidth is 5 MHz to 20 MHz [Ayad *et al.* 21], it provides up to 20 Mbps or more data transmission speed. The allocated 75 MHz frequency bandwidth is not enough spectrum for high speed IoV networks, as we can only get 4-15 channels from this allocated bandwidth. This number of channels is not enough for a large number of vehicles in an IoV networks.

Cognitive radio technology based VANETs (CR-VANETs) are a promising solution to maximize the utilization of the available frequency bandwidth by allowing the CRV as secondary users to use the allocated licensed spectrum frequency bands, when they are temporally idle [Duan *et al.* 18, Miah *et al.* 21a]. In order to prevent interference with PU, CRVs will access the licensed spectrum band opportunistically [Duan *et al.* 18]. The IoV is an emerging technology for ITS cyber-physical systems [Rawat *et al.* 18]. The IoVs as integrated as part of VANETs connects many heterogeneous vehicle sensors. The IEEE 802.11p DSRC/ WAVE communication standard used for wireless vehicular data transmission consists of 7 channels, where one channel is used to transfer the controlling data (i.e., control channel) and the other 6 channels are allocated for vehicular data transmission [Abeywardana *et al.* 18]. It supports three modes, i.e. (i) vehicle to vehicle (V2V), (ii) vehicle to roadside infrastructure (V2I), and (iii) vehicle to anything (V2X) [Raiyn 19]. However, the IEEE 802.11p DSRC/WAVE standard allocates only 7 channels and that is why when the number of vehicles increases then the transmission delay for SUs is also increased and an overload could occur when the number of vehicles increases. In addition, when large numbers of vehicles are connected in the network for data transmission with each other, this will lead to spectrum scarcity and a low system sum rate. The CR-VANETs, allow each CRV to find idle channels of other licensed networks (cellular, TV, WiMAX, etc.) to use the licensed spectrum conveniently using the spectrum sensing technique for transferring data in IoV networks.

In the SISO antenna based non-cooperative spectrum sensing scheme [Chehri 20, Miah *et al.* 21b] the ED technique is performed by a single CRV that discovers the idle spectrum frequencies. However, it cannot solve the hidden terminal problem, which arises for as a result of multi-path fading and shadowing. As a result, the sensing performance is degraded. On the other hand, a CSS scheme has been proposed to overcome the hidden terminal problem [Miah *et al.* 16], however the sensing gain and the sum rate of SISO based CSS technique is not enough for IoV networks. Today, the MIMO based CSS technique adds a new dimension in licensed spectrum detection. The concept of MIMO has drawn a lot of interest in CR research as it can mitigate fading and shadowing effects. With the emergence of MIMO systems, the existence of multi-path is effectively converted into a benefit for communication systems. As a result, MIMO systems can provide outstanding performance for detecting the PU signal over the SISO based CSS and NCSS schemes [Salarvan & Kurt 12]. By increasing the growth of the IoT which provides interconnection and communications between electronic devices and corresponding sensors, a large volume of data is exchanged by MIMO antenna systems [Khosravy *et al.* 20, Miah *et al.* 20].

5.1.1 Contributions

The main contributions of this chapter can be summarized as follows:

- The sensing gain, the system sum rate, and the global error probability are analyzed for the the proposed MU-MIMO antennas aided CB-CSS scheme and the conventional SISO antenna based NCSS and CSS schemes.

- I show that our proposed scheme achieves a superior detection result and system sum rate when compared to other conventional schemes. In addition, the proposed scheme obtains a lower global error probability and traffic overhead at the FC.

5.1.2 Publications

Mohammad Amzad Hossain, Michael Schukat and Enda Barrett. MU-MIMO Based Cognitive Radio in Internet of Vehicles (IoV) for Enhanced Spectrum Sensing Accuracy and Sum Rate. IEEE 93rd Vehicular Technology Conference (IEEE VTC2021-Spring), Helsinki, Finland.

Mohammad Amzad Hossain, Michael Schukat and Enda Barrett. Performance Analysis of MU-MIMO Based Cooperative Spectrum Sensing for Cognitive Radio Enable IoV. *Computer Networks (Submitted, May 2021)*

5.1.3 Chapter Structure

The rest of this chapter is organised as follows: Section 5.2 describes the related work. In Section 5.3 I discuss my proposed CR enabled IoV system model. In 5.4 I present the conventional SISO antenna based NCSS and CSS schemes. In Section 5.5 I explain the proposed MU-MIMO antennas aided CB-CSS scheme. The simulation results are given in Section 5.6, and the summary and future work of this chapter are addressed in Section 5.7. In addition, the parameters included in this chapter are summarized as follows in Table 5.1:

Table 5.1: Main parameters

Parameters	Corresponding Definitions
H_0	The hypothesis which indicates the absence of the PU signal
H_1	The hypothesis which indicates the presence of the PU signal
U/Z	The total number of PUs/CRVs
M	The number of antennas at each CRV
N/S	The number of cluster/cluster members
$x(k)$	Signal transmitted from PU
$n_{i,j}(k)$	The noise signal
$h_{i,j}(k)$	The channel gain between the PU and the CRV
$y_{i,j}(k)$	The signal received by the CRV
γ_i	The SNR at the CRV
$E_{i,j}$	The energy level of the received signal
L	The number of received samples
T	The frame duration
τ_s/τ_r	Time duration for sensing/reporting of the CRV
$P_d^{c1}(\lambda_1)$	The probability of detection of the NCSS
$P_f^{c1}(\lambda_1)$	The probability of false alarm of the NCSS
$P_{d,FC}^{c2}(\lambda_2)$	The probability of detection of the CSS
$P_{f,FC}^{c2}(\lambda_2)$	The probability of false alarm of the CSS
G_{FC}	The global decision statistic at the FC for the proposed scheme
$P_{d1,FC}^{p}(\lambda_p)$	The probability of detection for stationary CRV
$P_{f1,FC}^{p}(\lambda_p)$	The probability of false alarm for stationary CRV
$P_{d2,FC}^{p}(\lambda_p)$	The probability of detection for mobile CRV
$P_{f2,FC}^{p}(\lambda_p)$	The probability of false alarm for mobile CRV
$Pr(H_0)$	The probability of absence of the PU in the sensing range
$Pr(H_1)$	The probability of presence of the PU in the sensing range
R_{CB-CSS}^{p}	The sum rate of the proposed scheme
$Pe_{CB_CSS}^{p}$	The global error probability at the FC of the proposed scheme
$P(H_0)$	The probability of absence of the PU
$P(H_1)$	The probability of presence of the PU
TO_{FC}^{CSS}	The traffic overhead at the CH for the MU-MIMO based CSS scheme without cluster
TO_{CH}^{p}	The traffic overhead at the CH for the proposed scheme
TO_{FC}^{p}	The traffic overhead at the FC for the proposed scheme

5.2 Related works

Recently, researchers have been working to apply CR technology to IoV in order to reduce the spectrum deficiency problem. The authors in [Tarek *et al.* 20] analysed the allocation of channels and scheduling of packets by combining the CRNs and IoT networks. In [Aliyu *et al.* 18], the authors were presented with a comprehensive examination on video streaming in the IoT systems based on the perspective of vehicular communication. Moreover, the importance of video streaming in vehicular IoT systems was illustrated focusing on a combination of vehicular communication with 5G enabled IoT devices, and smart city oriented application areas for IoT. In [Kim & Krunz 13], the authors proposed a spectrum-aware beacon-less geographical routing protocol for CR-VANETs. In this protocol, CR-enabled vehicles can share TV-band spectrum to enhance the spectrum efficiency and minimize the end-to-end transmission delay. Abbassi, Shahid H., et al. [Abbassi *et al.* 15] proposed a cluster based CSS scheme for small highways road segments of the CR-VANETs. This spectral sensing method creates a database for the sensing data of the sensing time slots for each hour of the day. The future allocation of the spectrum for the SU is determined on the basis of this database. However, the authors did not analyse the sum rate and global error probability for the CR-VANETs with a MU-MIMO antennas approach.

In [Eze *et al.* 15], the authors proposed a cooperative three-state spectrum sensing scheme for a CR based IoV network to mitigate the spectrum scarcity problem by accessing the licensed user spectrum on the highways without serious interference. The first state happens if an idle licensed spectrum is sensed, the second state occurs if a PU exists, and the third state if a secondary user uses the licensed spectrum. However, the proposed scheme is a cluster-less CSS scheme which causes large overhead at the FC. In addition, the authors did not thoroughly investigate the traffic overhead at the FC and throughput of the system. In [Ali *et al.* 19], the authors proposed a clustering and position-based spectrum sensing scheme to transmit the emergency messages in IoV networks. The simulation results showed that the proposed scheme reduced the communication delay. However, they did not consider spectrum efficiency and overall throughput of the IoV network. In [Wang *et al.* 19], the authors proposed a social-aware routing scheme for cognitive radio–based VANETs to enhance the packet delivery ratio and decrease the overhead ratio. The results indicated that proposed routing scheme achieves a higher package delivery ratio and lower overhead ratio when compared with the existing cognitive radio–based VANETs routing schemes. However, the authors did not thoroughly analyse the spectrum sensing gain for the CR-VASNET user. In [Jalil Piran *et al.* 14], the author proposed a CR-based sensor networks framework for vehicular communication. The authors analyzed only the probability of detection for different SNR with a different time bandwidth factor. However, they did not analyse the sum rate for cooperative spectrum sensing for the CR-VASNET with a MU-MIMO antennas approach. In [Qian *et al.* 18], the authors investigated the transmission delay and proposed the path selection scheme to meet security requirements of the cognitive internet of vehicles (CIoV) networks. The authors analysed the path selection scheme and enhanced the security and reduced the packet transmission delay of the CIoV networks when compared to the conventional IoV networks. However, they did not analyse the detection performance and the sum rate in a CR-IoVT network.

In [Rawat *et al.* 18], the authors analysed and evaluated the overall effect of the unlicensed CIoV user mobility and the licensed PU activity for the CIoV networks. Moreover, they studied the dynamic spectrum allocation for opportunistic communications in the context of estimated transmission time, achievable sum rate and expected efficient communication transmission rate. However, they did not analyse the detection performance and the sum rate in a CR-IoVT using the MU-MIMO antennas approach. In [Chen *et al.* 18], the authors presented an outline of the CIoV consisting of its history, associated technology, and structure. Moreover, they highlighted critical cognitive structure problems from three points of view, such as inter-vehicle network, intra-vehicle network, and beyond vehicle network. However, the authors did not analyze the MU-MIMO antennas based on the detection performance and the average throughput in a CR-IoVT network.

In [Wang *et al.* 20], the author proposed a cognitive radio-capable IoV network to overcome the problem of conflict between the growing demand for IoV applications and the limited radio spectrum in the context of urban expressways. They developed a SISO antenna based multi-hop forwarding approach to reduce the end-to-end delay for such networks. However they did not investigate the spectrum detection accuracy, system throughput and probability of global error based on MU-MIMO antennas. In [Paul *et al.* 15], the authors proposed an efficient centralized CSS scheme in IoV networks. The renewal theory based fusion rule is used at the FC to enhance the detection accuracy. The results showed that the proposed scheme is more suitable against interference minimization and the hidden problem of the Primary User. However, they analysed the probability of false alarm and probability of detection based on the SISO and centralized CSS scheme. Moreover, the authors did not analyse the MU-MIMO antennas based detection performance, the average throughput, and the probability of global error in a CR-IoV network. Eze et al. [Eze *et al.* 18] have proposed a CR assisted IoV network that enabled vehicles to use the licensed spectrum for data transmission. Also, authors have introduced a three-stage spectrum sensing scheme to enhance the spectrum detection accuracy. The results showed that the proposed scheme improved the sensing performance based on the SISO and CSS scheme. However, they did not consider the MU-MIMO antennas based cluster CSS scheme and investigate the system sum rate and probability of global error.

5.3 System Model

I propose a MU-MIMO antenna aided cluster based CSS scheme for CR enabled IoV networks which consist of U PUs and Z CRVs, each CRV having the M antennas for receiving and transmitting the signal; the FC has M antennas. In my model, the CRV is considered as a secondary user that accesses the licensed frequency band in a opportunistic way to avoid interference with the PU signal. The proposed system model is shown in Figure 5.1.

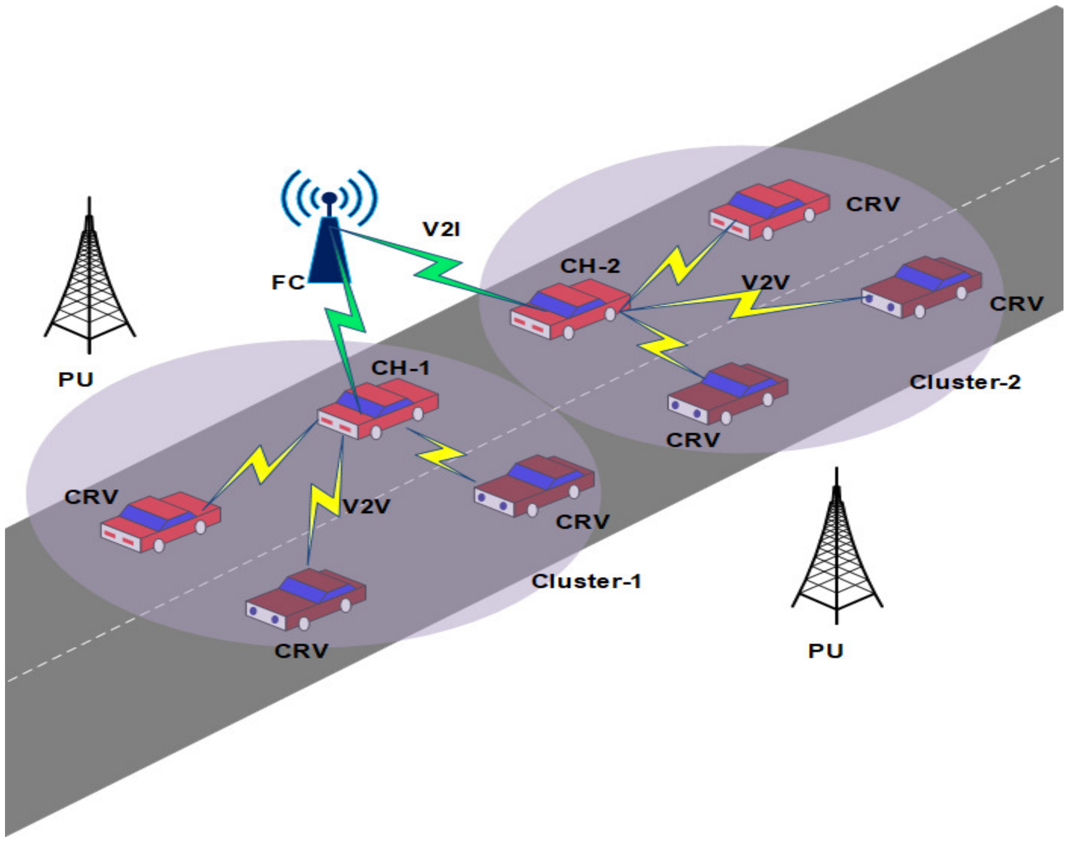

Figure 5.1: The proposed MU-MIMO antenna aided CB-CSS system model for CR enabled IoV networks.

In my system model, the FC applies the Fuzzy C-Means (FCM) clustering algorithm to create FC clusters and select CHs [Bhatti *et al.* 16b]. The working of the FCM algorithm is described in detail in Chapter 3 of this thesis. This algorithm requires the number of clusters to be specified. We consider that the number of clusters is N and each cluster consists of a number of CRVs S and a cluster head (CH). That is, all clusters have equal size. The number of clusters N is identified by using the following formula [Hoang *et al.* 10b]:

$$N = \frac{\sqrt{Z}}{\sqrt{2\pi}} \frac{E_{fs}}{E_{mp}} \frac{R}{d^2_{to-FC}} \tag{5.1}$$

where R is the network diameter,d^2_{to-FC} is the average distance from one CRV to its FC, E_{fs} and E_{mp} are the energy expenditure of transmitting one bit data to achieve an acceptable bit error rate that is dependent on the distance of transmission in the case of free space model and multi-path fading model.

The distance among the members of the cluster (i.e., CRVs) is very small due to the size of the small cluster. In a physically small cluster the CRVs can coordinate better with each other, which increases the network performance.

In each cluster, all the CRVs receive a signal from the PU through MIMO antennas and simultaneously pass their sensing data to the specific CH, each CH makes a local spectrum sensing decision by applying the data fusion rule like the equal gain combining (EGC) rule and the maximal ratio combining (MRC) rule on received sensing data from the CRVs [Lee *et al.* 09]. Thereafter, each CH sends the cluster sensing result to the specific FC via an error free reporting channel. The FC collects all cluster sensing results and makes a final global decision about the status (i.e., active or inactive) of the PU signal by applying the K-out-of-N fusion rule. At the FC, my proposed MU-MIMO antennas aided CB-CSS scheme reduces the extra communication overhead and complexity compared to the centralized CSS scheme. In my system model we consider that PUs are stable and CRVs are both stationary and mobile. For perfect spectrum detection, signals from PUs should be identified to be present or absent in a given time and location. The status (i.e., active or inactive) of the PU signal in the licensed spectrum is represented by a two state Markov process (A Markov process is a set of discrete states. The state of the Markov process at future time is decided by the system state at the current time and does not depend on the state at earlier time instants) [Sabat *et al.* 17]. The time duration of the active ($P_1 = ON$) state and the inactive ($P_0 = OFF$) state are represented by two random parameters C and D, respectively. These two random parameters C and D are exponentially distributed with an average time duration F and U, respectively. The probabilities of the PU signal being active and inactive are defined as $P_1 = F/(F+U)$ and $P_0 = U/(F+U)$, respectively.

The local spectrum detection condition can be formulated as two hypotheses where H_0 represents the PU being absent on the licensed channel and H_1 represents the PU being present on the licensed channel as follows:

$$y_{i,j}(k) = \begin{cases} n_{i,j}(k), & : H_0 \\ h_{i,j}(k)x(k) + n_{i,j}(k), & : H_1 \end{cases} \tag{5.2}$$

where $i = 1, 2, 3, ..., Z$, $j = 1, 2, 3, ..., M$ and $k = 1, 2, 3, ..., L$; here, $y_{i,j}(k)$ is the received signal of the i^{th} CRV with the j^{th} receiving antenna, $x(k)$ is the PU transmitted signal with variance, σ_x^2 and $n_{i,j}(k)$ is a zero-mean AWGN with variance, $\sigma_{n,i,j}^2$. Moreover, $h_{i,j}(k)$ is the channel gain of the i^{th} CRV with the j^{th} antenna.

5.3.1 Energy Detection Technique

The energy detection method is one of the most cost effective and least complex methods to calculate the received signal energy on a specific part of the spectrum [Hossain *et al.* 19]. It does not require any previous information about the PU signal for detection purposes. The energy detection steps at the CRV is indicated in Figure 5.2.

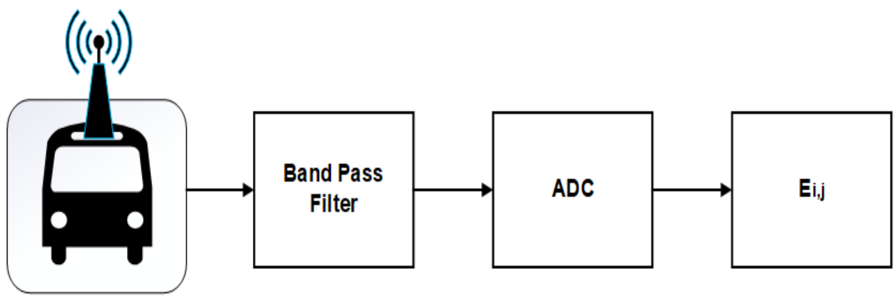

Figure 5.2: The energy detection technique

An estimation of the received PU signal energy at the i^{th} CRV with the j^{th} antenna is given as follows [Hossain *et al.* 19]:

$$E_{i,j} = \sum_{k=1}^{L} |y_{i,j}(k)|^2 \tag{5.3}$$

where L represents the total number of received samples, which is defined as $L = 2\tau_s f_c$ [Hossain *et al.* 20], here τ_s and f_c are the sensing time slot in ms and the sampling frequency in Hz, respectively.

The $E_{i,j}$ in (6.3) may be well approximated by a Gaussian distribution when L is fairly high. We can calculate the probability density function (PDF) of the test statistics of $E_{i,j}$ at the ith CRV with the j^{th} antenna for hypotheses H_0 and H_1 respectively, as follows:

$$E_{i,j} \sim \begin{cases} \mathcal{N}(\mu_{i,j}(H_0), & \sigma^2_{i,j}(H_0)) \\ \mathcal{N}(\mu_{i,j}(H_1), & \sigma^2_{i,j}(H_1)) \end{cases} \tag{5.4}$$

where $\mu_{i,j}(H_0)$ and $\mu_{i,j}(H_1)$ are the means and $\sigma^2_{i,j}(H_0)$ and $\sigma^2_{i,j}(H_1)$ are the variances of the E_i for the hypotheses H_0 and H_1 respectively. The above variables are presented as follows [Chen 10]:

$$\begin{aligned} \mu_{i,j}(H_0) &= L\sigma_n^2 \\ \mu_{i,j}(H_1) &= L\left(1+\gamma\right)\sigma_n^2 \\ \sigma^2_{i,j}(H_0) &= L\sigma_n^4 \\ \sigma^2_{i,j}(H_1) &= L\left(1+2\gamma\right)\sigma_n^4 \end{aligned}$$

where γ_i is a SNR defined as $\gamma_i = \frac{\sigma_x^2}{\sigma_n^2}$.

5.4 SISO Antenna Based Spectrum Sensing

In this section, I briefly explain the SISO antenna based NCSS and CSS schemes.

5.4.1 Non-Cooperative Spectrum Sensing

In the conventional NCSS scheme with a SISO antenna, a CRV senses the PU signal and calculates the test statistic $E^{c1}_{i,j}$ as follows:

$$E^{c1}_{i,j} = \sum_{j=1}^{M=1} \sum_{i=1}^{Z=1} \sum_{k=0}^{L-1} |y_{i,j}(k)|^2 \tag{5.5}$$

where M indicates the number of antennas, Z indicates the total number of CRVs in the networks, and L is the total number of samples.

In the conventional NCSS scheme with the SISO antenna, we can calculate the PDF of the test statistics of E^{c1} for a CRV with ($M = 1$) SISO antenna, which is given as follows: [Miah *et al.* 18a]:

$$E^{c1} \sim \begin{cases} \mathcal{N}\left(\mu_{c1}(H_0) = L\sigma_n^2, \quad \sigma_{c1}^2(H_0) = L\sigma_n^4\right) \\ \mathcal{N}(\mu_{c1}(H_1) = L\left(1+\gamma\right)\sigma_n^2, \quad \sigma_{c1}^2(H_1) = LW_1 \end{cases} \tag{5.6}$$

where $W_1 = \left(1+2\gamma\right)\sigma_n^4)$. Based on the PDF of the test statistics in (5.6), a single CRV calculates the probability of detection, $P_d^{c1}(\lambda_1)$ and the probability of false alarm, $P_f^{c1}(\lambda_1)$ as follows:

$$\begin{aligned} P_d^{c1}\left(\lambda_1\right) = Pr[E^{c1} \geq \lambda_1 | H_1] &= Q\left(\frac{\lambda_1 - \mu_{c1}(H_1)}{\sigma_{c1}(H_1)}\right) \\ &= Q\left(\frac{\lambda_1 - L\left(1+\gamma\right)\sigma_n^2}{\sqrt{L\left(1+2\gamma\right)}\sigma_n^2}\right) \end{aligned} \tag{5.7}$$

$$\begin{aligned} P_f^{c1}\left(\lambda_1\right) = Pr[E^{c1} \geq \lambda_1 | H_0] &= Q\left(\frac{\lambda_1 - \mu_{c1}(H_0)}{\sigma_{c1}(H_0)}\right) \\ &= Q\left(\frac{\lambda_1 - L\sigma_n^2}{\sqrt{L}\sigma_n^2}\right) \end{aligned} \tag{5.8}$$

where λ_1 is a decision threshold, and $Q\left(.\right)$ represents the Gaussian function defined as $Q\left(x\right) = \frac{1}{2\pi}\int_x^{\infty} e^{-\frac{t^2}{2}}\, dt$.

For the conventional NCSS scheme with a SISO antenna, a pseudo code algorithm is formulated as shown in Algorithm 1.

Algorithm 1 In the conventional NCSS scheme with a SISO antenna, a single antenna $(M = 1)$ based CRV user has obtained the samples (L).

Input: Select the appropriate number of CRVs $(N = 1)$, the number of antenna $(M = 1)$, the number of samples (L) and the decision threshold, λ_1.

Output: Calculate the probability of detection $(P_d^c(\lambda_1))$ and the probability of false alarm $(P_f^c(\lambda_1))$ at each CRV.

```
Initialize L, Z, M, λ1
for i from 1 to (Z = 1) do
    for j from 1 to (M = 1) do
        for k from 0 to L − 1 do
            Set: E^{c1}(EGC) = Σ_{j=1}^{M} Σ_{i=1}^{Z} E^{c1}_{i,j}(EGC); where E^{c1}_{i,j}(EGC) = Σ_{k=0}^{L−1} ||y_{i,j}(k)||^2; Using the EGC rule
            Set: E^{c1}(MRC) = Σ_{j=1}^{M} Σ_{i=1}^{Z} E^{c1}_{i,j}(MRC); where E^{c1}_{i,j}(MRC) = Σ_{k=0}^{L−1} ||y_{i,j}(k)||^2 × γ_i / sqrt(Σ_{i=1}^{Z} γ_i^2); Using the MRC rule
        end for
    end for
end for
Calculate: P_d^{c1}(λ1) = Q((λ1 − L(1+γ)σ_n^2) / sqrt(L(1+2γ)σ_n^2))
Calculate: P_f^{c1}(λ1) = Q((λ1 − Lσ_n^2) / sqrt(Lσ_n^2))
Calculate: R_{c1} = αP_d^{c1}(λ1)R_{PU} + (1 − α)(1 − P_f^{c1}(λ1)) R_{CRV,i}
Calculate: Pe_{c1} = P(H0)P_f^{c1}(λ1) + P(H1)(1 − P_d^{c1}(λ1))
```

5.4.2 Cooperative Spectrum Sensing

In the conventional CSS scheme with a SISO antenna, Z CRVs are sensing the PU signal, which results in the test statistic of $E_{i,j}^{c2}$ as follows:

$$E_{i,j}^{c2} = \sum_{j=1}^{M=1} \sum_{i=1}^{Z} \sum_{l=0}^{L-1} |y_{i,j}(k)|^2 \tag{5.9}$$

In the conventional MU-SISO antenna CSS scheme, I can calculate the PDF of the test statistics, E^{c2} for Z CRVs with $(M = 1)$ SISO antennas, which is given as follows [Miah *et al.* 18a]:

$$E^{c2} \sim \begin{cases} \mathcal{N}(\mu_{c2}(H_0) = ZL\sigma_n^2, & \sigma_{c2}^2(H_0) = ZL\sigma_n^4) \\ \mathcal{N}(\mu_{c2}(H_1) = ZL\left(1+\gamma\right)\sigma_n^2, & \sigma_{c2}^2(H_1) = ZLW_2 \end{cases} \tag{5.10}$$

where $W_2 = \left(1+2\gamma\right)\sigma_n^4)$. Based on the PDF of the test statistics in (5.10), the FC calculates the probability of detection, $P_{d,FC}^{c2}(\lambda_2)$ and the probability of false alarm, $P_{f,FC}^{c2}(\lambda_2)$ as follows:

$$\begin{aligned} P_{d,FC}^{c2}\left(\lambda_2\right) = Pr[E^{c2} \geq \lambda_2 | H_1] = Q\left(\frac{\lambda_2 - \mu_{c2}(H_1)}{\sigma_{c2}(H_1)}\right) \\ = Q\left(\frac{\lambda_2 - ZL\left(1+\gamma\right)\sigma_n^2}{\sqrt{ZL\left(1+2\gamma\right)}\sigma_n^2}\right) \end{aligned} \tag{5.11}$$

$$\begin{aligned} P_{f,FC}^{c2}\left(\lambda_2\right) = Pr[E^{c2} \geq \lambda_2 | H_0] = Q\left(\frac{\lambda_2 - \mu_{c2}(H_0)}{\sigma_{c2}(H_0)}\right) \\ = Q\left(\frac{\lambda_2 - ZL\sigma_n^2}{\sqrt{ZL}\sigma_n^2}\right) \end{aligned} \tag{5.12}$$

where λ_2 is a decision threshold for a conventional MU-SISO antenna CSS scheme.

For the conventional CSS scheme with SISO antenna, a pseudo code algorithm is formulated, as shown in Algorithm 2.

Algorithm 2 In the conventional CSS scheme with a SISO antenna, all CRV users Z with a single antenna ($M = 1$) has obtained more samples.

Input: Select appropriate the number of CRVs (Z), the number of antenna ($M = 1$), the number of samples (L) and the decision threshold (λ_2).

Output: Calculate the probability of detection ($P^{c2}_{d,FC}$) and the probability of false alarm ($P^{c2}_{f,FC}$) at the FC.

Initialize L, Z, $M = 1$, λ_2
for i from 1 to Z **do**
  for j from 1 to $(M = 1)$ **do**
    for k from 0 to $L-1$ **do**
      Set: $E^{c2}(EGC) = \sum_{j=1}^{M}\sum_{i=1}^{Z} E^{c2}_{i,j}(EGC)$; where $E_{i,j}(EGC) = \sum_{k=0}^{L-1}\|y_{i,j}(k)\|^2$; Using the EGC rule
      Set: $E^{c2}(MRC) = \sum_{j=1}^{M}\sum_{i=1}^{Z} E^{c2}_{i,j}(MRC)$; where $E_{i,j}(MRC) = \sum_{k=0}^{L-1}\|y_{i,j}(k)\|^2 \times \frac{\gamma_i}{\sqrt{\sum_{i=1}^{Z}\gamma_i^2}}$; Using the MRC rule
    end for
  end for
end for
Calculate: $P^{c2}_{d,FC}(\lambda_2) = Q\left(\frac{\lambda_2 - ZL(1+\gamma)\sigma_n^2}{\sqrt{NL(1+2\gamma)\sigma_n^2}}\right)$
Calculate: $P^{c2}_{f,FC}(\lambda_2) = Q\left(\frac{\lambda_2 - ZL\sigma_n^2}{\sqrt{ZL}\sigma_n^2}\right)$
Calculate: $R_{c2} = \alpha P^{c2}_{d,FC}(\lambda_2) R_{PU} + (1-\alpha)\left(1 - P^{c2}_{f,FC}(\lambda_2)\right) R_{CRV,i}$
Calculate: $Pe_{c2} = P(H_0) P^{c2}_{f,FC}(\lambda_2) + P(H_1)\left(1 - P^{c2}_{d,FC}(\lambda_2)\right)$

5.5 Proposed MU-MIMO Antennas Aided Cluster Based Cooperative Spectrum Sensing for CR enabled IoV Networks

In this section, I explain the proposed MU-MIMO antennas aided CB-CSS scheme using soft fusion rules like the EGC rule and the MRC rule.

5.5.1 Cluster Based Cooperative Spectrum Sensing

In the MU-MIMO antenna aided CB-CSS scheme, each CRV uses the ED technique to calculate the energy of the received PU signal and the CH uses the EGC fusion rule and the MRC fusion rule for making cluster test statistics; whereas the FC uses the K-out-of-N rule to take a final global decision. All receiving antennas are uncorrelated. For the MIMO antennas, in each CRV, the energy level of each antenna's received signal is calculated separately and the calculated energy level of multiple antennas is added linearly to detect the status of the PU signal in the CR-IoV networks. Figure 5.3 shows the energy detection and combining process of the multiple antenna system. At the FC, my proposed MU-MIMO antennas aided CB-CSS scheme reduces the additional communication overhead and processing time compared to the centralized CSS scheme.

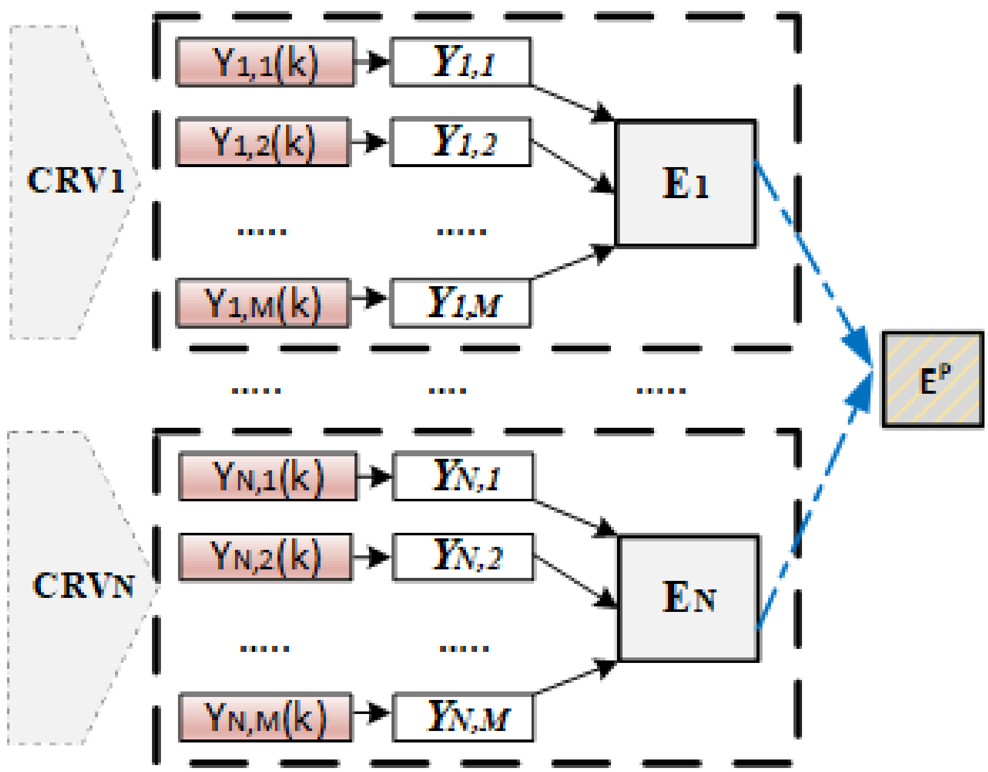

Figure 5.3: The PU signal sensing and energy integrating process of the proposed MU-MIMO scheme.

In the EGC rule, a calculation of the received signal energy at the i^{th} CRV with the

j^{th} antenna is given as follows [Srinu *et al.* 10]:

$$E_{i,j}(EGC) = \sum_{k=0}^{L-1} |y_{i,j(k)}|^2 \tag{5.13}$$

Similarly, in the MRC rule, an estimation of the received signal energy at the i^{th} CRV with the j^{th} antenna is given as follows [Sun *et al.* 11]:

$$E_{i,j}(MRC) = \sum_{k=0}^{L-1} |y_{i,j(k)}|^2 \times \frac{\gamma_i}{\sqrt{\sum_{i=1}^{S} \gamma_i^2}} \tag{5.14}$$

Each CRV transmits its test statistics result from the MIMO antennas directly to the corresponding CH through the control channel in an orthogonal manner. From (5.13), the cluster test statistic is calculated by using the EGC rule at the CH as follows:

$$E^p_{CB-CSS}(EGC) = \sum_{j=1}^{M}\sum_{i=1}^{S} E_{i,j}(EGC) \tag{5.15}$$

where S represents the number of CRVs in each cluster.

Similarly, from (5.14), the cluster test statistic is calculated by using the MRC rule at the CH as follows:

$$E^p_{CB-CSS}(MRC) = \sum_{j=1}^{M}\sum_{i=1}^{S} E_{i,j}(MRC) \tag{5.16}$$

The cluster decision is made for both fusion rule at the ith CH as follows:

$$D_i = \begin{cases} 1, \quad if \quad E^p_{CB-CSS} \geqslant \lambda_p \quad (Indicates \quad H_1) \\ 0, \quad if \quad E^p_{CB-CSS} < \lambda_p \qquad (Indicates \quad H_0) \end{cases} \tag{5.17}$$

where (λ) represents the threshold value for CH. The equation (5.17) is applicable for both the EGC and the MRC rules.

In the proposed MU-MIMO antenna aided CB-CSS scheme, I can calculate the PDF of the test statistics, E^p_{CB-CSS} of each CH for S CRVs (i.e., cluster members) with M antennas, which is given as follows [Hossain *et al.* 20]:

$$E^p_{CB-CSS} \sim \begin{cases} \mathcal{N}\left(\mu_p(H_0) = MSL\sigma_n^2, \sigma_p^2(H_0) = MSL\sigma_n^4\right) \\ \mathcal{N}\left(\mu_p(H_1) = MSW_3, \sigma_p^2(H_1) = MSW_4\right) \end{cases} \tag{5.18}$$

where $W_3 = L(1+\gamma)\sigma_n^2$ and $W_4 = L(1+2\gamma)\sigma_n^4$. The equation (5.18) is applicable for any type of modulation technique.

Each CH transmits its cluster spectrum detection result to the specific FC via the error free reporting channel. Thereafter, the FC applies the K-out-of-N fusion rule on the received cluster spectrum detection results to take the global decision (G_{FC}), it is presented as follows [Hossain *et al.* 20]:

$$G_{FC} = \begin{cases} H_1, & if \sum_{i=1}^{N} D_i \geq K \\ H_0, & Otherwise \end{cases} \tag{5.19}$$

where N is the number of clusters in the IoV networks. The equation (5.19) is applicable for both the EGC and the MRC rules.

5.5.1.1 When each CRV is stationary

The probability of detection, $P_{d1,CH}(\lambda_p)$ and probability of false alarm, $P_{f1,CH}(\lambda_2)$ at each CH is calculated based on the PDF of the test statistics in (5.18), as follows:

$$\begin{aligned} P_{d1,CH}\left(\lambda_p\right) &= Pr[E^p_{CB-CSS} \geq \lambda_p | H_1] \\ &= Q\left(\frac{\lambda_p - \mu_p(H_1)}{\sigma_p(H_1)}\right) \\ &= Q\left(\frac{\lambda_2 - MSL\left(1+\gamma\right)\sigma_n^2}{\sqrt{MSL\left(1+2\gamma\right)\sigma_n^2}}\right) \end{aligned} \tag{5.20}$$

and

$$\begin{aligned} P_{f1,CH}\left(\lambda_2\right) &= Pr[E^p_{CB-CSS} \geq \lambda_p | H_0] \\ &= Q\left(\frac{\lambda_p - \mu_p(H_0)}{\sigma_p(H_0)}\right) \\ &= Q\left(\frac{\lambda_p - MSL\sigma_n^2}{\sqrt{MSL}\sigma_n^2}\right) \end{aligned} \tag{5.21}$$

where λ_p is a decision threshold for the MU-MIMO antennas aided CB-CSS scheme.

The probabilities of false alarm ($P^p_{d1,FC}$) and detection ($P^p_{f1,FC}$) at the FC for my proposed scheme can be represented by using the K-out-of-N fusion rule are demonstrated as follows [Hossain *et al.* 20]:

$$P^p_{d1,FC} = \sum_{i=K}^{N} \binom{N}{i} P^{(i)}_{d1,CH}(1 - P_{d1,CH})^{(N-i)} \tag{5.22}$$

and

$$P^{p}_{f1,FC} = \sum_{i=K}^{N} \binom{N}{i} P^{(i)}_{f1,CH} (1 - P_{f1,CH})^{(N-i)} \tag{5.23}$$

5.5.1.2 When each CRV is mobile

When each CRV is mobile then the velocity of a CRV needs to be considered for calculating the probability of detection and the probability of false alarm at the CH. The probability of detection $P_{d2,CH}(\lambda_p)$ and the probability of false alarm $P_{f2,CH}(\lambda_p)$ at the CH for the proposed scheme can be represented by using the velocity of a CRV are demonstrated as follows [Rawat *et al.* 18]:

$$P_{d2,CH}(\lambda_p) = P_{d1,CH}(\lambda_p) \times Pr[H_0] \tag{5.24}$$

and

$$P_{f2,CH}(\lambda_p) = P_{f1,CH}(\lambda_p) \times Pr[H_1] \tag{5.25}$$

where λ_2 is a decision threshold for conventional MU-SISO antenna CSS scheme.

where $Pr[H_0]$ and $Pr[H_1]$ are probabilities of primary user is absent and present in the sensing range of the CRV, respectively.

Now I investigate the effect of the CRV velocity on spectrum sensing performance in the CR-IoV network: I analyse spectrum sensing performance based on the event A (PU 'absent' in a given channel) and the event B (PU channel 'busy'). The probability of the event A and B depends on the distribution function of separation distance between a fixed PU and a mobile CRV. When the separation distance between a PU and an SU is D and the sensing range of the CRV is S then the condition for the PU being inside the sensing range of SU is $D \leq S$. Therefore, we can compute the probability for the event B, that is, $Pr[H_1]$, the probability that the PU is inside the sensing range of CRV which is discussed as below.

When the lower speed limit is $v_{min} = \mu_v - 3\sigma_v$ and upper speed limit is $v_{max} = \mu_v + 3\sigma_v$ of the CRV and movement of the CRV follows the Gaussian distribution rule, then the

PDF can be defined as follows [Rawat *et al.* 18]:

$$f_v(v) = \frac{g_v(v)}{\int_{v_{min}}^{v_{max}} g_v(v)dv} \tag{5.26}$$

where $g_v(v)$ is the Gaussian PDF, v and μ_v are the speed and average speed of the CRV as well as σ_v^2 is the standard deviation. Now, $g_v(v)$ can be defined using a mean speed μ_v as well as a standard deviation σ_v^2 as follows:

$$g_v(v) = \frac{1}{\sigma_v\sqrt{2\pi}} exp\left(\frac{-(v-\mu_v)^2}{2\sigma_v^2}\right) \tag{5.27}$$

The PDF $f_v(v)$ can be rewritten as follows:

$$f_v(v) = \frac{2g_v(v)}{erf\left(\frac{v_{max}-\mu_v}{\sigma_v\sqrt{2}}\right) - erf\left(\frac{v_{min}-\mu_v}{\sigma_v\sqrt{2}}\right)} \tag{5.28}$$

Then, the expected value of speed can be computed as follows:

$$E[V] = \bar{v} = \int_{v_{min}}^{v_{max}} v f_v(v)dv \tag{5.29}$$

I can check whether a PU and an CRV are reachable or not after time t by using a CRV's initial speed, its acceleration and time interval. For a given vehicle with its initial speed $\bar{v}(0)$, the instantaneous speed $v(t)$ at time t can be computed as:

$$v(t) = \bar{v}(0) + \int_0^t a(y)dy \tag{5.30}$$

where a(y) is the acceleration of a vehicle at time y. Using Eq. (5.30), the distance traveled by a given vehicle for a given time interval [0, t] is defined as:

$$D_{CRV}(t) = \int_0^t v(y)dy \tag{5.31}$$

Thus, using Eq. (5.31), each vehicle can compute its distance traveled in time period t. Then, the distance between the mobile CRV and stationary PU for the interval [0, t], where the CRV is approaching PU and initial separation distance between them was D, is computed as:

$$D_e(t) = |I(CRV) \times D_{CRV}(t) + D| \tag{5.32}$$

where $I(CRV) \in [1, -1]$, i.e., if CRV is approaching PU, then $I(CRV) = -1$, and if the CRV is moving away from PU, then $I(CRV) = 1$.

I can easily derive the PDF of the random variable time $T = t$ as

$$g_T(t) = \int_0^{\bar{v}} v g_D |I(CRV) \times D_{CRV}(t) + D| g_v(v) dv \tag{5.33}$$

Then, we can further derive the probability of event B, $Pr[H_1]$, with respect to CRV's velocity v is defined as follows [Rawat *et al.* 18]:

$$\begin{aligned} Pr[H_1] &= Pr((|I(CRV) \times D_{CRV}(t) + D|) \leq S) \\ &= \int_0^t g_T(t) dt \\ &= \int_0^t \int_0^{\bar{v}} v \frac{1}{\sqrt{2\pi}\sigma_v} \left[exp\left(-\frac{(v - \mu_v)^2}{2\sigma_v^2} \right) \right]^2 dv dt \end{aligned} \tag{5.34}$$

I can calculate the probability $Pr[H_0]$ for the event H_0 as follows:

$$Pr[H_0] = 1 - Pr[H_1] \tag{5.35}$$

From Eq. (5.34) I can see that $Pr[H_1]$ depends on sensing range of CRV, velocity of CRV and initial distance between the PU and CRV.

The rapid speed of the CRV reduces the sensing time of the CRV to detect the PU signal. Therefore, the probability of detection will be decreased and the probability of miss-detection will be increased. Note that when a CRV user miss-detects that the primary user is absent whereas PU is actually present, then this CRV user cause harmful interference to PUs. Thus the miss-detection probability is more important than false alarm since false alarm does not lead to harmful interference to PUs. Therefore, the CRV user's spectrum sensing performance in the CR-IoV network decreases due to the speed of the CRV user.

When each CRV is mobile then the probabilities of false alarm ($P^p_{d2,FC}$) and detection ($P^p_{f2,FC}$) at the FC for my proposed scheme can be represented by using the K-out-of-N fusion rule and are demonstrated as follows:

$$P^{p}_{d2,FC} = \sum_{i=K}^{N} \binom{N}{i} P^{(i)}_{d2,CH}(1 - P_{d2,CH})^{(N-i)} \tag{5.36}$$

and

$$P^{p}_{f2,FC} = \sum_{i=K}^{N} \binom{N}{i} P^{(i)}_{f2,CH}(1 - P_{f2,CH})^{(N-i)} \tag{5.37}$$

5.5.2 Sum Rate Analysis

With some observations, I can calculate the sum rate of the CR-IoV networks for my proposed scheme. We can represent the sum rate for the primary user and CRV user based on round-robin scheduling and is presented as follows [Miah *et al.* 18a]:

$$R^{p}_{CB-CSS} = \alpha P^{p}_{d,FC} R_{PU} + (1 - \alpha) \left(1 - P^{p}_{f,FC}\right) R_{CRV} \tag{5.38}$$

where $R_{PU} = \log_2(1 + SNR_{PU})$ denotes the data transmission capacity of the primary user connection path, $R_{CRV} = \frac{T-\tau_s}{T} \sum_{i=1}^{N} \log_2(1 + SNR_{CRV,i})$ is the data transmission capacity of the CRV connection path, and $\alpha \in [0, 1]$ indicates the primary user activity. SNR_{PU} and $SNR_{CRV,i}$ are the SNR value of the primary user transmission path and the i^{th} CRV transmission path, respectively, the entire frame linear measure is represented by T and τ_s denotes the sensing duration of the CRV. The equation (5.38) is applicable for both conditions of CRV (i.e., when CRV is stationary or mobile).

5.5.3 Global Error Probability at the FC

At the FC, the global error probability can be calculated as follows [Shah & Koo 18a]:

$$Pe^{p}_{CB-CSS,FC} = P(H_0) P^{p}_{f,FC} + P(H_1) \left(1 - P^{p}_{d,FC}\right) \tag{5.39}$$

where $P(H_0)$ and $P(H_1)$ are the probability of H_0, and H_1, respectively. The equation (5.39) is applicable for both conditions of CRV (i.e., when the CRV is stationary or mobile).

5.5.4 Traffic Overhead Analysis at the FC

For the CSS scheme without a cluster, the traffic overhead at the FC increases with a growing number of antennas M and CVR users Z. In contrast my proposed MU-MIMO antenna aided CB-CSS scheme minimizes the traffic overhead at the FC, considering that during a specific sensing interval each CRV user in the IoV network receives L signal samples with B bits per sample, resulting in the transmission of $L \times B \times M$ bits to the corresponding CH. However, each cluster sends one bit (i.e., 1 or 0) to the FC for the cluster decision. The traffic overhead for the proposed scheme at the CH and the FC are given as follows:

$$TO^{p}_{CH} = (L \times B \times M \times S) \tag{5.40}$$

$$TO^{p}_{FC} = (N \times M) \tag{5.41}$$

where N denotes the number of clusters in the IoV networks. In contrast the traffic overhead for the MU-MIMO antenna based CSS scheme without a cluster at the FC is given as follows:

$$TO^{CSS}_{FC} = (L \times B \times M \times Z) \tag{5.42}$$

where $TO^{CSS}_{FC} > TO^{p}_{CH} > TO^{p}_{FC}$ because $Z > S$ and $Z > N$. Therefore, my proposed scheme reduces the traffic overhead compared to the MU-MIMO antenna based CSS scheme without a cluster at the FC.

For our proposed MU-MIMO antenna aided CB-CSS
scheme, a pseudo code algorithm is formulated, as shown in Algorithm 3.

Algorithm 3 In the proposed MU-MIMO antennas based CSS scheme with the EGC and MRC rules, all CRV users with MIMO antennas ($M > 1$) has obtained more samples.

Input: Select the number of CRV users in each cluster, S, the number of samples, L, the number of antennas, M, the number of clusters, N, the decision threshold, λ_p, and the number of bits per sample, B

Output: Calculate the global probability of detection, $P^p_{d,FC}(\lambda_p)$, the global probability of false alarm, $P^p_{f,FC}(\lambda_p)$, the sum rate, R^p_{CSS}, the global error probability, $Pe^p_{CB-CSS,FC}$, the traffic overhead of the proposed CB-CSS scheme, TO^p_{FC}, the traffic overhead for the conventional CSS scheme TO^{CSS}_{FC}.

Initialize L, S, M, λ_1
for i from 1 to S **do**
  for j from 1 to M **do**
    for k from 0 to $L-1$ **do**
      Set: $E^p_{CB-CSS}(EGC) = \sum_{j=1}^{M}\sum_{i=1}^{S} E_{i,j}(EGC)$; where $E_{i,j}(EGC) = \sum_{k=0}^{L-1} \|y_{i,j}(k)\|^2$; Using the EGC rule
      Set: $E^p_{CB-CSS}(MRC) = \sum_{j=1}^{M}\sum_{i=1}^{S} E_{i,j}(MRC)$; where $E_{i,j}(MRC) = \sum_{k=0}^{L-1} \|y_{i,j}(k)\|^2 \times \frac{\gamma_i}{\sqrt{\sum_{i=1}^{S}\gamma_i^2}}$; Using the MRC rule
    end for
  end for
end for
Calculate: $P_{d1,CH}(\lambda_p)$ by using (5.20)
Calculate: $P_{f1,CH}(\lambda_p)$ by using (5.21)
Calculate: $P^p_{d1,FC}(\lambda_p)$ by using (5.22)
Calculate: $P^p_{f1,FC}(\lambda_p)$ by using (5.23)
Calculate: $Pr[H_0]$ by using (**??**)
Calculate: $P[H_1]$ by using (**??**)
Calculate: $P_{d2,CH}(\lambda_p)$ by using (5.24)
Calculate: $P_{f2,CH}(\lambda_p)$ by using (5.25)
Calculate: $P^p_{d2,FC}(\lambda_p)$ by using (5.36)
Calculate: $P^p_{f2,FC}(\lambda_p)$ by using (5.37)
Calculate: $R^p_{CB-CSS} = \alpha P^p_{d,FC} R_{PU} + (1-\alpha)\left(1 - P^p_{f,FC}\right) R_{CRV}$
Calculate: $Pe^p_{CB-CSS,FC} = P(H_0) P^p_{f,FC} + P(H_1)\left(1 - P^p_{d,FC}\right)$
Calculate:$TO^p_{FC} = (N \times M)$
Calculate:$TO^{CSS}_{FC} = (L \times B \times M \times Z)$

5.6 Results and Discussions

In this section the simulation results and the related discussion are presented. To evaluate the performance of the proposed MU-MIMO antenna aided CB-CSS scheme, numerical evaluations are performed and compared with other conventional schemes using the Monte Carlo method. The simulations have been executed using MATLAB 2016a, and the results are obtained from the average of 40,000 independent simulation runs. The simulation parameters used are listed in Table 5.2. These simulation parameters are justified by related works which are referenced [Liu *et al.* 19b, Al-Amidie *et al.* 21, Hossain *et al.* 21b, Miah *et al.* 20, Miah *et al.* 18a]. The performance of the proposed MU-MIMO antenna aided CB-CSS scheme is compared with similar schemes, such as SISO antenna aided cluster-based CSS scheme [Hossain *et al.* 21b, Miah *et al.* 18a], SISO based NCSS scheme [Chen *et al.* 19]. I present some simulation results to analyze the sensing gain, the sum rate, the global error probability and the traffic overhead of my proposed scheme and other two conventional schemes.

Table 5.2: Simulation parameters

Parameters	**Value**
The sampling frequency, f_c	300 kHz
The PU signal, $x(k)$	QPSK
The number of samples, L	400
The sensing time slot, τ_s	5 ms
The reporting time slot, τ_r	2 ms
The number of CRVs, Z	12
The number of cluster, N	4
The number of cluster members, S	4
The number of antennas, M	3
The SNR value at the PU transmission link, SNR_{PU}	-12 dB
The SNR value at the CRV transmission link, SNR_{CRV}	-15 dB
The vehicle moves with velocity, v	[7,14,21] m/s
The transmission range of each vehicle	100 m
The noise signal for the channel, $n(k)$	AWGN

The receiver operating characteristic (ROC) curves at the FC are discussed for the following cases:

The sensing gain when each CRV is stationary: Figure 5.4 shows the probability of detection (P_d) versus the probability of false alarm (P_f) ROC curve for the proposed scheme and the other two conventional schemes at the FC. It is observed that my proposed MU-MIMO antennas aided CB-CSS scheme achieves better sensing gain, 97% for the MRC fusion rule and 94% for the EGC fusion rule, when the number of CRV users is $Z = 12$ and the number of cluster members is $S = 4$, the number of antennas is $M = 3$ and the SNR value is $\gamma = -15$.

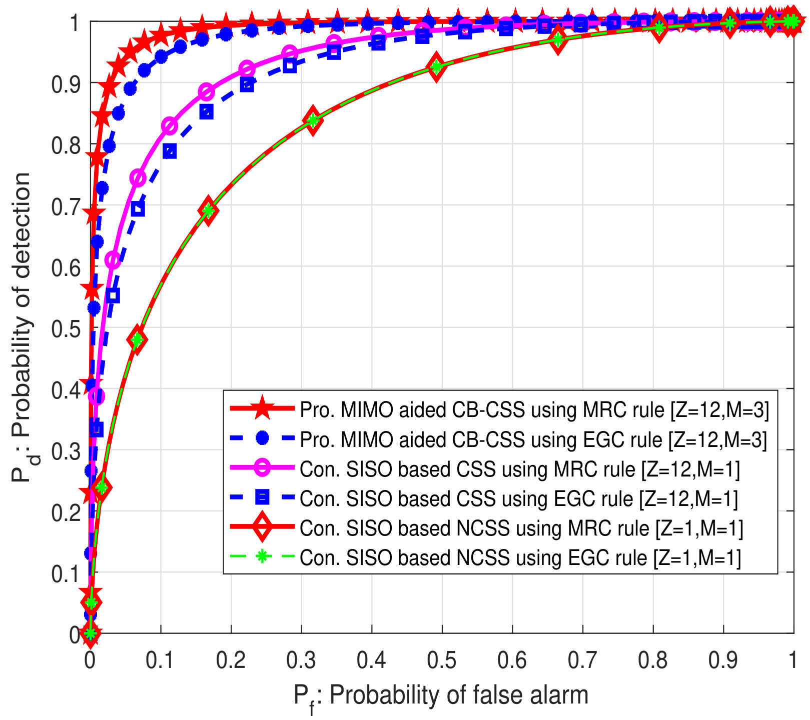

Figure 5.4: P_d vs P_f of the proposed scheme and the conventional two schemes when each CRV is stationary.

This is compared with both conventional SISO antenna based CSS schemes (77% with MRC fusion rule & 72% with EGC fusion rule) and the NCSS scheme (50% with both MRC and EGC fusion rules) at the $P_f = 0.1$. In addition, the MRC fusion rule is always better than the EGC fusion rule for the proposed scheme.

The sensing gain when each CRV is mobile: When each CRV is mobile in the CR enabled IoV networks. We plot the ROC curves of the proposed MU-MIMO antennas aided CB-CSS scheme where $Z = 12$, $M = 3$, $S = 4$ and $\gamma = -15$ as well as the different speeds of a CRV are $v = [7, 14, 21]m/s$, as depicted in Figure 5.5.

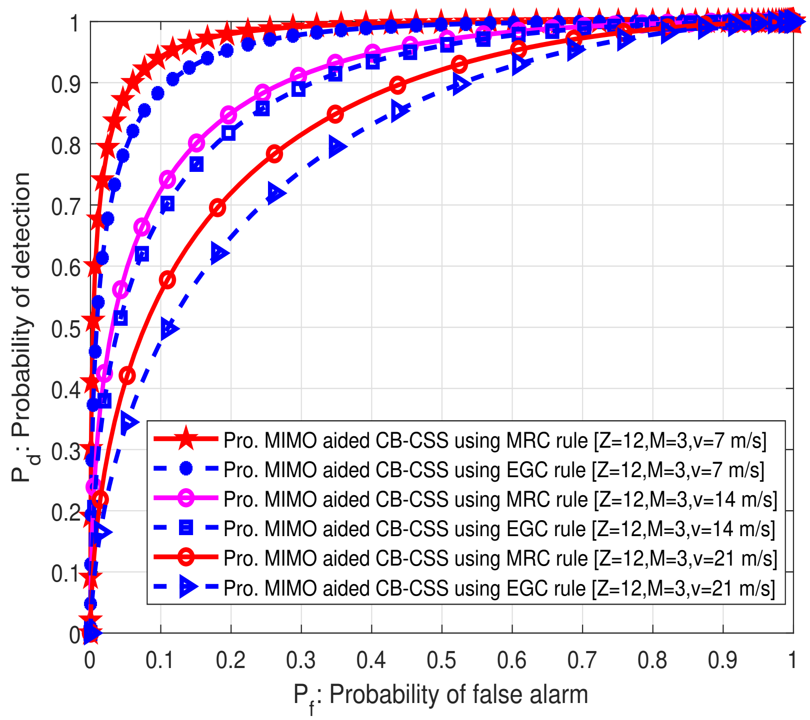

Figure 5.5: P_d vs P_f curve of the proposed MU-MIMO antennas aided CB-CSS scheme with $Z = 12$, $M = 3$, $S = 4$, $\gamma = -15$ and $v = [7, 14, 21]$ m/s.

It is observed that the P_d is decreased as the speed of the mobile CRV is increased for a stationary PU. The rapid speed of the CRV reduces the sensing time of the CRV to detect the PU signal. Therefore, the probability of detection has decreased. From Figure 5.5, we can observe that the probability of detection (at $p_f = 0.1$) is decreased by approximately 15% and 29% for the MRC fusion rule as well as 19% and 37% for the EGC fusion rule with CRV's speed from 7 m/s to 14 m/s and 7 m/s to 21 m/s, respectively.

The sum rate when each CRV is stationary: The system sum rate of the network is dependent on the probability of false alarm. The system sum rate at the FC is depicted in Fig. 5.6.

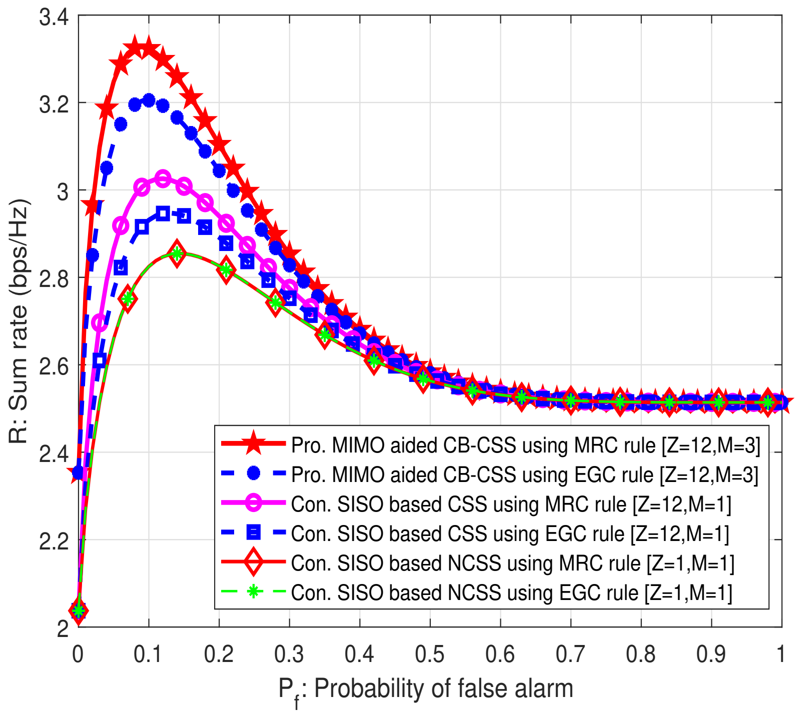

Figure 5.6: Sum rate of the proposed scheme and the conventional two schemes when each CRV is stationary and $\alpha = 0.7$.

It is observed that the system sum rate of the proposed CB-CSS scheme, conventional SISO antenna based CSS and the conventional SISO antenna based NCSS schemes for the MRC fusion rule at $P_f = 0.1$ is 3.32 bps/Hz, 3.01 bps/Hz and 2.83 bps/Hz respectively; whereas the system sum rate of the proposed CB-CSS scheme, conventional SISO antenna based CSS scheme and conventional SISO antenna based NCSS scheme for the EGC fusion rule at $P_f = 0.1$ is 3.00 bps/Hz, 2.92 bps/Hz and 2.83 bps/Hz respectively. The system sum rate of the proposed MU-MIMO antennas aided CB-CSS scheme is higher compared to the conventional SISO antenna based CSS and NCSS schemes. Moreover, the sum rate value of the MRC rule is better than the EGC rule for the proposed MU-MIMO antennas aided CB-CSS scheme. In addition, we can see that the network sum rate of the existing SISO antenna based NCSS scheme is same for both the EGC and MRC fusion rules. Therefore, my proposed scheme mitigates the lower sum rate problem of the future CR enabled IoV networks.

The sum rate when each CRV is mobile: From Figure 5.7, it is observed that the system sum rate of the proposed scheme for the MRC fusion rule at $P_f = 0.1$ is 2.7 bps/Hz, 2.55 bps/Hz and 2.42 bps/Hz when the CRV speed is 7 m/s, 14 m/s and 21 m/s, respectively; whereas the system sum rate for the EGC fusion rule is 2.65 bps/Hz, 2.5 bps/Hz and 2.32 bps/Hz when the CRV speed is 7 m/s, 14 m/s and 21 m/s, respectively. We can observe that the sum rate value of the MRC rule is better than the EGC rule for the proposed MU-MIMO antennas aided CB-CSS scheme. Basically, the system sum rate gradually decreases when the speed of the mobile CRV is increased for a stationary PU due to the rapid speed of the CRV's which reduces the sensing time of the CRV to detect the PU signal.

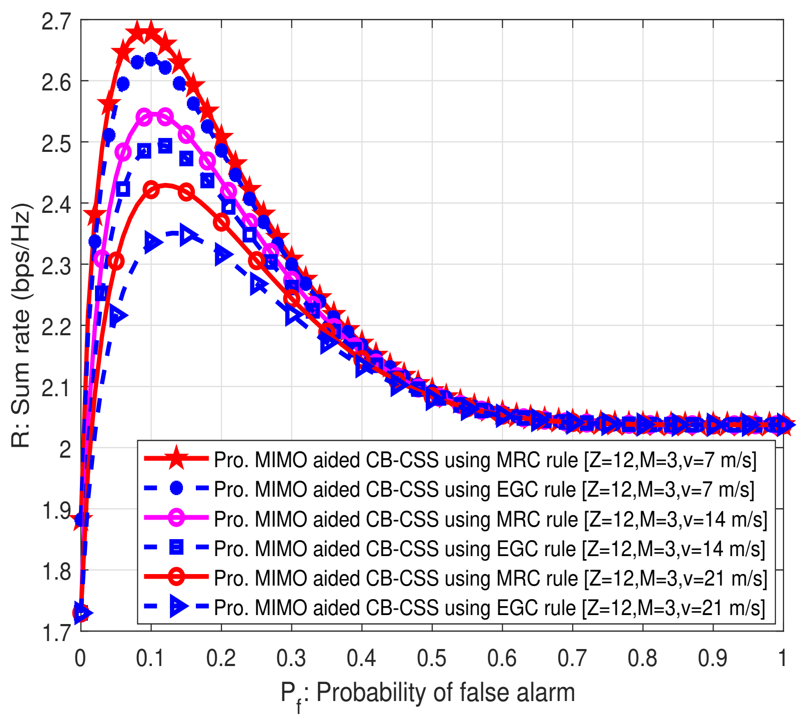

Figure 5.7: Sum rate of the proposed MU-MIMO antennas aided CB-CSS with $Z = 12$, $M = 3$, $S = 4$, $\gamma = -15$,$\alpha = 0.7$ and $v = [7, 14, 21]$ m/s.

The sum rate figures in chapter 4 and this chapter are different for the following reason: The sum rate of the cognitive radio network is depended on signal-to-noise ratio (SNR) value of the primary user transmission link and the secondary user (i.e., CRV user) transmission link. As the SNR value increases, the sum value increases. The SNR value in chapter 4 of the primary user transmission link and secondary user transmission link are 10 dB and 7 dB, respectively. Whereas, the SNR value this chapter of the primary user transmission link and secondary user transmission link are -12 dB and -15 dB, respectively.

The global error probability (P_e) when each CRV is stationary: The P_e at the FC versus the probability of false alarm (P_f) is depicted in Figure 5.8. It is observed that the P_e for the proposed MU-MIMO antennas aided CB-CSS scheme is lower than the conventional SISO antenna based CSS and NCSS schemes.

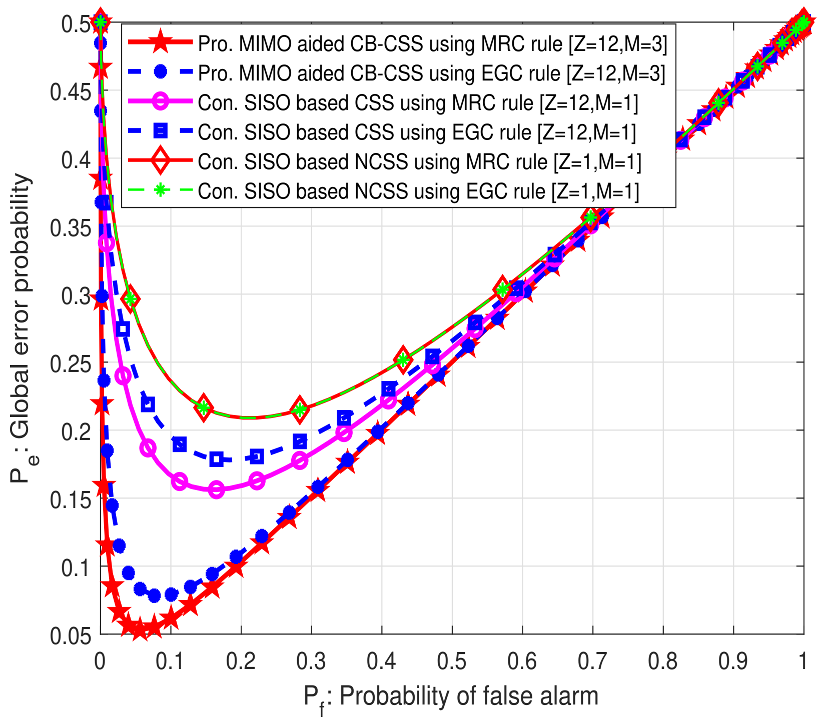

Figure 5.8: P_e versus P_f of the proposed scheme and the conventional two schemes.

The global error probability (P_e) when each CRV is mobile: Figure 5.9 shows the P_e versus P_f for the proposed scheme when each CRV is mobile in the CR enabled IoV networks. From Figure 5.9, it is observed that at the $P_f = 0.1$, the P_e of my proposed scheme for the MRC fusion rule is 0.1, 0.21 and 0.3 when the CRV speed is 7 m/s, 14 m/s and 21 m/s, respectively; whereas the global error probability for the EGC fusion rule is 0.14, 0.24 and 0.34 when the CRV speed is 7 m/s, 14 m/s and 21 m/s, respectively. Basically, the global error probability gradually increases when the speed of the mobile CRV is increased for a stationary PU.

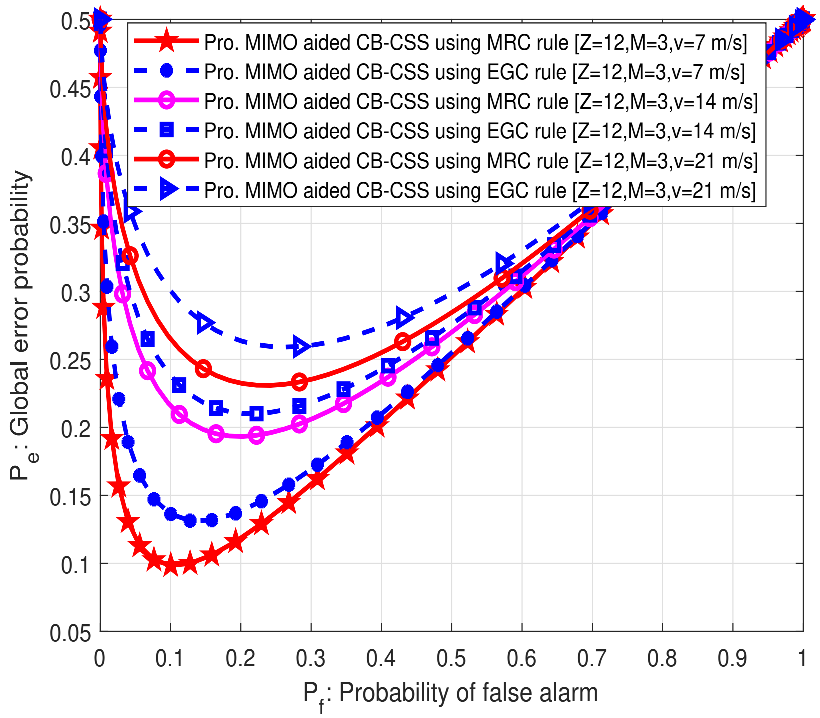

Figure 5.9: P_e versus P_f of the proposed MU-MIMO antennas aided CB-CSS scheme with $Z = 12$, $M = 3$, $S = 4$, $\gamma = -15$ and $v = [7, 14, 21]$ m/s.

From Figures. 5.8 and 5.9, It is observed that the proposed MU-MIMO antenna aided CB-CSS scheme using the MRC fusion rule achieves the lowest P_e when compared with the EGC fusion rule.

Traffic Overhead at the FC: According to the simulation parameters, each CRV user receives $L = 400$ signal samples with $B = 2$ bits per sample for each sensing interval. For my proposed scheme, each CRV with $M = 3$ antennas transmits $(400 \times 2 \times 3)$ bits to the corresponding CH. Finally, each CH sends one bit (i.e., 1 or 0) to the FC for the cluster decision. For the CSS scheme without cluster, each CRV with $M = 3$ antennas transmits $(400 \times 2 \times 3)$ bits to the corresponding FC. The traffic overhead for my proposed MU-MIMO antenna aided cluster based CSS scheme and the CSS scheme without cluster at the FC are calculated by using (5.41) and (5.42) respectively, which is shown in Table 5.3.

Table 5.3: Traffic overhead for proposed CB-CSS scheme and CSS scheme without cluster

Spectrum sensing scheme	Number of bits at CH	Total number of bits at FC
Proposed CB-CSS scheme	$L \times B \times M \times S$ $= 9600$	$N \times M = 16$
CSS scheme without cluster	N/A	$L \times B \times M \times Z$ $= 28800$

Therefore, my proposed scheme reduces the traffic overhead compared to the MU-MIMO antenna based CSS scheme without cluster at the FC.

5.7 Summary

In this chapter, a MU-MIMO antenna aided CB-CSS scheme was proposed for cognitive radio enabled IoV networks with the objective of enhancing spectrum sensing gain and system sum rate as well as reducing the global error probability and traffic overhead at the FC. In the sensing gain, the proposed MU-MIMO antenna aided CB-CSS scheme demonstrates a 47% and 20% improvement for the MRC rule as well as a 44% and 22% improvement for the EGC rule over the conventional SISO antenna based NCSS scheme and CSS scheme, respectively. In terms of the system sum rate, the proposed MU-MIMO antennas aided CB-CSS scheme shows a 17.19% and 10.96% better performance for the MRC rule as well as a 12.28% and 9.21% better performance for the EGC rule when compared to the SISO antenna based NCSS scheme and CSS scheme, respectively. The error probability of a global decision of the proposed scheme for the MRC rule and the EGC rule are 0.07 and 0.09, respectively. It is lower than the conventional SISO antenna based NCSS and CSS schemes. Furthermore, we observe that the proposed scheme provides good sensing gain, sum rate and lower global error probability for different CRV speeds. However, the sensing gain and system sum rate are decreased as well as global error probability is increased for the proposed scheme for both fusion rules with increasing CRV speed because the rapid speed of CRV reduces the sensing time to sense the PU signal. Finally, the traffic overhead of the proposed MU-MIMO antennas aided CB-CSS scheme is lower compared to the MU-MIMO antenna based CSS scheme without a cluster. Therefore, I conclude that our proposed MU-MIMO antenna aided CB-CSS scheme will be more applicable for the CR enabled IoV networks because it helps to reduce the spectrum shortage problem, enhances system sum rate and achieves lower global error probability.

My future work will analyse the required energy expenditure and potential lifetime for the proposed scheme in CR enabled IoV networks.

Chapter 6

Machine Learning Based Secure CSS for CR-IoT Networks

6.1 Introduction

The Internet of Things is rapidly emerging as a potential technology for all wireless communication systems that will host a huge number of communication devices to share data with each other intelligently [Mamdouh *et al.* 18]. With burgeoning IoT technologies, the demand of spectrum is increasing consistently, which yields scarcity in spectrum resource [Khan *et al.* 20b]. In the CR-IoT network, heterogeneous wireless devices are permitted to use the licensed spectrum when not in use by PU, therefore the CR-IoT networks are vulnerable to attack of various malicious users (MUs) (i.e. jamming attack) resulting in an increase of the spectrum demand, a decrease in the quality of service, security, and reliability of data [Sajid *et al.* 20]. Jamming attacks are a subset of denial of service (DoS) attacks in which malicious users block legitimate communication by causing intentional interference in networks [Vadlamani *et al.* 16]. Maintaining security within CR-IoT networks is an important component, to ensure secure operations of underlying network infrastructure [Liu *et al.* 17].

Malicious users sending false radio spectrum sensing results to the intelligent fusion centre (IFC) will result in incorrect global decisions, will increase the radio spectrum demand, and will reduce the spectrum sensing performance of the CSS in the CR-IoT network [Hossain & Miah 21].

Therefore, the issue of securing licensed spectrum access in CR-IoT networks has become an important research topic [Madbushi *et al.* 16].In contrast, in the previous three chapters (Chapter 3, Chapter 4 and Chapter 5), I propose three approaches to enhance the spectrum detection gain, sum rate, energy efficiency and spectral efficiency as well as minimizing the global error probability without considering the issue of securing licensed spectrum access in CR-IoT networks. As a result, in this chapter I propose a machine learning based secure CSS scheme for CR-IoT networks to enhance the accuracy of detecting malicious users, improve overall sensing gain and minimise the global error in CR-IoT networks.

6.1.1 Contributions

The main contributions of this chapter can be summarized as follows:

- I propose a machine learning based secure CSS for a CR-IoT Network.
- My proposed scheme significantly improves the sensing performance of detecting a PU, in the presence of malicious activity for three types of malicious users (i.e., Always Low Energy Malicious Users (ALEMUs), Always High Energy Malicious Users (AHEMUs), Random Energy Malicious Users (REMUs)) cases than the conventional(without security technique) scheme.
- In addition, it decreases the global error probability at the IFC over the conventional scheme.

6.1.2 Publications

Mohammad Amzad Hossain, Michael Schukat and Enda Barrett. Machine Learning Based Secure Cooperative Spectrum Sensing for Cognitive Radio based IoT Networks. *Physical Communication (Submitted, November 2021)*

6.1.3 Chapter Structure

The rest of this chapter is organized as follows: In Section 6.2 describes the related work. In Section 6.3 the system model considered through this chapter is presented. In Section 6.4 we explain the concept of my proposed ML-based secure CSS scheme. The performance evaluation and conclusions are presented in Section 6.5 and Section 6.6, respectively. In addition, the parameters included in this chapter are summarized as follows in Table 6.1:

Table 6.1: Main parameters

Parameters	Corresponding Definitions
H_0	The hypothesis which indicates the absence of the PU signal
H_1	The hypothesis which indicates the presence of the PU signal
N	The number of legitimate CR-IoT users
M	The number of malicious users
S	The total number of users in the network
$x(l)$	Signal transmitted from PU
$n(l)$	The noise signal
$\theta(l)$	The antenna gain
$y(l)$	The signal received by the CR-IoT user
γ	The SNR
E	The energy level of the received signal
L	The number of received samples
EV	The energy vector
$P_d(\lambda_c)$	The probability of detection of the legitimate CR-IoT user
$P_f(\lambda_c)$	The probability of false alarm of the legitimate CR-IoT user
P_{FC}^d	The probability of detection at the IFC
P_{FC}^f	The probability of false alarm at the IFC
P_{FC}^e	The global error probability at the IFC
$P(H_0)$	The probability of absence of the PU
$P(H_1)$	The probability of presence of the PU

6.2 Related Work

In order to enhance the radio spectrum sensing gain and minimize the interference between the CR-IoT users and the PUs, researchers have introduced several malicious user detection techniques. In [Paul *et al.* 15], the authors proposed a centralized CSS approach which enhances the spectrum detection gain at the fusion center. The authors examined the probabilities of detection and false alarm only. However, they did not consider the security issue and the global error probability. Wang et al. [Wang *et al.* 09] introduced a heuristic "onion-peeling approach" to identify the malicious user set in a batch-by-batch way. Firstly, the authors calculated a suspicion level of all users according to their reports. If the level of suspicious activity of a CR-IoT user is beyond a certain threshold, it will be considered as malicious and moved into the malicious user set. In [Khan *et al.* 19a], the authors introduced a double adaptive threshold concept to differentiate the legitimate users (LUs) and MUs based on the weight of each user such that the LU weight is higher then the MU. However, each user weight is calculated by using the maximal ratio combining rule which increased the calculation time.

In [Gul *et al.* 18], the authors proposed a Kullback Leibler Divergence technique for MU attack detection and mitigation. This proposed approach identified and separated the MUs based on the individual SU decision and the average spectrum sensing statistics received from all other users. FC first assigned weights against each normal SU and MU. MUs with abnormal behavior as compared with normal SUs are given lower weights by the proposed approach, while the normal SUs receive higher weights. FC further employs these weights in combining the sensing data of all SUs in making a global decision. The authors show that the MU has less impact on the global decision as compared to a normal SU. Simulation results reflect the proposed scheme in producing more precise and reliable decisions as compared with EGC and traditional KL fusion schemes. In [Cadena Muñoz *et al.* 20], the authors used a support vector machine for detecting a malicious primary user signal based on the SNR values and entropy of the received PU signal. However, the authors considered the non cooperative spectrum sensing approach for spectrum sensing. That is why spectrum sensing performance alone is not sufficient to avoid interference. Moreover, the authors considered only one type of malicious user (i.e., Always Yes Malicious Users). Therefore, we propose a ML-based secure CSS for CR-IoT Networks for detecting three types of MUs to enhance the sensing gain and minimise the global error probability.

6.3 System Model

6.3.1 Network Architecture

I propose a machine learning based secure CSS scheme for CR-IoT networks which consists of N legitimate CR-IoT users, M Malicious users, and a IFC. In our model, each legitimate CR-IoT user senses the PU signal status and transmits the sensing data (i.e. energy level of received PU signal) to the corresponding IFC. In the meantime, the MUs forward their false sensing results to the IFC in order to mislead the IFC into making wrong decisions about the PU status and further cause interference between the PUs and the legitimate CR-IoT users. The IFC receives the local sensing reports from all legitimate CR-IoT users and MUs. There are various forms of MU attacks which can target the CR-IoT network, highly degrading the overall performance of the network. In this work, we consider the three most common attacks in CR-IoT network, which are: (i) “Always Low Energy Malicious Users” attack, these types of MUs always send a sensing report indicating low energy levels (i.e., indicating that the PU is not present in the network) to the IFC at all times regardless of what is locally detected. Thus, it causes interference between the PU signal and CR-IoT user signal. (ii) “Always High Energy Malicious Users” attack, these types of MUs always report high energy levels (i.e., they indicate that the PU is present in the network) to the IFC at all times regardless of what is locally observed. Thus, its goal is to deny the CR-IoT users to access the vacant licensed spectrum. (iii) “Random Energy Malicious User” attack, these types of MUs randomly report high or low energy levels to the IFC, regardless of the local radio spectrum sensing results. It is the most dangerous attack.

The overall network architecture is illustrated in Figure 6.1, which contains two major concurrent links: the primary user to CR-IoT user, and the CR-IoT user to IFC.

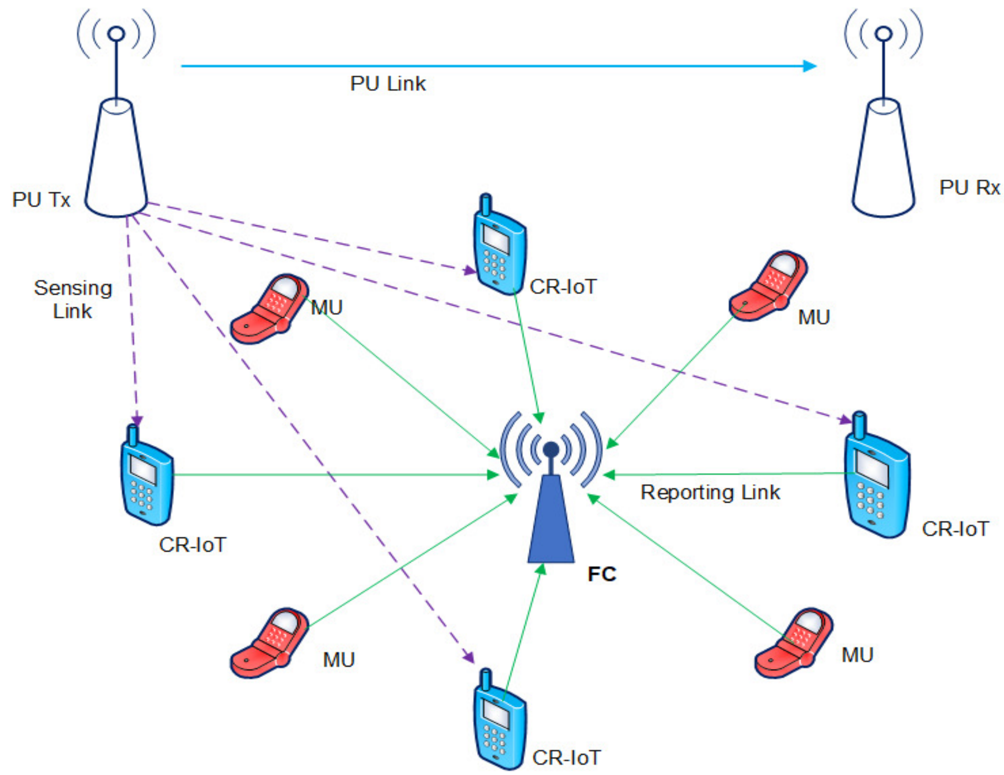

Figure 6.1: Proposed network model.

There are two states of the PU signal in the CR-IoT networks. These two states are represented by two hypothesis which is given as below:

$$\begin{cases} H_0: & \text{if the PU's signal is absent,} \\ H_1: & \text{if the PU's signal is present.} \end{cases} \tag{6.1}$$

The received signal at the ith CR-IoT user is represented for two hypotheses is given as below: [Miah *et al.* 17]:

$$y_i(l) = \begin{cases} n_i(l) & : H_0 \\ \theta_i(l)\, x(l) + n_i(l) & : H_1 \end{cases} \tag{6.2}$$

where $y_i(l)$, $x(n)$, $n_i(l)$, and $\theta_i(l)$ are the received signal, the PU signal, a AWGN noise signal and antenna gain at the ith CR-IoT user, respectively.

6.3.2 Energy Vector Generation Model

The energy detection process is a more suitable technique to calculate the energy level of the received PU signal, because it can calculate the energy level without any prior information about the PU signal and with less time complexity than other techniques. [Hossain *et al.* 19]. In this paper, I consider that each CR-IoT user uses the energy detection process for calculating the energy level of the received PU signals.

The energy calculation process at the CR-IoT user is shown in Figure 6.2.

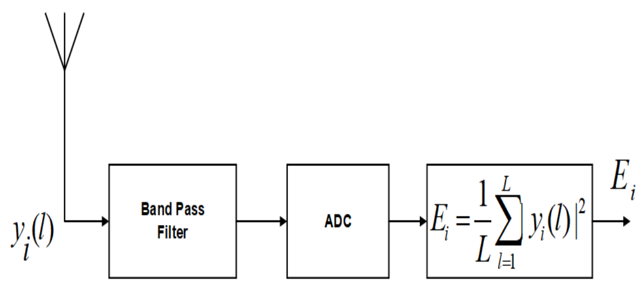

Figure 6.2: The process of energy level calculation

The energy level of the received PU signal at the i^{th} CR-IoT user is calculated as follows [Hossain *et al.* 19]:

$$E_i = \frac{1}{L}\sum_{l=1}^{L} |y_i(l)|^2 \tag{6.3}$$

where L represents the total number of received samples, which is defined as $L = 2\tau_s f_c$ [Hossain *et al.* 20], here τ_s and f_c are the sensing time slot in ms and the sampling frequency in Hz, respectively.

The E_i in (6.3) may be well approximated by a Gaussian distribution when L is fairly high. We can calculate the probability density function [Hariharan *et al.* 13] of the test statistics of E_i at the ith CR-IoT user for hypotheses H_0 and H_1 respectively, as follows:

$$E_i \sim \begin{cases} \mathcal{N}(\mu_i(H_0), & \sigma_i^2(H_0)) \\ \mathcal{N}(\mu_i(H_1), & \sigma_i^2(H_1)) \end{cases} \tag{6.4}$$

where $\mu_i(H_0)$ and $\mu_i(H_1)$ are the means as well as $\sigma_i^2(H_0)$ and $\sigma_i^2(H_1)$ are the variances of the E_i for the hypotheses H_0 and H_1 respectively. The above variables are presented as follows [Chen 10]:

$$\begin{aligned}
\mu_i(H_0) &= L\sigma_n^2 \\
\mu_i(H_1) &= L\left(1+\gamma\right)\sigma_n^2 \\
\sigma_i^2(H_0) &= L\sigma_n^4 \\
\sigma_i^2(H_1) &= L\left(1+2\gamma\right)\sigma_n^4
\end{aligned}$$

where γ_i is a SNR defined as $\gamma_i = \frac{\sigma_x^2}{\sigma_n^2}$.

All legitimate CR-IoT users and malicious users report the estimated energy levels to the IFC and the IFC generates the energy vector (EV), which is defined as:

$$EV = \left(E_1, ..., E_U\right)^T \tag{6.5}$$

where $U = N + M$ indicates the total number of CR-IoT users (i.e. legitimate CR-IoT users plus malicious users) in the network.

6.3.3 Sensing Performance

The probability of detection, $P_d(\lambda_c)$ and the probability of false alarm, $P_f(\lambda_c)$ at each legitimate CR-IoT user can be calculated as follows [Sumi & Ganesh 19]:

$$\begin{aligned}
P_d(\lambda_c) &= Pr[E_i \geq \lambda_c | H_1] \\
&= Q\left(\frac{\lambda_c - L\left(1+\gamma\right)\sigma_n^2}{\sqrt{2L\left(L(1+2\gamma)\sigma_n^2\right)^2}}\right)
\end{aligned} \tag{6.6}$$

and

$$\begin{aligned}
P_f(\lambda_c) &= Pr[E_i \geq \lambda_c | H_0] \\
&= Q\left(\frac{\lambda_c - L\sigma_n^2}{\sqrt{2L\sigma_n^4}}\right)
\end{aligned} \tag{6.7}$$

6.4 Proposed Machine Learning-based Secure CSS Scheme

In cognitive radio based IoT networks, the primary users share their licensed spectrum with CR-IoT users. It is critical and important to ensure a secure licensed spectrum sharing in CR-IoT networks. However, the CR-IoT networks are vulnerable to security attacks from malicious users. The malicious user connects to the network and uses free licensed spectrum from PUs, which reduces the chances of a legitimate CR-IoT user to get a free licensed spectrum from PUs for data communication in the networks. To improve authentication, integrity and secure licensed spectrum sharing in the CR-IoT networks, I propose a ML-based secure CSS Scheme. Figure 6.3 shows the schematic diagram for the proposed scheme for the CR-IoT networks.

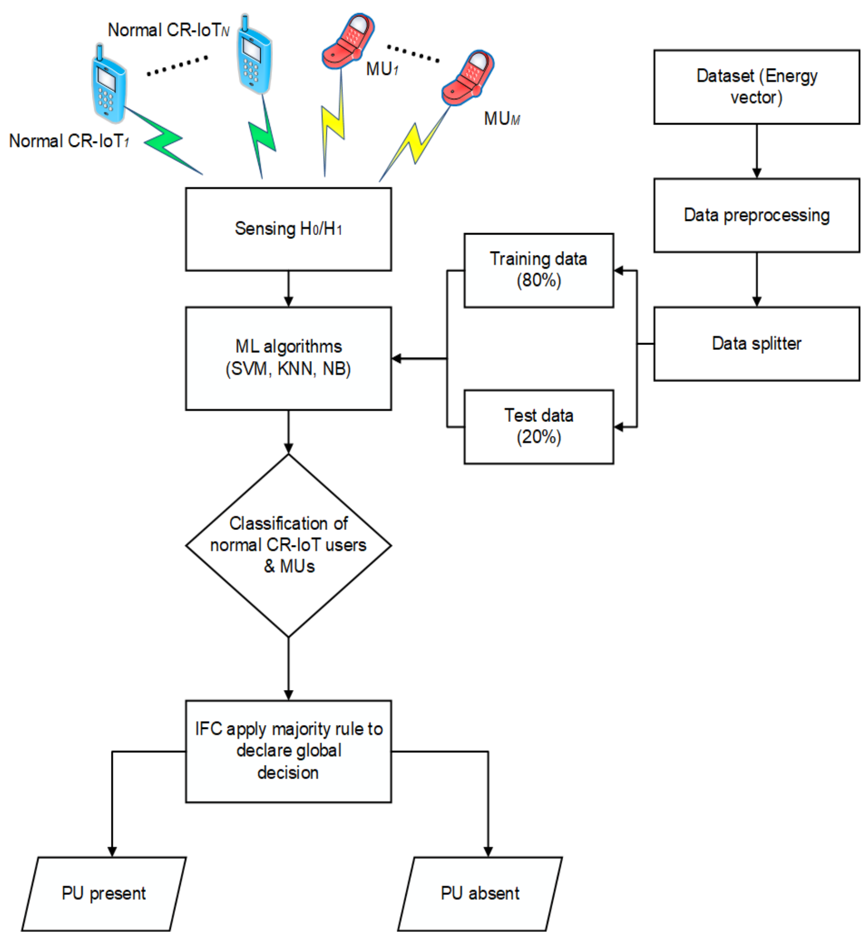

Figure 6.3: Flowchart of the proposed ML based CSS scheme

In the proposed scheme, each CR-IoT user continuously senses the status of the PU signal in the CR-IoT networks.

Thereafter, the sensing data is transmitted to the IFC through reporting channels. In the meantime, the MUs forward their false sensing results to the IFC. The IFC receives the local sensing reports from all legitimate CR-IoT users and MUs and creates an energy vector. The IFC then employs the machine learning techniques on these energy vectors to identify the legitimate CR-IoT users and the MUs on the basis of the energy levels reported in the sensing data. Once the MUs are identified they are removed to avoid the interference between the PU signal and the CR-IoT user signal. Thereafter, the IFC employs a majority fusion rule to declare a global decision about the presence of the PU in the CR-IoT network. At the IFC, it makes a robust global decision based on the radio spectrum sensing results of only legitimate CR-IoT users.

6.4.1 Machine-Learning Algorithms

There are different types of supervised classification algorithms in machine learning. However, not all supervised classification algorithms provide accurate classification results for specific data set. For this reason, testing the accuracy of each supervised classification algorithm is necessary. This can be used as a comparison in determining which types of algorithms are most accurate for specific dataset. In this thesis I examine three classification algorithms including Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Naïve Bayes (NB) algorithms for the classification of the legitimate CR-IoT users and the malicious users from my data set. SVM is useful in finding the separating hyperplane. Finding a hyperplane can be useful to classify the data correctly between different groups. The SVM-based classifier outperforms the other techniques in practical problems [Khan *et al.* 20b]. The KNN algorithm is the simplest machine learning algorithm, suitable for low-complexity requirements. The KNN algorithm is also the most stable machine learning algorithm [Shah & Koo 18a]. Naïve Bayes (NB) is a probabilistic classifier based on Bayes theorem, which has strong (naive) independence assumptions between the features. NB assumes that the value of a particular feature is independent of the value of any other feature, given the class variable [Mishra & Vijaykumar 18]. I use offline machine learning rather than online machine learning because offline learning is generally a lot faster than online machine learning, as offline learning only uses a dataset once throughout the entire model to modify weights and parameters. Online machine learning is much more difficult to operate in an operational environment than offline machine learning.

The next subsection briefly describes the three machine-learning classifiers:

6.4.1.1 Support Vector Machine

The SVM is defined as a machine learning approach based on vector space that chooses the best decision hyperplane between the classes so that the distance from it to the nearest data point on each side is maximised. It is a supervised ML algorithm that can be used for classification and regression. In a classification problem, it creates a set of hyper-planes in high dimensional feature space by the analysing data from the training data set [Zhu *et al.* 18]. In the CR-IoT network, I consider CR-IoT networks with N legitimate CR-IoT users, M malicious users resulting in the total number of users represented by $S = N + M$.

The notation of the training data set (X) of the proposed SVM algorithm is defined as follows [Khan *et al.* 20b]:

$$X = \left[(\psi_i, \beta_i) \,|\psi_i \in R^S, \beta_i \in [+1, -1]\right]_{i=1}^{S} \tag{6.8}$$

Here, (x_i, y_i) represents the data set for legitimate and malicious users which is defined as follows:

$$(\psi_i, \beta_i) = ((\psi_1, \beta_1), (\psi_2, \beta_2), ..., (\psi_S, \beta_S)) \tag{6.9}$$

where ψ_i represents the energy vector/training data of $M(i = 1, 2, 3, ..., S)$ users, $\beta_i \in [+1, -1]$ is the class vector/target output, and class $+1$ and -1 represents legitimate CR-IoT users and malicious users, respectively.

In SVM, the following optimization problem is defined which maximises the classifier margin as follows:

$$\left(\frac{1}{2}\|\omega\|^2\right)\beta_i\,(\omega.\psi_i + b)\geq 1 \tag{6.10}$$

where $\|.\|$ represents the norm which is defined as $\|\omega\|^2 = \omega.\omega$, and b denotes the bias that shifts the hyperplane away from its origin.

Now, the decision function of the hyperplane can then be calculated as follows:

$$g(\psi) = \delta\left(\sum_{i=1:\varphi_i>0} \beta_i \varphi_i \left(\psi.\psi_i\right) + b\right) \tag{6.11}$$

where, $g(\psi)$ is the decision function of the hyperplane, $\sum$ is the sum of support vector/data, δ is the sign function, $\psi.\psi_i$ is the kernel function and the sum is over support vectors. The classification process compares the new instance ψ with each of the support vectors. Moreover, the $(\psi_i.\psi)$ measures how similar the new instance ψ is to the training instance ψ_i. Here, φ_i are called support vectors that measure the contribution of ψ_i, i.e., φ_i measures how important the given support vector and the decision function are defined by these vectors. We multiply by β_i to take into account the influence of the given support vector on the classification.

6.4.1.2 K-Nearest Neighbor

One of the most simple supervised ML algorithms is the K-NN algorithm. Although it is used in the solution of both regression and classification tasks, it used mainly in the solution of classification tasks in industry [Abubakar 20]. In K-NN, the Euclidean distance is calculated based on the following equation as given:

$$d(\phi, \beta) = \sqrt{\sum_{i=1}^{S} c_i \left(\phi_i - \beta_i\right)^2} \tag{6.12}$$

where, c_i is the weight, and d represents distance between ϕ_i and β_i. To understand the detailed working of the algorithm, the steps are as follows [Taunk *et al.* 19]:

1 Load the data.

2 Initialise the value of K.

3 For getting the predicted class, iterate from 1 to total number of training data points.

4 Calculate the distance between test data and each row of training data. Here we will use Euclidean distance as our distance metric since it is the most popular method. The other metrics that can be used are Chebyshev, cosine, etc.

5 Sort the calculated distances in ascending order based on distance values.

6 Get top k rows from the sorted array.

7 Get the most frequent class of these rows.

8 Return the predicted class.

6.4.1.3 Naive Bayes

A Naive Bayes classifier is a probabilistic classifier which makes a strong assumption by using the Bayes' theorem. The attributes defining the items to be identified are considered to be statistically independent of one another [Wang & Shang 17]. If $a_1, a_2, a_3, ..., a_S$ are an objects to be classified, each object includes k feature variables $b_1, b_2, b_3, ..., b_k$. A Naive Bayes classifier classifies the objects based on Bayes theorem which as given as follows:

$$P(C|a_1, a_2, a_3, .., a_S) = \frac{P(a_1, a_2, a_3, .., a_S|C)P(C)}{P(a_1, a_2, a_3, .., a_S)} \tag{6.13}$$

where C is a class, $P(C)$ is a class probability, $P(a_1, a_2, a_3, .., a_S)$ indicates the probability of the objects, $P(a_1, a_2, a_3, .., a_S|C)$ indicates the conditional probability of the class C for the given objects $(a_1, a_2, a_3, .., a_S)$, $P(C|a_1, a_2, a_3, .., a_S)$ is the conditional probability that objects $(a_1, a_2, a_3, .., a_S)$ belong to class C, and S is the total number of CR-IoT users.

6.4.2 Performance Evaluation of ML Algorithm

The performance efficacy of four ML algorithms are evaluated based on precision, sensitivity/recall, specificity, F1-Score and accuracy. The values of precision, sensitivity/recall, specificity, and accuracy are determined based on the true positive value, true negative value, false positive value and false negative value.

- TP (True Positive): The ground truth observation details that there is a malicious user and the machine learning algorithm detects the malicious user from the given data.

- FP (False Positive): The ground truth observation details that there is no malicious user however the machine learning algorithm indicates that there is a malicious user in the given data.
- TN (True Negative): The ground truth observation details that there is no malicious user and the machine learning algorithm also detects that no malicious user is present within the given data.
- FN (False Negative): The ground truth observation details that there is a malicious user however the machine learning algorithm detects that no malicious user is present within the given data.

The ratio of True Positives to all Positives is known as precision. The precision, $\overline{\rho}$ is defined as follows:

$$\overline{\rho} = \frac{TP}{TP + FP} \tag{6.14}$$

Sensitivity/recall is the true positive rate. It measures how frequently the experiment detects the malicious user from the given data when the dataset really contains a malicious user.

It is the ability to correctly classify the malicious user. The sensitivity, $\overline{\alpha}$ is calculated as given:

$$\overline{\alpha} = \frac{TP}{TP + FN} \tag{6.15}$$

Specificity is the ability of a experiment to correctly classify the normal user.

It is the ability to test correctly classify the normal user. The specificity, $\overline{\beta}$ is calculated as given:

$$\overline{\beta} = \frac{TN}{TN + FP} \tag{6.16}$$

The F1-Score is a metric for determining how accurate a model is on a given dataset. It's used to assess the binary classification systems that categorize examples as either positive or negative. The F-score value is obtained by combining the precision and recall of the model. The F1-Score, $\overline{\psi}$ is defined as follows:

$$\overline{\psi} = 2 \times \frac{Precision * Recall}{Precision + Recall} \tag{6.17}$$

The measurement of real classification is known as accuracy (η) which is defined as follows:

$$\eta = \frac{TP + TN}{TP + TN + FP + FN} \tag{6.18}$$

6.4.3 Sensing Performance and Global Decision

The probabilities of false alarm ($P_{d,FC}$) and detection ($P_{f,FC}$) at the IFC for our proposed scheme can be represented by using the majority fusion rule (i.e., K-out-of-N fusion rule) and are demonstrated as follows [Hossain *et al.* 20]:

$$P_{FC}^{d} = \sum_{i=K}^{N} \binom{N}{i} P_d^i (1 - P_d)^{N-i} \tag{6.19}$$

$$P_{FC}^{f} = \sum_{i=K}^{N} \binom{N}{i} P_f^i (1 - P_f)^{N-i} \tag{6.20}$$

where N is the number of total legitimate CR-IoT users and K is the number of legitimate CR-IoT users that indicate that a PU signal is present ($N > K$) in the network.

The IFC applies the majority fusion rule (i.e., K-out-of-N fusion rule) on all received legitimate CR-IoT users' results to make the global decision to declare that the PU signal is present or not in the network. This final decision is then broadcast to all CR-IoT users. Let $Di = (0, 1)$ be the binary decision for the ith CR-IoT user, where $Di = 0$ and $Di = 1$ indicate the absence and presence of the PU signal in the network, respectively. According to the "K-out-of-N" rule, if at least K out of N CR-IoT users send the binary decision value $D = 1$ to the IFC, the IFC makes the global decision that the PU signal is present, otherwise the PU is absent in the network.

The IFC makes the global decision based on the following condition:

$$Global - Decision = \begin{cases} H_1 & : \sum_{i=1}^{N} D_i \geq K \\ H_0 & : \sum_{i=1}^{N} D_i < K \end{cases} \tag{6.21}$$

6.4.4 Global Error Probability

The global error probability (P^e_{FC}) for my proposed ML-based secure CSS scheme at the IFC can be measured as follows [Miah *et al.* 20]:

$$P^e_{FC} = P(H_0)P^f_{FC} + P(H_1)\left(1 - P^d_{FC}\right) \tag{6.22}$$

where $P(H_1)$ indicates the probability of activeness and $P(H_0)$ indicates the probability of idleness of the PU in the CR-IoT networks.

6.5 Performance Evaluation

In this section I verify the theoretical results and evaluate the performance of the proposed ML based secure CSS scheme for CR-IoT Networks. Performance evaluation of our proposed scheme is split into two parts. In the first part, we evaluate the malicious user detection accuracy of the three machine learning algorithms (i.e., SVM, KNN, and NB) for our data set. In the second part, I use Monte Carlo simulation to evaluate the spectrum sensing performance and global error probability of the proposed scheme. The simulation parameters used are listed in Table 6.2. These simulation parameters are justified by related works which are referenced [Shah & Koo 18a,Hossain & Miah 21, Miah *et al.* 21a, Khan *et al.* 20b].

Table 6.2: **Parameters used in simulations.**

Parameter	Value
The number of legitimate CR-IoT users, N	14
The number of malicious users, M	8
Sampling frequency, f_s	300 kHz
The number of samples, L	1000
The number of iterations, D	1000
Transmitted signal of the PU, $x(l)$	QPSK
The SNR value, γ	[-13 to -3] dB
The channel noise type, $n(k)$	AWGN

6.5.1 Performance Evaluation of Machine Learning Algorithms

In this section, I use the machine learning algorithms as a classifier in a CSS based CR-IoT network [Khan *et al.* 20b, Miah *et al.* 21a]. The ML algorithms classify legitimate CR-IoT users and malicious users at the IFC based on their transmitted energy level to the IFC. At the IFC, we consider that the legitimate CR-IoT users and malicious users transmit at the energy level of the received PU signal to the IFC. The range of sensing energy level of the legitimate CR-IoT users exists between 70 and 130 and the values outside of this range can belong to MUs. We consider that the sensing energy level of AHEMUs and ALEMUs are above 130 and below 70, respectively. We create a dataset which contains the energy level along with their corresponding decisions about the legitimate CR-IoT user or malicious user. To create the target variable, we use +1 and -1 to represent the legitimate CR-IoT users and the malicious users, respectively. We use 80% of data to train the ML algorithms and 20% of the data for testing purpose.

Figures 6.4, 6.5, and 6.6 show the confusion matrix for SVM ($TP = 80, FP = 0, TN = 48, FN = 0$), K-NN ($TP = 79, FP = 0, TN = 48, FN = 1$) and NB ($TP = 76, FP = 0, TN = 48, FN = 4$) algorithms, respectively. We can observe from these figures that the detection performance of the SVM algorithm is better compared to other two algorithms (i.e., K-NN, NB) for my data set.

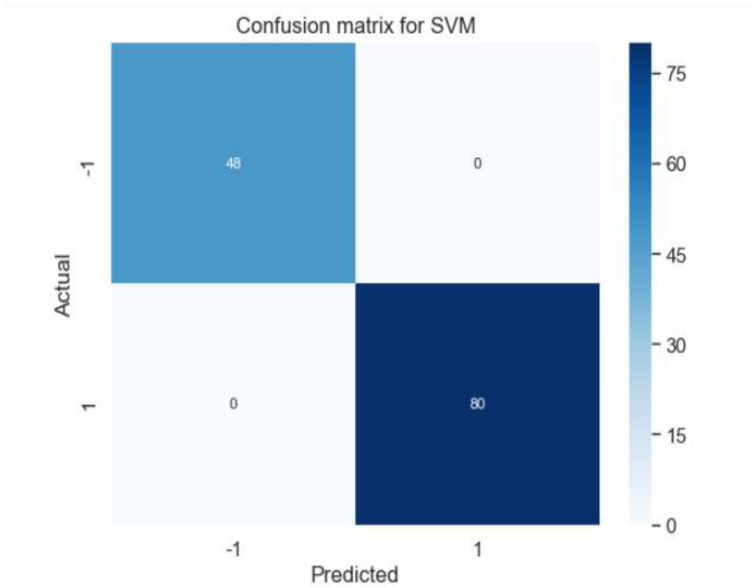

Figure 6.4: SVM Confusion Matrix

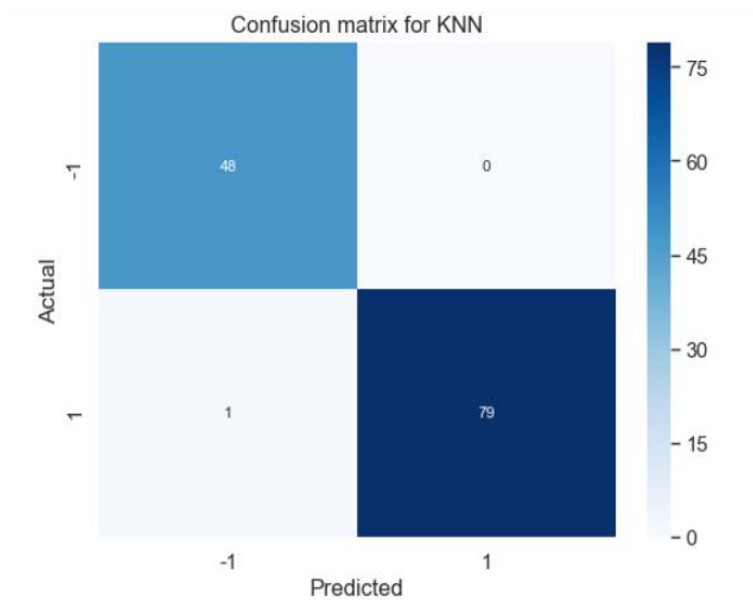

Figure 6.5: KNN Confusion Matrix

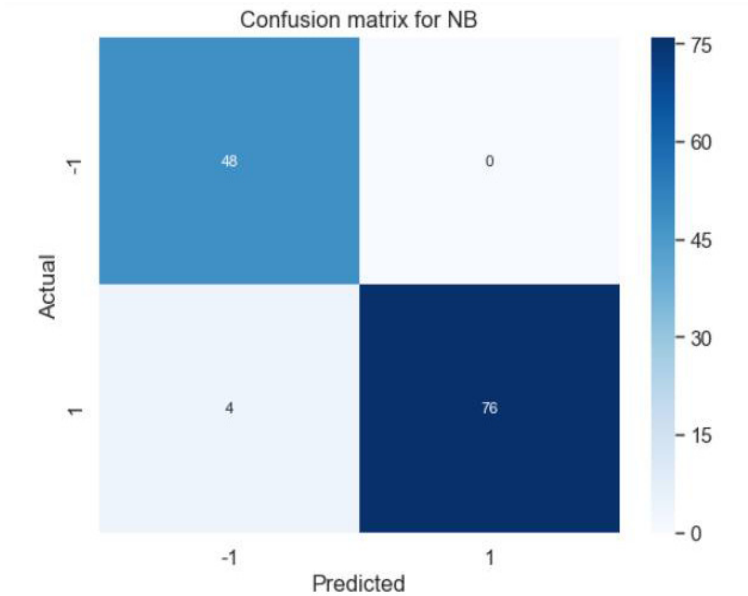

Figure 6.6: NB Confusion Matrix

Figure 6.7 shows the area under the receiver operating characteristics (AUROC) curve for the three ML algorithms. It is shown that the SVM algorithm efficiently classifies the legitimate CR-IoT users and the malicious users in comparison with other two machine learning algorithms (i.e., K-NN and NB).

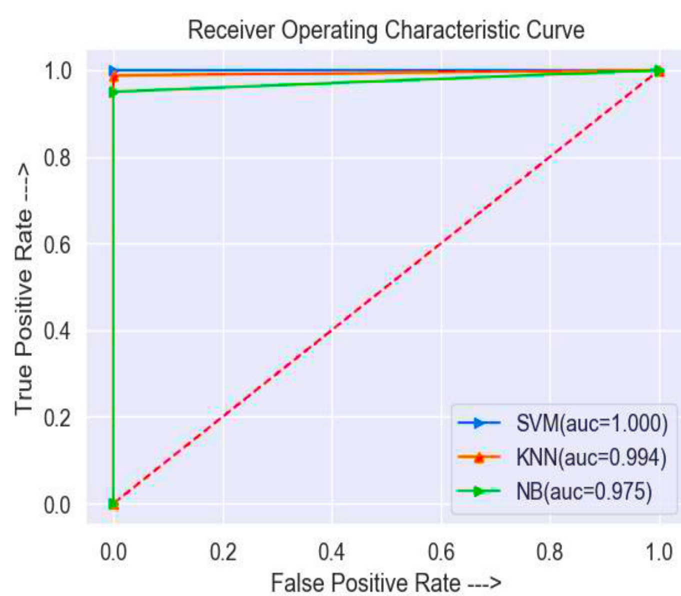

Figure 6.7: Area under the receiver operating characteristics (AUROC) for the three ML algorithms

In Table 6.3, shows the performance summary of the three machine learning algorithms. From this table it is observed that the malicious user detection accuracy of SVM, K-NN, and NB are 100%, 0.99%, and 0.97%, respectively.

Table 6.3: Performance Evaluation

Algorithm	**Accuracy**	**Precision**	**Recall**	**Specificity**	**F1 Score**
SVM	1.00	1.00	1.00	1.00	1.00
KNN	0.99	1.00	0.98	1.00	0.98
NB	0.97	1.00	0.95	1.00	0.97

From above result discussion, I can conclude that the SVM algorithm perfectly detects the malicious user and he legitimate CR-IoT user from my data set. As a result, I use only the SVM algorithm at the IFC to identify the malicious users among the three algorithms.

6.5.2 Sensing Performance and Global Error Probability Analysis at IFC

To evaluate the performance of the proposed machine learning based scheme, I conduct extensive simulations based on the parameters that are listed in Table 4.2 by using MATLAB 2019a. In this part of the simulation, I compare the performance of the proposed SVM-based majority fusion rule scheme with the conventional majority fusion rule scheme using the ROC curve for the following three cases:

Case 1 :: Always low energy malicious users: Figure 6.8 shows the ROC curve of the proposed SVM-based majority rule scheme and the conventional majority rule scheme, when the malicious users send low energy level reports to the IFC at all times regardless of what is locally determined. It is observed that the proposed SVM-based majority rule scheme provides better detection performance than the conventional majority rule scheme. Therefore, when ALEMUs remain in the CR-IoT networks, the probability of detection (P_{FC}^{d}) is low relative to after separating ALEMUs.

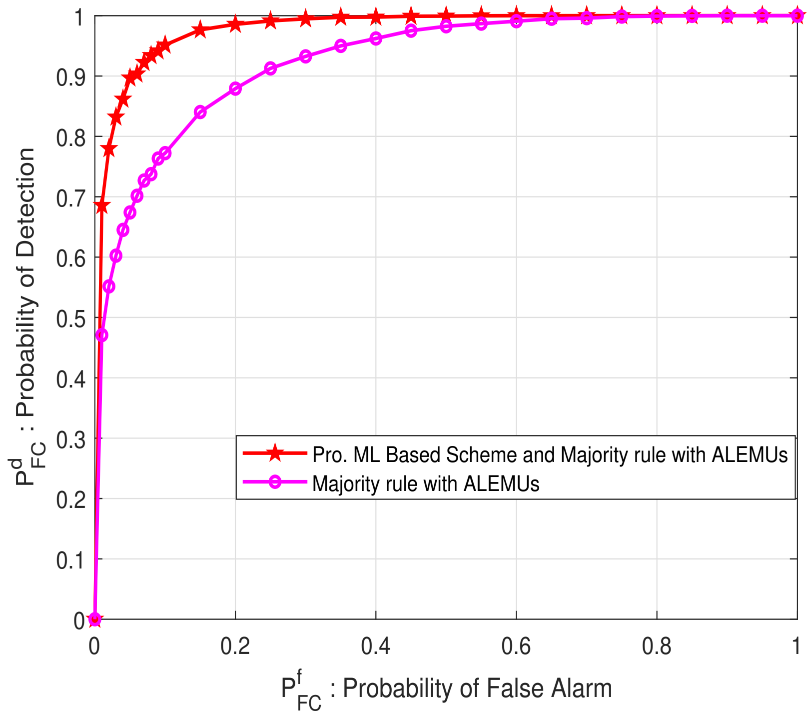

Figure 6.8: P^d_{FC} vs P^f_{FC} of the proposed scheme and the conventional scheme for ALEMUs.

It is shown from Figure 6.8 that the probability of detection for the proposed SVM based majority rule scheme and the conventional majority rule scheme is 0.95 and 0.79, respectively, while the probability of false alarm is 0.10. The global error probability (P^e_{FC}) versus the probability of detection at the IFC for ALEMUs is depicted in Figure 6.9. It is observed that the P^e_{FC} of the proposed SVM based majority rule scheme is lower than the conventional majority rule scheme, because the P^e_{FC} value depends on P^d_{FC} value.

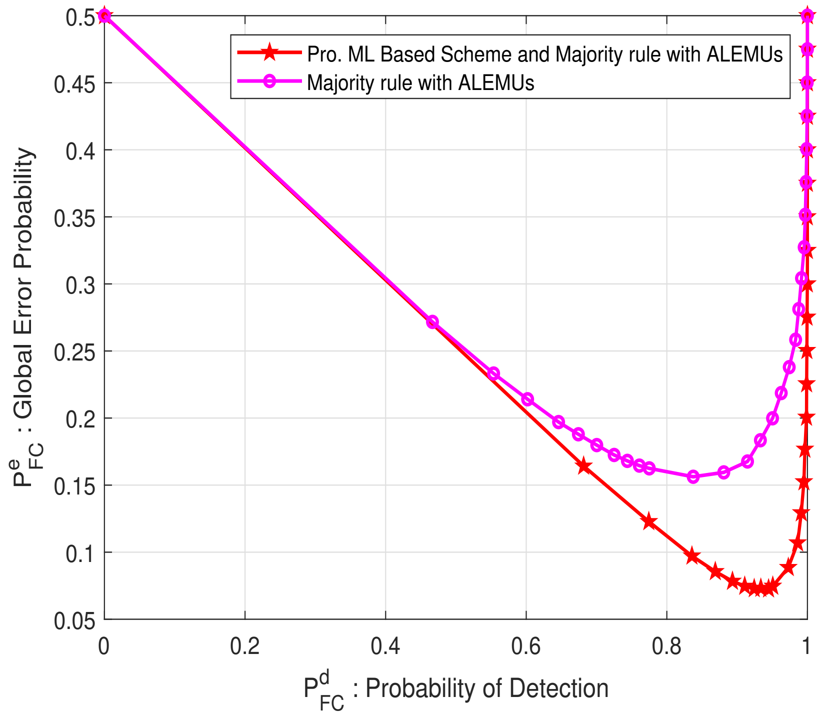

Figure 6.9: P^e_{FC} vs P^d_{FC} of the proposed scheme and the conventional scheme for ALEMUs.

It is shown in Figure 6.9 that the global error probability of the proposed SVM based majority rule scheme and the conventional majority rule scheme is 0.05 and 0.16, respectively, while the probability of detection is 0.90.

Case 2 :: Always high energy malicious users: Figure 6.10 shows the ROC curve of the proposed SVM-based majority rule scheme and the conventional majority rule scheme, when the malicious users send high energy levels to the IFC at all times regardless of what is locally determined. It is observed that the conventional majority rule scheme provides better detection performance than the proposed SVM-based majority rule scheme, because the proposed SVM based scheme efficiently classifies the legitimate CR-IoT users and AHEMUs. Therefore, when AHEMUs remain in the CR-IoT networks, the P^d_{FC} is high relative to after separating AHEMUs.

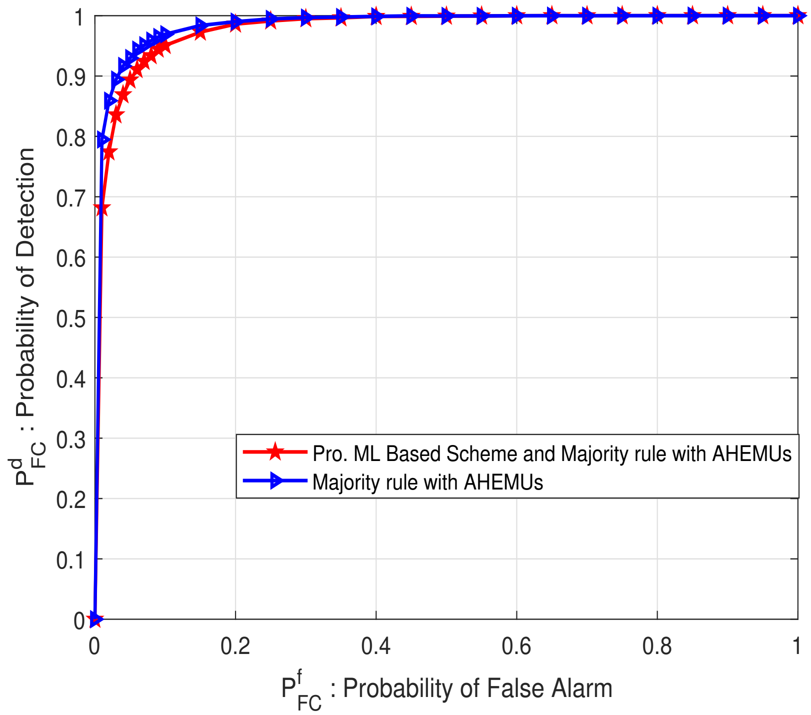

Figure 6.10: P^d_{FC} vs P^f_{FC} of the proposed scheme and the conventional scheme for AHEMUs.

It is shown from Figure 6.10 that the probability of detection for the proposed SVM based majority rule scheme and the conventional majority rule scheme is 0.95 and 0.98, respectively, while the probability of false alarm is 0.10.

The P^e_{FC} versus the P^d_{FC} at the IFC for AHEMUs is depicted in Figure 6.11. It is observed that the P^e_{FC} of the proposed SVM based majority rule scheme is lower than the conventional majority rule scheme, because the P^e_{FC} value depends on the P^d_{FC} value.

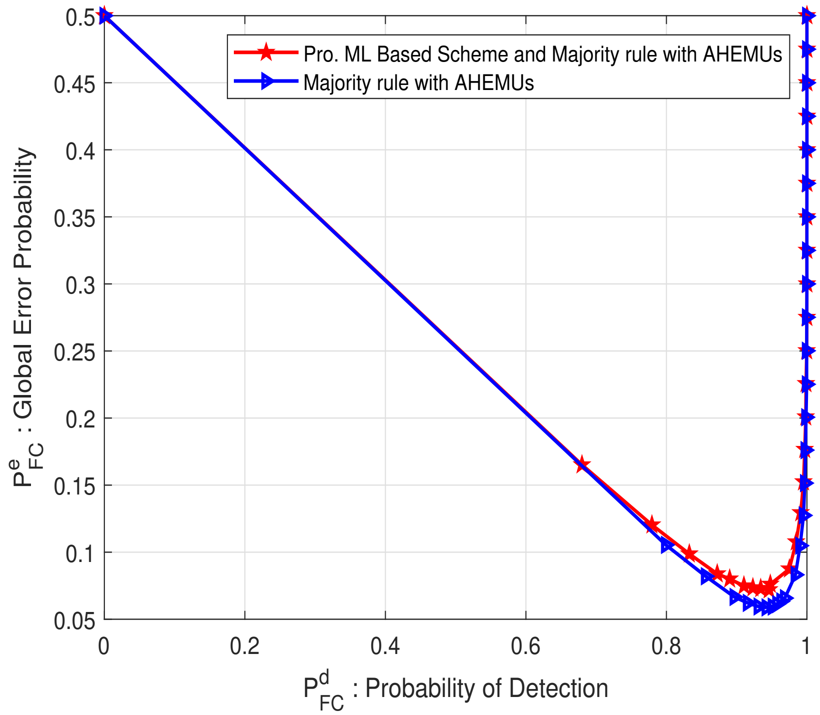

Figure 6.11: P^e_{FC} vs P^d_{FC} of the proposed scheme and the conventional scheme for AHEMUs.

It is shown from Figure 6.11 that the global error probability of the proposed SVM based majority rule scheme and the conventional majority rule scheme is 0.05 and 0.16, respectively, while the probability of detection is 0.90.

Case 3:: Random energy malicious users: Figure 6.12 shows the ROC curve of the proposed SVM-based majority rule scheme and the conventional majority rule scheme, when some random malicious users report low energy levels and some random malicious users report high energy levels to the IFC at all times regardless of what is locally determined. It is observed that the proposed SVM-based majority rule scheme provides better detection performance than conventional majority rule scheme, because the proposed SVM based scheme efficiently classifies the legitimate CR-IoT users and REMUs. Therefore, when the REMUs remain in the CR-IoT network, the P^d_{FC} is low after separating REMUs.

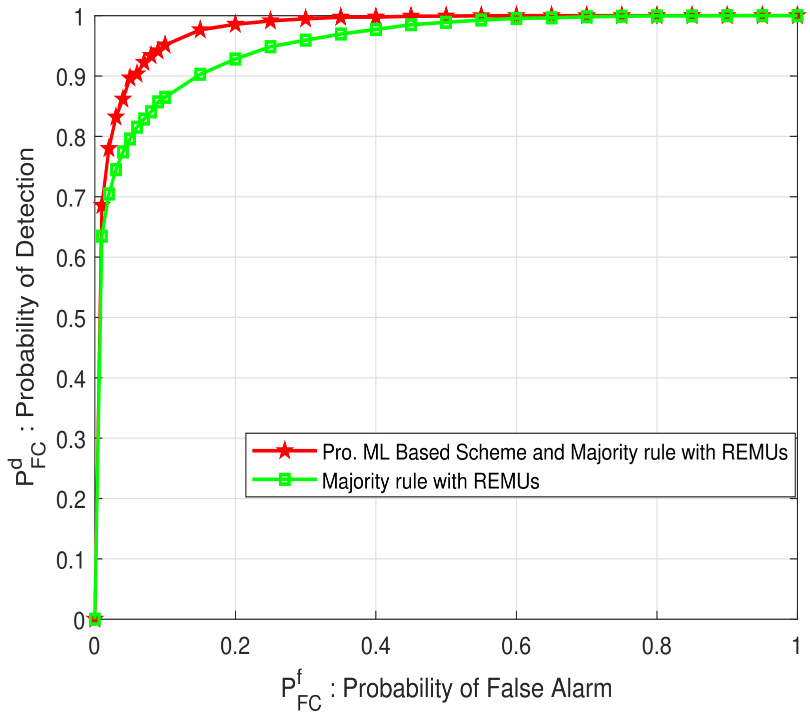

Figure 6.12: P_{FC}^{d} vs P_{FC}^{f} of the proposed scheme and the conventional scheme for REMUs.

It is shown from Figure 6.12 that the probability of detection for the proposed SVM based majority rule scheme and the conventional majority rule scheme is 0.95 and 0.88, respectively, while the probability of false alarm is 0.10. TheP_{FC}^{e} versus the P_{FC}^{d} at the IFC for REMUs is depicted in Figure 6.13. It is observed that the P_{FC}^{e} of the proposed SVM based majority rule scheme is lower than the conventional majority rule scheme, because the P_{FC}^{e} value depends on the P_{FC}^{d} value.

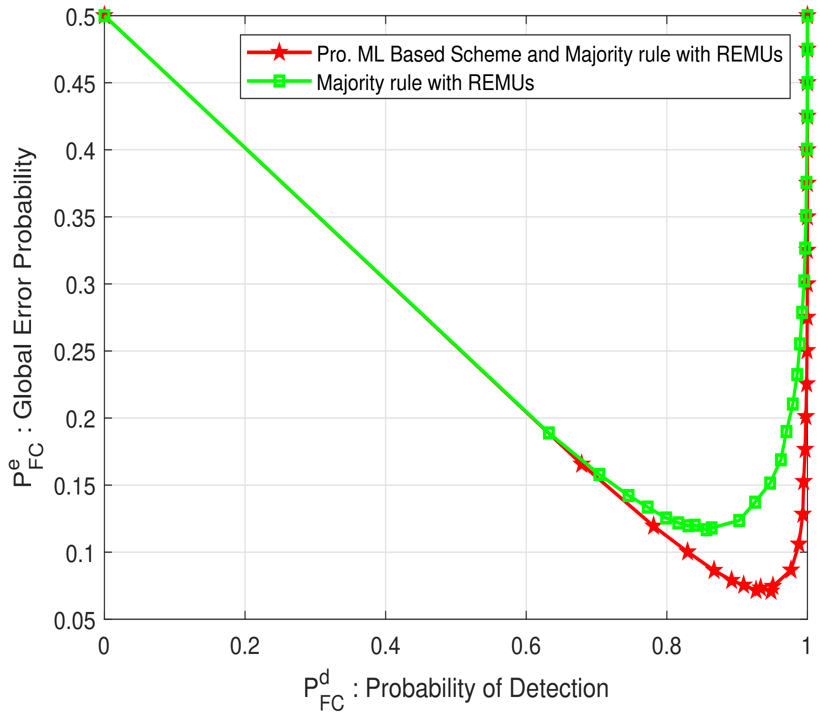

Figure 6.13: P^e_{FC} vs P^d_{FC} of the proposed scheme and the conventional scheme for REMUs.

It is shown from Figure 6.13 that the global error probability of the proposed SVM based majority rule scheme and the conventional majority rule scheme is 0.05 and 0.13, respectively, while the probability of detection is 0.90.

Sensing performance comparison for three cases:

Figure 6.14 shows the ROC curve of the proposed SVM-based majority rule scheme and the conventional majority rule scheme for three cases (i.e., ALEMUs, AHEMUs, and REMUs) at the IFC. It can be seen that the probability of detection of our proposed ML-based majority rule scheme is the same in all three cases because the proposed scheme detects three types of MU with 100% accuracy. However, the probability of detection of the conventional majority rule scheme for AHEMUs is better than when compared to the ALEMUs and REMUs due to AHEMUs always reporting high energy levels to the IFC. Moreover, the probability of detection of the conventional majority rule scheme for the REMUs is better than when compared to the ALEMUs due to some REMUs reporting high energy levels to the IFC.

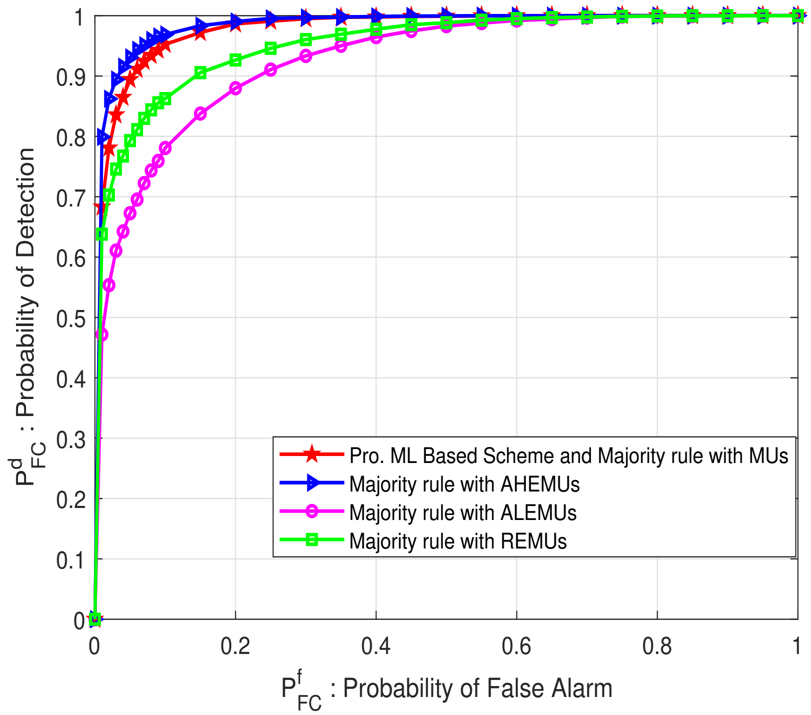

Figure 6.14: Sensing performance comparison of the ROC curves of the proposed scheme and the conventional scheme for ALEMUs, AHEMUs, and REMUs

Global error probability comparison for three cases:

From Fig. 6.15, it is observed that at $P_{FC}^{f} = 0.1$, the global error probability of my proposed ML-based majority rule scheme is 0.07 for three cases (i.e., ALEMUs, AHEMUs, and REMUs); whereas the global error probability for the conventional scheme is 0.06, 0.13, and 0.17 for the AHEMUs, REMUs, and ALEMUs, respectively. Basically, the P_{FC}^{e} value for the proposed ML based Majority rule scheme is the same in all three cases because the proposed scheme detects three types of MU with 100% accuracy. However, the global error probability of the conventional majority rule scheme for AHEMUs is low than when compared to the ALEMUs and REMUs due to AHEMUs always reporting high energy levels to the IFC. Moreover, the global error probability of the conventional majority rule scheme for REMUs is low when compared to the ALEMUs due to some REMUs reporting high energy levels to the IFC.

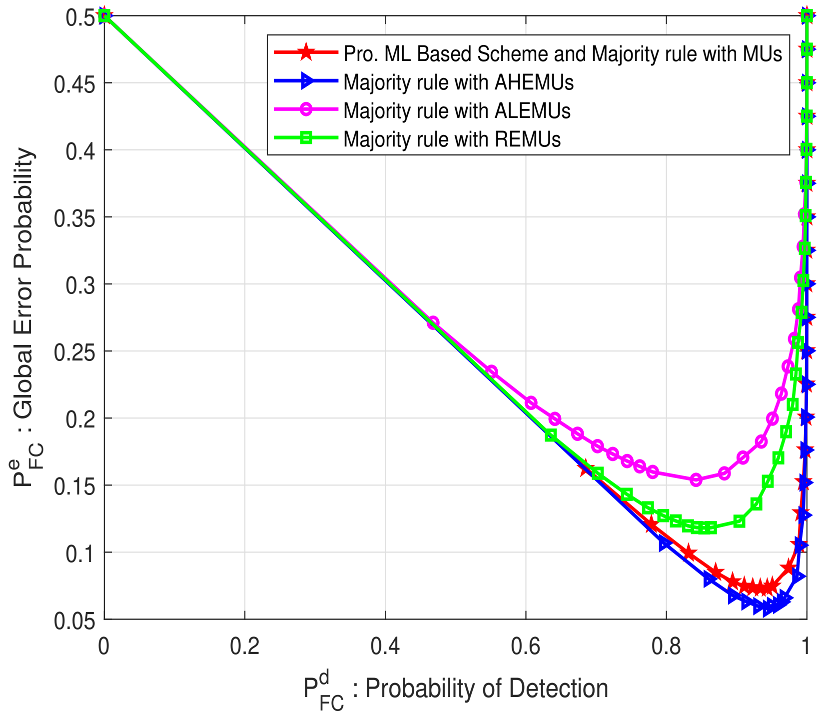

Figure 6.15: Global error probability comparison of ROC curves of the proposed scheme and the conventional scheme for ALEMUs, AHEMUs, and REMUs

6.6 Summary

In this chapter, I proposed a ML-based CSS scheme to classify the legitimate CR-IoT users and three kinds of MUs for improving the detection accuracy of PU activity. Our proposed ML-based scheme precisely classifies malicious users for three cases (i.e., ALEMUs, AHEMUs, and REMUs). After separating the malicious users through the proposed ML-based scheme, the FC combines the diversified sensing reports received from the legitimate CR-IoT users. Thereafter, the IFC applies the majority fusion rule on sensing results obtained from legitimate CR-IoT users to make a comprehensive global decision about the existence of PUs in the network. As a result, the proposed scheme significantly improves the sensing performance of knowing the activity of PUs for three kinds of malicious users (i.e., ALEMUs, AHEMUs, and REMUs) cases. In addition, the proposed ML-based scheme ensures the acceptable global error probability for three kinds of malicious users. Therefore, I conclude that my proposed ML-based secure CSS scheme will be more suitable for the CR-IoT networks due to it minimising the issue of spectrum deficit, preventing the malicious user attack, enhancing the sensing gain and achieving lower global error probability than the conventional (without security technique) scheme.

Chapter 7

Conclusions and Future Directions

In this chapter, I present the answers to my research questions in section 7.1, the main contributions of this thesis in section 7.2, the implementation challenges in section 7.3, and future research directions in section 7.4.

7.1 Answers of the Proposed Research Questions

In summary, my research addresses the proposed research questions as follows:

- **RQ1: How to increase the spectrum sensing gain and reduce reporting delays of cluster based CR-IoT networks?** To increase the spectrum sensing gain and reduce reporting delays of cluster based CR-IoT networks, the thesis proposed the concept of multiple reporting channels for cluster-based CSS for CRNs, as outlined in Chapter 3. This approach extends the sensing time of CR-IoT users by utilizing the reporting time slot of other CR-IoT users, thereby significantly enhancing the sensing time for all CR-IoT users as well as minimizing the reporting time delay of all CHs compared to the sequential single channel reporting approach. Simulation results show that the proposed approach significantly enhances the sensing gain and reduces the reporting time delay of CH compared to the conventional approach.

- **RQ2: How can the energy and spectral efficiency for CR-IoT networks be enhanced?** To enhance the energy and spectral efficiency for CR-IoT networks, this thesis proposed a novel energy efficient sequential ED spectrum sensing technique for each CR-IoT user in Chapter 4. In addition, each CR-IoT user calculates the weight factor based on the Kullback Leibler divergence score, which enhances the sensing gain and sum rate. The simulation results indicate that my proposed sequential ED spectrum sensing scheme achieves a better sensing gain, an increased sum rate and an enhanced energy and spectral efficiency when compared to the non-sequential conventional ED spectrum sensing scheme with interference constraints.

- **RQ3: How to increase the spectrum sensing gain and system sum rate as well as reduce the global decision error of cluster based CR-IoV networks?** To increase the spectrum sensing gain and system sum rate as well as to reduce the global decision error of cluster based CR-IoV networks, this thesis proposed a novel MU-MIMO antennas aided cluster based CSS scheme. Simulation results show that the proposed CSS scheme provides a better sensing gain, enhances the sum rate, and lowers global error probability when compared to both the conventional single-input and single-output antenna based CSS and NCSS schemes. In addition, the proposed scheme achieves a lower traffic overhead when compared to the MU-MIMO based CSS scheme without the cluster.

- **RQ4: How can we detect malicious secondary users in CR-IoT networks to enhance the security and sensing performance?**

  To mitigate malicious user attacks in CR-IoT networks, this thesis introduced ML-based secure CSS techniques. In the proposed scheme, the thesis investigated the use of SVM, KNN, and NB machine learning algorithms to classify legitimate CR-IoT users from MUs. The proposed scheme ensures secure sensing performance. In addition, the proposed scheme decreases the global error probability at the IFC compared to the conventional scheme.

7.2 Main Contributions

The core research contributions of this thesis can be summarised as follows:

- **Enhancing sensing performance:** An efficient sensing mechanism scheme based on the sequential multiple reporting channels approach in cluster-based CSS is proposed in Chapter 3. This scheme utilizes the reporting frameworks of CHs and the FC to achieve a better detection accuracy. It is shown that the probability of detection at the CH and the FC for the proposed sequential multiple reporting channel approach is 35% and 36% better than the non-sequential conventional approach, respectively. In Chapter 4, I propose a sequential ED spectrum sensing scheme with and without interference constraints. For scenario I (without interference), the probability of detection at the FC when using the proposed sequential ED scheme is 46.66% and 44.61% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. For scenario II (with interference), the probability of detection at the FC when using the proposed sequential ED scheme is 57.69% and 56.14% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. In Chapter 5, with respect to sensing gain, the proposed MU-MIMO antenna aided CB-CSS scheme demonstrates a 47% and 20% improvement for the MRC rule as well as a 44% and 22% improvement for the EGC rule over the conventional SISO antenna based NCSS scheme and CSS scheme, respectively. Finally, I propose a ML-based secure CSS scheme with three types of malicious users in Chapter 6, where the probability of detection at the FC when using the ML-based secure CSS scheme is 17.63% and 8.46% greater than the conventional scheme for the ANMUs and RMUs, respectively.

- **Enhancing sum rate/throughput:** Chapter 4 proposes the sequential ED spectrum sensing scheme with and without interference constraints. For scenario I (without interference), the sum rate of the CR-IoT user when using the proposed sequential ED scheme is 23.95% and 23.61% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. For scenario II (with interference), the sum rate of the CR-IoT user when using the proposed sequential ED scheme is 23.56% and 26.25% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. In Chapter 5, in terms of the system sum rate, the proposed MU-MIMO antennas aided CB-CSS scheme shows a 17.19% and 10.96% better performance for the MRC rule as well as a 12.28% and 9.21% better performance for the EGC rule when compared to the SISO antenna based NCSS scheme and CSS scheme, respectively.

- **Global error probability:** In Chapter 5, in terms of the global error probability, the proposed MU-MIMO antennas aided CB-CSS scheme provides a 0.07 and 0.09 global error probability for the MRC rule and the EGC rule, respectively. It is lower than the conventional SISO antenna based NCSS and CSS schemes. In Chapter 6, the global error probability of our proposed ML-based majority rule scheme is 0.07 for three cases (i.e., ALEMUs, AHEMUs, and REMUs); whereas the global error probability for the conventional majority rule scheme is 0.06, 0.13, and 0.17 for the AHEMUs, REMUs, and ALEMUs, respectively.

- **Energy efficiency:** Chapter 4 outlines the sequential ED spectrum sensing scheme with and without interference constraints. For scenario I (without interference), the energy efficiency of the proposed sequential ED scheme is 23.76% and 25% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5$ ms and $\tau_s = 10\ ms$, respectively. For scenario II (with interference), the energy efficiency of the proposed sequential ED scheme is 22.82% and 26.88% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10$ ms, respectively.

- **Spectral efficiency:** Chapter 4 outlines the enhanced spectral efficiency of the proposed sequential ED spectrum sensing scheme with and without interference constraints. For scenario I (without interference), the spectral efficiency of the network when using the proposed sequential ED scheme is 23.43% and 25.75% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively. For (ii) scenario II (without interference), the spectral efficiency of the network when using the proposed sequential ED scheme is 24.34% and 27.11% greater than the conventional ED scheme for the sensing time slot $\tau_s = 5\ ms$ and $\tau_s = 10\ ms$, respectively.

7.3 Implementation Challenges

This thesis improves upon the body of knowledge with regard to theoretical research within CR networks. However, there are number of potential issues and challenges that need to be addressed before CR can be deployed in a wide-scale manner [Shah *et al.* 16]. Some of the key research challenges, especially with regard to implementation challenges of cognitive radio, are as follows:

- **Practical implementation requirements of CR-IoT networks:** Cognitive radio networks are becoming increasingly popular due to their ability to use and reuse the unused licensed spectrum [Tarte & Hanchate 17]. However it has many challenges that need to be overcome. It needs a well defined architecture, good quality high end equipment, high sampling rates, high-resolution analog to digital conversion (ADC) and high-speed signal processors are all required for cooperating spectrum sensing in CR-IoT applications [Gupta & Kumar 19]. The receiver must be capable to perform fast processing. For better accuracy as well as optimal receiver design, several techniques like channel allocation, noise variance estimation and adaptive power control can be applied.

- **Regulatory issues and legal value:** Regularization and standardization have been a vital point of conflict that needs to be addressed on an urgent basis to implement CR-IoT networks [Shah *et al.* 13]. If CR-IoT users are to use the licensed spectrum, what would be the legal value for this usage? No wireless application would allow access to the propriety spectrum for free. This may cause inconvenience, security vulnerability, and disruption in the services to the primary/licensed user. If the CR-IoT user is to use the industrial, scientific, and medical (ISM) band like 802.11, then strong justification is required for the existence of a CR-IoT user in the ISM band. There should be a simple and widely acceptable regulation that could ensure proper and predictable operation of CR-IoT networks, but at the moment there is no such regulation.

- **Security challenges:** CR-IoT devices learn from their environment so something can also be taught things by malicious elements of their environment. Due to the dynamic spectrum sharing feature of CR-IoT, some malicious users may access the cognitive network arbitrarily and launch some special attacks, such as primary user emulation attacks, falsifying data or denial of service attacks, which will cause serious damage to the cognitive radio network.

- **Fault Tolerance:** Fault tolerance is one of the challenging issues in CR-IoT networks. CR-IoT networks should have self-forming, self-configuration and self-healing properties to enhance fault tolerance [Joshi *et al.* 13]. In other words, whenever some nodes (i.e., CR-IoT user) or links fail, an alternative path that avoids the faulty node or link must be derived. The protocols designed for CR-IoT networks should have a level of fault tolerance capability so that the overall function of the CR-IoT user should not be interrupted.

- **Hardware constraints:** The integration of cognitive radio technology with the IoT architecture (i.e., CR-IoT network) is expected to allow effective massive IoT deployment by providing huge spectrum opportunities to the IoT devices [Salameh *et al.* 19]. However, in practice, such an assumption is not feasible for hardware-constrained CR-IoT devices. That is why, in order to enable the CR-IoT device to sense and scan most of the available spectrum bands, there are some hardware constraints that need to be addressed. For example, a CR-IoT user's antenna capable of sensing and scanning unoccupied spectrum in 410MHz would be different from the antenna designed for 2.4GHz. The different antenna sizes and the transmission power rates, make the cognitive radio technology more hardware constrained.

7.4 Future Research Directions

This thesis has focused on the four main issues of CSS for CR-IoT networks. However, there are multiple other research directions within CSS based CR-IoT networks to develop upon the present work and to gain more improvements on spectrum sensing techniques, the following are possible suggestions for further work:

- **Enhancing security for CR-IoT:** This thesis proposed the ML-based CSS scheme in CR-IoT networks to detect malicious users based on their energy levels. In fact, CR-IoT networks are vulnerable to various new security attacks like all other existing wireless networks. In light of new security threats, new designs in spectrum sensing may need to be provided for resilience and security.

- **Enhancing the sensing performance under noise uncertain environment:** Most of the spectrum sensing techniques use a static threshold, which depends on the level of noise [Arjoune & Kaabouch 19a]. In a noise uncertain environment, the sensing performance of the existing techniques are degraded due to noise fluctuations [Wan *et al.* 19a]. In future research, there is a need to develop a novel sensing technique to measure the level of noise uncertainty for enhancing the sensing accuracy under a noise uncertain environment.

- **Full duplex CR-IoT networks:** This thesis only considers half-duplex (HD) CR-IoT networks. In HD CR-IoT networks, the CR-IoT user can either only perform spectrum sensing or transmit the data at a given time which limits the throughput of the CR-IoT user [Sabat *et al.* 17]. On the other hand, the full duplex (FD) technology facilitates the CR-IoT user to receive and transmit simultaneously in the same frequency band and decreases collisions with improved network throughput [Amjad *et al.* 17]. However, the extenuation of strong Self-Interference (SI) is a major challenge of FD networking. The dynamic spectrum sharing is very significant application area in CR-IoT networks, where FD can offer numerous benefits and opportunities like synchronized transmission and reception, extenuation of the hidden node problem, simultaneous sensing and transmission and enhanced sensing throughput and efficiency. These issues are also attractive topics for future research interest.

- **Network mobility:** This thesis presented spectrum sensing mechanisms that are compatible with stationary and mobile CRV users in CR-IoV networks, while the mobility of both primary users and cognitive users were not considered. Our future plan is to extend our work to study the effect of primary users and cognitive users mobility on the detection performance.

- **CR networks model for LTE/LTE-advanced network:** LTE/LTE-Advanced network supports the latest communication schemes like massive MIMO, D2D communication, carrier aggregation, and heterogeneous network with multiple small cells. Adaptive novel sensing schemes employed for CR networks would be promising in such communication schemes. For example, heterogeneous networks consist of multiple cells called macro, pico and femto cells. So, the interference minimization becomes more complex. Hence, a novel sensing scheme is of urgent need. The adaption of CR networks capabilities would help the spectrum sensing in heterogeneous networks, which is still an active area of research.

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