SPECTRUM SENSING FRAMEWORK FOR INFRASTRUCTURE BASED COGNITIVE VEHICULAR COMMUNICATIONS

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ABSTRACT

Vehicular communication is posed to aid road users overcome challenges faced today by sharing road conditions. However, vehicular communication still faces many challenges before deployment. One such challenge is insufficient radio frequency channels. Vehicular communications has been allocated 75MHz for dedicated short range communication (DSRC) at 5.9GHz bands. Nevertheless, the channels can get congested during peak hours or accident scenarios affecting the transmission of safety messages. To alleviate the problem of scarcity of channels in vehicular communications, dynamic spectrum access and Cognitive Radio (CR) technology is proposed. CR identifies spectrum opportunities in licensed frequency bands that can be accessed by unlicensed users through spectrum sensing. Spectrum sensing is performed by an individual vehicle or cooperation. In vehicular communications, spectrum sensing is challenging due to vehicle mobility and dynamic topological changes. Additionally, many challenges associated with spectrum sensing still exist such as shadowing, multipath fading and unknown primary user (PU) activities. This research aims at mitigating some of the problems of spectrum sensing in vehicular communication mentioned above by proposing a sensing framework. The proposed framework is divided in two parts. The first part involves sensing of PU signal by individual vehicles on the road using adaptive sensing. The adaptive sensing is based on energy detection and cyclostationary feature detection. The history of sensing results by vehicles is sent to road side unit (RSU) and used in aiding the framework to predict licensed channels likely to be free later. The results are used as reward for reinforcement learning at RSU. The second part of the framework involves RSU learning behavior of PU activity patterns using the sensing history. The framework is evaluated and validated through simulation under realistic VANET scenarios. The performance of the proposed framework is compared to history based approaches in literature.

ABSTRAK

Komunikasi kenderaan ditujukan untuk membantu pengguna jalan raya mengatasi cabaran yang dihadapi hari ini dengan berkongsi syarat jalan raya. Walau bagaimanapun, komunikasi kenderaan masih menghadapi banyak cabaran sebelum digunakan. Satu cabaran sedemikian adalah saluran frekuensi radio yang tidak mencukupi. Komunikasi kenderaan telah diperuntukkan 75MHz untuk komunikasi jarak pendek khusus (DSRC) pada jalur 5.9GHz. Walau bagaimanapun, saluran boleh menjadi sesak pada waktu puncak atau senario kemalangan yang menjejaskan penghantaran mesej keselamatan. Untuk mengurangkan masalah kekurangan saluran dalam komunikasi kenderaan, akses spektrum dinamik dan teknologi Radio Kognitif (CR) dicadangkan. CR mengenal pasti peluang spektrum dalam band frekuensi berlesen yang boleh diakses oleh pengguna yang tidak berlesen melalui penderiaan spektrum. Pengesan spektrum dilakukan oleh kenderaan atau kerjasama individu. Dalam komunikasi kenderaan, pendengaran spektrum mencabar kerana mobiliti kenderaan dan perubahan topologi dinamik. Di samping itu, banyak cabaran yang dikaitkan dengan pendengaran spektrum masih wujud seperti membayangi, memudar berbilang dan aktiviti pengguna utama (PU) yang tidak diketahui. Kajian ini bertujuan untuk mengurangkan beberapa masalah pengesanan spektrum dalam komunikasi kenderaan yang dinyatakan di atas dengan mencadangkan rangka kerja penginderaan. Rangka kerja yang dicadangkan dibahagikan kepada dua bahagian. Bahagian pertama melibatkan penderiaan isyarat PU oleh kenderaan individu di jalan raya menggunakan penderiaan penyesuaian. Penginderaan penyesuaian adalah berdasarkan pengesanan tenaga dan pengesanan ciri cyclostationary. Sejarah hasil penderiaan oleh kenderaan dihantar ke unit sampingan jalan (RSU) dan digunakan untuk membantu kerangka untuk meramalkan saluran berlesen yang kemungkinan akan bebas kemudian. Hasilnya digunakan sebagai ganjaran untuk pembelajaran tetulang di RSU. Bahagian kedua

rangka kerja melibatkan perilaku pembelajaran RSU pola kegiatan PU dengan menggunakan sejarah penginderaan. Rangka kerja ini dinilai dan disahkan melalui simulasi di bawah senario VANET yang realistik. Prestasi rangka kerja yang dicadangkan dibandingkan dengan pendekatan berdasarkan sejarah dalam kesusasteraan.

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Finally, I would like to thank and dedicate this thesis to my wife Mwanida. For the support and encouragement you have given me cannot be repaid in words. I am humbly honored to be part of your life.

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LIST OF ABBREVIATIONS

API	:	Application Programming Interface
AWGN	:	Additive White Gaussian Noise
CDF	:	Cyclic Density Function
CFAR	:	Constant False Alarm Rate
CPD	:	Constant Probability of Detection
CPFA	:	Constant Probability of False Alarm
CR	:	Cognitive Radio
CRAHN	:	Cognitive Radio Ad Hoc Network
CVANET	:	Cognitive Vehicle Ad Hoc Network
DSA	:	Dynamic Spectrum Access
FC	:	Fusion Center
GHZ	:	Gigahertz
ISM	:	Industrial, Scientific, Medical
ITS	:	Intelligent Transportation System
MAC	:	Medium Access Control
MANET	:	Mobile Ad Hoc Network
MDP	:	Markov Decision Process
MHZ	:	Megahertz
ML	:	Machine Learning
NAM	:	Network Animator
NS2	:	Network Simulator 2
NS3	:	Network Simulator 3
OOC	:	One Order Cyclostationary
OSM	:	Open Street Map

PDF	:	Power Density Function
PDL	:	Packet Delivery Rate
PHY	:	Physical
PLR	:	Packet Loss Rate
PSD	:	Power Spectral Density
PU	:	Primary User
QoS	:	Quality of Service
RL	:	Reinforcement Learning
ROC	:	Receiver Operating Characteristic
RSU	:	Road Side Unit
SCF	:	Spectral Correlation Function
SNR	:	Signal to Noise Ratio
SSF-CVANET	:	Spectrum Sensing Framework Cognitive Vehicle Ad Hoc Network
SU	:	Secondary User
SUMO	:	Simulator of Urban MObility
SVM	:	Support Vector Machine
SWANS	:	Scalable Wireless Ad hoc Network Simulator
TD	:	Temporal Difference
TV	:	Television
TVWS	:	Television White Spaces
VANET	:	Vehicle Ad Hoc Network
WAVE	:	Wireless Access Vehicular Environment
WRAN	:	Wireless Regional Area Network

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CHAPTER 1: INTRODUCTION

1.1 Background

There has been growth in the number of technologies aimed at improving human lives in all sectors in recent years, transportation included. Technologies that improve communication efficiency in transportation are grouped under the umbrella of Intelligent Transportation System (ITS). ITS will play a major role in automobile industry by providing means of vehicular communications. ITS applications are envisioned to reduce congestion on the road, increase safety to drivers and provide comfort infotainment to passengers. In recent years, new vehicles with wireless communication capabilities are being manufactured (Whaiduzzaman, Sookhak, Gani, & Buyya, 2014). These vehicles have capabilities to collect enough data from the surrounding environment and use that data to infer traffic conditions on the roads. This capability allows vehicles to become self-aware by using the contextual data obtained from the environment, hence becoming autonomous (Dressler, Hartenstein, Altintas, & Tonguz, 2014). The autonomous vehicles will allow smooth flow of traffic on the roads thereby reducing congestion and emission of CO_2 (Jin, Wu, Boriboonsomsin, & Barth, 2014; Lee, Lai, & Chen, 2015). The autonomous vehicles will share their contextual data with other vehicles. The types of information to be shared can include road traffic conditions such as accidents, traffic jams, road works, etc, and other service messages (e.g. sharing information about free parking lots). This kind of information could be shared either through vehicle to vehicle (V2V) in ad hoc manner or vehicle to infrastructure (V2I) communication. The two types of communication, V2V and V2I define what is known as vehicle ad hoc network (VANET) (Zeadally, Hunt, Chen, Irwin, & Hassan, 2012).

VANET is a network that relies on the wireless electromagnetic radio frequency to facilitate V2V and V2I communications. The first standard designed to support short to medium range vehicular communications services developed for V2V and V2I is called dedicated short range communications (DSRC) (Zeadally et al., 2012). The DSRC is designed to support transmission range of 300m and up to 1000m for vehicles moving up to 200km/h (Lin, Lin, Liang, & Chen, 2012). The DSRC have been allocated 75MHz of spectrum band at 5.9GHz to be used for ITS communications. In the United States of America, the Federal Communications Commission (FCC) allocated the 75MHz in the 5.850-5.925 GHz band covering 7 channels with 10MHz each and 5MHz reserved as a guard band (Kenney, 2011). Six of the 7 channels are reserved for service messages while one channel used as control channel for broadcasting safety related messages. In the European Union, the European Telecommunications Standards Institute (ETSI) allocated 70MHz in the 5.855-5.925 GHz band (Ström, 2011).

During peak hours and accident incidences, the density of vehicles on the road increases resulting in traffic jams. In high vehicle density, it is difficult to transmit delay sensitive safety messages on time because the number of vehicles contending for the same limited DSRC channels increase drastically (Jiang, Taliwal, Meier, Holfelder, & Herrtwich, 2006; W. Liang, Li, Zhang, Wang, & Bie, 2015; Wu et al., 2013). Many solutions have been proposed in literature to overcome the communication setbacks (Fallah, Huang, Sengupta, & Krishnan, 2010; Jiang et al., 2006). Many of the proposed schemes suggest protocols that guarantee quality of service (QoS) based on the ITS applications. Applications for safety and emergency messages are given high priority while applications for service messages are given low priority. However, these approaches perform poorly in high vehicle densities because of increased contention in the wireless channel medium (Wu et al., 2013). Furthermore, some importance service applications are deprived of communication channels because of low priority (Z. Wang & Hassan, 2008). Hence, the 7 channels reserved for vehicle exclusive communication at 5.9GHz band is not adequate. Consequently, other novel solutions are necessary to support ITS communications before deployment of VANET. Such solution should include increasing channel capacity for VANET communications.

Nevertheless, increasing channel capacity for VANET communication entails expanding the radio frequency band beyond 5.9GHz band. However, the current allocation of radio spectrum by government regulatory agencies around the globe is fixed (Withers, 1999). The current radio frequency technology exploits electromagnetic wave in the range from 3Hz to 300GHz (Coleman, 2004). Some spectrums within this range are designated as unlicensed bands which can be used by any technology or organization. Most of the unlicensed spectrum constitutes the Industrial, Scientific and Medical (ISM) bands. Some organization or individuals acquire license to exclusively operate on certain radio spectrum frequencies for a period of time and specific geographical region. The allocated spectrum is reserved for exclusive use for that organization or individual whether it is being used or not. This prevents communicating devices from interfering with each other. However, the fixed allocation of radio spectrum has created what is known as artificial scarcity of radio frequency spectrum. Many spectrum measurements and campaigns have shown that some radio frequency bands are heavily used while other frequencies are underutilized (Das & Das, 2015; Palaios, Riihijarvi, Holland, Achtzehn, & Mahonen, 2012; Patil, Prasad, & Skouby, 2011; Valenta et al., 2010; Wellens & Mähönen, 2010). Therefore, some mechanisms are needed to optimize the underutilized frequency bands provided no interference is caused to the primary owners of the license. Hence, in 2002 the FCC proposed a mechanism to optimize usage of underutilized radio spectrum through dynamic spectrum access (DSA) (Haykin, 2005). The concept of DSA is to allow unlicensed users access channels that are allocated to licensed users for exclusive use, provided no harmful interference is caused to the primary owners. In DSA, the incumbent licensed user is called primary user (PU) while unlicensed user is called secondary user (SU).

In VANET, vehicles can use extra channels obtained from other licensed bands through DSA and help alleviate the problem of channel shortage during congestion while optimizing the use of radio spectrum. This is achieved through a cognitive radio (CR) technology. The CR is an intelligent software defined radio (SDR) that reconfigures its transceiver parameters based on the current radio environment (Haykin, 2005). The major tasks performed by the CR are spectrum sensing, spectrum decision, spectrum sharing as well as spectrum handoff. Spectrum sensing is performed to identify spectrum opportunities in licensed frequency bands also called spectrum holes. The CR is responsible for deciding the presence or absence of the PU signal in the licensed frequency bands. In addition, a CR provides some mechanisms to vacate (handoff) the licensed channel when the PU signal is detected. All these tasks are performed by SU using a CR without involving the primary system (licensed users and telecommunication equipments). Therefore, a primary system assumes a passive role. Hence, novel algorithms that provide maximum protection to the primary system are needed in order to avoid interference while supporting an efficient management of the radio spectrum. The CR technology has potential to effectively manage radio spectrum in VANET that can alleviate the problem of limited channel capacity.

1.2 Statement of Problem

Despite many benefits that VANET is envisaged to bring to road users, it is still faced by various limitations of wireless communication systems, in particular, limited channel capacity. The 7 channels defined at 5.9GHz band for vehicular communications are not adequate during high vehicle density. In addition, the radio spectrum allocated for VANET communications at 5.9GHz band cannot be expanded because of the static spectrum allocation. This static allocation of radio spectrum by regulatory agencies has created an artificial scarcity of radio spectrum (Ting, Wildman, & Bauer, 2005). The fixed allocation of radio spectrum was designed to avoid interference among different telecommunication systems (Hazlett, 1990; Ting et al., 2005). Nevertheless, this has resulted in some radio frequency bands being over utilized (e.g. ISM bands) while other frequency bands being underutilized (Das & Das, 2015).

In recent years, research has focused on promoting the access of radio spectrum from a fixed access model to dynamic access models (Freyens & Alexander, 2015). The idea behind DSA is to optimize the underutilized radio spectrum. DSA allow unlicensed users that operate in congested frequency bands (e.g. ISM) to opportunistically utilize free radio spectrum when not in use by licensed users. The free radio spectrum not in use by licensed users in time and space is called spectrum holes or spectrum whitespace. Figure 1.1 illustrates the concept of spectrum holes.

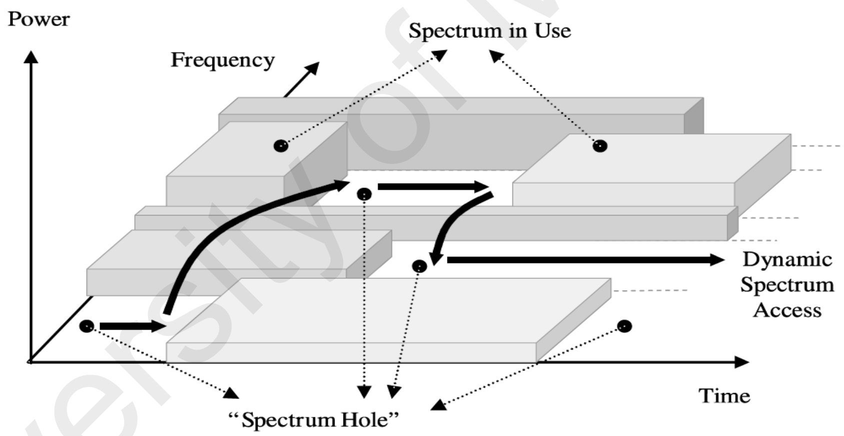

Figure 1.1: Spectrum hole concept (Akyildiz, Lee, Vuran, & Mohanty, 2006)

A CR is introduced to identify the spectrum holes from licensed frequency bands. The CR is responsible for monitoring and tracking changes in the radio environment (Haykin, 2005). This task is performed through spectrum sensing. Spectrum sensing is one of the major tasks performed by the CR. Accurate spectrum sensing results enables maximum protection of licensed users from interference in communication channels while optimizing the usage of radio spectrum. However, there are still challenges associated with spectrum sensing in vehicular communication environment before CR is realized for spectrum management in VANET.

One of the major challenges in spectrum sensing for VANET environment is mobility of vehicles (Rawat, Amin, & Song, 2015). A vehicle needs to identify spectrum holes within a short period of time before moving to some other areas where spectrum opportunities might not be available. This calls for developing spectrum sensing techniques that are effective and efficient in detecting spectrum holes. On the other hand, mobility can be leveraged by vehicles in obtaining spectrum opportunities at future time and location if the speed and velocity of the vehicle is known (K. D. Singh, Rawat, & Bonnin, 2014). Other challenges include multipath fading and shadowing of PU signal due to obstacles such as tall building (Akyildiz et al., 2006). In addition, Doppler Effect causes radio signal fading which result in poor signal-to-noise ratio (SNR) between sensing vehicle (SU) and the PU source. Furthermore, hidden PU problem is another issue for spectrum sensing in VANET environment (Chatziantoniou, Allen, & Velisavljevic, 2014). Different solutions have been proposed to solve some of the mentioned problems (Axell, Leus, Larsson, & Poor, 2012). What stand out to be the most promising approach is employing cooperative decision for identifying spectrum holes (Akyildiz, Lo, & Balakrishnan, 2011). However, there are still problems with cooperative decision that need attention. For example synchronization of spectrum sensing results among participating vehicles is a challenge, determining optimal number of vehicles to be involved in cooperative decision making constitutes a challenge. The choice of the common control channel for transmitting sensing results is another challenge (Lo, 2011). A detailed discussion of the challenges associated with spectrum sensing in VANET is presented in Chapter 3.

Nevertheless, many of the proposed techniques have not considered the effect of PU activity duty cycles (Chembe, Noor, et al., 2017). The performance of spectrum sensing scheme is dependent on the PU activity model assumed. Therefore, PU activities must be well understood to maximize accuracy of sensing results. There are many PU activity models proposed in literature (Y. Chen & Oh, 2016; Saleem & Rehmani, 2014). In VANET environment, the common PU activity model assumed by many spectrum sensing schemes is a fixed ON/OFF activity model. However, this model has shown to be unrealistic in practical environment, because the operation of the primary system is perceived to be random (V. Kumar, Sharma, Debnath, & Gangopadhyay, 2015). In addition, the fixed ON/OFF model does not perform well in the mobile PU environment (Saleem & Rehmani, 2014). Therefore, adaptive PU activity models which represent realistic PU activities in VANET environment should be developed.

1.3 Research Objectives

The general aim of this research work is to develop a spectrum sensing framework that identifies unused channels from licensed frequency bands for vehicular communication during congestion. Therefore, the following are specific objectives that are defined to achieve the main aim:

- To explore existing recent spectrum sensing strategies in VANET and study the impact of PU activity pattern on spectrum sensing.
- To develop an adaptive spectrum sensing model to be used by vehicles on the roads to identify free unused channels.
- To enhance the PU activity model using reinforcement learning at RSU.
- To develop spectrum sensing framework that utilize sensing history from vehicles on the road to mitigate problems associated with cooperative decision.

- To evaluate the framework using simulation tools (modified NS3 with SUMO) and compare the results with history based approaches in literature.

1.4 Scope of the Study

There are many challenges attributed to DSA and CR technology. Most of the challenges focus on how well to provide maximum protection to the licensed users while allowing optimum use of the radio spectrum. It is important to emphasize in advance that there is minimal interaction between PU system and SU network in spectrum management when using the CR. Hence, CR plays a major role in spectrum management for DSA including: spectrum sensing, spectrum decision, sharing, allocation and spectrum handoff. These stages are aimed at protecting the PU system from interference that maybe caused by unlicensed users. Nevertheless, spectrum decision, sharing and handoff rely on spectrum sensing results. Therefore, spectrum sensing is a vital stage in CR life cycle.

In this research, an investigation of challenges associated with spectrum sensing is presented. In addition, the research studies the impact of the PU activity cycles on spectrum sensing. The solution will be developing spectrum sensing framework that identify free unused licensed frequency band for vehicular communication. The sensing scheme considers the PU activity duty cycles. To achieve the objectives, this research investigated the three major spectrum sensing techniques proposed in literature based on energy detector, matched filter detector and cyclostationary feature detector (Akyildiz, Lee, Vuran, & Mohanty, 2008). After investigation, two techniques were identified and used to develop adaptive spectrum sensing technique. Furthermore, reinforcement learning was used to learn the traffic pattern of the PU transmitters and predict licensed channels likely to be free in future. This work only considers infrastructure based vehicular communication as the RSU plays a major role in coordinating the spectrum management. Distributed vehicular communication based on clustering is reserved for future work.

1.5 Motivation and Significance of the Research

Vehicular communication is posed to bring many benefits to both drivers and passengers. With many advances in the wireless technologies, many ITS applications which are bandwidth intense are being developed targeted at meeting the challenges of every day road use. The applications relate to both safety and non-safety messages. Most of non-safety applications involve some form of multimedia in their implementation. For example, passengers on a long journey can be entertained through Internet Protocol TV (IPTV) which is bandwidth intense (Oche, Noor, & Jalooli, 2015). A parent on a long journey can have children entertained through peer to peer gaming which require extra bandwidth. In the advent of big data and Internet of things, vehicular communication through the Internet will play a crucial role in providing many valuable data to executive personnel who want to keep up with updates on the stock markets in real time (Qin et al., 2014). The information from the online stock market can come in graphical form which is bandwidth intense. In addition, smart cities will require vehicles equipped with wireless capabilities that will be able to communicate with different devices (Vlacheas et al., 2013). Applications can also be safety related in nature. For instance, a collision avoidance system can provide drivers with both audio and video about the conditions on the roads in real time and this require bandwidth (S. S. Kumar et al., 2016). All these scenarios call for innovative ways to provide extra channel to vehicular networks for both V2V and V2I communications.

As mentioned earlier, the 7 channels reserved for vehicular communication at 5.9GHz band is not sufficient especially during traffic congestion. In addition, it is envisioned that by 2020, there will be more than 50 billion devices connected to the

Internet mostly through wireless communication (Skarmeta, Hernandez-Ramos, & Moreno, 2014). This poses a major challenge on the already scarce radio frequency spectrum which is a finite resource. To solve radio frequency challenges, CR technology has emerged as a promising solution to combat the scarcity of communication channels and provide bandwidth to emerging ITS applications through DSA. The benefits of VANET and the challenge of channel availability motivated this research, which advocates for DSA and CR technology. DSA will allow vehicles to access more channels that can be used by application envisaged for VANET while allowing for optimization of radio spectrum. Therefore, the significance of this research work can be summarized as follows:

- DSA will provide vehicles with extra channels that can be used whenever there is congestion in the DSRC channels reserved at 5.9GHz band. However, this is dependent on a spectrum sensing model that is able to identify spectrum holes effectively while protecting the licensed users.
- The adaptive spectrum sensing model proposed will help in identifying spectrum holes to be used for DSA by vehicles. The sensing model will maximize sensing performance while minimizing false alarm probability. This is importance to protect the licensed users while allowing for optimized use of radio spectrum bands. In addition, the PU activity model will work in collaboration with the spectrum sensing model to provide accurate sensing results that will protect the licensed users while maximizing use of licensed channels.
- The spectrum sensing framework will be very usefully not only in providing extra channel to vehicles during congestion, but cognitive radio based technology will also be useful in bridging the heterogeneous networks especially those envisaged for the Internet of Vehicles (Fangchun, Shangguang, Jinglin, Zhihan, & Qibo, 2014). This is possible because a cognitive radio adjusts its

network parameters (e.g. transceivers) based on the current radio environment before transmission. In addition, the technology based on the CR eliminates hardware upgrades whenever new protocols emerge. This is because CR is based on software defined radio that is programmable. Any changes in the protocols only require a software upgrade and not changing the hardware.

1.6 Organization of the Thesis

Having provided the general introduction to the research work, objective, scope, motivation and significance of the research, the remainder of the chapters will be organized as follows:

Chapter 2: in this chapter, a general description of VANET communication is given. An introduction to dynamic spectrum access is presented in this chapter. In addition, a brief introduction to cognitive radio technology is given with focus on spectrum sensing, spectrum decision and allocation.

Chapter 3: this chapter outlines spectrum sensing challenges faced in VANET. It goes in detailed to discuss spectrum sensing techniques proposed in literature with focus on energy detector, matched filter detector and cyclostationary feature detector. In addition, cooperative spectrum decision is presented with associated challenges. Furthermore, the chapter discusses performance metrics adapted for this work.

Chapter 4: this chapter details the methodology and steps adopted in development of the framework. Analytical formulation of adaptive spectrum sensing techniques is discussed in this chapter. Furthermore, the chapter details the PU activity model using reinforcement learning adapted for this work that is used to aid spectrum sensing model.

Chapter 5: this chapter details the implementation procedure of the spectrum sensing framework in network simulator (NS3) and mobility generator (SUMO). The modules of NS3 that are used in the implementation of framework are presented in this chapter. The chapter also describes the methods used to achieve the objectives.

Chapter 6: implementation results obtained from the previous chapter is discussed in this chapter. Various implementation scenarios are given. In particular, the scenarios considered are fading and non-fading. The results of simulation for the proposed framework are compared to other schemes proposed in literature.

Chapter 7: this chapter concludes the thesis and gives some future directions.

CHAPTER 2: BACKGROUND LITERATURE

2.1 Introduction

Vehicle ad hoc network (VANET) will form a central infrastructure for Intelligent Transportation System (ITS) to safeguard road users from accidents, reduce congestion on the roads and provide comfort to passengers through infotainment. Therefore, understanding communication background of VANET is an important task which is presented in this chapter in Section 2.2. The communication in VANET is facilitated by dedicated short range communication (DSRC) bands which are bound to get congested during high vehicle traffic density. Therefore, dynamic spectrum access (DSA) has been suggested as a mechanism to supplement DSRC channels during congestion by acquiring extra channels from unused licensed bands. Nevertheless, DSA relies on the cognitive radio technology which has to sense the radio spectrum to identify the extra channels from licensed bands. Spectrum sensing is one of the important functions of the cognitive radio and the main topic for this thesis. Therefore, a detailed discussion of spectrum sensing, problems associated with spectrum sensing and some of the proposed mechanisms to mitigate them have been presented in Chapter 3. In this chapter (Chapter 2) we outline the brief introduction to DSA in Section 2.3 and an introduction to cognitive radio technology in Section 2.4 while Section 2.5 concludes the chapter.

2.2 Vehicle ad hoc network

Vehicle ad hoc network (VANET) is the subset of mobile ad hoc network (MANET) in which communicating nodes are vehicles on the road (Conti & Giordano, 2014). As such it has unique characteristics not found in MANET including high mobility of nodes and dynamic network topology. The main objective of VANET is to support applications that assist road users to avoid accidents and provide comfort to passengers. The applications are divided into safety and non safety (Al-Sultan, Al-Doori, Al-Bayatti, & Zedan, 2014; Cunha et al., 2016). Safety applications are concerned with providing collision prevention and avoidance to road users to avoid accidents. Non safety applications are infotainment in nature. VANET defines two types of communications to enable transmission of such applications (R. Kumar & Dave, 2012; Rawat, Bista, Yan, & Olariu, 2014; Yuhang Zhao, Zhang, Sun, Bai, & Pan, 2014). The two types of communication are vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communications.

V2V communication involves vehicles establishing ad hoc communication on the road dynamically without any infrastructure support. The communication in V2V is multi-hop in which vehicles directly communicate to neighbors and exchange short messages. The messages have local significance and to nearby vehicles (e.g. announcing slippery roads, accident incidence, curves or road works to nearby vehicles). Thus, vehicles act as routers to pass messages to other nodes with ability to be source nodes as well as destination nodes. On the other hand, V2I communication is established between vehicles on the roads and infrastructure along the road. The road infrastructure includes traffic lights, toll gates, cellular towers etc. Vehicles use the facilities as gateway to access services from centralized server on the Internet such as traffic conditions, parking spaces and many more. The communication is established between the road side units (RSU) and the on-board units (OBU) in the vehicles. Figure 2.1 shows pictorial representation of VANET.

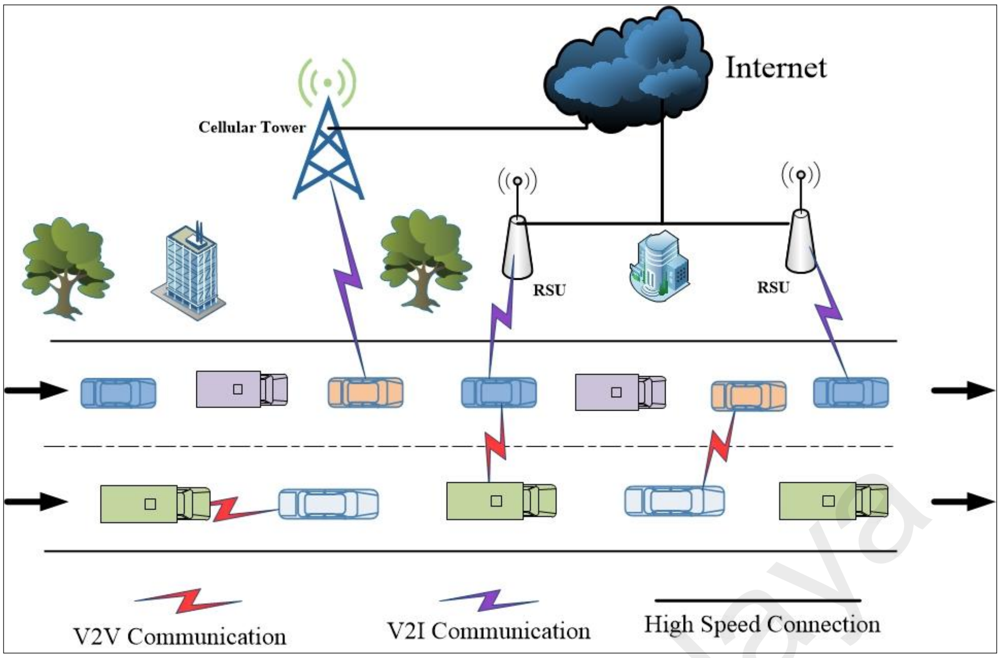

Figure 2.1: Concept of VANET

The figure above depicts a typical VANET communication scenario. V2V and V2I communication was designed to use IEEE802.11p standard to support the physical (PHY) and media access control (MAC) layers. The standard was meant to support vehicles moving at high speed (Jafari, Al-Khayatt, & Dogman, 2012). In addition, Wireless Access in Vehicular Environment (WAVE) standard was proposed to standardize both lower and upper layer protocols (Teixeira, e Silva, Leoni, Macedo, & Nogueira, 2014). Furthermore, 75 MHz is allocated at 5.9 GHz spectrum band for both V2V and V2I communication for Dedicated Short Range Communication (DSRC). WAVE standard and DSRC bands are discussed in details later in this chapter, but first a close look at characteristics of VANET is presented.

2.2.1 Characteristics of VANETs

VANET have unique characteristics that differ from MANET in many ways and have important implications in the design and implementation of the network protocols. These characteristics include driver behaviour on the roads, high vehicle speeds that result in dynamic topological changes and many more. Some of these characteristics include (Al-Sultan et al., 2014; Cunha et al., 2016):

a) Predictable mobility: unlike in MANET where communicating nodes can have random movements, VANET mobility is predictable. The mobility of vehicles on the road is constricted by the road layout and vehicles obey road signs while taking into account other road users. Therefore, it is possible to predict the movement of vehicles on the roads (Mota, Cunha, Macedo, Nogueira, & Loureiro, 2014).

b) No power constraints: most of the nodes in MANET are power constricted. This is not the case with VANET which has no power constraints. The OBU in the vehicle has constant power supply which is continuously recharged by the vehicle. Therefore, VANET applications can accommodate power intense algorithms without much worrying about power supply.

c) Ability for high computation: just like no power constraints, VANET has ability to accommodate a number of sensors that could increase the computational capabilities of the vehicle. In addition, the vehicle can increase the memory capacity and accommodate advanced antenna technology that makes global position system (GPS) more reliable.

d) Variable network density: in VANET, the variation in network depends on vehicle traffic density on the roads. The traffic density varies during the time of the day and location. For example, during rush hours there is high traffic density in urban environments compared to suburban regions. Therefore, there could be large network formed in urban areas compared to suburban areas.

e) Rapid changes in network topology: due to vehicle speed, VANET topologies are likely to be short lived. This is especially true if vehicles are moving in opposite direction. In addition, the driver behavior contributes to changes in the networks as they react to data received from the network.

2.2.2 Dedicated Short Range Communication (DSRC)

The DSRC standard was the first protocol developed to support vehicular communication in 1999 (Jiang et al., 2006). The Federal Communication Commission (FCC) allocated 75 MHz radio frequency at 5.9 GHz band for V2V and V2I exclusive use. The 75 MHz is divided into 7 channels as shown in Figure 2.2.

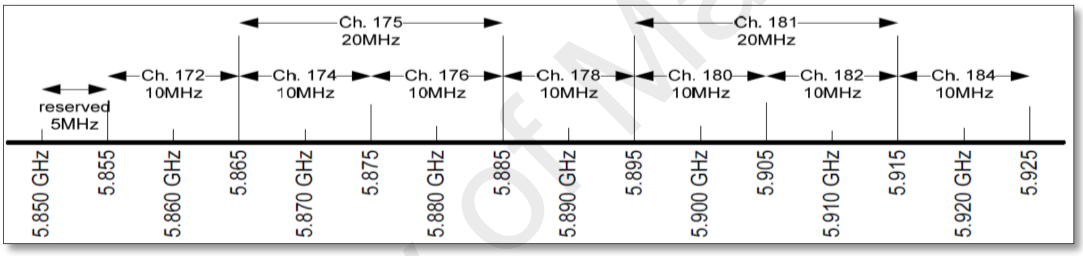

Figure 2.2: DSRC spectrum band and channel allocation (Kenney, 2011).

The first lower 5 MHz of 75 MHz band is reserved as guard band as shown in Figure 2.2. The other 70 MHz is divided into 7 channels with 10 MHz bandwidth each. The center frequency 5.890 GHz corresponding to channel 178 is designated as the control channel (CCH). The CCH is restricted to transmitting safety related messages only. The other six channels are called service channels (SCH) and can be used by both safety and non-safety applications. Sometimes two channels can be combined into 20 MHz channel as shown in Figure 2.2 to increase bandwidth. The seven channels are adequate to support vehicular communication as anticipated because the number of vehicles connecting to each other is currently very low. However, as the number of connected vehicles increase, there will be need to extend the DSRC channels beyond seven. Several research has shown that in the presence of heavy traffic jams during pick hours and during accident scenarios, the seven channels are not adequate to serve vehicular communication (Brahmi, Djahel, & Ghamri-Doudane, 2012; Hafeez, Anpalagan, & Zhao, 2016; Hartenstein & Laberteaux, 2008). Thus, dynamic spectrum access has been proposed as the alternative mechanism to increase channel capacity for VANET during congestion (see Section 2.3). A comprehensive review on DSRC is presented by (Kenney, 2011). A brief discussion of WAVE standard is given next.

2.2.3 Wireless Access in Vehicular Environment (WAVE)

The WAVE standard was developed to standardize DSRC protocol across VANET applications from developers (Y. J. Li, 2010). Therefore, WAVE combines the lower and upper networking layers into one standard protocol. The lower layers (i.e. PHY and MAC) are defined by IEEE802.11p while the upper layers are defined by the IEEE1609.X family (X relates to number i.e. IEEE1609.1, IEEE1609.2 etc). The upper layers include network, transport and application. In addition, the IEEE1609.X family coordinates management of communication among layers and provides security (IEEE, 2016). The WAVE protocol suite is illustrated in Figure 2.3 below.

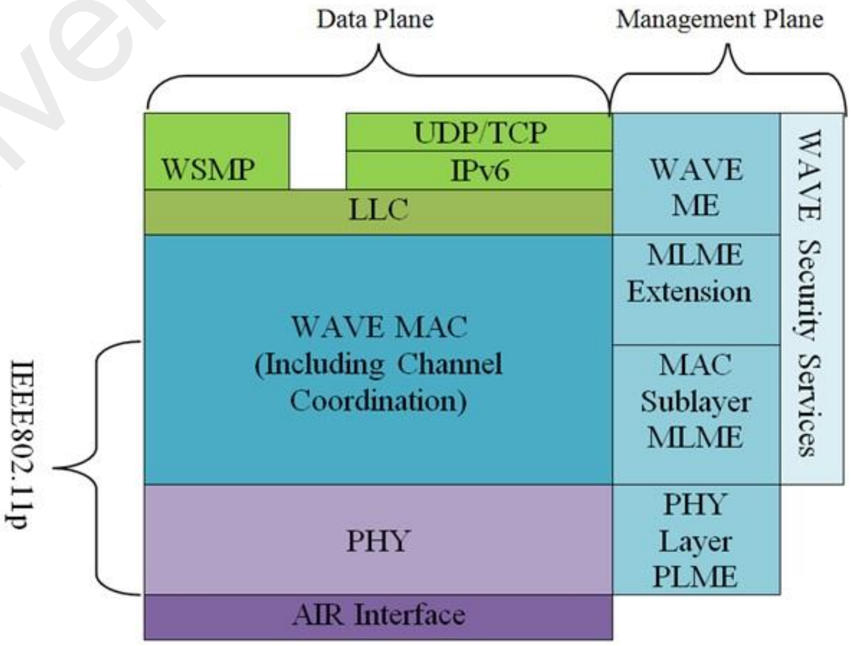

Figure 2.3: WAVE protocol suite (IEEE, 2016)

The lower layers PHY and MAC of IEEE802.11p are based on IEEE802.11a and IEEE802.11e respectively with some modification to support vehicular speed of about 200km/h (Jafari et al., 2012). The PHY layer of IEEE802.11p has adopted IEEE802.11a based on Orthogonal Frequency Division Modulation (OFDM) to support different data rates and operate on the 10 MHz channels in the 5.9GHz frequency band. On the other hand, the MAC layer adopted IEEE802.11e enhanced distributed channel access (EDCA) which support quality of service (QoS) (Miao, Djouani, Van Wyk, & Hamam, 2013). Based on EDCA, there are about four priority categories assigned to different VANET applications (Yao, Rao, & Liu, 2013). The categories are associated with emergency information, speed information advertised by vehicles, information requesting help from neighboring vehicles and non-safety information.

The upper layers of WAVE standard protocol stack are shown in Figure 2.3. The Management Plane defines the WAVE Management Entity (ME) to support networking services defined by IEEE1609.3 standard. The interaction between upper and lower layers is facilitated through the Physical Layer Management Entity (PLME) and MAC Layer Management Entity (MLME) in conjunction with the Link Layer Control (LLC) interface. In addition, the Management Plane is responsible for supporting rapid exchange of messages with strict delay requirement through the WAVE Short Message Protocol (WSMP). The other messages which have tolerant to delay such as non-safety messages are handled by UDP/TCP IPv6. A thorough review of VANET access technology has been presented by (Atallah, Khabbaz, & Assi, 2015).

The WAVE standard protocol and DSRC spectrum band indicate potential to support VANET applications for both V2V and V2I communication. Currently there are lots of wireless applications being developed for VANET. Therefore, the DSRC channels will not be adequate to support such applications especially during high vehicle density.

Hence, many mechanisms have been proposed to improve the DSRC channels to support emerging technologies (Samara & Alhmiedat, 2014; Zang et al., 2007). The research trend is to separate traffic into groups and assigning priority to those groups. Safety applications are given high priority while non-safety applications are given low priority. Nevertheless, in high vehicle density congestion is inevitable and such approach still fails as delay is increased and safety applications suffer despite getting high priority (Z. Wang & Hassan, 2008). Therefore, another mechanism of increasing channel capacity of DSRC bands to accommodate the increasing number of application being developed for VANET is needed. One of the solutions to increase channel capacity of DSRC bands to support growing number of VANET applications is through dynamic spectrum access which is discussed next.

2.3 Dynamic spectrum access

The traditional way of allocating radio spectrum frequency is on a fixed basis to avoid interference from competing technologies. Government agencies have mandate to allocate spectrum band from 3 kHz to 300 GHz for different use (Levin, 2013). Notably, the radio spectrum band can be assigned as licensed with exclusive use, licensed and shared or unlicensed for any organization with new technology to use (Berlemann, Dimitrakopoulos, Moessner, & Hoffmeyer, 2005). In the first category, the licensed user has exclusive right to use the allocated spectrum band within a defined geographical area without interference from other users. Examples of licensed spectrum with exclusive usage include Television (TV) broadcast bands and Universal Mobile Telecommunication System (UMTS) band. In the second category sometimes called command-and-control, licensed users can share the spectrum under specific conditions (Buddhikot, 2007). Changes to spectrum use require public comments. Examples of shared licensed spectrum include DSRC bands and Digital Enhance Cordless Telecommunication (DECT) bands (Berlemann et al., 2005). The third category unlicensed spectrum sometimes called Industrial, Scientific and Medical (ISM) bands is free for any organization to use without a license bidding its usage. The examples of technologies which operate in unlicensed spectrum bands include Wi-Fi, Microwave Oven, Bluetooth, etc.

The fixed allocation of radio spectrum bands has resulted in some radio frequency heavily utilized like the ISM bands because of many competing technologies using the bands while other spectrum underutilized such as the licensed bands (McHenry & Steadman, 2005). This has created what is termed as artificial spectrum scarcity. There have been numerous measurement campaigns around the world which have shown this phenomenon of artificial spectrum scarcity (Simon Daniel Barnes, Botha, & Maharaj, 2016; S Daniel Barnes, Van Vuuren, & Maharaj, 2013; Cardenas-Juarez, Diaz-Ibarra, Pineda-Rico, Arce, & Stevens-Navarro, 2016; Jaber, Aripin, & Salaim, 2013; Patil et al., 2011; Shaikh, Shah, Zafi, Ejaz, & Anpalagan, 2016; Valenta et al., 2010). Figure 2.4 illustrates such measurement campaign conducted in Vienna, VA (18km from Washington DC).

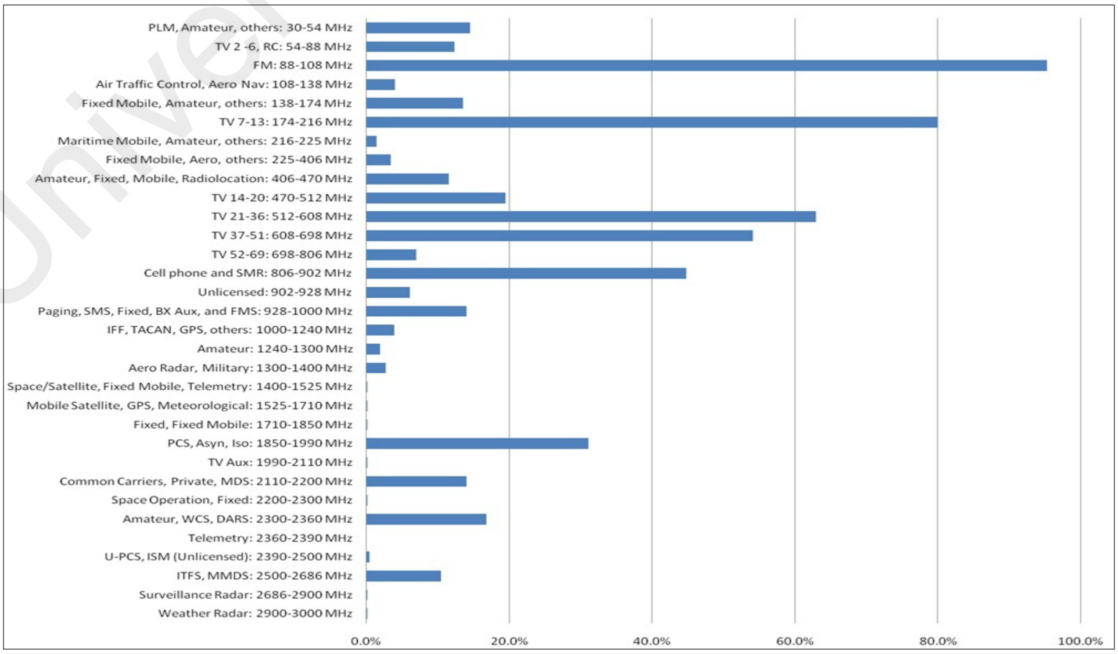

Figure 2.4: Measurement campaign for spectrum occupancy in Vienna, VA (18km from Washington DC) (Survey, 2010)

As noted from the figure above, there are some spectrum bands which have usage of over 60% while other bands have usage of almost 0%. The current fixed spectrum allocation policy prevents technologies from operating from one frequency band to another. However, the new trend has shifted to dynamic spectrum access (DSA).

DSA is a concept in which unlicensed users are allowed to access channels of licensed spectrum bands provided no harmful interference is caused to licensed users. Thus, DSA improves spectrum utilization by using underutilized channels from licensed bands. The licensed users are usually called Primary Users (PU) while the unlicensed users are termed as Secondary Users (SU). The network formed by PU is called primary network such as TV broadcasting network while secondary network is formed by SU. An example of the secondary network is wireless regional area network (discussed in the next Section). In the primary network, the PU has exclusive right to the licensed channels while the SU only use the PU channels in the absence of the PU. This is done to avoid interference. Before the spectrum from licensed bands can be used, SU needs to sense the licensed channels for any PU signal. Only when the channels from primary network are found to be free can the SU use the PU channels. Another way to acquire spectrum bands from licensed users is through spectrum databases proposed by the FCC (presented in Section 2.3.2). The enabling technology for DSA is cognitive radio which is based on software defined radio (discussed in Section 2.4).

2.3.1 Wireless regional area network based on DSA

The wireless regional area network (WRAN) was proposed in 2004 and amendments were made in 2011 to be standardized as IEEE 802.22 WRAN (Pyo, Zhang, Song, Zhou, & Harada, 2012; Stevenson et al., 2009). The standard was established to allow unlicensed devices to use vacant TV bands (TV white spaces) through DSA. The choice of TV bands was necessitated because TV frequencies have ideal propagation characteristics with wide cover area that would permit services to reach far places such as rural areas (Pyo et al., 2012). The WRAN transmission range can cover a wide area of between 20km to 30 km operating in the TV broadcast frequency bands between 54 MHz and 862 MHz with channel bandwidth of 6MHz (Popescu, Fadda, & Murroni, 2016). Therefore, the intended application of the WRAN is accessing wireless broadband in remote areas while maintaining performance which is comparable to other broadband technology such as cable modems (Y.-C. Liang, Hoang, & Chen, 2008). The only difference is that devices in WRAN will not be licensed when operating in the TV bands hence reducing the cost (Corderio, Challapali, Birru, & Shankar, 2006). Nevertheless, devices in WRAN must include cognitive radio features which must protect incumbent TV users from any interference. Therefore, one of the most crucial requirements for the IEEE802.22 air interface is adaptability and flexibility to operate in shared spectrum with TV users who should have maximum protection.

The communications in the WRAN standard is on the fixed-point basis in which the Base Station (BS) communicates to Consumer Premise Equipments (CPE). Thus, the BS coordinates all spectrum management including spectrum sensing and scheduling of operations. Therefore, the proposed IEEE802.22 WRAN PHY and MAC layers were designed to incorporate cognitive radio functions to manage spectrum utilization. The PHY is based on OFDMA scheme while the MAC is based on connected-oriented in which the BS coordinates all the connections (Cordeiro, Challapali, & Ghosh, 2006). The concept of WRAN has been extended to VANET in which the BS can be any RSU to coordinated spectrum management. In that sense, the FCC proposed establishing spectrum availability databases of free licensed channels that can be accessed by unlicensed devices through infrastructure support. We discuss spectrum availability database next.

2.3.2 Spectrum availability databases

The success of DSA will depend on protecting licensed users from interference that may emanate from devices of unlicensed user. Therefore, the FCC proposed creation of spectrum availability database of TV White Spaces (TVWS) and microphone bands that can be used by unlicensed users. TVWS represent vacant TV bands that can be used for DSA (FCC, 2010). The spectrum availability database can be created by any organization mandated by the government agencies that regular radio spectrum in the country. In United States for example, one of the organizations that have taken role in creating spectrum availability databases includes Google (Google, 2017). To access the TVWS spectrum availability database, the FCC proposed three kinds of devices. In VANET, the three devices were translated into ModeI, ModeII and sense-only vehicles (Di Felice, Ghandhour, Artail, & Bononi, 2013; FCC, 2010). Figure 2.5 depicts these devices.

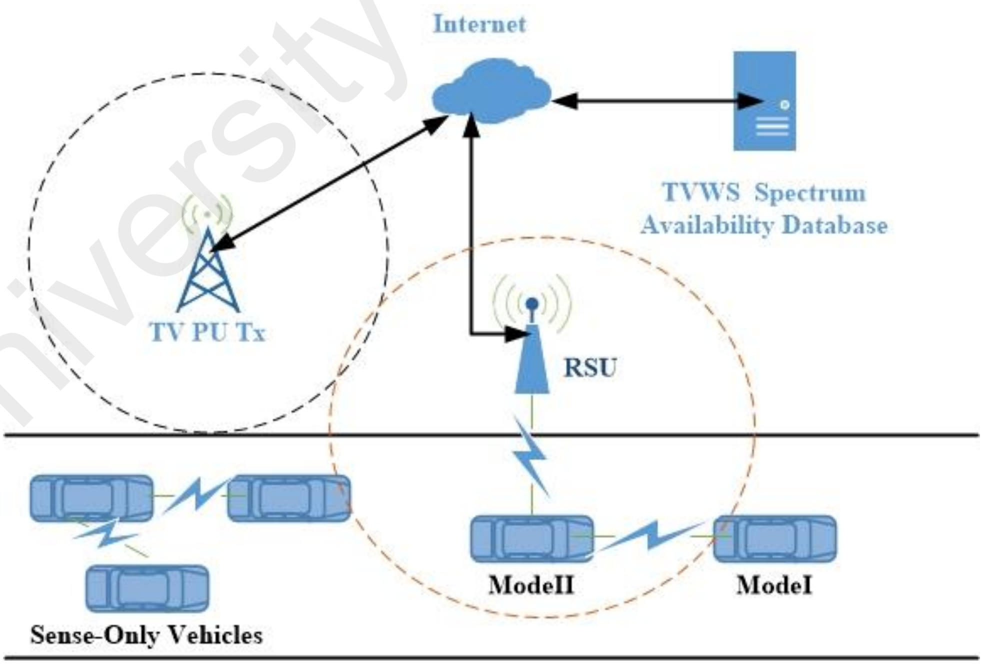

Figure 2.5: Vehicle operation mode to access the TVWS

ModeII vehicles are equipped with capabilities to access the TVWS spectrum availability database through road side infrastructure such as Cellular Towers along the highway. Alternatively, the database can be accessed through satellite connections as ModeII vehicles are presumed to be equipped with geo-location capabilities such as Geographical Position System (GPS). Nevertheless, ModeII vehicles are required to check the database every 60 seconds or when a vehicle moves 100 meters from its current position (FCC, 2010). ModeI vehicles acquire TVWS through ModeII vehicles using DSRC channels because they don't have capabilities to access the database directly. The last mode sense-only involves vehicles that perform cooperative spectrum sensing to decide on the occupancy state of the PU signal before accessing the TVWS in the absence of infrastructure support or ModeII vehicles.

Creating TVWS databases and frequently updating it increase protection to PUs. However, the database approach has its own shortcomings. Firstly, not all vehicles are equipped with capabilities to access the database on the Internet currently. Therefore, ModeI vehicles could large rely on ModeII vehicles which could pose access problem when ModeII vehicles are outside communication range. Secondly, frequently querying the database can create query bottleneck at the RSU especially during traffic jams in high vehicle density (Bedogni, Di Felice, Trotta, & Bononi, 2014; Cacciapuoti, Caleffi, & Paura, 2016; Gao, Park, & Yang, 2014). Thirdly, the GPS access method is not reliable as demonstrated by (Kremo, Vuyyuru, & Altintas, 2012). The mobility nature of vehicles and weather pattern can affect the operation of the GPS which can result in getting channels for wrong places. There have been efforts to circumvent some of these challenges outlined above. For example, (Cacciapuoti et al., 2016), (Altintas et al., 2016) and (Di Felice et al., 2013) propose an optimal ratio that allow cooperative sensing and accessing the TVWS database. (Di Felice et al., 2013) suggest a swarm-intelligence approach that allows vehicles to decide the type of mode to use based on the vehicle traffic condition. The assumption is that this approach could mitigate the congestion problem when querying the database and maximize reuse of spectrum resources. (Doost-Mohammady & Chowdhury, 2012) formulate analytical framework guidelines for placing RSU to access TVWS database. Another approach of acquiring TVWS is through queuing theory which is discussed next.

2.3.3 Queuing theory for DSA

Another approach in acquiring free licensed spectrum for DSA is by using queuing theory at the RSU. Many queue theories for DSA in VANET environment have been proposed (Bozkaya & Canberk, 2015; M. Khabbaz, Assi, & Fawaz, 2014; M. J. Khabbaz, Assi, & Ghrayeb, 2013). The basic idea is to create database of licensed channels and store them in the database at the RSU locally. This is opposed to TVWS Spectrum Availability database discussed previous which is populated by different organization and accessed on the Internet. In the queue theory a vehicle will request for channels to communicate on upon entry in the region covered by the RSU. If there is any channel available it would be served to requesting vehicle otherwise the request is queued. The RSU assign channels to vehicles on the first come first served basis and no priority is given to any vehicle. The drawback to this approach is that performance of the network degrades during high traffic density. Thus, (Bozkaya & Canberk, 2015) further suggest multi-channel selection algorithm instead of single-channel selection. Through simulation results they showed that multi-channel selection maintained network connectivity which outperformed single-channel selection.

TVWS spectrum availability databases and queuing theory has been proposed to protect incumbent licensed PU. Nevertheless, the spectrum availability database approach is currently not feasible because there are very few vehicles with Internet capabilities that could act as ModeII and access the database. In addition, placement of the RSU along the road to provide access to databases is costly and not straight forward as demonstrated by (Doost-Mohammady & Chowdhury, 2012). Conversely, the queue theory is not optimal because many vehicles could be deprived of accessing spectrum opportunities in high vehicle density. Spectrum sensing is the alternative approach to these two spectrum access methods for acquiring vacant licensed channels for DSA. Spectrum sensing which forms part of the three modes to access TVWS proposed by FCC (see Figure 2.5) entails identification of free spectrum opportunities in licensed bands. Spectrum sensing relies on the functionalities of a cognitive radio which is discussed next.

2.4 Cognitive radio technology

In a tradition radio technology system, transmission parameters such as modulation and coding are embedded in the hardware. This is facilitated to avoid interference when accessing different radio frequencies (Kapoor, Rao, & Singh, 2011). The new trend in radio technology has shifted to software define radio (SDR) (Del Re, 2012). A SDR is a radio technology which decouples hardware functionalities from software. Thus, radio functionalities and transmission parameters such as modulation, signal coding, filters, amplifiers are implemented in the software opposed to implementing in the hardware in case of traditional radio. This implies that the SDR can reconfigure the radio parameters to adhere to the wireless network environment. Therefore, SDR can operate in different radio frequencies depending on the network specifications. A cognitive radio (CR) adds intelligence to the SDR. Figure 2.6 shows the comparison among these radio technologies

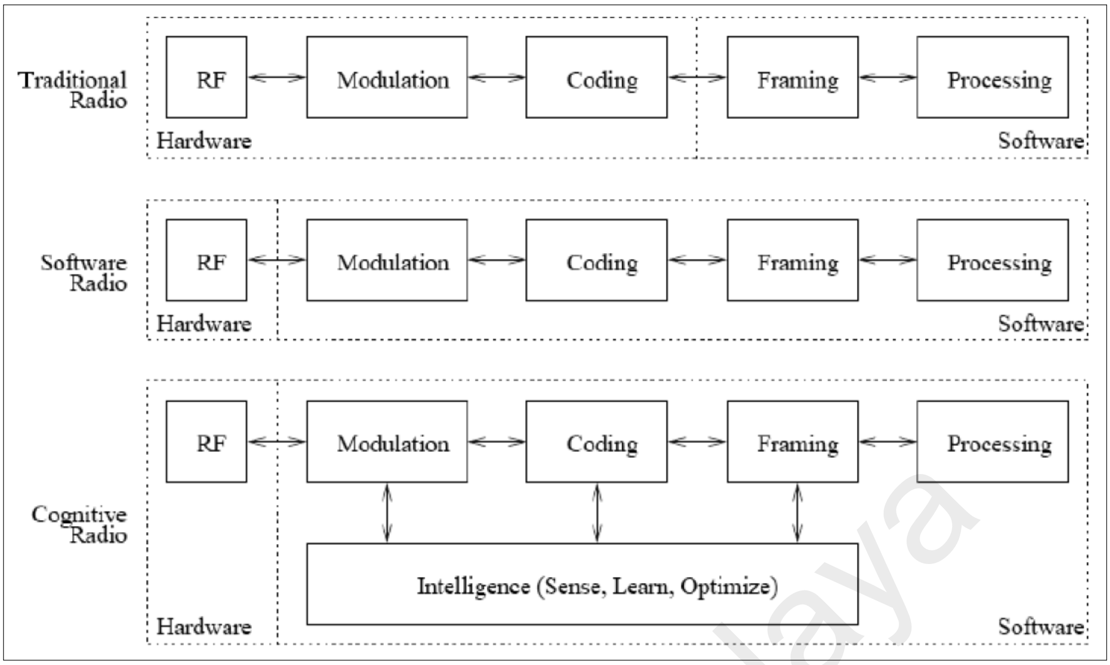

Figure 2.6: Comparison of radio technologies (Kapoor et al., 2011)

The CR technology has a profound impact on the way radio spectrum will be accessed in the future. The reconfiguration ability will allow spectrum reusability which is cardinal since radio spectrum is a finite resource (Silva, Nogueira, Kim, Cerqueira, & Santos, 2016). While there is no official definition of the CR, informally the CR is defined as a radio system that sense the radio spectrum and adjust its operation parameters based on the radio environment (Mitola & Maguire, 1999). This implies that the CR can operate across different range of radio frequency bands to meet the demand of the users. Furthermore, the CR allows for rapid reconfiguration of network parameters because it is done in the software. Rapid reconfiguration is important in VANET to maintain steady communication among vehicles moving at high speed. Therefore, CR technology is appropriate for VANET (Silva et al., 2016). The operation life cycle of the CR system is presented next.

2.4.1 CR operation cycle

The CR cycle consists of spectrum sensing, spectrum mobility, spectrum decision and spectrum sharing as shown in Figure 2.7 below. The main objective of the CR is to identify spectrum opportunities and utilize those opportunities to satisfy the communication needs of the users. Spectrum opportunities are sometimes referred to as spectrum holes (Haykin, 2005). A spectrum hole is a free channel that can be used for DSA such as vacant TV bands. Thus, the CR needs to sense the radio spectrum for any free spectrum holes before transmitting on them.

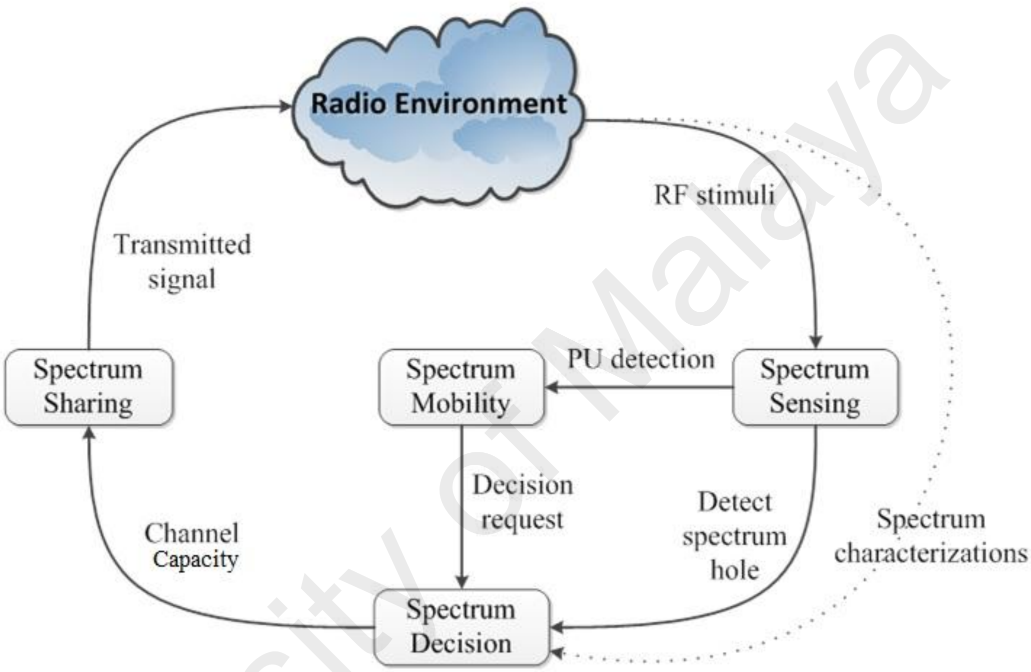

Figure 2.7: Operation cycle of the CR (Akyildiz et al., 2006)

The operation stages of the CR are elaborated in the following.

2.4.1.1 Spectrum sensing

Spectrum sensing is an important and fundamental stage in any wireless network based on cognitive radio technology. Spectrum sensing stage involves identification of idle licensed spectrum bands that can be used by unlicensed users through DSA. Accurate spectrum sensing results are important to help in protecting licensed users from interference. The success of DSA will largely depend on incumbent licensed users' willingness to tolerate interference from unlicensed user devices that are accessing their channels. Therefore, spectrum sensing techniques must be efficient and accurate in detecting the PU signals. There are two types of approach used in spectrum sensing (B. Wang & Liu, 2011). The first is interference based detection and second is primary transmitter detection.

a) Interference based detection: This approach allows SUs to operate in licensed frequency bands by detecting the PU receivers. There are two methods used in interference based detection which include temperature detection and primary receiver detection. Temperature detection allows SUs to coexist with PUs simultaneously by limiting the interference temperature. The SU control their interference by regulating their transmission power not to exceed some threshold by setting upper limit prescribed by regulators. The upper limit sets the amount of interference the PUs can tolerate. In the primary receiver detection method, the SU acquire spectrum opportunities by measuring the local oscillator (LO) leakage power of the PU receiver to determine its presence. The LO leakage power is emitted by the Radio Frequency (RF) front end of the PU receiver as it gets data from the PU transmitter. Both temperature and receiver based sensing require the SU to be in close proximity to the PU receivers to detect the spectrum opportunity. Due to mobility nature of vehicles, these methods are seldom used in the VANET environment because a vehicle will move from one place to another where different PU receivers may exist.

b) Primary transmitter detection: in this method, the SU detect the PU transmitter weak signal to determine the occupancy state. There are three methods commonly used in primary transmitter detection. The first is energy detection in which the SU measures the signal power at the receiver and compares it to some threshold. If the received power is above the threshold, the SU infer presence of the PU signal and does not transmit on that channel. On the other hand, if the received power signal is less than the threshold, the SU will decide absence of the PU and transmission can be performed on the PU channel. The second approach for primary transmitter detection is matched filter detection. This approach requires a perfect knowledge of the PU signal before sensing is done. The third approach is cyclostationary feature detection. Each of these approaches has its strength and weakness. Cooperative spectrum decision is used to mitigate some of the weakness of each. In cooperative decision SUs use spatial and diversity gain to decide on the PU spectrum occupancy state.

In VANET, primary transmitter detection is the commonly used approach to detect the PU signals to acquire spectrum opportunities. Therefore, in this thesis, primary transmitter detection is used. Spectrum sensing is the core of this thesis. Therefore, problems associated with spectrum sensing and review of spectrum sensing techniques in VANET is presented in Chapter 3.

2.4.1.2 Spectrum decision

Spectrum decision is another important stage in cognitive radio cycle which involves SUs deciding on the spectrum bands determined to be free and how to access them. The decision is based on the QoS requirement of the SU and channel characteristics as well as operations of the primary network (Akyildiz et al., 2008). As shown in Figure 2.7, the radio environment under consideration plays an important role in characterizing the observed spectrum as it influences the channels on which the SU can communication. After spectrum characterization, the SU chose the appropriate spectrum band that meets its QoS and reconfigure the network parameters to conform to the selected frequency band.

2.4.1.3 Spectrum sharing

Spectrum sharing includes many functions of the MAC layer protocol because of the shared nature of wireless channels (Akyildiz et al., 2008). Furthermore, the coexistence of PU and other SUs in the same frequency bands makes it difficult to share available spectrum among SUs. There are different sharing strategies proposed for SU including centralized, distributed, cooperative and non-cooperative. In the centralized spectrum sharing strategy, a central node coordinates resource allocation and how spectrum is accessed based on the needs of individual SU. Distributed spectrum sharing allows individual SU to access and allocate spectrum based on the local policy and distribute to other nodes. Cooperative and non-cooperative as the names suggest, SUs cooperate in sharing spectrum resource and no cooperation in involved in the latter.

2.4.1.4 Spectrum mobility

Spectrum mobility sometimes called spectrum handoff refers to an instance when the SU vacant the current PU channel when the PU activities are detected or the quality of the channel has become poor (Akyildiz et al., 2008). Therefore, spectrum mobility relies much on the functionalities of the spectrum sensing algorithm that monitors the activities of the PU and quality of the communication channel. During handoff, protocols associated with different layers of the network should adjust to new parameters of the channel where the SU migrate. In doing this, the spectrum handoff algorithms must take into account the current communication and the QoS need of the SU. Nevertheless, momentary break in communication is inevitable as the SU migrate to new channels. Therefore, spectrum handoff management schemes must be efficient to manage the associated latency introduced to guarantee smooth and fast transition that could minimize performance degradation.

2.4.2 Benefit of CR technology in VANET

The development of vehicular applications which demand more bandwidth cannot be overlooked as studied by (Ghandour, Fawaz, & Artail, 2011). In addition, the advent of Internet of Thing (IoT) will bring about more applications that will mainly be transmitted through wireless medium thereby putting more constraint on the radio spectrum which is finite (Gubbi, Buyya, Marusic, & Palaniswami, 2013). Thus, increase in production of vehicles with capabilities to communicate wirelessly through VANET will result in congesting the DSRC channels during high vehicle traffic jams. As a result new means to increase DSRC channels to accommodate new bandwidth intense application is needed. This is where the CR technology comes in with the following benefits:

a) *Satisfying QoS needs through provision of more channels:* delivery of delay sensitive messages such as safety and emergence within a short period of time is important in VANET. However, during congestion in the DSRC channel it is difficult to guarantee delivery of such messages (Z. Wang & Hassan, 2008). In this regard, a CR could be used to obtain extra channels from licensed bands such as vacant TVWS to supplement DSRC channels. The additional channels can be used to transmit low priority messages which in turn will decongest the DSRC channels. Extra channels would increase the chance of delivering both safety and non-safety applications.

b) *Supporting heterogeneous networks through common interface:* one branch of IoT is Internet of Vehicles (IoV) which involve interconnection of vehicles in VANET environment (Nitti, Girau, Floris, & Atzori, 2014). IoV envision many radio technologies operating together using different radio frequencies (Fangchun et al., 2014; N. Lu, Cheng, Zhang, Shen, & Mark, 2014). Some of the radio technologies include IEEE802.11p operating on DSRC bands, Bluetooth and WiFi using the ISM band, Long Term Evolution (LTE) technologies for cellular infrastructure and many more. These radio technologies require an interface that allows collaboration and exchange of different data packets. CR technology could provide such a platform to allow interoperability of diverse technologies to operate in unison in IoV. This is because the CR is sensitive to the environment and can reconfigure the network parameters based on the network needs.

c) *Support for radio spectrum reusability:* measurement campaign and experimental studies such as that conducted by (Pagadarai, Lessard, Wyglinski, Vuyyuru, & Altintas, 2013) demonstrate free and abundant vacant TVWS along the highways. Therefore, CR can exploit the vacant TVWS through DSA to increase channel capacity for vehicular communication thereby maximizing usage of the TV spectrum channel. In addition, CR can explore and discover other free licensed channels that can be used for vehicular communication.

d) *Radio hardware upgrade reduction:* with the traditional radio, any changes to radio technology such as operating frequency bands require upgrades to the hardware itself because network parameters such as modulation and coding are imbedded in the hardware. However, when using the CR technology there is no need to upgrade the hardware upon changing the radio frequency only upgrading the software to accommodate the new technology. This is because CR separate software and hardware implementation. Moreover, CR is capable of reprogramming to operate in new environment without changing the underling hardware architecture.

2.5 Chapter summary

This chapter has discussed the background literature necessary to understanding communication in vehicle ad hoc networks and dynamic spectrum access.

Understanding VANET communication is important to conceptualize how spectrum sensing will be performed. In addition, DSA depend on cognitive radio technology to identify licensed channels for opportunistic usage. Hence, introduction to both DSA and CR technology is important and it has been presented in this chapter. Spectrum sensing in a cognitive vehicular network environment is affected by many factors. High mobility of vehicles on the road is the main contributing factor which gives rise to other challenges. Spectrum sensing in vehicular networks is the main objective of this thesis and therefore the next chapter presents a detailed discussion of spectrum sensing, problems associated with spectrum sensing and some of the proposed mechanisms to mitigate them.

CHAPTER 3: PROBLEM ANALYSIS

3.1 Introduction

Spectrum sensing is one of the components in the cognitive radio (CR) operational cycle. It plays a fundamental and vital role in CR function on which the whole concept of dynamic spectrum access (DSA) is based. The fundamental role is detecting free radio frequency bands in licensed channels which can be used by vehicles on the roads whenever there is congestion in DSRC channels. Spectrum sensing still faces many challenges especially in VANET environment. In this chapter the challenges are discussed with attempted mechanism to solve them. Thus, the chapter is organized into five sections. In Section 3.2 challenges associated with spectrum detection in VANET environment are presented. Specifically, challenges associated with speed of vehicle, multipath and shadowing fading, hidden primary user (PU) problem and effect of PU activities are discussed. In Section 3.3 a comprehensive discussion of conventional spectrum sensing with associated challenges is given. While spectrum sensing using conventional techniques is susceptible to mentioned challenges, cooperative decision mitigates most of them. Therefore, in Section 3.4 cooperative spectrum decision approaches are presented with proposed algorithms for cooperative decision and their shortcoming is also presented. In addition, the section briefly introduces machine learning approach. Machine learning is used as part of the proposed framework in Chapter 4. And finally Section 3.6 concludes the chapter.

3.2 Analysis of spectrum sensing in VANET environment

The performance of spectrum sensing in vehicular networking environment is dependent on many factors. VANET environment is subject to unique properties which are not found in other networks. For example, vehicles as communicating nodes have high mobility which results in dynamic network topology as density of vehicle change. This in turn affects the sensing performance especially in cooperative decision which is dependent on density of vehicles to decide the PU occupancy state. Furthermore, spectrum sensing results are affected by multipath channel fading, shadowing of PU signals, hidden PU problem and activities of the PU system under consideration. In this section, the above issues are analyzed in details and how they affect spectrum sensing in VANET.

3.2.1 Effect of vehicle speed on sensing performance in VANET

Communicating nodes in VANET move at moderately high speeds in contrast from nodes in other wireless networks such as MANET. Consequently, spectrum opportunities should be detected and utilized within a short period of time. To illustrate how speed of vehicle affects sensing performance and DSA consider Figure 3.1.

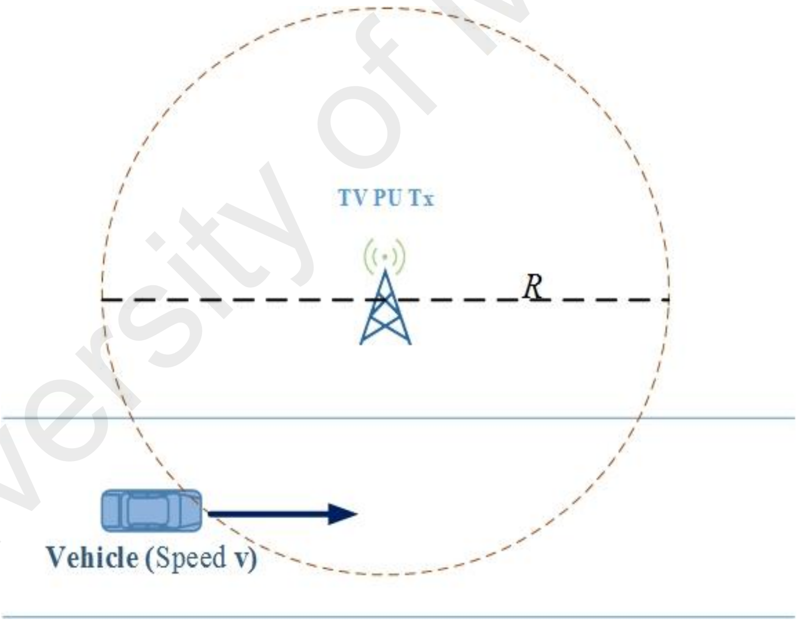

Figure 3.1: Spectrum opportunity under PU coverage R

When a vehicle needs a channel for communication through DSA in a region covered by the PU as shown in Figure 3.1, spectrum sensing must be performed within a short period of time. If the sensing period is S_t and required transmission duration is T_t, then a vehicle with velocity (v) must sense and transmit on desired licensed channel within time (T_{PUOFF}) when the PU is idle. Thus, $T_{PUOFF} \geq (S_t + T_t)$. This will enable the vehicle to fully utilize the channel if unoccupied and avoid any interference to the PU system. Nevertheless, S_t and T_t are dependent on the transmission range (R) of the PU transceiver, the velocity (v) and direction of the vehicle (Rawat et al., 2015). Hence, in order to utilize the spectrum opportunities within PU coverage range (R) and provide minimum interference to the PU activities, the following condition should hold:

$$v(S_t + T_t) < R \qquad 3.1$$

Subject to $T_{PUOFF} \geq (S_t + T_t)$. The direction and velocity of the vehicle will determine the maximum possible duration when the vehicle will be within the PU coverage area (R). Therefore, when a vehicle is moving with high speed, the likelihood of getting out of R is high resulting in missing spectrum opportunities (Rawat et al., 2015; Yanxiao Zhao, Paul, Xin, & Song, 2014). To maximize utilization of spectrum opportunities, a vehicle should quickly perform spectrum sensing and correctly determine the PU occupancy status in an efficient manner. Quick sensing entails collecting few PU signal samples to be used in determining the PU occupancy state. Depending on the sensing technique used, collecting few sensing samples increases false alarm opposed to increasing detection (see Section 3.3.1) which is the ultimate goal of a sensing technique.

The challenge is to balance the trade-off between fine (long) sensing and quick sensing for vehicles moving at high speed in VANET environment. Fine sensing is performed to allow the secondary user (SU) collect more samples of the PU signal thereby increasing detection accuracy (Shah & Akan, 2015). Accurate detection of the PU signal is desired in DSA to avoid interference to the PU system. However, in VANET the speed of vehicles is a disadvantage for fine sensing, because a vehicle is likely to move into multiple different areas before PU occupancy state is determined.

The different areas may have different PU characteristics. Therefore, quick sensing is preferred in VANET environment (Qian & Hao, 2014).

The speed of the vehicle has another negative impact on the performance of spectrum sensing, especially when the vehicle performs sensing individually. The moving vehicle experience Doppler effects that cause signal fading and shadowing resulting in uncertainties in noise levels (Alam, Balaei, & Dempster, 2011). In addition, due to limited cooperation between the vehicle and the PU system, the information regarding the PU signal characteristics and the channel state information (CSI) of the entire PU system is usually unavailable to the vehicles. On the other hand, the speed of the vehicle has positive impact on cooperative spectrum decision (De Nardis et al., 2012; Min & Shin, 2009). The cooperating vehicles exploit the spatial-temporal diversity in the received signal strength (RSS) to perform cooperative decision. Regardless, the sensing performance is also dependent on the direction and speed of the cooperating vehicles.

The speed of vehicles and its effect on spectrum sensing performance has not been fully studied in literature for both individual sensing performance and cooperative decision (Chembe, Noor, et al., 2017). Therefore, in this work, we exploit the benefit of speed and direction to study its effect on cooperative sensing decision. And thereafter devise a sensing framework that increases performance of spectrum sensing in the VANET environment.

3.2.2 Effect of multipath fading on sensing performance in VANET

Multipath fading refers to phenomena in which a signal arriving at the receiver follows two or more paths. It is also called small scale fading in which propagation loss happens over short distances. Multipath fading occurs in any terrestrial environment which experience multipath propagation coupled with bit of movement in radio communication system (Gozalvez, Sepulcre, & Bauza, 2012). Examples of terrestrial environments that cause multipath fading include mountainous areas, tall buildings and reflective environment such as water bodies. In addition, movement in either the transmitter or the receiver will induce a time varying Doppler shift on multipath components thereby resulting in random frequency fluctuation (Eichner, Maschlanka, Meuleners, & Degen, 2015). This is true especially in VANET environment where communicating nodes (vehicles) with transceivers move at high speed. Hence, multipath fading cause distortions in communication radio signal at the receiver.

Therefore, multipath fading has an effect on the performance of spectrum sensing in the VANET environment. Vehicles as sensing nodes are subjected to different terrestrial obstacles as they move on the roads. In addition, other vehicles on the roads add to the obstructions. These diverse obstacles introduce multipath fading, which affect sensing performance in urban, suburban and on highway environments differently (Meireles, Boban, Steenkiste, Tonguz, & Barros, 2010). The obstacles scatter the original PU signal received by sensing vehicles, thereby affecting the accuracy of sensing results. In such circumstances, realistic propagation models must be considered which capture the effects of multipath fading. In principal the fading environment can be modeled probabilistically. Experimental results have shown that the probability models can represent the real fading environment realistically (Hafeez, Zhao, Liao, & Ma, 2009; He et al., 2014; Mecklenbrauker et al., 2011). The propagation models widely used in VANET environment include Rayleigh, Rician, Nakagami and Weibull. Detailed description of these propagation models follows.

a) Rayleigh propagation model

The Rayleigh fading describes the form of fading which happen when the signal reaches the receiver from multiple paths. In this type of fading, there is no distinct signal path that dictates the other paths (Abo-Zahhad, Farrag, & Ali, 2016).

Therefore, different signals arriving at the receiver side are combined to come up with the overall signal. In some cases, the signals with varying strength will either be in or out of phase depending on the route used. Hence, some signals will add while others will subtract to form the overall signal. Thus, statistical approach is used to analyze the overall nature of the radio communication channel taking the discrepancies into consideration. To model such fading behavior, Rayleigh distribution is used. The probability density function (PDF) of the Rayleigh fading is given below (Skima, Ghariani, & Lahiani, 2014):

$$f_{ray}(x) = \frac{x}{\sigma^2} \exp\left(-\frac{x^2}{2\sigma^2}\right), \; x \geq 0 \qquad 3.2$$

Where x represent the signal envelop transmitted by the source and σ^2 is the average power of the received signal. The Rayleigh propagation model is very useful in modeling the fading environment with no clear line of sight (LOS) component between two transmitting nodes. Hence, it can be used to model the signal between the PU and the sensing vehicles in VANET, where the operational environment experience multipath fading (Qian & Hao, 2015). The model can also be used in conjunction with the energy detector which relies on received power spectral density (PSD) of the PU signal to determine the PU occupancy state.

b) Rician propagation model

The Rician fading describe the propagation model in which one path has a strong LOS component dominating other random weaker signal components (L.-C. Wang, Liu, & Cheng, 2009). The weaker components represent scattered signals arriving at the receiver from random paths caused by reflective and refractive obstacles. There are two important parameters that are used in defining the Rician fading channel which capture both the strong component and the weaker components (Simon & Alouini, 2005). The first parameter is called the K factor which defines the ratio of the signal power in the LOS dominant component over the scattered power of random weaker components. The second parameter defines the total power from both strong LOS component and the scattered signal power components. The K factor has impact on the overall estimation of the PDF of the Rician distribution. This is because the LOS component is likely to be strong compared to the scattered components in short range wireless channels. The PDF of the Rician propagation model is given as (Y. Wang, Zhang, & Liu, 2015):

$$f_{ric}(x) = \frac{K+1}{\gamma} \exp\left(-K - \frac{(K+1)x}{\gamma}\right) I_0\left(2\sqrt{\frac{K(K+1)x}{\gamma}}\right), x \geq 0 \qquad 3.3$$

Where x represent the SNR of the signal envelop from the source, K is the Rician factor, γ represent the average SNR of received signals from both the strong LOS and the scattered components. The component $I_0(.)$ is the modified Bessel function of the first kind and zero order (Jayaweera & Poor, 2005). In VANET environment, the K factor is time-varying which is dependent on the environment were the measurements are taken (Cooper, Mukunthan, Ros, Franklin, & Abolhasan, 2014; Cooper et al., 2015). Thus, the K factor is difficult to measure directly. Nevertheless, it can be estimated from the set of various samples of the channel using different frequencies. Rician fading model can be used in sensing environment which has a strong LOS with few obstacles especially in suburban highways. However, the Rician propagation model performances poorly compared to Rayleigh in the presence of many obstacles with weak LOS component at the receiver.

c) *Nakagami propagation model*

The Nakagami fading is considered to be a generalized fading model that can be reduced to either Rayleigh or Rician fading depending on certain conditions. It occurs when there is multipath scattering of signals with comparatively large time delay spreads with groups that differ in reflected signals (Rehman ur, Khan, &

Zia, 2014; Tarique & Hasan, 2011). When the envelope of the received signal follows the Nakagami distribution, the corresponding instantaneous SNR can be modeled as gamma distribution. The distribution is defined by two parameters (scale and shape) that exploit the Nakagami PDF. The shape parameter also named as m-parameter is called the fading parameter. Using the m-parameter, the Nakagami distribution can model signal fading conditions that vary from severe to moderate, or no fading (Islam, Hu, Onur, Boltjes, & de Jongh, 2013). The PDF of the Nakagami propagation model is given as (Ha, 2010):

$$f_{nak}(x) = \frac{2x^{2m-1}}{\Gamma(m)}\left(\frac{m}{\Omega}\right)^{m} \exp\left(-\frac{mx^2}{\Omega}\right), x \geq 0, m \geq 0.5 \qquad 3.4$$

In equation 3.4, the component $\Gamma(.)$ is the gamma function, $\mathrm{m} = \Omega^2/\mathrm{E}[(\mathrm{x}^2 - \mathrm{x})^2]$ represent the fading parameter while $\Omega = \mathrm{E}[\mathrm{x}^2]$ is scale parameter representing the average received power (Gholizadeh, Amindavar, & Ritcey, 2013). If $\mathrm{m} = 1$, Nakagami distribution reduces to Rayleigh distribution. If $\mathrm{m} = (\mathrm{M} + 1)^2/(2\mathrm{M} + 1)$ with $\mathrm{M} = \mathrm{A}/2\sigma$ in which A is peak amplitude of the signal and σ is received envelop signal, Nakagami is a Rician distribution. When $\mathrm{m} \to \infty$ Nakagami fading is the impulse channel, thus no fading is experienced (Proakis & Salehi, 2008).

Experimental results have shown that Nakagami fading propagation model is a good fit to multipath fading empirical data (Wen, Ma, Zhang, Jin, & Wang, 2012). Thus, it has been proposed as a good fading model for VANET environment (He et al., 2014; Wen et al., 2012). Therefore, Nakagami propagation model can be applied to spectrum sensing in VANET environment. The challenge is to approximate the fading parameter m to suit the sensing environment and the PU under consideration.

d) Weibull propagation model

The Weibull distribution model is another important propagation model that is used in modeling signals in the multipath fading environment. It has been used to model wireless channels in non-homogeneous environments which include both indoor and outdoor (Sofotasios, Fikadu, Ho-Van, & Valkama, 2013). In addition, it is considered as a generalized fading model which is reduced to either exponential or Rayleigh distribution when certain conditions are met (Cheng, Tellambura, & Beaulieu, 2003). The Weibull distribution is shaped by the Weibull fading parameter m and scale parameter Ω. The PDF of the Weibull distribution is given as (Hou, He, Wang, & Yang, 2013):

$$f_{wei}(x) = \frac{m x^{m-1}}{\Omega} \exp\left(-\frac{x^m}{\Omega}\right), m > 0, x \geq 0 \qquad 3.5$$

Where m is Weibull fading parameter, $\Omega = E[x^2]$ is scale parameter defined by the average signal power. If the fading parameter $m = 1$, the Weibull distribution becomes exponential distribution while if $m = 2$ the Weibull distribution reduces to a Rayleigh distribution (Cheng et al., 2003). Some literatures have shown that during spectrum sensing when using energy detector under same conditions, Weibull distribution performs better than other fading distributions (Dalai & Anuradha, 2015; Nallagonda, Roy, & Kundu, 2011). Nevertheless, the challenge is to determine the optimal m value of the fading parameter. Thus some researchers have opted to extend the Weibull distribution with introduction of two shape (m) parameters instead of one (Peng & Yan, 2014). It is also important to note that this distribution is not well studied in the VANET environment.

3.2.3 Effect of signal shadowing on sensing performance in VANET

Shadowing is sometimes called large scale fading in contrast to multipath fading which is considered as small scale fading. Large scale fading is caused by signal attenuation as the signal propagate over long distances and get absorbed, reflected or diffracted around large objects along the propagation path (Abdallah, Sarkar, & Salazar-Palma, 2015; Lavanya, Rao, & Bidikar, 2016). Shadowing is explained by the log-normal distribution of the mean signal power (L. Wang, Wan, & Washington, 2015). The log-normal shadowing model dispenses the received signal power in the logarithmic domain based on the normal distribution. The intensity of the severity of shadowing differs for LOS and NLOS (He et al., 2014; Segata et al., 2013). The shadowing effect is more severe when there is extra blockage in the LOS path between the two transceivers due to large obstacles. Nevertheless, shadowing and path loss affect vehicles communicating over a long distance which can easily be overshadowed in urban environments by multipath fading. In addition, the effects of shadowing can be accounted by multipath fading models. Thus, when spectrum sensing is performed in VANET environment, the multipath fading propagation model used should account for shadowing and path loss.

3.2.4 Effect of hidden PU problem on sensing results in VANET

Multipath fading and shadowing due to obstacles in the urban environment or along the highway can cause deep fading to the PU signal thereby affecting spectrum sensing results. In presence of numerous obstacles (e.g. tall buildings) especially in urban environment deep fading can lead to condition called hidden PU problem (Tchouankem, Zinchenko, & Schumacher, 2015). The concept of hidden PU problem is similar to hidden node problem which is well studied in wireless network (Boroumand, Khokhar, Bakhtiar, & Pourvahab, 2012; Kosek-Szott, 2012). Figure 3.2 illustrates an example of hidden PU problem.

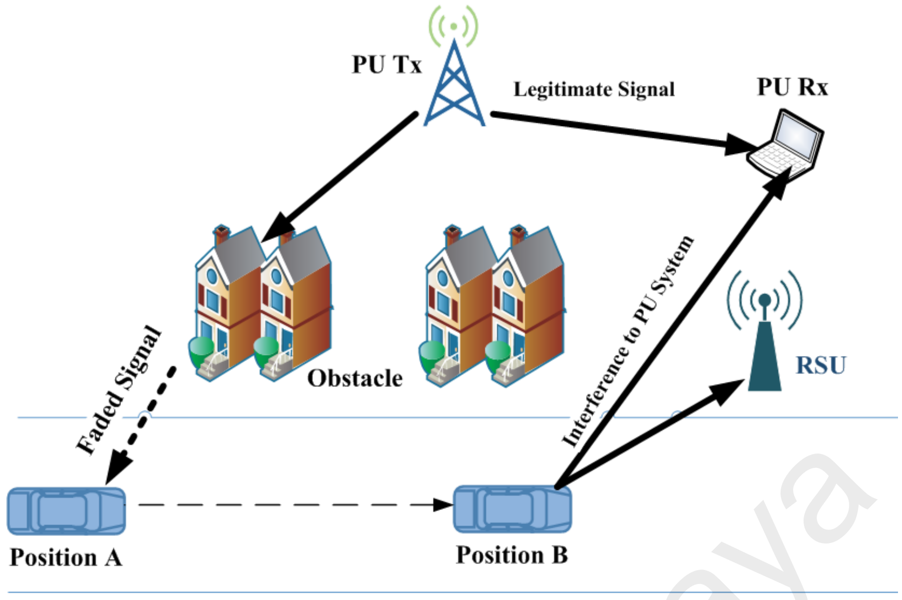

Figure 3.2: Hidden PU signal problem in spectrum sensing for VANET

When a vehicle in *Position A* senses for spectrum opportunities in an area covered by the PU transmitter (*PU Tx*), it gets faded signal due to obstruction by the building. Depending on the sensing technique used, the vehicle might determine absence of the PU signal because of the weak signal received. The PU signal is hidden or blocked by the obstacles. Hence, the vehicle might attempt to communicate on the PU channel as it moves to *Position B*. However, attempting to communicate on the PU channel in *Position B* will cause interference to the *PU Rx* because there are no obstacles to block the signal. The operation premise of DSA and CR is to avoid interference to the PU system at all times. Thus, accurate spectrum sensing results are desired. However, it is a challenge to accurately get spectrum sensing results in the presence of the hidden PU problem in VANET (Montealegre, Carvalho, & de Moraes, 2014; Paul, Daniel, Ahmad, & Rho, 2015). Nevertheless, the effects of multipath fading, shadowing and hidden PU problem can be mitigated by employing cooperative decision. Vehicles on the road can use spatial-temporal diversity to cooperate in deciding on the spectrum opportunity.

3.2.5 Effect of PU activities on the performance of sensing in VANET

The success of DSA will largely depend on avoiding interference or disruption to the PU communication systems. Therefore, spectrum sensing is an important fundamental stage in cognitive radio cycle that identifies spectrum opportunities for DSA. However, spectrum sensing is much dependent on the activities of the PU duty cycles under consideration (V. Kumar et al., 2015; Saleem & Rehmani, 2014). The PU duty cycles have a profound impact on the performance of spectrum sensing in any cognitive radio network including VANET, because they are considered to be random (MacDonald & Popescu, 2013). Hence, the spectrum sensing technique implemented should consider the underlying PU activity pattern. The PU duty cycles can be modeled using statistical or mathematical models that give details of the PU traffic patterns. For example, before the secondary network is deployed, the SUs (vehicles) can develop a model that studies the transmission pattern of the potential PU channels of interest along the roads that could be used for DSA. The PU pattern can be stored in database of the RSU along the roads which can later be used as reference for predicting future PU occupancy state. Furthermore, the PU activity traffic model can be used to optimize sensing parameters which are difficult to determine in unknown sensing environments (Ghasemi & Sousa, 2007). Different PU activity models have been proposed in literature to represent the PU traffic pattern that include the birth-death process (i.e. birth represents ON periods and death represents OFF periods), Markov process, queuing theory and time series (Saleem & Rehmani, 2014).

The birth-death process activity model is the most commonly used PU traffic pattern that describes the random process in which the PU state alternates between the ON and OFF states (Cacciapuoti, Akyildiz, & Paura, 2011). The ON state represents the active or busy state in which the PU is transmitting on the sensed channel. On the other hand, the OFF state denotes the instance where the PU is in the idle state or not transmitting on the sensed channel. The distribution of the ON and OFF states varies depending on the PU nature and the transmission pattern of the PU. For instance, the TV channels are considered to have long ON/OFF pattern while cellular channels can vary depending on the time and place (J. Chen et al., 2015; Pagadarai et al., 2013). The SUs are only permitted to transmit data during the OFF periods. The ON/OFF model is characterized by arrival (birth) rate α and departure (death) rate β of the PU transmission. Thus the probability of the steady state for ON (birth) and OFF (death) periods is given as $P_{ON} = \frac{\alpha}{\alpha+\beta}$ $and\ P_{OFF} = \frac{\beta}{\alpha+\beta}$ respectively (Cacciapuoti et al., 2011; MacDonald & Popescu, 2013; Zhu, Guo, Feng, & Liu, 2016). P_{ON} and P_{OFF} can then be used in conjunction with sensing techniques to increase the robustness of the technique. Markov process on the other hand is usually used in predicting the spectrum usage to improve sensing results and spectrum management (Y. Chen & Oh, 2016).

Most of the conventional spectrum sensing techniques in VANET assume static PU activities during a sensing cycle (Chembe, Noor, et al., 2017). For example they assume that a PU will be active for a specified period during transmission of data and idle for another specified period when not transmitting data. However, the static assumption is not realistic, because the practical behavior of activities of the PU is perceived to be random (V. Kumar et al., 2015; Ning, Chowdhury, Duan, & Nintanavongsa, 2013). A PU can change its state from active to idle and vice-versa while spectrum sensing is being performed which violate the static assumption made by conventional techniques. Despite some studies considering PU activities during sensing cycles, most assume the PU transmission period to be long (Paul et al., 2015). As a result they consider short sensing period. The problem with this assumption is that the SU could correctly identify absence of the PU signal during sensing cycle. However, the PU could arrive at the time when the SU starts to transmit its data thereby causing disruption to the communication and interference to the PU system (Luis, Furtado, Oliveira, Dinis, & Bernardo, 2013).

Thus, spectrum sensing technique must account for PU activities throughout transmission periods to guarantee every change in the PU state is within the sensing period. PU activity consequences coupled with speed of the vehicle has not been fully investigated in literature for VANET environment. Therefore, this research thesis is an effort to investigate such problem and put forward solutions through approaches that diverge from existing studies. The effect of PU activities and speed of vehicles on spectrum sensing in VANET environment cannot be overlooked.

3.3 Analysis of spectrum sensing techniques

To identify free licensed bands along the roads, vehicles should perform spectrum sensing while considering the sensing environment discussed in the previous section. An individual vehicle should sense the channel of interest and determine the PU occupancy state before deciding to use the licensed channel. To measure the accuracy of sensing results different performance metrics are used. Commonly used metrics include probabilities of detection, false alarm and missed detection. Another important metric is measuring spectrum sensing time on channel throughput. The sensing techniques use these metrics to optimize sensing performance. Conventional spectrum sensing techniques generally employed in VANET environment for detecting PU signal in licensed frequency bands include energy detection, cyclostationary feature detection, matched filter detection and wideband detection. In this section, a detailed discussion of these sensing techniques with their strength and shortcomings are given. But first an outlook of the performance metrics is discussed.

3.3.1 Performance metrics for spectrum sensing techniques

The activities of the PU can be categorized into two distinct states. The first state is when the PU is transmitting on the desired sensed channel also termed as active state or ON period. The ON or active state is denoted by H_1. The second state is when the PU is not transmitting on the sensed channel and is in the idle state or OFF period. The OFF or idle state is denoted by H_0. SUs are only permitted to transmit on licensed channels when the PU is idle (i.e. H_0) to avoid interference. Below are metrics used by sensing techniques to measure their performance in association with H_1 and H_0.

a. Probability of detection

Probability of detection ($\mathrm{P_d}$) defines the probability of the sensing technique to detect the presence of the PU signal given H_1 and some threshold (λ), thus $\mathrm{P_d} = \mathrm{P}(\mathrm{H}_1|\lambda)$. Alternatively, $\mathrm{P_d}$ can be defined as probability that the PU is transmitting on the licensed channel being true and the detector detecting the PU signal (Bhowmick, Chandra, Roy, & Kundu, 2015). The performance of every cognitive radio network is based on accuracy of detecting the PU signals effectively. Detection accuracy of sensing technique increases with increase in sensing period when the algorithm gets more samples of the PU signal (Shah & Akan, 2015). However, in VANET environment long sensing periods can lead to missing spectrum opportunities as vehicles can move in different areas where PU characteristics might be different. Consequently, the trade-off is between minimizing the sensing period and maximizing the $\mathrm{P_d}$ performance. Higher $\mathrm{P_d}$ is desired to minimize interference to licensed PU channels by SUs.

b. Probability of false alarm

Probability of false alarm ($\mathrm{P_f}$) describes the likelihood of the SU to mistakenly identify the presence of the PU signal when in reality the signal is absent. The $\mathrm{P_f}$ can also be defined as the probability of deciding H_1 when H_0 is true instead, thus $\mathrm{P_f} = \mathrm{P}(\mathrm{H}_1|\mathrm{H}_0)$ (Saraniya & Priya, 2014). The implication of decisive $\mathrm{P_f}$ is missing chances for the SU to communicate on free licensed channels. Thus, the target of a good sensing technique is to keep P_f as low as possible. Maintaining P_f as minimum as possible increases the chance of spectrum reuse among SUs whenever it is available. Hence, the sensing algorithm must minimize P_f while maximizing P_d.

c. *Probability of missed detection*

Probability of missed detection (P_{md}) defines the probability of the SU deciding the absence of the PU signal on the licensed channel when in fact the PU is active, therefore $P_{md} = P(H_0|H_1)$. The implication of decisive P_{md} is interference to PU activities when the SU attempt to communicate on the PU channels. For SU to provide a better spectral efficiency while avoiding interfering with licensed PU channels, the occurrence of missed detection should be kept at minimum level at all times. Both P_{md} and P_f play an important role in determining an effective and reliable communication system (A. Singh, Bhatnagar, & Mallik, 2011). Since P_{md} lead to interference while P_f lead to missed spectrum opportunities, the goal of a robust sensing technique is to minimize both P_{md} and P_f while maximizing P_d. To achieve that either P_{md} or P_f can be fixed at a certain value while optimizing another to improve P_d.

d. *Sensing time on transmission throughput*

The sensing trade-off between P_d and P_f discussed above has impact on transmission throughput as well. On one hand long sensing time increases P_d which provide maximum protection to licensed user. On the other hand, long sensing time reduces the transmission time which decreases the secondary network throughput. Therefore, transmission throughput is influenced by accuracy of spectrum sensing technique to achieve high P_d with low P_f and transmission time (Stotas & Nallanathan, 2010).

3.3.2 Energy detection sensing technique

Conventional energy detection technique also known as radiometer is the most commonly employed spectrum sensing method in cognitive radio networks. This is because the energy detector is simple to implement and no prior knowledge of the PU characteristics is required before sensing can be performed (Akyildiz et al., 2011). The energy detector has also been adopted as a sensing technique in vehicular environment by many works (Angrisani, Capriglione, Cerro, Ferrigno, & Miele, 2015; Jalil Piran, Cho, Yun, Ali, & Suh, 2014; Qian & Hao, 2014). The detector determines the PU occupancy state by measuring the power of the received signal (i.e. SNR) of the PU transmitter and compares it to a predetermined threshold. This makes the energy detector fast in deciding the PU occupancy state. The fast property has contributed to energy detector's wide use in VANET environment where vehicles need to detect spectrum opportunities in a short period of time before moving to different areas. The widely assumed PU activity model for conventional energy detector is static ON/OFF. The ON period is fixed to represent active PU while OFF is fixed to represent idle state. Hence the Neyman-Pearson lemma binary hypothesis is used to determine the PU occupancy state (Yanxiao Zhao et al., 2014). If we let the y signal be sampled at the receiving SU, then xth $(x = 1,2,3, \dots, M)$ sample of the binary hypothesis can be given as:

$$\mathrm{y(x)} = \begin{cases} \mathrm{n(x)} & \rightarrow \quad \mathrm{H_0} \\ \mathrm{n(x) + hs(x)} & \rightarrow \quad \mathrm{H_1} \end{cases} \qquad 3.6$$

Where $\mathrm{y(x)}$ is the signal envelop received by the sensing vehicle. The SNR signal originating from the PU transmitter is given by $\mathrm{s(x)}$ while h represent the amplitude signal gain between the PU and the sensor. The PU signal is distorted by Additive White Gaussian Noise (AWGN) given by $\mathrm{n(x)}$ which follow a Gaussian distribution with mean zero and variance σ_n^2 (i.e., $n(x){\sim}\mathcal{N}(0, \sigma_n^2)$)(M. Sun, Zhao, Yan, & Li, 2016). The presence of the PU signal is denoted by $\mathrm{H_1}$ while absence of the PU signal is represented by $\mathrm{H_0}$ in which case only noise is detected. Given M sensing samples of the PU signal, the energy test statistic (e) is represented by (Qian & Hao, 2015):

$$\mathrm{e} = \sum_{\mathrm{i=0}}^{\mathrm{M}} |\mathrm{y(x)}|^2 \qquad 3.7$$

The performance of the energy detector is measured by its ability to attain certain $\mathrm{P_d}$ and $\mathrm{P_f}$ for some given SNR and threshold (λ). The energy detector requires a perfect knowledge of the noise variance in the sensing environment. Therefore, a well thought λ should be decided that compensate the variances in noise uncertainties. The value of such λ is called SNR wall (Mariani, Giorgetti, & Chiani, 2011). Thus the three probabilities for measuring the performance of the energy detector are given by $P_f = P(e < \lambda | H_0)$, $P_d = P(e > \lambda | H_1)$ and $P_{md} = P(e < \lambda | H_1)$, implying $P_d = 1 - P_{md}$ (Kozal, Merabti, & Bouhafs, 2012; Qian & Hao, 2015). Regardless, the energy detector performs poor in low SNR as seen in Figure 3.3 (Chembe, Ahmedy, et al., 2017).

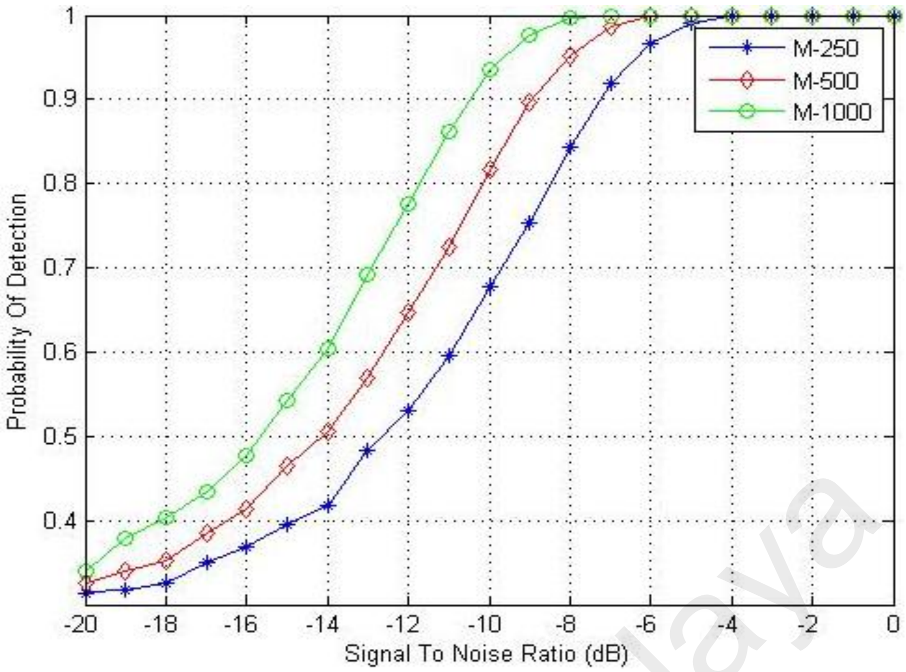

Figure 3.3: Performance evaluation of energy detector ($\boldsymbol{P_d}$) for different SNR

In Figure 3.3, M is the number of sensing samples in Rayleigh fading environment with P_f kept at 0.1 or 10% (Chembe, Ahmedy, et al., 2017). In low SNR the detection performance of the energy detector is very poor. Even when the number of samples collected increase, the P_d still remains poor with low SNR as can be seen from the figure. However, increasing sensing samples by increasing sensing period generally increase the performance of the energy detector as noted in the figure where simulation for *M=1000* performed better than other streams. In VANET environment however, increasing sensing time can lead to missed opportunities as vehicles move from one region to another with high speed where the characteristics of the PU might be different.

Poor performance of the energy detector in noise uncertainties and low SNR is viewed as one of the disadvantage. In addition, it is difficult to determine the value of λ to balance the trade-off between P_d and P_f (Atapattu, Tellambura, & Jiang, 2011). Because λ depends on noise and PU signal power which might not be known in advance to the SU in the sensing environment. On one hand, the noise power can be estimated because it is assumed to be AWGN following the Gaussian distribution (Cabric, Mishra,

& Brodersen, 2004). On the other hand, the PU signal power is not easy to estimate because it relies on the PU transmitter characteristics which might be unknown to the SU. In addition the PU signal strength depends on the distance between the location of the sensing SU and the PU. In practical scenarios, the value of λ is selected to achieve certain rate of P_f mainly between 0 and 0.1 (Lehtomaki, Juntti, Saarnisaari, & Koivu, 2005). In addition, other approaches adapt the threshold for energy detector to accommodate fading environment (Bagwari & Tomar, 2013; Martínez & Andrade, 2016). Another shortcoming of the conventional energy detector is failure to distinguish between the PU and SU signals. This is mainly because the detector only measures the power of received signal without a prior knowledge of the source of that signal. For example, the detector cannot distinguish whether a signal is being transmitted by the PU or the signal is being transmitted by another SU on the channel being sensed. In the case that the channel is occupied by the SU, the energy detector will decide the licensed channel to be occupied by PU which is not accurate. This can lead to missing spectrum opportunities by other SUs.

3.3.3 Cyclostationary feature detection sensing technique

Cyclostationary feature detection is another conventional sensing technique employed in detecting the PU signal in cognitive radio networks. The feature detector exploits the periodicities of the PU signal which can be found by taking their correlation. The periodicity of the PU signal is usually caused by either the pulse sequences or sine waves during modulation of the signal (Sadeghi, Azmi, & Arezumand, 2012). In addition, the correlation as a function of time is mostly identified in modulated PU signal features like hopping sequences, spreading code, sine wave carriers, etc. (K. Kim et al., 2007). The Fourier transform of the correlated the PU signal have peaks at certain frequencies specific to PU under consideration. The feature detector searches for these peaks to determine the presence or absence of the PU signal in the licensed channel of interest. Cyclostationary feature detector is robust to noise interference because noise is assumed to be stationary wide sense with no periodicity (M. Kim, Po, & Takada, 2010). Noise is random in nature as a result it is not correlated. Therefore, the cyclostationary feature detector can distinguish noise from the PU modulated signal by examining the spectral correlation function (SCF) of the signal. For a given PU signal $x(t)$ with period T_0 which is cyclostationary, the cyclic autocorrelation function (CAF) $R_x^{\alpha}(t,\tau)$ is given as (P. D. Sutton, Nolan, & Doyle, 2008):

$$R_x^{\alpha}(t,\tau) = E[x(t)x^*(t-\tau)\exp\left(-j2\pi\alpha\left(t-{}^{\tau}/_{2}\right)\right)] \quad 3.8$$

Where α is the cyclic frequency and * is a complex conjugation. The SCF or cyclic density function (CDF) of the PU signal at the SU is given by:

$$S_x^{\alpha}(f) = \int_{\tau=-\infty}^{+\infty} R_x^{\alpha}(\tau)\exp(-j2\pi f\tau)\, d\tau \quad 3.9$$

When a PU is transmitting on the channel being sensed in case of H_1, the frequency values of that PU signal will be at peak. On the other hand, the SCF function does not have any peak values in case of H_0 because of the non-cyclostationary of the noise. The test statistic $(I_x(\alpha))$ of the feature detector is calculated from the SCF of the PU signal. The aggregative SCF of PU signal under consideration is given by $I_x(\alpha_i) = \max\left(S_x^{\alpha_i}(f)\right)$ (Thomas & Sudha, 2014). The $I_x(\alpha)$ value is then compared to the threshold λ to determine the presence or absence of the PU signal. Thus, the probability of detection is given by $P_d = P(I_x(\alpha) > \lambda|H_1)$ and probability of false alarm is given by $P_f = P(I_x(\alpha) < \lambda|H_0)$.

As stated previously, the cyclostationary feature detector is robust to noise uncertainty because it relies on detecting the frequencies of the actual PU signal and not the spectral energy of the received signal in the case of energy detector. This property allow the feature detector to identify spectrum opportunities even in poor SNR (M. Kim et al., 2010). In addition, the feature detector can distinguish the type and nature of the PU system. Thus, it can differentiate signals originating from the PU transmitter from signals of the SU. Nevertheless, cyclostationary feature detection technique has its own shortcomings. The feature detector is computationally complex in terms of implementation (Mehdawi, Riley, Ammar, Fanan, & Zolfaghari, 2014; Satheesh, Aswini, Lekshmi, Sagar, & Kumar, 2013). In addition, the detector require long sensing or observation period to collect enough sensing sample to improve its detection performance (Ejaz, ul Hasan, Lee, & Kim, 2013). Consequently, it performs poor when the sample size is low. With few sensing samples it is difficult to estimate the SCF. This is challenging in VANET where time is a factor. Due to the speed of vehicles, spectrum sensing should be performed in a quick and timely manner. Hence, long sensing can lead to missed spectrum opportunities as vehicles are likely to move in multiple areas where the characteristics of the licensed channels might be different. Therefore, novel techniques should be developed that exploit the robustness of feature detector while reducing on the sensing time.

3.3.4 Matched filter detection sensing technique

Another conventional spectrum sensing technique used in cognitive radio networks is called matched filter detector. The detector is an optimal method that maximizes the received SNR in the presence of AWGN. However, matched filter detector requires a perfect prior knowledge of the PU signal at both PHY and MAC layer (Cabric et al., 2004). For instance, the detector should know in advance the modulation type and level, waveform, framing, pulse shaping, packet format of the PU signal before sensing is performed. To detect the PU signal, the matched filter detector projects the received signal envelop in the direction of the pilot sequence $p_x(n)$. Thus, the test statistic is given as (Mohamad, Wen, & Ismail, 2012):

$$T = \sum_N x(n) p_x^*(n) \qquad 3.10$$

With $x(n)$ the signal envelop received at the SU. The test statistic is then compared to some threshold λ. The probability of detection is given by $P_d = P(T > \lambda | H_1)$ and probability of false alarm is given by $P_f = P(T < \lambda | H_0)$.

The main advantage with a matched filter detection technique is reduced sensing time to attain a desired P_d constraint and accuracy of detection (Eduardo & Caballero, 2015). This is attributed to fewer samples needed to determine the PU signal because of a prior knowledge. Nonetheless, matched filter implement complex algorithms which are not energy efficient (Cabric et al., 2004). The complexity is mainly due to tasks performed by the SU such as timing, equalization and synchronization of the carrier PU signal. In addition, the detector requires dedicated antenna for each PU system because of a prior knowledge condition (Cabric et al., 2004). Along the roads, there are many candidate licensed frequency bands that can be used for DSA. If matched filter detector is used, the vehicle has to be equipped with different antennas to detect each licensed frequency band. This can result in increased implementation cost. In cognitive radio network a generic detector that can detect different radio frequency bands is desired. Therefore, matched filter detection technique is seldom used for spectrum sensing in VANET.

3.3.5 Wideband detection sensing technique

Wideband spectrum sensing defines sensing techniques that can detect spectrum opportunities in a wideband channels. In a communication system, channels can either be wideband or narrowband depending on how the bandwidth of the channel is compared to the coherence bandwidth (Simon & Alouini, 2005). Coherence bandwidth refers to a statistical measure over which array of frequencies for a channel is considered to be constant or flat. Wideband channels have bandwidth which is more than the coherence bandwidth of the channel. In contrast, narrowband channels have the bandwidth which is less than the coherence bandwidth.

Commonly used spectrum sensing techniques in narrowband are those described above including energy detection, cyclostationary feature detection and matched filter detection. On the other hand, wideband sensing examines range of frequency bands of the single channel to determine the sub-bands free to be used for DSA. This can be accomplished in two ways, by Nyquist wideband sensing or sub-Nyquist wideband sensing (Rashidi, Haghighi, Owrang, & Viberg, 2011; H. Sun, Nallanathan, Wang, & Chen, 2013). Nyquist sensing is the basic method in which the detector uses the analog-to-digital-converter (ADC) in association with digital signal processing approach to detect the PU activities. In sub-Nyquist sensing approach wideband signals are acquired using sampling rates that are lower than Nyquist rate. The most commonly used sub-Nyquist wideband sensing methods are compressive sensing and multi-channel sensing (H. Sun et al., 2013). The most common approach in both Nyquist and sub-Nyquist sensing is to use bank of tunable band-pass filters and use the narrowband sensing techniques to sense each narrow frequency band consecutively (De Vito, 2012).

Wideband spectrum sensing has received attention from both academia and industry recently because of the potential to detect wide range of frequency that can be used for DSA at the same time. However, it faces some challenges which should be resolved before it can be applied to spectrum sensing in VANET. Firstly, it requires an architecture that poses constraint in hardware platform required to control the high speed ADC conversion and digital signal processing (Tian, 2008; Yu, Sekkat, Rodriguez-Parera, Markovic, & Cabric, 2011). Secondly, it poses stringent time requirement needed to monitor dynamic varying spectrum in sub frequency bands within a short period of time (Tian, 2008). This entails high sampling rate. Thirdly, the wideband sensing approach is susceptible to interference that is caused by signal leakage in sub-bands (Yu et al., 2011). Nevertheless, some challenges can be resolved by cooperative sensing. For example, SUs can cooperate to accurately determine spectrum opportunity through compressive sensing by collecting few samples (De Vito, 2013). Each SU can collect few samples of the wideband channel of interest and make cooperative decision. However, the focus of this research work is to explore narrowband channels, hence narrowband sensing approaches are considered.

3.3.6 Local sensing combining two or more sensing techniques

The combined advantages of each individual conventional sensing scheme discussed above can be used to increase spectrum sensing performance. The approaches in which two or more sensing techniques are combined to get accurate sensing results have shown to improve spectrum sensing in cognitive radio networks. For example, energy detector, feature detector and matched filter detector are combined to sense the PU signal depending on the strength of the signal (Ejaz, ul Hasan, Azam, & Kim, 2012; Ejaz et al., 2013; A. Kumar, Bharti, & Jain, 2013). Another research approach combines energy detector and one order cyclostationary (OOC) detection approach to spectrum sensing (Ejaz, Hasan, & Kim, 2012; W. Yue & Zheng, 2010). The OOC determines the features of the PU signal using periodicity in time domain opposed to frequency domain. This reduces the implementation complexity (W. Yue & Zheng, 2010). Regardless, combining two or more sensing techniques increase implementation complexity depending on the approach taken. In addition, sensing time is increased when two or more sensing techniques are combined especially in low SNR.

In VANET environment, combining two or more sensing technique to improve spectrum sensing have not been exploited. In this work, the simplicity of energy detector and OOC are combined to form adaptive sensing at local individual vehicle level. The details are presented in Chapter 4. Despite the drawbacks mentioned above, the overall performance of combined techniques achieves better results than single sensing technique demonstrated in Chapter 6. Another approach in increasing performance of spectrum sensing is by cooperative decision from SU in the secondary network. Cooperative decision is discussed next.

3.4 Analysis of cooperation decision for sensing results in VANET

In the previous section, conventional spectrum sensing approaches were discussed. Conventional detection techniques are used to detect spectrum opportunities by individual SUs. Any SU or vehicle on the road will sense the licensed channels of interest and decide on the PU's occupancy without involving other vehicles. However, spectrum sensing performed by an individual vehicle is susceptible to various challenges as discussed in Section 3.2. Furthermore, PU activities are not known to the vehicles in advance and the PU system is not involved in the sensing process. Thus, when sensing is performed by the individual vehicle the sensing performance is not optimal which can result in interference to the PU system (Yucek & Arslan, 2009). The sensing results are affected by multipath fading, shadowing and hidden PU problem. In addition, it is difficult to accurately model the PU activity pattern in a non-cooperating sensing environment. To overcome some of the challenges encountered in conventional spectrum sensing methods, cooperative decision is proposed in literature. Vehicles on the road can use spatial and temporal diversity to cooperate in deciding the PU occupancy. Cooperative decision in VANET can be divided into two categories; centralized and distributed. Regardless, cooperative decision still faces challenges in the VANET environment. In this section, the two cooperative decision approaches and associated challenges are discussed. Later a discussion on machine learning approach to cooperative decision is presented.

3.4.1 Centralized cooperative decision on sensing results

Vehicle to infrastructure (V2I) communication is an important aspect of vehicular networks in which vehicles on the road establish communication with road side infrastructures or simply referred to as RSU. In centralized cooperative decision, vehicles on the road use the RSU as a fusion center (FC) where spectrum decision about the PU occupant status is determined. Alternatively, one vehicle in a cluster based communication will be chosen as the FC. To visually comprehend centralized cooperative decision, consider Figure 3.4 below.

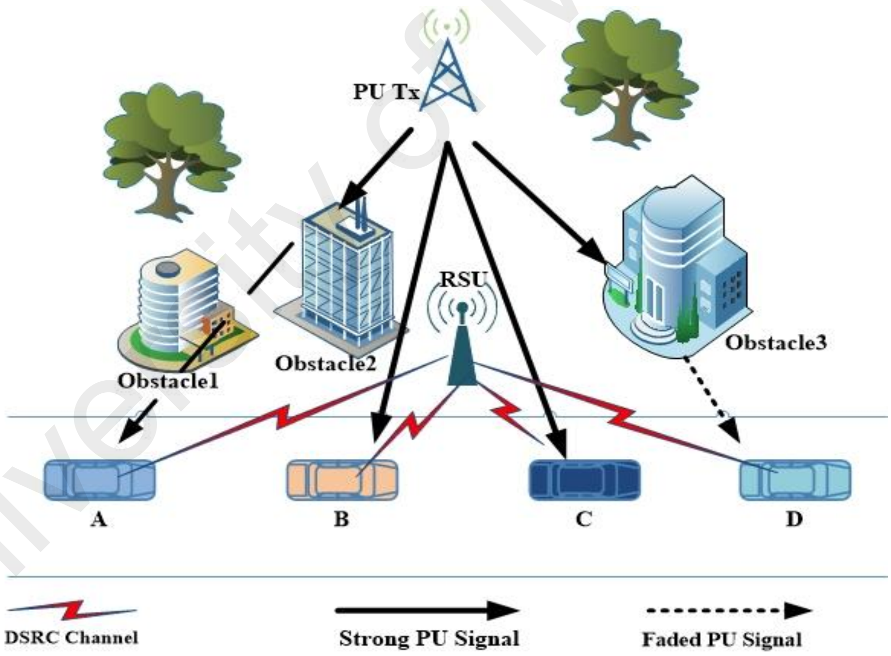

Figure 3.4: Centralized spectrum decision in VANET

In conventional individual spectrum sensing, each vehicle in Figure 3.4 will perform sensing to decide on the PU signal. Due to obstacles, *Vehicle A* and *Vehicle D* will receive faded PU signal as a result the vehicles might decide absence of the PU transmitter. When these two vehicles decide to communicate on the PU channel, they will cause interference to the PU system. On the contrary, in cooperative spectrum sensing decision each vehicle will sense for spectrum opportunity and send the result to the FC. The FC then decides on the global PU occupancy state. For example, in Figure 3.4 *Vehicle A* and *Vehicle D* will receive faded PU signals due to obstacles while *Vehicle B* and *Vehicle C* will receive strong PU signal. Consequently, the final decision at the FC should be presence of the PU signal. Once the decision is made at FC, the result is sent back to cooperating vehicles. Cooperative decision improves accuracy of spectrum sensing performance which in turn prevents interference to the PU system. In addition, the RSU can keep history of the PU activity which can be used to enhance the sensing performance in future.

The RSU or FC typically decide on the global sensing result from participating vehicles using hard fusion combining rule or soft combining rule. In hard fusion combining rule, each vehicle senses the desired licensed channel and only sends the binary digit to the FC (RSU) (Qian & Hao, 2015). The binary digit can either be 1 for H_1 representing presence of PU signal or 0 for H_0 representing absent of the PU signal. Once the individual results are collected, the FC will make the decision using AND rule, OR rule, K-out-of-M rule or Majority rule (Abbassi, Qureshi, Abbasi, & Alyaie, 2015; Borota et al., 2011; Duan, Li, & Ning, 2013; Xu, Bao, Luo, & Wang, 2013). When the decision is made at the FC, the consolidated result (i.e. H_1 or H_0) is send back to participating vehicles. Thereafter, vehicles can use the licensed channel if the global result was H_0 or avoid the licensed channel in case of H_1. Cooperative decision based on hard fusion rule is simple to implement because the SUs only send a bit (0 or 1) which is easy to manipulate. Nevertheless, hard fusion rule performs poor in low vehicle density especially if the K-out-of-M rule is used. In addition, the fusion rules cannot detect malicious data sent from participating vehicles. For example the FC cannot distinguish between a bit sent from a legitimate SU from malicious SU.

Furthermore, it is difficult to correct an error made by vehicles in instances where a vehicle decides H_1 instead of H_0 and vice-versa since only a bit is sent.

To mitigate some of the deficiencies noticed in hard fusion rule, cooperative decision based on soft combining demand the measurement of the channel samples obtained at local SU sent to FC (Qian & Hao, 2014). The FC thereafter combines the collected samples to derive a global PU measurement which is compared to some predefined threshold. At FC, the commonly used soft combining methods include weighted linear, equal gain combining and optimal combining (Alvi, Younis, Imran, & Fazal e, 2014; Baraka, Safatly, Artail, Ghandour, & El-Hajj, 2015; Borota et al., 2011). Compared to hard fusion, soft combining performs better in cooperative decision. However, soft combining is also susceptible to malicious attack. Malicious SUs can send distorted PU measurement which can affect the global result. In addition, there is need for extra bandwidth needed to send the weight of local results to FC by cooperating SUs. Like hard combining, the performance of soft combining degrades in low vehicle density (Duan et al., 2013). Furthermore, the proposed approaches do not make it clear how the threshold used in comparing the global PU measurement obtained from cooperating vehicles is determined.

Other centralized cooperative decision approach not based on hard fusion or soft combining include renewal process method proposed by Paul et al (2015), general likelihood ratio test (GLRT) using covariance matrix (Souid, Chikha, & Attia, 2014) and coordinated spectrum sensing (X. Y. Wang & Ho, 2010). The burden of spectrum decision in the renew process is on the RSU (Paul et al., 2015). It monitors the PU ON/OFF periods and selects which channels to sense. Other vehicles within coverage area of RSU are assigned channel to sense and report back the individual results to RSU. Then global result is sent back to participating vehicles. This approach lack clarity as the authors do not demonstrate the role assigned to RSU and PU. The description of the central sensing operation is altered between PU and RSU (Paul et al., 2015). In addition, the three way channel usage is redundant. Firstly the RSU communicate with vehicles by sending sensing instructions, secondly vehicles respond with sensed local results and finally the RSU send back the global result. The GLRT approach use test statistics obtained from blind Eigen values of the received covariance matrix of SUs to detect the PU signal. In the coordinated approach, the goal is to mitigate the disadvantage of conventional techniques by choosing a coordinator which can be RSU or vehicle.

Generally, cooperative decision in centralized approach is subject to synchronization problem which is overlooked by sensing methods presented above (Yucek & Arslan, 2009). Opposed to conventional individual sensing, cooperative decision require that sensed results are sent to FC for global judgment. Thus, each SU will incur some delay when reporting the local sensing result to the RSU. The cumulative delay from cooperating vehicles affects the sensing performance. Another delay is incurred when the RSU sends back the global result to cooperating vehicles. Due to speed of vehicles, the global result from the RSU might be determined to be useless if the vehicle moves in another area not covered by the RSU. This can result in missing many spectrum opportunities. One approach to mitigate synchronization problem is to use asynchronous method proposed by (Yi Liu et al., 2015). Another challenge associated with centralized cooperative decision is deciding on the optimal number of participating vehicles. The performance of centralized cooperative decision in low vehicle density is poor (Duan et al., 2013). Therefore, there is need to establish the trade-off between setting optimal number of vehicles to participate in cooperative decision and sensing performance.

3.4.2 Distributed cooperative decision on sensing results

Vehicle to vehicle (V2V) communication is another important aspect of VANET in which vehicles form multi-hop communication links in the distributed fashion. Thus, in distributed cooperative decision no infrastructure support is provided to act as FC. Vehicles cooperate among themselves in ad hoc manner to reach an agreement on the sensing results. The concept of distributed cooperative decision is illustrated in Figure 3.5 below. The difference between Figure 3.4 (centralized) and Figure 3.5 below is that in the latter the individual sensing result (H_1 or H_0) is not sent to any central node or FC. The sensing results are shared among cooperating vehicles to determine the global PU occupancy state.

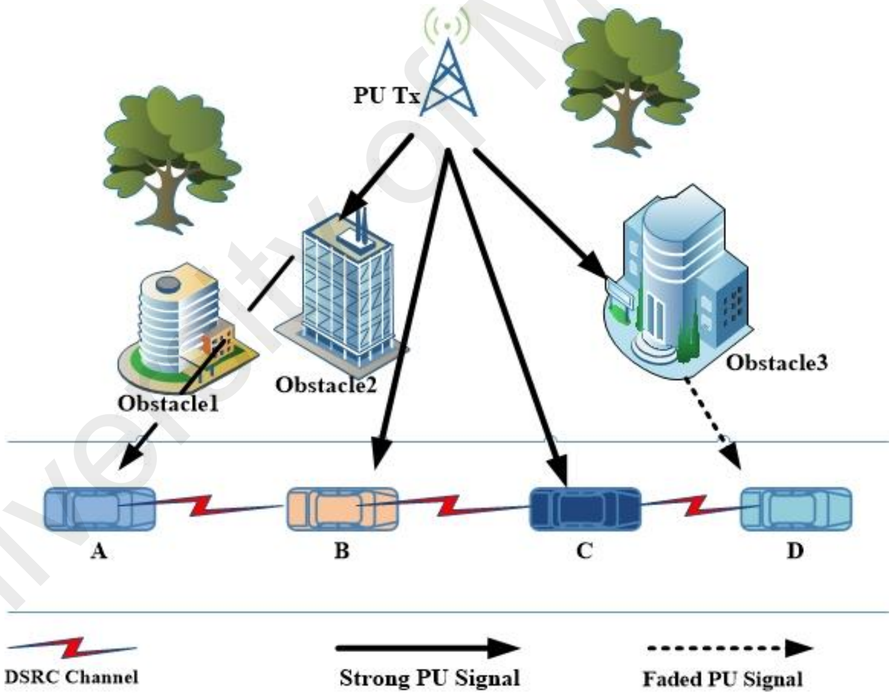

Figure 3.5: Distributed cooperative decision in VANET

Different distributed cooperative sensing decision algorithms have be proposed in literature which largely fall in the following categories; consensus based (Raza, Ahmed, Ejaz, & Kim, 2012; Wei, Yu, & Boukerche, 2015), belief propagation (H. Li & Irick, 2010) and weighted (Di Felice, Chowdhury, & Bononi, 2011; Yi Liu et al., 2015). In consensus based approach each individual SU determine the local PU signal status using any conventional technique available. Once the local measurement is obtained, the vehicle exchanges this local result with its immediate neighbors, the neighbor compares the result with its own and forwards the update to other neighbors. The process continues until a consensus is reached. Implementation of belief propagation approach is similar to consensus based. The minor difference is that in belief propagation sensing periods are divided into time slots. In each time slot the belief messages are sent to neighbors to generate new beliefs. The process continue iteratively within a time slot until a final results is computed by individual SU with help of belief messages from other vehicles. In weighted distributed cooperative decision each SU assign a weight to the local result. Then the weights are shared among vehicles to determine the global PU occupancy state. The global decision is made based on the weighted majority correlation decision.

Synchronization time among sensing vehicles is a challenge even in distributed cooperative decision. Another challenge overlooked in distributed cooperative decision is bandwidth demand to complete the iterative communication among vehicles to reach the global result. This is due to the fact that vehicles have to communicate with its neighbors using the available common channel. In VANET environment the use of control channel of the DSRC bands is proposed. However, this is counter intuitive because the concept of DSA is to free DSRC channels during congestion, therefore using control channel of DSRC band can led to further congestion. Furthermore, distributed cooperative decision performs poor under low vehicle density. Making the algorithms based on these approaches unbefitting in sparse environments like suburban areas with low vehicle density. In addition, the distributed cooperative decision approach is susceptible to malicious attacks that can introduce false data to be shared by other vehicles (Wei et al., 2015). The false data lure vehicles in reaching the wrong global PU occupancy state to the benefit of the malicious source.

In recent years machine learning to cooperative decision has been exploited in cognitive radio networks not based on VANET. A brief introduction of machine learning approach is give next.

3.4.3 Machine learning approach in spectrum sensing

Cooperative spectrum sensing decision based on machine learning has been explored in cognitive radio networks to increase the accuracy of spectrum sensing results (Bkassiny, Li, & Jayaweera, 2013; Sharma & Bohara, 2014; Thilina, Choi, Saquib, & Hossain, 2013). Machine learning can either be supervised or unsupervised. In supervised the learning agent needs to be taught how to recognize pattern in the data. Algorithms of supervised learning include support vector machine (SVM) and K-nearest-neighbor. On the other hand, in the unsupervised learning the agent must learn to recognize and work in the environment on its own. Examples include, reinforcement learning, K-mean clustering and Gaussian mixture model (Awe & Lambotharan, 2015; Thilina et al., 2013). Prior researches based on machine learning have shown some improvement in cooperative decision to accurately detect the PU signal (Awe, Zhu, & Lambotharan, 2013; Y. Lu, Zhu, Wang, & Fattouche, 2016). For example, we used SVM to improve the performance of cooperative decision among vehicles on the road and simulation results showed improved performance (Chembe, Ahmedy, et al., 2017). Other studies have shown similar trend (H. Yang, Xie, & Wang, 2012; Zhang & Zhai, 2011).

Nevertheless, machine learning algorithms have not been fully exploited in VANET environment. There are many areas where machine learning can be used. In this work, reinforcement learning is used to aid the RSU learn the behavior of the PU activity pattern in order to predict free licensed channels in future that can be used by vehicles during congestion. The activities of the PU plays an important role in spectrum sensing as discussed in Section 3.2.5. The detailed discussion of reinforcement learning and how it is applied in this work is presented in the next chapter.

3.5 Chapter summary

In this chapter, problems associated with spectrum sensing in VANET have been presented in details. In particular, the chapter presented challenges associated with sensing environment, analysis of conventional sensing techniques and cooperative decision. The chapter discussed challenges faced when performing spectrum sensing in VANET environment which include speed of vehicles, multipath fading, shadowing, hidden PU problem and unknown PU activities. In addition, the chapter discusses conventional sensing techniques in details in Section 3.3.2. Furthermore, the chapter discusses cooperative decision schemes proposed in literature.

Cooperative decision mitigates some of the challenges faced in conventional sensing techniques. However, cooperative decision incur some challenges associated with synchronization, communication overhead and demand for extra bandwidth to share sensing results among cooperating vehicles. In this research work, the focus is to develop sensing framework that will address PU activity modeling and synchronization problem in centralized cooperative decision. Thus, in the next chapter (Chapter 4) steps taken to address some of the problems discussed in this chapter are described. The spectrum sensing framework which combines best practices from energy detector and cyclostationary feature detector is described. In addition, Machine learning techniques are used at RSU to combine history of sensing results from vehicles for continuous decision.

CHAPTER 4: DEVELOPMENT OF THE FRAMEWORK

4.1 Introduction

This chapter details the design process undertaken to address the problems identified in Chapter 3 to meet the objectives outlined in Chapter 1. It describes the spectrum sensing framework that presents vehicles with extra channels for communication during congestion in DSRC channels. The chapter is divided into three sections. Section 4.2 describes the methodology taken in this research work. Section 4.3 details the sensing framework with emphasis on adaptive sensing and PU activity modeling. And finally Section 4.4 concludes the chapter.

4.2 Methodology

The methodology of this thesis consists of four main phases and these are: a) review of existing literature, b) modeling of problem identified c) implementation of the model and finally d) testing and evaluation of the proposed framework.

a) Review of literature: this phase is concerned with understanding the problem of spectrum sensing in VANET. In particular a detailed overview of VANET and spectrum sensing techniques is evaluated and gaps identified (Chapter 2 and 3). The most important out of this phase is reported in the published work (Chembe, Noor, et al., 2017).

b) Modeling of identified problem: this phase is concerned with proposing a solution for identified problems. In particular the challenges associated with VANET not covered by existing literature such as uncertainty in sensing results, communication overhead in cooperative decision, spectrum sensing data falsification problem in cooperative decision. Another pertinent challenge covered is PU activity modeling which is not addressed in literature.

c) Implementation: the proposed framework is implemented via simulation. In particular, NS3 is used as the simulation tool while SUMO is used for realistic mobility traffic generation. Simulation is performed for two reasons. Firstly, it is very expensive and currently not feasible to conduct real test-bed experiment in VANET at large scale, hence many research works in VANET rely on simulation (Martinez et al., 2013; Martinez, Toh, Cano, Calafate, & Manzoni, 2011). This is mainly because VANET is not yet deployed in real environment at large scale even though recent vehicles have such capabilities. Secondly, it is easier and faster to run multiple simulations to come up with desired features of the proposed framework (Zeadally et al., 2012). This is important for the work presented in this thesis since it is based on V2I where the RSU have to get a lot of history data from cooperating sensing vehicles. In addition, there are many simulation tools which are open source, hence reducing on the experimentation cost. Open source simulation environments also allow the source code to be modified and more specialized model to be added which is needed for many research works.

d) Testing and evaluation: this phase is mainly concerned with testing and run simulations to evaluate the proposed framework. To validate the performance, the tests are compared to other sensing schemes proposed in literature. Specifically, the results are compared to conventional energy detector and different cooperative decision based on history of sensing results. The evaluation is compared in terms of detection probability, false alarm and miss detection probabilities and detection performance in fading and non-fading environment.

The methodology followed in this work is summarized in Figure 4.1 below.

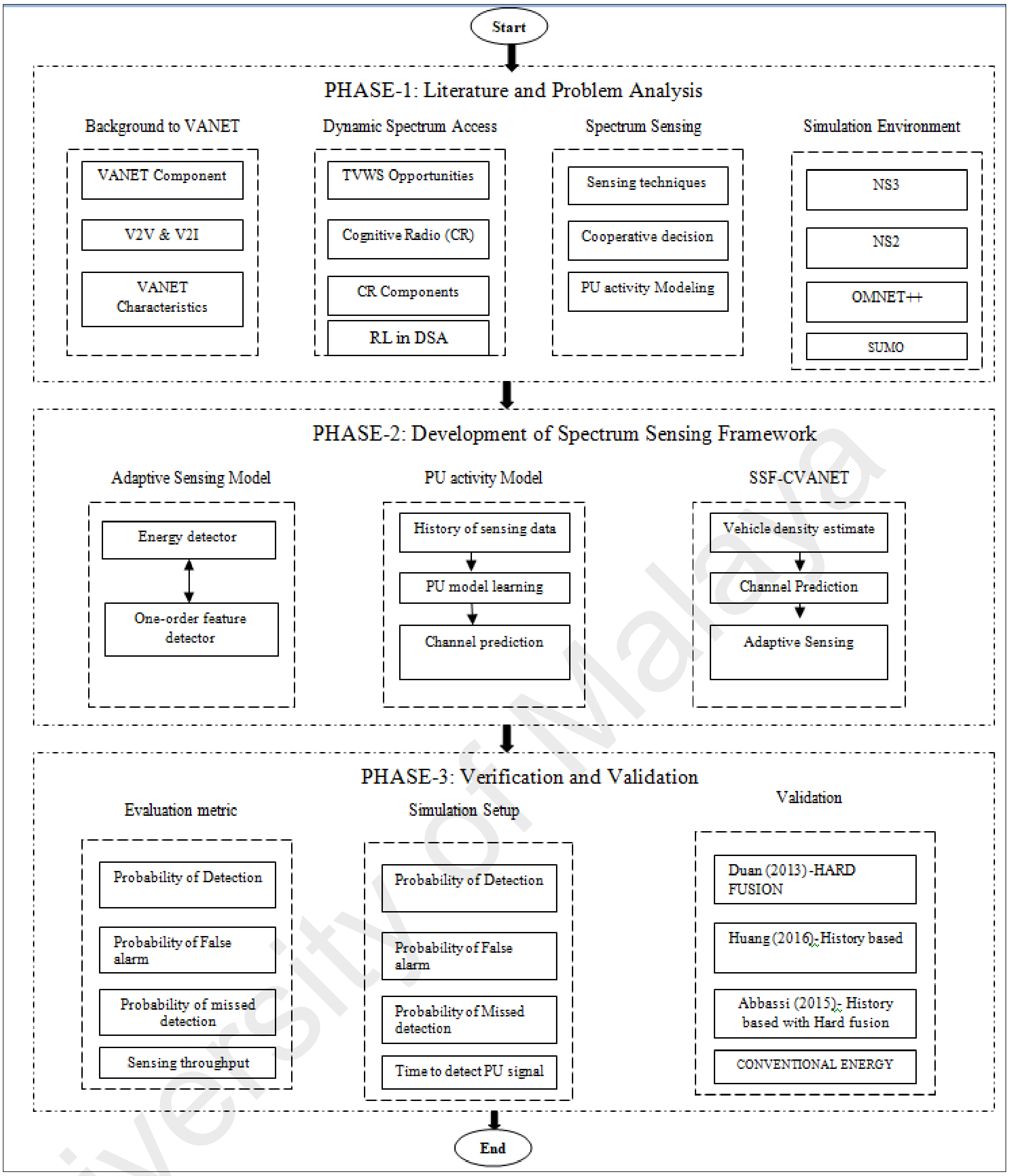

Figure 4.1: Methodology for spectrum sensing framework

In the next section we describe the details of the proposed sensing framework to account for identified problems in Chapter 3.

4.3 Spectrum Sensing Framework

Protection of licensed users at all times is the mandatory task for unlicensed users intending to opportunistically access licensed frequency bands. Therefore, spectrum sensing is an essential stage of a network based on cognitive radio. In addition, spectrum sensing is used to monitor other channels where an SU can migrate during handoff should the PU be detected. Nevertheless, there are still some challenges associated with spectrum sensing such as multipath fading, shadowing, unknown PU activities etc (see Chapter 3). In this section, a proposed Spectrum Sensing Framework for Cognitive Vehicle Ad hoc NETwork (SSF-CVANET) that attempt to solve some of the problems is presented. The proposed framework is divided into two main sections. The first section (4.3.2) describes the sensing component through CR to be used by vehicles on the roads. The second section (4.3.3) describes the PU activity model to be used at the RSU for predicting PU channels likely to be free for DSA. Both the sensing model and PU activity model are designed to increase the accuracy of spectrum sensing results while providing for maximum channel reuse. Figure 4.2 depicts the architecture of proposed SSF-CVANET.

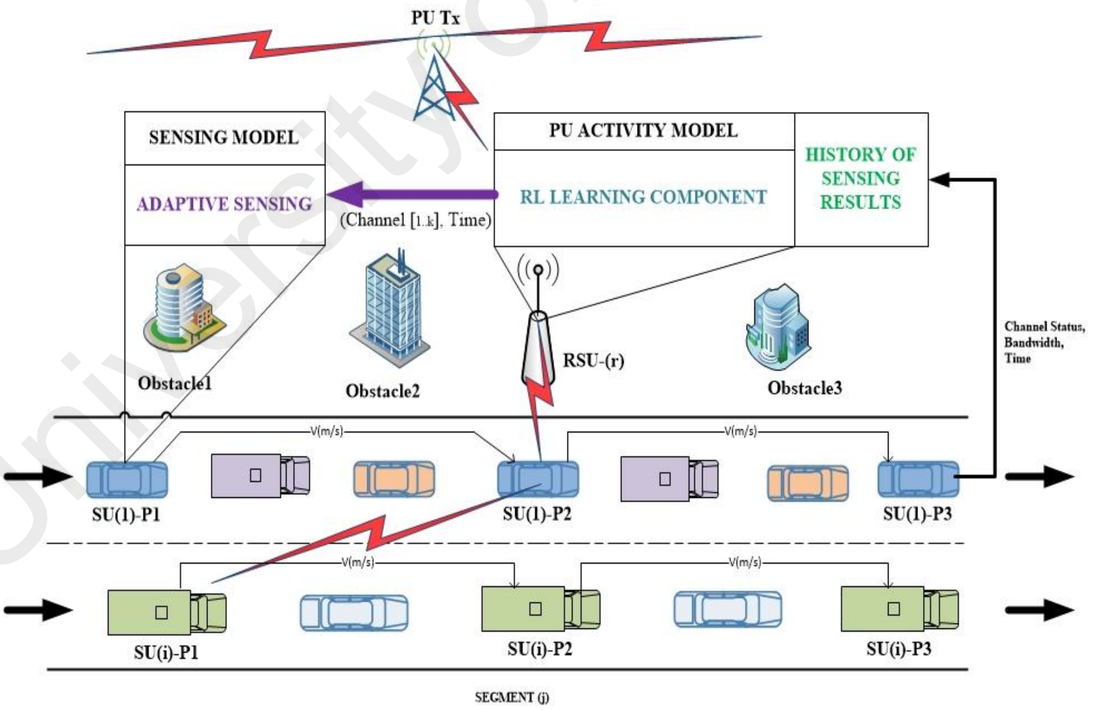

Figure 4.2: SSF-CVANET Architecture, *P* represents the position of the vehicle (SU) with velocity (v) as it move through the segment.

In this work, we consider a VANET environment based on infrastructure support where the RSU perform two main roles. The first role is estimating the density of vehicles on the road and second is predicting PU channels likely to be free and sending them to vehicles. Vehicles on the road are responsible for sensing the spectrum holes in licensed channels and transmitting on those channels if they are determined to be free. In addition, segmentation of the road is assumed with each segment covered by the RSU. The figure above is further explained using a flow chart in Figure 4.3 to comprehend the architecture of SSF-CVANET.

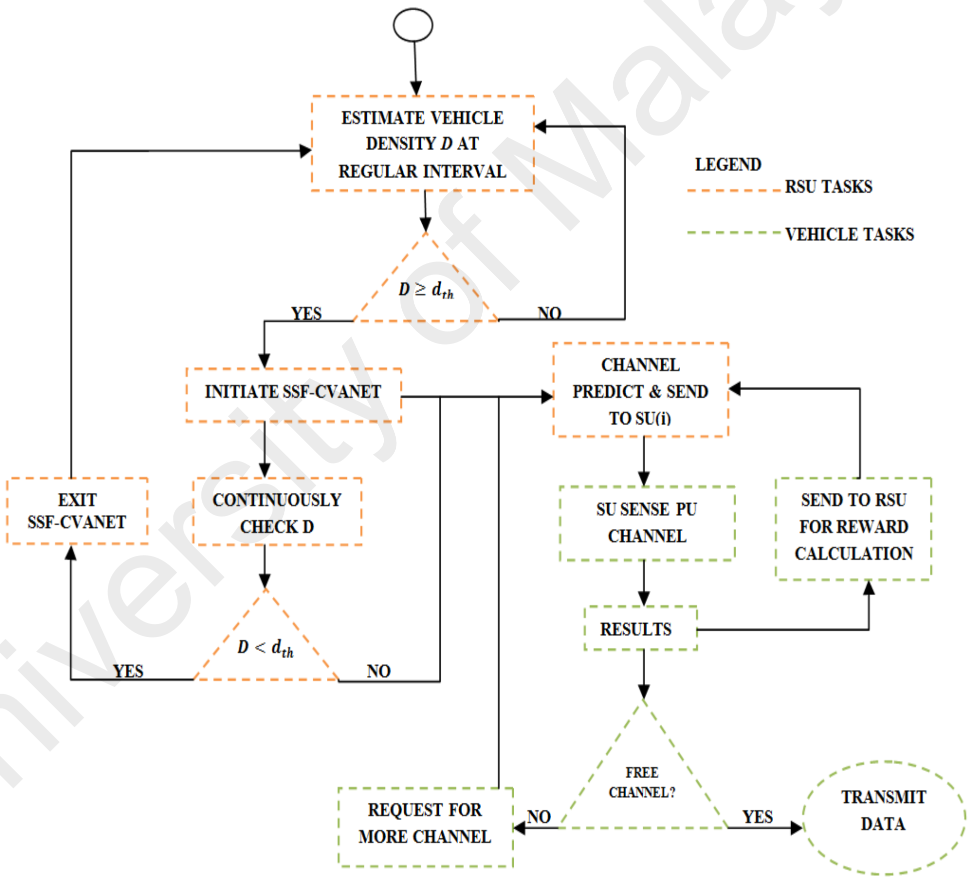

Figure 4.3: Flowchart of the proposed SSF-CVANET

In Figure 4.3 above, D represents the density of vehicles in the road segment while d_{th} represents the threshold for the number of vehicles. The flow chart of the figure above shows the working of the SSF-CVANET to provide extra channels to vehicles on the road. The main objective of the framework is to reduce sensing time while maximizing sensing performance. This is achieved by using predictive algorithm at RSU. The detailed working of the proposed framework shown in Figure 4.3 is discussed in Section 4.3.2 and Section 4.3.3. But first, a brief description of how vehicle density at RSU is estimated is given in the following section.

4.3.1 Vehicle density estimation in the road segment

The main emphasis of this work is providing extra channels for vehicular communication on the road to supplement DSRC channels. Therefore, the major factor to consider for initializing SSF-CVANET is congestion along the road segment as shown in Figure 4.3. The IEEE802.11p/WAVE system has being allocated 7 channels at 5.9GHz band for exclusive use. Therefore, extra channels from other licensed frequency band are only triggered if the DSRC channels are congested. In this regard, some mechanism to estimate vehicle density on the road is required. The vehicle density affects the number of channels that can be used by vehicles for VANET communication. With high vehicle density (.i.e. during congestion) more channels are needed for communication (Bauza & Gozálvez, 2013).

(Darwish & Bakar, 2015) review some of the techniques proposed for estimating vehicle density on the road. There are varieties of ways to estimate vehicle density. One method is to use inductive loop detection. The other one is to install surveillance cameras on sections of the road prone to traffic jams. Like camera surveillance method, inductive loop detection requires specialized devices to be pre-installed at specific location to capture volume of vehicles moving on the road segment of interest. Other methods include pressure pads, infra-red counters and wireless vehicle sensors (Darwish & Bakar, 2015). All the approaches mentioned above incurs extra installation and maintenance cost for devices to road agencies. Moreover, in case of surveillance camera approach, it requires additional time to record and process the raw data for getting a clear estimation of the vehicle density.

In order to estimate vehicle density in this work, the beacon message approach that exploits VANET communication is adapted (Barrachina et al., 2013; Sanguesa et al., 2013). The RSU is responsible for estimating the aggregated vehicle density in each road segment it covers. Whenever a vehicle enters a road segment covered by the RSU, it sends a request to RSU for some services. The RSU then use these beacons from vehicles to estimate the density for a particular time. If the estimated number of vehicles is more than some threshold $\mathrm{d_{th}}$ the RSU will initiate SSF-CVANET. The following sections describe each component of the SSF-CVANET in details starting with the sensing component (Section 4.3.2) followed by PU activity model (Section 4.3.3).

4.3.2 Spectrum sensing model

The sensing model is an important component of SSF-CVANET that is responsible for detecting spectrum opportunities at individual vehicle level. Vehicles on the road need to confirm the occupancy status of the PU activities through sensing on the licensed channels. CVANET is composed of frame by frame structure with each frame denoted by T consisting of sensing time T_s and transmission time $T - T_s$. In addition, vehicles need to continuously sense the licensed bands at start of each frame to monitor the PU activities in order to avoid any interference in the channels of licensed users. This is necessary because vehicles in the CVANET environment are unaware of the activities of the PU in advance (see Chapter 3, Section 3.2.5). Since vehicles are unaware of PU activities in advance it poses some design constraints depending on the sensing technique employed. For example, matched filter detection technique as described in Chapter 3 (Section 3.3.4) requires a perfect prior knowledge of the PU signal. Implying matched filter detector requires different antenna when sensing different PU channels with different characteristics. Alternatively, cyclostationary feature detector (Section 3.3.3) requires long sensing time in order to detect the desired features of the PU signal in question. Long spectrum sensing can led to missed spectrum opportunities in CVANET environment because of mobility of vehicles. Respectively, energy detector (Section 3.3.2) can detect spectrum opportunities without a prior knowledge of the PU signal. However, energy detector performs poorly in noise uncertainties and under low SNR. The noise uncertainties and low SNR are caused by varying sensing environment emanating from multipath fading and shadowing of the PU signal (Chapter 3, Section 3.2.2 & 3.2.3). Therefore, the tradeoff is to balance between sensing time and sensing performance. In addition, the desire is to consider sensing accurately as many different licensed channels as possible for DSA without a prior knowledge of the PU signal.

In order to increase the sensing performance in CVANET environment, in this research work, adaptive sensing is proposed to optimize the advantages of energy detector and cyclostationary feature detector in noise uncertainties and under low SNR. This section is divided into three sub sections. Firstly the energy detection scheme is described in details in Section 4.3.2.1. Secondly one order cyclostationary feature detection approach is presented in Section 4.3.2.2. And thirdly, the proposed adaptive sensing approach which combines the two methods (energy and feature detectors) is presented in Section 4.3.2.3.

4.3.2.1 Sensing based on energy detector

To detect the PU signal, the conventional energy detector estimates the power of the received signal and compares it with a predefined threshold (λ). To this end, the detection problem is formulated as a binary hypothesis (see Chapter 3, Section 3.3.2 Eq. 3.6). The null hypothesis H_0 corresponds to an instance when the PU signal is not present or the PU is not transmitting on the sensed channel ($represented\ as\ y(x) = n(x)$). The alternative hypothesis H_1 corresponds to an instance when the PU signal is present or the PU is transmitting on the sensed channel ($represented\ as\ y(x) = n(x) + hs(x)$). Where the received signal at SU (vehicle) is $y(x)$, $s(x)$ is the actual power signal transmitted by the PU which is distorted by noise $n(x)$ with h representing the channel gain between PU and SU. Vehicles are only permitted to transmit data on the licensed channels when the PU signal is OFF or H_0 is true. The functional block diagram of the energy detector is illustrated in Figure 4.4 below.

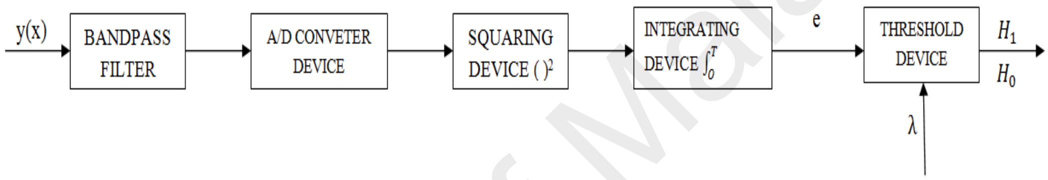

Figure 4.4: Energy detector block diagram

In the illustration of the block diagram in Figure 4.4, the band-pass filter is responsible for selecting the center frequency f_s and bandwidth W of the desired PU channel. In this work, the center frequency f_s is communicated by the RSU based on the prediction of free channels at that particular time. This result on reduction in time the SU spend on deciding frequency bands to sense. The Analog-to-digital (A/D) converter is responsible for converting the analog signal to digital. Thereafter, the received signal is measured by the squaring device and averaged through the integrating device with observation T. The product of the integrating device is the energy test statistic e (Chapter 3, Section 3.3.2 Eq. 3.7) which is compared to the threshold λ to decide the occupancy state of the PU signal. The energy test statistic e has a distribution that can be summarized using central limit theorem (Martínez & Andrade, 2016) given by:

$$e \sim \begin{cases} \chi^2_{2M} & H_0 \\ \chi^2_{2M}\,(2\gamma) & H_1 \end{cases} \qquad 4.1$$

Where M is the received signal samples, the terms χ^2_{2M} and $\chi^2_{2M}\ (2\gamma)$ corresponds to central and non-central chi-square distributions respectively, each with degree of freedom given by $2M$. The non-central chi-square has additional parameter 2γ which is representative of the transmitted SNR γ given as $\gamma = \sigma_s^2/\sigma_n^2$ where σ_s^2 is the power variance of the PU transmitted signal. Again based on the Central Limit Theory (CLT), with large number of sample size (i.e. $M\ \geq 250$) (W. Yue & Zheng, 2010) the energy test statistic can be approximated to Gaussian distribution written as:

$$e\sim\begin{cases}(M\sigma_n^2, 2M\sigma_s^4) & H_0\\(M(\sigma_n^2+\sigma_s^2), 2M(\sigma_n^2+\sigma_s^2)^2) & H_1\end{cases} \tag{4.2}$$

Using Eq. 4.2 and following the performance evaluation discussed in Chapter 3 (Section 3.3.1), the probability of detection P_d and probability of false alarm P_f for the energy detector (ED) can be written as:

$$P_{d,ED} = Q\left[\frac{\lambda - M(\sigma_n^2+\sigma_s^2)}{\sqrt{2M}(\sigma_n^2+\sigma_s^2)}\right] \tag{4.3}$$

$$P_{f,ED} = Q\left(\frac{\lambda - M\sigma_n^2}{\sqrt{2M}(\sigma_n^2)}\right) \tag{4.4}$$

In Eq. 4.3 and 4.4, the component Q(...) represents a generalized Marcum Q-function given as $Q(a) = \frac{1}{\sqrt{2\pi}}\int_a^\infty exp\left(\frac{-t}{2}\right)dt$, λ denotes the decision threshold. Note, $P_{f,ED}$ in Eq. 4.4 is dependent only on noise variance σ_n^2 and not the power variance σ_s^2 of transmitted PU signal. However, $P_{d,ED}$ is dependent on both the noise variance σ_n^2 and the power variance σ_s^2 transmitted by the PU signal. This signifies that the detection performance ($P_{d,ED}$) of spectrum sensing is subject to the transmission environment which is affected by the multipath fading as discussed in Chapter 3 (Section 3.2). The reasoning is that the sensing SU and the PU are located at different locations in the CVANET environment hence experiences some fading due to obstacles and mobility of vehicles. Therefore under multipath fading and shadowing, the Rayleigh fading channel in urban environment is considered in this work. Thus, Eq. 4.3 for $P_{d,ED}$ over fading channels can be averaged over Rayleigh PDF (Chapter 3, Section 3.2.2 Eq. 3.2) to give (Digham, Alouini, & Simon, 2007):

$$\bar{P}_{d,Ed} = \int_{0}^{\infty} Q(\dots) f_{ray}\,(\gamma) d\gamma$$

$$= (exp\left(-\frac{\lambda}{2\sigma_n^2}\right) \sum_{i=0}^{M-2} \frac{\left(\frac{\lambda}{2\sigma_n^2}\right)^i}{i!} + \left(\frac{2\sigma_n^2 + \bar{\gamma}}{\bar{\gamma}}\right)^{M-1}$$

$$* \left[exp\left(-\frac{\lambda}{2\sigma_n^2+\bar{\gamma}}\right) - exp\left(-\frac{\lambda}{2\sigma_n^2}\right) \sum_{i=0}^{M-2} \left(\frac{\left(\frac{\lambda\bar{\gamma}}{2\sigma_n^2(2\sigma_n^2+\bar{\gamma})}\right)^i}{i!}\right)\right]) \qquad 4.5$$

In Eq. 4.5 $\bar{\gamma}$ is the average SNR of scattered signals due to multipath fading while λ is the detection threshold. In conventional energy detector the value of λ is predetermined to achieve the designed constant false alarm probability rate (CFAR). Therefore, the threshold λ can be determined using noise power variance σ_n^2 using Eq. 4.4 as:

$$\lambda = \sigma_n^2 (Q^{-1}(P_{f,ED})\sqrt{2M} + M) \qquad 4.6$$

The fixed threshold λ is compared to energy statistic e obtained from sensing to determine the occupancy state of the PU signal. Respectively, the performance of the energy detector is measured by $P_{f,ED} = P(e > \lambda | H_0)$ and $P_{d,ED} = P(e > \lambda | H_1)$. In addition, the performance of energy detector on sensing time for average achievable transmission throughput of the CVANET is measured as follows

$$R = \left(\frac{T - T_s}{T}\right).(1 - P_f).P(H_0).CB_0 + \left(\frac{T - T_s}{T}\right).(1 - P_d).P(H_1).CB_1 \qquad 4.7$$

Where T is the frame length consisting of sensing period T_s and transmission time $T - T_s$, CB_0 and CB_1 denote the channel capacity (bandwidth) of CVANET network when operating without PUs and in presence of PUs respectively (Stotas & Nallanathan, 2010).

Nevertheless, the important issue with energy detector is inability to capture aggregation of noise in communication systems that emanate from random power sources such as thermal noise in antennas (Martínez & Andrade, 2016). In addition, the distance between the PU and the SU can affect the signal. These issues (including multipath fading) can lead to noise uncertainty in the received signal luring the SU to make uninformed judgment, thus causing interference to PU transmission system or missing the spectrum opportunities. The problem of noise uncertainty and low SNR in spectrum sensing results is addressed by using adaptive sensing. In this view, two thresholds are proposed that can be used to compare the sensing result. One threshold derived from Eq. 4.3 and the other from Eq. 4.4. When the sensing results fall within the two thresholds, no decision is made on the PU occupancy state. The scheme performs further sensing using feature detector to determine the features of the signal for the channel being sensed. The idea of adaptive sensing is further expanded in Section 4.3.2.3. For now, a description of one order cyclostationary feature detection technique follows.

4.3.2.2 Sensing based one order cyclostationary detection

Cyclostationary feature detection technique is one of the robust sensing techniques reported in literature (Bhargavi & Murthy, 2010). A more detailed introduction is given in Chapter 3 (Section 3.3.3). The focus of feature detector is to use the autocorrelation function (Eq. 3.8) to determine the desired features of the PU signal in frequency domain. Nevertheless, it requires long sensing time which contributes to its implementation complexity. This is mainly due to the requirement of searching all frequencies before spectral correlation function is generated. Feature detection technique based on frequency domain is sometimes called two order autocorrelation cyclostationary feature detection (Liu, Zhong, Wang, & Hu, 2015).

To reduce implementation complexity, one order cyclostationary (OOC) feature detection technique has been proposed in literature (Yang Liu et al., 2015; W.-J. Yue, Zheng, Meng, & Yue, 2010; W. Yue & Zheng, 2010). As explain in Chapter 3 (Section 3.3.3), cyclostationary feature detection exploits the periodic statistics such as the mean and autocorrelation of the PU signal. OOC exploits the mean periodicity characteristics of the PU signal in the time domain opposed to frequency domain, thus improving efficiency of spectrum sensing. Detecting the PU signal using mean periodicity reduce implementation complexity compared to using autocorrelation function used in frequency domain. Therefore, OOC can achieve simple implementation complexity and low power consumption while performing fast sensing opposed to traditional cyclostationary feature detection in frequency domain (W. Yue & Zheng, 2010). The OOC can be modeled as follows; when the PU signal $s_x(t)$ is transmitted through the AWGN channel $n_x(t)$ the combined signal received is given by $y_x(t) = n_x(t) + s_x(t)$. Thus, the mean function of $y_x(t)$ at the SU can be written as:

$$M_y(t)_T = E[y_x(t)] = s_x(t) \qquad 4.8$$

where $M_y(t)_T$ is the mean function and $E[\dots]$ is the expectation operator. Note that $n_x(t)$ is not considered in the mean function because noise is considered to be random and has no periodicity or its non-cyclostationary (Section 3.3.3). If the PU signal $s_x(t)$ is periodic with periodic function $T_0 = 1/f_s$ then it follows that the signal received at SU $y_x(t)$ is periodicity. Therefore, based on Eq. 4.8 it could be observed that the mean function $M_y(t)_T$ is also time varying with a periodic function of time given by period T_0. Given the period T_0, it is possible to extract the periodicity using synchronized averaging. Thus, $y_x(t)$ can be sampled periodically given $M_y(t) = M_y(t + kT_0)$ for $k = 0, \pm1, \pm2, \pm3, \ldots$, such characteristics is what is referred to as one order cyclostationary. The block diagram of OOC is given in Figure 4.5 below.

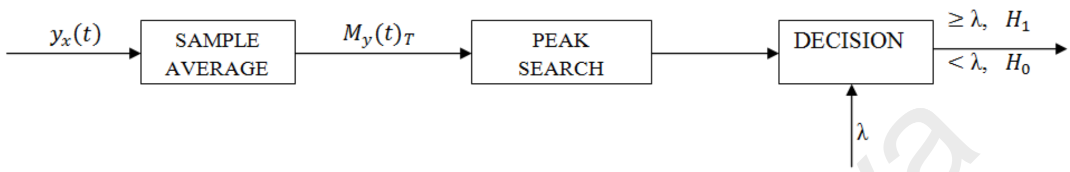

Figure 4.5: Block diagram of OOC

For the two hypotheses H_0 and H_1 the cumulative density function (CDF) of the envelope $M_y(t)_T$ over AWGN for defined threshold λ is given by:

$$P_{f,OOC} = \exp\left(-\frac{\lambda_{PU}^2}{2\delta_A^2}\right) \, for \; H_0 \qquad 4.9$$

$$P_{d,OOC} = Q\left(\frac{\sqrt{2\gamma}}{\delta}, \frac{\lambda_{PU}}{\delta_A}\right) for \; H_1 \qquad 4.10$$

In which γ is the instantaneous SNR, the component Q(,) represents a generalized Marcum Q-function while $\delta_A^2 = \delta^2/(2M + 1)$ with M the number of samples.

4.3.2.3 Adaptive spectrum sensing

The proposed adaptive spectrum sensing is based on the energy detector and OOC described above. The main purpose of a spectrum sensing scheme is to provide robust mechanism to accurately detect the PU signal to avoid interference to the PU systems while maximizing spectrum utilization. Success of CVANET will depend on the assurance licensed users will have to use their licensed spectrum without interference from unlicensed users. Therefore, a robust spectrum sensing that provide accurate sensing results in a timely manner is needed. On one hand, energy detector as described in Section 4.3.2.1 can detect different spectrum opportunities from different channels without a prior knowledge of the PU system in advance. It can also achieve the sensing in a quick and timely manner. However, many experimental and simulation results have shown that energy detector perform poorly in noise uncertainty and low SNR (Cabric, Tkachenko, & Brodersen, 2006; Tandra & Sahai, 2005). On the other hand, cyclostationary feature detector performs better in noise uncertainty even in low SNR. However, it requires long sensing time which increases implementation complexity especially if the sensing is performed in frequency domain. Therefore, there is need to exploit the advantages of both energy detector and cyclostationary detector in CVANET.

In this section, a detailed description of the proposed Adaptive Spectrum Sensing is presented. Adaptive spectrum sensing combines the advantages of both energy detector and feature detector to provide sensing technique in the CVANET environment. The emphasis of adaptive spectrum sensing is to provide a sensing technique that is robust to provide maximum protection to licensed users especially in noise uncertainties. Furthermore, the scheme should provide for maximum utilization of licensed bands for DSA whenever available. For that reason, the adaptive spectrum sensing is composed of two stages. In the first stage, the adaptive spectrum sensing relies on the energy detector to detect the PU signal. Two thresholds are defined to account for noise uncertainty and low SNR. The first threshold which is represented in Eq. 4.6 becomes $\lambda_1 = \sigma_n^2(Q^{-1}(P_{f,ED})\sqrt{2M} + M)$ while the second threshold is derived from Eq. 4.3 as $\lambda_2 = (\sigma_n^2 + \sigma_s^2)[Q^{-1}(P_{d,ED})\sqrt{2M} + M]$. The second threshold is provided to achieve a desired constant probability of detection (CPD). If the energy statistic $e < \lambda_1$the final decision on the occupancy state of the PU signal will be H_0 corresponding to null hypothesis. Alternatively, if the energy statistic $e \geq \lambda_2$ the final decision on the occupancy state of the PU signal will be H_1. However, if the energy statistic falls within $\lambda_1 < e < \lambda_2$, no decision is made. Instead, stage two sensing is performed using one order cyclostationary detection.

In stage two of adaptive spectrum sensing, OOC described in Section 4.3.2.2 is performed. OOC detect the PU signal in time domain opposed to frequency domain. Mean function is used to determine the time peaks in the PU signal which are later compared to some threshold λ_{PU} based on the channel and frequency of interest. Using the mean function and synchronized averaging method makes it possible to detect any PU or SU signal. This is because noise does not show periodicity (Gato, Martínez, & Torres, 2015). Therefore, any periodicity observed in the signal under consideration would be from communicating systems. Using OOC, it is possible to determine the nature of the signal whether it originated from the PU or other vehicles (SU). The importance of distinguishing between PU and SU signal is to allow fair usage and sharing of the PU channel should the SU signal be detected. Other SUs can wait for the current SU to finish its communication and use the same PU channel. Thus, allowing for maximum channel utilization. Figure 4.6 depicts the flowchart of the adaptive spectrum sensing.

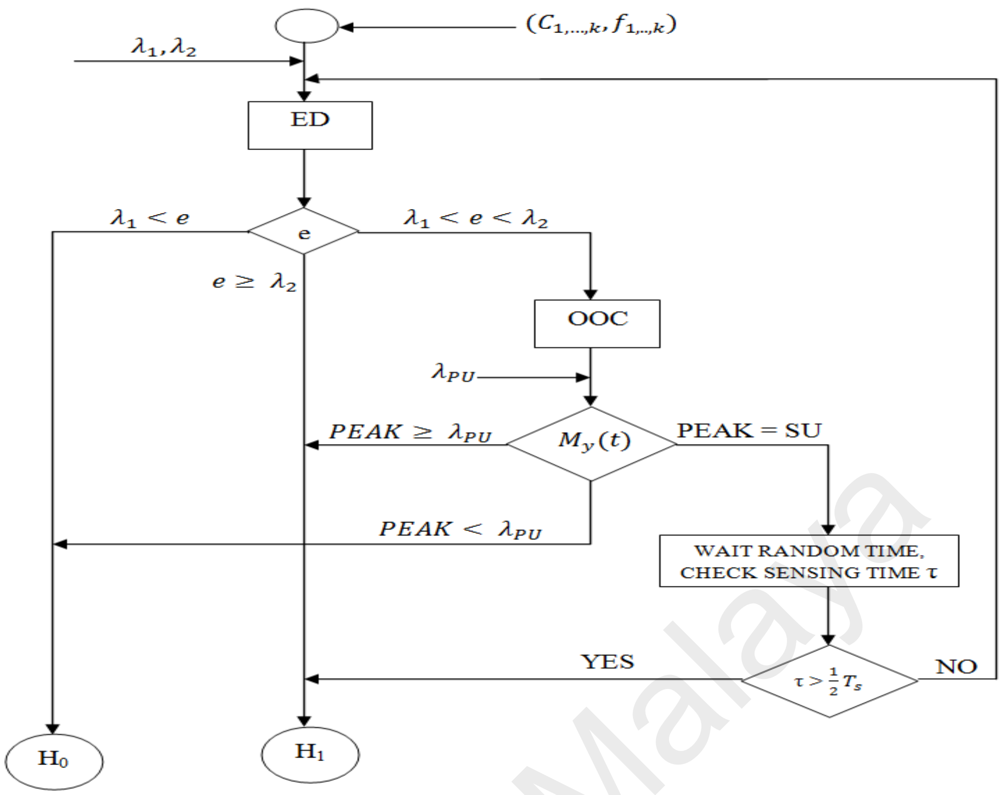

Figure 4.6: Proposed flowchart of adaptive spectrum sensing

In the figure above, $\lambda_1$is the first threshold, λ_2 is the second threshold, λ_{PU} is threshold for OOC, e represents the energy test statistics, τ is sensing period with T_s representing the overall sensing time. ED is energy detector, OOC is one order cyclostationary detector, $C_{1,\dots,k}$ represents channels of interest with center frequency ($f_{1,\dots,k}$). The OOC have three options as noted from Figure 4.6. In the first option, if the peaks are determined to be those of the PU signal, the final decision for adaptive spectrum sensing will be H_1. For the second option, if the mean peaks are determined to be noise or no periodicity is observed, the final decision will be H_0 and the SU can transmit on that channel. Finally for the third option, if the peaks are determined to be those of other SU, the scheme will wait some random time and attempt to sense again. This is reinforced to increase channel reuse. Nevertheless, the SU will check if the sensing time is less than the total sensing time allowed. If the sensing time is more than the total sensing time allowed, the scheme assumes H_1 and can check other channels that might be free for DSA. However, if the sensing time is less than the total sensing time allowed, the SU can check the same channel. The flowchart of Figure 4.6 is represented in an algorithm given below:

Algorithm 1 Adaptive Spectrum Sensing
Inputs: λ_1, λ_2, λ_{PU}, $C_{1,\ldots,k} \rightarrow f_{1,\ldots,k}$, M, T_s, T
Outputs: decide H_1, H_0 ‣ *Probability of detecting the PU signal or not*

1: **set** λ_1 *from Eq. 4.4*, λ_2 *from Eq. 4.3* and λ_{PU} *from Eq. 4.9*
2: **for** m=1 to M **do**
3: *perform sensing on* C_k *with sensing interval* τ *using ED Section 4.3.2.1*
4: **get** *e from* step 3
5: **if** $e < \lambda_1$ **then**
6: *decide* H_0
7: **else if** $e \geq \lambda_2$ **then**
8: *decide* H_1
9: **else if** $\lambda_1 < e < \lambda_2$ **then**
10: **for** m = 1 to M **do**
11: *perform sensing on* C_k *with sensing interval* τ *using OOC Section 4.3.2.2*
12: **get** $M_y(t)$ *from* step 11
13: **if** $M_y(t) < \lambda_{PU}$ **then**
14: *decide* H_0
15: **else if** $M_y(t) \geq \lambda_{PU}$ **then**
16: *decide* H_1
17: **else if** $M_y(t) = SU\ PEAKS$ **then**
18: *wait for random time*
19: *check the sensing time* T_s
20: **if** $T_s \geq \frac{1}{2}T$ **then**
21: *decide* H_1
22: **else if** $T_s < \frac{1}{2}T$ **then**
23: *go to step* 2
24: **end**

Step 1 sets the predefined threshold for both ED and OOC using respective equations. The other steps follow the flowchart shown in Figure 4.6. After step 6 or 14, the SU can transmit on the licensed channel C_k because it is determined to be free given that the decision is H_0. However, after step 8, 16 or 21 the SU is not permitted to transmit on the sensed channel because the decision is H_1. When the final decision is H_1 the case of steps 8, 16 and 21, the SU can start the sensing process on the next licensed channel obtained from the RSU. Furthermore, the results of sensing (decision) at the end of steps 6, 8, 14, 16 and 21 are sent to the RSU regardless of the outcome of the sensing (whether H_0 or H_1 is true). The results are used to model the PU activity pattern which is used in prediction licensed channels that might be free for future use. The PU activity modeling is described in the next section.

4.3.3 Primary user activity modeling

Spectrum sensing performance is much dependent on the activity pattern (duty cycles) of the PU transmitters (see Section 3.2.5 for further explanation). This is because the duty cycles of any communication systems are perceived to be random and not statically predetermined. However, many literatures in CVANET consider static PU activities or no PU model all together (Chembe, Noor, et al., 2017). For example, the schemes will consider the PU to transmit for a specified time and remaining idle for another specified time. In reality PU duty cycles are random, hence, cannot be limited to static assumption taken by proposed schemes in CVANET. At a particular point in time the PU will be transmitting on the channel which can be called ON state. At another point in time the PU will not be transmitting on the channel which can be called OFF state. To model the PU activity pattern the transition time between the ON and OFF states and vise versa must be taken into account. For instance, consider Figure 4.7 below.

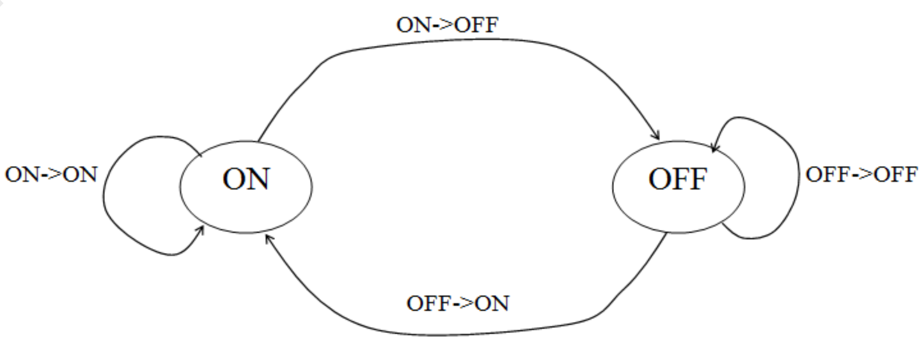

Figure 4.7: Two state Markov chain transition of the PU transmitter

The activities of the PU duty cycles can be modeled as Markov chain with two states corresponding to ON and OFF. The Markov chain models the state of a system with a random variable that changes through time. Let the ON period be represented by α and the OFF be represented by β. From Figure 4.7, the ON states can be taken as the time instance when the PU is ON and when the PU is transitioning from OFF to ON state. Similarly, the OFF states can be taken as time instance when the PU is OFF and when the PU is transitioning from ON to OFF. Therefore, the probability of steady ON and OFF states can be represented by $p_{ON} = \frac{\alpha}{\alpha+\beta}$ and $p_{OFF} = \frac{\beta}{\alpha+\beta}$. To comprehend this further, consider Figure 4.8 below.

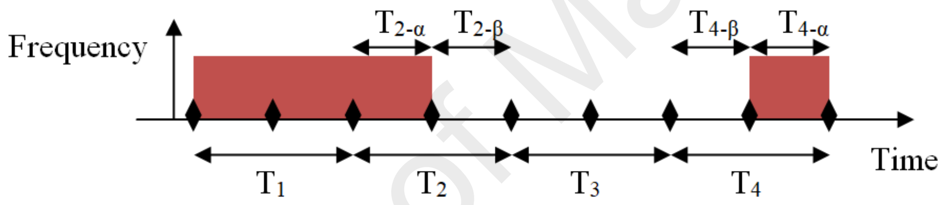

Figure 4.8: PU transition state within frame window ***T***

In Figure 4.8, the frame is taken to be T in which a vehicle can sense and transmit on the PU channel, thus there are two instances in which the PU transmission is not static (i.e. T_2 and T_4). For example, the PU is considered to be ON for the intervals T_1, part of T_2 and part of T_4. The total time for PU ON therefore is $T_1 + T_{2-\alpha} + T_{4-\alpha}$. On the other hand, the PU is considered to be OFF for the intervals T_3, part of T_2 *and* T_4 giving total of $T_{2-\beta} + T_3 + T_{4-\beta}$. Note in Figure 4.8 the transition state intervals (from Figure 4.7) are demonstrated by part of T_2 for PU ON->OFF and T_4 for PU OFF->ON.

The probability of the PU remaining in the stable ON or OFF periods for M sensing samples is exponentially distributed (Rawat et al., 2015) given by $exp\,(-\frac{M}{\alpha})$ and

$exp\ (-\frac{M}{\beta})$ respectively. Thus, the probability of the PU being ON for sensing window is given by:

$$P_{ON} = p_{ON}.\exp\ (-\frac{M}{\alpha}) \qquad 4.11$$

Similarly the probability of the PU being OFF for the sensing window is given by:

$$P_{OFF} = p_{OFF}.\exp\ (-\frac{M}{\beta}) \qquad 4.12$$

To account for transition states which is switching from ON to OFF and vise versa, a probability of switch state is formulated. Remember from Figure 4.8 that a PU can switch from ON to OFF and vise versa within a sensing cycle. Therefore, the probability of transition (P_T) is given by:

$$P_T = 1 - P_{ON} - P_{OFF} = 1 - (P_{ON} + P_{OFF})$$

$$= 1 - \left[p_{ON}.\exp\left(-\frac{M}{\alpha}\right) + p_{OFF}.\exp\left(-\frac{M}{\beta}\right)\right]$$

$$= 1 - \left[\frac{\alpha}{\alpha+\beta}.\exp\left(-\frac{M}{\alpha}\right) + \frac{\beta}{\alpha+\beta}.\exp\left(-\frac{M}{\beta}\right)\right]$$

$$= 1 - \left[\frac{1}{\alpha+\beta}\left(\exp\left(-\frac{M}{\alpha}\right)\alpha + \exp\left(-\frac{M}{\beta}\right)\beta\right)\right] \qquad 4.13$$

From Eq. 4.13, a plot of P_T can be obtained using different sensing samples and various values of α and β. Figure 4.9 shows the reliance of PU state transition for different M sensing samples given divergent PU activity patterns. The streams in the figure correspond to the values of α (ON period) and β (OFF period). The values used for the streams are as follows; Stream $1(\alpha = 40, \beta = 100)$, Stream $2(\alpha = 60, \beta = 150)$, Stream $3(\alpha = 100, \beta = 200)$, Stream $4(\alpha = 200, \beta = 10)$, Stream $5(\alpha = 120, \beta = 100)$ and Stream $6(\alpha = 300, \beta = 100)$. Streams in this case demonstrate random PU activity pattern. Therefore, the values are picked arbitrarily (i.e. assuming the PU activity pattern can take any of the streams given).

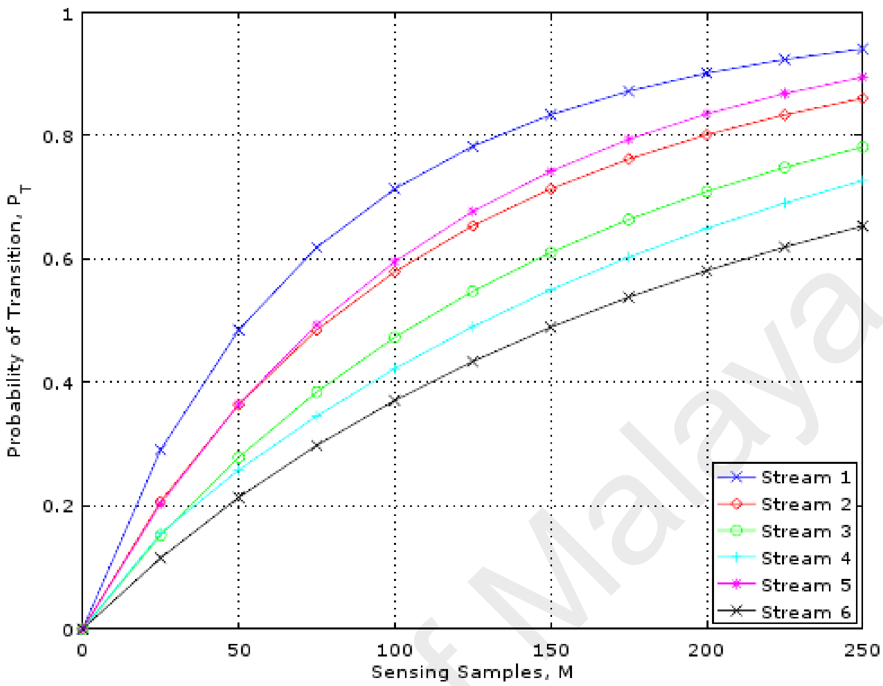

Figure 4.9: $\boldsymbol{P_T}$ for different sensing samples, $\boldsymbol{M}$

Figure 4.9 demonstrates that the PU transition state increases with increase in the number of sensing samples. For instance, the chance of the PU transition states for 250 sensing samples is above 60% for all streams. This is because increase in number of sensing samples increases the sensing time thereby increasing the chances for the PU to switch states. On the other hand, the values of P_T decreases with increased variation in the PU activity pattern. With increased duty cycles (i.e. increased ON or OFF periods), the chances of the PU changing state becomes minimal. For example, the values of P_T for Stream 6 are relatively low compared to other streams. This is demonstrated by long PU activity patterns ($\alpha = 300, \beta = 100$) compared to say Stream 1 with short activity pattern ($\alpha = 40, \beta = 100$). The implication of Figure 4.9 is that PU activity patterns can influence the sensing results. P_T is directly proportional to sample size and inversely proportional to PU activity pattern. Consequently, short sensing intervals are desired to account for transitional states. Furthermore, few samples should be collected when spectrum sensing is conducted to accommodate dynamic transition state. Short sensing intervals are important especially in CVANET because of mobility of vehicles. Therefore, the trade-off is between performing quick sensing and increasing accuracy of sensing results.

To account for transition state and sensing interval, machine learning is used in this research work to predict licensed channels of the PU systems which are likely to be free at a particular time. Simply put, the RSU should predict channels of the PU systems that exhibit long transitional state with long OFF periods. These channels are then communicated to vehicles upon entry on the congested road segment for sensing (using adaptive spectrum sensing) described in Section 4.3.2.3. The RSU is also responsible for updating the learning PU activity model by using results obtained from vehicles after sensing. The history of sensing results plays an important role similar to cooperative spectrum sensing decision (See Chapter 3, Section 3.4). In the following section, history of sensing results is described and how it is used compared to cooperative decision.

4.3.3.1 History of sensing results for modeling PU activities

One of shortcoming of conventional spectrum sensing techniques such as energy detection is being susceptible to fading and shadowing due to multipath of PU signal in the sensing environment. Cooperating sensing has been proposed to mitigate such drawbacks (See Chapter 3, Section 3.4). Cooperative decision exploits the temporal spatial and diversity gain from cooperating vehicles. However, cooperative decision has its shortcomings despite the gain from cooperating vehicles. For example, cooperative decision increases the demand for extra bandwidth to exchange local sensing results from participating SUs. During congestion, the priority is to free more channels for sensitive safety packets to be transmitted. With cooperative decision, the control channel (or any DSRC channel) can be overwhelmed by exchanging packets for spectrum sensing results due to increased vehicle density during congestion. This intuitively defeats the purpose of DSA. Furthermore, cooperative decision incurs accumulative time delay for reporting sensing results from individual SUs because of synchronization problem. This is because each SU has different sensing intervals and asynchronous transmission schedules (Yi Liu et al., 2015). Thus, the sensing results arrive at different times at the FC in centralized cooperative sensing or distributed cooperative sensing. Due to mobility of vehicles, the results from FC maybe rendered invalid because the vehicles would have moved to other areas where the characteristics of the PU might be different.

To overcome shortcomings of cooperative decision such as synchronization problem, machine learning is proposed in this work. In particular, reinforcement learning (RL) is used to model the behavior of the PU activity pattern which is used in predicting future PU channel state. RL is a machine learning approach that solves complex problems without prior detailed knowledge of the working environment (Di Felice, Chowdhury, Wu, Bononi, & Meleis, 2010; Szepesvári, 2010). Nevertheless, RL heavily utilize historical data of the operating environment to model and predict future actions. Therefore, RL can be used to model the PU activity based on the data learned from vehicles after sensing. In future the learned channel states by the RSU are sent to passing vehicles with optimized sensing parameters to increase the sensing accuracy while reducing on sensing time. History of sensing data is useful in predicting the future PU channels that might be free because channels within the same service area have shown to have high spectral correlation (Yin, Chen, Zhang, & Li, 2011). The service area in CVANET includes all possible PU systems in the road segment covered by the RSU. In addition, history of sensing results is essential in helping the RSU adapt to dynamic PU pattern based on RL. Hence, any changes in the behavior of the PU transmitter are easily learned over time from history of sensing data. The important history data transmitted to RSU at any successful sensing period (regardless of whether H_0 or H_1) include channel availability status, channel bandwidth, and opportunistic time (sensing and transmission time if any). These parameters are used to compute the reward (next section) of the channel that is used in the continuous learning process of the PU dynamics.

The difference between cooperative decision proposed in literature and the proposed scheme is that in the latter, the RSU is only involved at the beginning of sensing event when the vehicle enters the congested road segment (similarly, the scheme can be used in road segment not congested). As a consequence, no need for extra bandwidth to communicate sensing results to RSU for reaching a global consensus and sending back global result to participating vehicles in case of cooperative decision. Nevertheless, history of sensing results is still sent to the RSU for continuous cooperative learning after the vehicle has already transmitted its data. This can be achieved using acquired PU channels opposed to DSRC channels. The other difference is that once a vehicle determines free channel using sensing described in Section 4.3.2.3 (adaptive spectrum sensing), it can proceed and communicate on the channel. Thus, eliminating the synchronization problem encountered in cooperative decision. This further reduces the accumulative time delay overhead encountered in cooperative decision to get sensing results and communicating the result back after global decision. Reducing sensing and access time for SU is important to avoid interference to PU systems. In addition, short sensing period are desired in CVANET due to mobility and transient changes in the PU activity patterns (Figure 4.9).

Furthermore, the proposed approach indirectly eliminate spectrum sensing data falsification security problem encountered in cooperative decision. Since only the history is sent to the RSU, any attempt to falsify sensing data will have no impact on other vehicles. For example a malicious user can send huge reward (i.e. reward value in RL, next section) for some channel to fool the RSU into recommending that channel to other vehicles. Due to continuous learning, the RSU will be updated with small rewards for that channel if it is found to be occupied continuously by the PU, thereby eliminating the data falsification problem. Again note that the RSU only use the history data for predicting channels (through RL) that will be free for future vehicles and not the current vehicle that transmitted the sensing results. Therefore, history of sensing results from adaptive spectrum sensing obtained from vehicles on the roads is used as input to RL at the RSU. In the following section a detailed description of RL at RSU and how it utilizes history of spectrum sensing data from passing vehicles is presented.

4.3.3.2 Reinforcement learning for predicting PU activity pattern

Reinforcement learning is a branch of machine learning (ML) that map situations to actions in an environment in order to maximize some numerical reward signal (R. S. Sutton & Barto, 1998). It is defined by characterizing a learning problem opposed to characterizing learning methods the case of other ML techniques such as supervised learning. Therefore, RL is suited for learning complex problems in an environment without a prior knowledge of the dynamics of the environment. This is true especially in CVANET where the PU systems are not directly involved in the sensing process. The CVANET network (i.e. vehicles and RSU) needs to sense and figure out the characteristics of the PU systems as well as the PU transmission patterns. Two prominent entities of RL are agent and the environment (Szepesvári, 2010). The agent is an entity that learns and models the dynamics of the environment to achieve the target goal through desired actions. In this work, the agent is the RSU while the environment is the CVANET network which is divided into road segments. The goal is for RSU to find PU channels with good bandwidth throughput and long OFF periods (more spectrum opportunities) for vehicular communication during congestion. Therefore, the main function of the RSU in the proposed framework is to define the sensing policy by guiding vehicles to sense particular channels at the right time.

RL algorithms are associated with four main sub elements apart from agent and environment. These elements are *reward* function, *value* function, *policy* and *model* of the environment which is optional (R. S. Sutton & Barto, 1998). A *reward* function defines a scalar feedback signal value the agent gets from the environment by performing some action. The foremost objective of the agent is to maximize the total reward received in the long run. The *value* function on the other hand specifies what is desired in a long run. Thus, a value of a state is the total number of rewards that is expected by the agent to accrue in future given the current state. A *policy* defines the behavior of the agent at a given time as it learns the environment. Therefore, a policy maps perceived states of the environment to actions taken by the agent when in those states. Finally, optional element is *model* of the environment which is used for planning on which course of action to take while considering possible future situation before they even happen.

Recall from Figure 4.7 that PU duty cycles can be modeled as Markov process with two states represented by ON state and OFF state. Therefore, the problem of PU activity modeling can be formulated as a finite-horizon Markov decision process (MDP) (Szepesvári, 2010). MDP is Markov reward process with decision to make at each time instance. The MDP is considered because the RSU (agent) interact with the CVANET environment and make decisions by selecting the channels to send to vehicles in time step. The MDP is represented by set of states S representing the model (observations) of the environment, a reward function R in a given state, the set of actions A that an agent can take, a state transition probability ρ and a discount factor $\epsilon \in [0,1]$. If we let the episode during which the congestion is considered to be T_E, then the RSU will interact with the environment in time steps $t = 0,1,2, \dots, T_E$. At each step t, the RSU (agent) executes an action A_t by sending sensing information to vehicles in the CVANET environment. Then at step $t+1$, the vehicle (SU) sends back the observation $O_{t+1} \in O$ and reward $R_{t+1} \in R$. What happens next is determined by the state $S_{t+1} \in S$. Basically, S is the function of history $(H_t = O_1, R_1, A_1, \dots, A_t, O_{t+1}, R_{t+1}, \dots, A_{T_E-1}, O_{T_E}, R_{T_E})$ which can be represented as $S_t = f(H_t)$. A detailed pictorial representation of RL in CVANET environment is given in Figure 4.10 below.

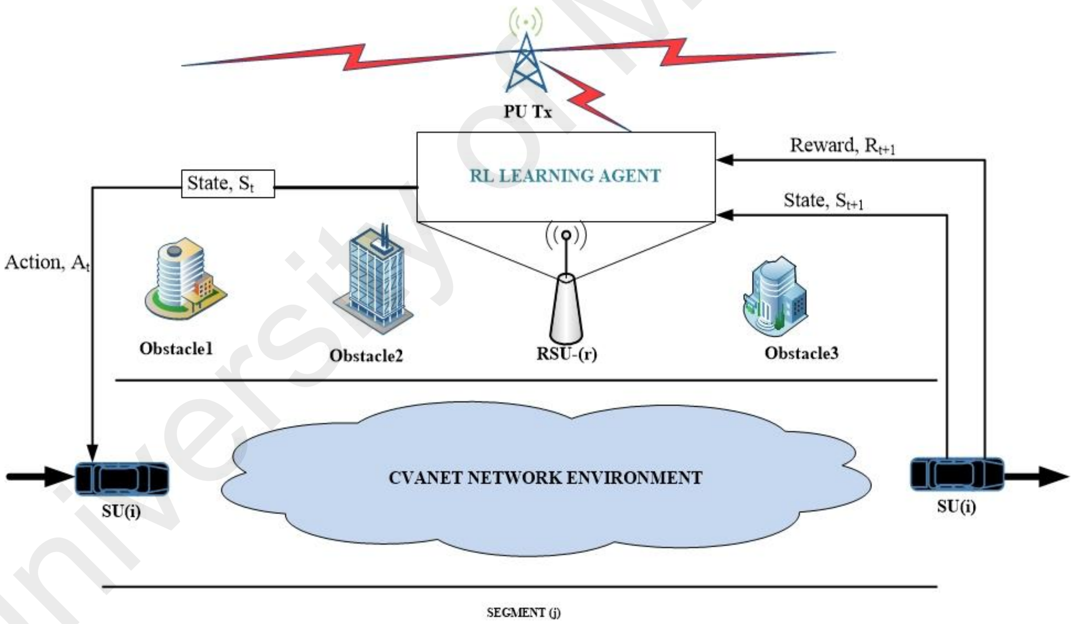

Figure 4.10: Reinforcement learning model for SSF-CVANET

The high level description of Figure 4.10 is like this. The RSU continuously estimate the vehicle density on the road segment. When the vehicle density is beyond some threshold d_{th}, the SSF-CVANET is initialized. The RSU will send channels to passing vehicles that wish to transmit its data on licensed channels which is termed as action $\mathrm{A_t}$. Then the vehicle will perform sensing based on adaptive sensing described in Section

4.3.2.3. Depending on the result of the sensing, the results are sent to RSU with new state $\mathrm{S}_{\mathrm{t+1}}$ and reward $\mathrm{R}_{\mathrm{t+1}}$ of sensing and using that channel if idle. Thereafter, the RSU will update the channel status with new state and reward. The RSU will choose channels with high reward to send to vehicles. The process continues until the congestion is cleared. Without loss of generality, the sate S_t represents the PU channel status. The cumulative reward R is weighted value calculated from three parameters; channel availability status CA_k, channel bandwidth CB_w and opportunistic time T_{ot}. Opportunistic time in this case denote the combination of sensing and transmission time. The three parameters used to calculate the reward are obtained from vehicles on the road using adaptive spectrum sensing. Therefore, a reward at $\mathrm{t}+1$ is given by

$$R_{t+1} = I_A\{CA_k\}(w_b CB_w + w_t T_{ot}) \qquad 4.14$$

Where w_b and w_t represent the weighted contribution for CB_w and T_{ot} respectively. The weights make sure channels with high OFF periods and high bandwidth get high reward. $I_A\{CA_k\}$ is the indicator function for channel availability with $CA_k \in \{0,1\}$. Zero represents no channel for DSA denoted by H_1 and one represents free channel for vehicle communication denoting H_0. The reward function R for a given state S and action A is $R_s^a = E[R_{t+1}|S_t = s, A_t = a]$ where E is expectation function (Szepesvári, 2010). The value of R after $t+1$ time–steps is given by $\epsilon^t R$ for $\epsilon \in [0,1]$. Values of the discount factor ϵ close to zero are concerned about the immediate rewards while values of ϵ close to one are concerned about rewards which are far-sighted.

a) Modeling the PU state activity pattern with MDP

In this work, the Bellman equations (R. S. Sutton & Barto, 1998) are used to model the MDP for RL problem while the temporal difference (TD) learning with lambda (TD(λ)) is used to solve the problem formulation. For a given policy π, which is a distribution of action for some state is given by $\pi(a|s) = P[A_t = a|S_t = s]$. $\pi(a|s)$ denotes the probability for action A_t being selected in state S_t using the policy π. The probability of the state S transition to another state S' is given by $\rho_{ss'} = P[S_{t+1} = S'|S_t = s]$. The transit in CVANET refers to PU changing state from ON to OFF and vice versa (see Figure 4.7). The state probability matrix P which define transition probabilities from all states S to all possible next states S' is given by

$$P = \begin{bmatrix} \rho_{ON\rightarrow ON} & \rho_{ON\rightarrow OFF} \\ \rho_{OFF\rightarrow ON} & \rho_{OFF\rightarrow OFF} \end{bmatrix} \quad 4.15$$

where each row in the matrix adds up to one. The *value* function $v_\pi(s)$ for the MDP is expected return following the policy π for state S given by

$$v_\pi(s) = E_\pi[G_t|S_t = s] \quad 4.16$$

Where $\mathrm{G_t}$ is the return function for total discounted rewards from time-step t given by $\mathrm{G_t} = \sum_{\mathrm{d}=0}^{\infty} \epsilon^{\mathrm{d}} \mathrm{R_{t+d+1}}$ (Szepesvári, 2010). Similarly, the state-action function $\mathrm{q_\pi(s, a)}$ is expected return from state S following policy π and taking action a. Thus, the action function is given by

$$\mathrm{q_\pi(s, a) = E_\pi[G_t|S_t = s, A_t = a]} \quad 4.17$$

Furthermore, value and action functions (Eq. 4.16 and Eq. 4.17) can be decomposed into immediate reward and discounted value of successor states for the return function $\mathrm{G_t}$ as $v_\pi(s) = E_\pi[R_{t+1} + \epsilon v_\pi(S_{t+1})|S_t = s]$ and $\mathrm{q_\pi(s, a) = E_\pi[R_{t+1} + \epsilon q_\pi(S_{t+1}, A_{t+1})|S_t = s, A_t = a]}$. The Bellman expectation equations for the two functions is given by

$$v_\pi(s) = \sum_{a\in A} \pi(a|s) q_\pi(s, a) \text{ and} \quad 4.18$$

$$q_\pi(s, a) = R_s^a + \epsilon \sum_{s'\in S} \rho_{ss'} v_\pi(S') \quad 4.19$$

The value function Eq. 4.18 has action-state function, therefore, $q_\pi(s,a)$ in Eq. 4.18 can be replaced by Eq. 4.19 to give

$$v_\pi(s) = \sum_{a\in A} \pi(a|s)(R_s^a + \epsilon \sum_{s'\in S} \rho_{ss'} v_\pi(S')) \qquad 4.20$$

To find the best possible performance for MDP, the optimal function is used. For value function, the optimal value that maximize $v_\pi(s)$ over all policies is given by

$$v_*(s) = \max_\pi v_\pi\,(s) \qquad 4.21$$

Similarly, the action function that maximize the $\mathrm{q}_\pi(\mathrm{s},\mathrm{a})$ for all policies is given by

$$q_*(s,a) = \max_\pi q_\pi\,(s,a) \qquad 4.22$$

b) MDP Solution for Value (V) function using TD(λ)

There are many algorithms that can be used to estimate the value function to optimal value of the MDP in RL problems. The most basic and often used include dynamic programming (DP), Monte-Carlo (MC) and temporal difference (TD) learning (Szepesvári, 2010). DP works well in an environment where the agents have full knowledge of the surrounding. On the other hand, MC and TD are based on model free in which the agents have partial or no knowledge of the environment. Algorithms based on MC and TD learns directly from experience obtained after interacting with the environment. Therefore, these two methods are suited for CVANET environment where the RSU only learns about the PU occupancy state after getting sensing history from vehicles participating in the sensing environment. With TD, predictions are used as targets towards the real value function during the course of learning using bootstrapping (R. S. Sutton & Barto, 1998). On the other hand, MC learns at the end of the episode.

In this work, TD (λ) is used to find the optimal value function. TD(λ) utilizes advantages of both MC and TD by introducing the return trace-decay parameter $\lambda \in [0,1]$ that set a trade-off between MC and TD. When $\lambda = 0$, TD (λ) is TD and for $\lambda = 1$ TD (λ) is MC. The difference between TD and TD (λ) is that the latter use TD learning with eligibility traces that increase the learning speed. The update equations used by TD (λ) to estimate the value function is given below:

$$\delta_t = R_{t+1} + \epsilon V(S_{t+1}) - V(S_t) \qquad 4.23$$

$$E_t(S) = \epsilon\lambda E_t(S) + 1(S_t = s) \qquad 4.24$$

$$V(S_{t+1}) \leftarrow V(S_t) + \theta_t \delta_{t+1} E_{t+1}(S) \qquad 4.25$$

Where $E_t(S)$ is the eligibility trace, δ_t is the TD-error that define difference in values of the state that correspond to successive time steps. θ_t is the step size sequence. The algorithm for finding the optimal $v_*(s)$ using TD (λ) is given below:

Algorithm 2 implement TD (λ) with eligibility traces, should be called after every transition.

Inputs: $|S|$, $|A|$, w_{ca}, w_b, w_t

Outputs: $V(S_t)$, E_t ‣ *$V(S_t)$ becomes optimal $v_*(s)$*

Initialize: $V(|S|)$, $\theta_t, \delta_t, E_t, \epsilon, \lambda$ ← arbitrary values
$\delta_t \leftarrow R_t + \epsilon V(S_{t+1}) - V(S_t)$
for all $s \in S$ **do**
  $E_t(S) = \epsilon\lambda E_{t-1}(S)$
  if $S = s$ **then**
    $E_t(S) \leftarrow 1$
  end if
  compute R_t from Eq. 4.14
  $V(S_t) \leftarrow V(S_t) + \theta_t \delta_t E_t(S)$
end for
return (V, E_t)

4.4 Chapter summary

This chapter has presented the spectrum sensing framework that answer some of the challenges identified in Chapter 3. The chapter starts by describing the methodology that defines the processes involved in developing and making a case for SSF-CVANET. Thereafter, a detailed description of the proposed SSF-CVANET is presented in Section 4.3. Each section in 4.3 starts by pointing out the gap identified in Chapter 3 then provides solution for such a gap. The gaps are identified both in per vehicle sensing and cooperative decision. Thus, adaptive sensing is proposed to overcome spectrum sensing uncertainty under low SNR in per vehicle sensing. Details are given in Section 4.3.2.3. The gaps identifiable with cooperative sensing such as communication overhead and SSDF attacks are mitigated by sending history of sensing results to RSU instead of real time cooperative decision. In addition, this chapter also details the PU activity model based on reinforcement learning, a machine learning technique in Section 4.3.3. Firstly we model the PU activities as two state Markov chain process (i.e. PU ON/OFF). Then, we show that changes in PU activities can affect sensing result in terms of number of sensing samples and sensing time (Figure 4.9). The patterns of the PU activities are learned at RSU using RL. The RSU then use history of sensing results obtained from cooperating vehicles to predict future state of PU pattern. The RSU is also responsible for sending channels to passing vehicles during congestion. The channels are those predicted to be free of PU transmission based on reward. In the next chapter, a detailed implementation procedure using simulation will be given while Chapter 6 provide testing and validation of the proposed framework in comparison to other state-of-art approaches.

CHAPTER 5: IMPLEMENTATION OF THE FRAMEWORK

5.1 Introduction

This chapter discusses implementation details of SSF-CVANET based on proposed methodology presented in Chapter 4. In particular, it presents the detailed implementation of SSF-CVANET through simulation. In this regard, a detailed description of simulation tools is given in Section 5.2 and the choice of one simulator versus others is given. Section 5.3 presents simulation tools for SSF-CVANET which is NS3 and SUMO. The chapter goes further in Section 5.4 to give a detailed description of implementation of framework regarding classes of NS3 used to support adaptive sensing and reinforcement learning as discussed in Chapter 4. In addition, Section 5.4 gives detailed steps for preparing SUMO mobility trace used in NS3 simulation. Finally, the chapter is concluded in Section 5.5.

5.2 Simulation tools for VANET

Implementation of vehicular communication in real world test beds involve high cost and not scalable in most circumstance (Mussa, Manaf, Ghafoor, & Doukha, 2015; Stanica, Chaput, & Beylot, 2011). This is mainly due to low distribution of vehicles with VANET communication capabilities on the roads. There are currently few vehicles with onboard units to facilitate vehicle to vehicle or vehicle to infrastructure communications. Therefore, simulation tools are used to model and evaluate the performance of new algorithms for vehicular networks (Al-Sultan et al., 2014; Sommer, Härri, Hrizi, Schünemann, & Dressler, 2015). Simulation tools in the VANET environment can be categorized as either network simulators or mobility generators. Network simulators are considered as computer software that models the real world networks. They model features of the network systems to provide analysis that validate and verify protocols or specific aspect of the network algorithms before implementing in real working environment. On the other hand, mobility generators are used to generate realistic vehicle behavior in VANET environment. Mostly, the mobility generators take road maps and scenarios to be simulated as input parameters. The output of mobility generators is mobility trace that is used as input to network simulators.

There are many simulation and mobility generation tools that have been developed by different researchers and developers to simulate various VANET scenarios (Sommer et al., 2015). Hence, it is sometimes difficult to select the simulation tools suitable to test the performance of the proposed algorithms without comprehensive analysis of exiting tools. Therefore, in this section, analysis of existing simulation tools is given. Nevertheless, the discussion is limited to simulation tools with some capabilities to perform functionalities of a cognitive radio. The discussion is divided into two subsections to include commercial and open source network simulation tools. Later, mobility generation tools are discussed.

5.2.1 Commercial network simulation tools

Commercial software needs a license before using packages of the software. In most cases, no changes can be made to the software without authority from the distributors of that software. In addition, source code of the software or implementation of the underlying packages is usually not provided to the general public. One of the advantages with commercial software is ability to request specific package suite from distributors based on the individual need. Nevertheless, the request will come at a cost. Another advantage is dedicated help which is provided by distributors including complete documentations which are frequently updated. There are many commercial network simulation software tools that have been developed for use. Our discussion is restricted to MATLAB (**MAT**rix **LAB**oratory), OPNET (**OP**timized **NET**work) and NetSim (**Net**work **Sim**ulator) which has been used by researchers to simulate cognitive radio in VANET. The discussion of each follows:

a) MATLAB: This is a proprietary programming language that was developed and distributed by MathWorks (MathWorks, 2017). MATLAB was especially developed to manipulate matrix, execution of algorithms and interface with other programs written in other languages such as C/C++, Java, Python, etc. MATLAB is mostly used in engineering to simulate real world applications such as automobile active safety systems, smart power grids, interplanetary spacecraft as well as LTE cellular networks and many more (Moore, 2014). In addition, it contains packages that are used for machine learning, image processing, communications etc. One such package which is used for communication and important to cognitive radio is called Simulink (Tabassam, Suleman, Kalsait, & Khan, 2011). The Simulink package is used to evaluate communication of the physical layer protocols of the network. Furthermore, the Simulink package supports communication toolbox for wireless communication which has been used for VANET communication (Lim, Lee, Chin, Yeo, & Teo, 2016).

   Nonetheless, Simulink is only good at modeling the physical/link layer of communication system with poor mechanism to model upper layer protocols (Flizikowski, Kozik, Gierszal, Przybyszewski, & Hołubowicz, 2010). In addition, the package does not implement WAVE/IEEE802.11p protocol standard which is important in the operation of vehicles in the VANET environment. Similarly, the Simulink package or MATLAB at large does not provide cognitive radio functionalities which are important to SSF-CVANET. If such functionalities were to be provided, a new license is needed with additional cost. Therefore, MATLAB is not considered as a network simulation environment for SSF-CVANET.

b) OPNET: a network software that was developed by OPNET Technologies Inc. and later acquired by Riverbed in 2012 (riverbed, 2017). OPNET is incorporated within the Riverbed systems of software called STEELCENTRAL which is designated to model and analyze communication in networks. It is a high level discrete event based network simulation tool that operates at packet-level. OPNET is based on object-oriented modeling with much of the library constructed in C/C++ to perform specific functions related to modeling, simulation and analysis. Modeling is used to provide graphical environment that is essential in generating various models of protocols. OPNET employ different complex simulation techniques to tackle various research studies. In particular, it provides accurate radio transmission pipeline stage for modeling physical layer which can be important in modeling cognitive radio functionalities. For analysis, OPNET provides easy tools to analyze and display simulation results effortlessly.

OPNET have been used to simulate VANET protocols previously (S. Yang, He, Wang, Li, & Lin, 2014). An important feature of OPNET is capability to simulate heterogeneous networks. However, OPNET does not extend the radio interface to incorporate cognitive radio functionalities. In addition, it does not implement WAVE/IEEE802.11p protocol standard to support vehicles moving at high speed similar to MATLAB. Furthermore, any changes to core software to include cognitive radio functions require new license with additional costs. Therefore, OPNET is not opted as a network simulation tool for SSF-CVANET.

c) NetSim: a discrete event network simulator and emulator developed by Tetcos and Indian Institute of Science with its first release in 2004 (TETCOS, 2017). It was developed to meet day to day simulation needs of both the industry and research and development (R&D) in networking field. NetSim protocols are written in C programming language. The protocols provide simulation platform to support many technologies including wireless sensor networks, wireless local area networks, WiMAX, MANET, LTE as well as cognitive radio. NetSim also provide emulation which allow simulation environment to be connected to real devices running live applications on the network. Emulation is very useful to test new algorithms to study the effect on the real network. Another important feature of NetSim is ability to provide an interface that connects to external environments such as MATLAB, Wireshark and SUMO.

For SSF-CVANET, the most important component of NetSim is the cognitive radio which support simulation related to spectrum sensing and incumbent detection (TETCOS, 2017). This feature is not common in most commercial network simulation software. Nevertheless, NetSim is still commercial software and does not allow one to add new models or change source code at least in the academic version even with license. Furthermore, the academic version does not provide interface that can allow one to connect to external links such as SUMO which is crucial for VANET simulation. These features are only proved in standard and profession versions with obviously additional cost. In addition, the distributor does not sell individual license, they can only sell to organizations in large numbers such as network license (i.e. minimum of 10 licenses). Therefore, NetSim is not considered as network simulation environment for SSF-CVANET.

Commercial simulation software provide simple graphical user interface to customers that make simulation and analysis of results easier. Nevertheless, commercial software is limited to functionalities provide by the distributors with limited support for extension. Support for extension allows researchers to development their own modules and incorporate with existing feature of the software. In addition, commercial network simulation software lack diverse support and collaboration of active research community associated with open source projects. The other drawback of commercial software in general is the stringent requirement not to modify the underlying architecture of the software without concert of distributor (optimus, 2015). This prevents researchers from developing additional modules to test their algorithms.

Therefore, open source simulation tools which overcome some of these limitations are considered in implementing SSF-CVANET. The following section discus some of open source network simulation tools that have been used in implementing VANET with cognitive radio and their relevance to SSF-CVANET.

5.2.2 Open source network simulation tools

In contrast to commercial software, open source software is provided with free license for the general public. Therefore, open source network simulators allow anyone to use the software and free to change the source code without any legal implication from the distributors. In most cases, open source software is not developed by a single distributor but involve various research communities around the globe working on different packages of the same software. The contribution from these researchers can be further modified by other researchers without legal implications. Hence, open source simulators are a good start for testing and validating new algorithms that require modifying existing software packages or developing new packages to meet the needs of the proposed algorithms. There are many open source network simulation tools that provide support for VANET simulation (Martinez et al., 2011; Mussa et al., 2015). In this section we look at some of simulators that has been used by researchers to simulate VANET and cognitive radio which include OMNET++ (Objective Modular NEtwork Testbed in C++), NS2 (Network Simulator 2) and NS3 (Network Simulator 3). Discussion of each follow:

a) OMNET++: is extensible, modular open source simulation framework architecture based on C++ library that provide base for building network simulators. For OMNET++, network is considered in wider sense to incorporate wireless and wired networks, queuing networks, on-chip networks, ad hoc networks and many more (OMNeT++, 2017). The simulators to simulate these networks are provided by independent researchers as add-on to the OMENT++ framework. In this sense, OMNET++ is considered as host framework and not a network simulator itself. The network modules are developed in C++ libraries which are assembled into larger components and modules using the NEtwork Description (NED) language. The modular approach allow for component and module reuse for the research community. The main module that is considered as standard protocol model library of OMNET++ is INET framework. This framework is composed of models that are used to simulate Internet stack, link layer protocols for both wireless and wired networks. In addition, it supports mobility for MANET protocols. Other important modules developed by independent researchers include OverSim for simulating peer-to-peer networks (Baumgart, Heep, & Krause, 2007), SimuLTE for simulating LTE and LTE Advanced networks (Virdis, Stea, & Nardini, 2016) as well as Castalia which is a module for simulating networks of low-power embedded devices such as Wireless Sensor Network (WSN) and Body Area Networks (BAN).

To facilitate simulation of vehicular communication in OMNET++, VEINS is used (Sommer, German, & Dressler, 2011). VEINS is an event-based network simulator for inter-vehicular communication that incorporates road traffic and microscopic simulation models. The simulator implements full detailed models of WAVE/IEEE802.11p standard protocol which is important for VANET. Nonetheless, OMNET++ has no modules that support cognitive radio functionalities. For SSF-CVANET, a simulator that support basis for simulating cognitive radio is important. Therefore, OMNET++ is not considered as network simulation tool for SSF-CVANET.

b) NS2: is a discrete event simulator developed by UC Berkely for simulating both wired and wireless networks (NS2, 2011). NS2 simulator is divided into two components which are core architecture and simulation frontend. The core architecture of NS2 is implemented using C++ programming language while OTcl scripting programming language is used to create the simulation frontend scenarios (Issariyakul & Hossain, 2011). The core architecture implement models that are used to simulate network protocols including Internet stack, network layer as well as lower layer protocols. Thus, C++ is used as a backend language to write module libraries for the protocols. On the other hand, OTcl is used as frontend language to write scripts that describe the simulation topology with varying network scenarios. A typical overview of NS2 simulation environment is shown in Figure 5.1 below:

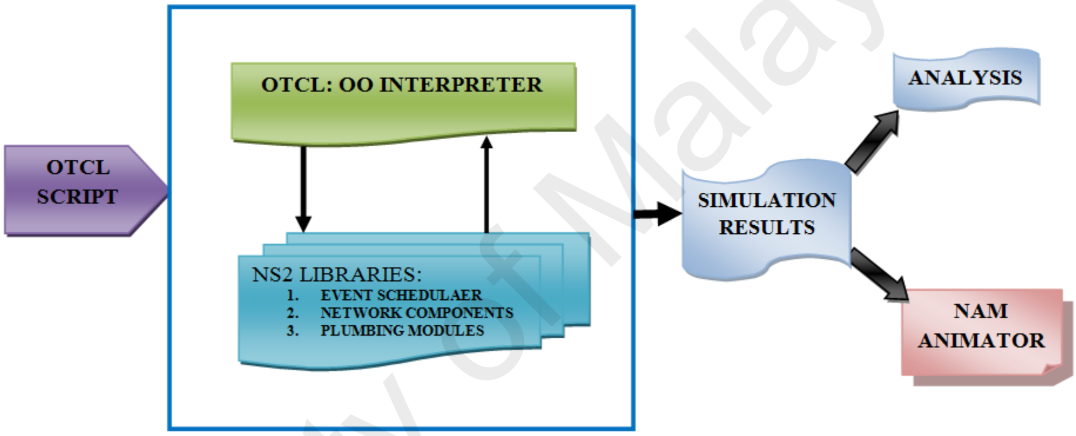

Figure 5.1: Simplified view of NS2

As stated before, the OTcl scripting language is used for setting up the network topology and providing mechanisms to initiate event schedulers. It also provide interface for simulation environment to interact with the core library modules. The simulation results are analyzed through various tools and can also be observed using network animator (NAM) which is part of NS2.

NS2 by itself does not provide modules that implement cognitive radio functionalities. However, there have been research teams that proposed extension to NS2 to support such functionalities. The first such extension is called Cognitive Radio Ad-Hoc Network (CRAHN) developed by Di Felice to simulate ad hoc networks (Di Felice, Chowdhury, Kim, Kassler, & Bononi, 2011). The second extension was developed by Esmaeelzadeh called CogNS, a simulation framework based on NS2 (Esmaeelzadeh, Berangi, Sebt, Hosseini, & Parsinia, 2013). The third extension was developed by Chigan called Cognitive Radio Cognitive Network (CRCN) (Chigan, 2014). Despite all the effort to extend NS2 to support cognitive radio, NS2 project in entirety have little or less active community participation of recent (ns2-wiki, 2014). The current latest version of NS2 (ns-2.35) was released in 2011 and no later version has been announced. In recent years, the research communities have shifted their contribution from NS2 to NS3 because of the many advantages offered by NS3. The current latest version for NS3 is ns-3.26 released in October 2016; next release ns-3.27 was scheduled for March 2017. Therefore, SSF-CVANET is implemented in NS3 which is introduced next.

c) NS3: is a discrete event based network simulation tool used for modeling and evaluating various networking protocols and algorithms. NS3 was developed from scratch therefore it is not a successor to NS2. In addition, NS3 is not backward compatible with NS2 (ns3-tutorial, 2016). All core modules of NS3 are developed entirely in C++ and wrapped through Python. Therefore, users can interact with NS3 library through either C++ or Python application which instantiates models to set simulation scenarios. Refer to Figure 5.2 to visualize the interaction.

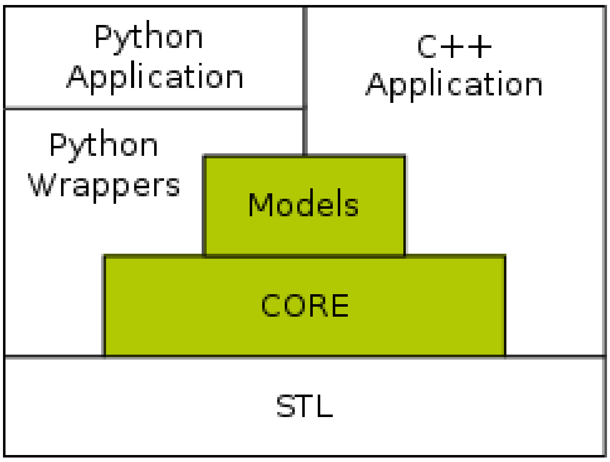

Figure 5.2: Overview of NS3 architecture (C++ and Python interaction)

The STL (Standard Template Library) written in C++ is wrapped to Python through *pybindgen* library which generate C++ binding glue by parsing C++ headers to *gccxml* and *pygccxml*. Thus, NS3 allow users to utilize full support of each language. This gives freedom for users to use either language or both depending on the simulation scenario and confidence of the user in the language selected.

The main aim of NS3 is to support networking researchers to implement protocols for both IP and non-IP based networks. Nevertheless, majority of research communities using NS3 focus on simulating wireless/IP based network which include modules that implement WiMAX, LTE, WAVE and Wi-Fi for lower layers and different routing protocols for IP-based applications (ns3-overview, 2016). One of the major advantages of NS3 over NS2 is help that can be obtained from active research community. Some other features that are found in NS3 but not in NS2 include:

- Scalability: NS3 allows for dummy applications that are defined by packets with virtual zero bytes and no memory is allocated for them. This is not true for NS2 which demand all packets to be allocated memory until simulation end, or unless freed up explicitly (Issariyakul & Hossain, 2011).
- Cross-layer approach: NS3 nodes implementation is similar to Linux networking architecture as such it facilitates code reuse which makes simulator control flow easier. In addition, NS3 permit events to be reported across non-contiguous layers (Mittag, Papanastasiou, Hartenstein, & Strom, 2011). The cross-layer approach allows the NS3 node to interact with two different layer protocols directly (e.g. PHY/MAC/NET layers).

- Emulation: this is another important feature of NS3 not found in NS2. NS3 is designed to allow the simulation environment to interact with real world application. The packet objects of the application are stored internally as packet byte buffers which can be easily serialized and sent on real network interface. This is achieved through direct code execution (DCE). DCE facilitates execution of existing implementations of user-space applications and kernel-space network protocols within the simulation environment without changing the application source code. For instance, NS3 allows use of real ping application instead of using ping-like application implemented by NS3. This can be achieved through Linux networking stack in the simulations.
- Use of real analysis tools: this is another important feature of NS3 not found in NS2 or OMNET++. NS3 allow simulation results to be analyzed using real network analysis tools such as Wireshark or tcpdump (i.e. Linux tool) directly. This is mainly due to use of real packet structure which is also important in emulation.

The network simulation tool for SSF-CVANET is NS3 because of important features that are not found in NS2 mentioned above. In addition, NS3 come with spectrum module that is used as a basis for spectrum sensing (see Section 5.3.1.1). Another important feature of NS3 is support for WAVE module which implements IEEE1609.4/IEEE802.11p standard protocol for VANET communication (see Section 5.3.1.2). The only limitation of the WAVE module provided by NS3 is its inability to provide vehicular mobility. The current version of WAVE relies on other mobility models provided within NS3 such as Random Waypoint mobility model (RWP). Nevertheless, NS3 allows third-party mobility module to be included during simulation. Therefore, SUMO is considered as mobility generator for SSF-CVANET. There are other mobility generation tools developed by many researchers for simulating realistic VANET scenarios. In the following section we discuss some of them.

5.2.3 Mobility generation tools for VANET

Vehicular communication is distinguished from other networks because of the unique characteristics of VANETs. Some of these characteristics include vehicle speed, dynamic vehicle density, constricted topology (i.e. along the road), behavior of drivers and many more. Therefore, vehicle mobility generators should account for such characteristics to make VANET simulation as realistic as possible. Simulation of traffic pattern in VANET is considered at micro and macro levels (Fogue et al., 2012). Micro level sometimes called microscopic modeling is concerned with behavior of individual vehicle and interaction with other vehicles within the simulation environment. On the other hand, macro level or macroscopic modeling is concerned with behavior of traffic flow at large scale such as section-by-section opposed to tracking individual vehicles. Other models commonly called mesoscopic combine the properties of micro and macro models (Martinez et al., 2011). In this work, the behavior of individual vehicle as it performs spectrum sensing is important. Therefore, microscopic modeling of vehicle traffic pattern is considered. The most common vehicular mobility generators used for VANETs are given next:

a) *VanetMobiSim:* this is a mesoscopic mobility generator. At microscopic level it implements mobility models that support V2V and V2I interaction with some support for intelligent driving models together with lane changing models. Following the microscopic modeling, vehicles regulate their speed depending on the road conditions such as nearby vehicles, traffic signs on intersections etc (Härri, Filali, Bonnet, & Fiore, 2006). At the macroscopic level, *VanetMobiSim* can import and use maps from databases such as Topological Integrated Geographic Encoding and Referencing (TIGER) from US Census Bureau. One of the important features of *VanetMobiSim* is ability to generate various mobility traces that can be used by different network simulators (e.g. NS2, QualNet, NET). However, *VanetMobiSim* is currently not an active project with the latest version released in 2007. Therefore, it is not considered as the vehicle mobility generator for SSF-CVANET.

b) *STRAW* (STreet RAndom Waypoint): was developed to overcome shortcoming of Random Waypoint (RWP) mobility model by incorporating mobility traffic flow that rely on maps of real US cities (Choffnes & Bustamante, 2005). The output of the mobility trace for STRAW is only limited to one simulator (JiST/SWANS) and cannot be used by other simulators. Therefore, STRAW is not considered as mobility generator for SSF-CVANET which is implemented using NS3 as network simulator.

c) *CityMob*: this is a mobility pattern generator that was designed to be used for NS2 simulator (Martinez, Cano, Calafate, & Manzoni, 2008). It implements three mobility models including Simple, Manhattan and Downtown. This mobility generator allows adding vehicle density similar to real town. Nevertheless, it does not allow importing real road maps like other mobility generators. *CityMob* project is inactivity (last version was in 2008) and it is not considered for generating mobility traces for SSF-CVANET.

d) *SUMO*: is an open source discrete microscopic road traffic mobility generation simulation tool developed to handle large road networks (Krajzewicz, Erdmann, Behrisch, & Bieker, 2012). It is highly portable with many features different from other open source mobility generators which make it widely used by research communities. The features include collision free movement of vehicles, different type of vehicles, individual vehicle routing, hierarchical junction type with right-hand rule routing and many more. In addition, SUMO project enjoys the active community support with the current latest version released on 16.02.2017. SUMO is implemented in C++ with some graphical user interface (GUI). Furthermore, SUMO support importing other formats based on real maps such as Open Street Map (OSM). Nevertheless, the mobility traces of SUMO cannot be directly used as input for many simulators, NS3 included. However, there are many APIs (Application Programming Interfaces) which can be used to convert SUMO mobility trace outputs into formats that can be used by various network simulators. SUMO is used as mobility generator for SSF-CVANET with further details given in Section 5.3.2.

The success of VANET simulation rely on producing realistic mobility models that mimic the real traffic of vehicles on the roads. Therefore, vehicle mobility generation tools should be up-to-date to reflect current trends in both software and modeling. From the generator discussed above only SUMO enjoy active research community that updates the software models frequently (with latest version released in February, 2017). Other mobility generators lack frequent updates to meet the new demands in software and inclusion of new techniques. Therefore, SUMO is preferred as mobility generation software for SSF-CVANET. In the next section, the two simulation tools (NS3 and SUMO) are further discussed. The discussion focuses on components that are important in the implementation of SSF-CVANET.

5.3 Simulation tools for SSF-CVANET

As mentioned before, NS3 and SUMO are used as networking simulator and mobility generation tools respectively for implementing SSF-CVANET. The two tools are selected because of the many benefits they offer discussed before and expanded in this section. In particular this section look at features that are important in implementing SSF-CVANET for both NS3 and SUMO. A detailed discussion of NS3 is given first followed by SUMO later.

5.3.1 Network Simulator 3 (NS3)

NS3 is a discrete event network simulator implemented in C++. Its libraries are linked to C++ main program dynamically or statically through simulation topologies that start the simulator. Alternatively, NS3 allow API to Python programs to access NS3 module libraries (see Section 5.2.2-c). All the source code of NS3 module libraries are contained in the directory or folder called *src*. NS3 project use the *waf* application to build the system. *Waf* is a Python-based framework that is used for installing, compiling and configuring applications (Nagy, 2013). The overall software representation of NS3 is represented in Figure 5.3.

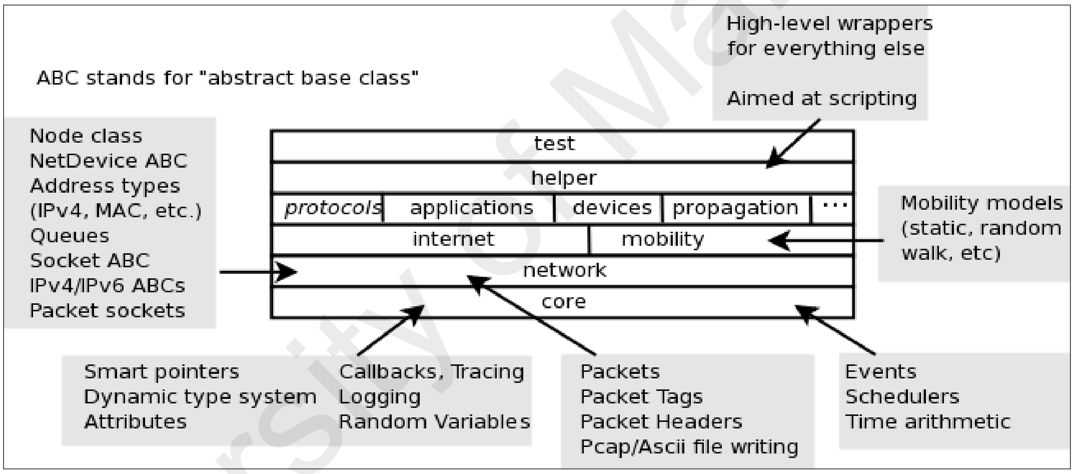

Figure 5.3: Software organization of NS3 (ns3-manual, 2016)

A brief description of each level of figure 5-3 is presented next:

a) *Core*: This module is the lowest level of NS3 library that contains components that are used across all protocols within NS3 environment regardless of the network type (e.g. wired or wireless even non-IP networks). The source code of Core module is implemented in the directory *src/core*. The Core module provide tasks that are related to time management, implement scheduler classes and it contain simulator class that is used to create, schedule and cancel events. Furthermore, the Core module implements Callback functions which are important feature of NS3.

Callbacks in C++ allow one piece of code to call a method without any specific inter-module dependency. Other important features contained within the Core module includes random variable generators, smart pointers, debugging tools, system wall clock interface (used in emulation) and many more.

b) *Network*: It provides basis for implementing basic network functions and contained within the directory *src/network*. Just like the Core module, the Network module implements generic simulation components that are independent of specific network and device modules. This module implement classes associated with packets which are fundamental objects in a network simulator. The classes of packets are contained in a packet framework that makes it easy to support fragmentation, defragmentation and concatenation of packets. The packet framework is an important feature of NS3 that was designed to avoid changes to the core of the simulator when new types of packet headers or trailers are introduced. The packet framework was also designed to provide ease of integration with real-world code and systems through emulation. Thus, the packet framework was designed to permit actual application data or dummy application bytes within simulation environment with improved memory management. Other generic frameworks implemented by the Network module include the *Node* class, *NetDevice* abstract class, *Address* abstract class and many more.

c) *Internet*: This module is implemented in source code directory *src/internet*. It provides implementation of TCP/IPv4 and IPv6 protocols that support the node functionality. The Internet stack support various protocols including UDP, TCP, ARP, Neighbor Discovery, IPv4, IPv6 and many more. The Internet module relies on the lower modules to implement most of these protocols. Nevertheless, it implements these protocols independent of the network type (i.e. wireless or wired).

d) *Mobility*: This module is implemented in source code directory *src/mobility*. It includes set of mobility models which are used to maintain and track the present Cartesian position and speed of node object. The Mobility module also includes a number of helper classes used to place nodes and setup mobility models. Furthermore, Mobility module includes route change notifiers that trace the source node as well as register listeners to monitor changes to the route of the mobility model. The Mobility module is used especially in wireless based simulation.

e) *Specific modules*: above the generic modules discussed so far come specific modules implemented in NS3 as *src/module-name*. The specific modules are implemented to simulate various network protocols and algorithms related to specific network types. For example, specific modules could be WAVE for VANET implemented as *src/wave*, WiFi implemented as *src/wifi*, Spectrum-aware for channel related functionalities implemented as *src/spectrum,* Applications implemented as *src/application* and so on. New protocols and modules are defined at this layer and rely on lower modules.

f) *Helpers*: These are C++ APIs used in NS3 to make programs easier to write and read without much interaction with low level interface. Few things to consider about the helpers is that firstly, the rest of *src/* is independent of helper API, meaning anything done with helper API can be coded at low-level API as well. Secondly, the helper API is not generic, as such, there is no much code reuse compared to low-level API. For example, different helper will be used for WAVE/IEEE802.11p device and WiFi device despite both sharing the same network wireless device. Thirdly, the helper API makes use of Container concept to group similar objects to which similar operations can be performed. And finally, the helper API works with stack-allocated opposed to heap-allocated objects.

g) *Tests*: NS3 implements *test.py* program written in Python that serves as the test execution manager. The *test.py* program can run test code and examples for NS3 modules implemented in *src/* to look for regressions and output results that can be in various formats for analysis using different tools.

With this general introduction to NS3, we can look at modules in NS3 that are important in the implementation of SSF-CVANET. The two most important modules are Spectrum module implemented in source code directory *src/spectrum* and WAVE implemented in directory *src/wave*.

5.3.1.1 Spectrum-aware channel module

The Spectrum module provides a set of classes that implement signal modeling that support frequency-dependent communication in NS3. The main goals of the Spectrum module is to model irradiate power into electromagnetic spectrum and representation of this irradiated power which occur due to signal processing at receiver and propagation in the channel (Baldo & Miozzo, 2009). In addition, the Spectrum module provide classes that define relationship between wireless channel and PHY layer based on power spectral density (PSD) signal representation that is independent of the underlying technology. Thus, two independent technologies can operate together through Channel implementation using Channel/PHY interface. This is an important property to cognitive radio that envisions two or more technology working in unison.

To model signals between wireless channel and PHY layer, Spectrum module implement *SpectrumModel* class. The *SpectrumModel* class owns a set of bands from *SetOfBands* class implemented as a vector of *BandInfo* class. The set of bands can be any bands from channels of interest. The set of bands is associated with the PSDs which are represented as set of discrete scalar values with each value mapping on band in frequency. The PSD value for each frequency is assumed to be constant for the duration the signal is being transmitted. The set of frequency bands to which the PSD refers to is defined by the instance of the *SpectrumModel* class. Nevertheless, the PSD itself is an instance of the *SpectrumValue* class with reference to instance of *SpectrumModel* class. The importance of *SpectrumValue* class is support for arithmetic operators that allow calculations to be performed on PSD instances. The *SpectrumValue* class and especially PSD are important to SSF-CVANET because they are used in energy detection spectrum sensing described in Chapter 4.3.2 (See Section 4.3.2.1) to represent energy test statistic. The *SpectrumModel* class also supports other features that enhance spectrum modeling API for developers with easy.

The Spectrum module also provides two abstract classes which are important in simulating the interaction of signals over the medium between the transmitter and receiver. The two abstract classes are *SpectrumChannel* and *SpectrumPhy*. On one hand, the *SpectrumChannel* class provides implementation member method called *SpectrumChannel::StartTx* which is called by PHY layer implementation when transmitting packets. There are two implementations of *SpectrumChannel* class which are *SingleModelSpectrumChannel* and *MultiModelSpectrumChannel* classes. Both of these implementations provide functionalities related to propagation loss and delay modeling. The implementation details for both models are similar. The only difference is that *MultiModelSpectrumChannel* class permits different instances of *SpectrumModel* class to be used with the same channel instance through converting PSDs among different models. On the other hand, *SpectrumPhy* class provides implementation of the member method called *SpectrumPhy::StartRx* which is called by channel implementation to notify a PHY layer that a signal is received.

The Spectrum module provides many implementations that extend *SpectrumPhy* class including *WaveformGenerator*, *MicrowaveOven*, *OfdmSpectrumWifiPhy*,

SpectrumWifiPhy, *ShannonSpectrumWifiPhy* and *SpectrumAnalyzer* classes. The first two classes, *WaveformGenerator* and *MicrowaveOven* are more generic and used as source of interference. Hence, implement non-communicating devices (i.e. no upper layer protocols are called). In the implementation of SSF-CVANET *ShannonSpectrumWifiPhy* class and *SpectrumAnalyzer* class are important. *ShannonSpectrumWifiPhy* class is used in calculating the maximum capacity of the channel within a given interval time which is an important aspect in determining the reward for RL (Chapter 4.3.3.2, Eq. 4.13). *SpectrumAnalyzer* class measures and records the total power irradiated into the spectrum at a particular location. Particularly, *SpectrumAnalyzer* class averages the PSD of all signals coming from the transmitter over time duration configured by the user. The *SpectrumAnalyzer* class is extended by SSF-CVANET to provide spectrum sensing for vehicles on the road.

Another important feature which is provided by the Spectrum module is implementation of TV transmitter model. The model is implemented by *TvSpectrumTransmitter* class that enables simulation of realistic TV signal transmission which can also be used for interference modeling. Currently there are three modulation types of TV transmitters implemented including 8-VSB (8-level Vestigial Sideband Modulation), COFDM (Coded Orthogonal Frequency Division Multiplexing) and analog. The importance of TV Transmitter model is provision of customized PSD model, signal bandwidth, PSD level, frequency and transmission duration which improves spectrum sensing for SSF-CVANET. In addition, TV license bands are considered as primary candidate for dynamic spectrum access (Release, 2010). Therefore, this model is an important aspect of evaluating the proposed SSF-CVANET. Another important module in the implementing of SSF-CVANET found in NS3 is WAVE module presented next.

5.3.1.2 WAVE Module

NS3 provides wireless based vehicular communication system architecture specified by IEEE called WAVE with focus on MAC layer and MAC extension layer. The WAVE module is implemented in the source code directory *src/wave*. The main focus of this module is to simulate IEEE802.11p and IEEE1609.4 standard protocols for VANET communications. The IEEE802.11p defines the MAC and PHY layer which is instantiated using *ns3::Wifi80211pHelper*. While IEEE1609.4 MAC extension layer is based on OCB (Outside the Context of a BSS) concept which provides devices with capabilities to switch between control and service channels. The support for WAVE involves the MAC, its MAC extension (IEEE1609.4) and PHY layer (IEEE802.11p) which is instantiated using *ns3::WaveHelper*. The WAVE module also implements Vendor Specific Action (VSA) frames which are used for transmitting management information. The detailed implementation of WAVE can be obtained at (https://www.nsnam.org/docs/release/3.26/models/singlehtml/index.html#document-wave).

One of the drawbacks to the WAVE module provided in NS3 is lack of support for customized vehicle mobility. The MAC layer only adapts to changes in MAC due to vehicle movement in the simulation environment. Therefore, it is suggested to use other mobility patterns implemented within NS3 such as *ns3::RandomWaypointMobilityModel* for node mobility. However, such mobility model does not capture the realistic vehicle movement and other characteristics unique to VANETs. Another suggestion is to generate mobility traces in ns-2-style from third-party tools such as SUMO and playback using *ns3::Ns2MobilityHelper* implemented in the source code directory *src/mobility*. In implementation of SSF-CVANET, WAVE module is used with mobility traffic pattern generated using SUMO. A detailed explanation of SUMO features is given next.

5.3.2 Simulation of Urban MObility (SUMO)

SUMO is a widely used discrete vehicle traffic generator which allows simulating large road networks. The major component of SUMO is developed by the Institute of Transportation System at German Aerospace Center. Nevertheless, SUMO being open source permits other researchers worldwide to contribute many features under the General Public License (GPL). SUMO is purely microscopic, thus it supports explicit modeling of vehicles at individual level movement through the network. For example, an individual vehicle is modeled with its own route and related traffic management. Furthermore, SUMO support simulation of large road networks with different features such as speed limits on the roads, traffic light, different types of vehicles, variety of junction layout and many more. In addition, SUMO support importing real world maps (i.e. OSM) into simulation environment.

At the simplest level, SUMO simulation consists of *nodes* (junctions) which are connected by *edges (streets or roads)*. All *nodes* are defined by x- and y-coordinate with an id for referencing. Once the *nodes* are defined, they are saved in the file with the extension *.nod.xml*. After the *nodes* are defined, they are connected by *edges* using source *node* id and target *node* id. An *edge* has a direction and id for referencing. The direction is used by vehicles travelling along the *edge* given the start and destination *nodes*. Once, the *edges* are defined with associated *nodes* the data is saved in the file with extension *.edg.xml*. To bid the two files (i.e. for *nodes* and *edges*) to create the road network, NETCONVERT a command-line application is used. The output file from using the command-line application is stored in the file with extension *.net.xml*. The actual command-line will look like:

netconvert --node-files=name.nod.xml --edge-files=name.edg.xml --output-file=name.net.xml where *name* is the filename for associated file. With a network in place, the next task is to define traffic for a vehicle. In SUMO vehicles have types which define their basic properties including acceleration and deceleration, length, maximum speed, id, and even color. In addition, the vehicle needs *sigma* parameter which introduces random behavior mimicking experience of drivers on the road. Once the attributes are defined, other entries to vehicle are given such as entry and departure times. The description of vehicle and associated data is stored in the traffic file with extension *.rou.xml*.

The network file with extension *.net.xml* and the traffic file with extension *.rou.xml* are glued together into a configuration file combined with duration for simulation. The resultant configuration file has extension *.sumo.cfg*. This file is used to generate mobility trace output file that is used by other third-party tools (it should be noted that the output of all SUMO files is xml). Simulating traffic can be achieved by calling the configuration file (*.sumo.cfg*) from command-line using SUMO application or through SUMO-GUI (GUISIM). To visualize the steps described above see Figure 5.4 below:

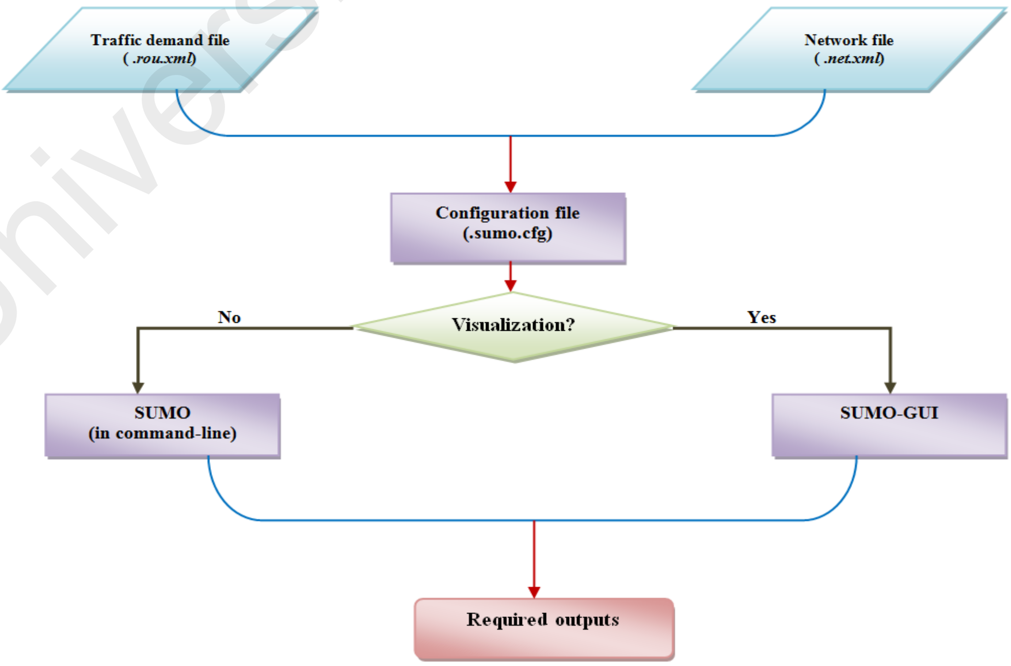

Figure 5.4: General simple steps in implementing traffic simulation in SUMO

The SUMO command-line option is an efficient way to simulate traffic especially when simulating sophisticated and large traffic networks. On the other hand, SUMO-GUI provides ways to execute traffic simulation allowing the user to observe and monitor the simulation in action. A detailed implementation and operation of SUMO is reported in (Krajzewicz et al., 2012).

Having discussed the two simulation tools (NS3 and SUMO) used for SSF-CVANET, the following section goes in details to describe steps taken in implementing SSF-CVANET through simulation.

5.4 Implementation of SSF-CVANET via simulation

This section presents implementation details and simulation steps taken to develop and implement SSF-CVANET using the advantages provided by NS3 and SUMO simulation tools discussed above. In addition, we extend classes and implementation approach provided by Al-Ali and Chowdhury who extended NS3 to include cognitive radio functionalities (Al-Ali & Chowdhury, 2014). The extension is called Cognitive Radio Extension for NS3 (CRE-NS3). CRE-NS3 implements functionalities of cognitive radio including spectrum sensing, spectrum decision, spectrum mobility, etc. Figure 5.5 gives a detailed depiction of the implemented building blocks of CRE-NS3.

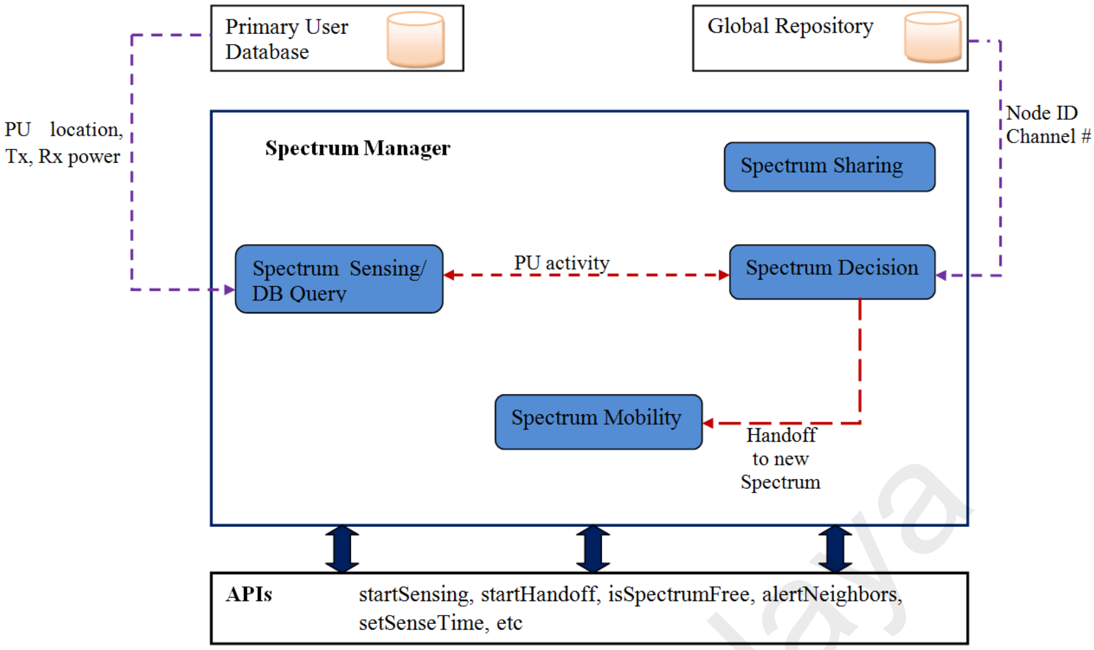

Figure 5.5: Building blocks of CRE-NS3 (Al-Ali & Chowdhury, 2014)

The full implemented source code can be obtained at GITHUB repository (*https://github.com/abdulla-alali/CRE-NS3*) while detailed implementation steps can be found at their website (Chowdhury & Al-Ali, 2014). As seen from Figure 5.5, CRE-NS3 provides detailed implementation of cognitive radio in NS3 that is accessed through APIs such as *startSensing*, *startHandoff*, *isSpectrumFree* and many others. Such APIs are defined in the Spectrum Manager module of CRE-NS3. The Spectrum Manager module also implements PU activity database which is queried by the nodes. Regardless, the PU activities are static defined by the user. Another extension to NS3 to provide cognitive radio capabilities is provided by Chigan termed as CRCN-NS3 (Chigan, 2017). To supplement the functionalities provided by CRE-NS3 and ideas provided in CRCN-NS3, we extent classes such as *SpectrumAnalyzer* and *TvSpectrumTransmitter* provided in the source code *src/spectrum* of NS3 (see Section 5.3.1.1).

New modules in NS3 are created using a special Python application called *create-module.py* which is found in the directory *src*. The new module house related classes, tests, examples, helper classes that can be combined with other NS3 modules. Thus, to create the new module the following command was issued in *src* directory (using Linux command-line):

$. / create-module.py ssfcvanet

The output of this command is creation of five directories in *src/ssfcvanet* and scripting file called *wscript*. The five directories are *doc*, *examples*, *helper*, *model* and *test*. The *doc* directory is intended to contain documentation files (with extension *.rst*) for the module. The *example* directory contains any examples of how the module is used. *Helper* directory contain any helper classes that are used to instantiated the model from simulation environment as described in Section 5.3.1. The *model* directory contains all classes that are core of the module. The *test* directory will have any test classes associated with the new module. The *wscript* file is an important component of the new module. It contains information that binds all files in the five directories and called by *waf* application for building the module. Another important feature of *wscript* is link to other dependent NS3 modules. For SSF-CVANET, the other important dependent modules include *src/network* and *src/spectrum*. Hence the main line in *wscript* which shows the link to other NS3 modules is presented below:

```
def build(bld):
    module = bld.create_ns3_module('ssfcvanet', ['network', 'spectrum'])
```

In the following subsections, a descriptive implementation detail of adaptive spectrum sensing (Chapter 4, Section 4.3.2.3) and PU activity modeling (Chapter 4, Section 4.3.3.2) is presented.

5.4.1 Implementation of adaptive sensing

All important classes are contained in the directory *src/ssfcvanet/model*. For adaptive sensing three classes are implemented namely: *energy-detection*, *ooc-detection* and *adaptive-sensing* with associated header files *energy-detection.h*, *ooc-detection.h* and *adaptive-sensing.h* respectively. The highlight of each class is as follows:

a) *energy-dection*: this class extends and implements methods of *SpectrumAnalyzer* class found in *src/spectrum/model* (refer to Section 5.3.1.1) to model energy detection described in Chapter 4 (Section 4.3.2.1). Some of important methods in this class include *GetDevice()*, *UpdateEnergyReceivedSoFar()*, *GenerateReport()* and *StartRx()*. *GetDevice()* is a method first defined in *src/network* model which gets the underlying device used for PHY layer communication. The device can be WiFi, WiMAX, WAVE, TV transmitter etc. The *UpdateEnergyReceivedSoFar()* keeps track of SNR (i.e. PSD) received by the PHY device of the SU to get the energy statistic described in Chapter 4.3.2.1. The *GenerateReport()* method is used to create the report of the occupant state of the PU after the sensing period. In addition to these methods, a new method *GetAveragePSD()* is defined that returns a value that represent the energy statistic which is compared with the threshold in *adaptive-detection* class. The *StartRx()* method is called from *adaptive-detection* class to start the sensing process. The implementation detail of *energy-detection* class is similar to *spectrum-analyzer* class in *src/spectrum/model* and borrows other codes from *src/cognitive/model* implemented in CRE-NS3 (Al-Ali & Chowdhury, 2014).

b) *ooc-detection*: this is another important class of adaptive sensing which implement feature detection described in Chapter 4 (Section 4.3.2.2). The class implements feature detection using periodicity in time-domain of radio bands opposed to frequency domain. In the implementation, the focus is given to periodicity in the

TV transmitter as an example of PU (regardless the method can be applied to any PU signal with known periodicity). In addition, the implementation is simplified as the periodicity of the signal is known a priori including the modulation of TV transmitter mentioned before (Section 5.3.1.1). The class uses some of the methods adapted from *SpectrumAnalyzer* class such as *GetDevice(), StartRx()* etc. The two most important methods implemented in this class are called *MeanPeaks()* and *Periodicity()*. *MeanPeaks()* calculates the mean peaks of the received signal by the PHY layer from sensing samples (See Chapter 4.3.2.2). It takes sensing samples as vector, where to start performing the mean and a determinant factor to clean the signal. The return value of *MeanPeaks()* is used in *Periodicity()* to compare with the threshold. The *Periodicity()* method makes the autocorrelation of the data and detects the peaks in it for determining periodicity of the signal. It takes threshold and sample rate as some of the inputs. To determine the presence of the PU signal, the *Periodicity()* compares the peaks from *MeanPeaks()* and the threshold. If there is a match with one of the periodicities, the PU signal is considered to be identified, otherwise is classified as noise. In other words when two signals are compared in time instance and returns a high value it implies similarities, a low value denotes closely correlated but with opposite sign, and zero when completely different.

c) *adaptive-sensing*: this class implements adaptive sensing described in Chapter 4 (Section 4.3.2.3). Specifically, it implements **Algorithm 1**. The important method in this class is called *AdaptiveAlgorithm()*. The method initializes all important values pertinent to sensing such as thresholds, sensing intervals, number of samples to be collected as described in Section 4.3.2. In addition, it gets the center frequency from the RSU as part of the input. To perform either energy or feature detection, *adaptive-sensing* class calls methods from respective classes described above through an object of each class.

Spectrum sensing is achieved through PHY layer implementation and results are sent to RSU through tagging NS3 packets (Al-Ali & Chowdhury, 2014). The results can either be active PU for which the vehicle is not permitted to transmit data or idle PU allowing the vehicle to transmit data. The combination of sensing time, transmission time, if any and channel bandwidth (i.e. determined using *ShannonSpectrumWifiPhy* class in Spectrum module) is used to calculate the reward for reinforcement learning (see Eq. 4.13 Chapter 4) at RSU discussed next.

5.4.2 Implementation of RL for PU modeling

Reinforcement learning is unsupervised machine learning technique in which an agent learn by interacting with the environment. In this research work, RL is used to learn and predict PU channels with good OFF periods and high bandwidth for vehicular communication (Chapter 4.3.3). Therefore, RL is implemented at RSU to model the PU activities using history from sensing vehicles as rewards. To achieve the objective, three classes are defined: *rl-agentRSU*, *rl-puactivity* and *rl-policy* with associated header files. Much of the source code have been reused from various research communities that have implemented RL for various projects found at (*http://www-anw.cs.umass.edu/rlr/domains.html*) maintained by Autonomous Learning Laboratory at the University of Massachusetts, Amherst. Other implementation of RL using Java can be found at (*http://www.cse.unsw.edu.au/~cs9417ml/RL1/sourcecode.html*).

The classes implementing RL are dependent on each other. The *rl-agentRSU* class initializes all parameters associated with MDP discussed in Section 4.3.3.2 such as discount factors, episodes etc. In addition, it implements three methods namely *runEpisode(), selectAction()* and *getPolicy()*. The *runEpisode()* is an important method that implements **Algorithm 2** for TD(λ). The *selectAction()* method implements mechanisms to select the best channels to send to vehicles for sensing and transmitting data thereafter. Nevertheless, the *rl-agentRSU* class is dependent on the other two classes for getting the policy and other tasks. The *rl-policy* class implements two methods: *initialValues()* and *getNextState()*. The two methods are used to define the best policy that set the trade-off between exploration and exploitation of PU channel usage. And finally *rl-puactivity* class implements six methods: *calcReward(), getState(), getReward(), getNextState(), validAction()* and *transitionProb()*. The methods perform tasks related to names associated with them.

In the simulation environment, the methods implemented for both adaptive sensing and RL are accessed through helper. The summary of the classes and methods described above is presented in the figure below.

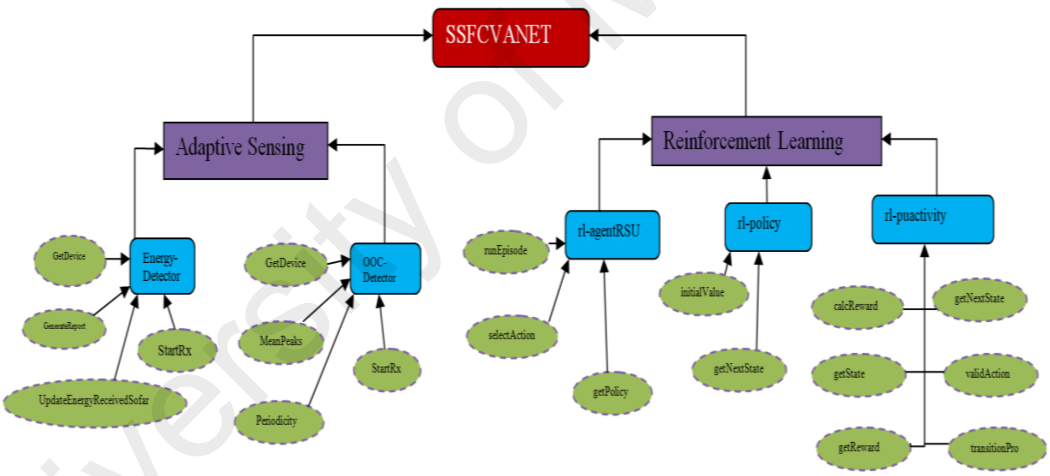

Figure 5.6: Summary of classes and methods for SSF-CVANET

5.4.3 Simulation steps

Much of implementation steps follow the flow chart presented in Figure 4.3 (Chapter 4). The RSU estimates the vehicle density based on the number of packets received from vehicles. If the number exceeds some threshold, the SSF-CVANET framework is initialized. Once the framework is initialized, the RSU will send channels to interested vehicles after selecting the good channels with high bandwidth and long OFF periods based on rewards obtained previously from RL (Chapter 4, Section 4.3.3.2 and Section 5.4.2 above). The procedure will continue until the traffic density of vehicles reduces below the threshold.

Nevertheless, the mobility pattern used in simulation is generated from SUMO. Therefore, in this research work, OpenStreetMap (OSM) is used to generate realistic map that is used as input to SUMO. OSM is an online source of the world maps that can be edited to suite the user needs. In addition, OSM provides the attributes for creating the network compatible with SUMO such as road types, speed limits, turn restrictions, traffic lights based on actual rules of the selected city. Thus, in this work an extract of OSM for Kuala Lumpur and Selangor is shown in Figure 5.7.

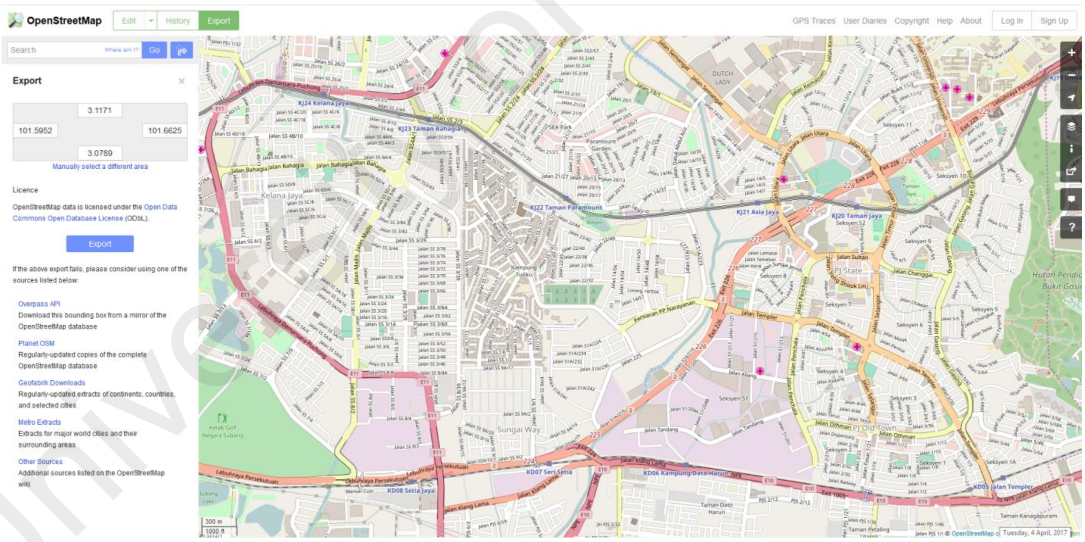

Figure 5.7: Extracted Road Map from OSM application

The aim of extracting this map was to simulate traffic along the Lebuhraya Persekutuan (Federal Highway) shown in Orange in Figure 5.7. The length of the extracted portion is 12km which is later divided into segments of 1km each covered by RSU. The choice of 1km (1000m) is considered to be maximum communication range for WAVE/IEEE802.11p based protocols (Y. J. Li, 2010). The output to Figure 5.7 is in the *xml* format and saved as *map.osm*. The *map.osm* file is later converted into a network file using the NETCONVERT command as follows:

Netconvert --osm-files map.osm --output-file ssfcvanet.net.xml

The *ssfcvanet.net.xml* file define the nodes, edges, junctions, streets and many other types of traffic information related to network environment. The OSM file of Figure 5.7 is transformed into Figure 5.8 using the command above.

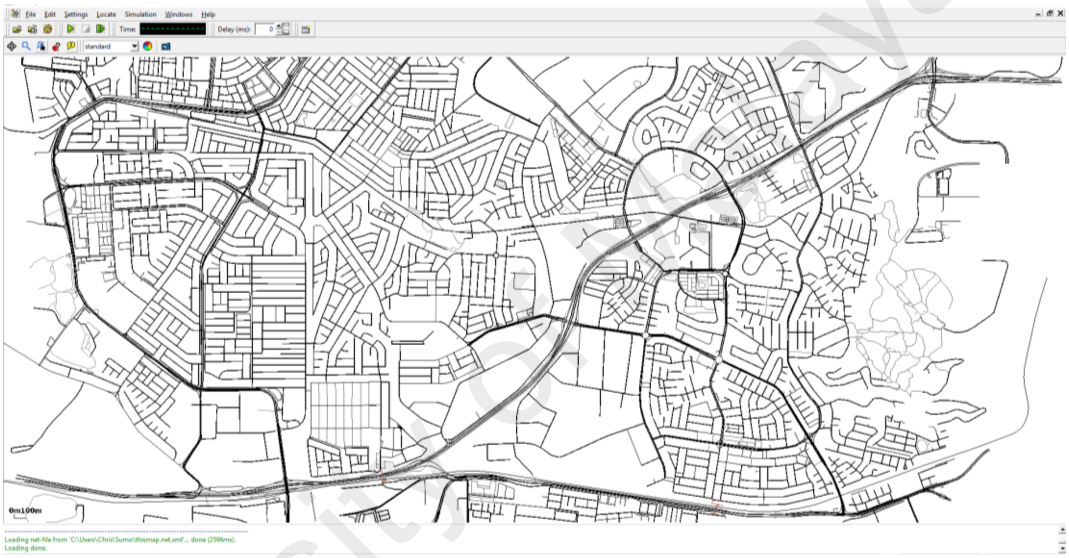

Figure 5.8: OSM file converted into SUMO format

Figure 5.8 shows the format which is considered valid for SUMO simulation opposite to Figure 5.7. Creating vehicle traffic for large network is sometime a difficult task. Therefore, SUMO TrafficModeler is used (Papaleondiou & Dikaiakos, 2009). TrafficModeler is a graphical user interface tool that is used to create vehicular traffic and high-level modeling. It supports different traffic definition models that represent various types of traffic patterns. Thus TrafficModeler is used to create vehicle traffic and related files for SUMO input. The configurations of TrafficModeler are presented in Figure 5.9 below.

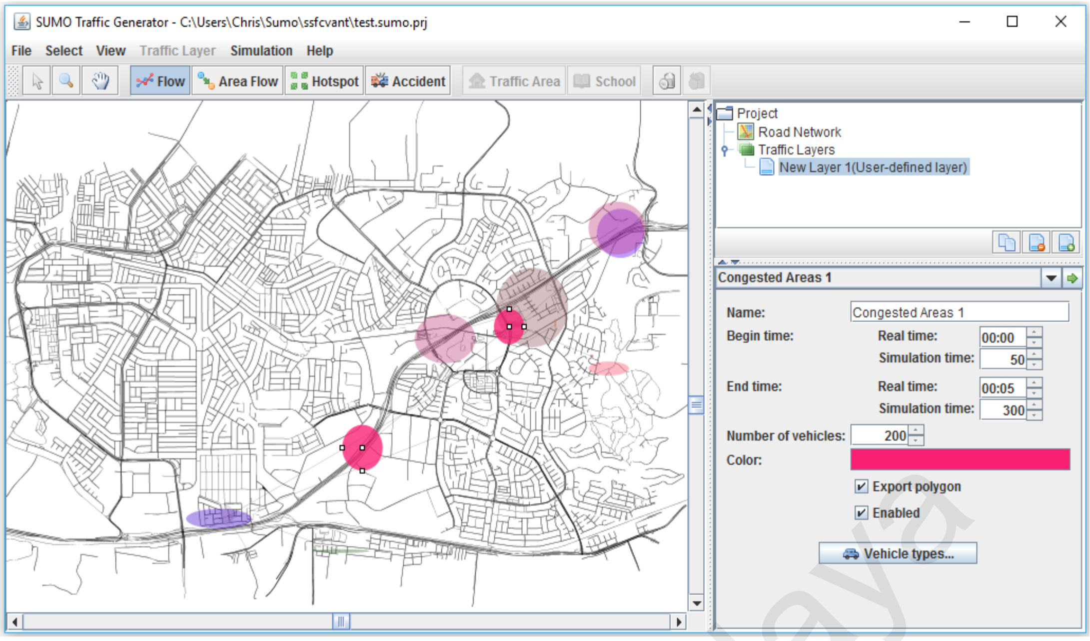

Figure 5.9: Movement of vehicle traffic in TrafficModeler showing patches congested areas

TrafficModeler configures flow of vehicles, density of vehicles at specified areas based on user preferences. Figure 5.9 shows areas highlighted in various colors to show possible traffic congestion due to number of vehicles in those areas along Federal Highway. Therefore, it is in those areas that SSF-CVANET is initiated. One of the outputs of TrafficModeler is file (*ssfcvanet.sumo.cfg*) that is used as input to SUMO. However, the output format of SUMO cannot directly be used as trace files for either NS2 or NS3. Therefore, the configuration file *ssfcvanet.sumo.cfg* is converted to *xml* format using the following command:

sumo -c ssfcvanet.sumo.cfg --fcd-output ssfcvanetTrace.xml

Thereafter, the *ssfcvanetTrace.xml* file is converted to vehicular traces compatible with NS2 using *TraceExporter* a Python tool using the following command:

traceExporter.py --fcd-input ssfcvanetTrace.xml --ns2mobility-output ssfcvanetmobility.tcl

It is the *ssfcvanetmobility.tcl* file that is used as mobility trace for NS3 simulation. Other important simulation parameters used for SSF-CVANET are presented in the following table.

Table 4.1: Simulation parameters for SUMO and NS3

Parameter	Value	Parameter	Value
Map dimension	13 km X 15 km	Simulation time	400 seconds
Road length	12km	MAC/PHY	WAVE/IEEE802.11p
Average segment length	1km	DSRC channel bandwidth	10 MHz
Placement of RSU	500m (at middle of segment)	DSRC channel frequency	5.9 GHz
Maximum number of vehicles	500	WAVE transmission power	13dBm
Vehicle length	5m, 10m	TV modulation	8-VSB
Vehicle speed	0 - 30 m/s	TV transmission power	22.2dBm/Hz
Vehicle acceleration	2.5	TV channel bandwidth	6 MHz
Vehicle deceleration	4.5	TV channel frequencies	500MHz – 524MHz
Sigma (diver imperfection)	0.5		

5.5 Chapter summary

This chapter has detailed the implementation of SSF-CVANET presented in Chapter 4. In particular, the chapter discussed various network simulation tools both commercial and open source as well as vehicular traffic generation tools that are used in VANET simulation. In this work, NS3 and SUMO are used as simulation tools. The justification for selecting the two simulation tools is presented in Section 5.2.2 and Section 5.2.3 respectively. NS3 is used as network simulator while SUMO is used to generate vehicular traffic that is used as mobility trace input to NS3. The use of SUMO is necessitated because NS3 does not support realistic mobility models. However, it supports importing of mobility traces from third-party tools like SUMO. The chapter goes further and discusses important features of NS3 which support implementation of SSF-CVANET. The two most important modules in NS3 are Spectrum and WAVE. In addition, the chapter presents some of the classes and helpers used within the Spectrum module and WAVE to support the implementation. Furthermore, detailed descriptions of classes and associated methods used to realize SSF-CVANET have been presented in Section 5.4 covering both adaptive sensing and reinforcement learning. Finally, steps used in preparing SUMO mobility trace files to be used in NS3 are presented. In the following chapter (Chapter 6), simulation results are given. Chapter 6 also compares the result for SSF-CVANET to other approaches proposed in literature for validation purposes.

CHAPTER 6: RESULTS AND DISCUSSION

6.1 Introduction

Following the implementation details presented in the previous chapter, this chapter discusses simulation results to achieve the objectives. Firstly, the chapter presents preliminary investigation of DSRC channels in Section 6.2. Secondly, a discussion of spectrum sensing results is presented in Section 6.3 for both fading and non-fading environment. This chapter also presents simulation results of adaptive sensing proposed in Section 4.3.2.3 of Chapter 4 and compares it with energy detector. Later in Section 6.4, the chapter presents evaluation of SSF-CVANET and compares it with other schemes proposed in literature with emphasis on spectrum sensing performance. And finally, Section 6.5 concludes the chapter.

6.2 Evaluation of VANET using DSRC channels

Success of any communication system is ability to provide guaranteed quality of service (QoS) for delay sensitive packets. In VANET, delay sensitive packets include safety and emergence messages that alert drivers on the roads of any dangerous scenarios. Therefore, packet delivery rate (PDR) and packet loss rate (PLR) are important performance metrics that should be improved to guarantee some form of QoS to delay sensitive packets. PDR describes the ratio of the number of data packets delivered to the destination against the number of packets sent while PLR defines the number of packets lost against the number of packets sent. Thus, PDR and PLR are represented by the following:

$$PDR = \frac{\sum number\ of\ packet\ received}{\sum number\ \ of\ packet\ sent} \qquad 6.1$$

$$PLR = \frac{\sum number\ of\ packet\ lost}{\sum number\ \ of\ packet\ sent} \qquad 6.2$$

Figure 6.1 shows the results of the preliminary simulations indicating the average PDR and PLR for different number of vehicles. The results are based on the simulation parameters and procedure described in Chapter 5 in which only DSRC channels are considered.

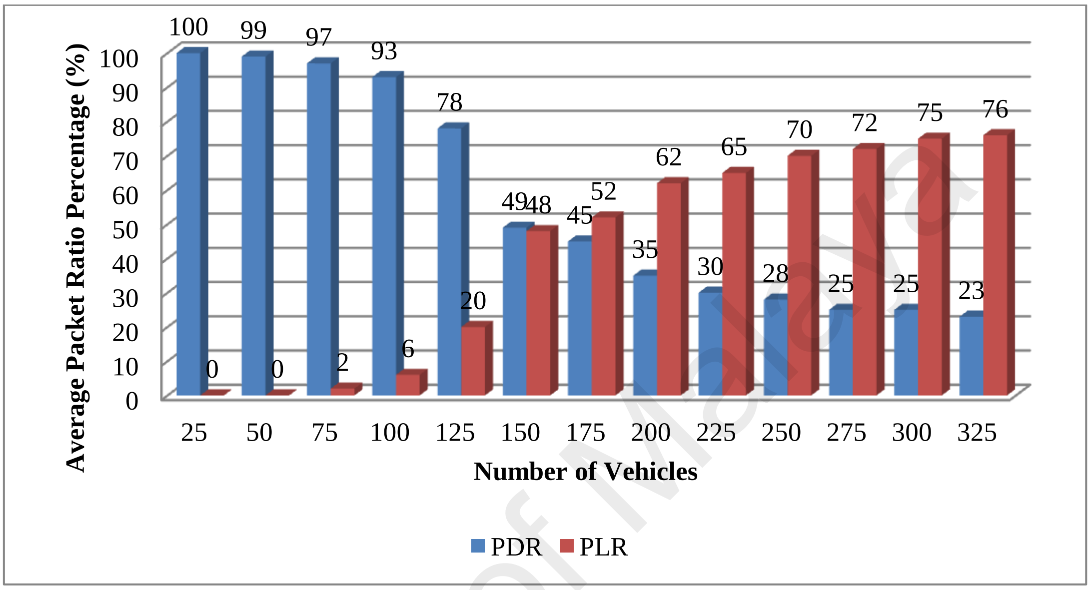

Figure 6.1: Simulation results for average PDR and average PLR for various numbers of vehicles communicating on DSRC channels.

The results of simulation shown in Figure 6.1 involved vehicles communicating to the RSU using DSRC channels only. Clearly, it can be seen that as the number of vehicles increase, the PDR decreases while the PLR increases. This is attributed to contention in the wireless channel when the number of communicating nodes increases. Hence, many packets are dropped due to collision. For example, with 150 vehicles communicating to the RSU, the PDR drops below 50% and continue dropping as the number of vehicles increase. This will pose a challenge to deliver safety related messages to intended recipients due to high drop rate. In addition, the broadcast nature of safety messages increase chances of collision and consequently packet drop with increase in the number of vehicles communicating (Jiang et al., 2006). Therefore, the desire is to have few packet drop (i.e. low PLR). Similarly, the average delay increases as the number of vehicles increase. This is illustrated in Figure 6.2 below.

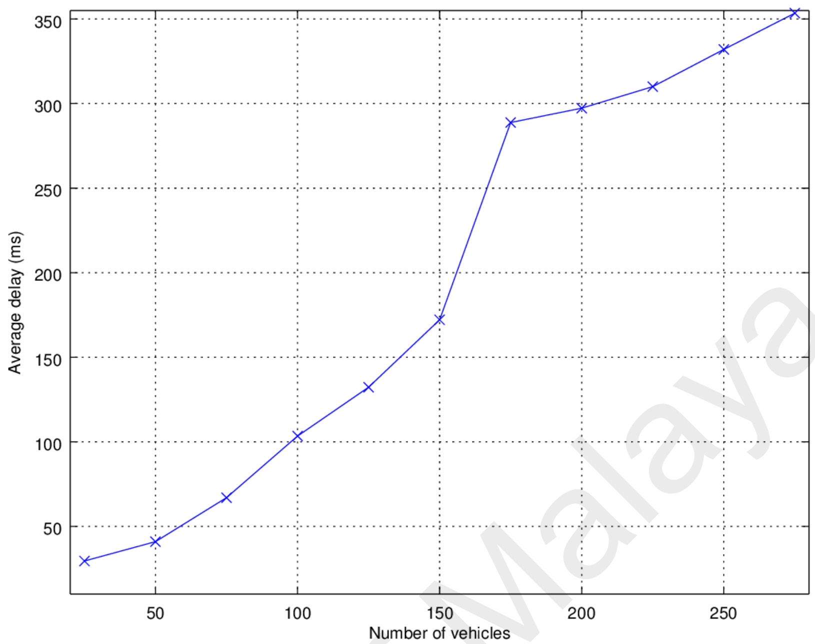

Figure 6.2: Average delay for various numbers of vehicles communicating on DSRC channels

Similar to PLR, low delay is an important metric needed in guaranteeing QoS to safety and emergency messages in VANET. Nevertheless, with increase in the number of vehicles communicating on DSRC channels, average delay increases as well, noted in Figure 6.2. Safety messages are delay sensitive (Atallah et al., 2015; Ghafoor, Lloret, Bakar, Sadiq, & Mussa, 2013). Hence increase in the number of vehicles can impair DSRC channels with negative impact on the safety messages. The two figures (6.1 and 6.2) show that the DSRC channels are not sufficient to serve VANET applications adequately during congestion on the roads. Therefore, additional channels are required to supplement channel demand during congestion to guarantee some QoS to safety messages. In this regard, dynamic spectrum access through cognitive radio technology is such approach that can be used to increase channel capacity to supplement DSRC channel during congestion.

Nevertheless, before additional channels can be used by vehicles, spectrum sensing is performed to identify free channels as described previously. This thesis is anchored on providing mechanism to identify the free channels in licensed frequency bands that can be used by vehicles on the road through spectrum sensing. Regardless, maximum protection to licensed users should be guaranteed to avoid interference to their communication systems. In the next sections, the evaluation of proposed SSF-CVANET in Chapter 4 is presented based on the simulation implementation described in Chapter 5.

6.3 Spectrum sensing for individual vehicles on the road

This section presents results for evaluating the performance of proposed adaptive sensing in two sensing environments. The environments considered include fading and non fading Additive White Gaussian Noise (AWGN). Spectrum sensing is very much affected by the sensing environment due to multipath fading and shadowing as describe in Chapter 3 (Section 3.2). Importantly, the performance of energy detector is poor in low SNR. Therefore, it is important to determine the optimal threshold for SNR (γ) that support the desired probability of detection. The performance metrics used in this section include probability of detection (P_d), probability of false alarm (P_f) and probability of missed detection (P_{md}) described in Chapter 3 (Section 3.3.1). In addition, we consider the speed of vehicle when sensing as well as mean sensing time as additional performance metrics. Before evaluating proposed adaptive sensing, we evaluate the energy detector on which part of the proposed approach is based.

The detection performance of the energy detector for different SNR (γ) is given in Figure 6.3 below. The analysis is based on varying sensing samples. The sample size is important in determining the energy test statistic and threshold as described in Chapter 4. Remember, for sample size greater than 250, the test statistic can be approximated to Gaussian distribution using the CLT (W. Yue & Zheng, 2010). Hence, AWGN is considered in determining the optimal SNR (γ) while fixing the probability of false alarm at 0.1. The desire is to get higher probability of detection even in low SNR.

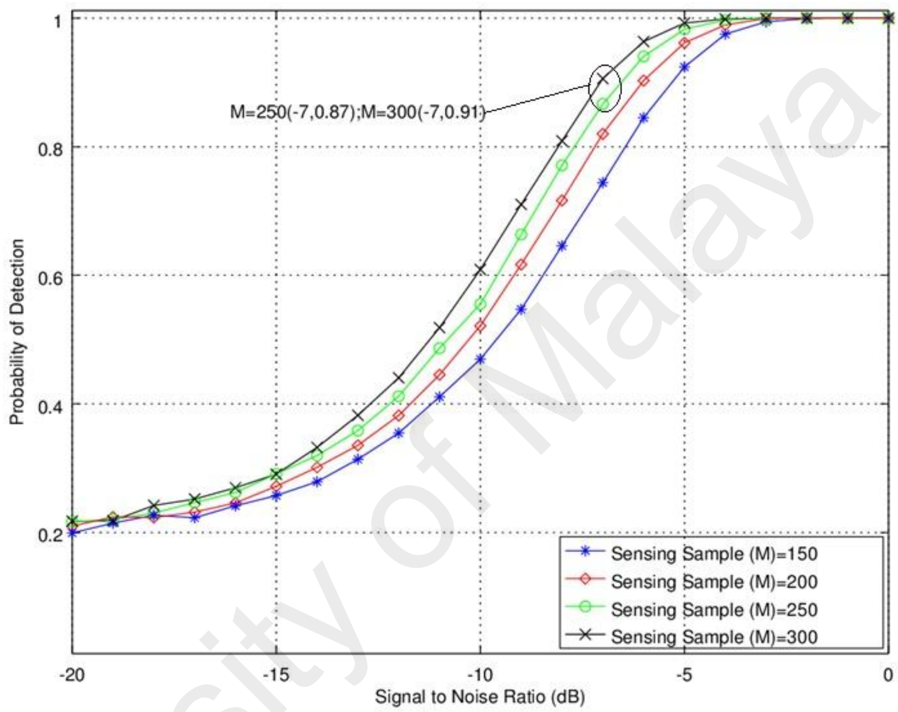

Figure 6.3: Probability of detection against SNR for various sensing samples

Figure 6.3 shows that in low SNR (γ) the performance of the energy detector is not optimal. Nevertheless, increase in sensing samples increase P_d as noted for M=300 and M=250. With SNR (γ) of -7dB, the P_d for 300 and 250 sensing samples are 0.91 and 0.87 respectively. When sensing samples are increased, the chances of detecting the PU signal also increases. However, increase in sensing samples also increase sensing time which is valuable in VANET communication due to mobility of vehicles. Hence, less sensing samples is preferred. Regardless, when the SNR (γ) is -10dB the probability of detection (P_d) is less than or equal to 0.6 (i.e. $\leq$ 60%) for all sensing samples from Figure 6.3. This implies that in fading environment with low SNR the performance of energy detector is not optimal. In fading environment, SNR (γ) is low due to multipath fading and shadowing of PU signal. In addition, the Doppler effects due to mobility of vehicles (i.e. sensing agents) can contribute to noise uncertainty. In the following section, we show the performance of the energy detector in fading environment.

6.3.1 Spectrum sensing in fading environment

In a wireless communication system, fading of radio signal due to various factors cannot be overlooked (see Chapter 3, Section 3.2 for more details). Therefore, the performance of energy detector is evaluated over Rayleigh fading and non-fading AWGN. The performance metric for evaluation is based on receiver operating characteristic (ROC) curves. The ROC curves are used in signal detection theory to quantify the tradeoff between P_d and P_f and describe the error rate of the energy detector as a function of SNR (Atapattu, Tellambura, & Jiang, 2010). Thus, the sensing metric P_d is referred to as power (SNR) which is sensitivity and P_f as level of detector or specificity of a sensing technique (Akyildiz et al., 2011). This is mainly because P_d and P_f have diverge implications when it comes to spectrum sensing performance in cognitive radio networks as described in Chapter 3 (Section 3.3.1). The ROC curve with high slope of P_d and negative curvature is desired for good sensing scheme. Figure 6.4 shows the relationship of P_d and P_f for Rayleigh and AWGN.

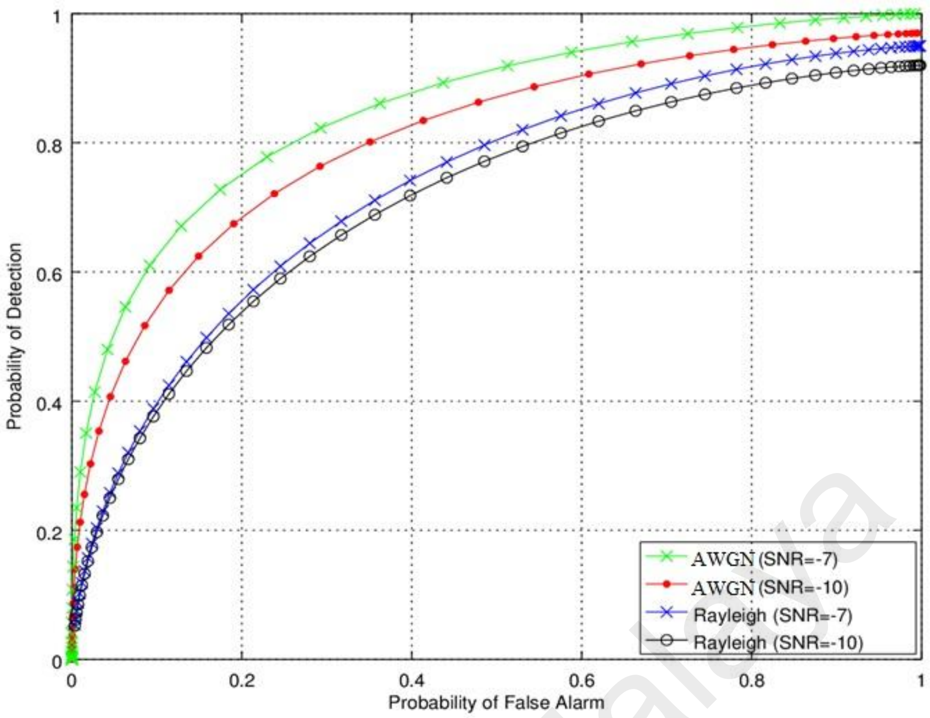

Figure 6.4: Complementary ROC curve showing $\boldsymbol{P_d}$ and $\boldsymbol{P_f}$ (energy detector) in Rayleigh fading and AWGN environment

In low SNR the energy detector performs lower than in high SNR as illustrated in Figure 6.3. Furthermore, the energy detector is affected by the fading of PU signal. This is demonstrated in Figure 6.4 where the performance of energy detector in Rayleigh fading environment is below the non fading AWGN in terms of probability of detection. The analysis of Rayleigh fading is based on probability of detection derived from Equation 4.5 in Chapter 4. Figure 6.4 shows that with SNR of -10dB, the non-fading AWGN performs better than the Rayleigh for both SNR considered (i.e. SNR=-7dB and SNR=-10dB). The SNR of -10dB is chosen because it demonstrates low performance of energy detector for low SNR in terms of probability of detection according to Figure 6.3. Similarly, SNR=-7dB demonstrate the high probability of detection for 250 sensing sample. Therefore, 250 sensing samples were considered for analysis shown in Figure 6.4. However, to reach a high probability of detection of 0.9 there is an increase in probability of false alarm (i.e. 0.8) in Rayleigh fading based on Figure 6.4. The implication of a huge probability of false alarm is resulting in missing spectrum opportunities (A. Singh et al., 2011). On the other hand, probability of missed detection is also affected in fading environment as demonstrated in Figure 6.5 below.

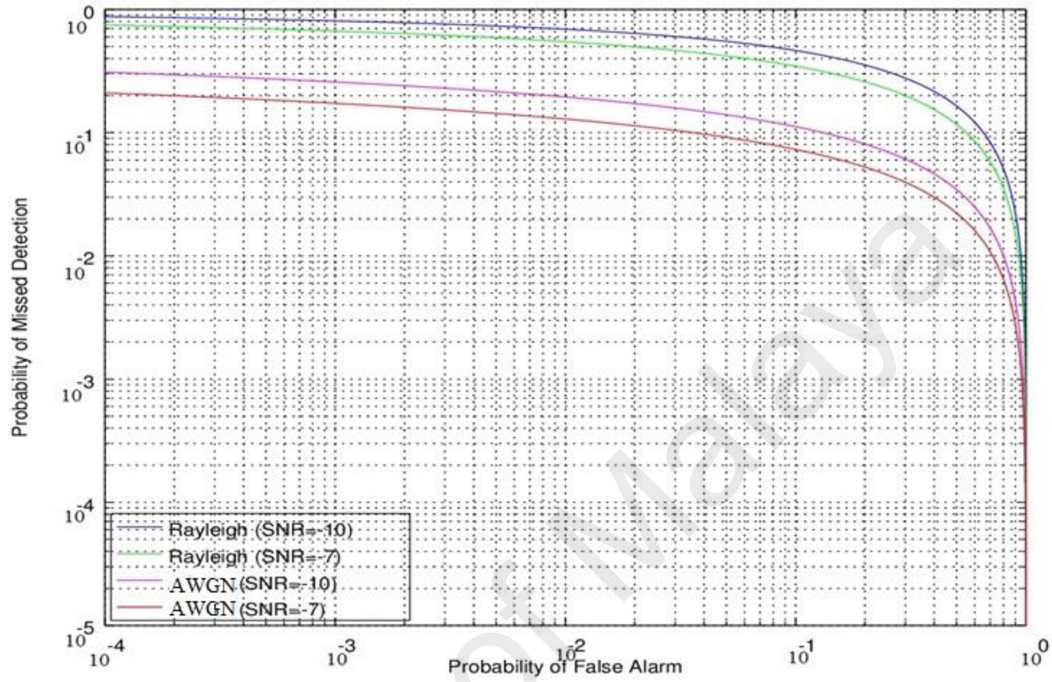

Figure 6.5: Complementary ROC for probabilities of missed detection and false alarm for energy detector in Rayleigh fading and non-fading AWGN.

The probability of missed detection ($\mathrm{P_{md}}$) measures the error rate of the energy detector. It measures the rate of falsely determining absence of the PU signal when in the actual sense the signal is present. In DSA, this could result in interference to the PU communication system if the vehicle attempt to communicate on the identified PU channels. Probability of missed detection is derived from probability of detection as $P_{md} = 1 - P_d$. Thus, the desire of the sensing technique is to maintain probability of missed detection as low as possible. However, the performance of energy detector degrades in presence of Rayleigh fading significantly as observed from Figure 6.5. For example, to achieve the $\mathrm{P_{md}} = 0.1\ or\ 10^{-1}$ requires the probability of false alarm higher than 0.5 (i.e. from Figure 6.5) for Rayleigh fading compared to about 0.1 for non-fading AWGN based on SNR=-10dB. Higher P_f results in low spectrum utilization as stated before while higher P_{md} results in interference to the PU communication system. In addition, as the fading increases due to obstacles in the sensing environment, the energy detector performance also deteriorates. This has also been shown in other research in literature (Bagheri et al., 2016).

Therefore, adaptive spectrum sensing has been proposed in this thesis to mitigate the shortfalls of energy detector in low SNR. The proposed method relies on feature detector in time domain to identify PU signals in low SNR (see Chapter 4 for further details). The performance evaluation of the proposed sensing scheme in CVANET is presented in the following section.

6.3.2 Adaptive spectrum sensing

Adaptive spectrum sensing proposed in this work is presented in Chapter 4 (Section 4.3.2.3) and implementation procedures outlined in Chapter 5. It is based on considering two detection thresholds of the energy detector. One threshold is set to achieve the desired constant probability of false alarm (CPFA) and the other threshold is set to achieve desired constant probability of detection (CPD). The lower threshold for target CPFA (i.e. 0.1) is obtained using Equation 4.6 and upper threshold for target CPD (i.e. 0.9) is obtained from Equation 4.3 (Chapter 4). If the energy test statistic obtained from spectrum sensing is less than the lower threshold, the energy detector decides absent of the PU signal. On the other hand if the energy test statistic is above or equal to the upper threshold, the energy detector decides presence of the PU signal. However, if the test statistic falls between the lower and upper thresholds the energy detector does not decide anything instead further sensing is performed using feature detection in time domain. In particular one-order cyclostationary (OOC) feature detector is used.

The performance of the adaptive sensing is compared to energy detector for fading and non-fading environment. Energy detection technique is one of the most implemented sensing techniques. In addition, it is used as base sensing technique for cooperative decision for spectrum sensing. Furthermore, it is implemented in NS3, the simulator considered for this work through *SpectrumAnalyzer* class in Spectrum Module as discussed in Chapter 5. Figure 6.6 presents the comparison between proposed adaptive sensing and energy detector in Rayleigh fading and non-fading AWGN.

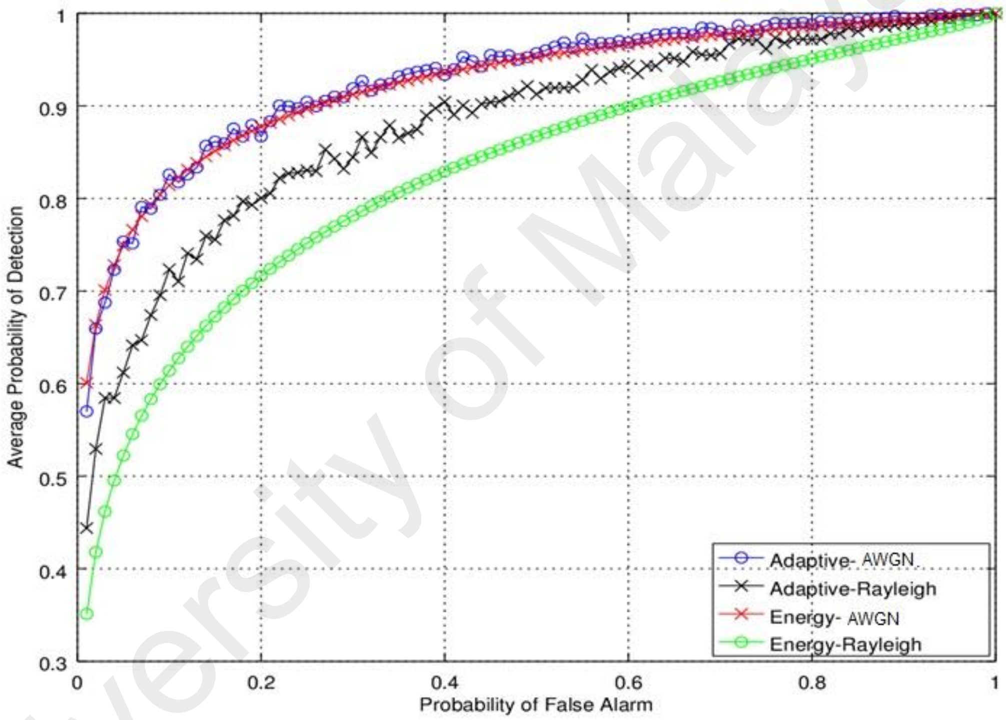

Figure 6.6: Complementary ROC curve for adaptive sensing compared with energy detector in Rayleigh fading and non-fading environment

The performance of adaptive sensing in non-fading AWGN is similar to energy detector as shown from Figure 6.6. The SNR considered for non-fading AWGN in this simulation is -7dB with 250 sensing samples. Thus, a probability of false alarm of 0.2 is required to reach the probability of detection of about 0.9 for both energy detector and proposed adaptive sensing. This is achieved because adaptive sensing is mainly based on energy detector in high SNR to reduce sensing time. However, in fading environment with low SNR the performance of energy detector degrades as shown in

Figure 6.4 and Figure 6.6. Nevertheless, the adaptive sensing maintains a better probability of detection compared to energy detector. This is because in fading environment with low SNR the adaptive sensing use feature detector. Thus, the adaptive sensing scheme could maintain the probability of detection of 0.8 (i.e. 80%) compared to energy detector with 0.7 (i.e. 70%) based on probability of false alarm of 0.2. Nevertheless, the performance is still not optimal because the feature detector requires long sensing period with increased sensing samples. In this simulation the maximum sensing time was kept constant for both energy detector and adaptive sensing at 10ms for fair comparison.

In Figure 6.7 the probability of missed detection of adaptive sensing is compared with energy detector for fading and non-fading environment.

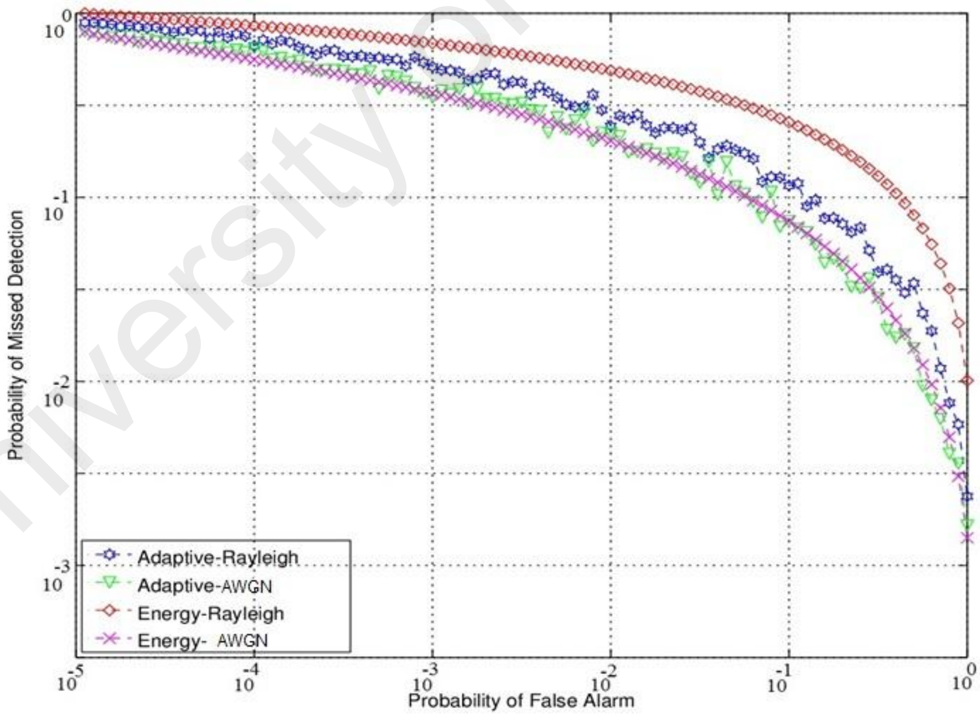

Figure 6.7: Complementary ROC for probabilities of missed detection and false alarm for adaptive sensing in comparison with energy detector

Just as observed in Figure 6.6, the adaptive sensing performance is better than the energy detector in fading environment but same in non-fading AWGN environment.

Figure 6.7 demonstrates that the probability of missed detection for both adaptive sensing and energy detector are similar in non-fading AGWN environment. For instance, both approaches require $P_f \approx 0.08$ for $P_{md} = 0.1\ or\ 10^{-1}$. However, in fading environment the performance of adaptive sensing is slightly better than energy detector. Considering the probability of missed detection of $0.1\ or\ 10^{-1}$ requires the probability of false alarm of about 0.2 for adaptive sensing compared to energy detector which require about 0.6. Higher probability of false alarm limit radio spectrum reuse while high probability of missed detection cause interference to PU systems.

Figure 6.8 demonstrates the mean sensing time overhead of proposed adaptive sensing in comparison to energy detector in fading and non-fading environment.

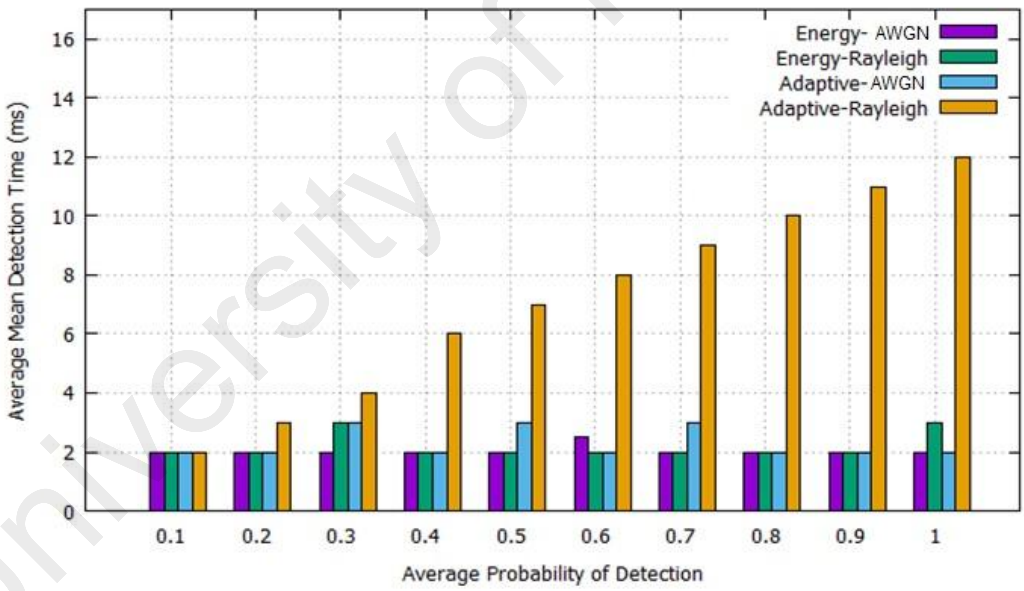

Figure 6.8: Comparative mean detection time for adaptive sensing and energy detector in fading and non-fading environment

Figure 6.8 shows the mean detection time against the probability of detecting the PU channel for adaptive sensing and energy detector. For non-fading AWGN the adaptive sensing has the same mean time as energy detector in most case as seen in Figure 6.8. This is because the adaptive sensing is based on energy detector on one part hence in high SNR the energy detection technique is used. However, the mean detection time in Rayleigh fading environment for adaptive sensing is higher than energy detector. For example, to reach a probability of detection of 0.9 requires on average 11*ms* for adaptive sensing compared to 2*ms* for energy detector. As stated before, in fading environment with low SNR the adaptive sensing uses OOC which perform sensing in time domain (opposed to frequency domain used by other feature detectors) to detect the PU signal. OOC like any feature detector require long sensing time to extract the features of the signal before deciding on the PU occupancy state. Hence, adaptive sensing takes more than twice the time to reach the probability of detection of as low as 0.5 as observed from Figure 6.8. This is due to combining time for energy detector in first stage and OOC in the second stage of adaptive sensing (see Chapter 4, Section 4.3.2.3 for further details). On the other hand, the energy detector maintains the same mean time for both fading and non-fading environments because it only measures the power or SNR in the channel being considered and compare to threshold. No extra time is needed for energy detector to check the features of the signal being sensed as opposed to feature detector.

6.3.3 Analysis of speed of vehicle on spectrum sensing

The speed of vehicles play an important role in spectrum sensing in CVANET environment as discussed in Chapter 3. The following figure shows the performance of adaptive sensing compare to energy detector for various vehicle speeds.

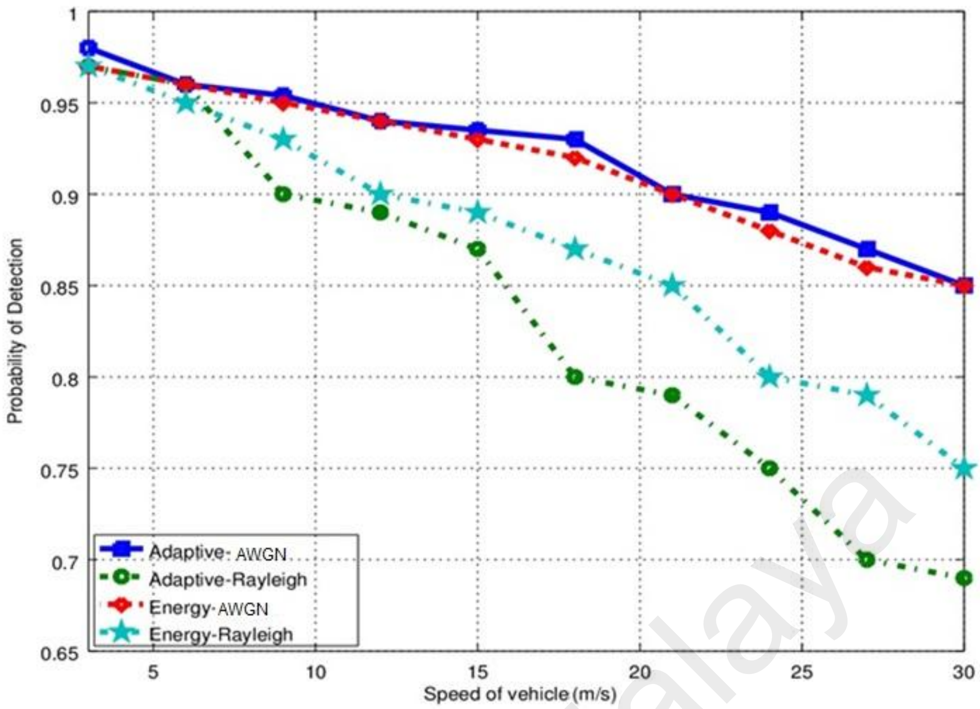

Figure 6.9: The effect of speed of vehicles on probability of detection

With increase in speed of vehicles the detection performance decrease as observed in Figure 6.9. This is mostly because the vehicle is likely to miss free channels with increased speed in the road segment of interest. When the vehicle is moving at high speed, there is high possibility of moving from the area with free licensed channels to areas without free channels. The effect of speed is more severe in fading environment compared to non-fading environment as observed in Figure 6.9. For instance, the probability of detection of about 0.85 is achieved with vehicle moving at 30m/s for both adaptive sensing and energy detector in non-fading AWGN. However, in fading environment the performance of adaptive sensing is lower than energy detector with increased speed. The probability of detection for adaptive sensing is about 0.68 compared to energy detector of about 0.75 for vehicles moving at 30m/s. In fading environment, adaptive sensing rely on OOC which require more sensing time as observed in Figure 6.8. With increased sensing time, the vehicle is likely to move into other areas where the characteristics of the sensed channels might be different. Thus, adaptive sensing is optimal for vehicles moving at low speed especially in congested areas. Figure 6.10 shows the relationship between vehicle speed and probability of missing spectrum opportunities on the road segment.

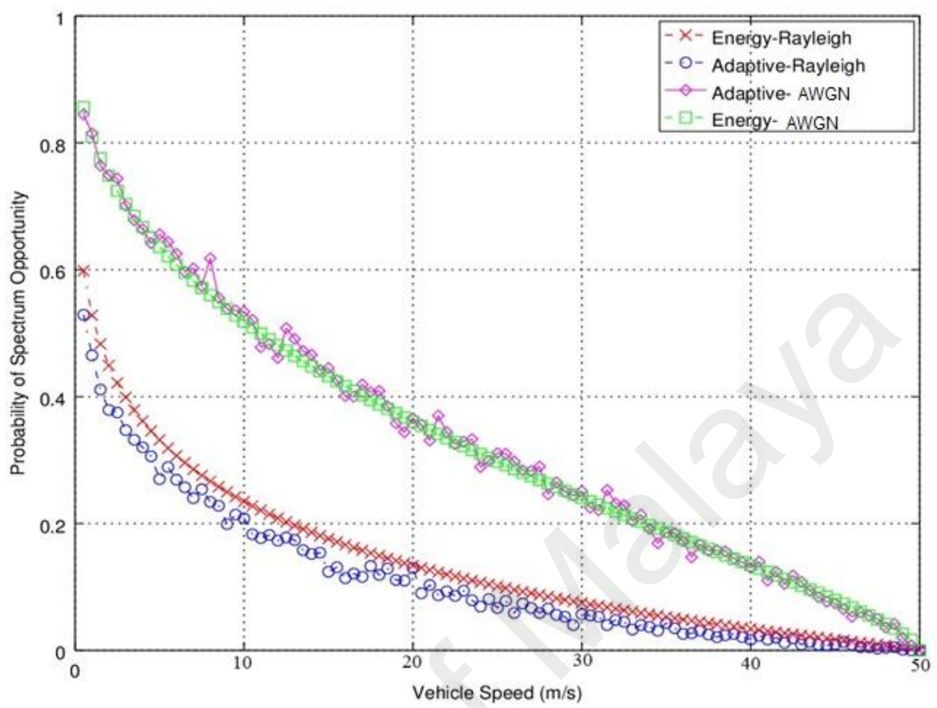

Figure 6.10: Probability of spectrum opportunities vs. the speed of vehicle

The speed of vehicle affects rate at which spectrum opportunities is identified. In Figure 6.10, a plot of probability of spectrum opportunities and speed of vehicle is given. Spectrum opportunities refer to instance when the vehicle is likely to identify free channels before getting outside the coverage area of the PU system while sensing is being performed. Thus, with increased speed, the vehicle is likely to move out of the PU coverage system hence missing spectrum opportunities. From Figure 6.10 it is observed that in fading environment a vehicle moving at 40m/s ($\approx 144km/s$) has close to 0% chance of identifying spectrum opportunities in the road segment of interest.

Although speed of vehicle affect the detection performance and increase missing spectrum opportunities, cooperative decision mitigate the effects (Aygun & Wyglinski, 2016; De Nardis et al., 2012). Cooperating vehicles use spatial and diversity gain to improve sensing decision. Furthermore, vehicles move at relatively slow speed in congested areas varying from 0-10km/h (≈2.8m/s) in highly dense traffic jams to 40km/h (≈11m/s) in medium traffic (Tyagi, Kalyanaraman, & Krishnapuram, 2012). Thus, adaptive sensing can be used for both fading and non-fading environment in congested areas. Based on Figure 6.9 the probability of detection for vehicles moving at 2.8m/s and 11m/s is 0.98 and 0.88 respectively which is acceptable. Nevertheless, the performance of adaptive sensing can be enhanced by considering the PU activities. Vehicles on the roads can concentrate on sensing channels that are likely to be free based on the activities of the PU system. This is achieved through reinforcement learning at RSU. The evaluation of adaptive sensing and PU activity influence on spectrum sensing is studied next.

6.4 Evaluation of SSF-CVANET

The previous sections demonstrate that adaptive sensing performs better than energy detector in fading environment as observed from Figure 6.6 and 6.7. However, the higher performance is at the expense of increased sensing time. Specifically Figure 6.8 shows the sensing time verses probability of detection in which adaptive sensing has higher mean detection time in fading environment. In addition, the adaptive sensing performs poor when the vehicle is moving at high speed in fading environment as observed in Figure 6.9 and 6.10. Therefore, reinforcement learning (RL) is used at RSU to increase the performance of adaptive sensing.

RL is used at the RSU to model the activities of the PU traffic pattern using sensing results sent from vehicles on the road as input for calculating the reward. In particular, when the vehicle sense and identify the free PU channel it will transmit data on it. After transmitting data, the vehicle will send a scalar value as reward to RSU. In this work, the temporal difference with lambda (TD(λ)) and eligibility traces is used to solve the RL problem formulation. The eligibility trace is included to increase the learning speed.

In addition, TD(λ) is associated with TD-error that defines difference in values of the state that correspond to successive time steps. Figure 6.11 shows the performance of TD(λ) in relation to root-mean-squared (RMS) error of value function estimated at the end of the 100 episodes.

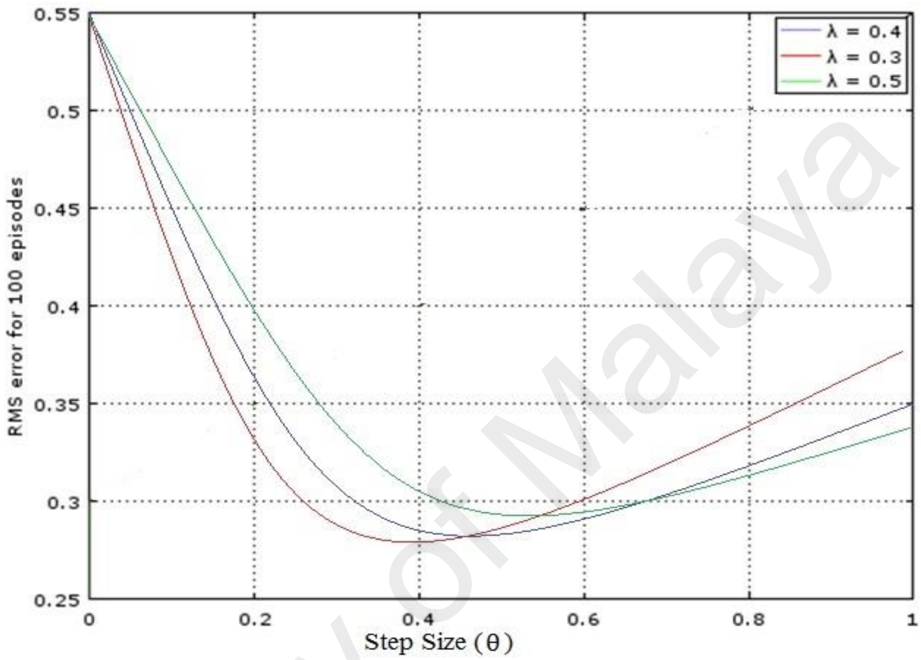

Figure 6.11: RMS error of state values at the end of 100 episodes

The RMS error measures the difference between the estimated and actual state values of each episode with respect to true values. The episode denotes the time between start and end of congestion on the road when SSF-CVANET is activated. The return value λ determines the rate at which the trace falls and estimate the expected return based on subsequent rewards. In addition, it sets a trade-off between TD and MC depending on the choice of values (see Chapter 4.3.3.2). From Figure 6.11 it is observed the value of step size θ and return value λ that achieve the lowest RMS error is 0.3. The goal of RL problem is to maximize cumulative rewards. Therefore, the initial parameters such as state probability P (Equation 4.15) and discounted factor (ϵ) can be set to arbitrary values without much effect on the state value over time. Nevertheless, these parameters influence how fast the RL algorithm converges to optimal value function (Equation

4.21, Chapter 4). In particular, ϵ which is sometimes called learning rate influence how fast the algorithm converges to optimal value based on the policy. The following figure shows different values of accumulative reward over different episodes.

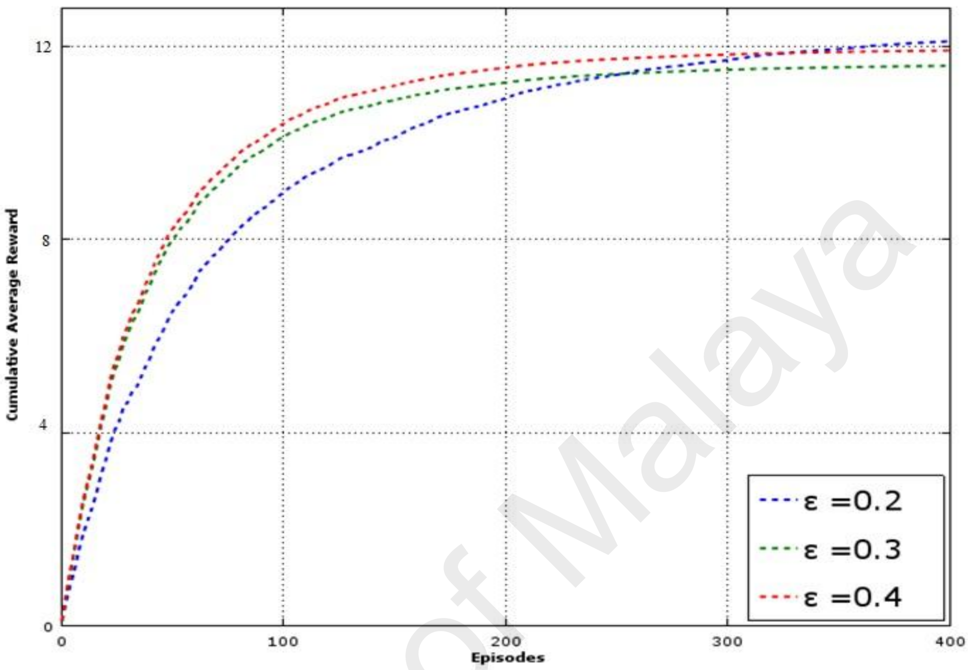

Figure 6.12: Cumulative rewards based on episodes and learning rate

Figure 6.12 shows the performance of learning rate (ϵ) over 400 episodes. From the figure above it is observed the learning rate of 0.4 performs better than other learning rates in terms of convergence to cumulative average reward over time. For instance, only about 250 episodes are required for algorithm to converge with maximize cumulative reward of 11.742 when learning rate is 0.4. On the other hand, the learning rate of 0.3 requires about 300 episodes to converge while the learning rate of 0.2 requires even more episodes. Nevertheless, the learning rate also set the trade-off between exploitation and exploration. Exploitation involves reusing the same channels with high OFF state as well as high bandwidth. Exploration involves searching for other licensed frequency bands which might be free for DSA. Figure 6.13 demonstrates the cumulative rewards for different PU channels.

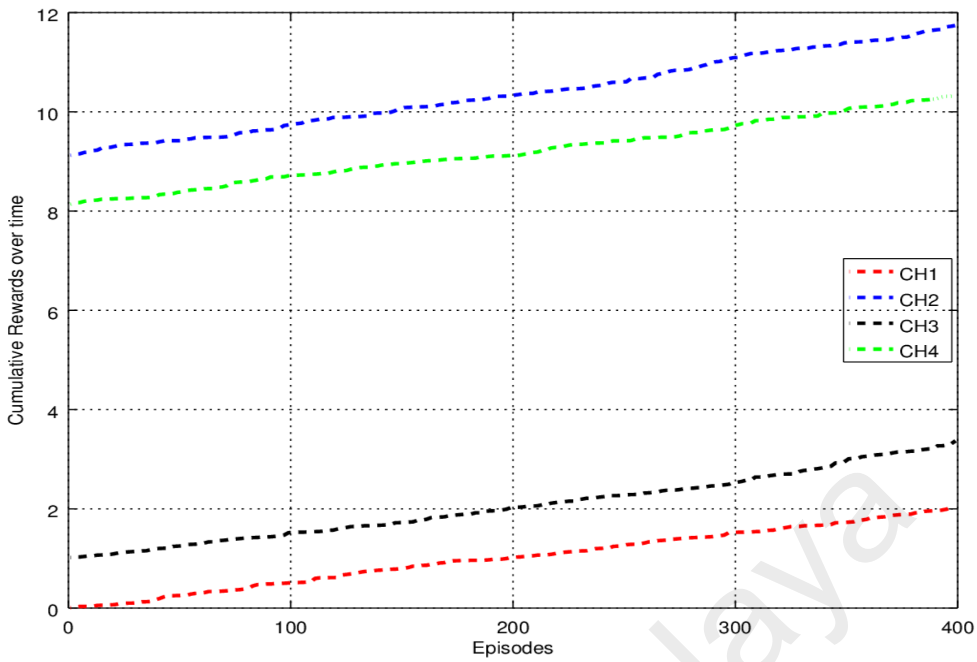

Figure 6.13: Cumulative rewards for PU channels over the episodes

The figure above shows the channel availability based on the cumulative reward. The channels with high bandwidth and availability time show higher cumulative reward. For instance, Channel 1 and 3 have low cumulative reward because they are used by the PU most of the times. Alternatively, Channel 2 and 4 have high cumulative reward with time because they are not constantly being used by the PU. The implication of high reward is that the RSU will recommend these channels to vehicles to be used during congestion. The reward is calculated based on Equation 4.14 from Chapter 4 in which the parameters used include sensing time plus transmission time if any, channel availability denoted by either 0 or 1 depending on the result of the sensing and channel bandwidth. The weight contribution w_b and w_t from Equation 4.14 are 0.4 and 0.6 respectively.

6.4.1 Performance evaluation of SSF-CVANET

In this section, the performance of SSF-CVANET is compared to other spectrum sensing schemes proposed in literature. In particular, infrastructure based sensing schemes which use history of sensing data to improve sensing results is considered.

First scheme is proposed by Huang et al (2016). The authors present a spectrum sensing scheme that use historical spectrum data mining to predict spectrum availability on the next road segment. The scheme is based on Bayesian model and hidden Markov model (HMM) to exploit spatial and temporal correlation. The algorithm for the proposed scheme is presented in Table 1 and 2 of the paper while implementation procedure is given in Table 3 (Huang et al., 2016). Another history based scheme is proposed by Abbassi et al., (2015). In the proposed scheme, the vehicles on the road utilize history of spatial-temporal diversity and frequency pattern controlled by the RSU through a database. The RSU coordinate the PU channels to send to passing vehicles based on time of the day. In addition, the RSU decide on the PU occupancy state from historical data using hard fusion (majority rule). The paper provides abstract of the flowchart for the model in Figures 5, 6 and 7 (Abbassi et al., 2015). Another scheme based on infrastructure support that use hard fusion rule at RSU to cooperatively decide on spectrum sensing results is proposed by Duan et al., (2013). The RSU use the OR, AND or majority rule to determine the final global sensing results (Duan et al., 2013).

The above schemes are considered because they use history of sensing results to improve accuracy of spectrum sensing results on which this work is based with exception of Duan et al., (2013). The proposed cooperative sensing by Duan et al., (2013) is based on hard fusion without considering history of sensing results. Duan et al., (2013) and Abbassi et al., (2015) consider TV bands as PU channels which are also considered in this work. Nevertheless, the approach in this work utilizes RL to learn the behavior of the PU channels which is different from the historical based scheme from literature. Unlike other schemes, RL in SSF-CVANET is used to learn and model PU traffic pattern by assigning high reward to channels with long OFF periods and high bandwidth. The hard fusion rule approach is used in comparison because it is one of the most used cooperative decision scheme and it is simple to implement.

6.4.1.1 Detection performance under ROC curve

The performance metrics used to compare SSF-CVANET and other schemes include probabilities of detection, false alarm and missed detection based on ROC curves. Other metrics include mean detection time and sensing overhead against throughput. For RL, values obtained in Figure 6.11 and 6.12 are used. The value for step size (θ) is taken to be 0.3, the discounted factor (ϵ) is taken to be 0.3 and finally the return value (λ) is 0.3. Figure 6.14 shows the detection performance for complementary ROC curve of probabilities of detection and false alarm.

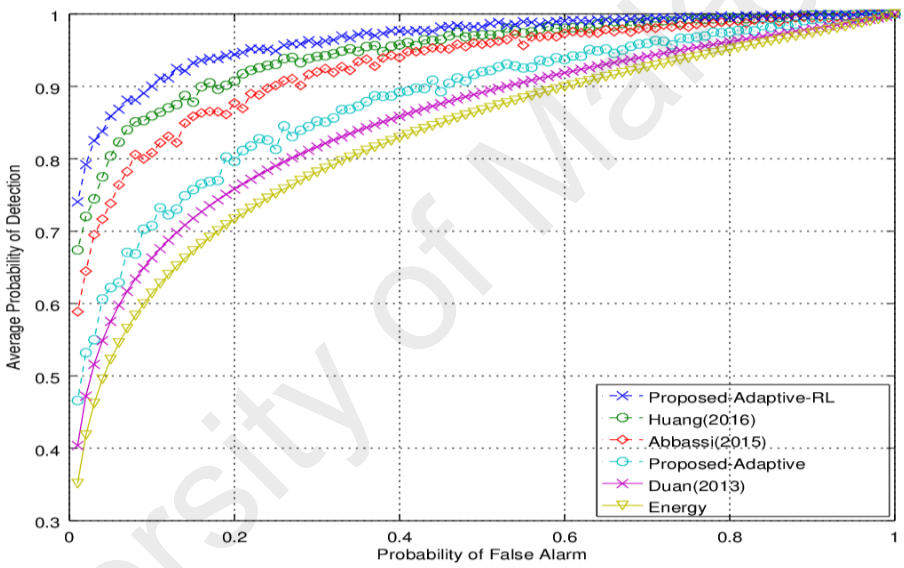

Figure 6.14: Complementary ROC curve of proposed scheme compared to other sensing approach in fading environment

The figure above presents simulation results of proposed scheme in comparison to other schemes in fading environment. The proposed scheme SSF-CVANET is represented by Proposed-Adaptive-RL. In addition, result from adaptive sensing without reinforcement learning is also included. As observed from Figure 6.14, energy detection technique performances last in fading environment followed by hard fusion rule by Duan et al., (2013). With probability of false alarm of 0.2, the energy detector has average probability of detection of 0.72 while scheme proposed by Duan et al., (2013) has probability of 0.75. Adaptive sensing performs better than energy detector and hard fusion rule with the probability of detection of 0.8 for the same probability of false alarm. However, its performance is below that of schemes using history to enhance sensing results. Schemes using history account for the PU traffic pattern which is sent to vehicles on the road before sensing is performed. Regardless, the proposed scheme using RL performs better than other history based. From Figure 6.14 the proposed adaptive sensing with RL achieves a probability of detection of 0.9 for probability of false alarm of 0.1, compared to Huang et al., (2016) and Abbassi et al., (2015) which require probability of false alarm of 0.2 and about 0.3 respectively to reach the same probability of detection of 0.9. Huang et al., (2016) approach predicts spectrum availability on next road segment and not the current segment using HMM. The drawback with this approach is that by the time the vehicle goes in the next road segment, the PU might be active in the road segment. On the other hand, Abbassi et al., (2015) rely on hard fusion to decide on the channels to send to vehicles using history data stored in the database. This adds more sensing time overhead by deciding on which channels to send to vehicles before sensing is performed. The RSU in our proposed approach use cumulative reward to assign channels of PU with higher reward in the current road segment to vehicles on the road.

6.4.1.2 Detection performance based on speed of the vehicle

The speed of vehicles has impact on probability of detection as noted in Figure 6.9. The following figure shows the performance of SSF-CVANET in terms of probability of detection and speed of sensing vehicle in comparison with other schemes in fading environment.

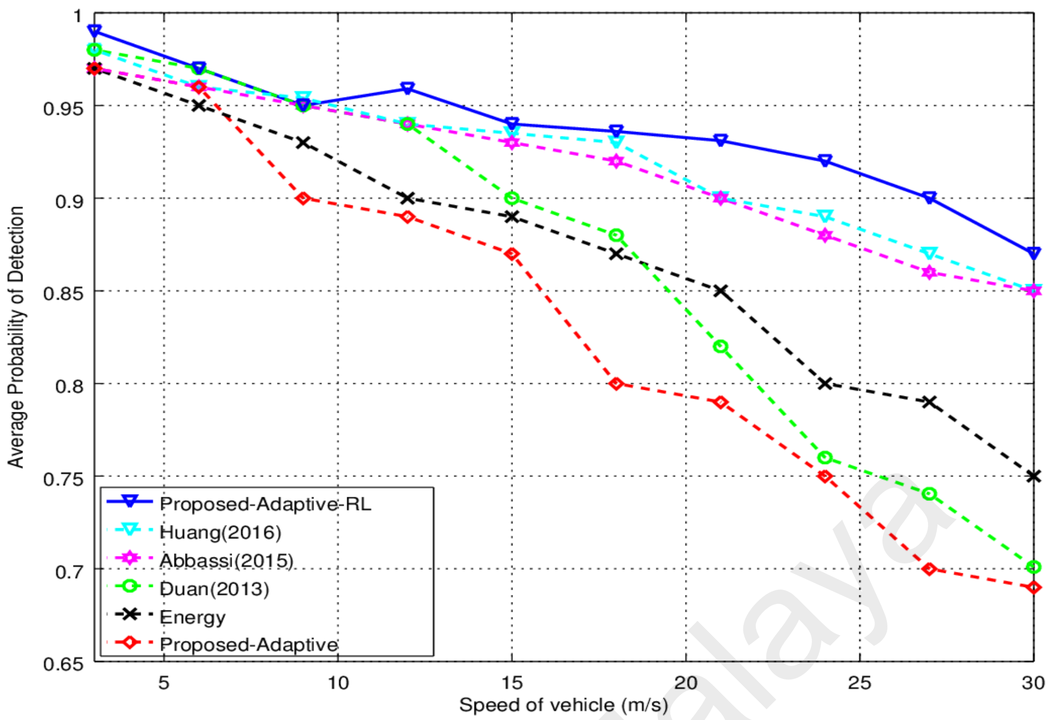

Figure 6.15: Performance of proposed RL based scheme compared to other approaches on the effect of speed on probability of detection

The performance of adaptive sensing without RL is poor in fading environment because more sensing samples are needed for accurate detection for OOC detector. Thus, based on Figure 6.15, adaptive sensing without RL performance is below other schemes. The probability of detection for vehicles moving at 30m/s is about 0.68 compared to other schemes which are above 0.7. On the other hand, adaptive sensing with RL has a best performance compared to other schemes under consideration (i.e. with probability of detection of 0.87 for vehicles moving at 30m/s). This is because when using the SSF-CVANET framework with RL, channels to sense are sent to the vehicles opposed to adaptive sensing which has to identify channels on its on. Therefore, few sensing samples are required to confirm the presence or absence of the PU signal when using RL. In addition, the channels sent to vehicles are those with high rewards and likely to be free at that particular time and space. Similarly, Huang et al., (2016) approach has good performance because of channel prediction based on HMM (with probability of detection of about 0.85 for vehicles moving at 30m/s). However, Huang et al., (2016) consider channels in the next road segment and no preference is given to channels which is not the case for SSF-CVANET in which preference is given to channels with high OFF times. The performance of hard fusion rule proposed by Duan et al., (2013) degrades with increase in speed of vehicles as observed in Figure 6.15. With increased speed few samples are collected from passing vehicles to be used for fusion at RSU. Hard fusion relies on large number of vehicles in order to provide accurate sensing results. However, in sparse environment there are few vehicles, hence, vehicles move at high speed.

6.4.1.3 Vehicle speed on spectrum opportunity on the road segment

Figure 6.16 shows the relationship between vehicle speed and probability of spectrum opportunities on the road segment in the fading environment. As stated before, spectrum opportunity refers to identifying free PU channels and transmitting on those channels within the road segment. However, with speed a vehicle is likely to move out of the road segment coverage area hence missing the spectrum opportunity.

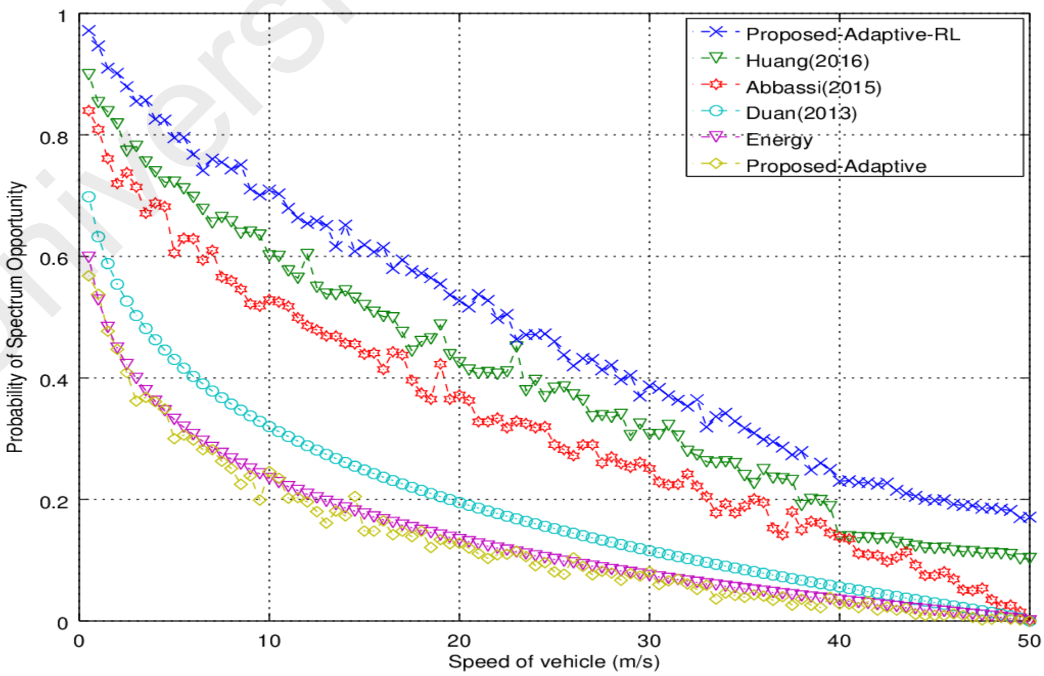

Figure 6.16: Probability of spectrum opportunities on the road segment versus vehicle speed

Adaptive sensing without RL performs as low as energy detector in fading environment for spectrum opportunity as observed from Figure 6.16. In fading environment, adaptive sensing relies on OOC which require more sensing samples to identify feature of the PU signal in time domain hence requires more sensing time. Thus, with increased vehicle speed the possibilities of moving outside the road segment where sensing is performed is high. The proposed adaptive sensing with RL shows good performance because it requires few samples to identify spectrum opportunities. The RSU sends channels and associated channel parameters to vehicles to sense hence reducing on sensing time compared to adaptive sensing without RL. Figure 6.16 shows probability of about 0.18 to get spectrum opportunity for adaptive sensing with RL when the vehicle is moving at 50m/s ($\approx 180km/h$) while other schemes is virtually 0 with exception of Huang et al., (2016) which is about 0.1.

6.4.1.4 Comparison of detection time

Spectrum sensing detection time is another important metric in cognitive radio networks. Figure 6.17 illustrates the mean detection time for probability of detection in fading environment.

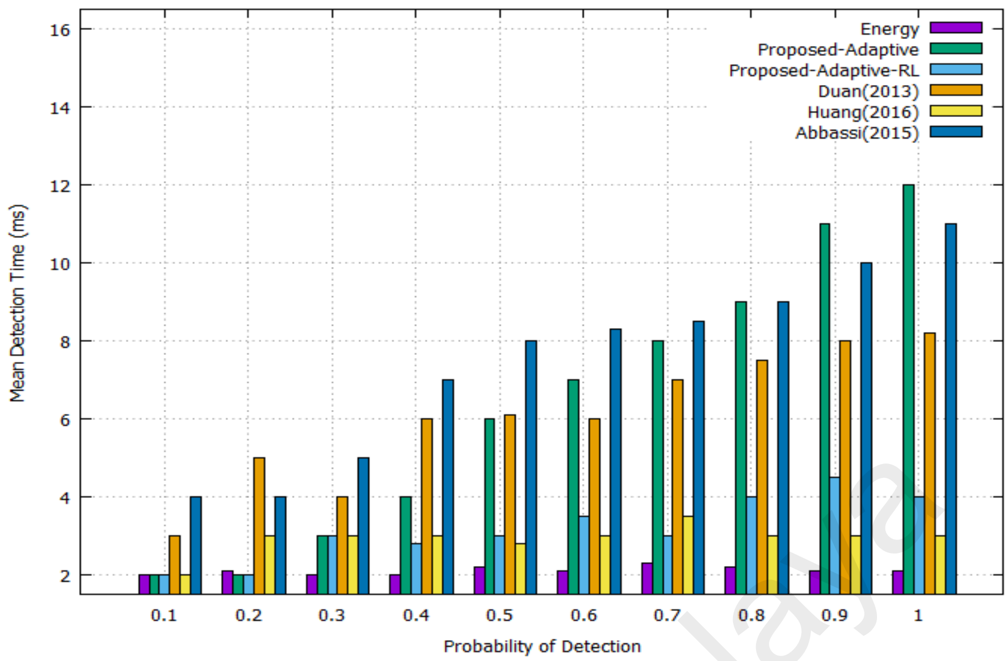

Figure 6.17: Comparison of mean detection time versus probability of detection of various sensing schemes

Compared to other schemes, conventional energy detector has the least mean detection time. The average detection time for energy detector is 2.11ms. The second best scheme in terms of average detection time is the proposed adaptive sensing with RL of about 3.18ms followed by Huang et al., (2016) of about 3.25ms. Overall, Abbassi et al., (2015) has long average detection time of 7.48ms followed by proposed adaptive sensing without RL of about 6.4ms. Abbassi et al., (2015) and Duan et al., (2013) require more sensing time because they get spectrum results first from cooperating vehicles before global decision on the PU occupancy state is made. In addition, Abbassi et al., (2015) use history of sensing results before sending to cooperating vehicles for a global decision to be made using majority rule thereby increasing sensing time. The main factor contributing to long mean detection time for adaptive sensing without RL is the fact that in fading environment more samples are needed to accurately quantify the PU signal. In addition PU signal characteristics are not known in advance hence more time to get the features of the signal using OOC. Adaptive sensing with RL on the other hand sense channels sent by the RSU with known PU signal characteristics hence few sensing samples are needed and no extra time is required to search for unknown channels.

6.4.1.5 Sensing time on channel throughput

A network throughput is another performance metric that is important to spectrum sensing. The channel throughput of the secondary network is measured using transmission time on the PU network using parameters given in Equation 4.7 of Chapter 4. The frame size $T = 100ms$ is used. Figure 6.18 shows the achievable average throughput of CVANET for the proposed SSF-CVANET with and without RL.

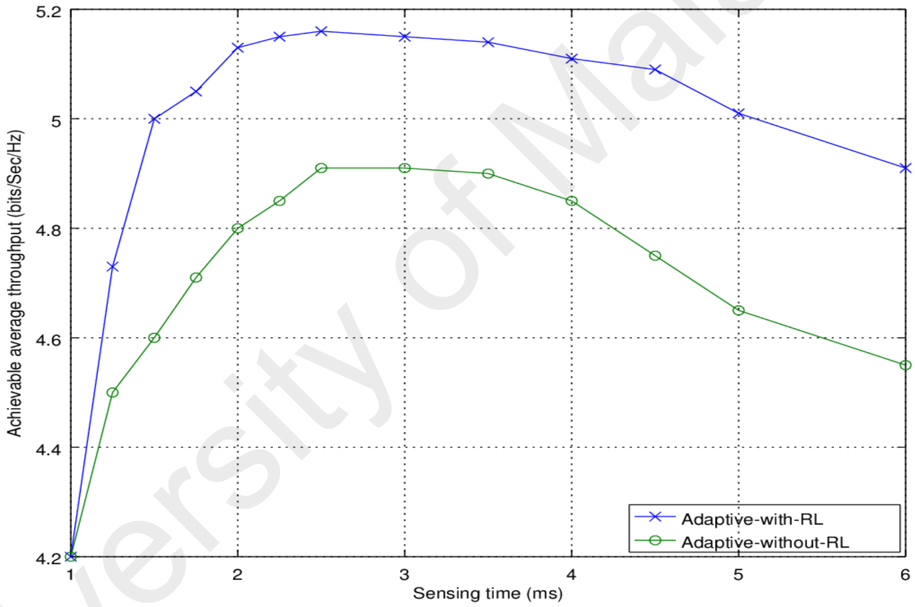

Figure 6.18: Achievable average throughput of CVANET network in fading environment

In Figure 6.18 the average throughput of adaptive sensing with RL is compared to adaptive sensing without RL in the fading environment. Spectrum sensing time has an impact on channel capacity throughput of the secondary network. Long sensing period provides accurate sensing result. However, this is at the cost of throughput as more time is spent on sensing less time is left for transmission on the identified channel for a given frame (frame accounts for sensing and transmission time). In fading environment, adaptive sensing without RL requires more sensing samples to measure the features of the PU signal hence low throughput as observed in Figure 6.18. With adaptive sensing using RL, the RSU send channels with PU characteristics to sense as a result, few sensing samples are required to achieve desired probability of detection hence more time is left for transmission.

6.4.2 Performance of VANET in presence of extra channels

In Section 6.2, the performance of VANET using DSRC channels is presented. Figure 6.1 presents PDR and PLR to show the effect of increasing the number of communicating vehicles. In this section, evaluation of SSF-CVANET in presence of extra channels from TV bands with bandwidth of 6MHz is presented in Figures 6.19, 6.20 and 6.21. When the number of vehicles increases, the RSU assigns extra channels from TV bands to vehicles for communication. This extends the 7 channels from DSRC bands.

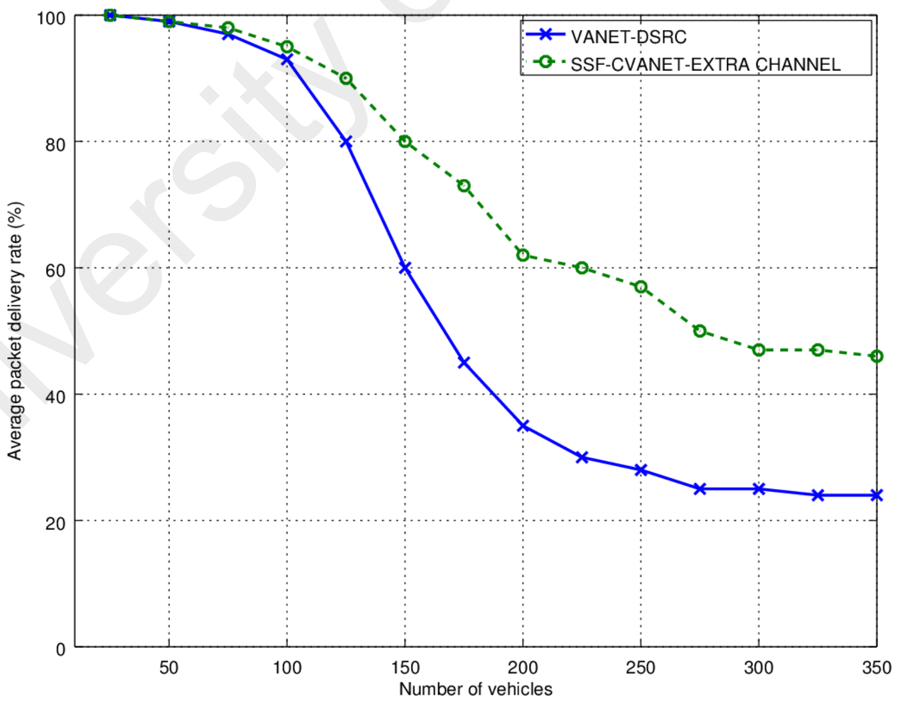

Figure 6.19: Evaluation of PDR for VANET using DSRC channel and SSF-CVANET

The figure above shows the simulation result for average packet delivery rate when using DSRC channel and proposed framework. The PDR of vehicles using DSRC channels drop sharply after 100 vehicles. This is mainly due to contention in the PHY layer as the number of packets colliding increases due to increased number of vehicles communicating. On the other hand, with increased number of channels when SSF-CVANET is activated the packet drop is improved. For example, the average PDR for 350 vehicles is more than 40% compared to VANET relying on DSRC channel alone which is about 24%. Therefore, there is an improvement of about 16% for PDR when using SSF-CVANET compared to using DSRC channels only for 350 vehicles. Figure 6.20 shows the PLR when using DSRC channels alone and proposed SSF-CVANET.

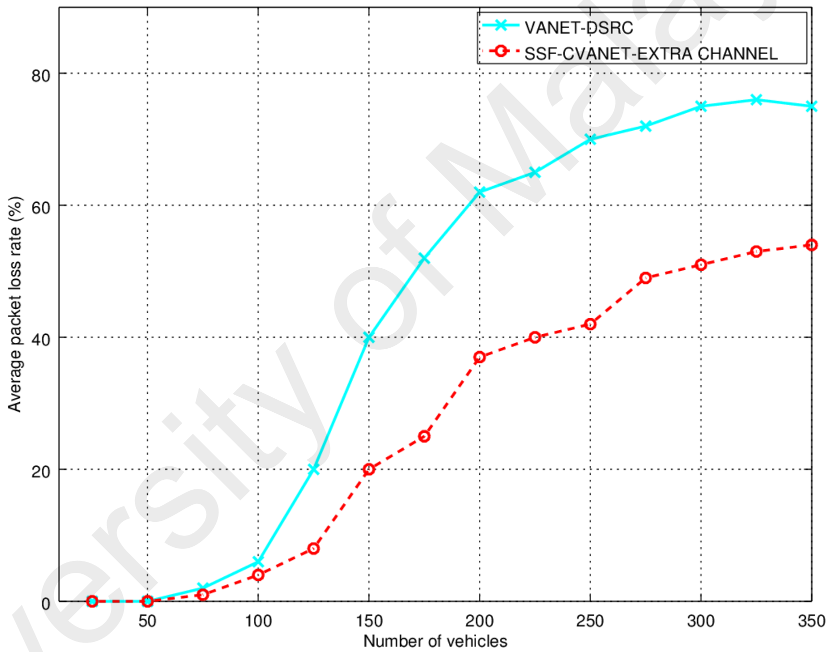

Figure 6.20: Evaluation of PLR for VANET using DSRC channel and SSF-CVANET

Packet loss rate refers to the rate at which packets are dropped due to increased number of vehicles communicating. PLR goes in hand with PDR hence after 100 vehicles there is sharp increase in the PLR for VANET with DSRC channels alone compared to SSF-CVANET as observed in Figure 6.20. When using the SSF-CVANET, the PLR is well below 55% for 350 vehicles compared to communication using DSRC channel alone which is about 75%. Therefore, there is improvement for average PLR of about 20% for 350 vehicles. Figure 6.19 and 6.20 demonstrate that

SSF-CVANET increase channel capacity by using extra channels from TV bands that are free. In addition, the SSF-CVANET demonstrates better performance on average delay compared to VANET with DSRC channels alone as shown in Figure 6.21.

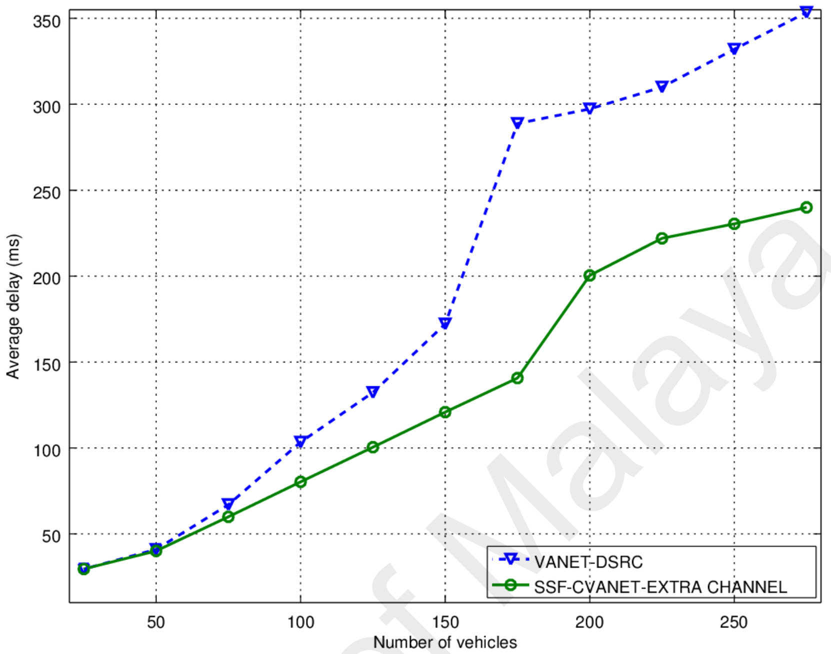

Figure 6.21: Average delay for vehicles using DSRC channels and SSF-CVANET

Figure 6.21 demonstrates improvement in average delay when using SSF-CVANET compared to DSRC channels alone. The extra channels from the TV bands increase the channel capacity of vehicular communication. Therefore, with increase in the number of vehicles, SSF-CVANET provides lower average delay compared to when DSRC channels alone are in use as observed from Figure 6.21. Low delay is important to safety application. In addition, with improved channel capacity more applications can be transmitted in the CVANET environment.

6.5 Chapter summary

This chapter has presented simulation results to demonstrate the performance of the proposed SSF-CVANET. Firstly, Section 6.2 presented some preliminary results to show the performance of VANET when using DSRC channels only. Figure 6.1 demonstrates that with increase in the number of vehicles, PDR reduces while PLR increases. This could have effect on the delivery of delay sensitive packets such as safety messages. The remainder of the chapter concentrated on evaluating SSF-CVANET on the performance of spectrum sensing, the main theme of this thesis. Section 6.3 evaluated spectrum sensing in both fading and non-fading environment. The section also compared energy detector to proposed adaptive sensing. Figure 6.6 demonstrates that adaptive sensing performances better in fading environment. However, this comes at the expense of sensing time as shown in Figure 6.8. Finally, Section 6.4 presented simulation results for SSF-CVANET using RL and compared with other sensing approach in literature. Figure 6.14 to 6.17 showed that the proposed scheme performs better in terms of probability of detection and maximizing spectrum opportunities compared to other schemes. In addition, Figure 6.18 demonstrates that adaptive sensing with RL performs better for sensing time on throughput compared to adaptive sensing without RL. In addition, Section 6.4 presented the performance of VANET when using DSRC channels alone and SSF-CVANET which use extra channels from TV bands. Figure 6.19 to 6.21 demonstrated that the proposed approach increases channel capacity. Hence, there is improvement of PDR of about 16% and PLR of about 20% when 350 vehicles are communicating on the road segment.

CHAPTER 7: CONCLUSION AND FUTURE WORK

This chapter presents conclusion remarks to the work presented in this thesis. Therefore, it starts by giving an overview of the problem statement in Section 7.1. Thereafter, a review of achieved objectives is presented in Section 7.2. The chapter then summarizes the contributions and gives some future direction in Section 7.3 and Section 7.4 respectively.

7.1 Overview

The motivation for Intelligent Transportation System (ITS) is developing technologies that can be used by people in transportation systems to reduce accidents and provide some comfort through infotainment. On the roads, ITS applications are envisaged to be transmitted through vehicular communication using Dedicated Short Range Communication (DSRC) channels defined at 5.9GHz band. Vehicular communication provides mechanism for vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communications. V2V and V2I rely on the radio spectrum using 7 DSRC channels which are subject to congestion during high vehicle density especially during peak hours or accident scenarios. Due to fixed radio spectrum allocation by assigning regulatory agents, the DSRC cannot be extended beyond 5.9GHz to provide more channels during congestion. Therefore, in this thesis we have explored the concept of dynamic spectrum access (DSA) as means of increasing channel capacity for vehicular communication beyond 7 channels defined at 5.9GHz bands. Nevertheless, DSA is only possible through cognitive radio (CR) technology. The CR is based on software defined radio that can operate across different ranges of radio spectrum.

DSA proposes a new trend in radio spectrum utilization which allows unlicensed users operating in congested radio frequencies to access licensed channels provided no harmful interference is caused to licensed users. Using CR, the unlicensed users are supposed to identify idle licensed channels through spectrum sensing. In VANET, vehicles on the roads using the CR are to perform spectrum sensing continuously to identify free licensed channels that can be used to extend DSRC channels during congestion. However, due to unique characteristics of VANETs, spectrum sensing is still a challenge. Therefore, in this work, we have attempted to highlight the challenges associated with spectrum sensing in Chapter 3 and proposed a framework that can help in mitigating the challenges in Chapter 4. Specifically, the challenges include multipath fading, shadowing and unknown primary (licensed) user activities. The challenges and proposed solutions are summarized in the objectives of this thesis. Therefore, in the next section, a look at the objectives and achievement accomplished for each objective is presented.

7.2 Achieved objectives

This thesis presented a spectrum sensing framework that identifies free licensed channels for vehicular communication. To achieve this aim, 5 specific objectives were outlined in Chapter 1. The first objective was to explore existing spectrum sensing strategies in VANET as well as study the impact of PU activities on spectrum sensing. The second objective was to develop an adaptive spectrum sensing model to be used by vehicles on the roads. The third objective was to enhance the PU activity model using reinforcement learning to be implemented at RSU. The fourth objective was to develop a sensing framework that utilize history of sensing result and allow adaptive sensing work together with PU activity model in identifying the licensed bands while mitigating some of the problems associated with spectrum sensing. And finally, the fifth objective was to evaluate the proposed framework through simulation and validates the results by comparing to other history based approach in literature. The following details how each of these objectives are achieved in this thesis.

- Exploring spectrum sensing strategies and studying impact of PU activity patterns: exploring spectrum sensing strategies is achieved through reviewing spectrum sensing techniques proposed for VANET environment which is presented in Chapter 3. Spectrum sensing can be achieved by individual vehicles or through cooperative decision. Individually, vehicles perform spectrum sensing by using sensing techniques such as energy detection, matched filter detection or cyclostationary feature detection. These sensing techniques have been presented in details (Section 3.3 of the same chapter). Nevertheless, individual sensing is susceptible to multipath fading, shadowing and hidden PU problems. Therefore, cooperative decision is proposed in literature to mitigate such problems. Cooperative decision in vehicular communication can be either centralized or distributed. The detailed discussion of cooperative decision was presented in Section 3.4 with associated problems. Pertinent to spectrum sensing is PU activity model used. The effect of PU activity pattern was discussed in Section 3.2.5 and impact on spectrum sensing was presented in Chapter 4 Section 4.3.3. Specifically Figure 4.9 shows the implication of PU changing its transmission pattern with spectrum sensing.

- Developing adaptive spectrum sensing: is based on the advantages of energy detector and cyclostationary detection technique. Energy detection and one order cyclostationary feature detection techniques are presented in Chapter 4 Section 4.3.2.1 and Section 4.3.2.2 respectively. Chapter 4 Section 4.3.2.3 details the adaptive spectrum sensing model developed to achieve the second objective. The proposed adaptive sensing scheme utilize OOC feature detector which determine the periodicity in the PU signal of interest in time domain opposed to frequency domain. The advantage of the proposed approach is reduced complexity.

- Enhancing PU activity model: most of the proposed spectrum sensing techniques for VANET assumes a static ON/OFF PU activity pattern. However, research has shown that static ON/OFF model does not represent a realistic PU pattern behavior. Therefore, this objective was to proposed mechanism to model the PU activity pattern using reinforcement learning at RSU. The proposed PU activity model is presented in Chapter 4, Section 4.3.3.2. PU activities can be modeled as Markov chain with two events representing instances when the PU is ON or OFF as show in Figure 4.7. Therefore, Markov decision process for reinforcement learning is used in tracking the behavior of the PU activities. Learning the behavior of the PU mostly rely on the history of sensing results from participating vehicles.

- Developing sensing framework: this objective aimed at unifying the adaptive sensing and PU activity model. The detailed discussion of development of the framework is echoed throughout Chapter 4. Figure 4.2 illustrate the architecture of the proposed framework while Figure 4.3 details the flowchart of the framework. The framework proposes coordination of spectrum management to be done by the RSU hence the term "infrastructure based" in the title of this thesis. The RSU monitors the number of vehicles in its road segment before the framework is initialized. Once a threshold is reached, the RSU distribute the channels to vehicles to sense and updates the PU activity model based on the reward obtained from vehicles. The rewards from participating vehicles are used to learn the PU behavior instead of the static ON/OFF. Therefore, the RSU learns the changes in the PU transmission over time. The framework, mitigates some of the challenges presented in cooperative decision such synchronization problem, cumulative delay to collect sensing results from participating vehicles and spectrum data falsification problem. In addition, adaptive spectrum sensing proposed in Section 4.3.2.3 improves the performance of spectrum sensing in low SNR through the use of OOC.

- Evaluation through simulations: in this work, evaluation of the proposed framework was only possible through simulation. Therefore, Chapter 5 is dedicated to discussing simulation tools used in this work. Particularly, NS3 and SUMO are tools used. The chapter argues why simulation was necessary and in particular the choice of these two simulation tools. Evaluation of the framework based on the results from the simulation is presented in Chapter 6. The proposed framework is compared to two other history based spectrum sensing schemes proposed in literature by Huang et al., (2016) and Abbassi et al., (2015) as well as a infrastructure based cooperative spectrum sensing decision technique by Duan et al., (2013). In addition, the adaptive sensing is compared to conventional energy detector. The results consider both fading and non-fading environment. Based on the simulation results, the main findings and contributions of this thesis are presented in the following section.

7.3 Summary of findings and contributions

The success of DSA in VANET will depend on effective spectrum sensing techniques that can identify idle licensed channels in fast and efficient manner to protect licensed users from interference while allowing maximum spectrum reuse. Therefore, the proposed spectrum sensing framework provides mechanisms to identify licensed spectrum for vehicular communication. Compared to other schemes, the SSF-CVANET using RL enjoys a better sensing performance based on the simulation results obtained. The proposed framework obtained better probability of detection and high spectral opportunities compared to other schemes as noted in Section 6.4.1. In addition, the proposed framework performs better than the other schemes for various vehicle speeds. In terms of sensing time, the proposed framework performs as good as the energy detector demonstrated in Figure 6.17. Furthermore, the proposed framework demonstrated that increasing the channels to vehicular communication increases packet delivery rate by 16% (i.e. for 350 vehicles) while reducing the packet loss rate and average delay for communicating vehicles as demonstrated in Section 6.4.2.

The simulation results of Figure 6.8 show that the detection time to reach a probability of detection of 1 for conventional energy detector is 3ms compared to adaptive sensing without RL which requires about 12ms to reach the same probability in low SNR. This is mainly due to usage of OOC which demands more time to extra periodicity in PU signal. Nevertheless, the sensing time is still minimal and within acceptable range. In addition, adaptive sensing demonstrated (see Figure 6.6) better performance (i.e. $P_d = 0.8$ for $P_f = 0.2$) in terms of probability of detection in fading environment compared to conventional energy detector (i.e. $P_d = 0.7$ for $P_f = 0.2$). In VANET, fading is a major factor that should not be overlooked due to the nature of VANET environment as discussed in Chapter 3.

When using SSF-CVANET, the mean sensing time is reduced to 3.18ms which is close to conventional energy detector of about 2.11ms. For the same probability of false alarm of 0.1, SSF-CVANET has the highest probability of detection of 0.90 followed by scheme proposed by Huang et al., (2016) with probability of detection of 0.85, followed by Abbassi et al., (2015) with 0.80, the other schemes have probability of detection below 0.7 for the same probability of false alarm of 0.1. The SSF-CVANET has high probability of detection because the PU channels with high probability of being OFF are sent to vehicles for sensing based on the reward. Similarly, SSF-CVANET has shown high probability of detection (0.87) for vehicles moving at high speed (30m/s) compared to Huang et al., (2016) and Abbassi et al., (2015) which is 0.85. The other schemes have probability of detection less than 0.75.

7.4 Future work

This research work focused on providing a spectrum sensing framework for vehicular communication. The simulation results provide assurance that this framework can be implemented in test-bed. However, the framework was evaluated only in infrastructure based vehicular communication. Therefore, in future the framework will be extended to distributed vehicular communication in V2V. One way to achieve this would be using cluster based approach for vehicles going in the same direction. The cluster head would assume the role of the RSU. Nevertheless, some mechanism should be used to learn the PU activities when the vehicles move from one PU system to another.

Spectrum sensing is just one stage in CR life cycle despite being the fundamental and vital stage. Other stages include spectrum decision, spectrum sharing and spectrum mobility as discussed in Chapter 2. Therefore, future work should consider how these stages can be integrated in the spectrum management for VANET.

REFERENCES

Abbassi, S. H., Qureshi, I. M., Abbasi, H., & Alyaie, B. R. (2015). History-based spectrum sensing in CR-VANETs. *EURASIP Journal on Wireless Communications and Networking, 2015*(1), 1-12.

Abdallah, M., Sarkar, T., & Salazar-Palma, M. (2015). *How to eliminate shadow fading in a cellular wireless system.* Paper presented at the Antennas and Propagation in Wireless Communications (APWC), 2015 IEEE-APS Topical Conference on.

Abo-Zahhad, M., Farrag, M., & Ali, A. (2016). *A fast accurate method for calculating symbol error probabilities for AWGN and Rayleigh fading channels.* Paper presented at the 2016 33rd National Radio Science Conference (NRSC).

Akyildiz, I. F., Lee, W.-Y., Vuran, M. C., & Mohanty, S. (2006). NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey. *Computer networks, 50*(13), 2127-2159.

Akyildiz, I. F., Lee, W.-Y., Vuran, M. C., & Mohanty, S. (2008). A survey on spectrum management in cognitive radio networks. *IEEE Communications magazine, 46*(4).

Akyildiz, I. F., Lo, B. F., & Balakrishnan, R. (2011). Cooperative spectrum sensing in cognitive radio networks: A survey. *Physical communication, 4*(1), 40-62.

Al-Ali, A., & Chowdhury, K. (2014). *Simulating dynamic spectrum access using ns-3 for wireless networks in smart environments.* Paper presented at the Sensing, Communication, and Networking Workshops (SECON Workshops), 2014 Eleventh Annual IEEE International Conference on.

Al-Sultan, S., Al-Doori, M. M., Al-Bayatti, A. H., & Zedan, H. (2014). A comprehensive survey on vehicular Ad Hoc network. *Journal of Network and Computer Applications, 37*, 380-392.

Alam, N., Balaei, A. T., & Dempster, A. G. (2011). A DSRC Doppler-based cooperative positioning enhancement for vehicular networks with GPS availability. *IEEE Transactions on Vehicular Technology, 60*(9), 4462-4470.

Altintas, O., Watanabe, T., Kremo, H., Tanaka, H., Nakao, H., Tsukamoto, K., & Tsuru, M. (2016). Design and Experimental Evaluation of a Database-Assisted V2V Communications System Over TV White Space. *Journal of Signal Processing Systems, 83*(1), 45-55.

Alvi, S. A., Younis, M. S., Imran, M., & Fazal e, A. (2014). A Weighted Linear Combining Scheme for Cooperative Spectrum Sensing. *Procedia Computer Science, 32*, 149-157. doi:http://dx.doi.org/10.1016/j.procs.2014.05.409

Angrisani, L., Capriglione, D., Cerro, G., Ferrigno, L., & Miele, G. (2015). *A dual step energy detection based spectrum sensing algorithm for cognitive vehicular ad hoc networks.* Paper presented at the 2015 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) Proceedings.

Atallah, R. F., Khabbaz, M. J., & Assi, C. M. (2015). Vehicular networking: A survey on spectrum access technologies and persisting challenges. *Vehicular Communications, 2*(3), 125-149.

Atapattu, S., Tellambura, C., & Jiang, H. (2010). Analysis of area under the ROC curve of energy detection. *IEEE Transactions on Wireless Communications, 9*(3).

Atapattu, S., Tellambura, C., & Jiang, H. (2011). *Spectrum sensing via energy detector in low SNR.* Paper presented at the 2011 IEEE International Conference on Communications (ICC).

Awe, O. P., & Lambotharan, S. (2015). *Cooperative spectrum sensing in cognitive radio networks using multi-class support vector machine algorithms.* Paper presented at the Signal Processing and Communication Systems (ICSPCS), 2015 9th International Conference on.

Awe, O. P., Zhu, Z., & Lambotharan, S. (2013). *Eigenvalue and support vector machine techniques for spectrum sensing in cognitive radio networks.* Paper presented at the Technologies and Applications of Artificial Intelligence (TAAI), 2013 Conference on.

Axell, E., Leus, G., Larsson, E. G., & Poor, H. V. (2012). Spectrum sensing for cognitive radio: State-of-the-art and recent advances. *Signal Processing Magazine, IEEE, 29*(3), 101-116.

Aygun, B., & Wyglinski, A. M. (2016). A Voting Based Distributed Cooperative Spectrum Sensing Strategy for Connected Vehicles. *IEEE Transactions on Vehicular Technology*.

Bagheri, A., Sofotasios, P. C., Tsiftsis, T. A., Ho-Van, K., Loupis, M. I., Freear, S., & Valkama, M. (2016). *Energy detection based spectrum sensing over enriched multipath fading channels.* Paper presented at the Wireless Communications and Networking Conference (WCNC), 2016 IEEE.

Bagwari, A., & Tomar, G. S. (2013). Two-stage detectors with multiple energy detectors and adaptive double threshold in cognitive radio networks. *International Journal of Distributed Sensor Networks, 9*(8), 656495.

Baldo, N., & Miozzo, M. (2009). *Spectrum-aware Channel and PHY layer modeling for ns3.* Paper presented at the Proceedings of the Fourth International ICST Conference on Performance Evaluation Methodologies and Tools.

Baraka, K., Safatly, L., Artail, H., Ghandour, A., & El-Hajj, A. (2015). An infrastructure-aided cooperative spectrum sensing scheme for vehicular ad hoc networks. *Ad Hoc Networks, 25*, 197-212.

Barnes, S. D., Botha, P. R., & Maharaj, B. (2016). Spectral occupation of TV broadcast bands: Measurement and analysis. *Measurement, 93*, 272-277.

Barnes, S. D., Van Vuuren, P. J., & Maharaj, B. (2013). Spectrum occupancy investigation: measurements in South Africa. *Measurement, 46*(9), 3098-3112.

Barrachina, J., Garrido, P., Fogue, M., Martinez, F. J., Cano, J.-C., Calafate, C. T., & Manzoni, P. (2013). *I-VDE: a novel approach to estimate vehicular density by* *using vehicular networks.* Paper presented at the International Conference on Ad-Hoc Networks and Wireless.

Baumgart, I., Heep, B., & Krause, S. (2007). *OverSim: A flexible overlay network simulation framework.* Paper presented at the IEEE Global Internet Symposium, 2007.

Bauza, R., & Gozálvez, J. (2013). Traffic congestion detection in large-scale scenarios using vehicle-to-vehicle communications. *Journal of Network and Computer Applications*, *36*(5), 1295-1307.

Bedogni, L., Di Felice, M., Trotta, A., & Bononi, L. (2014). *Distributed Mobile Femto-Databases for Cognitive Access to TV White Spaces.* Paper presented at the Vehicular Technology Conference (VTC Fall), 2014 IEEE 80th.

Berlemann, L., Dimitrakopoulos, G., Moessner, K., & Hoffmeyer, J. (2005). *Cognitive radio and management of spectrum and radio resources in reconfigurable networks.* Paper presented at the Wireless World Research Forum.

Bhargavi, D., & Murthy, C. R. (2010). *Performance comparison of energy, matched-filter and cyclostationarity-based spectrum sensing.* Paper presented at the Signal Processing Advances in Wireless Communications (SPAWC), 2010 IEEE Eleventh International Workshop on.

Bhowmick, A., Chandra, A., Roy, S. D., & Kundu, S. (2015). Double threshold-based cooperative spectrum sensing for a cognitive radio network with improved energy detectors. *IET Communications, 9*(18), 2216-2226.

Bkassiny, M., Li, Y., & Jayaweera, S. K. (2013). A survey on machine-learning techniques in cognitive radios. *IEEE Communications Surveys & Tutorials, 15*(3), 1136-1159.

Borota, D., Ivkovic, G., Vuyyuru, R., Altintas, O., Seskar, I., & Spasojevic, P. (2011). *On the delay to reliably detect channel availability in cooperative vehicular environments.* Paper presented at the Vehicular Technology Conference (VTC Spring), 2011 IEEE 73rd.

Boroumand, L., Khokhar, R. H., Bakhtiar, L., & Pourvahab, M. (2012). A Review of Techniques to Resolve the Hidden Node Problem in Wireless Networks. *Smart CR*, *2*(2), 95-110.

Bozkaya, E., & Canberk, B. (2015). Robust and continuous connectivity maintenance for vehicular dynamic spectrum access networks. *Ad Hoc Networks*, *25*, 72-83.

Brahmi, I. H., Djahel, S., & Ghamri-Doudane, Y. (2012). *A Hidden Markov Model based scheme for efficient and fast dissemination of safety messages in VANETs.* Paper presented at the Global Communications Conference (GLOBECOM), 2012 IEEE.

Buddhikot, M. M. (2007). *Understanding dynamic spectrum access: Models, taxonomy and challenges.* Paper presented at the New Frontiers in Dynamic Spectrum Access Networks, 2007. DySPAN 2007. 2nd IEEE International Symposium on.

Cabric, D., Mishra, S. M., & Brodersen, R. W. (2004). *Implementation issues in spectrum sensing for cognitive radios.* Paper presented at the Signals, systems and computers, 2004. Conference record of the thirty-eighth Asilomar conference on.

Cabric, D., Tkachenko, A., & Brodersen, R. W. (2006). *Experimental study of spectrum sensing based on energy detection and network cooperation.* Paper presented at the Proceedings of the first international workshop on Technology and policy for accessing spectrum.

Cacciapuoti, A. S., Akyildiz, I. F., & Paura, L. (2011). *Primary-user mobility impact on spectrum sensing in cognitive radio networks.* Paper presented at the 2011 IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications.

Cacciapuoti, A. S., Caleffi, M., & Paura, L. (2016). On the impact of primary traffic correlation in TV White Space. *Ad Hoc Networks, 37*, 133-139. doi:http://dx.doi.org/10.1016/j.adhoc.2015.08.001

Cardenas-Juarez, M., Diaz-Ibarra, M. A., Pineda-Rico, U., Arce, A., & Stevens-Navarro, E. (2016). *On spectrum occupancy measurements at 2.4 GHz ISM band for cognitive radio applications.* Paper presented at the Electronics, Communications and Computers (CONIELECOMP), 2016 International Conference on.

Chatziantoniou, E., Allen, B., & Velisavljevic, V. (2014). *An empirical polarization domain channel availability model for cognitive radio.* Paper presented at the Personal, Indoor, and Mobile Radio Communication (PIMRC), 2014 IEEE 25th Annual International Symposium on.

Chembe, C., Ahmedy, I., Noor, R. M., Oche, M., Kunda, D., & Tambawal, A. B. (2017). Cooperative spectrum decision in Cognitive Vehicular Network based on Support Vector Machine. *Malaysian Journal of Computer Science, Accepted, April 2017*.

Chembe, C., Noor, R. M., Ahmedy, I., Oche, M., Kunda, D., & Liu, C. H. (2017). Spectrum sensing in cognitive vehicular network: State-of-Art, challenges and open issues. *Computer Communications*, *97*, 15-30.

Chen, J., Liu, B., Zhou, H., Gui, L., Liu, N., & Wu, Y. (2015). Providing Vehicular Infotainment Service Using VHF/UHF TV Bands via Spatial Spectrum Reuse. *IEEE Transactions on Broadcasting*, *61*(2), 279-289.

Chen, Y., & Oh, H. (2016). A Survey of Measurement-Based Spectrum Occupancy Modeling for Cognitive Radios. *Communications Surveys & Tutorials, IEEE, 18*(1), 848-859. doi:10.1109/COMST.2014.2364316

Cheng, J., Tellambura, C., & Beaulieu, N. C. (2003). *Performance analysis of digital modulations on Weibull fading channels.* Paper presented at the Vehicular Technology Conference, 2003. VTC 2003-Fall. 2003 IEEE 58th.

Chigan, T. (2014). Cognitive Radio Cognitive Network Simulator (NS2 Based). Retrieved from http://faculty.uml.edu/Tricia_Chigan/Research/CRCN_Simulator.htm

Chigan, T. (2017). Cognitive Radio Cognitive Network Simulator (NS3 based) Retrieved from http://faculty.uml.edu/Tricia_Chigan/Research/CRCN_NS3.html

Choffnes, D., & Bustamante, F. E. (2005). *STRAW-An Integrated Mobility and Traffic Model for VANET*. Paper presented at the Proc. of the 10th International Command and Control Research and Technology Symposium (CCRTS).

Chowdhury, K., & Al-Ali, A. (2014). Cognitive radio extension for ns-3. Retrieved from http://krc.coe.neu.edu/?q=ns3

Coleman, C. (2004). *An introduction to radio frequency engineering*: Cambridge University Press.

Conti, M., & Giordano, S. (2014). Mobile ad hoc networking: milestones, challenges, and new research directions. *IEEE Communications magazine, 52*(1), 85-96.

Cooper, C., Mukunthan, A., Ros, M., Franklin, D., & Abolhasan, M. (2014). *Dynamie environmental fading in urban VANETs*. Paper presented at the 2014 IEEE International Conference on Communications (ICC).

Cooper, C., Mukunthan, A., Safaei, F., Ros, M., Franklin, D., & Abolhasan, M. (2015). Including general environmental effects in K-factor approximation for rice-distributed VANET channels. *Physical Communication, 14*, 32-44.

Cordeiro, C., Challapali, K., & Ghosh, M. (2006). *Cognitive PHY and MAC layers for dynamic spectrum access and sharing of TV bands*. Paper presented at the Proceedings of the first international workshop on Technology and policy for accessing spectrum.

Corderio, C., Challapali, K., Birru, D., & Shankar, S. (2006). IEEE 802.22: an introduction to the first wireless standard based on cognitive radios. *J. Commun, 1*(1), 38-47.

Cunha, F., Villas, L., Boukerche, A., Maia, G., Viana, A., Mini, R. A., & Loureiro, A. A. (2016). Data communication in VANETs: Protocols, applications and challenges. *Ad Hoc Networks, 44*, 90-103.

Dalai, D. P., & Anuradha, S. (2015). *Co-operative Spectrum Sensing for Cognitive Radio systems over fading channels*. Paper presented at the Signal Processing, Communication and Networking (ICSCN), 2015 3rd International Conference on.

Darwish, T., & Bakar, K. A. (2015). Traffic density estimation in vehicular ad hoc networks: A review. *Ad Hoc Networks, 24*, 337-351.

Das, D., & Das, S. (2015). A Survey on Spectrum Occupancy Measurement for Cognitive Radio. *Wireless Personal Communications, 85*(4), 2581-2598.

De Nardis, L., Di Benedetto, M., Tassetto, D., Bovelli, S., Akhtar, A., Holland, O., & Thobaben, R. (2012). *Impact of mobility in cooperative spectrum sensing: Theory vs. simulation*. Paper presented at the Wireless Communication Systems (ISWCS), 2012 International Symposium on.

De Vito, L. (2012). *A review of wideband spectrum sensing methods for cognitive radios*. Paper presented at the Instrumentation and Measurement Technology Conference (I2MTC), 2012 IEEE International.

De Vito, L. (2013). Methods and technologies for wideband spectrum sensing. *Measurement, 46*(9), 3153-3165.

Del Re, E. (2012). *Software radio: technologies and services*: Springer Science & Business Media.

Di Felice, M., Chowdhury, K. R., & Bononi, L. (2011). *Cooperative spectrum management in cognitive vehicular ad hoc networks*. Paper presented at the Vehicular Networking Conference (VNC), 2011 IEEE.

Di Felice, M., Chowdhury, K. R., Kim, W., Kassler, A., & Bononi, L. (2011). End-to-end protocols for cognitive radio ad hoc networks: An evaluation study. *Performance Evaluation, 68*(9), 859-875.

Di Felice, M., Chowdhury, K. R., Wu, C., Bononi, L., & Meleis, W. (2010). *Learning-based spectrum selection in cognitive radio ad hoc networks*. Paper presented at the International Conference on Wired/Wireless Internet Communications.

Di Felice, M., Ghandhour, A. J., Artail, H., & Bononi, L. (2013). *Integrating spectrum database and cooperative sensing for cognitive vehicular networks*. Paper presented at the Vehicular Technology Conference (VTC Fall), 2013 IEEE 78th.

Digham, F. F., Alouini, M.-S., & Simon, M. K. (2007). On the energy detection of unknown signals over fading channels. *IEEE transactions on communications, 55*(1), 21-24.

Doost-Mohammady, R., & Chowdhury, K. R. (2012). *Design of spectrum database assisted cognitive radio vehicular networks*. Paper presented at the Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM), 2012 7th International ICST Conference on.

Dressler, F., Hartenstein, H., Altintas, O., & Tonguz, O. (2014). Inter-vehicle communication: Quo vadis. *Communications Magazine, IEEE, 52*(6), 170-177.

Duan, J.-Q., Li, S., & Ning, G. (2013). Compressive spectrum sensing in centralized vehicular cognitive radio networks. *International Journal of Future Generation Communication and Networking, 6*(3), 1-12.

Eduardo, A. F., & Caballero, R. G. G. (2015). *Experimental evaluation of performance for spectrum sensing: matched filter vs energy detector*. Paper presented at the Communications and Computing (COLCOM), 2015 IEEE Colombian Conference on.

Eichner, T., Maschlanka, M., Meuleners, M., & Degen, C. (2015). *Evaluation of Space-Time Diversity Techniques in Car-to-Car Communications*. Paper presented at the 2015 IEEE 81st Vehicular Technology Conference (VTC Spring).

Ejaz, W., Hasan, N. U., & Kim, H. S. (2012). SNR-based adaptive spectrum sensing for cognitive radio networks. *International Journal of Innovative Computing, Information and Control, 8*(9), 6095-6105.

Ejaz, W., ul Hasan, N., Azam, M. A., & Kim, H. S. (2012). Improved local spectrum sensing for cognitive radio networks. *EURASIP Journal on Advances in Signal Processing, 2012*(1), 242.

Ejaz, W., ul Hasan, N., Lee, S., & Kim, H. S. (2013). I3S: Intelligent spectrum sensing scheme for cognitive radio networks. *EURASIP Journal on Wireless Communications and Networking, 2013*(1), 26.

Esmaeelzadeh, V., Berangi, R., Sebt, S. M., Hosseini, E. S., & Parsinia, M. (2013). CogNS: a simulation framework for cognitive radio networks. *Wireless Personal Communications, 72*(4), 2849-2865.

Fallah, Y. P., Huang, C., Sengupta, R., & Krishnan, H. (2010). *Congestion control based on channel occupancy in vehicular broadcast networks.* Paper presented at the Vehicular Technology Conference Fall (VTC 2010-Fall), 2010 IEEE 72nd.

Fangchun, Y., Shangguang, W., Jinglin, L., Zhihan, L., & Qibo, S. (2014). An overview of internet of vehicles. *China Communications, 11*(10), 1-15.

FCC. (2010). *In the Matter of: Unlicensed Operation in the TV Broadcast Bands (ET Docket No. 04-186) and Additional Spectrum for Unlicensed Devices Below 900 MHz and in the 3 GHz Band (ET Docket No. 02-380), FCC 10-174:Second*

Memorandum Opinion and Order. Retrieved from

Flizikowski, A., Kozik, R., Gierszal, H., Przybyszewski, M., & Hołubowicz, W. (2010). WiMAX cell level simulation platform based on ns-2 and DSP integration. *International Journal of Electronics and Telecommunications, 56*(2), 169-176.

Fogue, M., Garrido, P., Martinez, F. J., Cano, J.-C., Calafate, C. T., & Manzoni, P. (2012). *A realistic simulation framework for vehicular networks.* Paper presented at the Proceedings of the 5th International ICST Conference on Simulation Tools and Techniques.

Freyens, B. P., & Alexander, S. (2015). *Policy objectives and spectrum rights for future network developments.* Paper presented at the Dynamic Spectrum Access Networks (DySPAN), 2015 IEEE International Symposium on.

Gao, B., Park, J.-M., & Yang, Y. (2014). *Supporting mobile users in database-driven opportunistic spectrum access.* Paper presented at the Proceedings of the 15th ACM international symposium on Mobile ad hoc networking and computing.

Gato, L. M., Martínez, L., & Torres, J. (2015). *Blind Spectrum Sensing Based on Cyclostationary Feature Detection.* Paper presented at the Iberoamerican Congress on Pattern Recognition.

Ghafoor, K. Z., Lloret, J., Bakar, K. A., Sadiq, A. S., & Mussa, S. A. B. (2013). Beaconing approaches in vehicular ad hoc networks: a survey. *Wireless Personal Communications, 73*(3), 885-912.

Ghandour, A. J., Fawaz, K., & Artail, H. (2011). *Data delivery guarantees in congested vehicular ad hoc networks using cognitive networks.* Paper presented at the

Wireless Communications and Mobile Computing Conference (IWCMC), 2011 7th International.

Ghasemi, A., & Sousa, E. S. (2007). *Optimization of spectrum sensing for opportunistic spectrum access in cognitive radio networks.* Paper presented at the 2007 4th IEEE Consumer Communications and Networking Conference.

Gholizadeh, M. H., Amindavar, H., & Ritcey, J. A. (2013). Analytic Nakagami fading parameter estimation in dependent noise channel using copula. *EURASIP Journal on Advances in Signal Processing, 2013*(1), 1-11.

Google. (2017). Google spectrum database. Retrieved from https://www.google.com/get/spectrumdatabase/

Gozalvez, J., Sepulcre, M., & Bauza, R. (2012). Impact of the radio channel modelling on the performance of VANET communication protocols. *Telecommunication Systems, 50*(3), 149-167.

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future generation computer systems, 29*(7), 1645-1660.

Ha, T. T. (2010). *Theory and design of digital communication systems*: Cambridge University Press.

Hafeez, K. A., Anpalagan, A., & Zhao, L. (2016). Optimizing the Control Channel Interval of the DSRC for Vehicular Safety Applications. *IEEE Transactions on Vehicular Technology, 65*(5), 3377-3388.

Hafeez, K. A., Zhao, L., Liao, Z., & Ma, B. N.-W. (2009). *The optimal radio propagation model in VANET.* Paper presented at the 2009 Fourth International Conference on Systems and Networks Communications.

Härri, J., Filali, F., Bonnet, C., & Fiore, M. (2006). *VanetMobiSim: generating realistic mobility patterns for VANETs.* Paper presented at the Proceedings of the 3rd international workshop on Vehicular ad hoc networks.

Hartenstein, H., & Laberteaux, L. (2008). A tutorial survey on vehicular ad hoc networks. *IEEE Communications magazine, 46*(6).

Haykin, S. (2005). Cognitive radio: brain-empowered wireless communications. *IEEE Journal on selected areas in communications, 23*(2), 201-220.

Hazlett, T. W. (1990). The rationality of US regulation of the broadcast spectrum. *The Journal of Law & Economics, 33*(1), 133-175.

He, R., Molisch, A. F., Tufvesson, F., Zhong, Z., Ai, B., & Zhang, T. (2014). Vehicle-to-vehicle propagation models with large vehicle obstructions. *IEEE Transactions on Intelligent Transportation Systems, 15*(5), 2237-2248.

Hou, X., He, R., Wang, X., & Yang, Z. (2013). *A new form of the moment generating function of Weibull distribution.* Paper presented at the 2013 Ninth International Conference on Natural Computation (ICNC).

Huang, X.-L., Wu, J., Li, W., Zhang, Z., Zhu, F., & Wu, M. (2016). Historical Spectrum Sensing Data Mining for Cognitive Radio Enabled Vehicular Ad-hoc Networks. *IEEE Transactions on Dependable and Secure Computing, 13*(1), 59-70.

IEEE. (2016). IEEE Standard for Wireless Access in Vehicular Environments (WAVE) -- Multi-Channel Operation. *IEEE Std 1609.4-2016 (Revision of IEEE Std 1609.4-2010)*, 1-94. doi:10.1109/IEEESTD.2016.7435228

Islam, T., Hu, Y., Onur, E., Boltjes, B., & de Jongh, J. M. (2013). *Realistic simulation of IEEE 802.11 p channel in mobile vehicle to vehicle communication.* Paper presented at the Microwave Techniques (COMITE), 2013l Conference on.

Issariyakul, T., & Hossain, E. (2011). *Introduction to network simulator NS2*: Springer Science & Business Media.

Jaber, A. H., Aripin, N. M., & Salaim, N. (2013). *Evaluation of spectrum occupancy in Kuala Lumpur of UHF TV band for cognitive radio applications.* Paper presented at the Research and Development (SCOReD), 2013 IEEE Student Conference on.

Jafari, A., Al-Khayatt, S., & Dogman, A. (2012). *Performance evaluation of IEEE 802.11 p for vehicular communication networks.* Paper presented at the Communication Systems, Networks & Digital Signal Processing (CSNDSP), 2012 8th International Symposium on.

Jalil Piran, M., Cho, Y., Yun, J., Ali, A., & Suh, D. Y. (2014). Cognitive radio-based vehicular ad hoc and sensor networks. *International Journal of Distributed Sensor Networks, 2014*.

Jayaweera, S. K., & Poor, H. V. (2005). On the capacity of multiple-antenna systems in Rician fading. *IEEE Transactions on Wireless Communications, 4*(3), 1102-1111.

Jiang, D., Taliwal, V., Meier, A., Holfelder, W., & Herrtwich, R. (2006). Design of 5.9 GHz DSRC-based vehicular safety communication. *Wireless Communications, IEEE, 13*(5), 36-43.

Jin, Q., Wu, G., Boriboonsomsin, K., & Barth, M. (2014). *Improving traffic operations using real-time optimal lane selection with connected vehicle technology.* Paper presented at the Intelligent Vehicles Symposium Proceedings, 2014 IEEE.

Kapoor, S., Rao, S., & Singh, G. (2011). *Opportunistic spectrum sensing by employing matched filter in cognitive radio network.* Paper presented at the Communication Systems and Network Technologies (CSNT), 2011 International Conference on.

Kenney, J. B. (2011). Dedicated short-range communications (DSRC) standards in the United States. *Proceedings of the IEEE, 99*(7), 1162-1182.

Khabbaz, M., Assi, C., & Fawaz, W. (2014). *DSA-based V2I communication under the microscope.* Paper presented at the Wireless Communications and Networking Conference (WCNC), 2014 IEEE.

Khabbaz, M. J., Assi, C. M., & Ghrayeb, A. (2013). Modeling and analysis of DSA-based vehicle-to-infrastructure communication systems. *IEEE Transactions on Intelligent Transportation Systems, 14*(3), 1186-1196.

Kim, K., Akbar, I. A., Bae, K. K., Um, J.-S., Spooner, C. M., & Reed, J. H. (2007). *Cyclostationary approaches to signal detection and classification in cognitive radio.* Paper presented at the 2007 2nd IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks.

Kim, M., Po, K., & Takada, J.-i. (2010). *Performance enhancement of cyclostationarity detector by utilizing multiple cyclic frequencies of OFDM signals.* Paper presented at the New Frontiers in Dynamic Spectrum, 2010 IEEE Symposium on.

Kosek-Szott, K. (2012). A survey of MAC layer solutions to the hidden node problem in ad-hoc networks. *Ad Hoc Networks, 10*(3), 635-660.

Kozal, A. S., Merabti, M., & Bouhafs, F. (2012). *An improved energy detection scheme for cognitive radio networks in low SNR region.* Paper presented at the Computers and Communications (ISCC), 2012 IEEE Symposium on.

Krajzewicz, D., Erdmann, J., Behrisch, M., & Bieker, L. (2012). Recent development and applications of SUMO-Simulation of Urban MObility. *International Journal On Advances in Systems and Measurements, 5*(3&4).

Kremo, H., Vuyyuru, R., & Altintas, O. (2012). *Spectrum sensing in the vehicular environment: An overview of the requirements*. Paper presented at the Wireless Innovation Forum European Conference on Communication Technologies and Software Defined Radio (SDR'12 WInnCommEurope), Brussels. http://www.wirelessinnovation.org/assets/Proceedings/2012Europe/2012-europe-a-2.1-kremo.pdf

Kumar, A., Bharti, M. R., & Jain, S. K. (2013). An adaptive and efficient local spectrum sensing scheme in cognitive radio networks. *International Journal of Computer Applications, 72*(23).

Kumar, R., & Dave, M. (2012). A review of various vanet data dissemination protocols. *International Journal of u-and e-Service, Science and Technology, 5*(3), 27-44.

Kumar, S. S., Rajaguru, D., Vengattaraman, T., Dhavachelvan, P., Jesline, A. J., & Amudhavel, J. (2016). *Intelligent Collision Avoidance Approach in VANET Using Artificial Bee Colony Algorithm.* Paper presented at the Proceedings of the International Conference on Soft Computing Systems.

Kumar, V., Sharma, A., Debnath, S., & Gangopadhyay, R. (2015). Impact of Primary User Duty Cycle in Generalized Fading Channels on Spectrum Sensing in Cognitive Radio. *Procedia Computer Science, 46*, 1196-1202.

Lavanya, V., Rao, G. S., & Bidikar, B. (2016). Fast Fading Mobile Channel Modeling for Wireless Communication. *Procedia Computer Science, 85*, 777-781. doi:http://dx.doi.org/10.1016/j.procs.2016.05.265

Lee, W.-H., Lai, Y.-C., & Chen, P.-Y. (2015). A Study on Energy Saving and Emission Reduction on Signal Countdown Extension by Vehicular Ad Hoc Networks. *Vehicular Technology, IEEE Transactions on, 64*(3), 890-900.

Lehtomaki, J., Juntti, M., Saarnisaari, H., & Koivu, S. (2005). Threshold setting strategies for a quantized total power radiometer. *IEEE Signal Processing Letters, 12*(11), 796.

Levin, H. J. (2013). *The invisible resource: use and regulation of the radio spectrum*: Routledge.

Li, H., & Irick, D. K. (2010). *Collaborative spectrum sensing in cognitive radio vehicular ad hoc networks: belief propagation on highway.* Paper presented at the 2010 IEEE 71st Vehicular Technology Conference.

Li, Y. J. (2010). *An overview of the DSRC/WAVE technology.* Paper presented at the International Conference on Heterogeneous Networking for Quality, Reliability, Security and Robustness.

Liang, W., Li, Z., Zhang, H., Wang, S., & Bie, R. (2015). Vehicular ad hoc networks: architectures, research issues, methodologies, challenges, and trends. *International Journal of Distributed Sensor Networks, 2015*, 17.

Liang, Y.-C., Hoang, A. T., & Chen, H.-H. (2008). Cognitive radio on TV bands: a new approach to provide wireless connectivity for rural areas. *IEEE Wireless Communications, 15*(3).

Lim, K. G., Lee, C. H., Chin, R. K. Y., Yeo, K. B., & Teo, K. T. K. (2016). *Simulators for vehicular ad hoc network (VANET) development.* Paper presented at the Consumer Electronics-Asia (ICCE-Asia), IEEE International Conference on.

Lin, J.-C., Lin, C.-S., Liang, C.-N., & Chen, B.-C. (2012). Wireless communication performance based on IEEE 802.11 p R2V field trials. *Communications Magazine, IEEE, 50*(5), 184-191.

Liu, Y., Xie, S., Yu, R., Zhang, Y., Zhang, X., & Yuen, C. (2015). Exploiting temporal and spatial diversities for spectrum sensing and access in cognitive vehicular networks. *Wireless Communications and Mobile Computing, 15*(17), 2079-2094.

Liu, Y., Zhong, Z., Wang, G., & Hu, D. (2015). Cyclostationary detection based spectrum sensing for cognitive radio networks. *Journal of Communications, 10*(1), 74-79.

Lo, B. F. (2011). A survey of common control channel design in cognitive radio networks. *Physical communication, 4*(1), 26-39.

Lu, N., Cheng, N., Zhang, N., Shen, X., & Mark, J. W. (2014). Connected vehicles: Solutions and challenges. *IEEE internet of things journal, 1*(4), 289-299.

Lu, Y., Zhu, P., Wang, D., & Fattouche, M. (2016). *Machine learning techniques with probability vector for cooperative spectrum sensing in cognitive radio networks.* Paper presented at the Wireless Communications and Networking Conference (WCNC), 2016 IEEE.

Luis, M., Furtado, A., Oliveira, R., Dinis, R., & Bernardo, L. (2013). Towards a realistic primary users' behavior in single transceiver cognitive networks. *IEEE Communications Letters, 17*(2), 309-312.

MacDonald, S. L., & Popescu, D. C. (2013). *Impact of primary user activity on the performance of energy-based spectrum sensing in cognitive radio systems.* Paper presented at the 2013 IEEE Global Communications Conference (GLOBECOM).

Mariani, A., Giorgetti, A., & Chiani, M. (2011). *SNR wall for energy detection with noise power estimation.* Paper presented at the 2011 IEEE international conference on communications (ICC).

Martínez, D. M., & Andrade, Á. G. (2016). Adaptive energy detector for spectrum sensing in cognitive radio networks. *Computers & Electrical Engineering, 52*, 226-239.

Martinez, F. J., Cano, J.-C., Calafate, C. T., & Manzoni, P. (2008). *Citymob: a mobility model pattern generator for VANETs.* Paper presented at the Communications Workshops, 2008. ICC Workshops' 08. IEEE International Conference on.

Martinez, F. J., Fogue, M., Toh, C.-K., Cano, J.-C., Calafate, C. T., & Manzoni, P. (2013). Computer simulations of VANETs using realistic city topologies. *Wireless Personal Communications, 69*(2), 639-663.

Martinez, F. J., Toh, C. K., Cano, J. C., Calafate, C. T., & Manzoni, P. (2011). A survey and comparative study of simulators for vehicular ad hoc networks (VANETs). *Wireless Communications and Mobile Computing, 11*(7), 813-828.

MathWorks. (2017). MathWorks. Retrieved from http://www.mathworks.com/

McHenry, M. A., & Steadman, K. (2005). Spectrum Occupancy Measurements, Location 5 of 6: National Radio Astronomy Observatory (NRAO), Green Bank, West Virginia, October 10-11, 2004, Revision 3. *Shared Spectrum Company Report*.

Mecklenbrauker, C. F., Molisch, A. F., Karedal, J., Tufvesson, F., Paier, A., Bernadó, L., . . . Czink, N. (2011). Vehicular channel characterization and its implications for wireless system design and performance. *Proceedings of the IEEE, 99*(7), 1189-1212.

Mehdawi, M., Riley, N., Ammar, M., Fanan, A., & Zolfaghari, M. (2014). *Experimental detection using cyclostationary feature detectors for Cognitive Radios.* Paper presented at the Telecommunications Forum Telfor (TELFOR), 2014 22nd.

Meireles, R., Boban, M., Steenkiste, P., Tonguz, O., & Barros, J. (2010, 13-15 Dec. 2010). *Experimental study on the impact of vehicular obstructions in VANETs.* Paper presented at the Vehicular Networking Conference (VNC), 2010 IEEE.

Miao, L., Djouani, K., Van Wyk, B. J., & Hamam, Y. (2013). *Performance evaluation of IEEE 802.11 p MAC protocol in VANETs safety applications.* Paper presented at the Wireless Communications and Networking Conference (WCNC), 2013 IEEE.

Min, A. W., & Shin, K. G. (2009). *Impact of mobility on spectrum sensing in cognitive radio networks.* Paper presented at the Proceedings of the 2009 ACM workshop on Cognitive radio networks.

Mitola, J., & Maguire, G. Q. (1999). Cognitive radio: making software radios more personal. *IEEE personal communications, 6*(4), 13-18.

Mittag, J., Papanastasiou, S., Hartenstein, H., & Strom, E. G. (2011). Enabling accurate cross-layer PHY/MAC/NET simulation studies of vehicular communication networks. *Proceedings of the IEEE, 99*(7), 1311-1326.

Mohamad, M., Wen, H. C., & Ismail, M. (2012). *Matched filter detection technique for GSM band.* Paper presented at the Telecommunication Technologies (ISTT), 2012 International Symposium on.

Montealegre, J. C., Carvalho, M. M., & de Moraes, R. M. (2014). *Deadline-constrained optimal broadcasting under hidden terminals in cognitive networks.* Paper presented at the Proceedings of the Latin America Networking Conference on LANC 2014.

Moore, H. (2014). *MATLAB for Engineers*: Prentice Hall Press.

Mota, V. F., Cunha, F. D., Macedo, D. F., Nogueira, J. M., & Loureiro, A. A. (2014). Protocols, mobility models and tools in opportunistic networks: A survey. *Computer Communications, 48*, 5-19.

Mussa, S. A. B., Manaf, M., Ghafoor, K. Z., & Doukha, Z. (2015). *Simulation tools for vehicular ad hoc networks: A comparison study and future perspectives.* Paper presented at the Wireless Networks and Mobile Communications (WINCOM), 2015 International Conference on.

Nagy, T. (2013). The WAF book. Retrieved from https://waf.io/book/

Nallagonda, S., Roy, S. D., & Kundu, S. (2011). *Performance of cooperative spectrum sensing in Rician and Weibull fading channels.* Paper presented at the 2011 Annual IEEE India Conference.

Ning, G., Chowdhury, K. R., Duan, J., & Nintanavongsa, P. (2013). Licensed user activity estimation and track in mobile cognitive radio ad hoc networks. *Computers & Electrical Engineering, 39*(6), 1705-1716.

Nitti, M., Girau, R., Floris, A., & Atzori, L. (2014). *On adding the social dimension to the internet of vehicles: Friendship and middleware.* Paper presented at the Communications and Networking (BlackSeaCom), 2014 IEEE International Black Sea Conference on.

ns2-wiki. (2014). nsnam wiki. Retrieved from http://nsnam.sourceforge.net/wiki/index.php/Main_Page

NS2. (2011). The Network Simulator - ns-2. Retrieved from http://www.isi.edu/nsnam/ns/

ns3-manual. (2016). NS3- Manual. Retrieved from https://www.nsnam.org/docs/release/3.26/manual/singlehtml/index.html ns3-overview. (2016). What is ns-3. Retrieved from https://www.nsnam.org/overview/what-is-ns-3/

ns3-tutorial. (2016). ns-3.26 Tutorial. Retrieved from https://www.nsnam.org/docs/release/3.26/tutorial/singlehtml/index.html

Oche, M., Noor, R. M., & Jalooli, A. (2015). Quality of service management for IPTV services support in VANETs: a performance evaluation study. *Wireless Networks, 21*(1), 315-328.

OMNeT++. (2017). OMNeT++ Discrete Event Simulator. Retrieved from https://omnetpp.org/

optimus. (2015). Open-Source vs. Proprietary Software Pros and Cons. Retrieved from http://www.optimusinfo.com/downloads/white-paper/open-source-vs-proprietary-software-pros-and-cons.pdf

Pagadarai, S., Lessard, B. A., Wyglinski, A. M., Vuyyuru, R., & Altintas, O. (2013). Vehicular communication: Enhanced networking through dynamic spectrum access. *IEEE Vehicular Technology Magazine, 8*(3), 93-103.

Palaios, A., Riihijarvi, J., Holland, O., Achtzehn, A., & Mahonen, P. (2012). *Measurements of spectrum use in London: exploratory data analysis and study of temporal, spatial and frequency-domain dynamics.* Paper presented at the Dynamic Spectrum Access Networks (DYSPAN), 2012 IEEE International Symposium on.

Papaleondiou, L. G., & Dikaiakos, M. D. (2009). *Trafficmodeler: A graphical tool for programming microscopic traffic simulators through high-level abstractions.* Paper presented at the Vehicular Technology Conference, 2009. VTC Spring 2009. IEEE 69th.

Patil, K., Prasad, R., & Skouby, K. (2011). *A survey of worldwide spectrum occupancy measurement campaigns for cognitive radio.* Paper presented at the Devices and Communications (ICDeCom), 2011 International Conference on.

Paul, A., Daniel, A., Ahmad, A., & Rho, S. (2015). Cooperative Cognitive Intelligence for Internet of Vehicles. *IEEE Systems Journal, PP*(99), 1-10. doi:10.1109/JSYST.2015.2411856

Peng, X., & Yan, Z. (2014). Estimation and application for a new extended Weibull distribution. *Reliability Engineering & System Safety, 121*, 34-42.

Popescu, V., Fadda, M., & Murroni, M. (2016). Performance analysis of IEEE 802.22 wireless regional area network in the presence of digital video broadcasting–second generation terrestrial broadcasting services. *IET Communications, 10*(8), 922-928.

Proakis, J. G., & Salehi, M. (2008). *Digital Communications* (5 ed.): McGraw-Hill.

Pyo, C.-W., Zhang, X., Song, C., Zhou, M.-T., & Harada, H. (2012). *A new standard activity in IEEE 802.22 wireless regional area networks: Enhancement for broadband services and monitoring applications in TV whitespace.* Paper presented at the Wireless Personal Multimedia Communications (WPMC), 2012 15th International Symposium on.

Qian, X., & Hao, L. (2014). *Spectrum sensing with energy detection in cognitive Vehicular Ad hoc Networks.* Paper presented at the Wireless Vehicular Communications (WiVeC), 2014 IEEE 6th International Symposium on.

Qian, X., & Hao, L. (2015). *On the performance of spectrum sensing in cognitive vehicular networks.* Paper presented at the Personal, Indoor, and Mobile Radio Communications (PIMRC), 2015 IEEE 26th Annual International Symposium on.

Qin, Y., Sheng, Q. Z., Falkner, N. J., Dustdar, S., Wang, H., & Vasilakos, A. V. (2014). When things matter: A data-centric view of the internet of things. *arXiv preprint arXiv:1407.2704*.

Rashidi, M., Haghighi, K., Owrang, A., & Viberg, M. (2011). *A wideband spectrum sensing method for cognitive radio using sub-Nyquist sampling.* Paper presented at the Digital Signal Processing Workshop and IEEE Signal Processing Education Workshop (DSP/SPE), 2011 IEEE.

Rawat, D. B., Amin, T., & Song, M. (2015). *The impact of secondary user mobility and primary user activity on spectrum sensing in cognitive vehicular networks.* Paper presented at the Computer Communications Workshops (INFOCOM WKSHPS), 2015 IEEE Conference on.

Rawat, D. B., Bista, B. B., Yan, G., & Olariu, S. (2014). *Vehicle-to-vehicle connectivity and communication framework for vehicular ad-hoc networks.* Paper presented at the Complex, Intelligent and Software Intensive Systems (CISIS), 2014 Eighth International Conference on.

Raza, A., Ahmed, S. S., Ejaz, W., & Kim, H. S. (2012). *Cooperative spectrum sensing among mobile nodes in cognitive radio distributed network.* Paper presented at the Frontiers of Information Technology (FIT), 2012 10th International Conference on.

Rehman ur, S., Khan, M. A., & Zia, T. A. (2014). *Wireless transmission modeling for Vehicular Ad-hoc Networks.* Paper presented at the 2014 20th IEEE International Conference on Parallel and Distributed Systems (ICPADS).

Release, F. (2010). Second Memorandum Opinion and Order (FCC 10-174). *ET Docket Nos. 02-380 and 04, 186*.

riverbed. (2017). OPNET Technologies-Network Simulator (Riverbed). Retrieved from https://www.riverbed.com/my/products/steelcentral/opnet.html

Sadeghi, H., Azmi, P., & Arezumand, H. (2012). Cyclostationarity-based cooperative spectrum sensing over imperfect reporting channels. *AEU-International Journal of Electronics and Communications, 66*(10), 833-840.

Saleem, Y., & Rehmani, M. H. (2014). Primary radio user activity models for cognitive radio networks: A survey. *Journal of Network and Computer Applications, 43*, 1-16.

Samara, G., & Alhmiedat, T. (2014). Intelligent emergency message broadcasting in VANET using PSO. *arXiv preprint arXiv:1406.7399*.

Sanguesa, J. A., Fogue, M., Garrido, P., Martinez, F. J., Cano, J.-C., Calafate, C. T., & Manzoni, P. (2013). An infrastructureless approach to estimate vehicular density in urban environments. *Sensors, 13*(2), 2399-2418.

Saraniya, E., & Priya, B. L. (2014). *Performance optimization of cognitive radio with wideband spectrum sensing.* Paper presented at the Information Communication and Embedded Systems (ICICES), 2014 International Conference on.

Satheesh, A., Aswini, S., Lekshmi, S., Sagar, S., & Kumar, H. (2013). *Spectrum sensing techniques A comparison between energy detector and cyclostationarity detector*. Paper presented at the Control Communication and Computing (ICCC), 2013 International Conference on.

Segata, M., Bloessl, B., Joerer, S., Sommer, C., Cigno, R. L., & Dressler, F. (2013). *Short paper: Vehicle shadowing distribution depends on vehicle type: Results of an experimental study.* Paper presented at the 2013 IEEE Vehicular Networking Conference.

Shah, G. A., & Akan, O. B. (2015). Cognitive adaptive medium access control in cognitive radio sensor networks. *IEEE Transactions on Vehicular Technology, 64*(2), 757-767.

Shaikh, B., Shah, S., Zafi, S. M., Ejaz, W., & Anpalagan, A. (2016). Worldwide Spectrum Sensing Measurements and the Way Forward for Cognitive Radio Networks: A Survey. *Asian Journal of Engineering, Sciences & Technology*.

Sharma, V., & Bohara, V. (2014). *Exploiting machine learning algorithms for cognitive radio.* Paper presented at the Advances in Computing, Communications and Informatics (ICACCI, 2014 International Conference on.

Silva, C., Nogueira, M., Kim, D., Cerqueira, E., & Santos, A. (2016). Cognitive radio based connectivity management for resilient end-to-end communications in VANETs. *Computer Communications, 79*, 1-8.

Simon, M. K., & Alouini, M.-S. (2005). *Digital communication over fading channels* (Vol. 95): John Wiley & Sons.

Singh, A., Bhatnagar, M. R., & Mallik, R. K. (2011). *Cooperative spectrum sensing with an improved energy detector in cognitive radio network.* Paper presented at the Communications (NCC), 2011 National Conference on.

Singh, K. D., Rawat, P., & Bonnin, J.-M. (2014). Cognitive radio for vehicular ad hoc networks (CR-VANETs): approaches and challenges. *EURASIP Journal on Wireless Communications and Networking, 2014*(1), 1-22.

Skarmeta, A. F., Hernandez-Ramos, J. L., & Moreno, M. V. (2014). *A decentralized approach for security and privacy challenges in the internet of things.* Paper presented at the Internet of Things (WF-IoT), 2014 IEEE World Forum on.

Skima, M. A., Ghariani, H., & Lahiani, M. (2014). A multi-criteria comparative analysis of different Rayleigh fading channel simulators. *AEU-International Journal of Electronics and Communications*, *68*(6), 550-560.

Sofotasios, P. C., Fikadu, M. K., Ho-Van, K., & Valkama, M. (2013). *Energy detection sensing of unknown signals over Weibull fading channels.* Paper presented at the 2013 International Conference on Advanced Technologies for Communications (ATC 2013).

Sommer, C., German, R., & Dressler, F. (2011). Bidirectionally coupled network and road traffic simulation for improved IVC analysis. *IEEE Transactions on Mobile Computing*, *10*(1), 3-15.

Sommer, C., Härri, J., Hrizi, F., Schünemann, B., & Dressler, F. (2015). Simulation Tools and Techniques for Vehicular Communications and Applications *Vehicular ad hoc Networks* (pp. 365-392): Springer.

Souid, I., Chikha, H. B., & Attia, R. (2014). *Blind spectrum sensing in cognitive vehicular ad hoc networks over Nakagami-m fading channels.* Paper presented at the Electrical Sciences and Technologies in Maghreb (CISTEM), 2014 International Conference on.

Stanica, R., Chaput, E., & Beylot, A.-L. (2011). Simulation of vehicular ad-hoc networks: Challenges, review of tools and recommendations. *Computer networks*, *55*(14), 3179-3188.

Stevenson, C. R., Chouinard, G., Lei, Z., Hu, W., Shellhammer, S. J., & Caldwell, W. (2009). IEEE 802.22: The first cognitive radio wireless regional area network standard. *IEEE Communications magazine*, *47*(1), 130-138.

Stotas, S., & Nallanathan, A. (2010). *Overcoming the sensing-throughput tradeoff in cognitive radio networks.* Paper presented at the Communications (ICC), 2010 IEEE International Conference on.

Ström, E. G. (2011). On medium access and physical layer standards for cooperative intelligent transport systems in Europe. *Proceedings of the IEEE*, *99*(7), 1183-1188.

Sun, H., Nallanathan, A., Wang, C.-X., & Chen, Y. (2013). Wideband spectrum sensing for cognitive radio networks: a survey. *IEEE Wireless Communications*, *20*(2), 74-81.

Sun, M., Zhao, C., Yan, S., & Li, B. (2016). A Novel Spectrum Sensing for Cognitive Radio Networks with Noise Uncertainty. *IEEE Transactions on Vehicular Technology*, *PP*(99), 1-5. doi:10.1109/TVT.2016.2596789

Survey. (2010). *General Survey of Radio Frequency Bands 30 MHz to 3 GHz*. Retrieved from http://www.sharedspectrum.com/wp-content/uploads/2010_0923%20General%20Band%20Survey%20-%2030MHz-to-3GHz.pdf

Sutton, P. D., Nolan, K. E., & Doyle, L. E. (2008). Cyclostationary signatures in practical cognitive radio applications. *IEEE Journal on selected areas in Communications*, *26*(1), 13-24.

Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction* (Vol. 1): MIT press Cambridge.

Szepesvári, C. (2010). Algorithms for reinforcement learning. *Synthesis lectures on artificial intelligence and machine learning, 4*(1), 1-103.

Tabassam, A. A., Suleman, M. U., Kalsait, S., & Khan, S. (2011). *Building cognitive radios in MATLAB Simulink—A step towards future wireless technology.* Paper presented at the Wireless Advanced (WiAd), 2011.

Tandra, R., & Sahai, A. (2005). *Fundamental limits on detection in low SNR under noise uncertainty.* Paper presented at the Wireless Networks, Communications and Mobile Computing, 2005 International Conference on.

Tarique, M., & Hasan, M. T. (2011). Impact of Nakagami-m fading model on multi-hop mobile ad hoc network. *International Journal of Computer Applications, 26*(2), 5-12.

Tchouankem, H., Zinchenko, T., & Schumacher, H. (2015). *Impact of buildings on vehicle-to-vehicle communication at urban intersections.* Paper presented at the 2015 12th Annual IEEE Consumer Communications and Networking Conference (CCNC).

Teixeira, F. A., e Silva, V. F., Leoni, J. L., Macedo, D. F., & Nogueira, J. M. (2014). Vehicular networks using the IEEE 802.11 p standard: an experimental analysis. *Vehicular Communications, 1*(2), 91-96.

TETCOS. (2017). NetSim-Network Simulator & Emulator. Retrieved from http://www.tetcos.com/index.html

Thilina, K. M., Choi, K. W., Saquib, N., & Hossain, E. (2013). Machine learning techniques for cooperative spectrum sensing in cognitive radio networks. *IEEE Journal on selected areas in communications, 31*(11), 2209-2221.

Thomas, A. A., & Sudha, T. (2014). *Primary user signal detection in cognitive radio networks using cyclostationary feature analysis.* Paper presented at the Communication, Signal Processing and Networking (NCCSN), 2014 National Conference on.

Tian, Z. (2008). *Compressed wideband sensing in cooperative cognitive radio networks.* Paper presented at the IEEE GLOBECOM 2008-2008 IEEE Global Telecommunications Conference.

Ting, C., Wildman, S. S., & Bauer, J. M. (2005). *Government policy and the comparative merits of alternative governance regimes for wireless services.* Paper presented at the New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on.

Tyagi, V., Kalyanaraman, S., & Krishnapuram, R. (2012). Vehicular traffic density state estimation based on cumulative road acoustics. *IEEE Transactions on Intelligent Transportation Systems, 13*(3), 1156-1166.

Valenta, V., Maršálek, R., Baudoin, G., Villegas, M., Suarez, M., & Robert, F. (2010). *Survey on spectrum utilization in Europe: Measurements, analyses and* *observations*. Paper presented at the Cognitive Radio Oriented Wireless Networks & Communications (CROWNCOM), 2010 Proceedings of the Fifth International Conference on.

Virdis, A., Stea, G., & Nardini, G. (2016). Simulating LTE/LTE-Advanced Networks with SimuLTE *Simulation and Modeling Methodologies, Technologies and Applications* (Vol. 402, pp. 83-105): Springer.

Vlacheas, P., Giaffreda, R., Stavroulaki, V., Kelaidonis, D., Foteinos, V., Poulios, G., . . . Moessner, K. (2013). Enabling smart cities through a cognitive management framework for the internet of things. *Communications Magazine, IEEE, 51*(6), 102-111.

Wang, B., & Liu, K. R. (2011). Advances in cognitive radio networks: A survey. *IEEE Journal of selected topics in signal processing, 5*(1), 5-23.

Wang, L.-C., Liu, W.-C., & Cheng, Y.-H. (2009). Capacity fades analysis of MIMO Rician channels in mobile ad hoc networks. *Performance Evaluation, 66*(12), 742-753. doi:http://dx.doi.org/10.1016/j.peva.2009.08.006

Wang, L., Wan, P.-J., & Washington, W. (2015). Connectivity of multihop wireless networks with log-normal shadowing. *Wireless Networks, 21*(7), 2279-2292.

Wang, X. Y., & Ho, P.-H. (2010). A novel sensing coordination framework for CR-VANETs. *IEEE Transactions on Vehicular Technology, 59*(4), 1936-1948.

Wang, Y., Zhang, X., & Liu, D. (2015). *Performance of dual-hop multi-relay cooperative communication system in Rician fading*. Paper presented at the Software Engineering and Service Science (ICSESS), 2015 6th IEEE International Conference on.

Wang, Z., & Hassan, M. (2008). *How much of dsrc is available for non-safety use?* Paper presented at the Proceedings of the fifth ACM international workshop on VehiculAr Inter-NETworking.

Wei, Z., Yu, F. R., & Boukerche, A. (2015). *Cooperative Spectrum Sensing with Trust Assistance for Cognitive Radio Vehicular Ad hoc Networks*. Paper presented at the Proceedings of the 5th ACM Symposium on Development and Analysis of Intelligent Vehicular Networks and Applications.

Wellens, M., & Mähönen, P. (2010). Lessons learned from an extensive spectrum occupancy measurement campaign and a stochastic duty cycle model. *Mobile networks and applications, 15*(3), 461-474.

Wen, Y., Ma, Y., Zhang, X., Jin, X., & Wang, F. (2012). *Channel fading statistics in high-speed mobile environment*. Paper presented at the Antennas and Propagation in Wireless Communications (APWC), 2012 IEEE-APS Topical Conference on.

Whaiduzzaman, M., Sookhak, M., Gani, A., & Buyya, R. (2014). A survey on vehicular cloud computing. *Journal of Network and Computer Applications, 40*, 325-344.

Withers, D. J. (1999). *Radio spectrum management: management of the spectrum and regulation of radio services* (Vol. 45): IET.

Wu, X., Subramanian, S., Guha, R., White, R. G., Li, J., Lu, K. W., . . . Zhang, T. (2013). Vehicular communications using DSRC: challenges, enhancements, and evolution. *Selected Areas in Communications, IEEE Journal on, 31*(9), 399-408.

Xu, X., Bao, J., Luo, Y., & Wang, H. (2013). Cooperative wideband spectrum detection based on maximum likelihood ratio for CR enhanced VANET. *Journal of Communications, 8*(12), 814-821.

Yang, H., Xie, X., & Wang, R. (2012). *SOM-GA-SVM Detection Based Spectrum Sensing in Cognitive Radio.* Paper presented at the Wireless Communications, Networking and Mobile Computing (WiCOM), 2012 8th International Conference on.

Yang, S., He, R., Wang, Y., Li, S., & Lin, B. (2014). *OPNET-based modeling and simulations on routing protocols in VANETs with IEEE 802.11 p.* Paper presented at the Systems and Informatics (ICSAI), 2014 2nd International Conference on.

Yao, Y., Rao, L., & Liu, X. (2013). Performance and reliability analysis of IEEE 802.11 p safety communication in a highway environment. *IEEE Transactions on Vehicular Technology, 62*(9), 4198-4212.

Yin, S., Chen, D., Zhang, Q., & Li, S. (2011). Prediction-based throughput optimization for dynamic spectrum access. *IEEE transactions on vehicular technology, 60*(3), 1284-1289.

Yu, T.-H., Sekkat, O., Rodriguez-Parera, S., Markovic, D., & Cabric, D. (2011). A wideband spectrum-sensing processor with adaptive detection threshold and sensing time. *IEEE Transactions on Circuits and Systems I: Regular Papers, 58*(11), 2765-2775.

Yucek, T., & Arslan, H. (2009). A survey of spectrum sensing algorithms for cognitive radio applications. *IEEE Communications Surveys & Tutorials, 11*(1), 116-130.

Yue, W.-J., Zheng, B.-Y., Meng, Q.-M., & Yue, W.-J. (2010). Combined energy detection and one-order cyclostationary feature detection techniques in cognitive radio systems. *The Journal of China Universities of Posts and Telecommunications, 17*(4), 18-25.

Yue, W., & Zheng, B. (2010). Spectrum sensing algorithms for primary detection based on reliability in cognitive radio systems. *Computers & Electrical Engineering, 36*(3), 469-479.

Zang, Y., Stibor, L., Cheng, X., Reumerman, H.-J., Paruzel, A., & Barroso, A. (2007). *Congestion control in wireless networks for vehicular safety applications.* Paper presented at the Proceedings of the 8th European Wireless Conference.

Zeadally, S., Hunt, R., Chen, Y.-S., Irwin, A., & Hassan, A. (2012). Vehicular ad hoc networks (VANETS): status, results, and challenges. *Telecommunication Systems, 50*(4), 217-241.

Zhang, D., & Zhai, X. (2011, 23-25 Sept. 2011). *SVM-Based Spectrum Sensing in Cognitive Radio.* Paper presented at the 2011 7th International Conference on Wireless Communications, Networking and Mobile Computing.

Zhao, Y., Paul, P., Xin, C., & Song, M. (2014). *Performance analysis of spectrum sensing with mobile sus in cognitive radio networks.* Paper presented at the Communications (ICC), 2014 IEEE International Conference on.

Zhao, Y., Zhang, H., Sun, W., Bai, Z., & Pan, C. (2014). *Performance evaluation of IEEE 802.11 p vehicle to infrastructure communication using off-the-shelf IEEE 802.11 a hardware.* Paper presented at the Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on.

Zhu, S., Guo, C., Feng, C., & Liu, X. (2016). *Performance Analysis of Cooperative Spectrum Sensing in Cognitive Vehicular Networks with Dense Traffic.* Paper presented at the Vehicular Technology Conference (VTC Spring), 2016 IEEE 83rd.

LIST OF PUBLICATIONS AND PAPERS PRESENTED

Published works and paper presented at seminar pertaining to the research topic of the thesis include:

- Christopher Chembe, Rafidah Md Noor, Ismail Ahmedy, Micheal Oche, Douglas Kunda, Chi Harold Li, "Spectrum Sensing in Cognitive Vehicular Network: State-of-Art, Challenges and Open Issues" *Computer Communications*, Volume 97, 1 January 2017, Pages 15-30 (IF = 2.099, Q1) (*ISI-Indexed*)
- Christopher Chembe, Ismail Ahmedy, Rafidah Md Noor, Douglas Kunda, Michael Oche, Abubakar Bello Tambawal, "Cooperative Spectrum Decision in Cognitive Vehicular Network based on Support Vector Machine" *Malaysian Journal of Computer Science* (Accepted April 2017) (*ISI-Indexed*)
- Christopher Chembe, Rafidah Md Noor, Ismail Ahmedy, Douglas Kunda, "Spectrum Sensing in Licensed Channels to Increase Channel Capacity for ITS Applications", *Intelligent Transport System Seminar and Exhibition*, 21-23 February 2017, Bangsar South, Kuala Lumpur.

Articles under review

- Christopher Chembe, Rafidah Md Noor, Ismail Ahmedy, Douglas Kunda, Michael Oche, Abubakar Bello Tambawal, Mohammad Hossein Anisi, "Increasing channel capacity for Internet of Vehicles through Cognitive Vehicular Communication", *IEEE Internet of Things Journal* (Under review submitted 9, June 2017)

- **Christopher Chembe**, Rafidah Md Noor, Douglas Kunda , Ismail Ahmedy , Abubakar Bello Tambawal and Michael Oche, “Adaptive spectrum sensing for cognitive VANET in fading environment”, *IEEE Systems Journal* (ISI Indexed)
- **Christopher Chembe**, Douglas Kunda, Ismail Ahmedy, Radah Md Noor, Aznul Qalid Md Sabri, Md Asri Ngadi, “Infrastructure based spectrum sensing scheme in VANET using reinforcement learning”, *Vehicular Communications* (ISI Indexed)

<u>Other articles</u>

- Michael Oche, Rafidah Md Noor, Chembe Christopher, "Multivariate Statistical Approach for Estimating QoE of Real-Time Multimedia Applications in Vehicular ITS Network", *Computer Communications, http://doi.org/10.1016/j.comcom.2016.12.022*, January 2017. (ISI-Indexed)
- Chembe Christopher, Rafidah Md. Noor, Ehsan Mostajeran "Optimizing Wireless Channel Using Adaptive Modulation To Improve QoS In VANET", *Malaysian Journal of Computer Science* (ISSN 0127-9084), Vol.26, No.1, 2013 (IF=0.167) (*ISI-Indexed*)