Enabling Cognitive Radios through Radio Environment Maps

Youping Zhao

Dissertation submitted to the Faculty of the
Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Electrical Engineering

Dr. Jeffrey H. Reed, Chair
Dr. Brian G. Agee
Dr. R. Michael Buehrer
Dr. Scott F. Midkiff
Dr. Hanif D. Sherali

May 8, 2007
Blacksburg, Virginia

Keywords: Cognitive Engine, Cognitive Radio, Radio Environment Map,
802.11 WLAN, 802.22 WRAN

Enabling Cognitive Radios through Radio Environment Maps

Youping Zhao

Abstract

In recent years, cognitive radios and cognitive wireless networks have been introduced as a new paradigm for enabling much higher spectrum utilization, providing more reliable and personal radio services, reducing harmful interference, and facilitating the interoperability or convergence of different wireless communication networks. Cognitive radios are goal-oriented, autonomously learn from experience and adapt to changing operating conditions. Cognitive radios have the potential to drive the next generation of radio devices and wireless communication system design and to enable a variety of niche applications in demanding environments, such as spectrum-sharing networks, public safety, natural disasters, civil emergencies, and military operations.

This research first introduces an innovative approach to developing cognitive radios based on the *Radio Environment Map* (REM). The REM can be viewed as an integrated database that provides multi-domain environmental information and prior knowledge for cognitive radios, such as the geographical features, available services and networks, spectral regulations, locations and activities of neighboring radios, policies of the users and/or service providers, and past experience. The REM, serving as a vehicle of network support to cognitive radios, can be exploited by the *cognitive engine* for most cognitive functionalities, such as situation awareness, reasoning, learning, planning, and decision support. This research examines the role of the REM in cognitive radio development from a network point of view, and focuses on addressing three specific issues about the REM: how to *design* and *populate* the REM; how to *exploit* the REM with the cognitive engine algorithms; and how to *evaluate* the performance of the cognitive radios. Applications of the REM to wireless local area networks (WLAN) and wireless regional area networks (WRAN) are investigated, especially from the perspectives of interference management and radio resource management, which illustrate the significance of cognitive radios to the evolution of wireless communications and the revolution in spectral regulation. Network architecture for REM-enabled cognitive radios and framework for REM-enabled situation-aware cognitive engine learning algorithms have been proposed and formalized. As an example, the REM, including the data model and basic application programmer interfaces (API) to the cognitive engine, has been developed for cognitive WRAN systems. Furthermore, REM-enabled cognitive cooperative learning (REM-CCL) and REM-enabled case- and knowledge-based learning algorithms (REM-CKL) have been proposed and validated with link-level or network-level simulations and a WRAN base station cognitive engine testbed. Simulation results demonstrate that the WRAN CE can adapt orders of magnitude faster when using the REM-CKL than when using the genetic algorithms and achieve near-optimal global utility by leveraging the REM-CKL and a local search. Simulation results also suggest that exploiting the Global REM information can considerably improve the performance of both primary and secondary users and mitigate the hidden node (or hidden receiver) problem. REM dissemination schemes and the resulting overhead have been investigated and analyzed under various network scenarios. By extending the optimized link state routing protocol, the overhead of REM dissemination in wireless ad hoc networks via multipoint relays can be significantly reduced by orders of magnitude as compared to plain flooding. Performance metrics for various cognitive radio applications are also proposed. REM-based scenario-driven testing (REM-SDT) has been proposed and employed to evaluate the performances of the cognitive engine and cognitive wireless networks. This research shows that REM is a viable, cost-efficient approach to developing cognitive radios and cognitive wireless networks with significant potential in various applications. Future research recommendations are provided in the conclusion.

Acknowledgments

I wish to thank my advisor, Dr. Jeffrey H. Reed, for his motivational discussions, consistent support, and encouragement throughout my Ph.D. study. Dr. Reed's encouraging words, "I have faith in your capability," always kept my spirits up and enabled me to pass through the hard times at the initial stage of my Ph.D. study. Dr. Reed's expertise and insight in software-defined radio and cognitive radio greatly help me to formalize the idea of the radio environment map and exploit it as the navigator for cognitive radio. I would also like to thank Dr. Brian G. Agee, Dr. R. Michael Buehrer, Dr. Scott F. Midkiff, and Dr. Hanif D. Sherali for serving on my committee and for their constructive comments and suggestions. I am very grateful to Dr. Kyung K. Bae, Dr. Claudio da Silva, Dr. Carl Dietrich, Dr. Shiwen Mao, Dr. Chris Anderson, Dr. James Neel, Dr. Max Robert, Dr. Ramesh Chembil Palat, Dr. Swaroop Venkatesh, Dr. Bruce Fette, Dr. Y. Thomas Hou, our cognitive radio research team members, Joseph Gaeddert, Lizdabel Morales, Kyouwoong Kim, and Rekha Menon, and my friends, David Raymond, Carlos R. Aguayo Gonzalez, Ingrid Burbey, Bin Le, and Thomas Rondeau, for their productive discussion, collaboration, and great help on my research. I would also like to thank Lori Hughes for her careful revisions to the initial draft of this dissertation. The MPRG staff, Shelby, Hilda, Jenny, and Cindy, are also acknowledged for their kind help and support.

My research work has been supported by funding from Army Research Office (ARO), CISCO Systems, Inc (CISCO), Electronics and Telecommunications Research Institute (ETRI), Tektronix Instruments, Texas Instruments (TI), and Wireless@Virginia Tech Partners. Any opinions, findings, and conclusions or recommendations expressed in this dissertation are those of the author(s) and do not necessarily reflect the views of the sponsors.

Portions of this dissertation were previously published in *Cognitive Radio Technology* (edited by Dr. Bruce Fette) by Elsevier/Newnes in 2006, ISBN 0-7506-7952-2.

This dissertation is dedicated to my parents, especially to my father who has been ill for years during my Ph.D. studies. I also appreciate my mother's words, "Conduct your research with passion." Without passion, it is almost impossible to get original ideas and meaningful results. Finally, I would like to thank my wife and daughter for their love, patience, and support.

Contents

List of Figures

List of Tables

Glossary

3G	third generation mobile communication systems
4G	fourth generation mobile communication systems
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANSI	American National Standards Institute
AP	Access Point
AWGN	Additive White Gaussian Noise
BS	Base Station
BT	Bluetooth
CE	Cognitive Engine
CPE	Customer Premise Equipment
CR	Cognitive Radio
DARPA	(U.S.) Defense Advanced Research Project Agency
DBMS	Database Management System
DMP	Dominant Mode Prediction
DSSS	Direct Sequence Spread Spectrum
E-R diagram	Entity-Relationship diagram
FAR	False Alarm Rate
FCC	(U.S.) Federal Communication Commission
GA	Genetic Algorithm
GIS	Geographical Information System
GPIB	General Purpose Interface Bus
GPS	Global Positioning System
HMM	Hidden Markov Model
IEEE	Institute of Electrical and Electronics Engineers
IR	Interference Range
LMDS	Local Multi-point Distribution Service
LS-CMA	Least Square-Constant Modulus Algorithm
MWO(L)	Microwave Oven (Leakage)

NTIA	(U.S.) National Telecommunications and Information Administration
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
OSSIE	Open Source SCA Implementation::Embeded
OWL	Web Ontology Language
PAM	Pulse Amplitude Modulation
PU	Primary User
SCBR	Soft Case-Based Reasoning
SDR	Software Defined Radio
SQL	Structured Query Language
SR	Sensing Range
SU	Secondary User
REM	Radio Environment Map
REM-CKL	REM-enabled Case- and Knowledge-based Learning algorithms
REM-SDT	REM-enabled Scenario-Driven Testing for Cognitive Radios
RF	Radio Frequency
RMS	Root Mean Square
RRU	Radio Resource Unit
WANN	(U.S. DARPA) Wireless Adaptable Network Node (program)
WiMAX	Worldwide Interoperability for Microwave Access (IEEE 802.16)
WLAN	Wireless Local Area Network (IEEE 802.11)
WM	Wireless Microphone (Wireless MIC)
WPAN	Wireless Personal Area Network (IEEE 802.15)
WRAN	Wireless Regional Area Network (IEEE 802.22)
UE	User Equipment
UML	Unified Modeling Language
UNII	Unlicensed National Information Infrastructure (radio band)
USRP	Universal Software Radio Peripheral
XG	(U.S. DARPA) neXt Generation (program)
XML	eXtensible Markup Language

1 Introduction

In recent years, cognitive radio (CR) and cognitive wireless networks have been introduced as a new paradigm for enabling much higher spectrum utilization, providing more personal and reliable radio services, reducing harmful interference, and facilitating the interoperability or convergence of different wireless networks. CR in particular could find niche applications in demanding environments, such as spectrum sharing networks, public safety, natural disasters, civil emergencies, and military operations.

Several events that occurred during my Ph.D. study have convinced me that CR technology would drive the next wave of wireless communications. One is the rescue after hurricane Katrina in 2004: when the telecommunication infrastructure was totally destroyed, rescue workers had to carry multiple radio terminals for communication with people from different groups, since current public safety radios equipped for different departments usually employ different waveforms[1]. The problem is that these legacy radios cannot “talk” to each other without infrastructure-based “translators” (“adapters”). Ideally, CR that can understand and speak different “languages” (“waveforms”) would elegantly solve this interoperability problem. Another event is a civil emergency story: in late November 2006, a family traveling by car were lost and trapped in Oregon mountain areas after a snowstorm. Unfortunately, this area is an out-of-service area for cellular phones. In the end, the father died of hypothermia after he left the car to walk and seek help. If current cellular phones become cognitive enough, this tragedy could be avoided. The CR could place a “911” emergency call by exploiting whatever radio resource (for example, satellite networks) and technologies (such as beamforming, mesh networks) were available when it is out of service area of a cellular network. The third event is the spectrum auction and refarming of the TV broadcast bands in the United States (U.S.), which could generate billions of dollars of revenue for the government and industry. Spectrum is a limited resource, thus making full use of spectrum is critically important for sustainable development of future wireless communications. Refarming the analog TV spectrum promotes the development of CR technologies. For

[1] Note that the waveform here is a combination of frequency, modulation, coding, protocol, etc.

example, the IEEE 802.22 wireless region area network (WRAN) will be the first worldwide CR-based standard to support unlicensed operation in the TV bands (54–862 MHz).

In the remainder of this chapter, I will formally introduce CR, discuss the general motivations and the specific problems addressed in my research, summarize original research contributions, and overview the organization of this dissertation.

1.1 Introduction to Cognitive Radio

Soon after I started my research on CR, the following questions were on my mind.

- What does CR really mean?
- Do we really need CR?
- What are the differentiating features of CR compared to current adaptive radio and software defined radio (SDR)?

The term "cognitive radio" was coined by Dr. Joseph Mitola III in late 1990s [1, 2]. However, no commonly accepted definition of CR exists yet, mainly because different people or organizations have various views on or expectations of CR [3, 4, 5]. For example, the Virginia Tech CR research group views CR as an adaptive radio that is capable of the following:

- awareness of its environment and its own capabilities,
- goal-driven autonomous operation,
- understanding or learning how its actions impact its goal, and
- recalling and correlating past actions, environments, and performance.

The U.S. Federal Communications Commission (FCC) views CR as "a radio that can change its transmitter parameters based on interaction with the environment in which it operates. The majority of cognitive radios will probably be SDRs (Software Defined Radios), but neither having software nor being field programmable are requirements of a cognitive radio" [6].

As we know, wireless communication technology has a relatively short history, which may date back to about one century ago around 1897 when Guglielmo Marconi invented the wireless telegraph. Even though mobile communications are evolving into the third and fourth generations (featuring wideband and broadband wireless communications, respectively), the current radio devices and wireless communication networks have very limited *cognition functionality*. In other words, the current radios' behaviors are mostly predefined by the developers and their performance cannot be improved autonomously through learning from experience and environment. The ever-growing wireless communication demands in the limited radio spectrum or unpredictable radio scenarios have driven the inter-disciplinary research efforts in CR around the world in recent years.

CR is extremely important for spectrum conservation and addressing the "spectrum scarcity" problem, for it can share the spectrum with the primary users (often licensed users with priority rights) on a non-interfering basis. The radio spectrum is a precious resource. Despite the recent rapid advancements in wireless communication technologies and emerging wireless networks, such as Multiple Input Multiple Output (MIMO), Orthogonal Frequency Division Multiple Access (OFDMA), the third and fourth generation mobile communications (3G/4G), wireless personal area network (WPAN), wireless local area network (WLAN), wireless metropolitan area network (WiMAX), and Ultra Wideband (UWB), it is still hard to envision how a truly universally connected information society could be established, given today's regulation of radio spectrum. With the existing regulatory framework, most parts of the spectrum are allocated to licensed radio services. The spectrum allocations are already very crowded in the U.S., as illustrated in Figure 1-1. Ironically, the reality of the spectrum scarcity problem is low utilization of spectrum. Many measurements show that less than 20% of the licensed spectrum is in use at any location and at any given time [7, 23]. CR has emerged as a possible solution to the spectrum scarcity problem by allowing dynamic accessing and sharing the spectrum. Therefore, the immediate interest in fielding CR is to provide support for new spectrum access methodologies under consideration by the U.S. FCC and National Telecommunications and Information Administration (NTIA) [8]. For example, the ongoing IEEE standardization on 802.22 WRAN is to exploit the underutilized TV spectrum based on CR technology. CR is also considered to be an environmentally friendly radio system, in the sense that "it can use the radio spectrum more effectively and ensure that interference is kept to a minimum" [9].

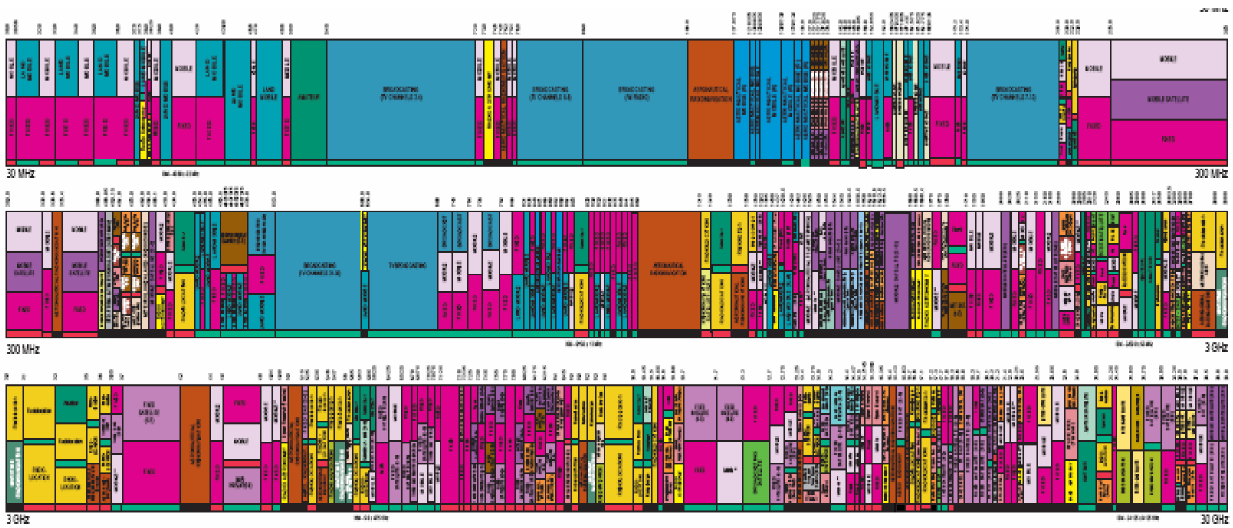


Figure 1-1: U.S. Frequency Allocations[2] from 30 MHz to 30 GHz: The radio spectrum is too crowded to show the details of allocations in this figure.

In summary, several paradigm shifts are anticipated with the emergence of CR [3]:

- from static and centralized spectrum allotment to dynamic spectrum access;
- from preset (and known) radio behavior to awareness of and adaptation to the environment by the radio; and
- from transmitter centricity to receiver centricity, whereby interference power rather than transmitter emission is regulated.

SDR provides an ideal platform for the realization of CR [1]. It is expected that CR will evolve from current SDR and adaptive radio by adding more and more cognition features, such as comprehensive situation awareness and learning capability.

Currently CR research is in the very preliminary stage. Although CR functionality can reside in any layer of a wireless communication protocol stack, most current CR research focuses on lower layers. For example, the biologically inspired CR engine proposed by C. J. Rieser focuses on the physical layer and MAC layer only [10]. A true CR needs to be aware of any situation regarding all layers with goal-oriented, focused attention. Many issues have to be resolved before putting CR into practice: technical issues, such as spectrum sensing, primary

---

[2] Source: http://www.ntia.doc.gov/osmhome/allochrt.pdf

user protection, and cognitive engine algorithms; business issues, such as new business models; and regulatory or political issues.

1.2 Motivations of This Research and Specific Problems

For this research, the general thrusts are to address the following important issues.

(1) Many people think that CR would be very expensive, and it might take decades to put it into practice. How can we develop CR in a cost-efficient way and facilitate its implementation?

(2) The cognitive engine is the brain of CR; it is the new function block to be added to SDR to support cognitive functionalities. What is the architecture of the cognitive engine and how can it be developed?

(3) Since the behavior of CR is not predefined and might change with the operating environment, evaluating the performance of CR could be fairly challenging. How can the performance of CR be evaluated?

Our vision is ***"****Enabling Cognitive Radios through Radio Environment Maps****"*** [97]. The radio environment map (REM) is proposed as an abstraction of real-world radio scenarios and represented by an *integrated* database that consists of multi-domain environmental information and prior knowledge, such as the geographical features, available networks and services, spectral regulations, locations and activities of radios, policies of the users and/or service providers, and past experience [11]. The REM can be exploited by the cognitive engine for most cognitive functionalities, such as situation awareness, learning, reasoning, planning, and decision support. The REM can be viewed as a vehicle of network support and an innovative system approach to developing CR and cognitive wireless networks. Specifically, the following problems are addressed in this research.

(1) Designing and populating the REM

This task details the motivations of the REM, the main attributes of the REM, the implementation options of the REM, and the signal processing and networking techniques for populating the REM.

(2) Exploiting the REM with cognitive engine algorithms

This task develops REM-enabled cognitive engine architecture and learning algorithms for CR to obtain radio scene awareness, learn from experience, and make fast adaptations.

(3) Evaluating the performance of CR networks

This task develops performance metrics for evaluating CR networks and compares the performance of REM-enabled CR networks to that of non-CR networks.

1.3 Research Contributions

The main contributions of this research work are as follows:

- **Developed the REM from an original idea to a detailed system architecture design and implementation for cognitive WRANs**
- **Developed the framework of REM-enabled cognitive engine (REM-CE) and employed it in the WRAN base station cognitive engine testbed**
- **Developed the REM-enabled case- and knowledge-based learning (REM-CKL) algorithm and evaluated its performance against genetic algorithms**
- **Proposed cognitive cooperative learning based on REM dissemination (REM-CCL) and analyzed the overhead of REM dissemination in various network scenarios with different dissemination schemes**
- **Investigated the definition of proper/dynamic performance metrics and utility functions for CR and cognitive wireless networks**
- **Proposed REM-based scenario-driven testing (REM-SDT) as the methodology for CR performance evaluation and employed it in evaluating the WRAN base station cognitive engine testbed**
- **Estimated the impact of REM-enabled CRs on incumbent primary users with link-level and network-level simulations**

These contributions are further elaborated as follows:

- The REM and REM-enabled CR have been developed from an original concept to system design and preliminary testing. The architecture of REM-enabled CR networks has been proposed and is a novel and generic approach to developing low-cost and flexible CRs through Local and Global REMs. Several implementation options have been proposed for REM development. For the WRAN cognitive engine testbed, current REM information has been implemented with a C++ class, while the historical REM information has been stored in a REM data file for statistical analysis. Common application programmer interfaces (APIs) have been defined to allow independent and flexible development of different building blocks of CR, such as REM, cognitive engine, and sensing modules.

- The framework for a REM-enabled cognitive engine (REM-CE) learning algorithms has been formalized, which leverages various machine learning algorithms with two-level learning loops for efficient learning and fast adaptation. The architecture of REM-CE has been successfully implemented in a WRAN base station cognitive engine testbed.

- The REM-enabled case- and knowledge-based learning (REM-CKL) algorithms have been developed for the WRAN base station cognitive engine testbed. The performance of REM-CKL has been evaluated against genetic algorithms. Based on REM information, similarity function has been developed for WRAN scenarios. Furthermore, a novel approach to characterize WRAN radio resource utilization scenarios has been proposed and employed, which is based on the radio resource unit (RRU) profile. It is shown that REM-CE can dramatically accelerate CR adaptation and obtain (near-) optimal utility as well by synergistically leveraging both REM-CKL and local search algorithms.

- Cognitive cooperative learning through REM dissemination (REM-CCL) has been proposed to facilitate peer-to-peer learning in CR networks, improve system performance, and reduce system cost. The goal of cooperation among CR nodes may change with radio scenarios and/or applications. To support REM-CCL, various approaches to disseminating an REM in a CR network have been investigated. Efficient REM dissemination schemes have been proposed and evaluated with simulations under various network scenarios. REM dissemination can also serve as a feedback mechanism that makes a CR node aware of not only its own performance but also its impact on other nodes, which is critically important for practical implementation of CR learning algorithms.
- The performance metrics have been defined for a WRAN cognitive engine, and a preliminary cognitive engine performance evaluation has been conducted. To evaluate

cognitive wireless networks, we may need to adopt a new methodology, which should be able to measure the performance of CRs under various radio scenarios. One way to generate sufficient testing scenarios is to exploit the REM and apply the *Monte Carlo simulation method* to produce a large amount of radio scenarios. We call this approach *REM-based scenario-driven CR testing* (REM-SDT) [72].

- A network-level simulation environment for evaluating REM-enabled spectrum-sharing networks has been developed, which can be used to simulate the performance of both primary users and CR nodes, such as throughput, latency, and packet drop rate. This network simulator can incorporate appropriate routing protocols, mobility models, and radio propagation models based on the radio scenarios and the adaptation schemes of CR nodes.
- Proposal contributions include the following proposals:
    1) "Development of a Cognitive Engine and Analysis of WRAN CR Algorithms," ETRI Project Phase II proposal and
    2) "Network Centric Characterization and Geolocation of Non-802.11 Interference in 802.11 WLANs," CISCO Project *Aegis* Phase II proposal.

1.4 Resulting IP Disclosures, Testbeds, and Publications

[Intellectual Property (IP) Disclosures]

A couple of Virginia Tech Intellectual Property (VTIP) disclosures have been filed that relate to REM exploitation methods and algorithms for cognitive radio engines and cognitive wireless networks.

- **Y. Zhao**, L. Morales, K. K. Bae, J. Gaeddert, J. H. Reed, and J. Um, *A generic cognitive engine design based on radio environment map (REM)*, 2007.
- **Y. Zhao**, L. Morales, K. K. Bae, J. Gaeddert, J. H. Reed, and J. Um, *A case- and knowledge-based learning (REM-CKL) method for cognitive radios based on radio environment map*, 2007.

[Testbed Development]

The testbed development contributions include:

- Development of an automatic 2.4 GHz ISM band interference monitoring system using LabVIEW® and Tektronix digital oscilloscopes. 802.11b/g WLAN interferences, such as microwave oven leakage, have been collected for post-processing.
- Development of the 802.22 WRAN base station cognitive engine testbed together with Joseph Gaeddert and Lizdabel Morales. Basic APIs between REM and cognitive engine, such as REM information update and retrieval, have also been implemented.

[Book Chapter]

Y. Zhao, B. Le, and J. H. Reed, "Network Support – The Radio Environment Map," in *Cognitive Radio Technology,* B. Fette, Ed., pp. 337–363, Elsevier/Newnes, 2006.

[Published Papers]

Y. Zhao, L. Morales, J. Gaeddert, K. K. Bae, J. Um, and J. H. Reed, "Applying Radio Environment Map to Cognitive Wireless Regional Area Networks," in *Proceedings of the Second IEEE International Symposium on Dynamic Spectrum Access Networks* (DySPAN 2007), April 17–20, 2007, Dublin, Ireland.

Y. Zhao, J. Gaeddert, K. K. Bae, and J. H. Reed, "Radio Environment Map Enabled Situation-Aware Cognitive Radio Learning Algorithms," in *Proceedings of Software Defined Radio (SDR) Technical Conference*, Nov. 13–17, 2006, Orlando, FL.

Y. Zhao, J. H. Reed, S. Mao, and K. K. Bae, "Overhead Analysis for Radio Environment Map Enabled Cognitive Radio Networks," in *Proceedings of the First IEEE Workshop on Networking Technologies for Software Defined Radio Networks*, Sept. 25, 2006, Reston, VA.

D. Raymond, I. Burbey, **Y. Zhao**, S. Midkiff, and C. P. Koelling. "Impact of Mobility Models on Simulated Ad Hoc Network Performance," in *Proceedings of the Ninth International Symposium on Wireless Personal Multimedia Communications* (WPMC), Sept. 17–20, 2006, San Diego, CA.

Y. Zhao, B. G. Agee, and J. H. Reed, “Simulation and Measurement of Microwave Oven Leakage for 802.11 WLAN Interference Management,” in *Proceedings of IEEE 2005 International Symposium on Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications*, Beijing, China, Aug. 8–12, 2005.

[Papers Submitted or in Progress]

Y. Zhao, J. Gaeddert, L. Morales, K. K. Bae, and J. H. Reed, “Development of Radio Environment Map Enabled Case- and Knowledge-Based Learning Algorithms for IEEE 802.22 WRAN Cognitive Engines,” accepted to *the Second International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM 2007)*

Y. Zhao, D. Raymond, C. da Silva, J. H. Reed, and S. Midkiff, “Performance Evaluation of Radio Environment Map Enabled Cognitive Spectrum-Sharing Networks,” submitted to *2007 Military Communications Conference (MILCOM 2007)*.

Y. Zhao, J. Gaeddert, L. Morales, K. K. Bae, and J. H. Reed, “Development and Performance Evaluation of Radio Environment Map Enabled Case- and Knowledge-Based Learning Algorithms for IEEE 802.22 WRAN Cognitive Engines,” to be submitted to *IEEE Journal on Selected Areas in Communications*.

Y. Zhao, D. Raymond, C. da Silva, J. H. Reed, and S. Midkiff, “Performance Evaluation and Optimization of Radio Environment Map Enabled Cognitive Spectrum-Sharing Networks,” to be submitted to *IEEE Journal on Selected Areas in Communications*.

K. K. Bae, J. Gaeddert, K. Kim, R. Menon, L. Morales, **Y. Zhao**, J. Neel, and J. H. Reed, “The Application of Machine Learning Algorithms to Cognitive Engine Design,” to be submitted to *IEEE Communications Magazine*.

C. R. Aguayo Gonzales, J. Gaeddert, K. Kim, K. K. Bae, L. Morales, M. Robert, **Y. Zhao**, C. Dietrich, and J. H. Reed, “Design and Implementation of an Open-Source Software-Defined Cognitive Radio Testbed,” to be submitted to *IEEE Journal on Selected Areas in Communications*.

B. G. Agee, **Y. Zhao**, and J. H. Reed, “Robust Fractional Spaced Equalizer Based Clock Offset Estimation for Cooperative 802.11 WLANs,” unpublished.

[Posters]

Y. Zhao and J. H. Reed, "Radio Environment Map Enabled Cognitive Radios," 2006 *Wireless@Virginia Tech Wireless Personal Communications Symposium*, June 7–9, 2006, Blacksburg, VA.

Y. Zhao, B. G. Agee, and J. H. Reed, "Collaborative Synchronization for Macrodiverse Exploitation of Conventional 802.11 Enterprise Networks," 2005 *MPRG Wireless Personal Communications Symposium*, Blacksburg, VA, June 8–11, 2005.

J. Gaeddert, L. Morales, **Y. Zhao**, K. K. Bae, and J. H. Reed, "Development of a Cognitive Engine in 802.22 WRAN Base Stations," *Wireless@Virginia Tech Workshop*, Northern Virginia, Nov. 6, 2006.

[Technical Reports]

Y. Zhao and J. H. Reed, "Radio Environment Map Design and Exploitation," MPRG Technical Report, Virginia Tech, Dec. 2005.

J. H. Reed, C. Dietrich, J. Gaeddert, K. Kim, R. Menon, L. Morales, and **Y. Zhao**, "Applying Artificial Intelligence to Cognitive Radio," Final Report to ARO, Virginia Tech, July 2006.

J. H. Reed, C. Dietrich, J. Gaeddert, K. Kim, R. Menon, L. Morales, and **Y. Zhao**, "Development of a Cognitive Engine and Analysis of WRAN Cognitive Radio Algorithms," Phase I Final Report to ETRI, Virginia Tech, Dec. 2005.

J. Gaeddert, K. Kim, R. Menon, L. Morales, **Y. Zhao**, K. K. Bae, and J. H. Reed, "Development of a Cognitive Engine and Analysis of WRAN Cognitive Radio Algorithms," Phase II Final Report to ETRI, Virginia Tech, Dec. 2006.

Y. Zhao, B. G. Agee, and J. H. Reed, Technical Report (*Aegis*-001): "Literature Survey for Project *Aegis* – Network-Based 802.11 WLAN Interference Management," 2004.

Y. Zhao, B. G. Agee, and J. H. Reed, Technical Report (*Aegis*-002): "Microwave Oven Leakage Modeling: Simulation and Measurement," 2004.

Y. Zhao, B. G. Agee, and J. H. Reed, Technical Report (*Aegis*-003): “Bluetooth Interference Modeling and Detection Algorithms,” 2004.

Y. Zhao, B. G. Agee, and J. H. Reed, Technical Report (*Aegis*-004): “WLAN Interference Monitoring System and WLAN Beacon Measurement,” 2005.

Y. Zhao, B. G. Agee, and J. H. Reed, Technical Report (*Aegis*-005): “Fractional Spaced Equalizer-Based WLAN Cross-Access Point Clock Offset Estimation,” 2005.

[White Papers]

J. H. Reed, M. Robert, L. Morales, **Y. Zhao**, and C. Aguayo, “Development of a Cognitive Radio Testbed using Tektronix Off-the-Shelf Components,” White Paper for Tektronix (Version 2.0), Mar. 2005.

Y. Zhao, B. G. Agee, and J. H. Reed, “Software Radio Enabled Cognitive RFID Tag (SmaRTag): Connecting Real World with Virtual World (Information Networks),” June 2005.

1.5 Overview of the Dissertation

This dissertation is organized as follows. Chapter 1 introduces CR, discusses the motivations and scope of this research, summarizes the original contributions, and overviews the organization of this dissertation. Chapter 2 presents an introduction to REM and provides relevant technical background. Two interesting analogies are presented which provide insights into both CR and REM. This chapter also reviews the related work and introduces some new terms in CR research. Chapter 3 presents a novel approach to developing CR and cognitive wireless networks based on REM. This chapter discusses the role of REM in CR networks, summarizes various types and levels of situation awareness, and presents the applications of Local and Global REMs in different radio scenarios. Chapter 4 focuses on the REM data model and main attributes, and presents a reference REM design for a specific CR application: the IEEE 802.22 WRAN base station cognitive engine. This chapter also summarizes various approaches to populating the REM. Chapter 5 focuses on the signal processing techniques in the context of WLAN interference management, which are employed to populate the REM in the radio domain. Applications of REM to cognitive

WRAN systems are also discussed.

Chapter 6 details how to exploit the REM with cognitive engine algorithms. This chapter presents the framework of REM-based situation-aware cognitive engine learning algorithms, details the REM-enabled case- and knowledge-based learning algorithm (REM-CKL) and compares its performance against the genetic algorithm. REM-enabled cognitive cooperative learning (REM-CCL) is also proposed to support dynamic objectives of learning or cooperation among CR nodes. REM dissemination schemes and the resulting overhead are analyzed under various network scenarios. Chapter 7 discusses the performance metrics and utility functions with more details and addresses the performance evaluation methodology for CR networks. This chapter also defines the performance metrics and utility functions for various CR networks, introduces the REM-based scenario-driven CR testing (REM-SDT), and evaluates the performance of REM-enabled spectrum-sharing networks.

Chapter 8 summarizes the main conclusions of this research, gives more insight into the characteristics of CR and the key features of REM, provides recommendations for future research, and provides a view of the future of REM-enabled CR.

Appendix A summarizes the waveforms in the TV, ISM, and UNII bands, which are of concern for WLAN or WRAN systems. Appendix B provides mathematical models for the signals in the TV, ISM and UNII bands.

2 Introduction to REM and Interdisciplinary Technical Background

This chapter starts with some insightful analogies about the cognitive radio engine (CE) and radio environment map (REM) and then explains the new concepts and terms of CR research. Due to the inter-disciplinary nature of CR research, the technical background for a wide range of areas (such as artificial intelligence, database design, signal processing, and wireless networking) is briefly reviewed.

2.1 Insightful Analogies for CR and REM

Let us first discuss an interesting analogy between two intelligent agents – a taxi driver and a CR, and then introduce the REM as a cost-effective navigator for CR. The CE, which is the cognition core of the CR, is typically implemented as a software system consisting of learning and adaptation algorithms.

2.1.1 An Analogy between a Taxi Driver and a Cognitive Radio

The analogy between a taxi driver and a CR is shown in Figure 2-1. In this figure, the CR is symbolized as a "brain"-empowered radio. The comparison of cognition components between these two intelligent agents are listed in Tables 2-1 and 2-2. The situation awareness and performance measure for a taxi driver or pilot have been extensively discussed [12, 13]. Having the capability of comprehensive situation awareness is one of the most important features that differentiate a CR from an adaptive radio.

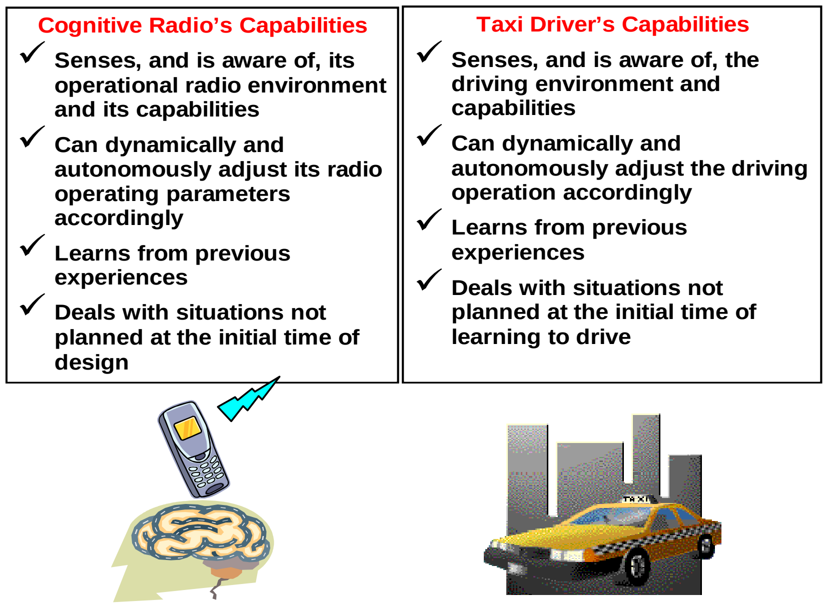


Figure 2-1: An Analogy between Two Intelligent Agents: a CR and a Taxi Driver

It is apparent that both intelligent agents observe the operational environment and become aware of their situations, make *in situ* decisions according to their observations, anticipations, and experiences, and then execute intelligent adaptations to maximize their utilities subject to many constraints. They evolve by a spiral learning process (also known as the "cognition cycle") throughout their lifetime.

Table 2-1: Analogy between Two Intelligent Agents: a Taxi driver and a CR Engine

Agent Type	Environment	Performance Measure	Sensors	Actuators
Taxi Driver [12]	Roads, other traffic, pedestrians, and customers.	Safe, fast, legal, comfortable trip, maximize profits, minimize collisions.	Cameras, sonar, speedometer, GPS, odometer, accelerometer, engine sensors, keyboard.	Steering, accelerator, brake, signal, horn, display.
Cognitive Radio Engine	Radio spectrum, other traffic by primary user and secondary user, jammer, RF noise, and interference.	Spectrum utilization, reliable, fast, legal, cost-efficient, low power consumption; minimize interference.	GPS, antenna, BER/PER/FER, interference temperature, QoS.	Transmission power control, MAC, beamforming.

Like the taxi driver, the CR may also have three levels of situation awareness, as shown in Table 2-2.

Table 2-2: Three-Level Situation Awareness

Agent Type	Level 1 Awareness	Level 2 Awareness	Level 3 Awareness
Taxi Driver (or Pilot) [13]	*Looks* for and *perceives* basic information.	*Thinks* about and *understands* the meanings of that information.	Uses the environmental understanding to *anticipate* what will happen ahead in time and space.
Cognitive Radio Engine	With focused attention, *observes* the RF spectrum, as well as waveform and surrounding activities.	Performs calculation, estimation, and reasoning, and *understands* the radio activities around it.	Performs prediction and planning to *anticipate* radio performance, network requirements, and user needs.

To appreciate the significance of three-level awareness, consider the following scenario: Suppose you are driving from your office to a restaurant for lunch. You may make many "cognitive" decisions and adaptations according to your current situation, observations, and previous experience.

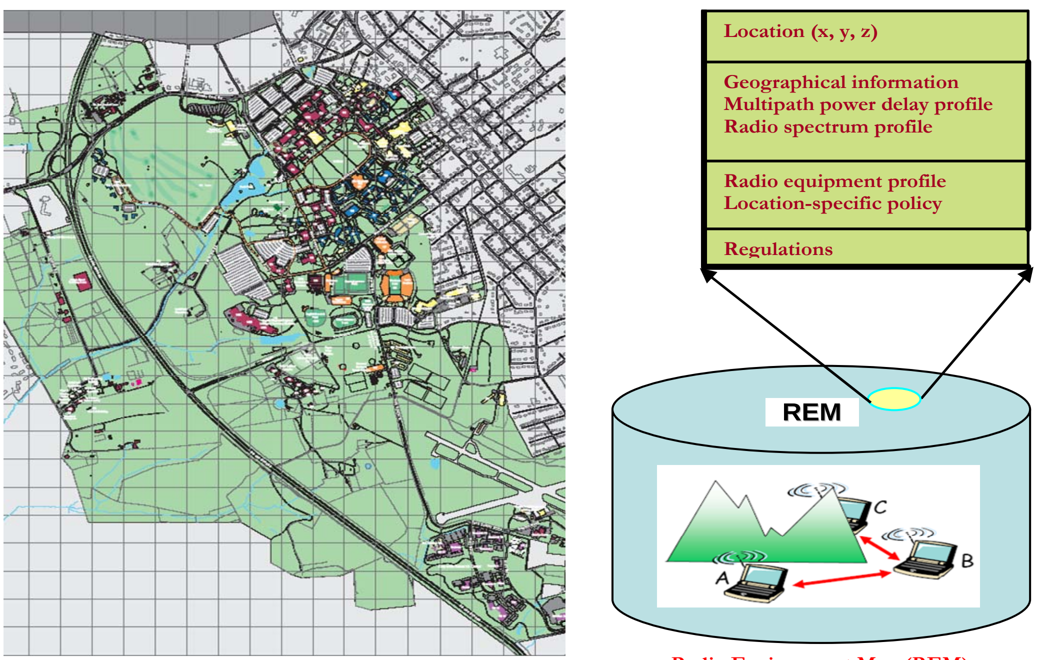
- If you have a tight schedule for lunch, you may prefer to drive through a nearby fast-food restaurant.
- If it is a sunny Friday and you want to enjoy the lunch with your buddies, you may carpool with your friends to a nice restaurant in another town.
- If it is a rainy day and the road is curvy, you may turn on the headlights and drive slowly to avoid accidents.
- As you drive, you still need to be aware of the traffic lights, road signs, and speed limits.
- You may look up a map for directions, or recall from your memory the most convenient way (or perhaps a short-cut) to the restaurant.
- When you learn from the radio news broadcast that there is an accident ahead, you may anticipate that it will result in slow traffic and choose an alternative route.

This list could be extensive, considering the many other possible situations and their adaptations for a simple automotive errand. Obviously, the CR has both awareness and learning capability, but with an REM the ability to predict radio performance is facilitated as readily as predicting the path distance for the trip.

2.1.2 An Analogy between City Map and Radio Environment Map (REM)

This section presents another insightful analogy about CR and then introduces the REM as a cost-efficient navigator for CR. The REM is essentially a comprehensive spatio-temporal database and an abstraction of the real-world radio scenarios [11, 14].

Similar to how a city map helps a traveler, the REM can help the CR know the radio environment by providing information on, for example, spectral regulatory rules and user-defined policies to which the CR should conform; spectrum opportunities; where the radio is now and where it is heading; the appropriate channel model to use; the expected path loss and signal-to-noise ratio (SNR); hidden nodes present in the neighborhood; usage patterns of primary users[3] (PU) and/or secondary users (SU); and interference or jamming sources. Figure 2-2 shows such an insightful analogy.



City Map for Travelers

Radio Environment Map (REM)
for Cognitive Radios

Figure 2-2: City Map versus REM. A REM provides services to cognitive radios similar to the way a map aids a driver with local navigation. The REM database must be current to be useful.

Figure 2-3 illustrates various layers of information that might be included in the REM. The REM can provide both current and historic radio environment information, so most cognitive

---

[3] Primary users usually hold the license to use certain spectrum. Therefore, primary users have higher priority over secondary users. For more discussion on primary and secondary users, please refer to [15].

functionalities in the cognitive radio network can be realized in a cost-efficient way. By leveraging the REM, cognitive radio can conduct the spectrum sensing with prior knowledge rather than *continually* and *blindly* scanning over the whole spectrum all the time. Thus, observation time and energy consumption in the radio front-end can be significantly reduced. Together with collaborative information processing techniques, the costs of a cognitive radio system can be further reduced by relaxing the requirements on transmission power, dynamic range, and sensitivity of the individual radio device. By combining reasoning and learning with data mining the REM, the network intelligence directly enables cognitive capabilities for its network nodes whether or not these node radios are cognitive. In this sense, even legacy networks can become cognitive by resorting to a REM. The REM also supports a system-level solution to the fundamental CR technical challenges, such as situation awareness, hidden node and/or exposed node problem, load balancing across the network, and dynamic spectrum regulation or policy. REM may affect the network architecture, system design, and operation and management of CR. REM helps on both "node intelligence" and "network intelligence."

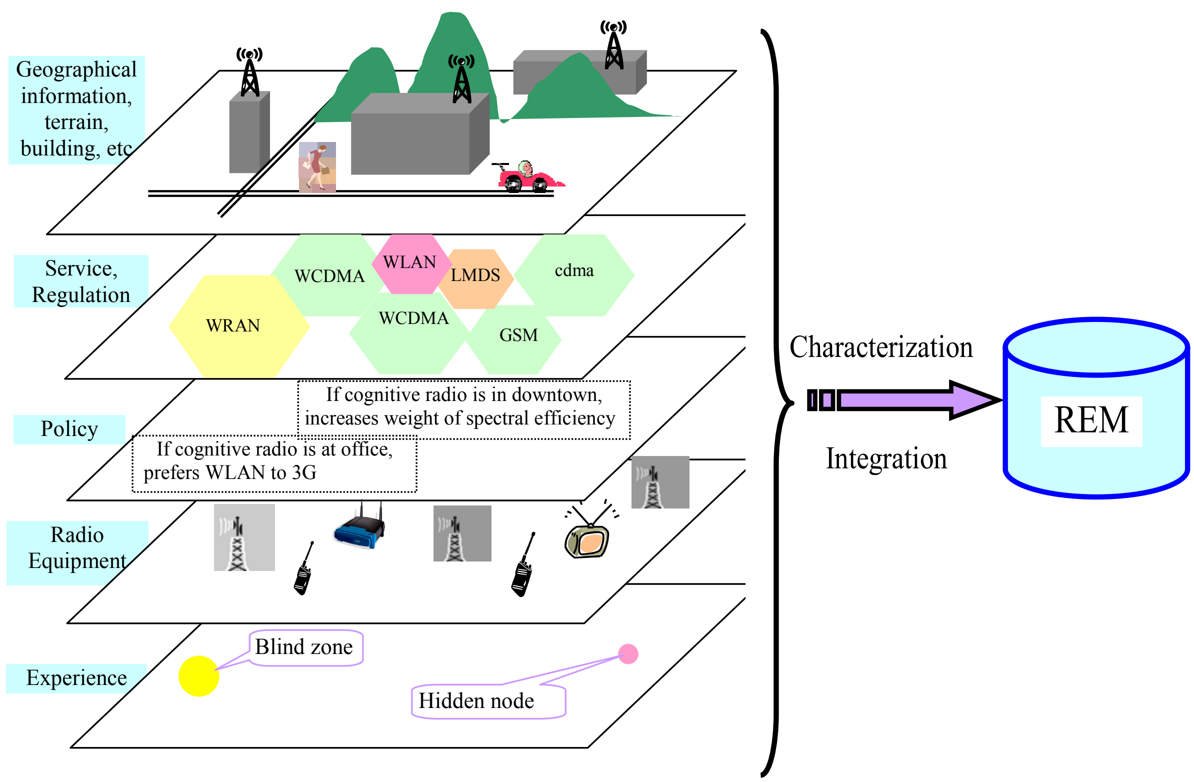


Figure 2-3: REM: An Integrated Database Characterizing the Real-World Radio Scenario

2.1.3 What Can We Learn from the Analogies?

Transportation and telecommunication share many common issues, such as the concept of throughput, channel capacity, routing, signaling, rules, etiquette, and efficient utilization of resources. Enlightened by these analogies, some lessons from transportation may be drawn and employed in the field of CR.

Just like a good road map can effectively guide you to reach your goal, the REM is a vehicle of intelligence for CR. The radio itself may not necessarily be very smart, but the informative (intelligence-embedded) REM can support the radio to make sensible adaptations. This means the REM enables or supports cognitive functionality to the CR user terminal. Building up and maintaining a good REM is very important for CR.

There are various types of city maps for different purposes (such as shopping and sightseeing); similarly, there would be various types of REMs for different CR applications. There is no single fixed performance measure suitable for all CRs. It is better to design the REM and performance measures according to what one actually wants in the environment rather than according to how one thinks the agent (CR) should behave.

Rewards and punishments may be used as a method of supervised learning for CR, just like the police issue traffic tickets to violators and insurance companies reward good drivers with lower rates. Certification, etiquette, and regulation are needed for both vehicle transportation and CR. Furthermore, learning is life-long practice for both the taxi driver and the CR.

2.2 New Concepts and Terms in the Field of CR Research

CR research has introduced several new concepts and terms, such as the interference temperature, spectrum hole, cognitive engine, and policy engine. These concepts and terms are explained in this section.

2.2.1 Interference Temperature

The U.S. FCC proposed an *interference temperature* model for quantifying and managing interference [16] [4]. Interference temperature (IT) is “a measure of the RF power generated by undesired emitters plus noise sources that are present in a receiver system ($I + N$) per unit of bandwidth,” or, in other words, the temperature equivalent of such RF power measured in units of “Kelvin” (K).

$$IT = \frac{I}{kB} \tag{2-1}$$

where I is the upper limit of interference power, N is the noise power, k = 1.38x10^{-23} joules per degree Kevin, and B is the bandwidth of receiver.

This new concept could shift the current method for managing interference which is based on strict predetermined transmission policy, to an approach that is based on the actual radio environment, real-time measurement, and opportunistic spectrum availability. The interference temperature model could represent a fundamental paradigm shift in the FCC’s approach to spectrum management by allowing opportunistic use of the spectrum and hence result in more efficient use of spectrum. The interference temperature limit for the band would serve as an upper bound or “cap” on the potential RF energy that could be introduced into the band, as illustrated in Figure 2-4. With the interference temperature in a specific part of the wireless spectrum, it may provide a means for unlicensed devices to operate within an occupied spectrum without causing any significant performance degradation.

Interference temperature has aroused controversy. Broadcasters expressed doubts about the technical feasibility of establishing an interference temperature metric. The National Association of Broadcasters and Maximum Service Television, Inc., in addition to Cingular, Verizon Wireless, Wireless Communications Association, Motorola, AT&T Wireless, CTIA, and the Wi-Fi Alliance all claimed that the interference environment is extremely difficult to

---

[4] The FCC has recently dropped all forms of the proposal on introducing “interference temperature”. According to the order (FCC-07-78) released on May 4, 2007, the FCC is “terminating this proceeding without prejudice to its substantive merits.”

monitor [17]. It was also pointed out that the difficulty (of using the interference temperature model) lies in effectively measuring the interference temperature, where the characteristics of a victim's receiver are unknown (e.g., the receiver's antenna pattern) [18]. This problem is one example of the "hidden node" problem that has been a key stumbling block for CR [19]. Therefore, the "interference temperature" metric itself cannot effectively protect the licensee in many situations. Furthermore, interference tends to be a very complicated issue in wireless communications. However, the current definition of interference temperature does not take the interference excision capability at the receiver, the spectral and temporal features and the spatial distribution of interference source into consideration. The REM may help to turn "interference temperature" into a more practical approach for spectral management by providing the needed information on interference source and radio equipment (including antenna pattern, receiver specifications such as noise figure, and the interference excision capability of the receiver) and sharing such information to protect the incumbent radios and mitigate the hidden node (or hidden receiver) problem. The interference temperature distribution map can also be viewed as a layer (or a variant) of the comprehensive REM and could be employed for interference-aware routing or topology control in CR networks.

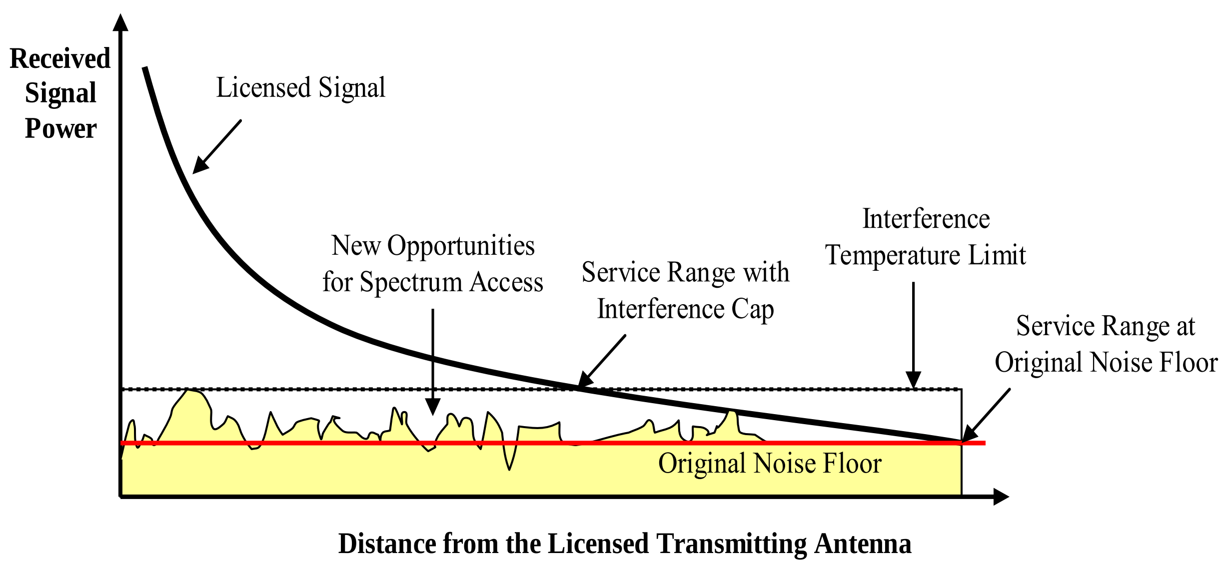


Figure 2-4: Interference Temperature: A Model for Quantifying and Managing Interference

2.2.2 Spectrum Hole (Spectrum Opportunity)

A *spectrum hole* is a band frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not being utilized by that user [Haykin 05]. Detecting spectrum hole is one of the most important observation objectives for CR.

2.2.3 Cognitive Engine

The *cognitive engine* (CE) is the "brain" or intelligent agent of a CR. The CE is essentially "a *software package* that can make *any* electronically agile radio platform cognitive" [20] in the sense that "the radio is:

- aware of itself, its user, and its environment;
- capable of experimenting and learning;
- capable of configuring itself to achieve a wide variety of goals" [20]

Conceptually, the CE responds to the user's commands by configuring the radio for whatever combinations of waveform, protocol, operating frequency, and networking are required. It monitors its own performance continually and adjusts the radio's settings to deliver the needed quality of service (QoS) subject to an appropriate combination of user policy, operational limitations, and regulatory constraints.

2.2.4 Policy Engine

Policy engine is a term from the U.S. DARPA next generation (XG) program. The policy engine constrains the behaviors of the CR so as not to violate certain conditions such as frequency, bandwidth, and transmit power restrictions for various locations.

The XG program intends to solve two emerging problems, i.e., spectrum scarcity and difficulty of wireless communication system deployment, by introducing a protocol for spectrum and policy agility. Policy agility is achieved by exchanging policies using machine-understandable policy language among XG nodes, such as Web Ontology Language (OWL). The policy can be loaded into the radio node on-the-fly or by using an offline method. To accomplish policy agility, the XG program uses an approach that decouples policies from behaviors and behaviors from protocols [21].

Through abstraction, the XG program decouples policy, behavior, and protocol. Decoupling allows adaptation to policies that vary over time and geography. Decoupling behaviors from protocols allows us to control what needs to be done separately from how it is implemented, resulting in a simple and more flexible architecture. A decoupling approach is not just beneficial but pretty much a requirement for harnessing the full potential of opportunistic spectrum access. One of the benefits of decoupling is traceability, that is, the ability to associate each emission with a policy or a set of policies that permit this emission. Traceability is a valuable feature that will help address the painful verification and validation problem. For the XG Program, a policy database is proposed for the policy engine. The policy may be a broad concept, covering networking, routing, and spectrum [80]. Policy awareness of CR can be achieved through a relational search by the policy engine.

2.3 Interdisciplinary Technical Background

2.3.1 Artificial Intelligence

Artificial intelligence (AI) began to emerge as a separate field of study during the 1940s and 1950s, when the computer became a commercial reality. AI means the simulation of human behavior and cognitive processes on a computer [88]. The field of AI is generally associated with computer science. Nevertheless, it has important links with fields such as mathematics, cognition, biology, and philosophy among others. AI is both an art and a science [88]. The ability to learn or adapt one’s behavior to a new situation is a vital component of intelligence. The fundamental issues of AI involve knowledge representation, search, perception, and inference. Knowledge can be available as collections of logical assertions, heuristic rules, procedures, statistical correlations, etc. Organizing knowledge is an important issue in the learning process. Knowledge also includes a framework in which the various facts and aspects of experience can be stored [88]. Searching techniques are very important, which can help to avoid the combinatorial explosion problem encountered by brute force attempts. Inference is the process of creating explicit representations of knowledge from implicit ones, which can be viewed as the creation of knowledge itself. A number of techniques that are currently popular within the area of applied AI include expert systems, fuzzy systems, neural networks, genetic algorithms, swarm intelligence, and (soft) case-based reasoning [67, 88]. A quantum jump in capabilities of traditional case-based reasoning systems is achievable through the recent development of soft case-based reasoning (SCBR) [67]. SCBR is based on soft computing, a computing methodology that is a coalition of methodologies which collectively provide a foundation for the conception, design, and utilization of intelligent systems. The principal members of the coalition are fuzzy logic, neurocomputing, evolutionary computing, probabilistic computing, chaotic computing, rough set theory, self-organizing maps, and machine learning. An essential tenet of soft computing is that, in general, superior results can be achieved by employing the constituent methodologies of soft computing in combination rather than in a stand-alone mode [67].

The term "cognitive" comes to the radio community via the AI and computational science realm. The study of intelligence and reasoning systems in the AI sense falls into two broad categories: (1) systems that think and act like humans and (2) systems that think and act in a purely rational (e.g., "logical") manner [22].

In the AI literature, the term "cognitive" is consistently applied to systems that exhibit human-like qualities in their processing. Cognitive science is concerned with modeling machine reasoning processes in accordance with those exhibited by humans. The human-like processes are not limited to purely rational ones but can encompass processes that are inconsistent with strict rationality when reasoning, problem solving, planning, and learning. Furthermore, the inputs, outputs, and internal behaviors of a cognitive system are consistent with human behavior in both conduct and timing [22].

In 1950, Alan Turing proposed a set of tests (known as the "Turing Test") for a system to possess intelligence:

- Natural Language Processing: communicates in human-understandable language,
- Knowledge Representation: stores information (in an ordered manner),
- Automated Reasoning: answers questions and develop new conclusions, and
- Machine Learning: adapts to new circumstances and detects/extrapolates new patterns

Looking at the Turing Test criteria, most of the four criteria are applicable to establishing CR characteristics. CR with appropriate memory, software, and processing capabilities can store information (knowledge representation) and reasoning in an automated manner to develop new conclusions, and employ machine learning processes [22].

Russell's book, *Artificial Intelligence: A Modern Approach,* is an excellent reference and details how cognition is traditionally viewed in an engineering context [12].

2.3.2 Database

The database is at the heart of most business transaction processing systems. If we envision CRs' activities as "radio transactions," then it becomes apparent that databases would be at the heart of future CR networks for various cognition functions, such as situation awareness, case-based learning (CBL), and knowledge-based learning (KBL). This motivates us to develop an integrated database, radio environment map (REM), which combines environmental information, past experience, and radio knowledge altogether. The goal is to enable CR to become situation-aware by simply referencing the REM. Note that database technologies have been developing rapidly to meet the challenging requirements of new applications, such as web-based and mobile databases. This subsection presents an overview of the database technology and the latest developments and discusses the role and special requirements of databases in CR networks. For more details about databases, refer to [24, 47].

Figure 2-5 illustrates the role of databases in the cognition cycle of CR [2] and the underlying database techniques, such as database design, access, and management.

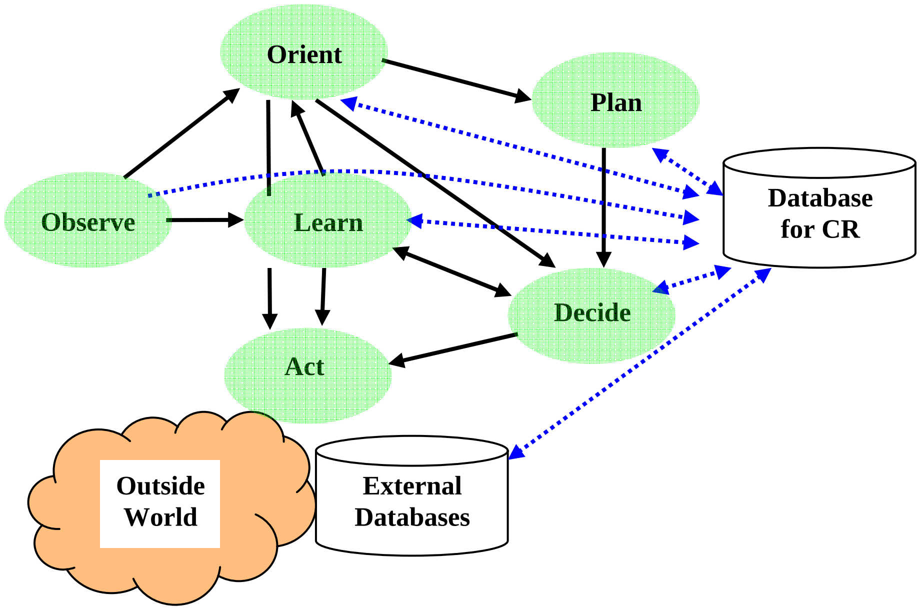


Figure 2-5: The Role of the Databases in the CR Cognition Cycle

2.3.2.1 Special Requirements on the Database for CR

Modern computer and communication technology has led to significant advances in the architecture, design and use of database and transaction processing systems. Their enhanced functionality has led to important new opportunities for CR and includes a number of additional requirements on their operation, as listed below.

- High availability: The database is online at all times when the CR system is in operation.
- High reliability: The database must accurately reflect the current results of all "radio transactions."
- High throughput: As CR networks may support many users, the database must be able to support many transactions per second during the busiest periods.
- Low response time: To reduce harmful interference to the lowest level, the database needs to respond quickly, for example, when the primary user is detected.
- Security and integrity assurance: The information in the database must not be corrupted or read by an attacker.
- Small footprint: The database's memory requirement should be appropriate for a portable radio.

2.3.2.2 Comparisons between Different Types of Databases

A brief overview of various types of databases is presented in Tables 2-3, 2-4, and 2-5. Careful selection should be made according to the specific application scenario and system requirements of the CR network.

Table 2-3: Relational vs. Object-Oriented vs. XML Databases

Types of databases	Key features	Status
Relational database	A relational database consists of relations, which are sets of tuples.	Simple and well standardized; Widely used.
Object-oriented database	An object database consists of classes, which are sets of objects.	Becoming popular in mainstream both independently and as extensions to existing relational products.
Object-relational database	An object-relational database consists of a set of top-level classes and could be implemented as conservative extensions to the existing relational database.	Started in early 1990s, SQL: 2003 gave support for the full object-relational submodel of conceptual object data model.
XML database	An XML database deals with web-data, which is semi-structured data with the following characteristics: object like, schema-less, and self-describing.	Represents an emerging field that is expected to become important once the underlying standards and tools are developed.

Table 2-4: Centralized vs. Distributed vs. Mobile Databases

Types of databases	Key features	Status
Centralized database	A single logical database located at one site under the control of a single database management system.	Traditional database, may become obsolete in the future
Distributed database	A logically interrelated collection of shared data physically distributed over a computer network.	Experiencing rapid development in recent years; Difficult integrity control, lack of standards, lack of experience, more complex design.
Mobile database	A database that is portable and physically separate from the database server.	Mobile computing is emerging and challenging.

Table 2-5: On-Disk Database vs. In-Memory Database

Types of databases	Key features	Status
On-disk database	Disk I/O process is needed.	Traditional database
In-memory database	A database that keeps all active records in main memory rather than on disk. Accessing in-memory records is considerably faster than retrieving them from the disk. This database can be used for mission critical applications. The problems are start-up time and memory footprint.	Commercially available (e.g., McObject's eXtremeDB™). If the database has less than a million tuples, in-memory database can be very good (Source: http://www.mcobject.com/).

2.3.3 Spectrum Sensing, Signal Classification, and Positioning

2.3.3.1 Spectrum Sensing

The most common methods for spectrum sensing include, but are not limited to, the following methods:

- energy detector,
- matched filter,
- feature detection (e.g., the cyclostationary method [87, 89]),
- periodogram, and
- multitaper method.

For more details about these methods, refer to [14, 77, 87].

2.3.3.2 Signal Classification

Many algorithms can be used for automatic modulation classification (or recognition) of radio signals [25, 26]. Common approaches include:

- decision-theoretic approach [27],
- nearest neighbor rule [28],
- artificial neural networks [27],
- hidden Markov models [89], and
- fuzzy logic [29].

These algorithms have some limitations. They can be used for traditional narrowband analog/digital modulated signals (such as AM/FM, ASK, PSK, QAM, and MSK) and may not be effective for DSSS/FSSS/OFDM wideband signals. They only can work well at high SNR conditions. For AM, FM, MASK, MPSK, and MFSK signals, it is reported that the threshold SNR for correct signal classification is about 10–15 dB [25, 26].

Specific physical layer properties of the signals in the TV/ISM/UNII bands (see Appendix A and B for a summary of waveforms and mathematical models for the common signals in these bands) enable techniques that are better than neural network/fuzzy logic for performing signal classification. For example, algorithms in the "SCORE" class of signal processing [30, 31, 32] and fast detection techniques such as "DMP" [33] can be employed.

2.3.3.3 Positioning

Location information is one of the most important attributes to CR. A lot of research has been done on positioning techniques. Different categories of wireless positioning techniques have been introduced for various communication systems. Several different implementations exist for each communication system, resulting in a fairly large diversification of the market. For example, the accuracy of WLAN-based positioning systems is approximately 3–30 m, with an update rate in the range of a few seconds [34]. Techniques employed for wireless geolocation include the following:

- received-signal strength (RSS) based systems,
- angle-of-arrival (AOA) based systems,
- propagation-time based systems, which can further be divided into three different subclasses: time-of-arrival (TOA), roundtrip-time-of-flight (RTOF), and time-difference-of-arrival (TDOA). For example, reciprocity exploitation techniques are based on the propagation time and exploit known symmetries in the uplink and downlink propagation channels. This method includes the RTOF approaches, as well as other approaches exploiting two-way handshakes between terminals, e.g., RTS/CTS exchanges in 802.11 WLAN.
- RF fingerprinting techniques extend the techniques described above to environments with significant or dominating multipath [35, 36].

- Hybrid methods combine more than one of the above techniques.

However, it should be cautious when using of the position information for CR's adaptations. Note that the path loss cannot be reliably estimated solely using the location and range information, since the geographical environment and node mobility are important factors that also need to be considered for choosing the right channel model and applying the channel model with proper parameters. For example, the path loss cannot be exactly inferred from the range between the transmitter and the receiver in the presence of shadowing and fading. This observation suggests using REM cautiously for path loss related decisions. In the absence of any information about statistical variation in path loss at the PU nodes and SU nodes, decisions made solely based on the median path loss model (such as Hata Model [45]) could lead to serious problems (e.g., "harmful interference" to PU nodes). The CR nodes may have to be forced to adopt overly conservative decision criteria to avoid such errors. This affects the "utility" of position as a metric to make decisions, especially in the presence of severe statistical path loss variations. Additional attributes, such as position accuracy of radio nodes and confidence interval of path loss estimation should be added to the REM in order to make it more valuable and to solve the potential miss-leading problem as well.

2.3.4 Wireless Ad Hoc Network Routing Protocols

An ad hoc routing protocol is a convention or standard that controls how nodes come to agree which way to route packets between computing devices in wireless ad-hoc networks. The many existing ad hoc networking protocols can be classified into three general classes as follows: proactive, reactive, and hybrid protocols.

Proactive (table-driven) algorithms maintain fresh list of destinations and their routes. For example, OLSR (Optimized Link State Routing Protocol)–RFC 3626 and TBRPF (Topology Dissemination Based on Reverse-Path Forwarding Routing Protocol)–RFC 3684. The OLSR is a table-driven proactive protocol [37]. As its name suggests, it uses the link-state scheme in an optimized manner to diffuse topology information. Reactive (on-demand) protocols find a route when no designed route is found. For example, AODV (Ad hoc On-demand Distance Vector Routing Protocol)–RFC 3561. The Zone Routing Protocol (ZRP), as an example of hybrid (proactive/reactive) protocol, uses Intra-zone Routing Protocol (IARP) as proactive and Inter-zone Routing Protocol (IERP) as its reactive components.

The performance of a protocol may depend on many factors, such as mobility of nodes, network topology, geographical environment features, traffic patterns, service types, and performance metrics. Therefore, cognition and adaptation are needed for dynamically choosing the most appropriate protocol for a specific radio scenario. Currently, wireless ad hoc networks usually employ the predefined static routing protocol. SDR-based cognitive wireless networking may present more flexibility and compatibility to wireless ad hoc networks. REM can be exploited for cognitive networking, owing to its rich global or local environmental information and prior knowledge.

3 Network Support with REM: A New Approach to Realizing CR

This chapter discusses the motivations and the important role of network support in cognitive radios and then explains how the REM can provide network support to cognitive radios for various applications. The main concerns and research issues of network support are also addressed in this chapter.

3.1 Introduction to Network Support for CR

3.1.1 Motivations

The motivations for network support for cognitive radio are threefold. First, with powerful network support, the requirements on cognitive radio user equipment could be significantly relaxed because many computation-intensive cognition functionalities can be realized at the network infrastructure. Distributed and collaborative information processing over the network can reduce the workload of a single user's equipment and speed up the adaptation process of the CR. This is an important strategy to facilitate the commercialization of CR technology, considering the many constraints imposed on cost-sensitive user equipment, such as limited battery power, signal processing capability, and memory footprint.

Secondly, key cognitive functionality, such as incumbent primary user detection, cannot be reliably accomplished by user equipment itself due to the shadowing or fading effects of radio propagation and the practical system limitations of the sensitivity, dynamic range, and noise floor [14, 19]. The radio has to resort to network support for many situations to mitigate the hidden node (or hidden receiver) problem and achieve the operational goals of CR.

Lastly, network support is critically important to the evolution of wireless communications from legacy radios to CRs as well as from the coexistence of various disparate radio networks to converged cooperative networks. As explained in this chapter, network-enabled CR offers maximal flexibility to the government, regulator, and service provider by supporting dynamic policies on spectrum access and utilization.

The REM is proposed as a vehicle for network support of CR [11, 14]. The REM is an abstraction of real-world radio scenarios and characterizes the radio environment of CRs in multiple domains, such as the geographical features, regulation, policy, radio equipment profile and radio frequency (RF) emissions. The REM, which essentially is an integrated spatio-temporal database, can be exploited to support cognitive functionality of the user equipment, such as situation awareness, reasoning, learning, and planning even if the subscriber unit is relatively simple.

The REM can also be viewed as a generalization of the Available Resource Map (ARM), which is proposed to be a real time map of all radio activities in the network for CR applications in Unlicensed Wide Area Networks (UWAN) [19, 38]. REM differs from ARM in three aspects. First, the contained information is different. ARM provides the available radio resource information only, while the REM provides multi-dimensional information, e.g., REM incorporates geographical information, local radio spectrum policy information, and the radio transceivers information as well. Ideally, REM is scalable and could include all needed information for CR.

Secondly, the host is different. ARM is hosted (stored) at a centralized node (i.e., the base station of UWAN), where it is updated and maintained; while REM supports both centralized approach (Global REM) and distributed approach (Local REMs). Each CR may have a built-in Local REM.

Thirdly, the applications are different. Because the information contained in ARM and REM is quite different, the applications enabled by ARM and REM are also quite different. For example, REM could be employed to optimize the radio network topology and routing protocol, relax the RF specification requirements, or take preemptive (or proactive) measures to avoid interference, whereas ARM does not support such a wide range of applications.

3.1.2 Internal and External Network Support

From the CR user's point of view, the network support to the CR can be classified into two categories: internal network support and external network support. The "internal network" refers to the radio network with which the CR is associated. Along with various communication services, the internal network can provide some cognitive functionality as well. For example, the CR network can provide location information and location-based services to the user; it can also characterize the usage pattern of other users in the neighborhood. The "external network" refers to any other networks that can provide meaningful knowledge to support the cognition functionalities of the radio, e.g., a separate sensor network could be dedicated to gather information for CR networks as proposed in [18]. The external network could be legacy networks or other CR networks. Both internal and external networks can contribute to building up the REM and can be employed in a collaborative way. For instance, location information needed for a CR can be obtained either from internal network support through a network-based positioning method for indoor scenarios or from an external network support through the Global Positioning System (GPS) for outdoor scenarios.

As depicted in Figure 3-1, network support can be realized through the Global REM and Local REMs. In this figure, the CR is symbolized as a "brain"-empowered radio. The Global REM maintained on the network keeps an overview of the radio environment, while the Local REM stored at the user equipment presents only a more specific view to reduce memory footprint and communication overhead. The Local REMs and Global REM may exchange information in a timely manner to keep the information stored at different entities current. A common control channel can be employed for disseminating REM information between nodes[5].

---

[5] The dissemination of REM cannot rely on data links because no data link may exist between some nodes. In practice, the common control channel can use UWB, ISM, or UNII bands or a dedicated radio channel.

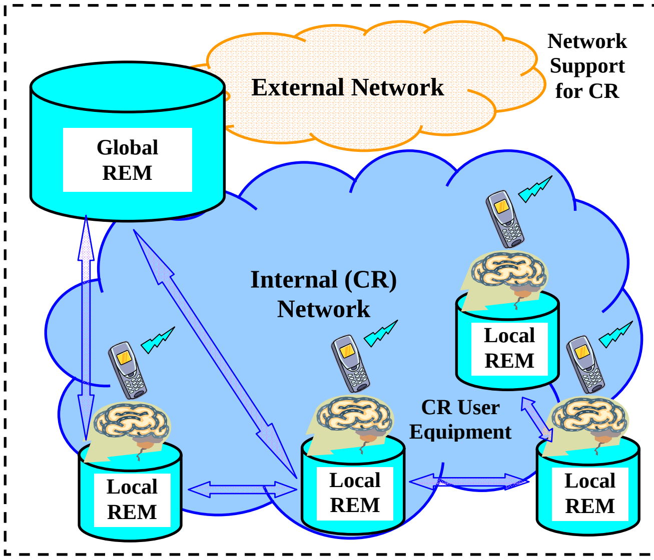


Figure 3-1: Internal and External Network Support for CR. The REM provides cognitive services to both the associated internal networks and a useful awareness of external networks such as non-cognitive legacy systems.

3.2 Obtaining Situation Awareness with REM

3.2.1 Classification of Awareness

Situation awareness means that the CR knows its current radio scenario, the intent of the user, and the regulations with which it must comply. In summary, situation awareness may include, but is not limited to, the following key types of awareness.

- *Location awareness*: The CR knows where it is, in the form of latitude, longitude, and altitude, or a location relative to some reference nodes.
- *Geographical environment awareness*: The CR knows the building, street, and terrain information related to the radio propagation and channel characteristics. This awareness is critically important for a CR to choose the appropriate spectrum, channel model, radio access technology, antenna configuration, and networking techniques.
- *RF environment and waveform awareness*: The CR knows the spectrum utilization, the existence and the distribution of primary and/or secondary users, the topology of the users, the interference profile, and other RF characteristics that may be of concern.
- *Mobility and trajectory awareness*: The CR knows its moving speed and direction. For example, in conjunction with geographical awareness, the CR can know it is moving

south along Main Street at a speed of 45 miles per hour, and it can "foresee" the radio environment ahead, such as the available channel after the user passes over the next hill or the radio standards supported along the route.

- *Power supply and energy efficiency awareness*: The CR knows the source of its power, the remaining battery life, and the energy efficiency of alternative adaptation schemes.
- *Regulation awareness*: The CR knows the spectrum allocation and emission masks at specific locations and frequency bands, which are regulated by government authorities such as the U.S. FCC.
- *Policy awareness*: The CR knows the policy defined by the user and/or the service provider. For example, the user may prefer to use the wireless local area network (WLAN) from a specific service provider at some locations for quality of service (QoS) or security reasons.
- *Capability awareness*: The CR knows its own capabilities as well as those of its team members and/or the network. Such awareness may include knowing which waveforms are supported, the maximum transmit power, and the sensitivity of the CR.
- *Mission, context, and background awareness*: The CR understands the intent of the user and knows what mode and volume of traffic it is going to generate and what the impact of that traffic will be to the local networks. The CR understands the QoS requirements and how overhead activities may trigger additional network traffic and latency.
- *Priority awareness*: The CR knows the user's priorities. For example, the user may prefer to use low-cost services whenever possible (e.g., to switch to WLAN from a 3G system when entering a Wi-Fi® zone) or may prefer reliability over low cost.
- *Language awareness*: The CR knows the signs, ontologies, and etiquette used among CRs to communicate with each other.
- *Past experience awareness*: The CR remembers and learns from past experiences.

Note that all these items can be interrelated and considered together in various ways. For example, the CR may adapt network topology and make dynamic spectrum access decisions based on the user's location, mission goal, RF environment, regulations, and service priority.

Table 3-1 summarizes various types of awareness a CR may have, the relative significance of each type of awareness, and how to obtain such awareness. The REM can support all these types of awareness directly or explicitly.

Table 3-1: Summary of Situation Awareness for CR

Type	Significance	Approaches to Obtain Awareness	Current Status
Location	High	- GPS (or assisted GPS) - network-based positioning - landmark or RF fingerprinting - combination of inertial navigation and GPS	Many kinds of positioning techniques are commercially available.
Geographical Environment	Low to Medium	- query and exploit geographical information system (GIS) database - terrain recognition - site-specific propagation prediction	The GIS database is available, e.g., from U.S. Geography Survey [78]. Many site-specific propagation tools can predict path loss, delay spread, and service coverage.
RF Environment \waveform	Medium to High	- radio transceiver database - collective observations by CRs - sensor network - field measurement	Microwave point-to-point radio, FM, and TV station databases are available and maintained by FCC, which provides radio station information, such as site location and transmission power [39].
Mobility and Trajectory	Low to Medium	By analyzing the change of locations over a period of time and correlating with GIS, the moving speed and trajectory of the user can be estimated.	Can be addressed with current technologies together with the REM
Power Supply and Energy Efficiency	Battery: High AC: Low	Measure the voltage and/or current of power supply	Mature technique, e.g., the cellular phone knows the source of its power supply and the remaining power.
Policy	High	Defined by the service provider and/or the user	Can be addressed with the policy database in the REM
Regulation	High	Defined by the government authorities.	Can be addressed with the regulation database in the REM
Capability	High	Provided by the CRs and/or networks.	Can be addressed with the capability database in the REM
Mission/ Context/ Background Environment	Low to Medium	- Using machine intelligence, various sensors. - Applying speech and/or image recognition and understanding techniques.	Common industry software tools demonstrate some context-awareness, and even interact with the user occasionally.
Priority	Low to Medium	Defined by the service provider and/or the user.	Can be addressed with the priority database in the REM
Language	Medium to High	Standardizing CR languages and etiquettes.	This is under development, e.g., by the U.S. DARPA XG Program.
Past Experience	Medium to High	Long and short term memory of experience for recall.	Can be realized with case-based decision making and other technologies

3.2.2 Obtaining Situation Awareness

The CR can obtain situation awareness through three different approaches:

(1) direct observation, e.g., through field measurement;

(2) inference from network support, e.g., through a network-maintained REM; and

(3) synergistically leveraging both direct observation and network support.

Using the analogy from Chapter 2 and supposing you are driving a car, you cannot rely on only your own vision when you drive, especially under unfavorable weather conditions (a snowstorm, for example) or at night. The map complements your limited local vision and helps you know the road conditions ahead and how far you must drive to reach the destination. You can make an informed decision about whether you need to stop at a gas station. You may take extra caution since you know the road ahead will be winding. You may schedule to have a dinner at the next rest area 10 miles ahead. In summary, you easily obtain helpful contextual information. Therefore, when we drive, we can examine the map, refresh our past experience if we have been in this location before, or just take a "trial and error" learning approach if the map or previous experience is insufficient.

Shadowing, fading, and Doppler spread are the most common degradation or distortion imparted by the wireless channel. While the multipath delay spread leads to time dispersion and frequency selective fading, Doppler spread leads to frequency dispersion and time selective fading [45]. The REM can provide the CR channel characteristics associated with a location and direction of a mobile user. Channel information can be obtained through observing instantaneous measurements of the environment as well as long-term measurements and learning of the general characteristics of the environment. Once these channel measurements are available, models can be created to predict the performance of the link. Of course, these models are stochastic and produce outputs that are random variables. The variance of model outputs can be incorporated into the decision process of CR. Furthermore, CR can take advantages of channel awareness for planning. With the awareness of shadowing and fading characteristics, CR may adopt the appropriate waveform (i.e., PHY and MAC layer) to adapt to or take advantage of the propagation characteristics. For example, in a multipath-intensive environment, CR may choose to apply multiple input/multiple output (MIMO) techniques to improve its performance. CR can also anticipate emerging call drop due to multipath or shadowing and take pre-emptive measures such as switching on the backup power amplifier, increasing the number of Rake fingers, leveraging smart antenna resources or spreading gain, altering the power control policy, or making an inter-system handoff.

The REM can exist at the user's terminal equipment (the Local REM) and/or at the network level (Global REM). The Local REM may be unique to each user's device. Each CR uses its own Local REM to memorize its past experience as well as its current status. For example, the experience of a blind zone stored at the REM of a high-quality radio could be different from that of a low-quality, less sensitive radio. As shown in Figure 3-2, by using a Global REM, it is possible that even the legacy radio network can be upgraded to support some cognitive functionality and behave as if it were a CR system. For instance, through a software upgrade to the network level radio resource management system, the legacy network can know the subscriber's location and the interference environment and instruct the radio to use the most effective physical and MAC layer supported by the user's device. A simple radio with limited cognition capability can become more capable by leveraging the REM-based network support. The Local REM may exchange information with the Global REM, for example, through some common control channel. Note: in Figure 3-2, the term "radio" may refer to any type of radio device. It could even be a cognitive RFID (radio frequency identification) tag.

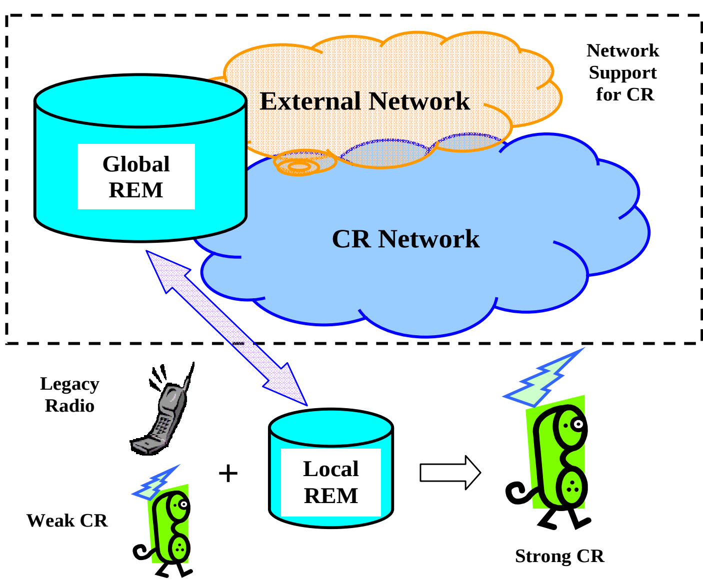


Figure 3-2: Situation Awareness through the REM. The REM helps radios become situation aware by bootstrapping them with local accumulated experience customized to each radio's functionality requirements.

3.3 Network Support Scenarios and Applications

In this section, the implementation of the REM for CR network support is illustrated through the analyses of various application scenarios requiring different network structures and services. It is shown that REM-based network support is independent from specific network topology and fits into the core of CR functional architecture.

3.3.1 Infrastructure-Based Networks and Centralized Global REM

The centralized Global REM can play an important role in many infrastructure-based radio systems, such as IEEE 802.22 Wireless Regional Area Network (WRAN) and cellular radio systems. For example, 802.22 WRAN is the first worldwide wireless standard based on CRs. It is composed of WRAN Base Stations (BS), Repeaters, and Consumer Premise Equipment (CPE). 802.22 systems are primarily targeted at rural and remote areas offering fixed wireless access services. Figure 3-3 shows a typical WRAN scenario where TV stations, TV receivers, wireless microphones, and public safety systems that operate on certain TV channels are primary users and 802.22 system subscribers are secondary users [40, 41]. Coexistence is the key requirement for 802.22 systems since the secondary users must avoid generating harmful interference to the primary users and/or other collocated secondary users.

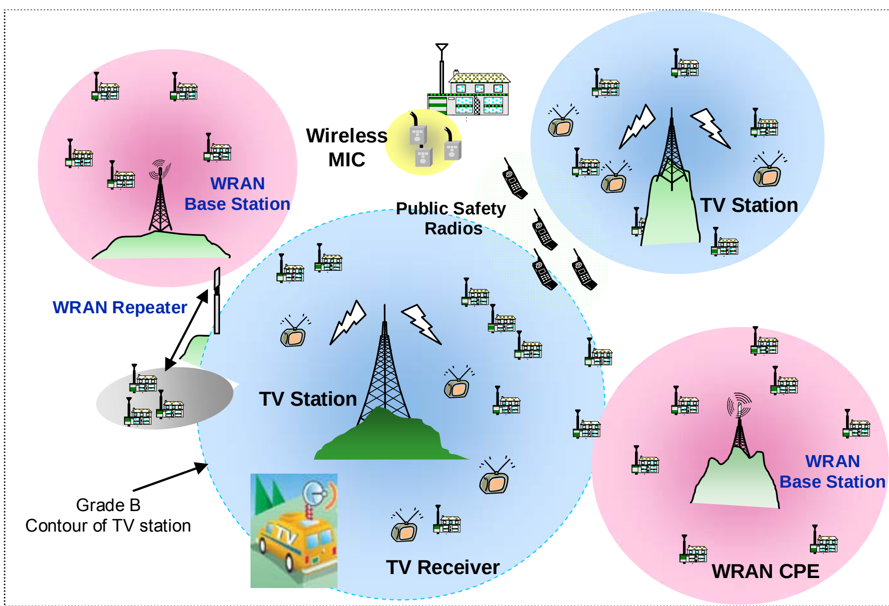


Figure 3-3: A Typical Radio Environment for Cognitive WRANs. This map aggregates the knowledge of all local wireless activities.

With a Global REM maintained at the WRAN network infrastructure, the WRAN BS can know the location, antenna height, and the transmit power of nearby TV stations; the local terrain; the Grade B service contours of TV station; the forbidden spectrum used by public safety radios; the demographical distribution of TV receivers; and the available TV channels for use; and the distribution and usage patterns of other WRAN service subscribers. Such information helps the WRAN BS choose the best spectrum opportunity to use at the optimal transmission power [49]. Smart antenna techniques can be more efficiently employed at the BS and/or the CPE with the radio environment information from the REM.

3.3.2 Ad Hoc Networks and Distributed Local REMs

Local REMs can be used in ad hoc (mesh) networks that consist of CRs. The Wireless World Research Forum (WWRF) has established a working group (WG3) to study cooperative and ad hoc networks as an integral and evolving part of the future communication infrastructure taking into account both wireless and fixed aspects [15]. In such networks, the topology can be self-organized and optimized; various modulation and coding schemes can be adapted; smart antenna and MIMO techniques can be selected dynamically; and information sharing and collaboration methods can be employed to achieve the goal(s) defined by the network or participating radios, such as maximal throughput, improved reliability, or extended transmit range. For ad hoc CR networks, distributed learning is another effective way of learning that can increase the power of CRs greatly. By sharing or exchanging the Local REMs, CRs may learn to match the right routing protocol, either proactive or reactive. Master nodes may be selected, which are responsible for collecting the distributed Local REMs and combining them into a complete radio environment map for the network. Such a complete map can be accessed by each individual node in a role similar to the routing table for an ad hoc network.

The U.S. DARPA Program *Adaptive Cognition Enhanced Radio Teams* (ACERT) intends to create a “distributed radio” greater than the sum of its parts [42] as illustrated in Figure 3-4. There are two teams of people forming two ad hoc networks in this scenario. Both intra-team and inter-team communications may be needed. Under an ad hoc mesh network scenario, the network support can be accomplished through distributed Local REMs, where multipath profile and path loss experienced by each user can be shared. Node and channel awareness can be realized by disseminating Local REMs.

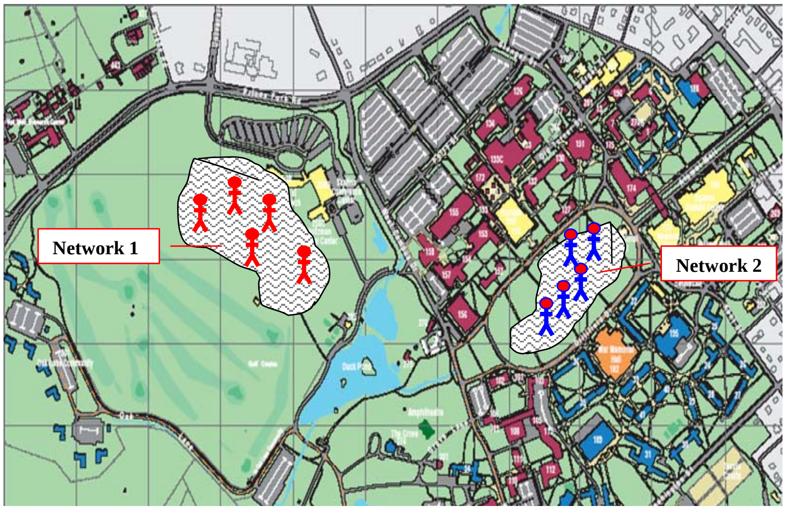


Figure 3-4: A Typical Radio Environment for Ad Hoc CR Networks. Two ad hoc networks form around two teams of users with intrateam and interteam command requirements, supported by a distributed REM database among both teams.

3.3.3 Hybrid Networks

For some applications, e.g., tactical military operations, natural disasters, or civil emergencies, a hybrid network that combines both infrastructure-based and ad hoc networks capabilities could be robust for long operating ranges and adverse conditions [43]. For such hybrid networks, both a Global REM and Local REMs could be employed at the network infrastructure and user terminals (CR nodes).

3.4 REM-Enabled CR: A New Approach to Realizing CR

3.4.1 The Role of REM in CR: A System View

The REM plays an important role in the cognition cycle of the REM-enabled CR as illustrated in Figure 3-5. Both direct observations from the radio and knowledge derived from network support can contribute to the Global and/or Local REM. The radio environment awareness of the radio can be obtained from direct observation, such as spectrum sensing, and/or from the REM. Reasoning and learning help the CR to identify the specific radio scenario and learn from past experience and observations. With reasoning and learning, decision and planning can be made to meet the goals of the CR. In turn, the Global REM and/or the Local REM should be updated once action is taken or scheduled by the radio to keep the REM's information current. It should be noted that each cognition functionality of the CR may require or affect multi-layer information contained in the REM including the radio frequency (RF) and physical layer up to the application layer.

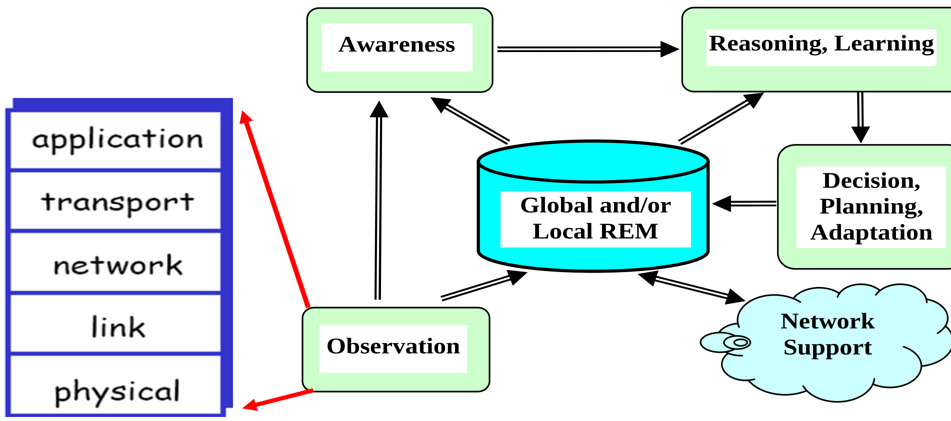


Figure 3-5: The Role of REM for CR. The REM provides the infrastructure to support the fusion of multiple cognitive services to the local subscribers.

3.4.2 Class Structure of CR: A System Design Model

A unified modeling language (UML) diagram[6] of REM-enabled CR is illustrated in Figure 3-6, which shows how the relationships between the different parts of the system are established even though the interfaces are not described [44]. At the core of the CR system is the cognitive engine (CE), which makes the decisions concerning the functionality of the system. For a CE to be useful across a variety of different environments, it must operate at a level of relative independence from the environment. Thus, the CE must be isolated from the underlying modems, thereby controlling these devices with a high level of abstraction. Furthermore, quality of service (QoS) is not only a function of the underlying modem, but also of the application that the modem is supporting, requiring the CE to also be isolated from a direct evaluation of the link QoS. Finally, the CE is a logical entity, not an environment-

[6] Note: In Figure 3-6, "1" means one entity occurrence and "1..*" means one or many entity occurrences. Software Communication Architecture (SCA), an open architecture developed by the JTRS program of the U.S. Department of Defense, may be unsuitable or unnecessary for CR due to some performance and overhead issues. For example, SCA is a static framework, which means it fails to support modifications on the fly. The limitations of SCA may have some negative impact on its application to CR.

specific construct, thus the CE must have access to a REM even though the REM remains as a separate entity used by the CE.

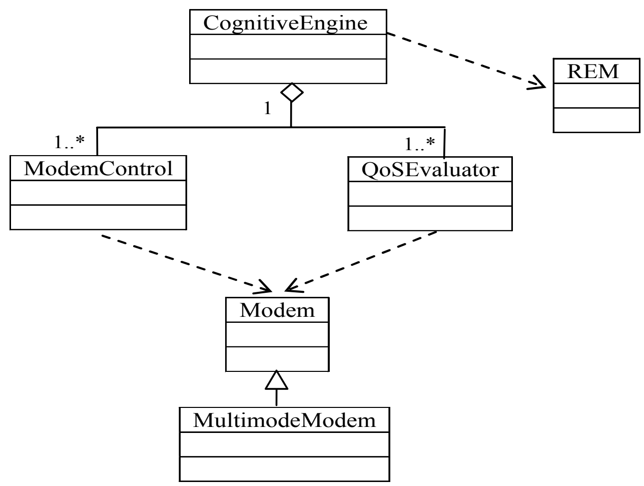


Figure 3-6: Class Structure of REM-Enabled CR

The Modem Control class contains system-specific information that allows it to either alter the operating parameters of existing modems, such as a multimode modem, or create an instance of a new modem with a new set of parameters. The modem class is the control interface for any single modem. Some modems are more complex, allowing the control structure to request a wide variety of operational parameters. For such modems, a multimode modem class is described, which is a child of the modem class. The QoS Evaluator class has the ability to evaluate service-specific parameters and convert them to a simple metric for the CE to evaluate. By isolating the CE from the evaluation of the system QoS, the QoS evaluator allows the development of relatively generic CEs.

The REM is also a separate class. Several issues concerning the mapping of environment values to a concrete set of numbers remain as research issues. Aspects like level of granularity, update cycles, depth of information, and other parametric aspects are difficult to describe in a generic fashion. Instead, it is more likely that the REM contains information that is relevant to both the underlying meaning of the QoS metric evaluated by the QoS Evaluator and the level of control available to the modems. The isolation of the REM from the CE allows the developer to create a variety of REM instances that can apply to different system implementations.

3.4.3 Enabling Techniques for Implementing and Exploiting REM

Figure 3-7 shows the inter-disciplinary research nature of the REM development for CRs. To implement and exploit the REM, various technologies are to be employed, such as artificial intelligence (AI), detection and estimation, pattern classification, cross-layer optimization, database management, data fusion and data mining, site-specific propagation prediction, and web-based ontology language.

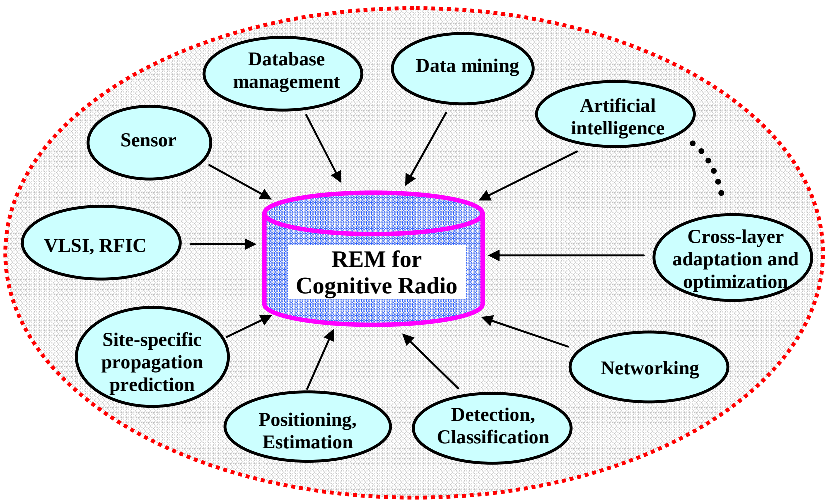


Figure 3-7: Inter-Disciplinary Research for Implementing and Exploiting REM

With the advancement of data storage technology, very large scale integration (VLSI), and radio frequency integrated circuits (RFICs), a geographical information system (e.g., 3-D digital map) and GPS receiver can be integrated into future CRs and their supporting infrastructure. For example, several electronics manufacturers have recently developed handheld products with Giga-Byte storage capacity, and many cellular phones have already been equipped with GPS receivers. Therefore, it is quite possible that future CRs will have enough memory to contain a comprehensive database, such as the REM. Radio propagation simulation tools can predict many important parameters such as path loss, signal-to-noise ratio (SNR), or signal-to-interference and noise ratio (SINR), as long as the geographical environment information is available [45]. Compared to the empirical channel model based prediction, the advanced site-specific radio propagation techniques and software tools using a three-dimensional digital map have been successfully employed to provide much more reliable predictions for radio system planning and management [46]. This makes it possible to embed several contours into the REM, such as service contour, blind zone, and interference region, which are very helpful for CRs to make decisions and adaptations.

3.5 Summary

This chapter addresses the important role of network support in developing CRs for various application scenarios including infrastructure-based networks and infrastructure-less ad hoc networks. As a vehicle to providing network support to CRs, the REM is proposed to be an integrated database that consists of multi-domain information. The REMs can be exploited by the CE to achieve or enhance most cognitive functionality. Leveraging both internal and external network support through Global and Local REMs presents a sensible approach to implementing CRs in a reliable, flexible, and cost-effective way.

Network support can dramatically relax the requirements on a CR device and improve the reliability of the whole CR network. Considering the dynamic nature of spectral regulation and operation policy, the REM-based CR is attractive and future-proof in the sense that it allows regulators or service providers to modify or change their rules or policies simply by updating the REMs accordingly. As the REM is a comprehensive database that contains multi-domain information needed for CRs, even a low-cost/low-complexity radio device can obtain basic cognitive functionalities by referring to the REM.

4 REM Data Model and Design

This chapter first presents a high-level REM design with an entity-relationship (E-R) diagram and then details a reference REM design for 802.22 WARN BS CE. This chapter also discusses the implementation options and various possible types of REMs and summarizes various approaches to populating the REM at a high level.

4.1 Conceptual Design of REM

In general, a database design can be conducted by following six steps listed below [47].

(1) Requirements Analysis: Determine user needs and understand what the database should provide.
(2) Conceptual Design: Develop a high-level description, often done with an E-R model.
(3) Logical Design: Translate an E-R model into the database management data model.
(4) Schema Refinement: Check consistency and normalization.
(5) Physical Design: Develop indexes and disk layout.
(6) Security Design: Create constraints on what information can be accessed.

More specifically, the design process for a relational database typically consists of three main phases: *conceptual*, *logical*, and *physical* design, respectively. For more detailed explanations on the (relational) database design methodology and design process, refer to [47].

The REM contains information from multiple domains as illustrated in Figure 4-1. A foreign key (e.g., radio equipment ID) can be used to link disparate databases together. By integrating or correlating various databases, the REM supports cognitive functionality for radios with different levels of intelligence. Just as a city map is informative to travelers, whether driving a car or taking the bus, the REM is transparent to the specific radio access technology to be employed.

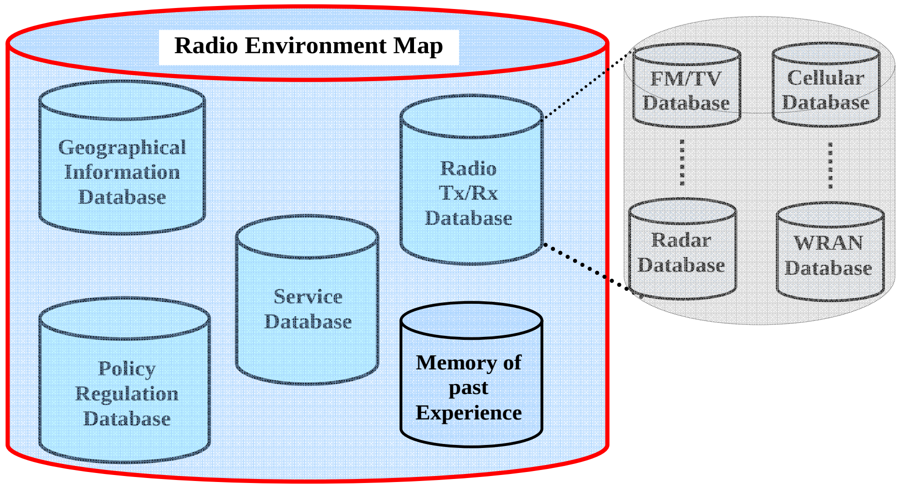


Figure 4-1: Integrating Various Databases for Building up the REM

The REM would be a multi-dimensional database, which contains both static environmental information (such as geographical information) and dynamic information (such as radio nodes' locations). The REM may not necessarily be a relational database since object-oriented and object-relational databases have their own merits. The REM could be a centralized or distributed database, depending on the radio network topology and applications. Figure 4-2 shows the E-R diagrams for a reference REM modeled as a relational database.

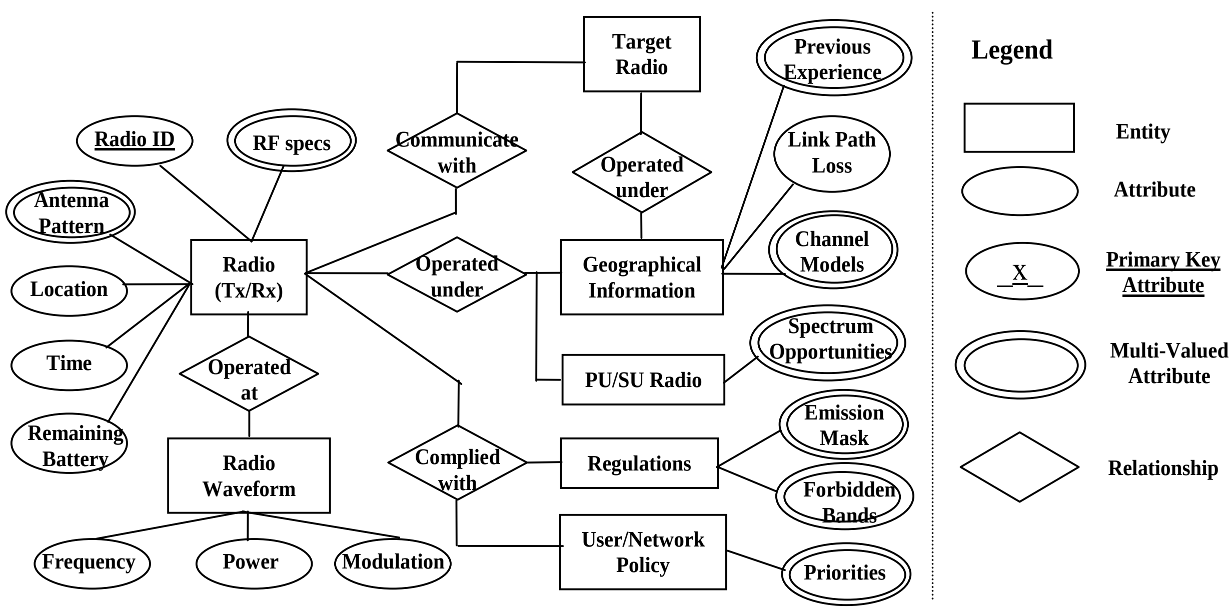


Figure 4-2: An Example of Entity-Relationship (E-R) Diagrams for REM

4.2 Classifications of REM and Illustrative Examples

In practice, we may design various types or forms of appearance of REM. According to the application of CR, the REM can be classified into application specific REM (e.g., REM designed for a specific region or for a specific application) and general purpose REM. According to the host location, we can classify REM into Local (distributed) REMs and Global (centralized) REMs. According to the appearance, REM can be classified into embedded (virtual) REMs, where the REM information is embedded into the CE and stand-alone REMs, where The REM is an independent entity which interfaces with the CE with APIs. Note that a comprehensive REM can also be "projected" onto (or "sliced" into) many sub-maps for some specific applications, such as the interference map, radio node energy map, radio node carrier offset map, PU and/or SU distribution map, and available resource map.

An instance of a CR relation is shown in Table 4-1, which shows an illustrative REM.

Table 4-1: An Illustrative Example of Simplified REM

Radio ID	Time Stamp	Location and Speed	Type of Geographical Environment	Maximal Transmit Power	Spectrum Opportunity Map	Antenna Type and Gain	Power Source or Remaining Power
0001	11/30/2005: 14:00:00	(x_1, y_1, z_1) Fixed	D*	33 dBm	0001**	4-element linear array antenna;	AC power
0002	11/30/2005: 14:00:00	(x_2, y_2, z_2) Slow moving at 3 km/h	B	20 dBm	0010	Omni; 5 dBi	Battery 100mAH
0003	11/30/2005: 14:00:00	(x_3, y_3, z_3) Fast moving at 75 km/h	C	30 dBm	0100	Directional; 12 dBi	Battery 800mAH
….	….	….	….	….	….	….	….

***** Radio environnent type index:
A - dense urban; B - urban; C - suburban; D - rural, open land; E - rural, mountains; F - indoor.
** Spectrum opportunity map index:
0001 – channel #1; 0010 – channel #2; 0100 – channel #3.

Table 4-2 shows an example of a CR capability schema with object-oriented data model: CR_Capability (CR_ID: INTEGER, Freq_Range: REAL, Max_Pwr: REAL, Mod: {STRING}, Coding: {STRING}, Ant_Number: INTEGER, Proc_Pwr: INTEGER). Table 4-3 shows an example of policy database for CRs. Table 4-4 shows an example of priority database for CRs used at different radio environments. The priority information can be used by CE when defining the utility function for optimizing the performance of CR.

Table 4-2: An Illustrative Example of CR Capability Database

Radio ID	Frequency Range	Maximal Transmit Power	Modulation Type	Coding Rate	Number of Antennas	Processing Power
0001	[50, 1000] MHz	33 dBm	{BPSK, QPSK, GMSK, 16QAM}	{½, 2/3, ¾}	2	400 MIPS
0002	[50, 2500] MHz	20 dBm	{BPSK, QPSK, GMSK, QAM16, 64}	{½, 2/3, ¾}	3	600 MIPS
0003	[50, 6000] MHz	30 dBm	{BPSK, QPSK, GMSK, QAM16, 64, 256}	{½, 2/3, ¾}	4	800 MIPS
….	….	….	….	….	….	….

Table 4-3: An Illustrative Example of Policy Database

Radio ID	Geographical Location	Most Preferred Radio Access Technology	Second Choice	Last Choice	Forbidden Bands
0001	Home	WLAN_HOME	3 G	WRAN	[700, 720] MHz
0002	Office	WLAN_MPRG	WLAN_VT	3 G	[5250, 5300] MHz
0003	Campus	WLAN_VT	WRAN	3 G	[5900, 6000] MHz
….	….	….	….	….	….

Table 4-4: An Illustrative Example of Priority Database

Geographical Location	Weight for QoS (such as BER)	Weight for Power Efficiency	Weight for Spectrum Efficiency	Weight for Costs
Home	50%	10%	20%	20%
Office	50%	10%	30%	10%
Campus	30%	40%	10%	20%
….	….	….	….	….

4.3 REM Reference Design

4.3.1 REM Information Element for Cognitive WRAN Systems

IEEE 802.22 WRAN is the first worldwide commercial application of CR networks refarming the TV broadcast bands. Tables 4-5 and 4-6 show the attributes, estimated memory size, and index of preliminary REM information elements for WRAN BS and CPE, respectively. Note that additional information elements could be added in the future along with the further development of WRAN systems (especially the mobile ad hoc operational mode of WRAN systems) and the size of the information element is a rough estimation. Most of these information elements were employed in the WRAN BS CE testbed, which has been developed by the Mobile and Portable Radio Research Group (MPRG) of Virginia Tech [91].

Table 4-5: Preliminary REM Information Elements for the WRAN BS

Attribute Index	Syntax	Estimated Size	Notes
1	BS_ID	2 bytes	BS_ID = WRAN Network ID + internal BS ID
2	BS_Location	12 bytes	GPS coordinates (longitude, latitude, and altitude)
3	BS_TxPower	1 byte	Transmit power of BS
4	Active Channel Set*	16 bytes	"*" indicates the information element is of "short-term memory" nature.
5	Candidate Channel Set*	16 bytes	
6	Occupied Channel Set*	16 bytes	
7	Geographical Environment Type	2 bytes	Type of geographical environment (such as mountainous, open rural, suburban, and urban), corresponding to different radio propagation channel models
8	CPE_Information {CPE_ID, CPE_Type, CPE_Location, Status of Connection}	44 bytes per CPE entry	CPE ID = BS_ID + subscriber ID
9	TV_Station_Information {TV Station_ID, TV_Station_Location, TV_Station_Channel, TV_Station_Power}	32 bytes per TV station entry	
10	WM_Information {WM_Location, WM_Channels, WM_in_use_likelihood, etc}	1 byte per WM entry	The value of likelihood can range from 1 to 0, which indicates the different likelihood of the presence of wireless microphone (WM), e.g., highly likely, possible, or rare.
11	Timestamp	4 bytes	The time when this observation is made

Table 4-6: Preliminary REM Information Elements for the WRAN CPE

Attribute Index	Syntax	Estimated Size	Notes
1	CPE_ID	2 bytes	Unique ID for each radio device
2	CPE_Location	12 bytes	GPS co-ordinates such as longitude, latitude, altitude, or relative position in the network.
3	CPE Location Accuracy	1 byte	Indication of the accuracy of the position estimation
4	CPE_Tx_Power	1 byte	Transmit power of CPE
5	Favorite Channel Set (i.e., "Channel Reputation" graded by this CPE)	16 bytes	Observed spectrum usage at this location; actually only about 80 TV channels are allocated between 54–862 MHz; more bits are reserved for error correction or future use.
6	Geographical Environment Type	1 byte	Type of local radio environment: indoor, mountainous, open rural, suburban, dense urban, etc., which indicates the appropriate radio propagation channel model to apply
7	Interference Temperature	2 bytes	The interference temperature estimated by the wireless node at this location
8	CPE TYPE and Capability	2 bytes	CPE type and its capability such as interference excision capability
9	Timestamp	4 bytes	The time when this observation is made
10	Channel Reciprocity Flag	1 byte	The confidence in reciprocity of the channel
11	Channel Model and Statistics	4 bytes	The proper channel model that can be applied for the CPE's current scenario, such as Rician, Rayleigh channel model and the corresponding parameters such as Rician *K* factor.
12	Path Loss Correlation	1 byte	The confidence in determining the path loss based on the geographical locations of the radios
13	CPE Velocity, Acceleration, and Orientation	6 bytes	This set of parameters provides mobility support.
14	CPE Carrier and Timing Stability and Offset	2 bytes	The carrier and timing accuracy is important information for improving network synchronization and radio resource management.

4.3.2 REM Implementation Options

The REM characterizes the real-world radio scenarios for CR. Ideally, it is a highly comprehensive and integrated database. However, when implementing it, according to the specific application and system design considerations, the REM can be deployed with any appropriate data format, as long as it can provide the comprehensive radio environment information. For example, a C++ class/structure, a multi-dimensional array (vector), a data file, or a database, are all candidate implementation options. For some applications, the REM can even be implemented in an embedded (implicit) way without a standalone REM entity, which we may call "embedded (or virtual) REM." Just as when driving, various forms of road maps may actually be used, which could be a simple sketch or as sophisticated as a three-dimension digital map. As discussed in Chapter 2, the database management system (DBMS) is a well-developed technology and many DSMSs are commercially available, such as SQL, DB2, Oracle, and so on. Commercial databases may be appropriate for managing huge radio environment information. However, commercial databases usually require much more memory footprint, and tend to be too "heavy" for the WRAN BS CE testbed. Therefore, for the current WRAN BS CE testbed, the REM is implemented in a hybrid approach: the current REM information is implemented with a C++ class "RadioEnvironmentMap," as shown below. The historical REM information can be periodically stored in data files. Also note that the current REM implementation approach is fairly general and it allows easy extension or updating to incorporate new environmental information or functionality.

```
class RadioEnvironmentMap
{
  public:
       RadioEnvironmentMap();                          // Default constructor
        ~RadioEnvironmentMap();                        // Destructor
       void AddEntry(REMDataEntry & _rde);             // Add entry to database
       bool IsEntry(const REMDataEntry & _rde);        // Query database to see if entry exists
       void Merge(RadioEnvironmentMap & _rem);                 // Merge REM databases
       bool LoadDatabaseFromFile(const char * filename);       // Load database from file
       bool StoreDatabaseToFile(const char * filename);        // Store database to file
       void AnalyzeChannelStatistics(int *& tv_channels, int & num_channels);
                                                                // Rank channel reputations
       float GetChannelReputation(unsigned int tv_channel_id);
                               // Retrieve the particular TV channel reputation from REM database
      void PrintDatabase();          // Print database to screen
      RadioEnvironmentMap & operator = (const RadioEnvironmentMap & _rde);

   protected:
       RadioEnvironmentMap(RadioEnvironmentMap & );
       REMDataEntry * database;
```

```
        unsigned int database_length;
        unsigned int database_length_max;
};

class REMDataEntry
{
  public:
    REMDataEntry();                    // Default constructor
    ~REMDataEntry();                   // Destructor
    void Print();                      // Print entry
    REMDataEntry & operator = (const REMDataEntry & _rde);
    bool operator == (const REMDataEntry & _rde);
    bool operator != (const REMDataEntry & _rde);
     // ------------------ Object variables ------------------
    int timestamp;
    int device_id;
    DeviceType device_type;
    ObjectPosition device_location;
    int geo_environment_type;
            // corresponding to the channel model or path loss exponent index for the BS-CPE radio link
    int frequency;
    int bandwidth;
    int tx_power_dBW;
};
```

Figure 4-3 shows the E-R model for the WRAN BS REM, which can be used in the REM design for the WRAN BS CE.

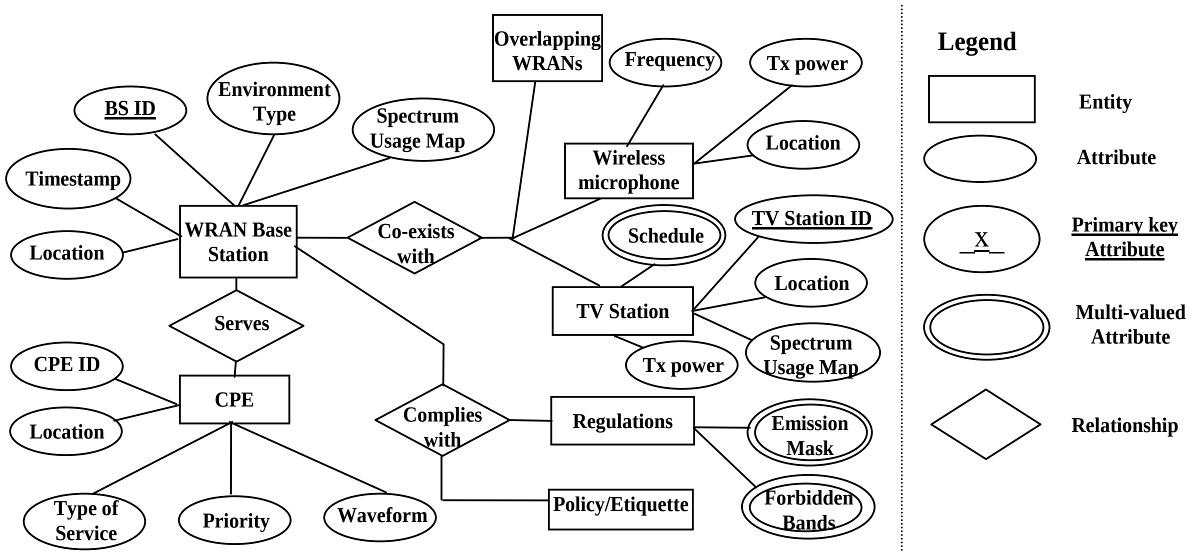


Figure 4-3: Entity-Relationship (E-R) Diagrams of the WRAN BS REM

4.3.3 Memory Management

4.3.3.1 REM Memory Footprint Estimation

Memory requirements of the REM may highly depend on the several factors:

(1) scale of network (e.g., the number of nodes, number of channels, size of network coverage, etc);

(2) granularity of REM information;

(3) specific applications of CR; and

(4) expected capability or functionality of CR.

Furthermore, the REM memory footprint may grow larger and larger along with the network operation, which indicates more and more radio scenarios will be stored, and therefore, more and more experience will be accumulated. A rough estimation of the REM memory footprint for a typical WRAN application is depicted here. Supposing a REM (database) is developed for a WRAN BS supporting up to 600 subscribers and twelve simultaneous active CPEs, the radius of the cell is 30 km and the service area of the BS is about 2,826 km^2. Each CPE entry in the REM may require 39 bytes of memory, as estimated in Table 4-6. Therefore, supporting 600 CPEs requires roughly 23.4 KB memory for one record. Storing one record per minute and 1440 records per day will require about 34 MB memory for one day and 12 GB for one year's records. Considering that the current storage device is getting cheaper with an even larger capacity and smaller form factor, the memory requirements for the REM will not be a limiting factor. By applying memory management techniques, the memory footprint of the REM could be further reduced.

4.3.3.2 Long-Term and Short-Term Memory

To efficiently manage memory for storing and accessing REM information, the REM information can be generally classified into two broad types: long-term, static or slow changing information and short-term, fast changing information. Different forgetting factors (or, equivalently, different updating rates) can be applied to these two types of information elements, such that the required memory and the access delay can be minimized. Some radio environment information is static or quasi-static, such as the location of TV stations and TV receivers, WRAN BSs, and CPEs. The locations of TV stations are available from the FCC database whereas the locations of TV receivers can be roughly identified with the demographical information (such as the population, location and distribution of residence). This kind of information can be stored in the long-term memory, and the update period for such kind of information tends to be longer than that for the short-term memory.

Figure 4-4 shows the TV channel "reputation", which indicates the probability of presence of PUs at a TV channel. The TV channel reputation can be determined based on the historical radio environment observation (sensing) information and should be stored in the long-term memory. Some radio environment information may dynamically change, such as the PU activity and the location of a mobile device. Such kind of information is short-term information in the sense that the updating period could be quite short. The short-term REM information for 802.22 system has been marked with "*" in Tables 4-5 and 4-6. Some types of long-term REM information that requires huge memory (e.g., geographical information) could be stored in a database, whereas the short-term radio environment data could be stored in the main memory of processor for fast access. The partition and update rates for long-term and short-term radio environment information are implementation issues, which could depend on many systems design considerations, such as the specific application of the CR and the available memory at the CR node.

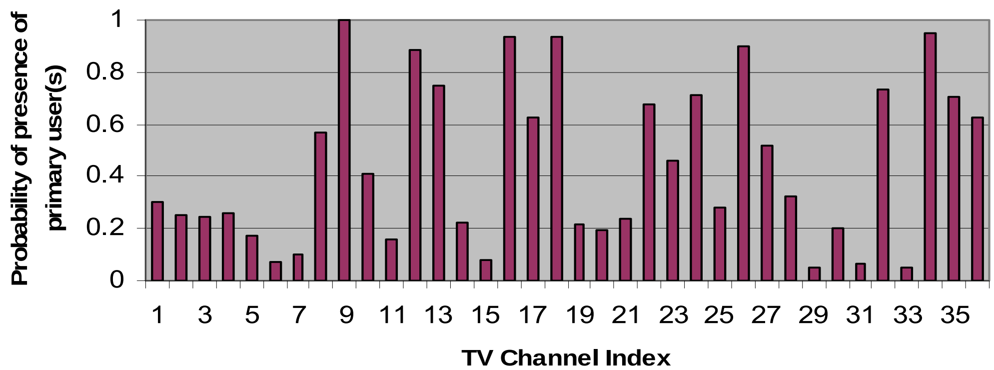


Figure 4-4: TV Channel Reputation: An Information Element of Long-Term Memory Nature

4.3.4 Indexing and Retrieving REM Information

Indexing and retrieving are two closely related issues. A good indexing scheme enables efficient retrieving. The key idea behind REM is digitizing and indexing radio environment information. Just as we can "Google" the needed information from the Internet for various applications, future CRs can "Google" autonomously the desired radio environment information from the Global and Local REMs for various cognitive functionalities. Table 3-3 presents a simple indexing scheme for radio environment information. Various retrieval algorithms can be employed for REM information retrieving, such as *k*-nearest neighbor, binary tree, and cover tree. Furthermore, if the REM is implemented with a commercial relational database, many existing information retrieval tools (e.g., SQL) are ready to use and relational database theories (such as relational algebra and relational calculus) can be further exploited for finding the needed radio environment information. For example, in the WRAN BS testbed, an API function has developed between the CE and the REM, called "*AnalyzeChannelStatistics*( )" that can retrieve the historical REM data file and rank the TV (WRAN) channel reputation based on the probability of being occupied by incumbent PUs.

4.3.5 APIs between the REM and the CE

Common APIs between the REM and the CE have been defined to allow independent and flexible development of different building blocks of CRs, such as the REM module, CE module, and spectrum sensing module. REM access could be classified into two broad categories: queries and updates. Some typical API functionalities have been defined for the WRAN BS CE testbed as follows.

```
AddEntry(REMDataEntry & _rde);                    // add one entry to REM data structure array
LoadDatabaseFromFile(const char * filename);      // load database from file
StoreDatabaseToFile(const char * filename);       // store database to file
MergeREM(RadioEnvironmentMap &_rem);              // merge REM files
AnalyzeChannelStatistics( );                      // rank  the TV channel reputation
GetChannelReputation();                           // retrieve the TV channel reputation
                                                     from REM database
PrintDatabase();                                  // print database to screen
```

After the spectrum sensing module is integrated into the WRAN BS CE testbed, the following APIs can be added.

```
REM_Update_PU_Detection (Location, Freq_Channel, PU_ID, timestamp);
REM_Update_SU_Detection (Location, Freq_Channel, SU_ID, timestamp);
REM_Query_WhiteSpace (Location, Freq_Channel, Max_TxPwr, timestamp);
```

For the WRAN BS CE testbed, the REM has been implemented with a C++ abstract class, containing both static radio environment information and dynamic information (i.e., the data part) and various APIs (i.e., the function part). APIs between the REM and the CE enable flexible deployment of the REM for various applications. Furthermore, both the REM and CE can be developed and/or updated independently of each other due to the use of APIs.

4.4 Approaches to Populating the REM

In general, information to populate the REM can be obtained by

(1) integrating and/or correlating various existing databases, like GIS databases, radio equipment database;

(2) sensing the spectrum with collaborations among distributed nodes;

(3) observing from a dedicated sensor network and/or other external networks;

(4) probing the radio environment with channel sounder; and

(5) estimating the radio propagation characteristics with software tools.

Signal processing techniques that can be employed for populating the REM include but are not limited to the air interface (waveform) classification or recognition algorithms, spectrum sensing algorithms, signal or interference geolocation algorithms. Some of these signal processing algorithms will be further discussed in Chapter 5.

4.5 Summary

This chapter presents both a high-level REM design with E-R data model and a detailed reference REM design for a WRAN BS CE testbed. Various types of REMs and implementation options are discussed and summarized. Defining appropriate APIs is very important for independent development of the REM and CE. Though the current REM and API design and implementation are mainly targeted for the concept-proof WRAN BS CE testbed, it is fairly generic and easy to be extended or adapted for accommodating new information elements, supporting additional functionality, or applying to other CR applications. Furthermore, the REM could also be employed as an independent abstract class for OSSIE[7] to make SDRs situation-aware.

---

[7] OSSIE: Open-Source SCA Implementation::Embedded, a software suite developed by the Mobile and Portable Radio Group (MPRG) of Virginia Tech for developing SDR. For more details about OSSIE, please refer to http://ossie.mprg.org

5 Applications of REM to Cognitive Wireless Networks

This chapter presents some example applications of REM-enabled CR, especially in the context of interference management for cognitive wireless networks. This chapter first reviews the standardization activities in IEEE 802.11 WLAN, 802.16 WiMAX, and 802.22 WRAN in which CR technology comes into play and then illustrates how REM can be populated in the radio domain with various signal processing algorithms, such as signal detection, classification, and location. It is also realized that REM could be a generic tool for implementing cognitive wireless networks other than WLAN/WiMAX/WRAN. Both Global and Local REMs can be exploited by radio devices for various cognitive functionalities.

5.1 Review of IEEE 802.11(h, k), 802.16(h), and 802.22 Standards

5.1.1 802.11h and 11k

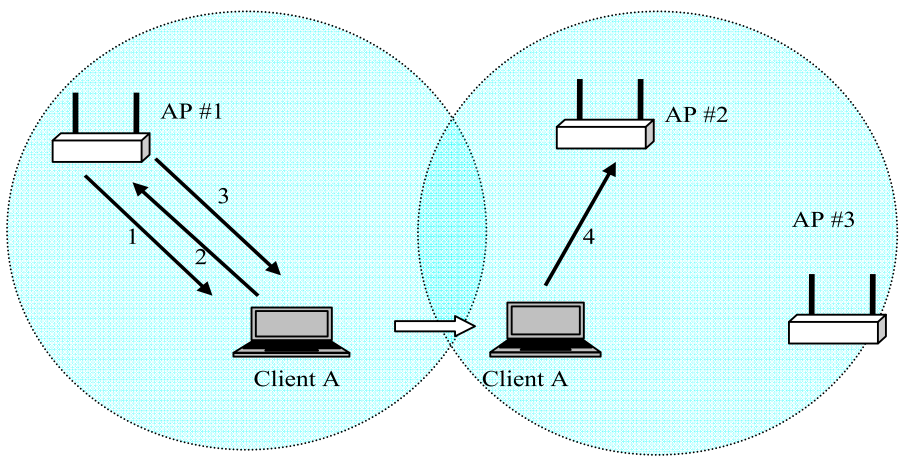
IEEE 802.11h is intended to resolve interference issues introduced by the use of 802.11a in some locations, particularly with military radar systems and medical devices. With the introduction of 802.11h, a modern WLAN behaves like a simple CR sharing spectrum in the unlicensed band.

Two schemes are used to minimize interference: dynamic frequency selection (DFS) and transmit power control (TPC). DFS detects the presence of other devices on a channel and automatically switches the network to another channel if and when such signals are detected. TPC reduces the radio frequency (RF) output power of each network transmitter to a level that minimizes the risk of interference to and from other systems while still allowing satisfactory network performance.

As a proposed standard for radio resource measurement, 802.11k aims to provide key client feedback to WLAN access points (AP) and switches. 802.11k defines a series of measurement requests and reports that detail Layer 1 and Layer 2 client statistics. In most cases, APs or WLAN switches ask clients to report data, but in some cases clients might request data from

APs. The measurements that 802.11k defines include roaming decisions, RF channel knowledge, hidden nodes, client statistics, and TPC.

802.11k is intended to improve the way in which traffic is distributed within a network [81], as explained in Figure 5-1. In a WLAN, each device normally connects to the AP that provides the strongest signal. Depending on the number and geographic locations of the subscribers, this arrangement can sometimes lead to excessive demand on one AP and underutilization of others, resulting in degradation of the overall network performance. In a network conforming to 802.11k, if the AP having the strongest signal is loaded to its full capacity, a wireless device is connected to one of the underutilized APs. Even though the signal may be weaker, the overall throughput is greater because more efficient use is made of the network resources.



Step 1: When Client A is moving away from AP #1, AP #1 sends a message to Client A and informs it to be prepared for switching to another AP.
Step 2: Client A requests a list of preferred APs nearby.
Step 3: AP #1 responds to Client A by sending it a site report.
Step 4: Client A immediately switches to the "best" AP (i.e., AP #2 in this figure) listed in the site report and connects to it. This procedure contributes to faster handoff and better load balancing of WLAN systems.

Figure 5-1: Example Procedures of IEEE 802.11k

5.1.2 802.16h – Improved Coexistence Mechanisms for License-Exempt Operation of WiMAX

IEEE 802.16's License-Exempt (LE) Task Group is developing a draft under the P802.16h project authorization request (PAR), which was approved by the IEEE-SA Standards Board on December 8, 2004. The objective of this amendment is to provide improved coexistence measures to increase the efficiency and robustness of license-exempt WiMAX operation. It will reduce the interference caused by 802.16 systems. The mechanisms specified in 802.16h need to be widely implemented and interoperable for their benefits to be realized, so standardization is required. As a result, there will be improved user service experience and increased robustness and efficiency of spectrum use. This will expand the market opportunities for enterprise, service provider, and consumer applications.

5.1.3 802.22 – the 1st CR Standard for Spectrum Sharing in TV Bands

IEEE 802.22 will be the first worldwide CR-based standard to support the unlicensed operation in TV bands (54–862 MHz), which is to coexist with incumbent users and provide wideband internet access to rural and suburban areas. The IEEE 802.22 Work Group kicked off in November 2004 and approved the functional requirements document for WRAN systems in September 2005 [48]. Ten initial proposals were merged into a single one in March 2006, and the draft standard was developed in May 2006 [49]. The complete WRAN standard is expected to be approved by May 2007.

For 802.22 WRAN systems, the PUs, those with priority rights, mainly include incumbent analog and digital TV stations, TV translators, TV boosters, TV receivers, and wireless microphones. 802.22 systems are initially targeted at rural and remote areas for fixed wireless access services. The 802.22 system is composed of BSs, repeaters, and Consumer Premise Equipment (CPE). For a WRAN scenario, 802.22 systems are SUs and should avoid generating harmful interference to the PUs.

5.2 Applying REM to WLAN Interference Management

5.2.1 Overview of Interference Management

The IEEE 802.11 WLAN has been the fastest growing segment of the telecom industry in recent years. 802.11 WLANs must contend with disparate numbers and varieties of interferers, including but not limited to microwave ovens, cordless phones, VoWiFi phones, Blue-tooth devices, radar, ZigBee devices, wireless video surveillance cameras, and adjacent 802.11 networks (refer to Appendix A for a list of interference sources). The accelerating adoption of WLANs based on the IEEE 802.11 standards creates a strong need for developing tools to characterize and manage WLAN interference, thereby optimizing the network operation.

Interference management for cognitive WLAN generally requires characterization, detection, location, and classification of various interferers operating in the ISM/UNII bands, based on temporal-spectral-spatial analysis of the radio spectrum. REM-based interference management can take advantage of distributed spectrum sensing from both APs and client devices. Figure 5-2 shows the typical radio environment of an 802.11 WLAN in an office building where various interferers may co-exist. A Global REM can be built up at the WLAN network management center for both interference management and radio resource management (such as load balancing). Once WLAN interference is detected, classified, and located, the Global REM will be updated accordingly. Therefore, the WLAN network management center can identify the sources of interference and then make adaptations at the AP or the client device to mitigate the interference. AP actions may include changing the channel, turning ON/OFF the diversity, selecting proper MIMO schemes for interference mitigation or excision, and switching OFF some APs. No changes to the current WLAN PHY/MAC standards are required; however, flexibility in the APs or client device is needed. REM-enabled cognitive WLANs can significantly improve interference management capability by enabling the distributed sensing (including AP and client), learning from experience, and conducting collaborative signal processing through sharing the REM.

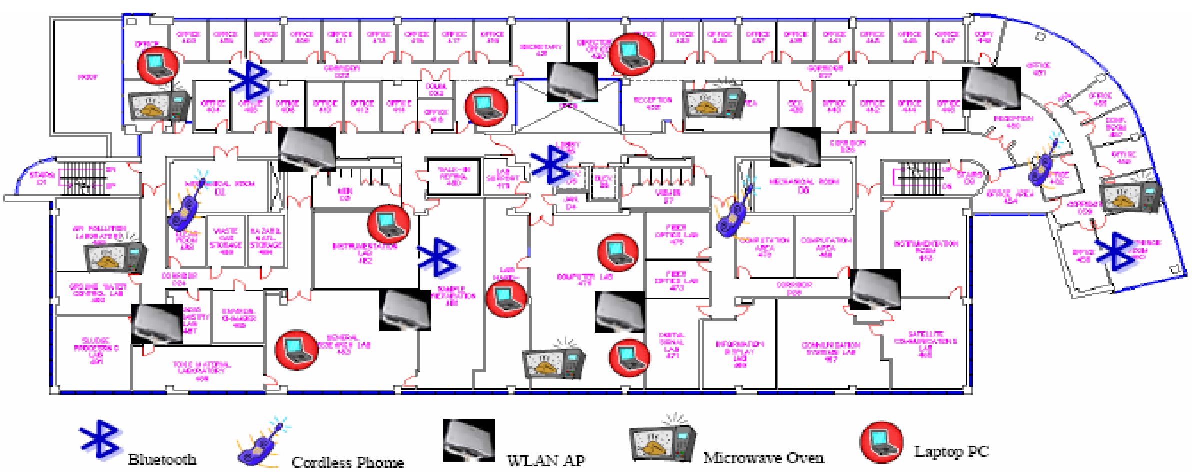


Figure 5-2: A Typical Radio Environment of 2.4 GHz WLAN. This map supports WLAN interference management.

The Global REM collects and disseminates useful information to and from Local REMs and can be employed for global network interference management and performance optimization. REM-based interference management enables interference mitigation through data mining in the REM and identifying the emission pattern of the interferer. Client-assisted radio environment monitoring offers a more reliable spectrum management mechanism by exploiting distributed measurements, collaborative signal processing, and data fusion (especially when considering the shadowing or fading environment) and helps to detect the hidden interferer or hidden nodes.

Figure 5-3 shows the system setup for WLAN interference measurement, which has been used to collect 2.4 GHz WLAN interference (such as microwave oven leakage) and WLAN beacon signals. The measurement setup consists of a general purpose RF front-end, digital oscilloscope (for sampling the received waveforms) and laptop computer that runs LabView® for data collection and MATLAB® for post-processing the collected data.

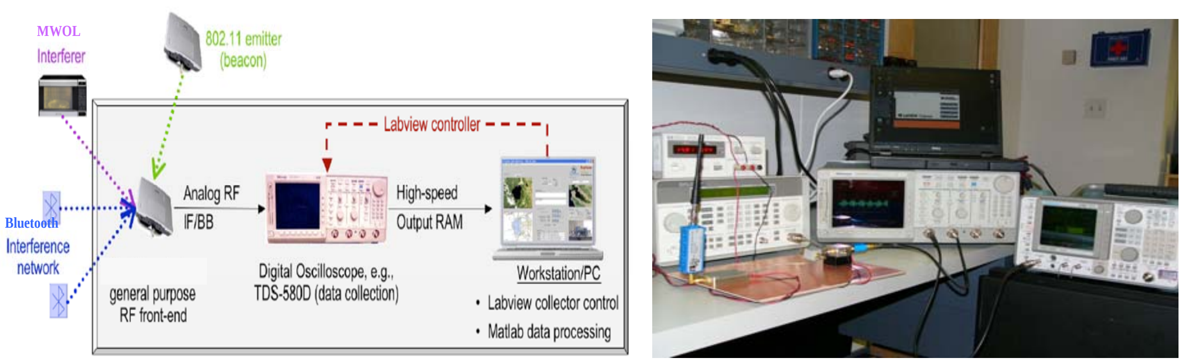


Figure 5-3: Schematic Diagram and System Setup of WLAN Interference Measurement

5.2.2 Populating the REM in the Radio Domain

For applications in cognitive WLAN/WRAN, we may populate the radio domain of the REM by using *feature-based* signal detection, classification/recognition, and geolocation algorithms since most waveforms in the WLAN/WRAN frequency bands are well-known (refer to Appendix A and B for a list of waveforms in the WLAN/WRAN bands and their signal models).

5.2.2.1 Detection Algorithms

To detect the interference, we may apply various algorithms, such as energy detection, matched filter, and dominant mode prediction (DMP) [33]. The detection algorithms may require snapshot data or stream data (continuous sensing) of the received signal.

5.2.2.1.1 Microwave Oven Leakage Detection

Microwave Oven (MWO) leakage (MWOL) is a prevalent source of interference to 802.11b/g WLANs operating in the 2.4–2.485 GHz ISM band. MWOL is the most commonly experienced interference at home, office, and hospital where many MWOs might be in use. As shown in Figure 5-4, an extended AM-FM model has been developed to model the frequency wander effects of MWOL and validated through both simulation and measurement [50].

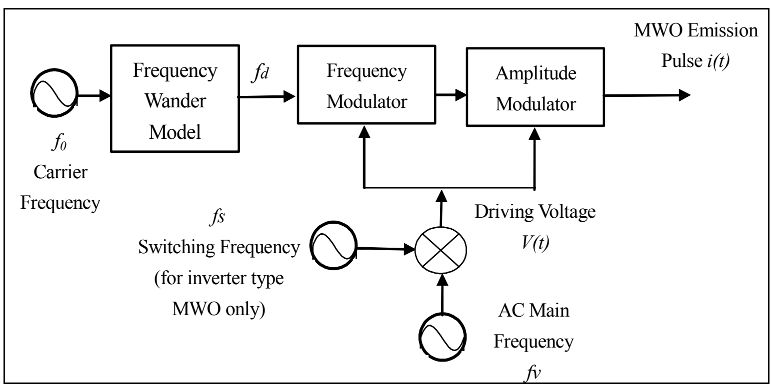
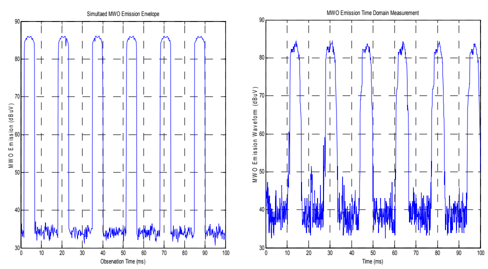


Figure 5-4: An Extended AM-FM Microwave Oven Leakage Model

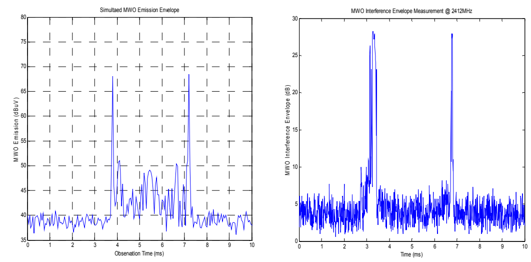
One important feature of MWOL is that MWOs emit RF power in periodic pulses. MWOs of different types have different emission patterns as listed in Table 5-1. One notable finding through MWOL measurement is that the MWOL envelope may change considerably when received at different WLAN channels or at different times due to the frequency wonder effect of MWOL [50]. Figure 5-5 shows the simulated envelopes of MWOL and the measured results, respectively. Therefore, MWOL can be identified by detecting the presence of its unique spectral components (e.g., multiple tones at AC power line frequency for transformer type MWOs) as shown in Figure 5-6. Additional features of MWOL, such as stationary location in the space domain and strong emission in the power domain can be also leveraged for reliable MWOL detection.

Table 5-1: MWO Emission Patterns

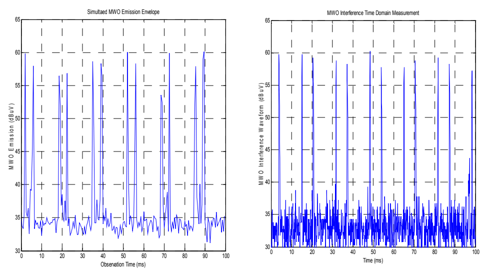
Types of MWO	MWO Emission Pattern
Transformer Type (most popular)	emits *once* per AC power cycle (16.7 ms in the U.S.)
Switching Type	emits *twice* per AC power cycle (16.7 ms in the U.S.)
Inverter Type I	emits *once* per inverter switching cycle (20–35 µs)
Inverter Type II	emits *twice* per inverter switching cycle (20–35 µs)



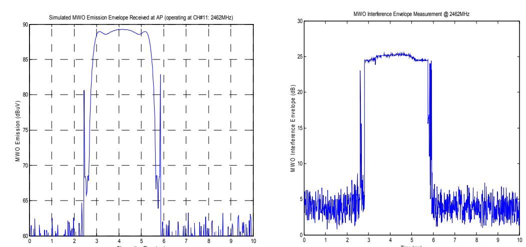
MWO emission envelope at observation time t_1



snapshots of MWO emission envelope observed at WLAN CH #1- 2412MHz



MWO emission at time t_2 ($t_2 = t_1 + 5$ seconds), and the frequency wander cycle is 20 seconds



snapshots of MWO emission envelope observed at WLAN CH #11- 2462MHz

Figure 5-5: Simulated vs. Measured Envelopes of MWOL Interference to WLAN

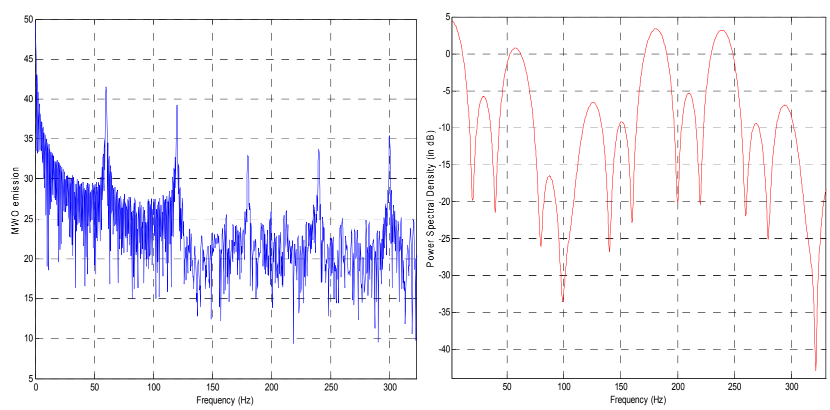


Figure 5-6: Spectral Analysis of Transformer Type MWOL Based on the Proposed MWOL Model (left) and Real Measurement (right)

To detect and classify the MWO interference to the WLAN in a network-based approach, the distributed WLAN APs monitor the radio environment and send the collected data to a central processing unit for interference analysis. Two specific questions should be considered: (i) how can interference due to MWO leakage be distinguished from non-MWO interference and (ii) how can the detected MWO interference be classified. Knowing the type of MWO can be useful in avoiding MWO leakage interference or in identifying a unit that is a nuisance to the RF environment.

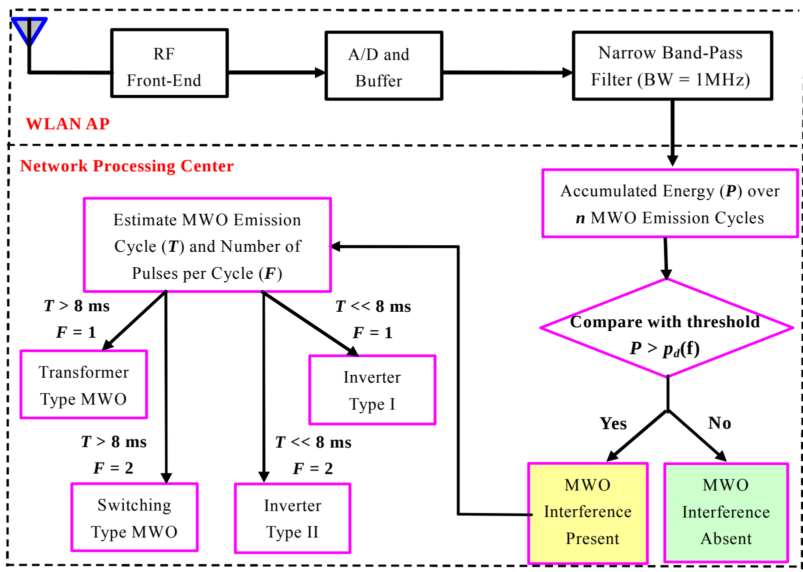


Figure 5-7: Block Diagram of MWOL Detection and Classification

The above problems can be solved by exploiting two features of MWO leakage.

(1) MWOs emit in a periodic pulsed manner, and the power spectral density of transformer type MWO emission (as shown in Figure 5-6) has *unique* spikes at integer multiples of about 60 Hz in the U.S. (or 50 Hz in some countries), which corresponds to the AC power line frequency.

(2) MWO emission consists of CW-like narrowband spikes (less than 1 MHz). Using this property, MWO emission can be distinguished from other wideband signals or interference in the same frequency band, such as the Bluetooth Frequency Hopping Spread Spectrum (FHSS) signal and 802.11b/g Direct Sequence Spread Spectrum (DSSS)/Orthogonal Frequency Division Multiplexing (OFDM) signals.

In Figure 5-7, a network-based MWO emission detection and classification scheme has been proposed. The radio environment is sensed by distributed WLAN APs, and the sampled data are filtered by a narrow band-pass filter. The collected data is then sent to a central processing unit at WLAN network management center via the wired LAN for interference analysis. If MWO emission is present, the accumulated RF energy over a period of time will exceed the detection threshold $p_d(f)$ specific to the WLAN carrier frequency. The type of MWO can be further classified according to the emission patterns described in Table 5-1.

5.2.2.1.2 Bluetooth Detection

Bluetooth (BT) devices are getting more popular, which is another important source of WLAN interference. For Bluetooth interference (and co-channel WLAN interference detection), a front-end channelizer is employed at each WLAN AP as shown in Figure 5-8. The sampling rate at AP is 40 MSps, and the scan period of each snapshot is 128 μs, which consists of 128 Bluetooth symbols. Therefore, the total memory required for one snapshot is 5.12 kB (= 128 μs × 40 MSps × 2 [for sampling both in-phase and quadrature components] × 4 bits/sample = 128 × 40 × 8 bits), which fits in the storage size of a typical WLAN AP.

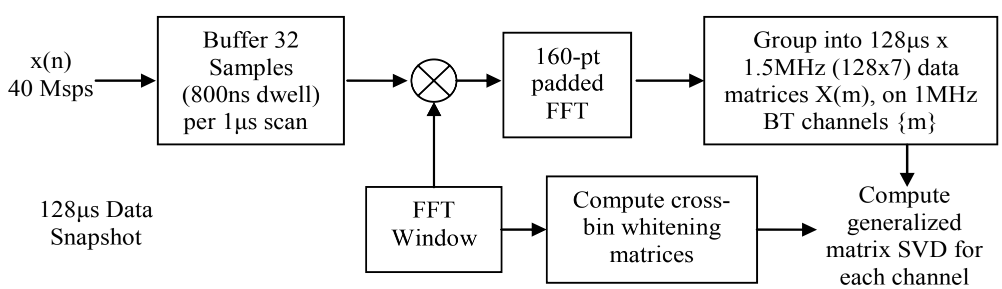


Figure 5-8: Block Diagram of Channelization with Whitening for BT/WLAN Signal Detection

In Figure 5-9, mode spread is defined as the ratio between the dominant and lesser eigenvalues in decibels. The purpose of whitening (in Figures 5-8 and 5-9) is to reduce the inter-bin correlation introduced by zero-padding and windowed FFT employed in channelizer.

The Dominant Mode Prediction (DMP) algorithm [33] can be employed for interference (e.g., Bluetooth) ON/OFF detection. We assume that WLAN APs and client device are monitoring a "cloud" of Bluetooth signals, comprised of a set of overlapping, uncoordinated piconets in which each node in a piconet is time-coordinated but the piconets themselves are not time-coordinated. In this case, independent events are likely where a single GFSK signal transitions ON in the presence of a small number of other GFSK signals that are already transmitting. Each Bluetooth GFSK signal received at the channelizer will induce a *single-rank* signal component, i.e., that GFSK signal can be approximated by

$$s(k,n) = a(k)d(n) \tag{5-1}$$

where k is the frequency channel index, n is the channelizer dwell index, $a(k)$ is the cross-frequency response of the GFSK signal (for GFSK, this will be the channelized frequency response of the first Laurentian mode of the signal, multiplied by a phase ramp due to the timing offset between the channelizer and that signal), and $d(n)$ is some data-dependent modulation (also derivable from the Laurent decomposition of the GFSK signal[8]).

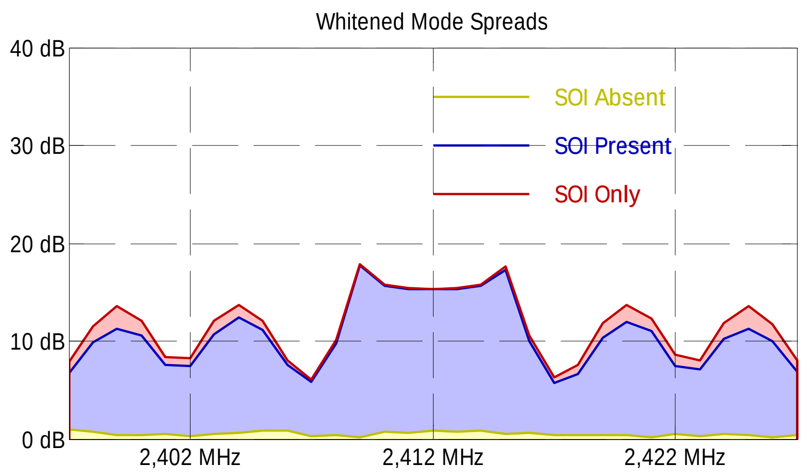


Figure 5-9: Whitened Mode Spread Analysis with GFSK Laurent Decomposition

This can be rewritten as

$$\mathbf{s}(n) = \mathbf{a}\, d(n) \tag{5-2}$$

where $\mathbf{s}(n) = [s(1,n), \ldots, s(M,n)]^T$ and $\mathbf{a} = [a(1), \ldots, a(M)]^T$ are the $M\times 1$ vector representations of $s(k,n)$ and $a(k)$, respectively, and where ^{T} denotes the transpose operation.

[8] GFSK and, in general, Continuous Phase Modulation (CPM) signals can be written as a sum of pulse amplitude modulation (PAM) waveforms. A Bluetooth GFSK signal can be expressed as a sum of the main pulses by using Laurent decomposition. For a Bluetooth signal, the first pulse contains about 99% of the signal power. So, the GFSK signal can be approximated by using only this pulse, which simplifies the analysis of the Bluetooth signal.

Since the singular value decomposition (SVD) of $N \times M$ data matrix $\boldsymbol{S} = [s(1), \ldots, s(N)]^H$ has a single dominant mode (as if $\boldsymbol{S}$ could be modeled by $\boldsymbol{S} = \boldsymbol{d}\,\boldsymbol{a}^H$ where ^{H} denotes the conjugate (Hermitian) transpose operation), the above approximation holds closely. This model is exactly analogous to the model for a signal received by a narrowband antenna array. Using this model, we can directly apply the DMP algorithm that Agee describes [33].

In the following eigenequations, $\boldsymbol{Rxx}(0; k)$ and $\boldsymbol{Rxx}(1; k)$ are the data autocorrelation matrices computed before and during, respectively, the Bluetooth transmission on channelizer output frequency channel k.

For Bluetooth signal "ON" detection,

$$g(k)\boldsymbol{Rxx}(0; k)w(k) = (\boldsymbol{Rxx}(1; k) - \boldsymbol{Rxx}(0; k))w(k) \tag{5-3}$$

For Bluetooth signal "OFF" detection,

$$\boldsymbol{Rxx}(0; k)w(k) = \frac{1}{g(k)}(\boldsymbol{Rxx}(1; k) - \boldsymbol{Rxx}(0; k))w(k) \tag{5-4}$$

For a Bluetooth signal switching "ON" detection, $g(1)$ is plotted as DMP detection statistics; for a Bluetooth signal switching "OFF" detection, $\frac{g(M)}{1+g(M)}$ is plotted as DMP detection statistics, where $g(1)$ and $g(M)$ are the maximum and minimum eigenvalues of eigenequation (5-3), respectively. Figure 5-10 shows the "ON/OFF" detection of Signal-of-Interest (SOI) Bluetooth interference based on the DMP algorithm. The SOI Bluetooth interference starts at 64 μs and ends at 131 μs, whereas the background Signal-Not-of-Interest (SNOI) Bluetooth signals start at 0 μs and end at 214 μs.

Monte Carlo simulations for DMP detectors have been conducted in over 100,000 trials under AWGN channels. The detection statistics of DMP detectors approximately follow Gaussian distribution since their Kurtosis[9] is close to three. To meet the same false alarm ratio (FAR) requirement, the larger the time-bandwidth product (TBP) of the channelizer in use, the lower the detection threshold (which means it is more sensitive to Bluetooth interference) as shown

[9] Kurtosis is the degree of peakedness of a distribution, defined as the fourth standardized moment: μ_4 / σ^4, where μ_4 is the fourth moment about the mean and σ is the standard deviation. The Kurtosis of normal distribution is three [51].

in Figure 5-11. In this figure, the duration of snapshots at the WLAN AP for Bluetooth "ON/OFF" detection are 32 μs, 64 μs, and 128 μs, respectively, and the linear combiner dimensionality (i.e., the number of frequency bins used for detection) is seven.

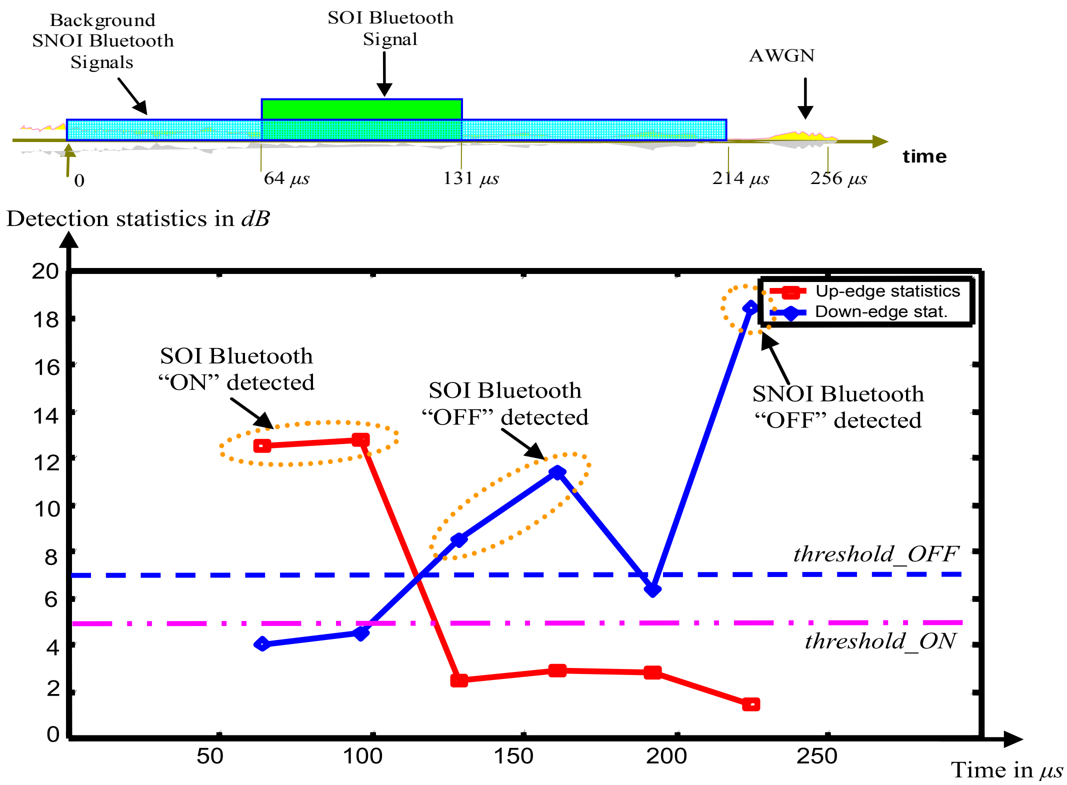


Figure 5-10: Bluetooth Interference Scenario and ON/OFF Detection Using the DMP Algorithm

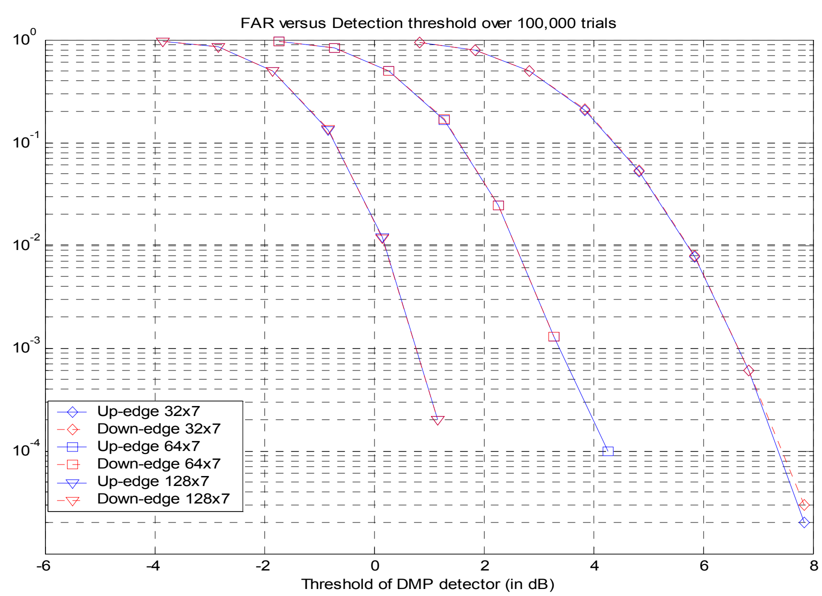


Figure 5-11: False Alarm Rate vs. Threshold of DMP Detector with Various Time-Bandwidth Products

5.2.2.1.3 WLAN (DSSS/OFDM) Signal Detection

The WLAN APs periodically emit strong beacon signals as shown in Figure 5-12. The detected periodic beacon signal can be an indicator of the overlapping WLAN signals. The typical emission period of WLAN beacon signals is about 100 *ms*.

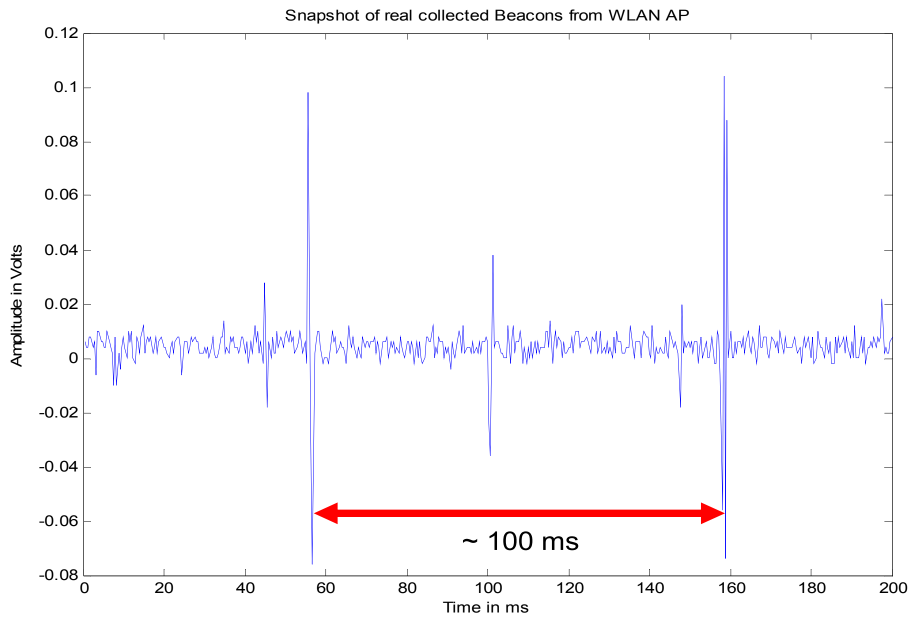


Figure 5-12: Measured Periodic WLAN Beacons over the Air

5.2.2.2 Classification Algorithms

Common approaches for signal classification include (but are not limited to) a feature-based classification/recognition method and a cyclostationary method combined with neural networks [52]. With the feature-based classification/recognition method, the signal classification is realized in an ad hoc approach, which is based on the unique known characteristics (features) of each possible signal or interference in the environment. For example, MWOL can be classified via spectral analysis, Bluetooth interference via mode spread analysis, and penetrating WLAN interference via temporal analysis (periodic beacons). The cyclostationary method combined with neural networks is a more generic, but computationally complex approach. A further downside is that severe Nyquist filtering can significantly reduce cyclostationary features of QAM signals.

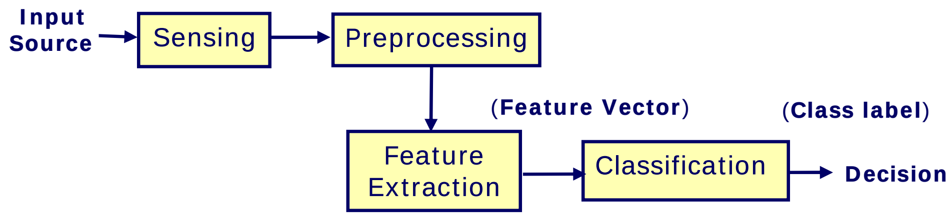


Figure 5-13: Block Diagram of Feature-Based Classification Systems

Figure 5-13 shows the generic block diagram of feature-based classification systems. The key to signal classification is to define the feature vector and feature space for various signal/interference in TV/ISM/UNII bands. Some commonly used features include periodicity in the time domain, carrier frequency, bandwidth, a beacon or pilot signal, a spectral component, and cyclic signature of signals, as listed in Tables 5-2 and 5-3.

Table 5-2: Feature Vector for Interference Classification in ISM/UNII Bands

Type of Interference to 802.11	Time Domain Features	Spectral Domain Features	Power Domain Features	Spatial Domain Features
MWOL (transformer type MWO)	Periodicity same as AC power line	Around 2.45 GHz	Strong emission	Static in location
BT (Bluetooth)		Large mode spread		
DSSS/OFDM WLAN	Periodic beacon	Beacon/Pilot subcarriers	Strong	Stationary AP
FM (cordless phone)	Constant envelope			Stationary base station

Table 5-3: Feature Vector for Interference Classification in TV Bands

Type of Interference to 802.22	Time Domain Features	Spectral Domain Features	Power Domain Features	Spatial Domain Features
Analog TV	More continuous than intermittent; well known signature	Strong audio/video subcarrier	Generally high transmission power	TV transmitters located at fixed locations
Digital TV	More continuous than intermittent; well known signature	Strong pilot tone	Generally high transmission power	TV transmitters located at fixed locations
FM (wireless microphone)	Constant envelope	Narrow band (less than 200 kHz)	Typically 10–50 mW	Stationary base station
OFDM (overlapping WRAN)	Well-known signature	Standardized pilot subcarriers	Max. EIRP 4W	Stationary base station and CPE

5.2.2.3 Positioning Algorithms

The location of the interference source can be estimated with TDOA measurements from multiple APs or clients of WLAN. An enhanced location algorithm can be developed with the clock offset calibration (see Section 5.3.3). Locations may also be estimated by building a Markov model of the multi-path environment and comparing the received data against those predicted by a Markov model representing various locations [79]. With the help of the REM, the network security can also be enhanced, since any abnormal radio activity or traffic pattern can be identified and located in the REM.

5.3 Applying REM to Cooperative CR Networks

Unfortunately, analog and RF components are still expensive relative to digital components, because they follow the "Moore's Law". Low-cost radios usually have poor linearity, less accurate or unstable clocks and local oscillators (LO), low transmit power, high noise figure, and small dynamic range (which may result in larger carrier frequency offset, more spurs, and out-of-band emissions). However, the digital processing and storage are getting cheaper. Therefore, system costs may be reduced with cooperative CR networks, in which radios work together for a common goal. Cooperative MIMO system is such an example. CR can adapt around the spurs (just like another interference source) or hardware limitations and intelligently determine how to reduce the spurs and enhance the overall network capability in a collaborative way. By employing cooperative MIMO, the transmit power can be reduced for the nodes with low-quality RF amplifiers, thus further reducing the spurs. In addition, with the help of REM, the channel (frequency) planning of CR networks can be made more intelligently to mitigate the spurs. The U.S. DAPRA Adaptive Cognition Enhanced Radio Teams (ACERT) program intends to create a "distributed radio" greater than the sum of its parts [42]. The U.S. DARPA Wireless Adaptable Network Node (WANN) program seeks to develop and demonstrate technologies and system concepts that will enable intelligent adaptive wireless networks consisting of densely deployed low cost wireless nodes. The premise of the WANN program is that significant advantages can be realized by densely deploying low cost nodes that have been jointly optimized with network operations. WANN networks should adapt to changing conditions by adjusting the topology of the network and the operational mode of the nodes to reduce the demands on the nodes, in particular on the physical and link layers [53].

Technologies currently used to organize and adapt mobile ad hoc networks (MANETs) do not scale beyond 50 to 100 nodes, partially due to lack of sufficient information needed for node collaboration [54]. The REM has the potential to support collaboration among a large number of CRs by disseminating multi-domain information, such as the location, spectrum usage, traffic pattern, radio equipment profile (e.g., the reference clock offset), and local radio environment information (e.g., the multipath profile, detection of PU or interference). DARPA is funding MANET programs that foresee self-organizing wireless networks of millions of nodes [92]. Multi-disciplinary knowledge is required in developing cooperative CR networks as illustrated in Figure 5-14.

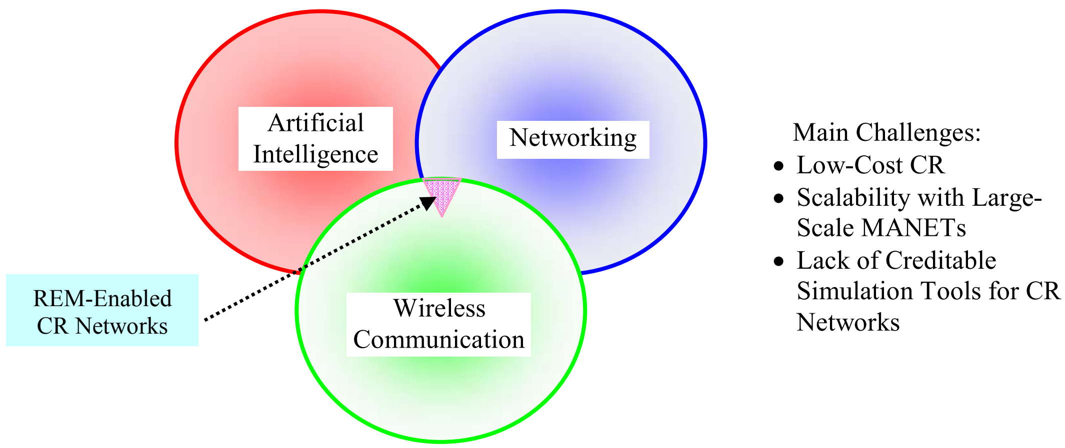


Figure 5-14: Multi-Disciplinary Research for Developing REM-Enabled CR Networks

The hardware limitations of low-cost radios can be offset or overcome by applying collaborative signal processing over CRs. The REM can help to decide whether cooperative (e.g., macrodiversity) is needed, how much gain can be expected, and what is the most effective cooperation method to reach certain goal. The REM can also facilitate cognitive cooperative learning among nodes in CR networks (to be further discussed in Chapter 6).

5.3.1 REM Information Dissemination

To support cooperative CR networks, some important information in the REM must be efficiently disseminated among cognitive nodes. The type of information of interest may vary with the situations. A generic protocol to support REM dissemination in ad hoc CR networks is to be investigated. Statistics analysis (e.g. confidence interval) may also be introduced to determine how often the REM needs to be updated and the weight for which the information should be used in the decision process. The goal is to minimize the load and latency of the overhead associated with REM dissemination. The REM information can be viewed as a generalized "site report" used in 802.11k. The multi-domain information in the REM should be well-organized and concise. For example, the radio equipment profile can be regarded as the "passport" of a radio.

In Chapter 6, the Optimized Link State Routing Protocol (OLSR) has been extended to include REM information in addition to the topology control information. The network simulator (such as NS-2)[10] is used to estimate the overhead load, latency, and reliability of REM dissemination.

5.3.2 Collaborative Signal Processing

As an example of collaboration among CRs, a collaborative synchronization scheme for WLAN has been proposed [55] and demonstrates the network-concentric snapshot processing techniques for macrodiverse exploitation of conventional 802.11 WLANs. This scheme can be applied to various applications, such as WLAN interference detection, location, and mitigation. With collaborative signal processing, the benefits of spatially adaptive processing (such as collaborative interference excision and interferer geolocation) can be achieved in networks of conventional APs without the higher costs associated with spatially adaptive APs. Key calibration steps performed for collaborative synchronization using AP beacon signals are as follows [55].

(1) Detect and identify the beacon periods for each AP

(2) Collect data during the beacon preamble transmission period

(3) Transfer the collected snapshots of beacon signals back to a processing center

---

[10] The Network Simulator, version 2 (NS-2), is an open-source, discrete-event simulator developed for networking research [56]. NS-2 supports many networking protocols, including TCP and its variants, multi-cast, wired or wireless, ad hoc protocols, and propagation models. NS-2 is a discrete event simulator that supports the link layer upward on the OSI stack, i.e., the network, transport, session, presentation, and application layer, respectively. It can support both wired and wireless simulations and works on most platforms.

(4) Determine the cross-AP carrier/timing offsets

(5) Determine the carrier and timing offset between all beacons and a common (unknown) center offset.

Synchronization is critically important for collaborative signal processing because effective macrodiverse processing requires removing timing offset between different nodes, such as the traditional 802.11 WLAN APs. The collaborative synchronization scheme can also be used for synchronizing distributed measurement or scheduling (collision avoidance) in CR networks.

As an enabling technique for node collaboration, a robust fractional spaced equalizer (FSE) based clock offset estimator was developed for estimating the cross-node clock offset (or RF carrier offset, assuming they are locked). In the following investigation, the radio nodes are WLAN APs. This estimator can be used for collaborative synchronization as discussed in the previous section. Figure 5-15 shows the block diagram of an FSE-based carrier offset estimation simulator. The transmitting AP generates a Direct Sequence Spread (DSS) beacon at a symbol rate of 10^6 symbols per second, i.e., 1 MSps, and the simulated transmitter output has 160 samples per symbol. The clock offset effect is simulated in the DSS beacon generation process with a frequency-shifted symbol sequence. The DSS beacon signal is modeled as a pulse amplitude modulation (PAM) signal. A channelizer-type FSE front-end was developed and employs the Least Square-Constant Modulus Algorithm (LS-CMA) to adapt the front-end combiner coefficients (weight vector). The clock offset estimation is initialized with LS-CMA and then optimized by the decision directed method after demodulating the beacon sequence. This approach has advantages over other methods, e.g., the traditional delay-multiply clock rate estimation method, which has limited input SNR due to the self-noise problem, especially when it is used to estimate the symbol rate of a PAM waveform or of a waveform that can be approximated as a PAM waveform such as the Bluetooth signal (refer to Appendix C for the mathematical model of a PAM waveform).

To evaluate the performance of the clock offset estimator, a Cramer Rao Lower Bound (CRLB)-like bound is derived based upon a simplified mathematical model as follows. A typical line frequency estimation under AWGN uses the complex data model defined by

$$\tilde{x}[n] = Ae^{j(2\pi f_0 n+\phi)} + \tilde{w}[n] \qquad n = 1,.., N-1 \tag{5-5}$$

where $A > 0$ and $0 < f_0 < ½$ and $\tilde{w}$ is independent and identically distributed (*i.i.d.*) complex zero mean AWGN with variance $\sigma^2 = N_0/2$ for the independent real and imaginary components, i.e., $E[w_k(w_k)^*] = N_0$ for any k.

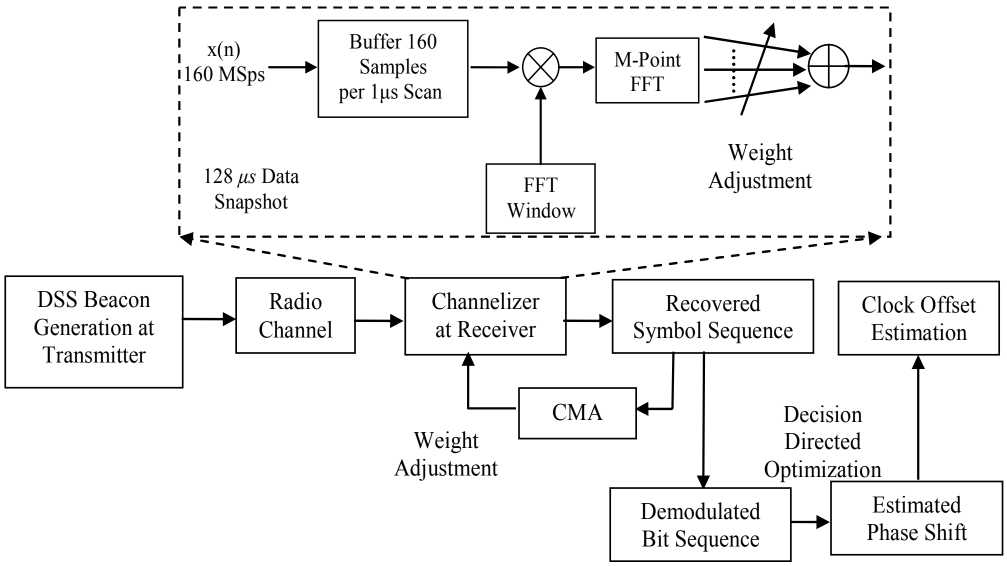


Figure 5-15: Block Diagram of FSE-Based Cross-Node Clock Offset Estimation

Assuming f_0 is not near 0 or 0.5 f_s, (note that f_s is the sampling rate. f_s = 1 MSps), the CRLB-like bound for clock offset estimation is expressed by [57]:

$$\sigma_{CRLB}(\hat{\omega}_{line}) = \sqrt{\frac{6}{\gamma_{line} N_{collect}(N_{collect}^2 - 1)}} \tag{5-6}$$

where $\gamma_{line} = SNR = \frac{A^2}{2\sigma^2}$ is the signal to noise ratio of the input signal and $N_{collect} = N$ is the number of samples used for clock offset estimation.

Figure 5-16 shows the simulated RMS error of clock offset estimation under the AWGN channel and the CRLB-like bound, which indicates that the performance of the proposed clock offset estimator is quite reliable and can attain the CRLB-like bound when SNR is above 2 dB.

As the 802.11b/g WLAN operates in the 2.4 GHz license-free industrial, scientific, and medical (ISM) band, the performance of the clock offset estimator must be checked under various interference scenarios, such as MWOL and emission from Bluetooth devices or adjacent WLANs.

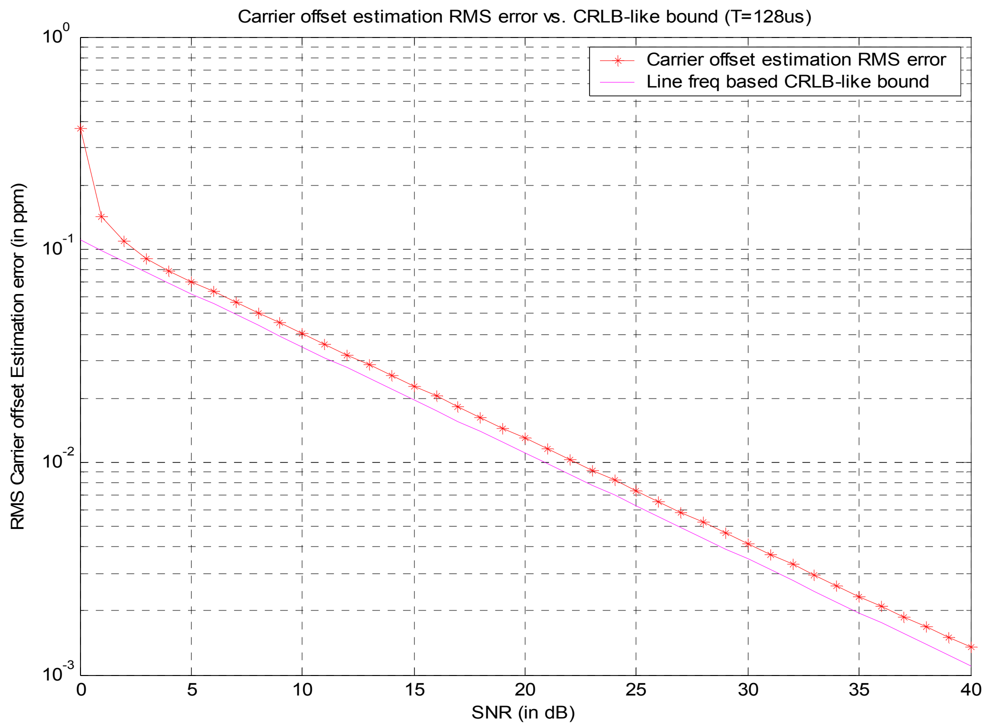


Figure 5-16: Simulated RMS Error of Clock Offset Estimation under AWGN

Based on the extended AM-FM model of MWOL [50], the RMS error of clock offset estimation under various levels of MWOL interference has been simulated and plotted in Figure 5-17, which implies that the clock offset estimator could be quite resistant to serious MWOL interference. For example, when the SIR is as low as 0 dB, the estimator is still reliable in sense that the RMS estimation error approaches the CRLB-like bound. Even if the SIR is as low as -10 dB, the clock estimator still produces clock offset estimation with RMS error less than 0.1 *ppm* at SNR levels greater than 10 dB.

To validate the simulated clock offset estimations against measurement, the clock offset of a commercial 802.11b/g WLAN AP was first calibrated with Global Position System-Disciplined Oscillator (GPS-DO) as shown in Figure 5-18. The GPS-DO outputs a 10 MHz reference frequency, which is very accurate and stable (better than 0.5 *ppb* = 0.5 x 10^{-9}). The RF signal generator, using the GPS-DO's 10 MHz output as external reference, generates a stable 2472 MHz LO for the data collection system. The 10 MHz reference signal, combined with the down-converted WLAN signal from the AP under test (set to Channel #11: 2462 MHz), is collected by a digital oscilloscope. By comparing the difference between the GPS-DO reference frequency and the down-converted LO leakage from the AP under test, the clock offset of the commercial AP, whose clock offset is under estimation, can be calibrated.

Figure 5-17: Simulated RMS Error of Clock Offset Estimation under MWOL Interference

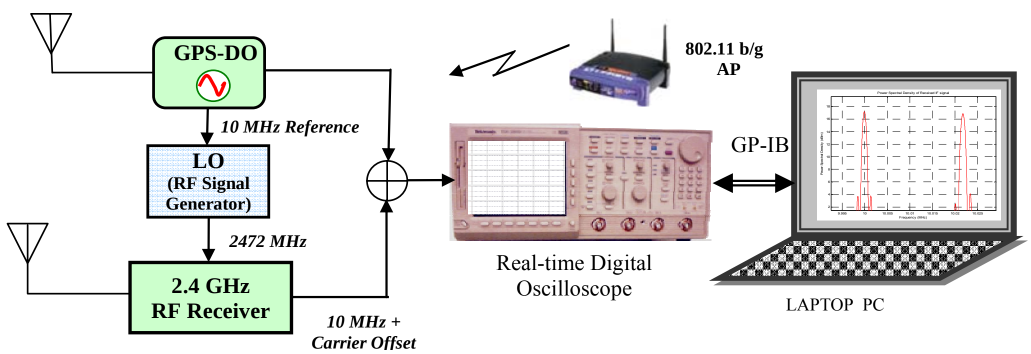


Figure 5-18: WLAN AP Clock Offset Calibration with GPS-DO

The calibrated (true) clock offset of the AP under our test is about -8.5 *ppm*. Furthermore, to validate the clock offset estimator's robustness, measurements have been made to estimate the WLAN AP's clock offset under strong MWOL interference, which is regarded as one of the most serious and common types of interference to WLAN [50]. Even if the MWOL is much stronger than the WLAN beacon signal, the clock offset estimator is shown to still work well.

As an example, for SIR = -37 dB, as shown in Figure 5-19, the estimated AP carrier offset is about -9.05 *ppm* and the estimation error is about 0.55 *ppm*.

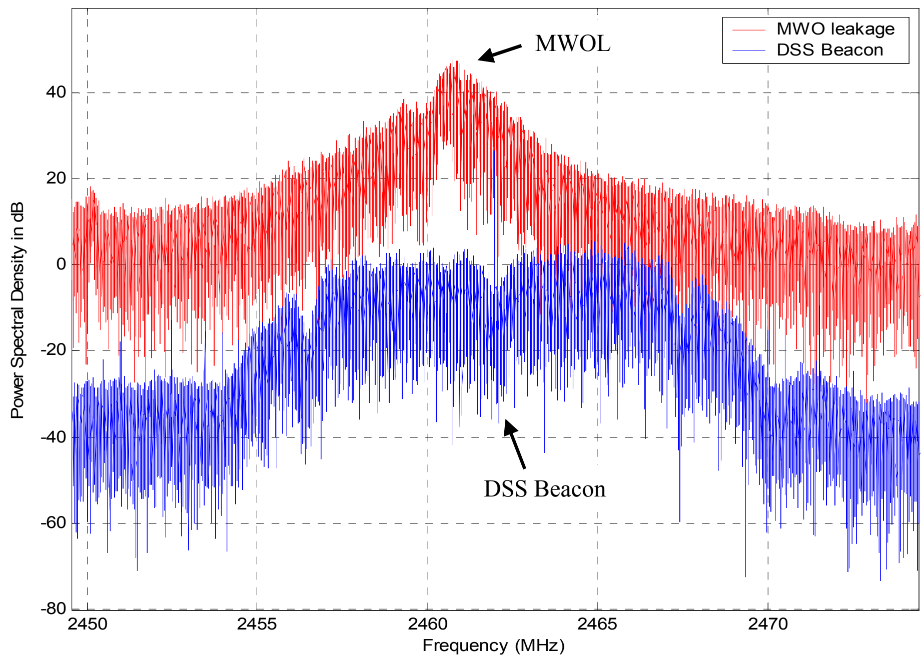


Figure 5-19: Spectrum of the Measured Strong MWOL and DSS Beacon

The frequency response of the channelizer-type FSE front-end is shown in Figure 5-20. A noticeable "dip" occurs around 2461MHz, which corresponds to the strongest frequency component of MWOL. With such a "notch" filter, the MWOL interference can be excised by the FSE front-end, and therefore, robust clock offset estimation can be achieved.

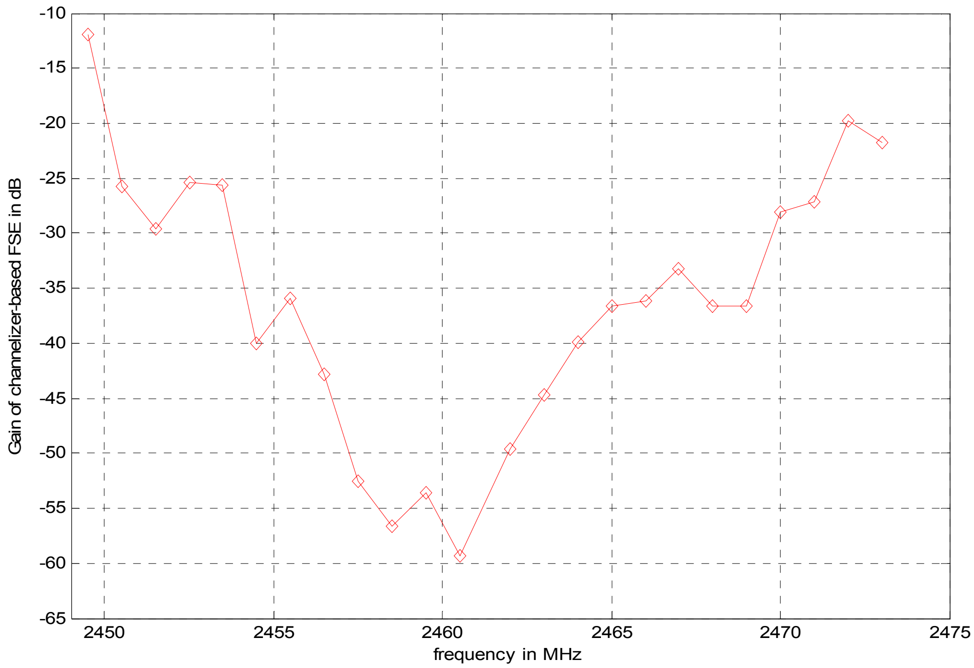


Figure 5-20: Frequency Response of FSE under Strong MWOL Interference

After the clock offset of each AP is calibrated, the TDOA-based WLAN interference positioning algorithms can be enhanced by taking the clock offset of each AP into account.

The WLAN interference positioning requires continuous and simultaneous spectrum sensing from multiple APs as illustrated in Figure 5-21.

If all APs have the same reference clock and the cross-AP clock offset between any two APs is zero,

$$\Delta d = d_1 - d_2 = [(t_{12} - t_{02}) - (t_{11} - t_{01}) - a] \times c \qquad (5\text{-}7)$$

Otherwise, assuming that AP #2 and AP #1 have clocks offsets ε_2 and ε_1, respectively,

$$\Delta d = d_1 - d_2 = [(t_{12} - t_{02})(1+\varepsilon_2) - (t_{11} - t_{01})(1+\varepsilon_1) - a] \times c \qquad (5\text{-}8)$$

where Δd is the distance difference from the interferer to two APs, AP #1 and AP #2, respectively; c is the speed of light in the air; a is the TDOA calibration factor of the beacon signal from AP #3 based on the location of WLAN APs, $a = (D_{32} - D_{31})/c - (t_{02} - t_{01})$; and ε_1 and ε_2 can be estimated with the clock offset estimation algorithm discussed in this subsection.

In Figure 5-21, the UTC standard time refers to *Coordinated Universal Time*. Based on the known topology (i.e., locations) of WLAN APs, t_{01} and t_{02} can be calculated. Therefore, a more accurate estimation of Δd can be obtained with the estimated clock offsets of AP #1 and AP #2.

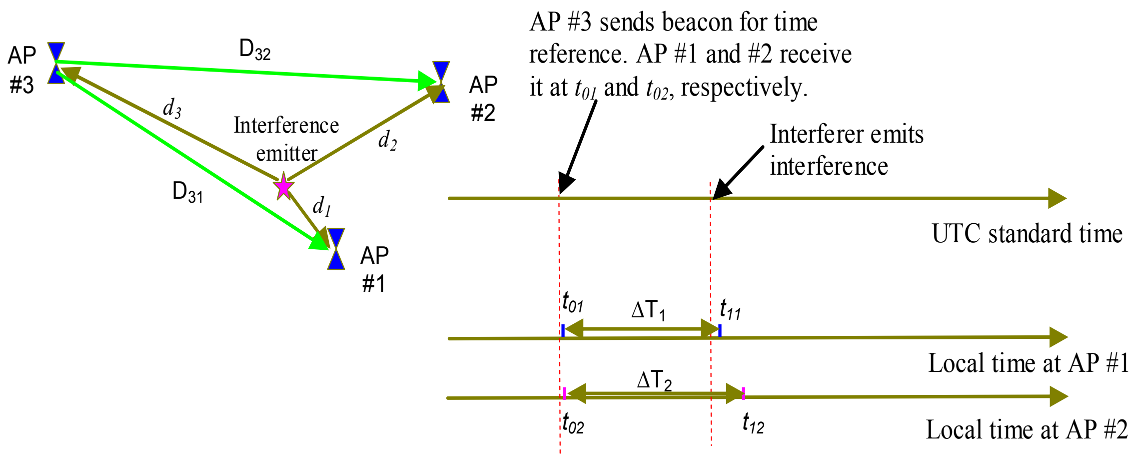


Figure 5-21: Enhanced TDOA-Based WLAN Interferer Geolocation with Clock Offset Calibration

5.4 Applying REM to Cognitive WRANs

On December 19, 2005, the U.S. House of Representatives approved legislation to complete the country's transition to higher-quality digital TV by February 17, 2009. Refarming the analog TV spectrum promotes the developments of CR technologies. IEEE 802.22 will be the first worldwide CR-based standard to support unlicensed operation in TV bands (54–862 MHz), which is to coexist with incumbent users and provide wideband internet access to rural and suburban areas. According to the U.S. FCC's recent public notice, products refarming TV bands are scheduled to be available to the market by February 2009 [58].

When applying to cognitive WRAN systems, the REM can be viewed as a spatiotemporal database that contains multiple dimension radio environment information of WRAN systems, such as geographical locations of TV stations, WRAN BSs and CPEs, TV channel reputation, and spectrum mask set by the 802.22 standard. The most distinctive features of the cognitive WRAN are situation-awareness, self-diagnosis, and automatic radio resource management and optimization. The potential applications of REM in 802.22 systems are summarized as follows [72].

(i) Network Initialization: "The WRAN BS starts by consulting the TV usage database and the regional WRAN information base to find potentially empty channels," [49]. In this sense, the BS can be initialized by downloading the relevant REM entries.

(ii) Efficient Spectrum Sensing and Optimal Channel Assignment: The most important functionality of the WRAN BS is to allocate radio resources to CPEs such that it minimizes harmful interference to PUs. From the historical REM information, the BS can derive the usage patterns of both PUs and SUs, which can be exploited for efficient spectrum sensing and channel state prediction.

(iii) CPE Transmission Power Control: Based on the selected operation channel and the REM, the allowed maximum transmission power of each CPE can be determined with the procedure defined by the 802.22 draft standard [49]. In addition, by learning from past experience CPEs can fine-tune its transmission power even faster, and therefore, reduce the interference to PUs.

(iv) Awareness and Protection of PUs: By exploiting the REM-CKL algorithm (to be explained in Chapter 6), typical hidden PU scenarios could be identified or anticipated promptly by learning from previous experience. Therefore, pre-emptive measures could be taken to avoid or mitigate the interference subjected to the hidden PU node. For example, the WRAN CE can anticipate the presence of (hidden) PU nodes for certain radio scenarios. Statistical analysis can be employed to derive usage patterns, such as duty ratios, arrival rates, and intervals of arrival. TV channel statistics, such as channel reputation, can be obtained by analyzing the historical radio environment information. TV channel reputation can be used for ranking the candidate channels. In this way, the possibility of interfering with the PUs could be further reduced. Prior knowledge of the radio environment, such as spatiotemporal statistics of the PUs, can also help a CR to improve the PU detection rate by adjusting the detection threshold [57]. Furthermore, by applying Monte Carlo simulation, the WRAN CE may predict the possible areas where the PUs might not be detected by the BS and the distributed CPEs and then take pre-emptive measures accordingly.

(v) Fast Adaptation: By leveraging prior knowledge of the radio environment and applying REM-CKL techniques, the BS can become immediately aware of its current radio scenario to narrow down the solution space over which it must search. Therefore, it can make faster adaptations and evacuate the channel more quickly when the PUs re-appear.

(vi) Radio Resource Management and Optimization: During different phases of WRAN network deployment or during different times of the day, the WRAN service providers may want to have different goals or priorities. For example, at the initial stage, the operator usually has higher priority to the network coverage. However, when more CPEs need to be served, e.g., during the peak hours of the day, improving the network throughput and spectrum efficiency becomes a major concern. Ideally, upon service request from CPE(s) and REM information, the WRAN CE could adaptively determine an appropriate utility function to fit its current situation rather than using a static utility function.

(vii) REM-Based CPE Positioning Enhancement: By taking advantage of CPEs' wideband spectrum sensing capabilities, wideband RF fingerprinting techniques can be exploited to enhance the CPE ranging. For example, triangulation-based location methods can be employed with more reference radio stations from various wireless systems other than WRANs. The advantage of this method is more apparent when the number of WRAN BSs is less than the number required for traditional location techniques.

(viii) REM-Enabled WRAN Interference Management and Network Security: A detection scheme for malicious PU emulation attacks could be based on location verification, as proposed in [59]. Furthermore, such attacks could also be detected based on the unique features of PU mobility, usage patterns, and transmission power. With the help of the REM, PU detection, classification, and location can be conducted at the BS to further improve the interference management and security of WRAN systems. For example, the WRAN systems can set up authorized service areas in which only registered CPEs can access the network.

(ix) Performance Evaluation and Testing of CRs: Testing CRs is much more challenging because they operate very differently from traditional radios due to their flexibility and learning capabilities and to their demanding or unpredictable operation environments. REM-based radio scenario-driven testing (REM-SDT) is a viable approach to evaluating the performance of the WRAN CE. REM-SDT will be further discussed in Chapter 7.

5.5 Summary

This chapter presents potential applications of the REM in various cognitive wireless networks. REM-based WLAN interference management is examined in more details. Solely relying on snapshot-based signal processing might not be reliable for WLAN interference management. By offering prior knowledge about the environment and past experience to CR, the REM can be exploited to complement the snapshot-based approach for more reliable and efficient WLAN interference management. This method can also be applied to other cognitive wireless networks such as 802.16h WiMAX and 802.22 WRAN since co-existence with incumbent PUs and other SUs is the prerequisite for these networks. Signal processing algorithms (such as signal detection, classification, and location) for populating the REM in the radio domain are also developed. By disseminating REM information and collaborative signal processing, REM-enabled CR can be employed for developing low-cost, large-scale cooperative networks with enhanced capability.

6 REM-Enabled Situation-Aware CE Algorithms

By integrating radio environmental information, past experience, and prior knowledge altogether, the CE can exploit the REM for various cognitive functionalities. Prior knowledge can help enormously in situation awareness, efficient learning, and probabilistic approaches to decision making.

This chapter first explains how CR can exploit the REM for situation awareness from a system point of view and then presents the framework of REM-enabled situation-aware CE learning algorithms. Finally, REM-enabled case- and knowledge-based learning (REM-CKL) algorithms are developed and explained in detail, which have been employed in the 802.22 WRAN BS CE testbed. The CE testbed is fairly generic and can be extended or adapted for various CR applications in the future. Preliminary testing of different WRAN CE algorithms has been conducted with the CE testbed, which demonstrates the capability of the CE. REM-enabled cognitive cooperative learning (REM-CCL) can be realized through REM dissemination in cognitive wireless networks. The overhead of REM dissemination has been analyzed and simulated under various network scenarios. The beauty of REM is that it enables the CE to efficiently obtain comprehensive situation awareness in a top-down approach with goal-oriented focused attention. REM-based radio scenario matching is a prerequisite for the CE to employ case- and knowledge-based learning.

6.1 Overview of REM-Enabled Cognitive Engine (REM-CE)

As shown in Table 6-1, the CE can apply various methods to exploit the REM for cognitive functionalities, such as situation awareness, reasoning, learning, planning, decision support, and adaptation. The overall system flow of an REM-enabled CE (REM-CE) is illustrated in Figure 6-1. The REM-CE can recognize the radio scene based on the timestamp, the CR's location and geographical environment information inferred from the REM and select the applicable channel model, mobility model, and most significant performance metric(s) to meet the user's goal for the specific radio scenario. With REM-CKL, the CE can choose the most efficient learning method and make (near-)optimal adaptations subject to constraints of regulation, policy, and radio equipment capability.

Table 6-1: Approaches to Obtaining Cognitive Functionalities for REM-Enabled CR

Cognitive Functionality	Approaches	Notes
Situation Awareness	Radio scene matching Radio scene forecasting Data mining	Data mining can be used for extracting hidden information and predicting future events. For example, data mining can be used to find out hidden patterns of PU, SU, or interference from large quantities of data, based on intelligent technologies, such as decision tree, neural networks, neural-fuzzy systems, and hidden Markov models (HMM).
Reasoning and Learning	Case-based reasoning Feature-clustering Statistical learning Neural networks (NN) Hidden Markov models	HMM can be used for radio scene classification and making predictions based on training data (past experience); Initially trained by providing a set of known inputs and desired outputs, a neural network is used to learn the desired behaviors of CR.
Planning	REM-based radio scenario prediction and planning	CR can take preemptive measures or reserve radio resource for expected upcoming events.
Decision and Adaptation	Search engines Decision tables Optimization techniques	Search engines can be used for searching the optimal operational parameters for CR.

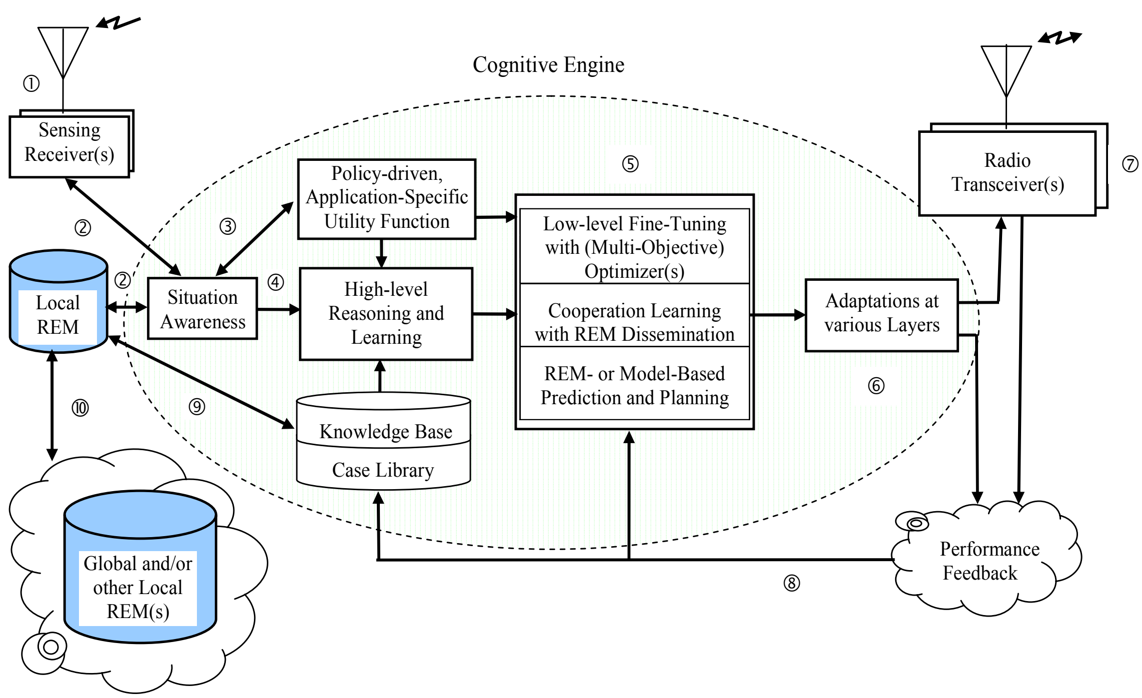


Figure 6-1: Framework and System Flow of a Generic REM-Enabled Cognitive Engine (REM-CE)

The procedures of the generic REM-CE are detailed as follows.

① Observe the operational environment with sensor(s). Note that the sensing module may include functionalities such as spectrum sensing, positioning, and so on.

② Obtain the comprehensive situation awareness about the current radio scenario with sensor(s) and the REM, and update the REM with the latest sensing results. Certain sensing actions may be triggered to collect the needed information, and this is referred to as *proactive sensing*.

③ Determine the utility function based on the policy and the specific application or radio scenario, and make application- or utility-oriented situation awareness if the utility function has been preset.

④ Initiate the case- and/or knowledge-based high-level reasoning and learning (for example, the REM-CKL).

⑤ Continue with low-level learning with a bank of optimization and modeling algorithms. Possible options are optimizing operational parameters with an appropriate (multi-objective) optimizer (such as genetic algorithms, local search, and simulated annealing); conducting cooperative learning; and applying the REM- or model-based (such as hidden Markov model and neural networks) prediction and planning.

⑥ Make final adaptation decision(s) in all relevant layers (such as physical layer, MAC, network layer, and up to application layer).

⑦ Execute the selected adaptations by radio transceiver(s).

⑧ Collect performance feedback from other radio nodes or environment sensing, and update the case library and/or knowledge base accordingly.

⑨ Exchange information/intelligence between the REM, case library, and knowledge base.

⑩ Disseminate and share information/intelligence in CR networks between REMs (such as the Global REM and the Local REMs).

6.2 Orientation: REM-Enabled Radio Scenario Awareness

Adaptation of CR requires comprehensive situation-awareness with goal-oriented focused attention and being aware of the available options for adaptation. Chapters 2 and 3 have discussed how REM helps CR to become situation-aware. The key idea behind the REM is digitizing and indexing radio environment information for CR access and sharing. Table 6-2 and Figure 6-2 classify various common radio scenarios. Table 6-3 illustrates how radio environment information could be digitized and indexed.

Table 6-2: Classification and Characteristics of Typical Radio Scenarios

Radio Scenario		**Key Feature**
In-vehicle	Airplane	High speed relative to ground
	Train/Subway	High speed relative to ground
	Bus/Ship	Low/medium speed relative to ground
Indoor	Office	Quasi-static, multipath-intensive
	Home	Quasi-static, multipath-intensive, various interferences
	Hospital	Quasi-static, multipath-intensive, restricted RF emission
Outdoor	Campus	Low speed
	(Dense) Urban	Low/medium speed, Manhattan mobility and propagation models, multipath intensive, large shadowing attenuation
	Suburban	Less severe multipath fading than urban area, less shadowing attenuation
	Rural	(Mountain area) Large delay spread
	Battle field	(Jungle or desert area) Random waypoint mobility model

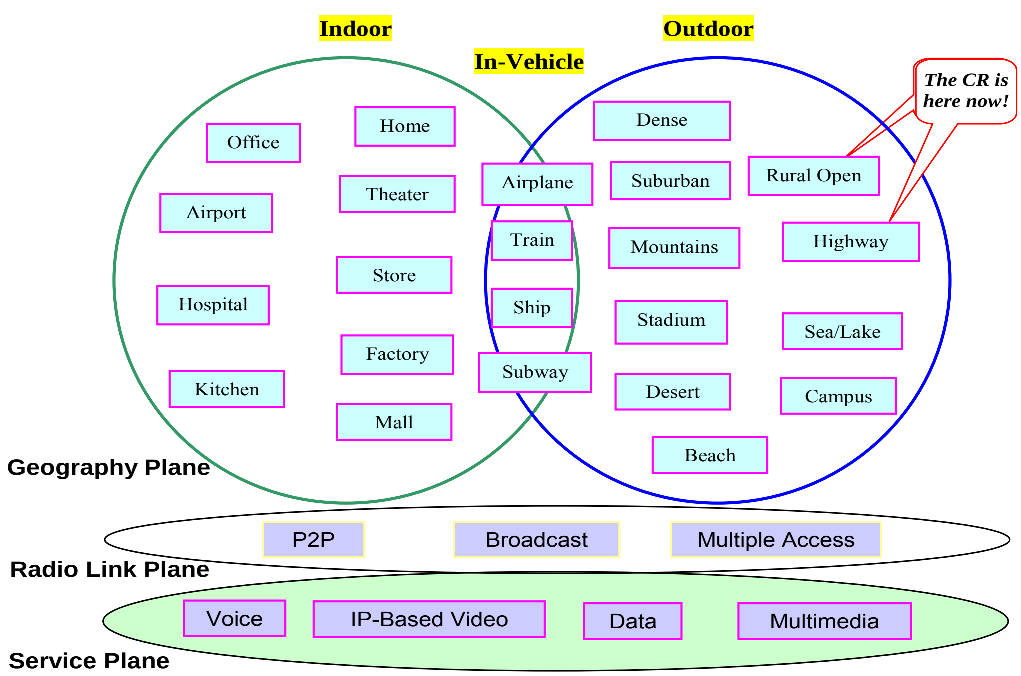


Figure 6-2: REM-Based Radio Scene Classification and Recognition

Table 6-3: Digitizing and Indexing Radio Environment Information Elements

Domain and Index Range	**Syntax and Index**
Application Type => 700–799	Voice (701), packet data (702), video conference (703), etc
Optimization Layer => 600–699	Minimize interference to PU (600), maximize SU throughput (601), etc
Topology and Network => 500–599	Infrastructure-based network [WCDMA(500), cdma2000 (501), WRAN (502), etc.]; ad hoc network (510), mesh network (520), sensor network (530), etc
MAC and Duplex => 400–499	TDMA (400), FDMA (401), CDMA (402), OFDMA (403); FDD (410), TDD (411), etc
Geography and Mobility Information => 300–399	Indoor [home (300), office (301), airport (302), factory (303), etc.]; outdoor [urban (310), suburban (311), open rural (312), highway (313), etc.]; In-vehicle [train (320), bus (321), car (322), plane (323), etc.], etc.
Modulation Type => 200–299	AM (200); FM (210); M-PSK [BPSK (220), QPSK(221), etc.]; M-QAM [16-QAM (230), 64 QAM (231), etc.]; etc
Radio Device Capability => 100–199	Channel coding [Convolutional coding (100), Turbo Coding (110), etc.]; maximum RF transmit power (120), sensitivity (130), operational bands (140); antenna type (150), etc
Experience => 0–99	Blind zone (10), hot spot (20), hidden node (30), etc.

Radio scene characterization and analysis are useful for the CE to update its current goal, determine appropriate performance metrics and utility function, and then select proper learning methods. Basically, the utility function determined and employed by the CE is a weighted combination of various performance metrics that are taken into account. There are various approaches to define the utility function. A well-defined utility function could facilitate the learning (optimization) process and help to obtain the desired solution in a prompt and reliable manner. In general, the CE could take all pertinent REM information elements into account when dynamically defining the global utility function in use, i.e.,

$$u_{global} = f(u_1, u_2, ..., u_N, w_1, w_2, ..., w_N) = g(REM\ inormation\ elements) \qquad (6\text{-}1)$$

where the weight w_i corresponding to u_i could be determined by the REM information elements through an ad hoc function or a lookup table (decision table).

The following performance metrics (which by no means are exhaustive) could be considered for a generic CE.

(1) u_1 = QoS of the CR radio network, in terms of the average bit-error-rate (BER), packet-error-rate (PER), or frame-error-rate (FER) of all CR nodes.

(2) u_2 = Spectral efficiency of the CR network, in terms of the amount of spectrum occupied by the CR nodes.

(3) u_3 = Energy efficiency, in terms of the average power consumption of the CR network.

In general, the global utility function for the CR network could be defined by

$$u_{global} = \prod_i (u_i)^{\omega_i} \qquad or \tag{6-2a}$$

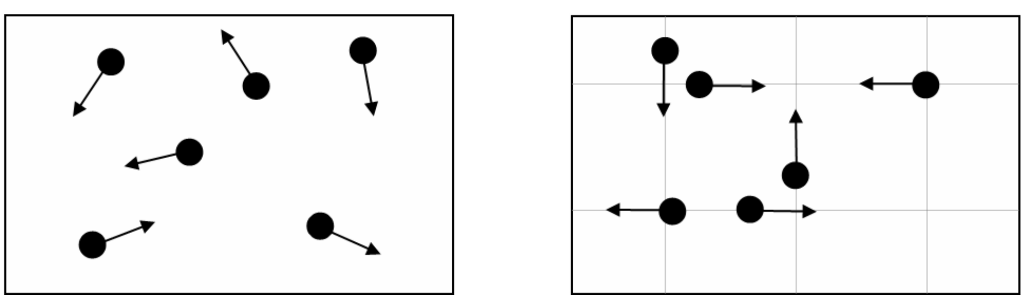
$$u_{global} = \sum_i \omega_i u_i \tag{6-2b}$$

where w_i is the weight applied to the i-th performance metric (u_i). Different weight vectors could be applied to adjust the global utility function. Similar to the geometric mean, (6-2a) accentuates low utility metrics, thus providing a fair and balanced combination of various performance metrics. The arithmetic mean (6-2b) may give a more flexible tradeoff. For some CR applications or scenarios, it may be appropriate to define a utility function that combines both geometric mean and arithmetic mean. The global utility should increase as the overall performance of the CR network is improved or the adaptation taken by the CR node(s) is in the right direction. The performance metrics and utility function employed in the current WRAN BS CE testbed are discussed in more details in Chapter 7 (refer to Section 7.1.3).

The dynamic selection of performance metrics and the weight vector for utility function can be accomplished by employing the REM-based radio scene classification and recognition, which is followed by case- and knowledge-based reasoning/learning. For example, if the CR network is deployed in an outdoor rural environment, higher weight might be given to the power efficiency over the spectral efficiency; if the CR network is deployed in some interference-sensitive areas (such as a hospital), additional metric like the interference emission level need to be considered.

As we know, case-based reasoning considerably reduces the time required for solving problems because it provides solutions from past cases, thus avoiding the long inference chains typical of rule-based reasoning. Three key issues must be addressed for case-based reasoning: (1) case retrieval, (2) solution transformation, and (3) case storing. Among these issues, case retrieval is the most important task. It is possible to group the governing attributes into qualitative and quantitative types. Depending on the type of attributes, procedures can be developed for determining the actual similarities of the retrieved cases with the current problem. The case selected from the retrieval process may not match exactly with the current problem, and a past solution may need to be adapted to meet the requirements of the current situation. This process is called *solution transformation*. The differences between the existing case and the new case are examined to determine whether or not the new case is worth storing (thus becoming another existing case) [60].

Radio scene analysis and recognition is also important for CR to select the most significant performance metrics and apply the appropriate mobility model and channel model to predict its performance. Existing mobility models include the Random Waypoint model, Group Mobility model, Freeway model, and Manhattan model [61, 62]. The Random Waypoint model and Manhattan model are illustrated in Figure 6-3. By referring to the REM, it is easier to know which mobility model matches the current CR (network) situation best. Under a given mobility pattern, routing protocols such as DSR and AODV may have different performance, possibly because each protocol differs in the basic mechanisms it uses [62]. Therefore, the CR network may adapt a networking protocol to different radio scenarios so that the desired network performance can be achieved. The relative importance of each performance metric dynamically changes with the situation to meet the needs of CR end users and/or CR operators. The REM can help determine the proper performance metrics and utility function for the desired adaptation and learning.



In the *random waypoint* model, CR nodes move to randomly selected destinations.

In the *Manhattan* model, CR nodes must move along a grid representing city streets. Destinations are still chosen randomly at the crossing.

Figure 6-3: The REM helps CR to determine the applicable mobility model.

The most important features of CR are the capabilities of autonomously obtaining situation awareness, learning from experience and environment, and adapting to new scenarios to maximize the utility. These features differentiate CR from the traditional SDR or adaptive radio. Cognitive behavior usually takes place in a rich and complex environment and is goal-oriented and a function of the dynamic environment. Therefore, obtaining comprehensive radio environment information is imperative for CR. Radio environment information is digitized, indexed, and then stored into the REM. The more clearly the radio environment is characterized and modeled, the better the CR can learn from experience and environment. As depicted in Figure 6-4, network support to CR can be realized by referencing the Global REM and Local REMs. The Local REMs and Global REM need to exchange information in a timely manner to keep the information stored at different entities current. Through REM dissemination and sharing, CR nodes can obtain up-to-date radio environment information and gain collective intelligence. In addition, the REM can incorporate information from various layers, such as policy, application, optimization, topology, and network layers, all of which are important to CR and cognitive wireless networks.

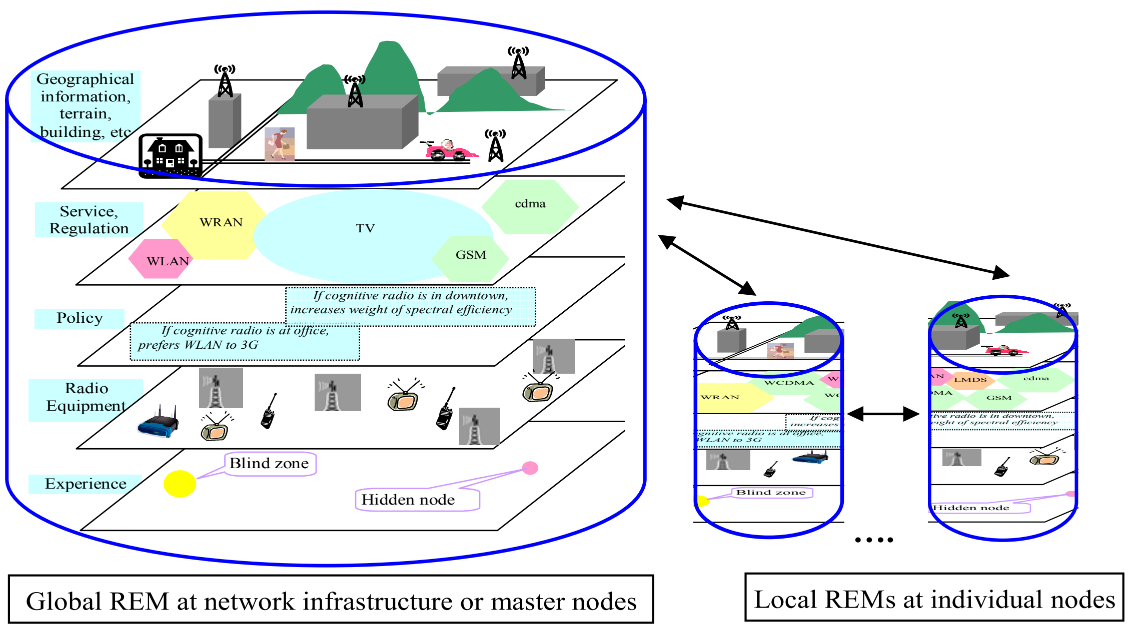


Figure 6-4: Global and Local REMs: Network Support for CR

Rather than observing the radio environment with blind and wide spectrum sensing, REM-enabled CR may choose to have a scalable view of the radio environment with an application-specific observation range. To obtain situation awareness, not every CR needs to conduct sophisticated spectrum sensing as long as it maintains or has access to an up-to-date REM. From a system standpoint, the REM enables a top-down approach for a CR to obtain situation awareness in a very efficient way. For example, the REM can inform the CR what kind of radio networks could be in service at a certain location. Based upon the specific air interface specification, the CR will know the possible frequency bands and modulation types used by PUs. The CR can even obtain some prior knowledge of PUs by analyzing the historical REM data. Therefore, CR can conduct PU detection with focused attention instead of spending excessive processing time performing complex spectrum sensing and signal classification algorithms. This top-down approach for PU detection and/or classification is more effective and efficient. Furthermore, the REM has the potential to support global cross-layer optimization by enabling CR to "look" through various layers from the policy, application, optimization, and topology layers down to the network, MAC, and physical layers. The REM also facilitates proactive sensing and adaptation, which means the REM provides the CR with advance information about the environment before the CR runs into possible problems.

6.3 Framework of REM-Enabled Situation-Aware Learning Algorithms

This section first briefly reviews various machine learning techniques and then proposes the framework of REM-enabled situation-aware CE learning algorithms. REM-enabled case- and knowledge-based learning (REM-CKL) algorithms leverage both case-based learning and knowledge-based learning in conjunction with the REM. Cognitive cooperative learning based on REM dissemination (REM-CCL) is an innovative peer-to-peer learning method for CR networks, especially for ad hoc CR networks.

6.3.1 Overview of Learning Algorithms for CR

Common learning techniques include, but are not limited to, case-based learning (CBL), knowledge-based learning (KBL), search engine-based learning (such as classical, mathematical optimization techniques [82, 83], simulated annealing, evolutionary genetic algorithms (GA) [93, 94], ant colony optimization [88], and Tabu search), artificial neural networks (ANN) [88], statistical learning such as Hidden Markov Models (HMM) [94] and

Bayesian learning, and cooperative learning. Table 6-4 summarizes the characteristics of each learning method, such as the strengths, limitations, and the possible combinations of algorithms that are expected to yield better results. For more details about these learning techniques, please refer to [63].

6.3.2 Framework of REM-Enabled Situation-Aware CE Learning Algorithms

The key idea of REM-enabled CE algorithms is to leverage the Global and/or Local REMs for comprehensive situation-awareness and efficient learning. By exploiting prior knowledge from the REM, the learning can be highly focused, which may, for example, lead to improved detection rates even if the signal (or interference) is weak and to lower modulation classification complexity compared to blind methods. Data mining in the REM can be employed for discovering the usage pattern of PUs or SUs and predicting future trend of the spectrum usage. The most popular tool used for data mining is a decision tree, which consists of nodes, branches and leaves [64].

Two topics have been discussed: first, radio scene classification and recognition, and second, case-based learning. Now they can be tied together. A case-based system is used to store information about the modeled environment and is tied to a set of objectives to be solved by the learning algorithms. Another entry to the case library is the past experience of CR. When the CR observes similar environmental situations, similar learning methods and actions should produce comparable results. If these past solutions gave positive results, the case-based learning process can be aided by starting with this knowledge.

Figure 6-5 indicates that the framework of REM-enabled situation-aware CE learning algorithms includes both a high-level and a low-level learning loop. The high-level loop is based on case- and knowledge-based reasoning/learning, which leverages various learning algorithms and selects the most appropriate learning method for the current radio scenario. The low-level loop optimizes the corresponding parameters used in the specific learning algorithm.

Table 6-4: Relative Merits of Various Learning Methods

Algorithm	Strengths	Limitations	Hybrid Options
Case-Based Learning (CBL)	▪ Close to human reasoning ▪ Can work in a chaotic situation with lots of variables ▪ Allows fast acquisition of knowledge ▪ Allows learning in the absence of domain knowledge	▪ Relies solely on previous case ▪ Large case memory required ▪ Might include irrelevant patterns	▪ Combining CBL and KBL yields a more robust problem solving system that does not rely solely on experience
Knowledge-Based Learning (KBL)	▪ Ability to tackle unforeseen situations ▪ Ability to include only relevant features while formulating a rule	▪ Perfect domain knowledge required which is not always available	▪ Can be combined with CBL to avoid a system that relies solely on deductive reasoning
Search-Based Learning (SBL)	▪ Excellent for parameter optimization and learning involving relationship between parameter values	▪ Formulation of rule space is difficult when learning or optimization is not restricted to parameter values	▪ Can be used in conjunction with KBL ▪ Learning can also be used in the search process
Hidden Markov Model (HMM)	▪ Can model complicated statistical processes ▪ Good for pattern matching ▪ Easily scalable ▪ Can predict based on past experiences	▪ Requires good training sequence ▪ Cannot cope with unforeseen situations ▪ Time-consuming for large classes ▪ Computational complexity	▪ REM can help HMM with providing training sequence for specific region or channel usage pattern. ▪ Based on previous knowledge, CBL and KBL can help HMM with determining the observation duration for a specific application.
Artificial Neural Network (ANN)	▪ Ability to describe a multitude of functions ▪ Easily scalable (adding new networks/neurons is easy) ▪ Excellent for classification problems ▪ Can identify new patterns	▪ Possibly slow training depending on network size ▪ Overtraining possible ▪ No theory to link application with required network	▪ Can use other learning techniques in the training phase (i.e., GA training) ▪ Can be combined with CBL and KBL
Cooperative Learning (CL)	▪ Enables distributed learning ▪ More reliable and comprehensive situation awareness by providing local information that might be hard to obtain ▪ Relaxes processing power requirement of individual nodes	▪ Network overhead ▪ Much more challenging to implement in ad-hoc networks, but probably more useful	▪ Can be implemented with any learning algorithm listed above ▪ Supports various hybrid leaning approaches ▪ Different nodes can adopt different learning methods

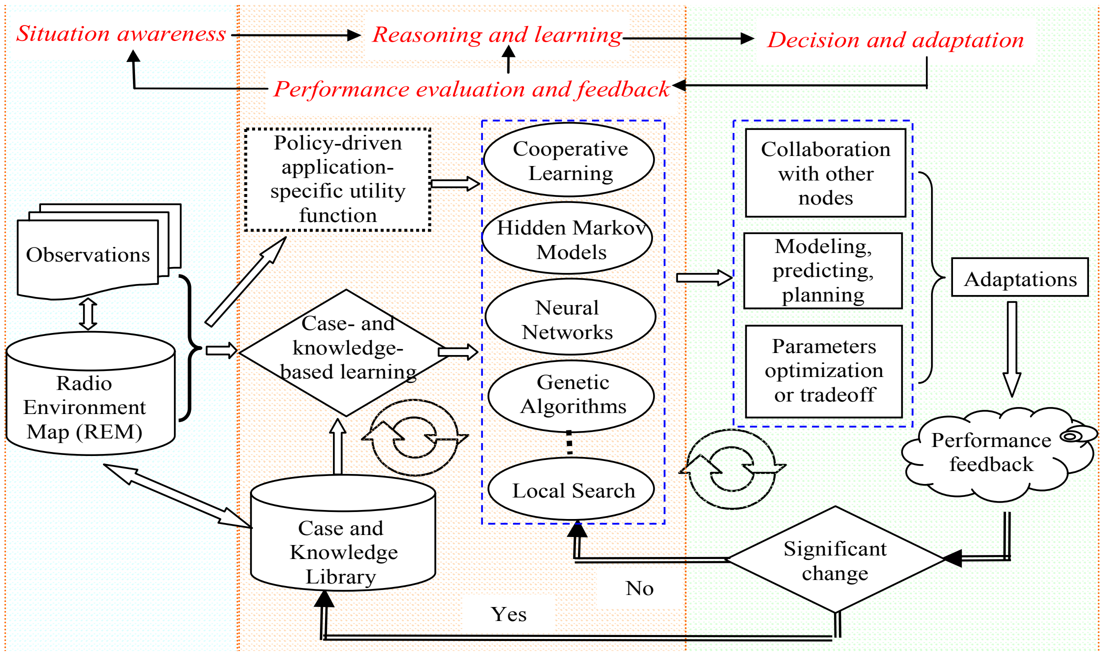


Figure 6-5: Framework of REM-Enabled Situation-Aware CE Learning Algorithms

Under a given radio scenario, a CR first chooses the most effective high-level learning method to use (e.g., cooperative learning or local search) and finds an initial (high-level) solution with case- and knowledge-based reasoning, then it starts the low-level learning and fine-tuning. For each new case, e.g., a new radio scenario that has not been previously experienced, the CR may take a "trial and error" approach and memorize its experience into case memory and REM (if the experience is associated with a certain location) for future reference. In this way, the CR will be able to learn from both its own and other nodes' experience.

With case- and knowledge-based learning, a CR can continually accumulate its experience or update its knowledge. The adaptation time shortens as the CR gains more experiences through various radio scenarios. Furthermore, the CR will adopt a better starting point and further reduce the solution space over which it must search. Case- and knowledge-based learning performs very well in dynamically changing environments and is well suited for implementation with the REM. By indexing REM information, radio scenarios can be characterized clearly and retrieved efficiently, not unlike indexing a dictionary. Further details regarding to REM-CKL will be explained in next subsection.

Similar to the proverb, “history is the world’s finest teacher,” historical system-level REM information is valuable to CR. For example, prior knowledge about the radio environment, such as spatiotemporal statistics of the PUs, can help a CR to improve the PU detection rate by adjusting the detection threshold [57]. Furthermore, a CR can derive the periodicity or model of PUs traffic based on REM information and specifications of wireless network standards and then opportunistically access the spectrum with fewer collisions by exploiting the inherent periodicity of widely employed TDMA or CSMA systems [65]. Some “slow” learning algorithms (such as data mining) can be employed offline as long-term learning.

6.4 REM-Enabled Case- and Knowledge-Based Learning (REM-CKL)

CBL is an inductive learning technique, which recalls prior experiences (cases) to solve current problems [66, 67]. KBL is a deductive learning technique that employs prior knowledge for similar purposes. REM-CKL is proposed to leverage both CBL and KBL techniques in conjunction with the REM. In this section, REM-CKL is further explained with an example application to the WRAN BS CE testbed.

6.4.1 Motivations of Applying REM-CKL to WRANs

WRAN systems have the following unique features compared to cellular systems: the radio links of WRAN systems are quasi-static, considering that both the PU and SU nodes could be assumed to be quasi-stationary; the spectrum usage patterns of PUs and SUs are usually periodic over one day and/or one week; the nature of TV signals is not bursty; and TV signals usually have predefined schedules, operate on fixed, pre-allocated TV channels, and are not changing dynamically. Wireless microphone operational bands are also fixed. Therefore, previous “cases” may recur. Furthermore, system performances (e.g., the BER of a connection) do not have explicit underlying analytical models. All these features motivate to employment of the CKL in a WRAN CE. The REM provides an efficient tool to characterize radio scenarios, which is a prerequisite for employing CKL and is why this is called REM-CKL.

Applying REM-CKL to WRAN systems offers two advantages: first, fast adaptation and second, optimal spectrum sensing and radio resource management. Based on past experience and prior knowledge, REM-CKL can provide a good initial solution for the CE to accelerate the optimization process. Leveraging knowledge-based learning helps to overcome the shortcoming of pure case-based learning and reduce the size of case library as well. Based on the REM information and REM dissemination among the CPEs and BSs, the BS is more knowledgeable about the usage pattern of each CPE (even if the CPE is associated with a neighboring BS) and the possible state of each channel. The spectrum sensing of WRAN systems can be conducted more efficiently with the help of the Global REM information.

6.4.2 Architecture of REM-CKL

An architectural diagram of REM-CKL for the IEEE 802.22 WRAN BS CE is shown in Figure 6-6. REM-CKL may consist of the following three major functional blocks.

(1) The pre-processor ("radio scene interpreter") characterizes the current radio scenario.

(2) The main processor ("case/knowledge reasoner") searches over the case library and/or knowledge base and finds an initial (high-level) solution through case retrieval/adaptation, applicable rules, and/or decision fusion.

(3) The post-processor ("high-level solution translator") maps the high-level solution to a set of operational parameters for immediate adaptation or further fine-tuning with the optimizer.

Note that REM and case library are two different logical entities. As illustrated in Figure 6-6, some APIs may exist between REM and case library and enable them to exchange certain information. For example, based on historical REM data, various statistical analysis (such as the channel reputation) can be made, which can be exploited in the CKL module to protect PUs even better; on the other hand, past experience can be recorded (or "marked") in the REM such that CR can make pre-emptive adaptations or planning/scheduling based upon past experience.

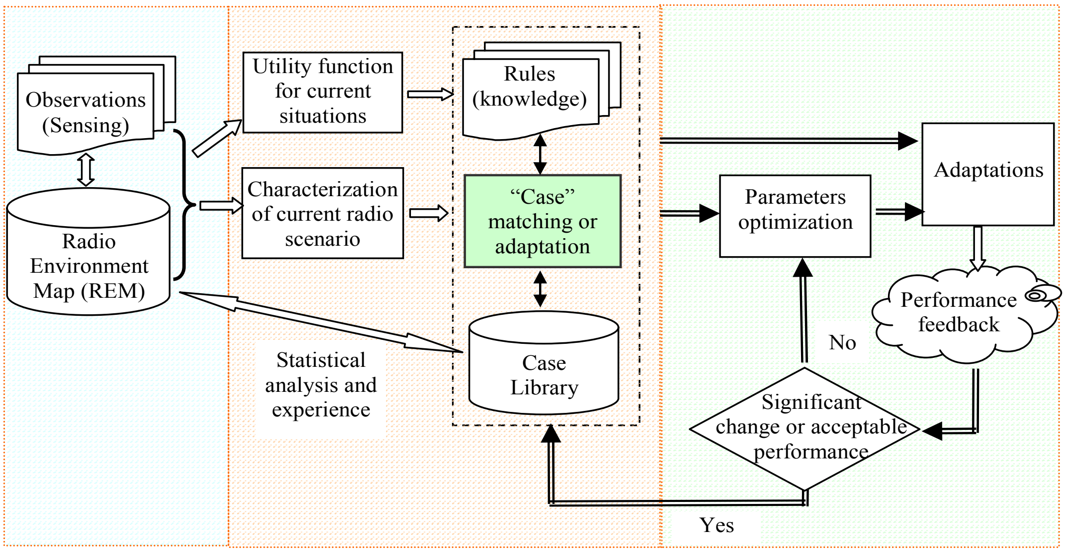


Figure 6-6: Architectural Diagram of REM-CKL

6.4.3 Procedures of REM-CKL

The detailed procedures of REM-CKL are discussed in this subsection. First, the CR needs to be aware of its situation by characterizing and indexing the current radio scenario and then retrieving the case library and/or knowledge base for applicable experiences and/or rules. For WRAN systems, the radio scenario can be identified by a set of state parameters, such as active CPE identities, the requested services, and the active/candidate/occupied channel sets, which altogether present the geographical layout of radio links, the required and the available radio resources at the BS, and the RF environment of CPEs.

An important step for the REM-CKL is to determine the similarity between radio scenarios. To accomplish this, various similarity functions can be defined [67]. For the WRAN REM-CKL CE, the similarity function can be defined as

$$f(\cdot) = w_1\Delta_1 + w_2\Delta_2 + w_3\Delta_3 \qquad (6\text{-}3)$$

where w_1, w_2, and w_3 are weights to the radio link similarity, radio environment similarity, and radio resource similarity, respectively and Δ_1, Δ_2, and Δ_3 represent the similarity of the geographical layout of CPEs and their service requests, the similarity of RF environment, and the similarity of available radio resource at the WRAN BS, respectively. Fuzzy logic could be employed to measure the similarity of qualitative metrics, such as terrain features and priority. For example, the priority of a certain performance metric could be indicated with a fuzzy slice such as *low*, *medium*, and *high*; the possibility of the presence of PUs in certain radio environments could be indicated with *probably*, *possible*, and *rare*. With fuzzy logic, the radio scene can be better characterized for CR.

More details about the REM-CKL implementation for the WRAN BS CE testbed are presented in Figure 6-7 and Tables 6-5, 6-6, and 6-7, and are documented in the 802.22 WRAN CE Testbed Users Manual [95].

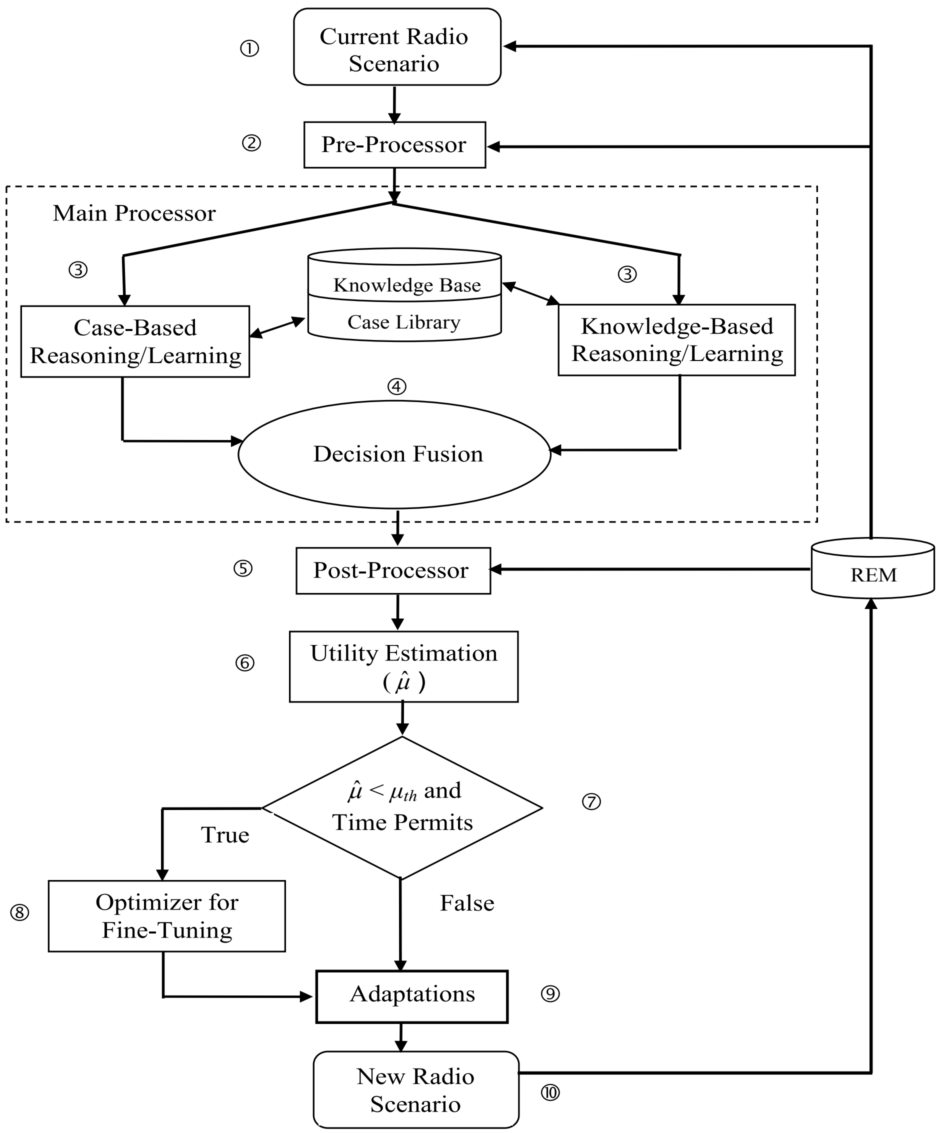


Figure 6-7: Flow Chart of the REM-CKL Algorithms

The procedures of REM-CKL algorithms are illustrated in Figure 6-7 and further explained as follows.

① Collect current radio scenario information from the REM and/or direct sensory observation.

② Pre-Processor: Characterize the current radio scenario by processing the REM information with goal-oriented focused attention and translate that into a generic and abstract problem represented by a state vector $\{S_1, S_2, \ldots, S_N\}$. The REM can be referenced directly by the pre-processor. For the WRAN BS CE, the state vector consists of the path loss of the radio link between the CPE and the BS, the service requested from the CPE, the required RRU and the allocated RRU, the available RRU for each active channel, the candidate channel set, and the occupied channel set.

③ Main Processor: Search the case library and knowledge base with the state vector and find an initial solution. For case-based learning, the similarity measure is employed to find the most matched case. For knowledge-based learning, the applicable knowledge ("rule") is applied to derive an initial high-level solution.

④ Decision Fusion: Combine results from CBL and KBL to determine the final abstract solution. Different combination methods could be applied, such as selective combination and optimal weighted combination, which is further explained later in next subsection. Update the case library and/or knowledge base with the estimated or measured performance of CRs.

⑤ Post-Processor: Map the abstract (high-level) solution parameter set to a set of M operational parameters $\{\theta_1, \theta_2, \ldots, \theta_M\}$ for the radio transceiver to make immediate adaptations or further fine-tuning with the optimizer. The REM can also be referenced at the post-processor.

⑥ Estimate the achievable utility ($\hat{\mu}$) with the resulting operational parameters.

⑦ Compare the estimated utility with the target utility (μ_{th}).

⑧ Fine-tune the operational parameters with a multi-objective optimizer if the estimated utility is less than the target utility and time permits. The optimizer should exit either when the resulting utility exceeds the preset threshold or when the search time has been exhausted.

⑨ Make adaptations according to the final (fine-tuned) operational parameters.

⑩ Update the REM accordingly with the changes to the environments. Return to Step 1.

6.4.4 Implementation Issues

To implement case- and knowledge-based learning, a certain level abstraction is needed to relax the requirements on case memory footprint or perfect knowledge base. For radio resource management at the WRAN BS, characterizing the radio scenario with a RRU (radio resource unit) allocation profile is proposed and is illustrated in Figure 6-8. The RRU profile shows the allocated RRU for each active channel at a WRAN BS at a given time instance. Using the RRU allocation profile enables the abstraction of various radio scenarios and facilitates the implementation of case- and knowledge-based reasoning/learning. The role of RRU profile is to abstract "real-world" radio scenario and to facilitate the Case- and Knowledge-based learning. In some sense, the RRU allocation profile at the WRAN BS is similar to the "power delay profile" used to characterize a multi-path radio channel. By examining the RRU allocation profile, the CE knows the current network radio resource allocations and the RF environment as well, and then retrieves the applicable knowledge or closely matched experience to quickly find an initial solution for the current radio scenario.

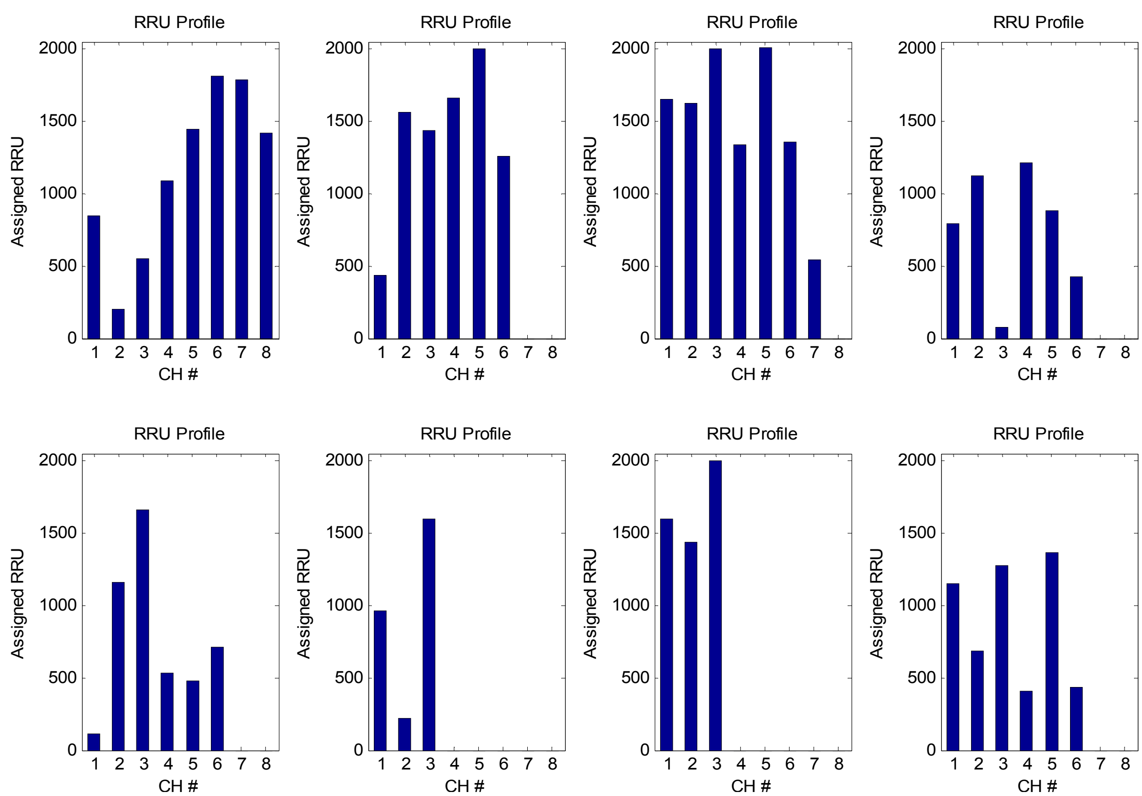


Figure 6-8: The RRU Allocation Profiles Characterize the Radio Resource Utilization at the WRAN BS. This figure shows the RRU allocation profiles at eight different time instances.

For real-world radio scenarios of WRAN systems, the distributed CPEs may have various locations and different types of service requests (such as voice, data, and video). To facilitate the radio resource management, the WRAN BS CE needs to know how much radio resource is required to setup a new connection for a CPE. To obtain a generic and convenient measure of the available radio resource at the BS and the requested radio resource from CPEs, a unitless metric–RRU–is proposed. For example, the required RRU (RRU_{req}) for a new connection can be estimated by

$$RRU_{req} = (1+\alpha)\frac{R}{\eta BW_{sc}} \tag{6-4}$$

where α is the overhead factor (unitless) that takes the overhead of the WRAN protocol into consideration and can be determined by the WRAN system specification; R is the data rate of the new connection (in units of "bps") and determined by the service type; η is the spectral efficiency (in units of "bps/Hz") jointly determined by the highest applicable modulation level and channel coding rate; BW_{sc} is the bandwidth of the WRAN OFDM sub-carrier (in units of "Hz") which is defined by

$$BW_{sc} = \frac{TV\ Channel\ Bandwidth}{FFT\ Mode} \tag{6-5}$$

In the context of the OFDM modulation format assumed for the WRAN, the physical meaning of RRU_{req} is the number of OFDM sub-carriers that needs to be allocated per WRAN frame for a given service request from the CPE. Equation (6-4) has taken the WRAN protocol overhead into consideration. Intuitively, the larger the associated protocol overhead, the more RRU will be required. For current CE testbed, α is set to 0.1.

Table 6-5 lists the spectral efficiency of various typical modulation and coding schemes used in WRAN systems[11].

---

[11] As suggested by Dr. Brian Agee, a quasi-information theoretic formula that defines the relationship between the spectral efficiency and the codec input SINR is as follows: $\eta = \log_2(1 + \frac{SINR}{gap_{codec}})$, where $SINR$ is the channel SINR, and the gap_{codec} is the codec "SNR gap" (or codec efficiency) which is to characterize the degree to which a codec can reach the capacity limit of a channel [98].

Table 6-5: Spectral Efficiency of Various Modulation and Coding Schemes for WRAN

Modulation Level	Coding Rate	Spectral Efficiency (bps/Hz)
QPSK	1/2	1
QPSK	3/4	1.5
QPSK	1 (no coding)	2
16QAM	1/2	2
16QAM	3/4	3
16QAM	1 (no coding)	4
64QAM	2/3	4
64QAM	3/4	4.5
64QAM	1 (no coding)	6

Table 6-6 provides the initial modulation and coding scheme based on a rough SINR estimation. Note that the values of SINR in Table 6-6 are used in the WRAN BS CE testbed for simulations under additive white Gaussian noise (AWGN) channels only without considering any type of interference (such as the intra-cell or inter-cell interference) [95]. In the real-world implementation, these values and the corresponding rules can be further fine-tuned with field measurements.

Table 6-6: Initial Modulation and Coding Scheme Based on a Rough Codec Input SINR Estimation

Estimated Codec Input SINR (dB)	Modulation and Coding Scheme for an Initial Solution
≤ 3	Service denied due to low SINR
(3, 3.5]	QPSK, 3/4 (convolutional coding rate)
(3.5, 4.5]	QPSK, no coding
(4.5, 6.5]	16QAM, 3/4 (convolutional coding rate)
(6.5, 10]	16QAM, no coding
> 10	64QAM, no coding

Table 6-7 summarizes the typical tasks of WRAN CE, key attributes of radio scenarios ("cases"), and the high-level solutions resulted from the CKL module. Basically, there are three types of problems encountered by the WRAN BS CE: allocating radio resource to the newly added connections and satisfying their QoS requirements when new service requests are generated from the CPEs; evacuating a WRAN (TV) channel and re-allocating radio resource to those interrupted connections promptly (within 2 seconds [48]) when PUs are detected; and managing and optimizing the radio resource all the time, especially when some radio connections are disconnected. The WRAN radio scenarios (“cases”) can be characterized by a set of state parameters, such as the path loss between the CPE and the BS, the type of requested services and the desired QoS, the requested RRU from the CPE, the allocated RRU profile at the BS, the active, candidate, occupied, and disallowed channel sets at the BS, and so on. High-level solutions are employed in the REM-CKL algorithm to quickly produce an initial solution.

Table 6-7: Details of REM-CKL Design for a WRAN BS CE

Type of Problems	Case Attributes	High-Level Solutions
[1] Add New Connections to the BS [2] Evacuate a TV Channel for PUs [3] Optimize Network Radio Resource	[1] CPE Profile (such as path loss, type of service, location, and priority*) [2] RRU_{Req} [3] $RRU_{assigned}$ [4] Active Channel Identity with Maximum Available RRU [5] Active Channel Identity with Minimum Available RRU [6] Active Channel Set [7] Candidate Channel Set [8] Occupied Channel Set * The priority of CPE could be ranked by $PL*R_0/BER_0$ (PL: path loss; R_0: Requested data rate; BER_0 : Target BER)	[1] Reject a new connection [2] Activate a candidate channel with the highest channel reputation [3] Use the active channel with minimal available RRU [4] Use the active channel with maximal available RRU [5] Use the active channel with most closely matched available RRU [6] Use the active channel with the largest number of CPEs [7] Use the active channel with the smallest number of CPEs [8] Radio resource reallocation (reshuffle) for optimization

For implementing CBL, a case library needs to be created. For each entry of the case library, it consists of attributes to describe the radio scenario, the solution, and the expected or measured utility. To reduce the footprint of the case library, in addition to leveraging the KBL, a unified entry design is employed, such that each case is an abstraction from the real-world scenarios. For example, CPEs in one cluster with similar path loss and applications will be matched to the same entry in the case library. For current WRAN BS CE testbed development, after the radio scenario is characterized, KBL is always applied to seek an appropriate solution for the initial testing due to lack of "experience" in the case library. Future field testing results can be employed to populate the case library, which should be updated continually with feedback information from the network operations. An inference engine is needed for KBL in order to evaluate and update the "rules" in knowledge base since these rules ("domain knowledge") may be neither perfect nor complete. Knowledge base need to be updated with future real-world performance feedback by the inference engine. For the current WRAN CE testbed, a preliminary knowledge base is developed and represented as a collection of "if–then" clauses, as illustrated below.

```
if Sum_RRU_Demand > Sum_RRU_Capacity
        actionID = 1;
elseif Sum_RRU_Demand > Max_RRU_ActiveSet
        actionID = 2;
elseif RRU_NewReq < MinAvailable_RRU
        actionID = 3;
elseif MinAvailable_RRU < RRU_NewReq < MaxAvailable_RRU
        actionID = 5;
elseif RRU_NewReq > MaxAvailable_RRU
        actionID = 8;
end
```

The REM-CKL algorithms aim to leverage both experience and knowledge such that (near-) optimal utilities can be obtained. Very similar to a human being's reasoning/learning process of tackling a new problem, CR may have different options for solving certain problems. It may prefer KBL when there is little experience. When CR gains more experience, it may tend to resort to CBL to solve a specific problem even better than by relying purely on "hard-coded" rules. An (near-) optimal solution may result from leveraging both CBL and KBL. Two combination methods for decision fusion are selective combination and optimal weighted combination, respectively. Selective combination simply picks the solution with better utility resulting from CBL or KBL. For optimal weighted combination, a weighting vector $\{w_1, w_2, \ldots, w_M\}$ needs to be determined for combining the sets of abstract solution parameters $\{\xi_{1C}, \xi_{2C}, \ldots, \xi_{MC}\}$ and $\{\xi_{1K}, \xi_{2K}, \ldots, \xi_{MK}\}$ resulting from CBL and KBL, respectively. The weighting vector should to be adjusted such that the combined solution can achieve a (near-) optimal utility. The weighting vector can be determined in various ways, for example, by employing fuzzy logic, neural networks, genetic algorithms, or heuristic methods. The weights may depend on many factors, such as the similarity between radio scenarios, the confidence level of applying KBL or CBL, and the size of case library or the completeness of domain knowledge. The combined solution is represented by a set of M operational parameters $\{\theta_1, \theta_2, \ldots, \theta_M\}$, and can be determined by

$$\theta_j = w_j \xi_{jC} + (1 - w_j)\xi_{jK} \qquad j = 1, 2, \ldots, M \tag{6-6}$$

where w_j is a non-negative real numbers between 0 and 1.

For the current WRAN BS CE testbed, the weights corresponding to KBL results are set to all "ones" since the current REM-CKL CE solely relies on the KBL due to lack of experience (i.e., experiment data).

6.4.5 Simulation Results and Comparisons

6.4.5.1 Baseline Algorithm

The REM-CKL CE and GA-based CE have been developed with C++ over Linux operation system and evaluated with the 802.22 WRAN BS CE testbed under various radio scenarios [72, 76, 95]. Theoretically, exhaustive search can produce the optimal solution. Due to the computational complexity of exhaustive search, the utility resulting from the GA is used as the approximate optimal utility (performance bound).

The GA is a well-known multi-objective optimizer that can provide globally optimal solutions [88]. Recently, the GA has also been investigated by the CR researchers for developing the CE [10, 93]. Furthermore, GAs use only objective (utility) function information, not derivatives, therefore GAs can deal with the non-smooth, non-continuous, and non-differentiable functions; GAs also can easily handle integral or discrete variables since GAs work with a coding of the parameter set, not the parameters themselves [88]. In this subsection, the GA-based CE has been employed to produce a performance benchmark for evaluating the REM-CKL algorithms. The procedures of GA are summarized as follows [88, 95].

① Initialization of the GA parameters, such as the population size (i.e., the number of chromosomes or "individuals"), selection size, chromosome size (i.e., the number of genes within one chromosome), the number of mutation, and the maximum number of generations.

② Production of the initial chromosomes. The initial solution of WRAN radio resource management is encoded as a chromosome. For example, a chromosome (i.e., a solution of the WRAN radio resource allocation) can be encoded as a binary string.

③ Evaluation of the fitness (i.e., the global utility as defined by Equation 7-2) of individuals (i.e., the chromosomes)

④ Selection of the fittest chromosomes (by ranking the global utility of each chromosome) for the new generation according to the selection probability

⑤ Crossover and mutation for production of new individuals (i.e., the new solutions). The crossover is conducted randomly between the parent chromosomes randomly selected from the set of fittest chromosomes (in previous Step 4). The mutation rate is the probability that mutation occurs on the offspring's chromosome. There are many ways to implement it. For the current CE testbed, the mutation operation is conducted by randomly selecting a number of genes from the offspring chromosome and invert them.

⑥ Replacing the old population with the new population. *Generation* is increased by one.

⑦ If *Generation* ≤ maximum number of generations, go back to Step 3, else, exit[12].

For the current WRAN BS CE testbed (version 3.0), the parameters used in the GA are summarized in Table 6-8. Note that these parameters are selected in a heuristic manner based on a lot of experiments. Future investigation may further fine-tune these parameters.

[12] The exit criterion used in the CE testbed is the number of generations. The complexity of GA could be reduced by lowering the number of the generations, but the penalty in doing so is the (near-) optimal utility might not be reached due to early stop. Another possible exit criterion is a preset threshold of global utility.

Table 6-8: Parameters Used in the GA for the 802.22 WRAN BS CE Testbed

Parameter	Value
Population Size	10
Chromosome Size	Variable (vary with the number of new connections, the number of operational parameters to be optimized, and the range and granularity of each adaptable parameter.)
Selection Probability	40% (the top 40% chromosomes are selected for reproduction through random crossover and mutation)
Number of Mutations	Max (2, chromosome_size/2000)
Number of Generations	Max (4, chromosome_size/population_size)

A section of the chromosome for GA-based WRAN CE is shown below. The size of the chromosome (in units of "bits") increases with the number of new connections, the number of adaptable parameters ("knobs") of the CR node, and the adaptation range of each "knobs".

……..	
TV Channel Index	Adaptable parameters (knobs) for the radio resource allocation for one connection between the BS and the CPE
Transmit Power (Downlink) Index	
Transmit Power (Uplink) Index	
Modulation and Coding Scheme (Downlink) Index	
Modulation and Coding Scheme (Uplink) Index	
Number of assigned RRU (Downlink) Index	
Number of assigned RRU (Downlink) Index	
……..	

6.4.5.2 Simulation Parameters and Adjustable Parameters

In the WRAN BS CE performance simulations, the cell radius of the BS is set to 33 km. According to the type of requested service, the bit-error-rate (BER) requirement for each connection is chosen among three levels ranging from 10^{-2} to 10^{-6} and the data rate of each connection ranges from 10 kbps to 750 kbps. The supported modulation schemes include QPSK, 16QAM, and 64QAM. Three channel coding rates are considered in the CE testbed: 1/2, 2/3, and 3/4. TDD duplex is adopted in the simulation with adjustable uplink to downlink duty ratio. The FFT mode adopted in the testbed is 2,048, which means each TV channel consists of 2,048 sub-carriers. The maximum effective isotropic radiated power (EIRP) at BS and CPE is 36 dBm (4 Watts), which is subject to the EIRP profile defined by the 802.22 WRAN standard [49] and local spectrum regulations. The radio link bit-error-rate (BER) performance under AWGN channel is estimated based on the SINR and the modulation and coding scheme in use [95]. The simulation parameters and adjustable parameters are listed in Tables 6-9 and 6-10, respectively.

Table 6-9: Simulation Parameters for the WRAN BS CE Testbed

Parameter	Value or Range
Number of BSs	1
Cell Radius	33 km
Number of New Connections to be Setup	1–256
Distribution of CPEs	Random uniformly distributed or clustered
Types of Service (Data Rate) Requested from CPEs and QoS (Target BER)	- Voice: 10kbps, target BER: 10^{-2} - Video: 100bps, target BER: 10^{-3} - Low Data Rate: 250kbps, target BER: 10^{-6} - High Data Rate: 750 kbps, target BER: 10^{-6}
Channel Model	AWGN channel
Multiplexing/Duplexing	OFDMA/TDD (downlink to uplink ratio is 3:1.)
FFT mode	2,048 (each TV channel has 2,048 sub-carriers.)
(TV) Channel Bandwidth	6 MHz
Number of Total TV Channels Supported at the BS	8

Table 6-10: Adjustable Parameters (Knobs) at WRAN BS and CPE

Parameter	Value or Range
Frequency Channel	VHF/UHF (54–862 MHz)
CPE and BS Transmission Power	Up to 4 Watts, subject to the EIRP profile (emission mask) defined by the 802.22 standards and local regulators. The EIRP profile may vary with the location of the WRAN BS/CPE. For the WRAN BS CE testbed, the CPE transmit power range: [-30, 6] dBW; The BS transmit power range: [-6, 3] dBW.
Modulation Schemes	QPSK, 16QAM, and 64QAM
Channel Coding	None, 1/2, 2/3, and 3/4 (convolutional coding rate)
Number of UL/DL Sub-carriers Allocated to the New Connection	Variable from 4 to 256

6.4.5.3 Simulation Scenarios and Results

First, the performance of REM-CKL is evaluated against that of GA under five typical WRAN scenarios, as described in Table 6-11. For each scenario, a number of new connections are added to an existing WRAN network. A CPE may have multiple connections for different services simultaneously, such as voice, data, and video. Each service is provided through one logical connection. For the current WRAN BS CE testbed, it is assumed that each CPE has at most one connection with the BS. Each scenario was run for twenty times and the new CPEs have random locations with respect to the BS for each run. Figures 6-9 and 6-10 show the WRAN BS CE performance simulation results in terms of average adaptation time and average utility. The preliminary results are focusing on evaluating the overall system performance in a statistical manner rather than the performance of an individual CPE. Future research may investigate the performance metrics such as BER or power efficiency of the CPEs at the (near-)optimal utility. The adaptation time is defined as the time period that takes the CE to produce a solution for a given radio scenario ("problem"). The utility is a weighted combination of spectrum efficiency, power efficiency, and link performance. The performance metrics and utility functions used in the WRAN CE testbed are detailed in Chapter 7 (refer to Equations 7-1 to 7-6). Note that all the simulations described in this subsection are programmed with C++ and run on a LINUX PC (3 GHz CPU clock rate and 2 GB RAM). The adaptation time is measured by the CPU run time[13]. The 95% confidence intervals of the average adaptation time and utility are also computed using the method as described by Jain [90] and shown in Figures 6-9 and 6-10 with error bars. Also note that the preliminary results shown here are demonstration of what the CE testbed is capable of achieving. More comprehensive testing is to be conducted along with the further development and enhancement of the CE.

---

[13] Note that using the CPU run time as the performance metric for comparing the computational complexity of different algorithms is a simple yet unreliable approach, since the CPU run time may vary (significantly) with the specific implementation of the algorithm, rather than the algorithm itself. Employing profiling tools that can evaluate the algorithms in terms of the number of basic operations such as the number of "adds", "multiplies", and "memory allocations" is under investigation. OProfile may be used for such purpose (refer to http://oprofile.sourceforge.net/ for more information about the OProfile).

Table 6-11: Testing Scenarios for WRAN BS CE Performance Evaluation

Scenario #	Number of Existing CPEs	Number of CPEs to Add to Network	Number of Initial Active Channels	Number of Initial Candidate Channels
1	2	3	1	9
2	10	5	2	8
3	10	10	2	8
4	10	20	3	7
5	10	40	3	7

As can be seen from Figure 6-9, by using the REM-CKL algorithm, the WRAN CE can adapt much (up to orders of magnitude) faster than using the GA. This is more apparent under complicated scenarios when more new connections need to be established. Fast adaptation is critically important for time-sensitive CR applications, for example, evacuating a channel for PU(s). Figure 6-10 shows that the WRAN CE can produce a consistently better average utility when using the GA. It was also shown in Figure 6-10 that the variation of the utility resulting from the GA is usually smaller than that resulting from the REM-CKL.

The initial solution derived from REM-CKL can be further fine-tuned through a local search[14] (LS). In the simulations shown in Figure 6-11, the WRAN BS CE tries to establish a number of new connections (ranging from one up to two hundred) for the distributed CPEs. There is no existing connection at the BS. One hundred runs are conducted for each scenario. For each run, the CPEs' location and type of service are randomly generated. Therefore, the simulation emulates various real-world WRAN radio scenarios. The simulation results show that the WRAN CE can achieve near optimal utility by synergistically leveraging both the REM-CKL algorithm and LS. It also indicates that the LS and REM-CKL may simply not be able to find a viable solution under some extreme radio scenarios (e.g., when the required RRU from

[14] A local search algorithm starts from a candidate solution and then iteratively moves to a neighbor solution. Typically, every candidate solution has more than one neighbor solution. The choice of which one to move to is taken using only information about the solutions in the neighborhood of the current one, hence the name *local* search. The choice of the neighbor solution is done by taking the solution that locally maximizes the criterion [86].

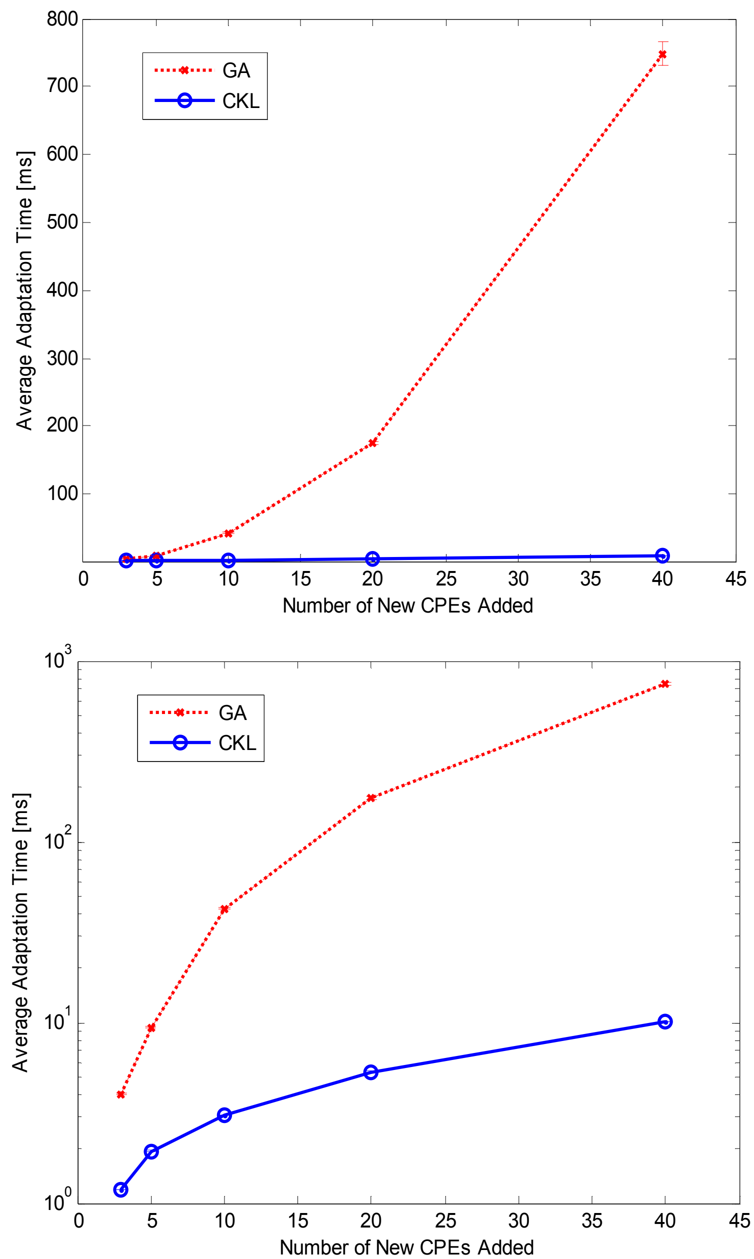
CPEs approaches the capacity limit of WRAN systems[15]). This is because the GA is a generic search and optimization tool that is independent from or insensitive to the specific radio scenario and/or the specific utility function in use. However, the rules and experience may be useful (applicable) *only* for closely matched situations with the similar utility. Therefore, the case library and knowledge base need to be updated accordingly when the radio scenario or utility function changes. To deal with challenging scenarios (such as the extreme cases) even better with the REM-CKL, case adaptation and inference engine are required, which can incorporate the artificial neural networks. This could be an interesting research issue in the future.

Again, note that the adaptation time measured by the CPU run time is simple to implement but may not be a reliable approach, considering the performance of the algorithms may highly depend on the specific operation system and the programming language in use[16]. It is preferred to estimate the complexity of algorithms in terms of the number of basic operations such as "adds", "multiplies", and "memory allocations". However, manually estimate the number of basic operations performed by a CE algorithm seems challenging (e.g., it might be difficult to estimate the computational complexity of a hyperbolic tangent function used in the global utility.) and incredible. Using profiling tools (such as OProfile) could be appropriate approach in terms of efficiency and credibility. OProfile is a low overhead, system-wide performance monitoring tool that uses the performance monitoring hardware on the processor to retrieve information about the kernel and executables on the system, the number of cache requests, and the number of hardware interrupts received (refer to http://oprofile.sourceforge.net/ for more information about the capability of OProfile). It is also an important future research issue to use the OProfile or other similar tools to make a more thorough and credible complexity comparison between different CE algorithms. Another potential issue about the complexity (e.g., adaptation time) comparison between the REM-CKL and the GA is that the GA might run excessive generations for some scenarios due

[15] The normal capacity of a WRAN BS is about twelve simultaneous connections per TV channel [48]. For a BS with eight active channels, the normal capacity is about 96 simultaneous connections from CPEs.

[16] Compared to MATLAB®, there is a closer relationship between the complexity of an algorithm and the CPU cycles for C++.

to the stopping criterion (i.e., a pre-defined number of generations) in use. However, how to (analytically) determine the minimum number of generations needed for the GA to converge remains a research issue. Though it is preferably to adopt a performance-driven stopping criterion for the GA, setting the target performance (i.e., threshold utility) properly might be a challenging issue for CR applications, especially under new scenarios where no prior experience is available.



(a) Time in linear scale

(b) Time in logarithm scale

Figure 6-9: Adaptation Time Comparison between REM-CKL and GA

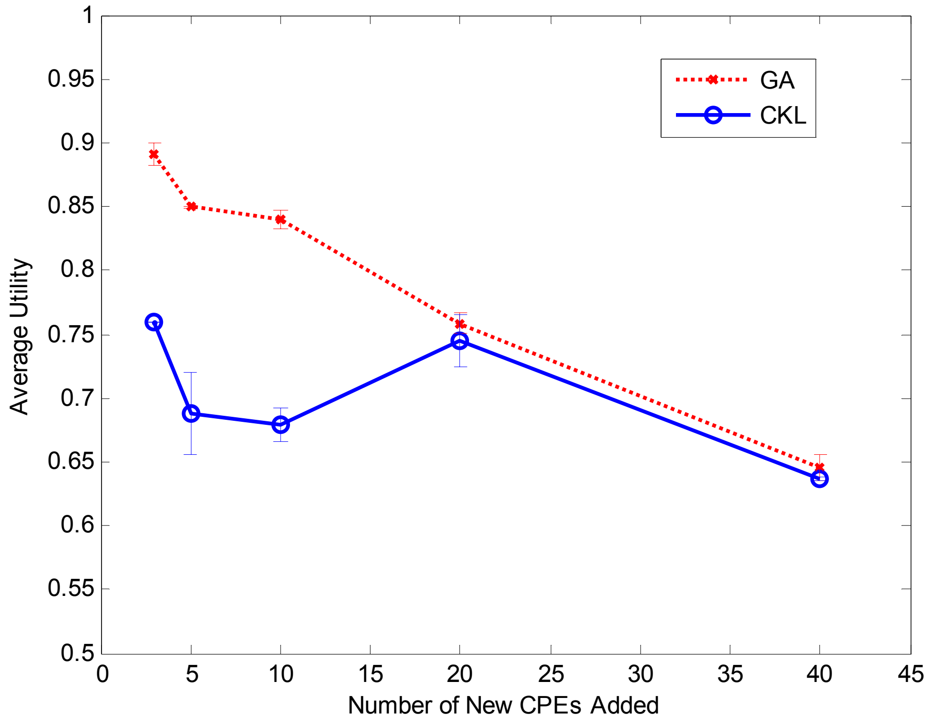


Figure 6-10: Utility Comparison: REM-CKL (without fine-tuning) vs. GA

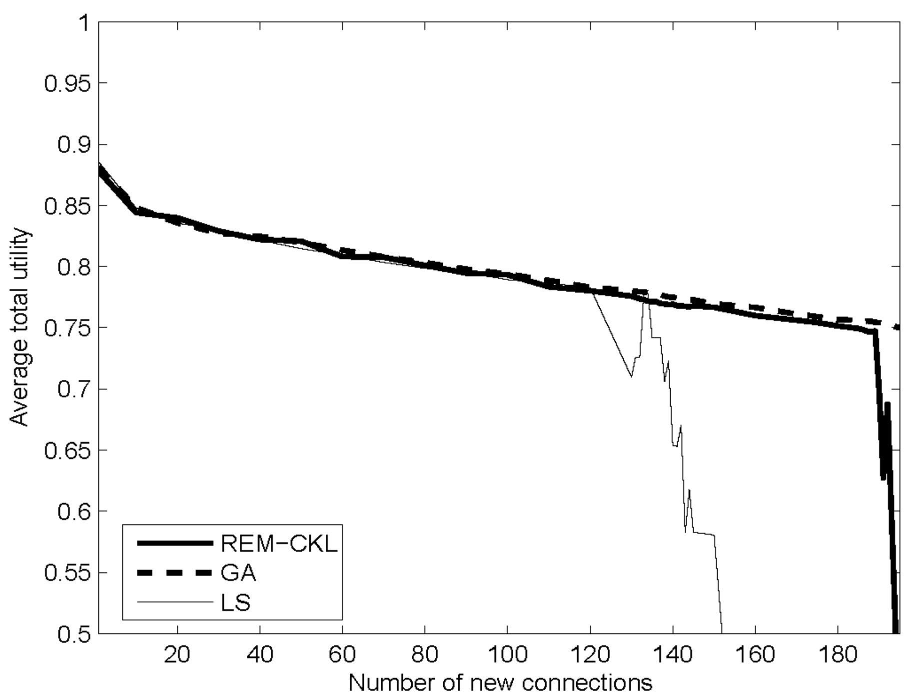


Figure 6-11: Utility Comparison: REM-CKL (with fine-tuning by LS) vs. GA

6.5 REM-Enabled Cognitive Cooperative Learning (REM-CCL)

In schools, cooperative learning has been adopted as an effective way of organizing the classroom to promote student-centered learning. No relevant report on applying cooperative learning to CR networks appears to have been published in the literature yet. In this section, REM-enabled cognitive cooperative learning (REM-CCL) is presented, focusing on the REM dissemination schemes and overhead analysis. The cooperative learning is enabled by REM dissemination, and the objective of learning and the specific information to be disseminated with REM could be *cognitive*, i.e., *varying* with applications and/or radio scenarios. That is why it is called REM-CCL.

6.5.1 Motivations and Key Issues

Cooperative learning is a collective learning method, which enables the CR node to learn from others. By leveraging cooperative learning, CR can learn in a collective and more efficient way for some challenging scenarios. REM-enabled cooperative learning is an innovative learning method that has great potential for low-cost large-scale CR networks. Cooperative learning enables the CR node to learn from other nodes' experience and/or observations and complement learning from its own experience and/or observations. As we know, key cognitive functionality, such as incumbent PU detection, cannot be reliably accomplished by user equipment itself due to the shadowing or fading effects of radio propagation and the practical system limitations of the sensitivity, dynamic range, and the noise floor. Distributed detection and data fusion can be viewed as a special application of cooperative learning. Essentially, cooperative learning in CR networks may have many applications by exploiting distributed signal processing techniques. The REM-CCL is not limited to cooperative signal processing. For example, it may also support distributed cooperative CKL, where the case library and knowledge base could be distributed and shared among CR nodes in a network. In this section, we discuss the general approach to cooperative learning and how to employ it with the help of the REM.

To implement REM-CCL, the major issues include, but are not limited to,

(1) Data structure for representing the radio environment information, i.e., *radio environment information representation.*
(2) Protocols and mechanisms for efficiently exchanging and sharing radio environment information among nodes, i.e., *radio environment information dissemination.*
(3) Cooperative learning algorithms to improve the performance of CR node or whole network, i.e., *radio environment information (data) fusion and exploitation.*

Figure 6-12 illustrates the idea of cooperative learning for CR networks in a battlefield application. To speed up the adaptation process (e.g., find the optimal spectrum and waveform to use), the CR nodes may learn from each other by sharing or exchanging their own learning experience. Furthermore, simple CR nodes can resort to more powerful CR nodes (e.g., sophisticated radio nodes dedicated for spectrum sensing and signal processing) for decision support.

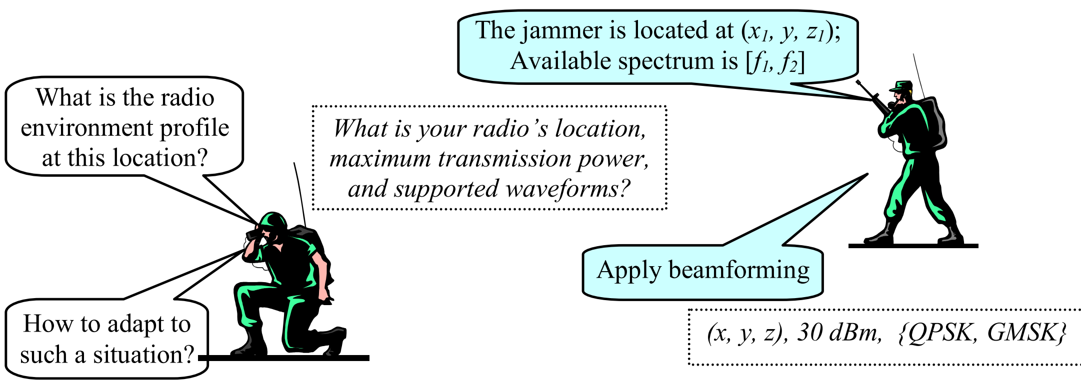


Figure 6-12: Illustration of REM-Enabled Cognitive Cooperative Learning (REM-CCL)

6.5.2 Typical Network Scenarios for REM Dissemination

802.22 WRAN systems are initially intended to offer fixed wireless access services in a centralized mode, though supporting mobility in an ad hoc network (or a mesh network) mode could be the natural evolution of current 802.22 standards in the near future.

For REM dissemination in CR networks, the following typical scenarios are considered [74].

Case 1(a): REM information sharing or exchanging between a central node and distributed nodes in infrastructure-based (centralized) CR networks;

Case 1(b): REM information sharing or exchanging between multiple central nodes and distributed nodes in infrastructure-based (centralized) CR networks;

Case 2: REM information sharing or exchanging between distributed nodes in ad hoc (infrastructure-less) CR networks; and

Case 3: REM dissemination in hybrid wireless networks combing both infrastructure-based and ad-hoc networks (mesh networks)

For Case 1(a), disseminating the REM with broadcasting (from central node to distributed nodes) or requesting/reporting messages (from distributed nodes to central node) is fairly straightforward; for Case 1(b), Case 2, and Case 3, the REM information can be disseminated in a way similar to that in which topology information is passed for routing table construction. Analyzing the overhead of REM dissemination in ad hoc CR networks is the focus of this subsection.

6.5.3 Performance Metrics of REM Dissemination

To evaluate the performance of various REM dissemination schemes, several performance metrics could be considered, such as load of overhead, latency, reliability, reachability, and correctness.

The load of overhead indicates the efficiency of the REM dissemination algorithm. Latency refers to the time delay from the REM information source to its destination, which can be estimated with maximum delay or average delay. The overall delay may consist of propagation delay, processing delay, queuing delay, and transmission delay. The REM information could be static (e.g., terrain features) or dynamic (e.g., RF spectrum usage). Latency can affect the freshness and utility of REM information since some dynamic REM information required for real-time adaptation could become useless if the dissemination delay is too big. Reliability is a measure of the percentage of REM packets received without error by network nodes, and reachability refers to the total number of unique nodes reached by the dissemination process. Correctness can be evaluated with the deviation between the original REM from the source node and the recovered REM at the destination node.

Note that there may be different considerations for REM dissemination compared to the control message flooding in ad hoc networks. For example, the REM information originated from one node may not be required to reach all other nodes in the CR network since only some nodes actually need such information. How often the CR node needs to disseminate the REM information may depend on the characteristics of the radio environment as well as the specific application.

6.5.4 REM Dissemination Schemes

The REM information can be disseminated in various methods. In this subsection, three schemes are considered, and their performance is compared in the next subsection.

A first and naive scheme is to periodically broadcast REM information to the entire network via plain flooding. This approach is straightforward though it tends to be prohibitively costly in terms of energy and spectrum consumption. The merit of this scheme is that it is simple, easy to implement, and requires no specific protocol support. It may be appropriate for small CR networks consisting of a limited number of nodes.

Motivated by the analogy between routing information dissemination in link state-based routing protocols and REM dissemination in CR networks, the optimized link state routing protocol (OLSR) can be extended for REM dissemination. More specifically, REM dissemination in ad hoc networks can be viewed as setting up a "generalized routing table" in CR networks. Considering that OLSR is a proactive protocol and uses the link-state scheme in an optimized manner to diffuse topology information, the Topology Control (TC) message in OLSR can be extended to support other dimensions of REM information in addition to topology; TC messages are broadcast and retransmitted by the multipoint relays (MPRs) in order to diffuse the messages in the entire network.

The OLSR protocol developed for mobile ad hoc networks is an optimization of the classical link state algorithm tailored to the requirements of a mobile wireless LAN. The key concept used in the protocol is MPRs, which are selected nodes that forward broadcast messages during the flooding process. This technique substantially reduces the message overhead compared to a classical flooding mechanism, in which every node retransmits each message when it receives the first copy of the message. In OLSR, link state information is generated only by nodes elected as MPRs. Thus, a second optimization is achieved by minimizing the number of control messages flooded in the network [71]. OLSR provides optimal routes (in terms of number of hops). The protocol is particularly suitable for large and dense networks as the technique of MPRs works well in this context. Figure 6-13 illustrates the MPR employed in OLSR and how it works. As we can see from this figure, MPRs are selected in a way such that messages from current node can reach all of its two-hop neighbors via retransmissions by MPRs only.

Finally, application-specific ad hoc methods can be used to further reduce the control overhead. For example, the REM dissemination rate can be adaptively adjusted according to the features of the incumbent PUs or interference; we may also disseminate only the selected REM information (rather than complete map) in an "on-demand" mode. A clustered approach may also be effective in optimizing the cooperative CR network performance while keeping the overhead to a minimum. Note that the dissemination algorithms for an ad hoc network may also apply to a multi-BS WRAN system in which CPEs are clustered by cells.

The REM information can be disseminated through a common control channel, which could be implemented with one of the following four options:

(1) a (narrowband) channel in licensed band,
(2) a channel in the license-free ISM or UNII band,
(3) an ultra wideband (UWB) channel, and
(4) sharing with the traffic channel.

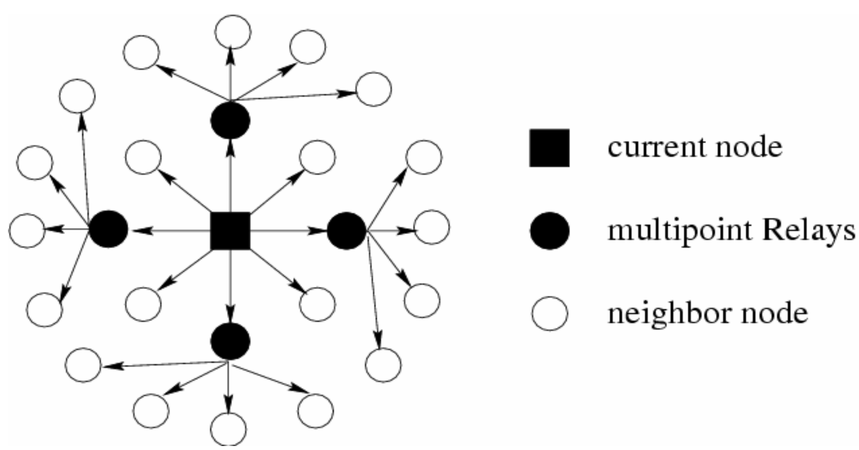


Figure 6-13: Illustration of MPRs Employed in OLSR Protocol

In summary, to minimize the traffic load of REM dissemination, we may try to minimize the number of retransmissions, reduce the message size of REM, and limit the sources of REM (i.e., the number of overhead originators).

6.5.5 REM Dissemination Overhead Analysis and Simulation Results

6.5.5.1 Analytical Models

Jacquet et al. present a theoretical analysis on the performance of OLSR multipoint relay (MPR)-based flooding and develop two graph models for indoor and outdoor scenarios, respectively [69]. These analytical models can also be used for REM dissemination overhead analysis for the scheme based on OLSR and are summarized below.

Case I: Random Graph Model for indoor ad hoc networks: the overhead of topology broadcast via MPRs in the random graph model is $O((\log N)^2)$ when N tends to infinity. (Note that N is the number of wireless nodes in the network.) This is a great reduction in overhead compared to $O(N^2)$ associated with the plain link state algorithm[17].

Case II: Random Unit Graph Model for outdoor ad hoc networks: the overhead of topology broadcast via MPRs in the random unit graph model is $O((N)^{2/3})$ when N tends to infinity.

Figure 6-14a plots the analytical upper bound of topology broadcasting overhead via plain flooding and MPR flooding, respectively. As can be seen, the broadcasting overhead can be significantly reduced via MPR flooding by orders of magnitude than that of plain flooding, especially for a network consisting of a large number of nodes. Figure 6-14b shows that the MPR flooding overhead for ad hoc networks with different link probabilities based on the random graph model. The link probability is p, in other words, a link exists between two nodes with probability p. Higher link probability indicates the radio nodes are closely connected each other and therefore results in much less MPR flooding overhead than that when the nodes are loosely connected. Figure 6-14b is a close-up of the details of the overlapping curves in Figure 6-14a.

[17] Classic link-state algorithms declare all links with neighboring nodes and flood the entire network with routing messages.

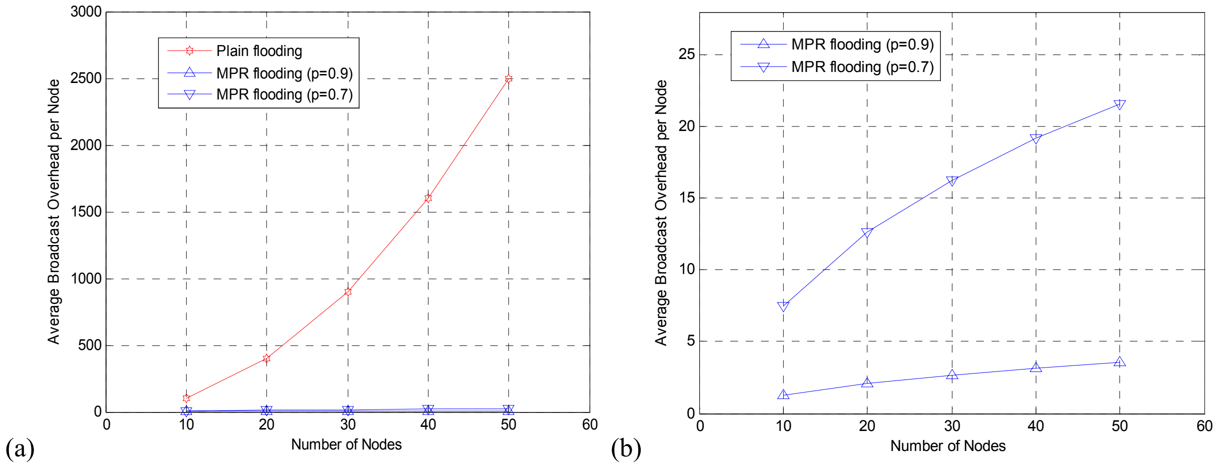


Figure 6-14: Broadcast Overhead Comparison: Plain Flooding vs. MPR Flooding

6.5.5.2 Simulation Model

In this subsection, the NS-2 network simulator ([56], version 2.29) is used to simulate the MPR flooding overhead under various mobile ad hoc network scenarios. The UM-OLSR [70] model was used in the NS-2 simulations. The UM-OLSR complies with RFC 3626 [71] and supports all core functionalities of OLSR. The simulation parameters are listed in Table 6-12.

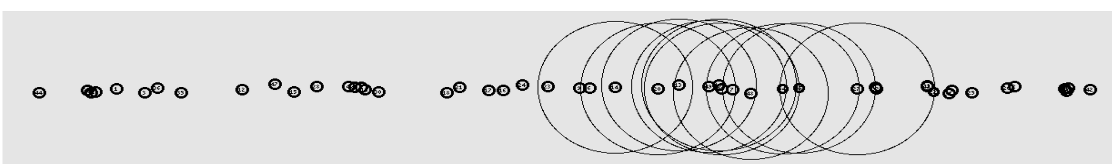
Table 6-12: Simulation Parameters for REM Dissemination

Parameter	Value
Communication Range of Wireless Nodes	250 meters
Maximum Moving Speed of Wireless Nodes	10 m/s unless stated otherwise
Pause Time in Random Waypoint Mobility Model	0
TC Interval in OLSR	2 seconds
HELLO Interval in OLSR	same as TC interval
REM Dissemination Interval	same as TC interval
Data Rate of Wireless Channel	2 Mbps
Interface Queue Length	50 packets
CBR Packet Size	512 bytes
CBR Traffic Rate	1 CBR packet per second
Radio Propagation Model	Two-ray ground model
Simulation Period	100 seconds

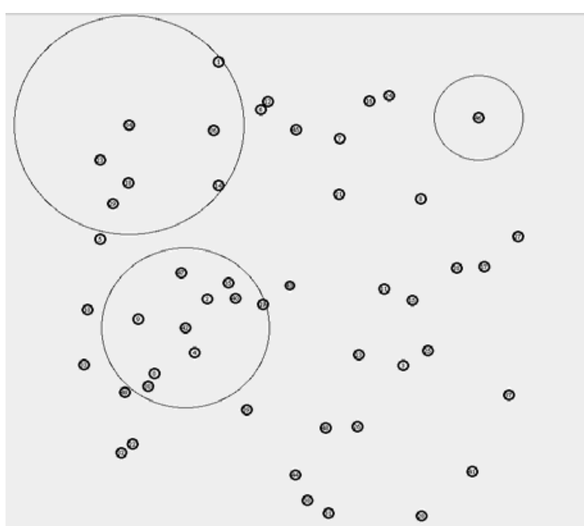
For all of the simulations described in this subsection, the wireless nodes comply with IEEE 802.11b PHY/MAC. The channel model used in NS-2 simulation is a two-ray ground reflection model. The REM information packet is to be piggybacked as part of the TC message. The overhead of REM dissemination is estimated in terms of the average REM information packets to be transmitted at each node by averaging the total number of TC messages sent during the simulation period.

6.5.5.3 Network Topologies for Overhead Simulations

Figure 6-15 shows the network topologies used in the NS-2 simulations. Topology A shown in Figure 6-15a emulates a mobile ad hoc CR network deployed along a street; Topology B shown in Figure 6-15b emulates a mobile ad hoc CR network deployed in an open square area. (Note that the circles in Figure 6-15 just show the instantaneous wavefront of radio waves radiated from different nodes at the time of snapshot. The radius of these circles does not mean the transmission range of different nodes. In these NS-2 simulations, all wireless nodes use the same transmission power.)



(a) Topology A: CR Nodes Located in a Street-Like Area (2000m × 20m)



(b) Topology B: CR Nodes Located in an Open Square Area (1000m × 1000m)

Figure 6-15: Screen Shots of NS-2 Simulations for Different Network Topologies

6.5.5.4 Overhead Simulations under Different Network Sizes, Topologies, and Node Densities

Simulations have been conducted to investigate the impact of network size, topology and node density on the overhead of REM dissemination [74]. Figure 6-16 shows the REM dissemination overhead for various node densities, network sizes, and topologies. In general, the simulation results are quite consistent with the analytical results shown in Figure 6-14b. In addition, note the following observations from Figure 6-16.

(1) If the network size is very small (e.g., 250m × 250m) such that most nodes are within one-hop range, the overhead load is low and almost constant (close to one REM packet per node) regardless the node density since no MPR is needed for such scenarios.

(2) If the network is of medium size (e.g., 1000m × 1000m) such that most nodes can communicate with each other through relays, the overhead load normally increases with the node density.

(3) If the network size is very large (e.g., 2000m × 2000m) such that many nodes cannot reach each other, the overhead load decreases again due to the decrease in the number of MPRs.

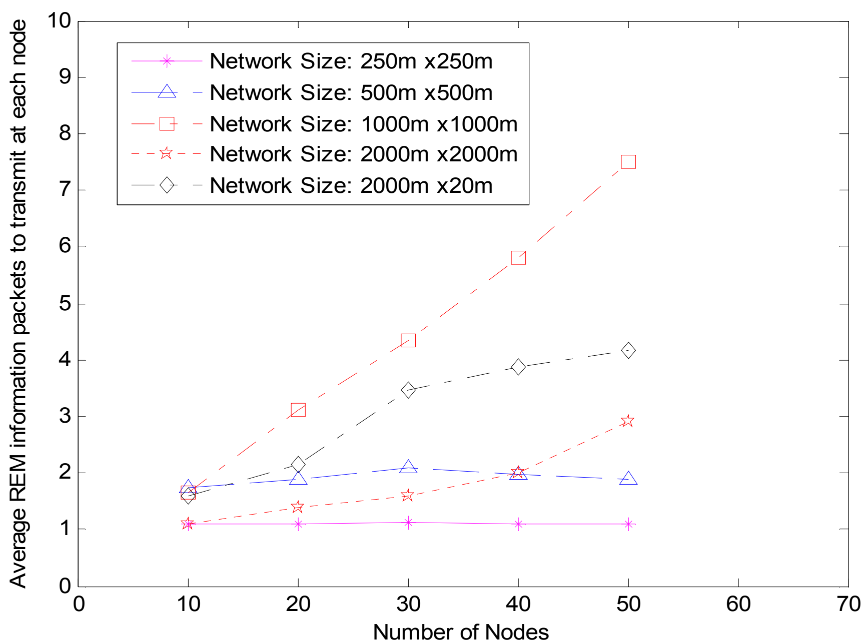


Figure 6-16: Overhead under Various Network Sizes and Node Densities

For the simulations in this subsection, the random waypoint mobility model is employed. In this model, each node randomly chooses a destination within the specified network area and a random speed from within a given range and moves toward it. When the node arrives at the destination, it pauses for a random period of time from a specified range and then chooses another destination and moves on.

To investigate the impact of moving speed to the overhead, the REM dissemination has been simulated with two different network topologies for comparison. For network topology A, the speed of each node varies from a low speed (1 m/s) to a very high speed (50 m/s). For network topology B, the speed of each node varies from a very low speed (0.1 m/s) to a medium high speed (10 m/s). Figure 6-17 shows the simulation results. For both types of network topologies, the speed of wireless node has little impact on the overhead load. This observation is reasonable since the overhead load mostly depends on the number of REM retransmissions, supposing that the REM dissemination rate is fixed (as is the case for these simulations). However, if the REM dissemination rate needed to change with the speed of wireless nodes, then the total overhead load would be affected by the speed of nodes, too.

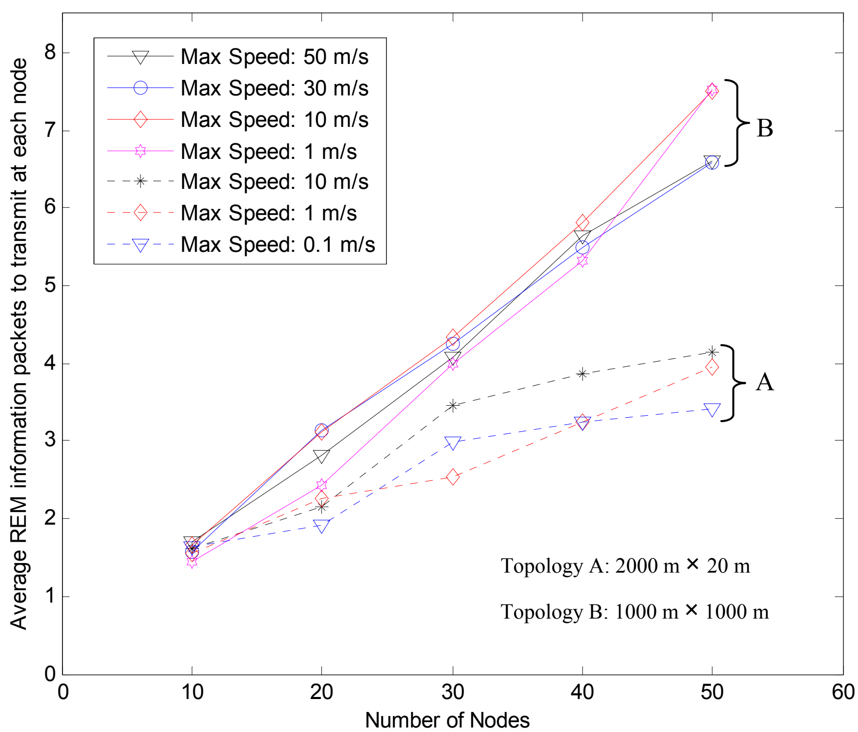


Figure 6-17: Overhead under Various Node Moving Speeds

6.5.5.5 Reliability of REM Dissemination

The reliability of REM dissemination is evaluated with the REM packet drop ratio in the simulations. Figure 6-18 shows the simulated REM dissemination reliability under different network scenarios using the following two different implementation schemes: the REM is disseminated through a dedicated control channel or the REM is disseminated by sharing a traffic channel with constant bit rate (CBR) stream. Figure 6-18 shows that (i) REM dissemination is more reliable when using a dedicated control channel, compared to using a shared traffic channel, and (ii) the REM packet drop ratio increases with the node density. This occurs mainly because REM packets are more likely to be dropped when REM dissemination is shared with other traffic or with an increasing number of nodes due to the capacity limit of the wireless channel and the finite queue at a node. Note that the bandwidth requirement is different for implementing these two schemes. For example, if the bandwidth of the traffic channel and dedicated control channel are BW_1 and BW_2, respectively, then the total required bandwidth for the first scheme is the sum of BW_1 and BW_2, (note that BW_1 is used for REM dissemination and BW_2 for traffic data), whereas all traffic data and REM packets share the bandwidth of BW_1 in the second scheme.

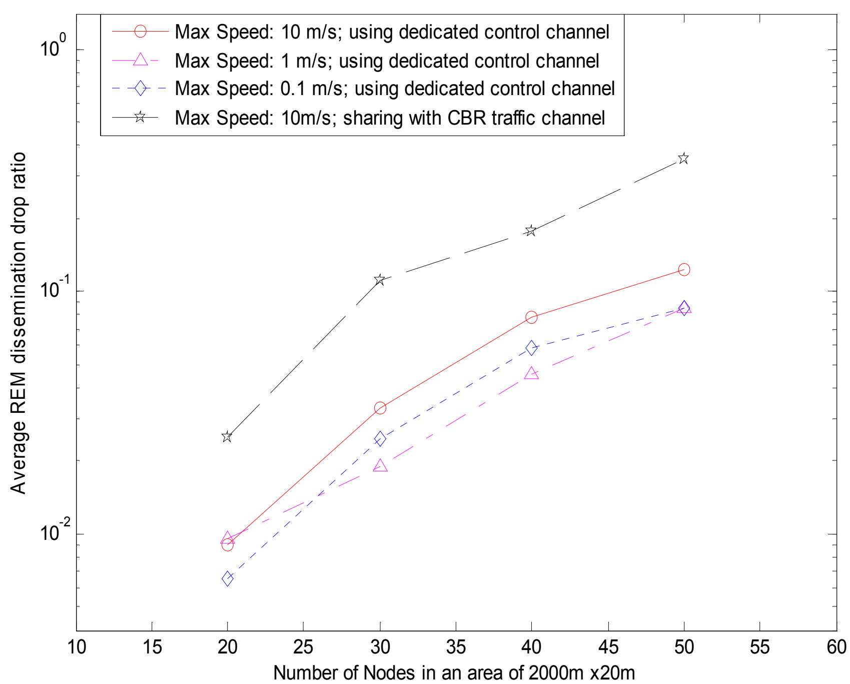


Figure 6-18: REM Packet Drop Ratio under Various Conditions using Different Dissemination Channels

6.5.5.6 Latency of REM Dissemination

The latency of REM dissemination is simulated under different network size. Figure 6-19 shows that for MANET, the REM dissemination delay ranges from 0.01 seconds to 0.06 seconds when the number of hops (retransmissions) ranges from 1 to 7. This figure shows that the latency of REM dissemination via MPRs may increase (approximately) linearly with the number of hops from the source to the destination. This is as expected when the traffic load is low (no queuing delay). A message will spend some time at each node, and such processing delays are approximately the same at each relay node.

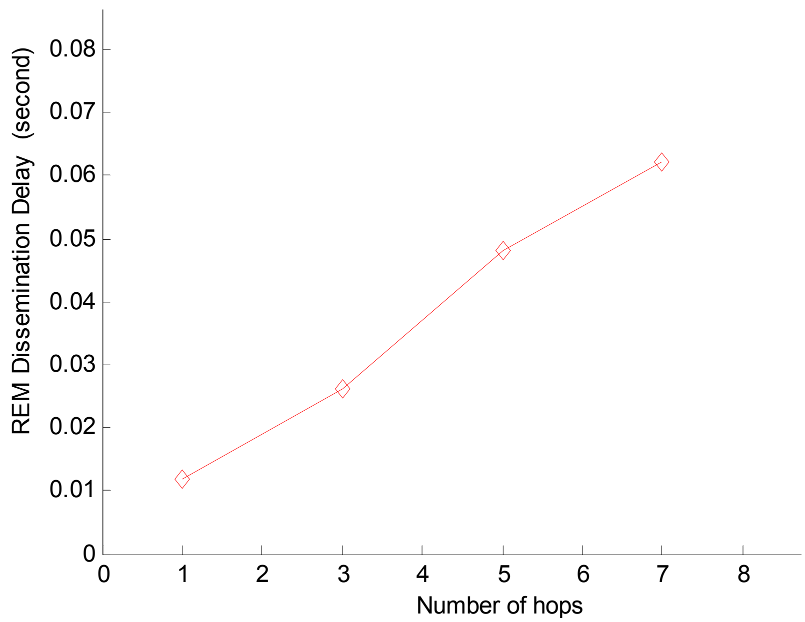


Figure 6-19: REM Dissemination Delay vs. Number of Hops

6.6 Summary

This chapter addresses the CE functionalities at different stages of the cognition cycle: orientation, reasoning, learning, and adaptation. By referencing the REM, the cognition functionality of the CE can be either enabled or enhanced. The framework of the REM-enabled CE has been formalized and may consist of two learning loops, i.e., a high-level learning loop and a low-level learning loop. The CE cannot reply on a single machine learning technique; it should leverage various machine learning techniques for different applications since each machine learning technique has its own merits and limitations. For

REM-CKL, one important finding is that some kind of abstraction is needed for similarity evaluation. Without abstraction of radio scenarios, the number of cases and/or rules in the case library or knowledge base could be prohibitively large. The tradeoff is between the level of abstraction and the details of the solutions for adaptation: if the abstraction level is high in the case library, then the solution offered by REM-CKL will be of a high level as well.

When using REM-CKL algorithms, the CE makes adaptations much (up to orders of magnitude) faster than when using GAs, especially under complicated scenarios. Fast adaptation is critically important for some time-sensitive CR applications. Using GAs, the CE produces a consistently better average utility, and the GA is more generic and robust to changes of utility functions or radio scenarios. Leveraging both the REM-CKL algorithm and a local search (or GAs) is a promising approach to obtaining (near-) optimal utility as well as fast adaptation. This is mainly because memory, i.e., past experience or knowledge, can help the local search or GAs with a better starting point. The performance and convergence of local search and GA are sensitive to the initial starting point (i.e., the initial solution). REM dissemination enables cognitive cooperative learning between CR nodes. The performance of REM dissemination in ad hoc networks with various network topologies, sizes, node density, and mobility are evaluated and compared. Efficient REM dissemination schemes have been proposed for different network architectures. By extending the existing OLSR protocol, REM can be efficiently disseminated via MPRs flooding in ad hoc CR networks. Simulations also show that the speed of the wireless node has little impact on the overhead load if the REM dissemination rate is fixed.

7 Performance Evaluation of Cognitive Wireless Networks

This chapter addresses one of the most challenging issues of CR: how to efficiently evaluate the performance of CR (or the CE). First of all, we discuss the performance metrics that could be used to evaluate CR networks' performance. Obviously, different performance metrics must be chosen for various CR applications. Next, a series of radio scenarios must be defined to validate the cognitive functionality of CR from aspects of spectral efficiency and utilization, interference mitigation, or PU protection. REM-based scenario-driven testing (REM-SDT) has been proposed and employed for comprehensive performance evaluation of the CE. The performance of the REM-enabled CR network coexisting with an incumbent PU network has been simulated under various radio scenarios.

7.1 Performance Metrics

7.1.1 Overview

Defining proper performance metrics for CR is a challenging task. Since CR has a lot of potential applications, such as supporting dynamic spectrum access and sharing, network coexistence, and interoperability, the applicable performance metrics will be application-specific and/or scenario-specific. The utility function employed by the CE could be defined as a weighted combination of the selected performance metrics. To be flexible for various radio scenarios or applications, the CE needs to adopt *dynamic situation-aware* utility functions rather than a *predefined static* one.

Some working performance metrics for CR are proposed in Table 7-1, which is by no means exhaustive. Also, note that for each performance metric, we may consider not only the average, but also its range and variance so that we know the performance under the worst-case scenario.

Table 7-1: Performance Metrics for Evaluating CR

Domain	Performance Metric
Situation Awareness	1. PU detection rate and false alarm rate 2. SINR (or BER) degradation at the PU receiver in presence of CR
Learning and Adaptation	3. Adaptation time to new scenarios 4. Channel evacuation time when PU (re)appears
Overall Network Performance Improvement for Spectrum-Sharing Networks	5. Increased spectrum utilization (in terms of sum throughput) 6. Negative impact to PU networks (in terms of increased average packet delay experienced by the incumbent PUs)

7.1.2 Performance Metrics for DAPRA XG Program

For DAPRA XG program, the performance metrics, which have been used during the field test, were defined for the following three scenarios [75].

(1) The XG network causes no harmful interference to non-XG systems in terms of
- abandon time (abandon a frequency channel within 500 ms) or
- interference limitation (maintain less than 3 dB SNR degradation at a protected receiver).

(2) XG network forms and maintains dynamic connectivity in terms of
- network formation/rendezvous time (establish an XG network of 6 nodes within 30 seconds)
- network join time (join a node to an existing XG network within 5 seconds) and
- channel re-establishment time (reestablish an XG network of 6 nodes within 500 ms).

(3) XG network adds value by reducing spectrum management setup time (no pre-assigned frequencies increase deployment flexibility) and increasing spectrum access (communications capacity) in terms of 60% or more spectrum occupancy with XG network of 6 nodes.

Note that the above metrics defined by DARPA are used as a threshold for establishing early confidence in the viability of dynamic spectrum access technologies. XG field testing conducted in 2006 has successfully demonstrated reliable networking without harming legacy nodes in dense spectrum environments [75].

7.1.3 Performance Metrics and Utility Functions for 802.22 WRAN

For 802.22 WRANs, the services and QoS requirements are similar to those for 802.16 WiMAX [49, 68]. The IEEE 802.22 draft standard defines the following four types of services, each of which has different QoS requirements. The Unsolicited Grant Service (UGS) supports constant-bit-rate (CBR) traffic such as voice over IP. Generally, for this service type, the BS allocates a fixed amount of bandwidth to each of the flows in a static manner. The Real-Time Polling Service (rtPS) supports real-time traffic in which delay is an important QoS requirement. The amount of bandwidth required for this type of service is determined based on the required QoS performances (i.e., delay), the channel quality, and the traffic arrival rates of the sources. The Non-Real-Time Polling Service (nrtPS) requires a QoS guarantee that is more flexible than that for rtPS. This is suitable for applications such as file transfer with guaranteed long-term throughput. The bandwidth allocation is also adaptive as in the case of rtPS. The Best-Effort Service (BE) is for best-effort traffic with no QoS guarantee. The amount of bandwidth allocated to BE connections is adaptively changed depending on other types of connections in the network.

Adopting appropriate utility functions is critical for the CE to achieve the desired performance of CR. The following performance metrics are proposed for the WRAN BS CE testbed [76].

(1) u_1 = QoS satisfaction of all connections, in terms of the average utility of all downlink and uplink connections between CPEs and the BS.

(2) u_2 = Spectral efficiency, in terms of the number of available candidate channels or the sum RRU assigned per active TV channel. This metric is more important for multi-cell scenarios or a single cell with a large number of CPEs.

(3) u_3 = Power efficiency, in terms of the transmit power of individual CPEs. This metric is more important for mobile or portable user devices or overlapping WRANs operated by different service providers.

In general, the global utility function for the WRAN CE is defined by

$$u_{global} = \prod_i (u_i)^{\omega_i} \tag{7-1}$$

where w_i is the weight applied to the i-th performance metric (u_i). Different weight vectors could be applied to adjust the utility function. Similar to the geometric mean, (7-1) accentuates low utility metrics, thus providing a fair and balanced combination of various performance metrics.

For the current WRAN BS CE testbed, the global utility (u_{global}) is subdivided between individual CPE utilities (u_{cpe}) and the normalized spectral efficiency of the BS (u_{BS}).

$$u_{global} = (\prod_{i}^{N} u_{cpe}^{i})^{\frac{w_1}{N}} u_{BS}^{w_2} \tag{7-2}$$

where N is the total active CPEs connected with the BS, and w_1 and w_2 are the weight for the geometric mean of individual CPE utilities and the spectral efficiency of the BS, respectively. The weights (w_1 and w_2) can be determined by the WRAN operator based on its priority and goal. For the WRAN BS CE testbed, w_1 is set as 0.9 and w_2 is 0.1. The individual CPE utility is defined as

$$u_{cpe} = f_1(P_b^{-1}, P_{b0}^{-1})^2 f_2(R_b, R_0)^2 f_3(P_t^{-1}, P_{t0}^{-1}) \tag{7-3}$$

where P_b, R_b, and P_t are the measured or estimated bit-error-rate, data rate, and transmit power (linear) of the CPE, respectively; P_{b0}, R_0, and P_{t0} are the target bit-error-rate, data rate, and transmit power of the CPE, respectively; and the utility function f is defined by a modified (shifted and spreaded/compressed) hyperbolic tangent function[18]

$$f_i(x, x_0; \eta_i, \sigma_i) = \frac{1}{2}\left\{ \tanh[\log(\frac{x}{x_0}) - \eta_i]\sigma_i + 1 \right\} \quad (\, i = 1, 2, \text{ and } 3) \tag{7-4}$$

where x and x_0 are the performance metric and the target value, respectively; and η and σ are the threshold and the spread parameter, respectively. The utility function f is monotonic and bounded by 0 and 1, as shown in Figure 7-1. For the WRAN CE testbed, the threshold (η) and spread parameter (σ) are chosen such that when the utility is 0.95 when the metric (x) achieves the target (x_0) and is 0.05 when the metric is one decade away. Note that the individual CPE

[18] The hyperbolic tangent function is defined by

$$\tanh x = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{e^{2x} - 1}{e^{2x} + 1} = -i \tan ix.$$

utility function (u_{cpe}) represents the degree of satisfaction of the user to the overall radio resource management. The modified hyperbolic tangent function is a type of sigmoid function[19] that can accommodate a large range of performance variations and capture the value of the service to the user quite naturally [76, 96]. If the solution does not meet the target goal, the utility is decreased sharply, whereas solutions that result in excessively high QoS provide little value to the user, thus the increase of utility is marginal. Note that the hyperbolic tangent sigmoid function is also widely used in artificial neural networks as activation function [88].

The normalized BS spectral efficiency (u_{BS}) is further determined by averaging the number of available subcarriers per WRAN channel, i.e.,

$$u_{BS} = \frac{1}{M}\sum_{i=1}^{M} u_{BS}^{i} \tag{7-5}$$

where M is the total number of channels supported by the BS; u_{BS}^{i} is the spectral efficiency for the i-th WRAN channel and also indicates radio resource utilization of this channel at the BS ($i = 1, 2, \ldots, M$). For the current WRAN BS CE, u_{BS}^{i} is defined by

$$u_{BS}^{i} = 1 + \tanh\left(\frac{RRU_{available} - RRU_{capacity}}{\sigma_{RRU}}\right) \tag{7-6}$$

where the $RRU_{available}$ is the number of available RRU for the i-th WRAN channel at the BS, ranging from 0 to $RRU_{capacity}$; the $RRU_{capacity}$ is the maximal number of available subcarriers of a WRAN channel; σ_{RRU} is spread parameter for the modified hyperbolic function. Note that for current WRAN BS CE testbed, the $RRU_{capacity}$ for a WRAN channel is 2048; σ_{RRU} is set to 800; u_{BS}^{i} is also monotonic and bounded by 0 and 1, as shown in Figure 7-2. The rationale to adopt such a modified hyperbolic tangent function (refer to Equation 7-6) as the

---

[19] A sigmoid function is a mathematical function that produces a sigmoid curve — a curve having an "S" shape. Sigmoid functions include the logistic function, ordinary arc-tangent, the hyperbolic tangent, and the error function.

utility function for overall WRAN BS spectrum efficiency is that it helps the CE to squeeze the spectrum used by the WRAN BS (in terms of the number of channel or subcarrier in use) through the optimization process. For example, the solution will produce a lower BS utility (u_{BS}) if the CPEs are assigned to subcarriers spreaded into two or more WRAN channels as compared to the more spectral efficient solution in which the CPEs are assigned to subcarriers within the same WRAN channel (if possible).

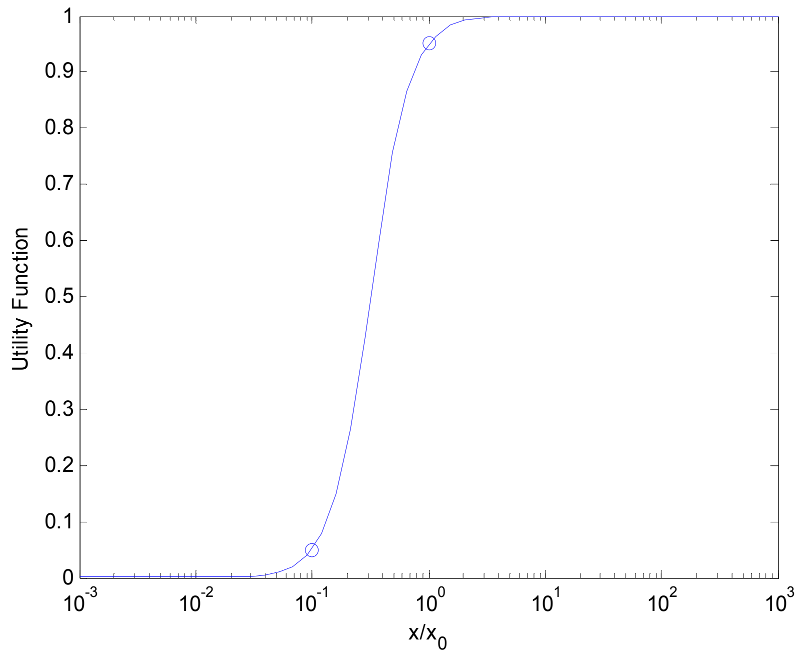


Figure 7-1: Utility Function Used in the WRAN BS CE Testbed

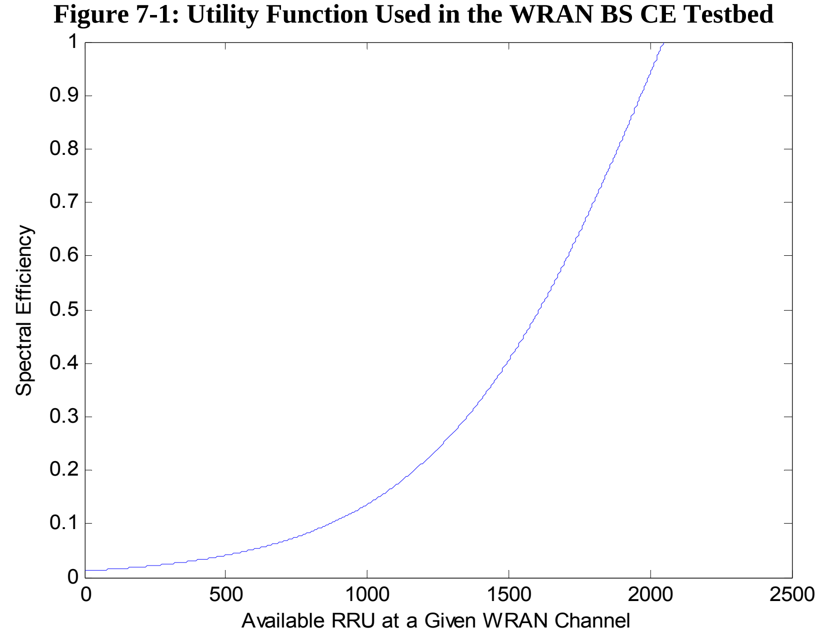


Figure 7-2: Spectral Efficiency of the WRAN BS vs. Radio Resource Utilization

Note that the metric and utility function employed by the current WRAN CE tetsbed are selected or defined in an ad hoc manner. Alternate metric or refined utility function that may improve true performance of the CR networks is a potential area of further research. For example, in future investigation, the next generation of WRAN BS CE may include some metric of spectral efficiency that takes the application layer (service type) into consideration, such that it takes the network overall utility into account and helps to produce a better scheduling scheme. Note that scheduling is not considered yet for the current WRAN BS CE testbed. The CE may also include some power efficiency metric that takes the power *consumed* by the CPE into account such that it helps to produce energy-aware adaptations for the future mobile ad hoc operational mode of WRAN systems; Furthermore, the WRAN CE may adopt some metric that addresses the aerial radiation of environment in terms of the penetrating interference level to the neighboring WRAN cells.

7.2 Methodology for CE Performance Evaluation

7.2.1 CE Testing Methodology

CR testing is a challenging issue for CR developers, testing equipment manufacturers, and regulators because CR operates very differently from traditional radios due to its flexibility, learning capabilities, and the demanding or unpredictable operation environments. The most accurate predictor of the future performance of CR is to emulate it in a similar situation, not unlike the behavior-based interview. REM-based radio scenario-driven testing (REM-SDT) is a viable approach to evaluating the performance of the WRAN CE [72].

The REM could also be used as a virtual "radio environment generator" together with other test equipment, such as arbitrary waveform generators, for testing the CR's performance under various radio scenarios. The CR under test is subjected to various realistic situations stored in the REM, which could be in form of machine-readable XML (eXtended Markup Language) files. For example, the CR tester could emulate various PU waveforms with certain usage patterns in certain frequency bands and then measure the performance of the CR under test through its RF emission. This can indicate the cognition levels and the effects of its adaptations. For WRAN systems, typical radio scenarios, extreme scenarios (e.g., no CPE is active in the BS service area or the number of active CPEs exceeds the normal capacity of the BS), and hidden PU scenarios should be considered when testing the WRAN CE. A virtual REM-based CR testing system may also be used to create a "controlled" radio environment for performance comparisons of CRs powered by different CEs.

For cognitive wireless network evaluation/simulation, a new methodology may be required and should be able to measure the performance of CRs under various radio scenarios. The scenario here is a combination of radio environment, wireless network configurations, and communication activities. In other words, it will be *scenario-driven* simulations/testing rather than the traditional *clock-driven* link-level bit error rate (BER) performance simulation or *event-driven* network-level performance simulation. One way to generate sufficient testing scenarios is to exploit the REM and apply the Monte Carlo simulation method to produce a large amount of random (or following certain distributions) radio scenarios. Hence the name REM-based scenario-driven CR testing (REM-SDT). The proposed CR performance testing system setup is illustrated in Figure 7-3, which focuses on the use of testable responses for evaluating CR's performance. The CR (or the CE) under test is subjected to various realistic situations depicted by radio scenario files.

REM-SDT has been employed to evaluate the performance (e.g., the achieved global utility and the adaptation time) of the WRAN BS CE through a series of test scenarios described in XML files. It is a cost-efficient testing approach since possible problems can be identified before the CE is deployed in the real world.

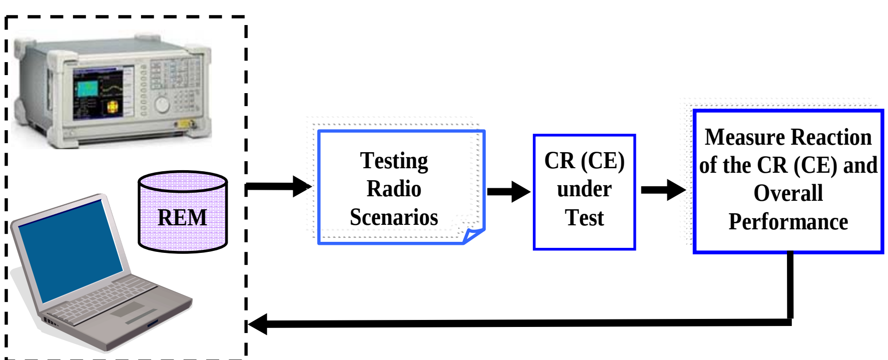


Figure 7-3: Block Diagram of REM-Based Scenario-Driven CR Testing (REM-SDT)

7.2.2 Test Scenarios for WRAN Systems

Three types of “problems” should be considered in the test case (testing radio scenario) design for evaluating the performance of 802.22 WRAN CE: adding new connections to the BS, evacuating a TV channel when PU (re)appears, and optimizing network radio resource (e.g., after disconnection). In this section, typical, extreme, and hidden node scenarios of WRAN systems are examined [49, 72].

For a typical WRAN system, we may have the following three types of operational scenarios:

The first scenario consists of a single BS with up to twelve simultaneous users per TV channel being served, the number of channel cards at WRAN BS is limited by eight, and the maximum number of CPEs in one WRAN cell is about 600. Furthermore, two geographical distributions of CPEs are considered: the CPEs are uniformly distributed in the WRAN cell and the CPEs are clustered, but uniformly distributed in the cell. The second scenario involves multiple BSs operated by the same operator and with REM information shared among the different BSs. The third scenario involves multiple BSs operated by different WRAN operators with the REM information *not* be shared among different BSs.

In addition to typical scenarios, the following extreme scenarios must also be considered.

- There is no active CPE in the WRAN cell.
- CPEs are clustered and non-uniformly distributed CPEs, e.g., at the initial deployment stage of WRAN system, the CPEs are located so close to the BS that they cannot detect a remote PU.
- More than 100 CPEs simultaneously have service requests, i.e., the number of service requests is greater than single BS’ capacity.

Three typical hidden PU scenarios are discussed below [49, 72].

Case 1: One typical hidden incumbent PU scenario is shown in Figure 7-4a. The PU is undetected by the WRAN BS mainly because the CPE’s RF front-end is saturated by strong emissions from nearby TV stations. Such a CPE cannot decode messages from the WRAN BS and therefore cannot report anything to the BS.

Case 2: Another typical hidden incumbent PU scenario is shown in Figure 7-4b. A sectorized WRAN BS uses different TV channels for different sectors. As the wireless microphone operating in Channel #1 cannot be detected by CPEs operating on Channels #2 and #3. To address this problem, REM-CKL can be employed together with situation anticipation and cooperative sensing such that for each WRAN channel, the WRAN BS's signal coverage should not exceed its sensing range.

Case 3: When very few CPEs are in operation at the initial stage of WRAN deployment or when CPEs are clustered and non-uniformly distributed in the cell, detection of PU (TV station) signals could be unreliable, i.e., the PU detection rate tends to be low.

WRAN CE should be aware of these hidden node situations with the help of the REM and take pre-emptive measures accordingly.

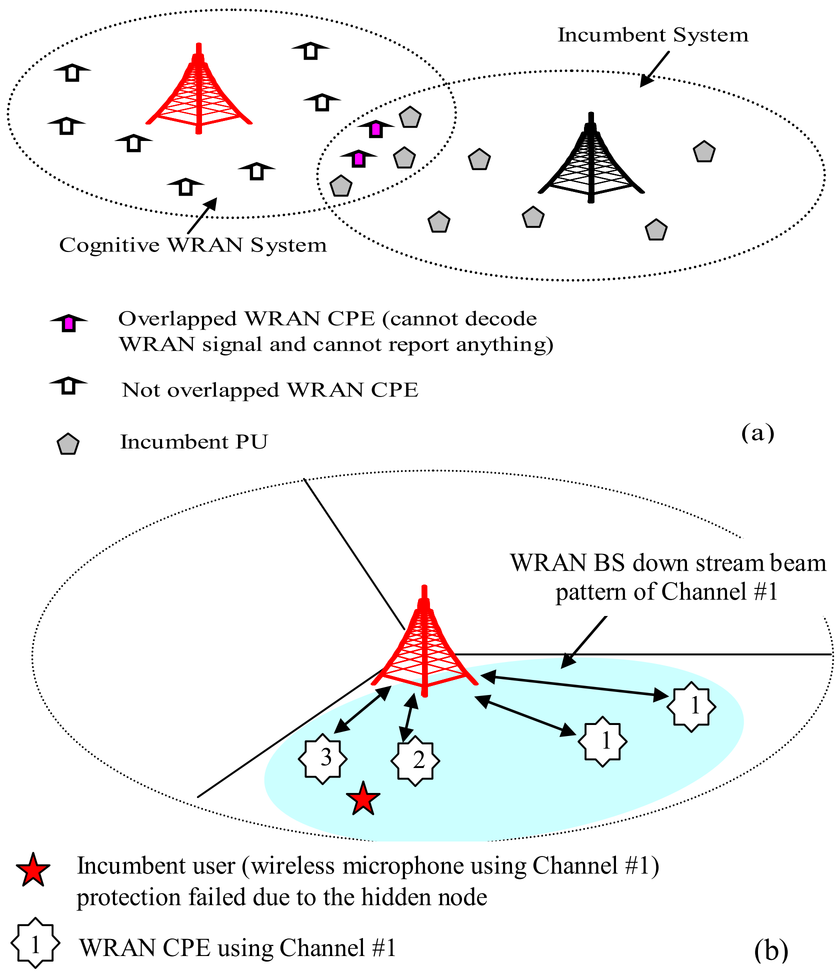


Figure 7-4: Typical Hidden Incumbent User Scenarios in WRAN Systems

7.3 Performance of REM-Enabled Spectrum-Sharing Networks

This section focuses on evaluating the performance of an REM-enabled CR network coexisting with PUs. The CRs are SUs and share the same spectrum with PUs. The impact of REM-enabled situation awareness on network convergence, channel quality, and overall utility of both PUs and SUs has been emulated with link-level and network-level simulations [73]. In all simulations, a number of SUs attempt to share the spectrum with some stationary incumbent PUs in an area of 1000 meters by 1000 meters. The convergence time of the network is evaluated as the mobile SUs adapt to share spectrum with PUs. Both open rural areas and dense urban areas are emulated with appropriate radio propagation models.

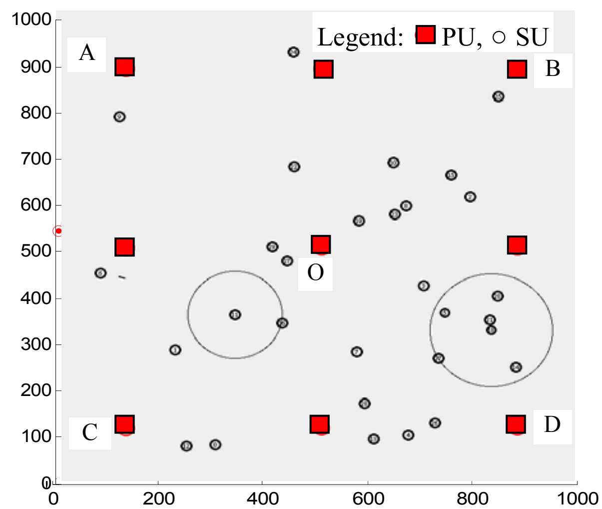


Figure 7-5: Simulation Scenario (I): Open Area

For simulation scenario (I) as shown in Figure 7-5, all SUs are moving randomly within the simulation area. The simulation parameters are listed in Table 7-2. Both PU and SU nodes comply with IEEE 802.11 MAC. REM-enabled CRs adopt an adaptive transmission scheme: if the SU detects a PU is transmitting or falls within its interference range, it will suspend transmission. Figure 7-6 shows the average SINR improvement at the central PU node (node O in Figure 7-5) in the presence of thirty SUs. The SUs are moving randomly in the simulation area. When these SUs make adaptations with the help of the Global REM or Local REMs, the average SINR at the central PU receiver is increased by 24.3 dB and 14 dB, respectively. The results also indicate the benefits of hidden PU protection due to cooperative learning, which is enabled by disseminating Local REMs among SU nodes [74]. Each SU node can obtain a Global REM by integrating Local REMs from distributed SU nodes.

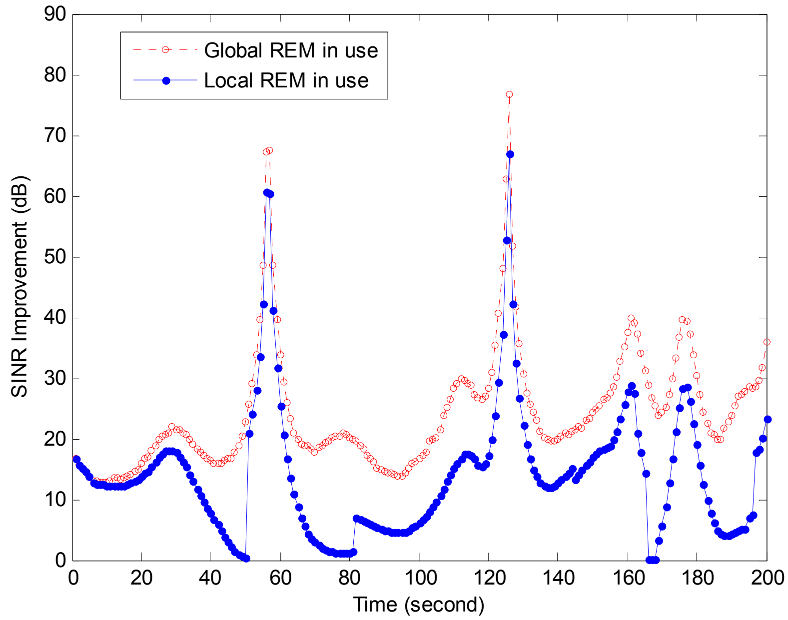


Figure 7-6: Simulated Received SINR at a PU Node

Table 7-2: Simulation Parameters for Performance Evaluation (I)

Parameter	Value
Number of PUs, Mobility, and Protocol in Use	9, stationary, AODV
Number of SUs, Mobility, and Protocol in Use	30, random waypoint model, OLSR
Transmission Range of Radio Node (PU or SU)	450 meters
Sensing Range of SU	450 meters
Interference Range of SU	450 meters
Speed of SUs	Uniformly distributed in (0, 10m/s)
Data Rate of Wireless Link	2 Mbps
Interface Queue Length	50 packets
Radio Channel Model	two-ray ground model
Simulation Period	200 seconds

The UM-OLSR protocol [70] and the NS-2 network simulator (version 2.29) were used for network-level simulation on PUs' performance in the presence of SUs. In the network-level simulations, two constant bit rate (CBR) connections are established between PU nodes A and

D and between nodes B and C, respectively (see Figure 7-5), and the PUs' CBR traffic has a fixed periodic pattern. Cognitive SUs can model PUs' spectrum usage pattern after a period of observation and then transmit during the PUs' idle time to avoid collisions. Note that a coordinated quiet period for all SUs is required to detect PUs' spectrum usage pattern. Figure 7-7 shows the average delay of data flow between PUs under various scenarios. REM-enabled CR SUs are shown to introduce little latency increase, whereas non-CR SUs may result in significant delay to PUs' packet deliveries due to frequent collisions. Note that in Figure 7-5, the first data flow is from node A to node D while the second data flow is from node B to node C. For scenarios 1, 2, 3, and 4, the PUs co-exist with 10, 20, 30, and 30 SUs, respectively. In scenario 3, SUs generate one 512-byte CBR packet per second, whereas in scenario 4, SUs generate ten times more CBR traffic (one 5120-byte CBR packet per second). Simulations show that the PUs have nearly the same throughput for these four scenarios. Therefore, for packet data communication networks, the packet delay of incumbent PUs is a more sensitive indicator of harmful interference from SUs.

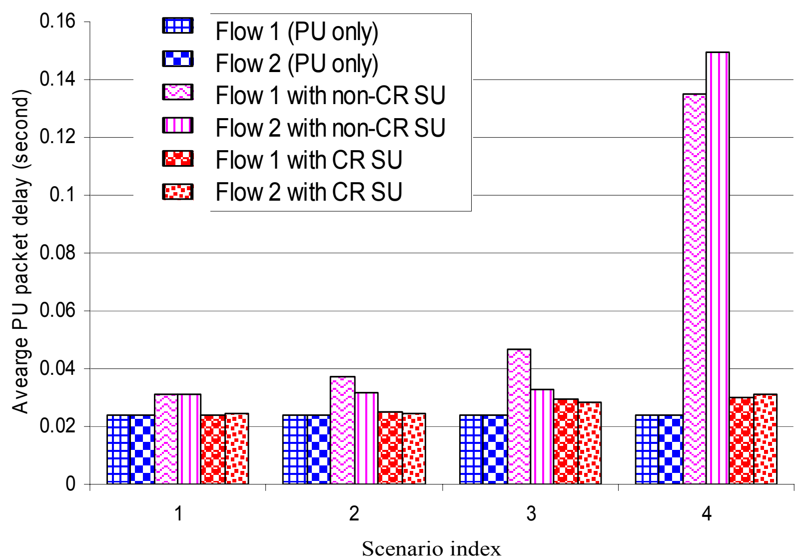


Figure 7-7: Simulated Average Packet Delay of PUs under Various Scenarios

For simulation scenario (II) as shown in Figure 7-8, twenty SUs are moving along the streets within the simulation area. Twenty PU nodes are stationary and clustered at a street crossing or inside one building block, and CBR traffic is generated by two connections between two pairs of PU nodes. The simulation parameters are listed in Table 7-3.

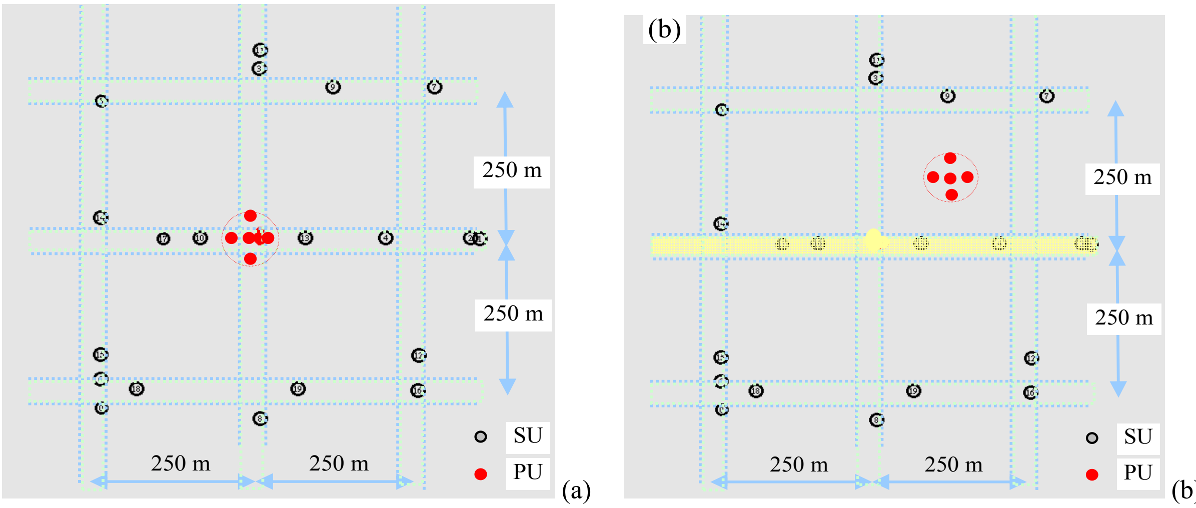


Figure 7-8: Simulation Scenario (II): Manhattan Urban Environment. The clustered PU nodes are at the street corners (a) or inside a building block (b). The SU nodes move along the streets.

Table 7-3: Simulation Parameters for Performance Evaluation (II)

Parameter	Value
Number of PUs and Mobility	20, stationary
Routing Protocol in Use for PUs	AODV
Number of SUs and Mobility Model in Use	20, Manhattan mobility model [62]
Routing Protocol in Use for SUs	OLSR
Transmission Range of PU	250 meters
Transmission Range of SU	Adaptive (0–250 meters)
Free Space Interference Range of SU	Selected from 250–400 meters
Speed of SUs	Uniformly distributed in (0, 10m/s)
Data Rate of Wireless Link	2 Mbps
Interface Queue Length	50 packets
Radio Channel Model	Two-ray Manhattan model [61]
Simulation Period	500 seconds
Number of Replications	20

The following utility function is proposed to evaluate the performance of overall networks (including both PU and SU networks).

$$u = \frac{(u_1)^{w_1}}{(u_2)^{w_2}} \qquad (7\text{-}7)$$

where u_1 denotes the sum throughput (including the throughput from both PU and SU networks), u_2 denotes the average packet delay of the PU network, w_1 and w_2 are the weights corresponding to u_1 and u_2, respectively. In some sense, u_1 is an indicator of the overall spectrum utilization whereas u_2 is an indicator of the performance degradation experienced by the PU network [73]. Therefore, u is the overall network utility. In practice, the weight vector could be determined according to the spectrum "subleasing" agreement between the PU (operator) and the SU (operator) or simply determined by the spectrum regulator like the FCC.

REM-enabled CRs can choose appropriate radio propagation models to predict the path loss to the PU nodes and then use various adaptation schemes to optimize the overall utility. Assuming the CR nodes have the current Global REM information, the topology, transmit power, and interference range of CR can be adjusted to share the spectrum with the PUs more efficiently. When a PU node is within the interference range of a CR node, the CR may take different power adjustment schemes. One scheme is that the CR simply stops transmitting; another scheme is that the CR estimates the minimal path loss to the PU nodes and then reduces its transmit power accordingly such that no harmful interference is generated to the PU nodes. In addition to the existing two-ray ground model (suitable for open area environment), a two-ray Manhattan model (suitable for dense urban environment) is developed for the NS-2 simulator [61] and can be employed by the REM-enabled CR nodes.

Figure 7-9 shows the increased network utility due to REM-enabled CR and demonstrates the advantages of REM-enabled CR in context of spectrum sharing with incumbent PUs. The overall network utility is defined by Equation 7-7, and the weights are set as $w_1 = w_2 = 1$. The 90% confidence intervals of the average utility are also computed and shown in this figure. Four different simulation settings and adaptation schemes are considered, as depicted in Table 7-4. For Case 1, the CR nodes are unaware of the topographical environment. Therefore, they have to take a conservative spectrum-sharing approach: when any PU node falls into the free-space interference range of a SU node, the SU node will simply stop transmission. For Case 2, compared to the previous case, the SU nodes estimate the path loss to the PU nodes using the two-ray ground model based on the physical distance to the PU nodes and adaptively adjust the transit power when the PUs are within the interference range. For Case 3, the REM-enabled CRs (SUs) are fully aware of the radio environment and apply the Manhattan propagation model for path loss prediction. A two-ray Manhattan model was developed, which is based on the two-ray ground model included with NS-2 and takes radio signal attenuation caused by buildings into account. This model only allows communication down city streets and around a corner if both nodes are within 5 meters of the same intersection [61]. The Manhattan propagation model differentiates the line-of-sight (LOS) and non-line-of-sight (NLOS) conditions for appropriate path loss prediction. The penetration loss due to the buildings along the street in urban area enables much higher spectrum reuse, which can be exploited by the REM-enabled CR nodes. Therefore, the network utility for Case 3 is higher than those for Case 1 and Case 2. For Case 4, it is assumed that the PUs are cooperative and move from the street crossing into a street block (refer to Figure 7-8), which helps to further improve the overall network utility. This indicates that the REM-based topology control could be an effective approach for network optimization. Note that for Case 3 and Case 4, the CR node adjust its transmit power solely based on the geographical environment and the path loss between the CR node and the PU node regardless the free-space interference range.

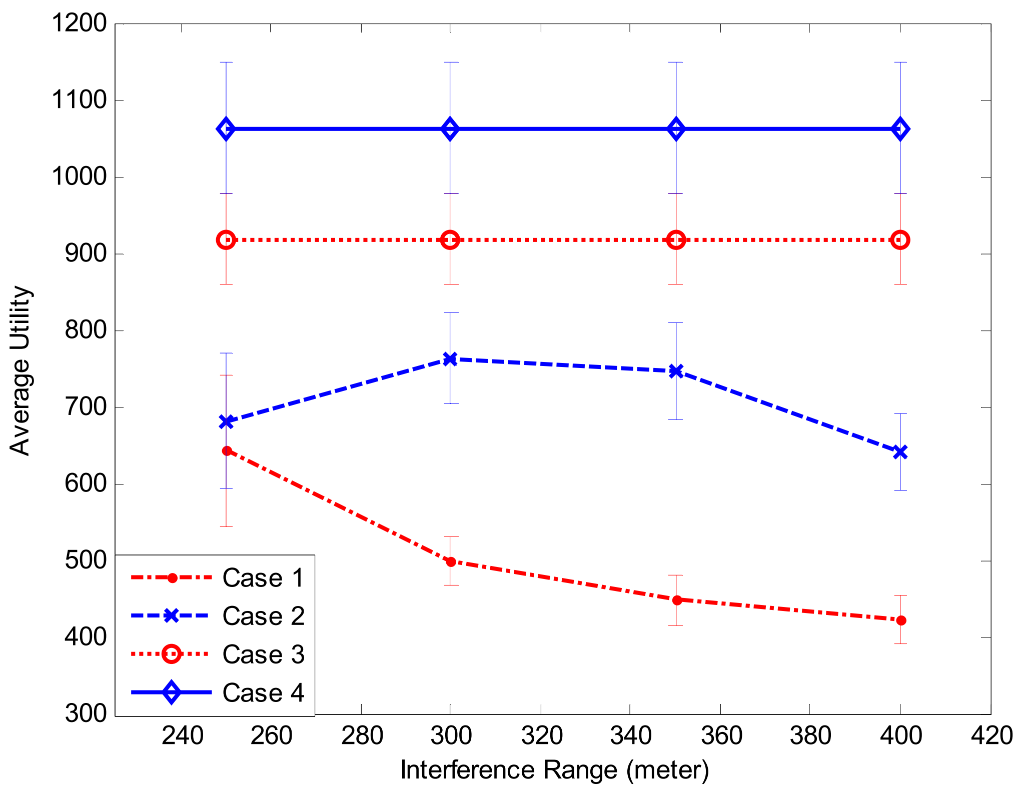


Figure 7-9: Network Utility When Using Different Adaptation Schemes

Table 7-4: Simulation Scenarios for Spectrum-Sharing Networks

	Exploited REM information	Newly Developed Channel Model for NS-2	Adaptation scheme
Case 1	Location of PUs	Two-ray ground PU-aware model	The CR node switches off its transmission once PU is within its interference range.
Case 2	Location of PUs	Two-ray ground adaptive transmit power model	Adaptively adjust transmit power of the CR nodes
Case 3	Location of PUs Location of SUs Map of street blocks	Two-ray Manhattan PU-aware model.	Adaptively adjust transmit power of the CR nodes
Case 4	Location of PUs Location of SUs Map of street blocks	Two-ray Manhattan adaptive transmit power model	Adaptively adjust transmit power of the CR nodes and the topology

The REM-based adaptive transmit power scheme is further described as follows. If the transmitting node is a CR node, then it adjusts the transmit power using the following procedures.

(1) Initialize the minimum distance between the PU node and the CR node with free-space interference range (IR) of the CR node at full transmit power (P_{tmax}), i.e., $d_{min} = IR$.

(2) Loop through all PU nodes and find the closest "visible" PU node to the CR node. Note that the PU node is visible to the CR node if they are on the same street, where the Line-of-Sight (LOS) condition is satisfied, or either node is just around the corner and has quasi-LOS to the other node [10]. Calculate the distance (d_{min}) between the closest visible PU node and the CR node.

(3) Attenuate the full transmit power of the CR node by a factor of A. If $d_{min} < IR$, the adjusted transmit power is defined by

$$P_t^a = \frac{P_{t\max}}{A}, \quad where \ A = 10^{4\log\frac{IR}{d_{\min}}} \tag{7-8}$$

If $d_{min} \geq IR$, the CR node can transmit at full power P_{tmax}.

(4) Based on the REM, check whether LOS or quasi-LOS condition exists between the transmitting CR node and each receiving node in the spectrum-sharing networks. If LOS or

quasi-LOS condition is satisfied, then the received power is determined by

$$P_r = \frac{P_t^a}{10^{\frac{PL(dB)}{10}}} \tag{7-9}$$

where path loss (*PL*) between the transmitting node and the receiving node is estimated with two-ray ground reflection model defined by

$$PL(dB) = 10\log\frac{P_t}{P_r} = \begin{cases} -10\log\dfrac{G_t G_r h_t^2 h_r^2}{d^4} & for\ d >> \sqrt{h_t h_r} \\ -10\log\dfrac{G_t G_r \lambda^2}{(4\pi)^2 d^2} & otherwise \end{cases} \tag{7-10}$$

where d is the distance between the transmitter and the receiver; h_t, G_t, P_t, h_r, G_r, and P_r are the transmit antenna height, gain, transmit power, the receiver antenna height, gain, and received power, respectively; and λ is the wavelength of the carrier frequency [45].

Otherwise, for non-LOS conditions, the path loss is assumed to be infinity, i.e., $P_r = 0$.

The impact of minimizing stationary SUs' interference to PUs is also investigated [73]. A densely populated area containing twenty PUs (with forty links) and thirty SUs (sixty links) is presented in Figure 7-10. All users are stationary and occupy a single frequency channel and time slot. Multiple users located in the same radio resource set (frequency channel, time slot) cause interference to each other, but separate sets are orthogonal. In all simulations, all PU links are located on orthogonal sets, and therefore do not cause one another interference. However, there are too few orthogonal sets for all links, thus many channels and time slots must be shared by SUs. PUs have static channels, but SUs may change their parameters at the risk of causing interference to both primary and other secondary users. For the simulation, each SU makes one of four simple (heuristic) adaptations: increase power, decrease power, change frequency channel or time slot, or make no change. In the first case, information about the radio environment is unknown, and the SUs must make their adaptations based upon their links' received SINRs and the measured interference levels. In the second case, the SUs have additional information about all links, including the transmitter and receiver locations and the channel/time slot they currently occupy. Each radio, however, still acts independently of others, and therefore a global network optimum is not guaranteed in either case.

PU links were initially established to have a received power 10 dB above the noise floor, taking into account antenna gains and propagation losses. Note in Figure 7-11 that with Global REM information, the SUs cause minimal interference to the PUs (a SINR degradation of only 0.2 dB). Without REM, however, this degradation extends to nearly 2.5 dB on average, and, in some cases, more than 20 dB. Furthermore, the average SINR of SUs increases with REM knowledge a full 1.2 dB over that without the REM (see Figure 7-11). This suggests that the SUs with REM information can simultaneously maintain PU link quality as well as their own [73]. Additionally, as areas become more congested, these differences increase.

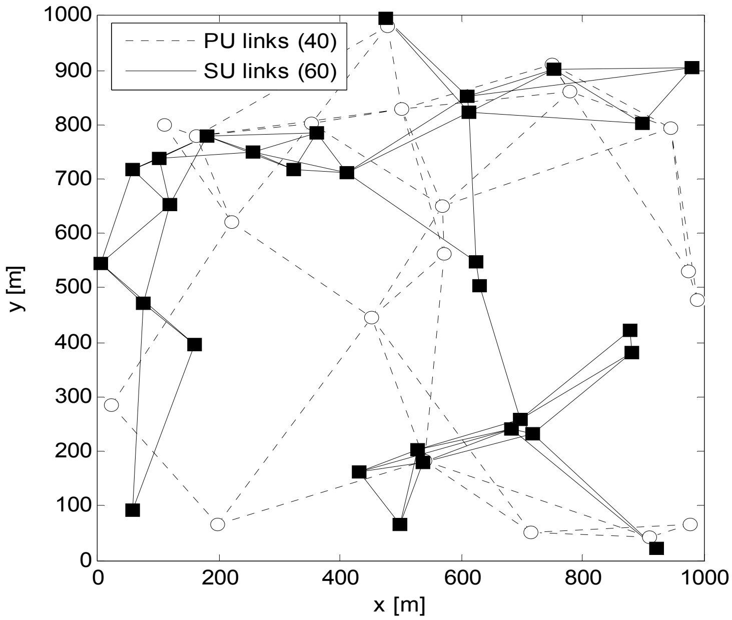


Figure 7-10: Simulation Scenario (III)

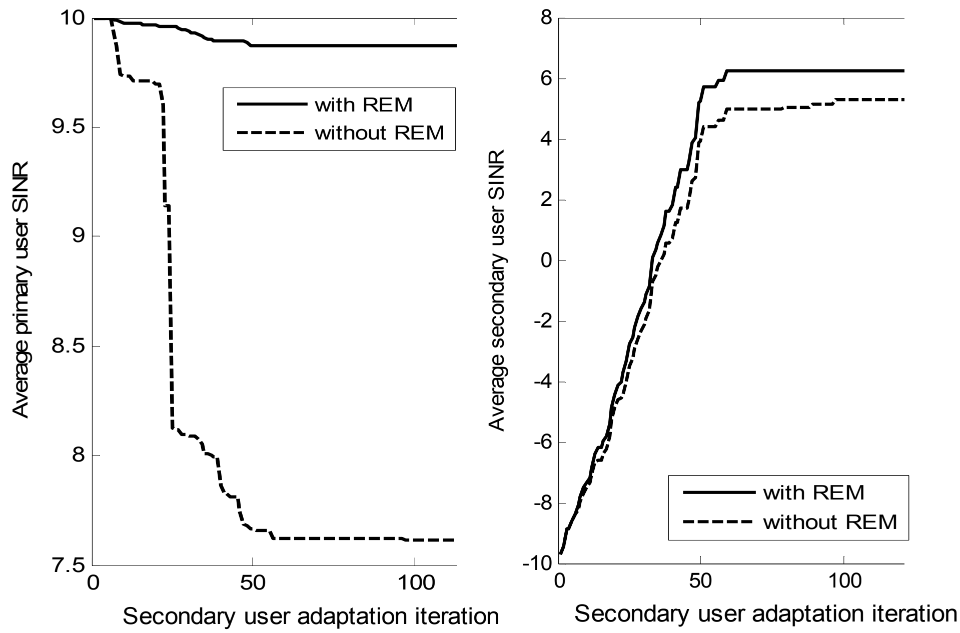


Figure 7-11: Average SINR at PU and SU nodes

7.4 Summary

Defining proper performance metrics and utility functions for CR is very important to achieve desirable cognition functionality and overall system performance. The metrics and utility may dynamically change with the application of CR and the specific operational scenario, which is quite different from those for conventional radios. This chapter presents some working performance metrics for CR and proposes a new method for CR testing, i.e., REM-based scenario-driven CR testing. The performance of REM-enabled CR has been evaluated for spectrum sharing with a PU network. Global situation awareness and coordination help CR to make desired adaptations beyond the single node's capability. Both link-level and network-level simulation results suggest that Global REM information can significantly improve the performance of both primary and secondary users, reduce CR network adaptation time, and mitigate the hidden node problem. The impact of an REM-enabled CR network on the performance of an incumbent PU network has also been investigated and shows that the REM is a viable approach to dynamic spectrum sharing and REM-enabled CR generates negligible (or acceptable-level) interference to PU nodes.

8 Summary and Conclusions

CR is an emerging research area that requires interdisciplinary collaboration. Although it might be too early to tell how successful CR will be, we conclude that it will play an important part in future wireless communications.

CR is both a *revolutionary* technology and an *evolutionary* technology. On one hand, with the introduction of CR, a variety of paradigm shifts in wireless communications are expected: from *static* spectrum allocation to *dynamic* spectrum access and sharing; and from *predefined* behavior and limited adaptation capability to *flexibility* and intelligence to deal with unpredictable demanding scenarios. CR changes the way in which we *view*, *design*, *test*, *certify,* and *operate* the radio. On the other hand, CR will evolve from current SDR by gradually embedding more and more cognition functionality. Future CR will have cognition and intelligence everywhere: from physical layer up to application layer; from baseband signal processing up to RF transceiver and antenna; and from a single node to whole networks.

IEEE 802.22 WRAN is the first commercial application of CR networks refarming the TV broadcast bands. The standardization and deployment of cognitive WRAN systems will have significant impact on the future advancement of CR.

8.1 Summary of the Dissertation

The primary goal of this research is to find a cost-efficient approach to developing CR and quantifying its performance. In this dissertation, enlightened by the analogy between two intelligent agents–a taxi driver and a CR, I first proposed a novel integrated database–REM–as the navigator for CR. The REM includes multi-domain information such as RF and geographical environment information and prior knowledge. The vision is that future CR may have a built-in Local REM and can access the Global REM maintained by the CR networks. The class structure of CR has been developed, where the REM is a separate class. The isolation of the REM from the CE allows the developer to create a variety of REM instances that can apply to different system implementations. Through APIs, the CE can "Google" the REM for comprehensive situation awareness, efficient learning, and fast adaptation.

Secondly, I investigated various applications of REM to 802.11 WLAN interference management and 802.22 WRAN radio resource management. Signal processing techniques (such as signal detection, classification, and location) can be employed for populating the REM in the radio domain. A reference REM design, basic APIs, and memory footprint estimation were provided for the WRAN BS CE.

Thirdly, I formalized the framework of REM-enabled situation-aware CR learning algorithms. To leverage various artificial intelligence and machine learning techniques, the generic REM-enabled CE consists of two learning loops: a high-level learning loop and a low-level learning loop. Furthermore, REM-enabled case- and knowledge-based learning (REM-CKL) and REM-enabled cognitive cooperative learning (REM-CCL) are proposed for CR and cognitive wireless networks. REM-based radio scenario matching and situation awareness are prerequisite for applying CKL and CCL. The REM-CKL was implemented for the WRAN BS CE testbed and evaluated against the genetic algorithms. Preliminary simulation results demonstrate that the WRAN CE can adapt orders of magnitude faster when using the REM-CKL than when using the genetic algorithms and achieve near-optimal global utility by synergistically leveraging the REM-CKL and a local search. The REM-CCL aims to support dynamic or multiple goals of cooperation among CR nodes and to facilitate cooperative signal processing. Efficient REM dissemination with minimal overhead is important for CR nodes to obtain up-to-date Global REM information or to exchange Local REM information. Various REM dissemination scenarios are examined and several efficient REM dissemination schemes are proposed. The overhead of REM dissemination via MPR flooding has been estimated with analytical models and network simulations.

Finally, I reviewed the performance metrics and utility functions for various CR networks. REM-enabled scenario-driven CR testing (REM-SDT) is proposed and employed for the WRAN CE testbed performance evaluation. It is shown that REM-SDT is a viable and efficient approach to testing the CE and cognitive wireless networks. The performances of REM-enabled spectrum-sharing CR networks have been evaluated. By fully exploiting the

Global REM, CR can significantly improve the spectrum utilization with various adaptation algorithms. More importantly, the painful hidden node (or hidden receiver) problem could be mitigated and therefore more reliable PU protection can be achieved with the REM-enabled CR.

8.2 Summary of Contributions

This dissertation has four major contributions. The primary contribution is the proposal and design of REM-enabled CR and cognitive wireless network architecture. This research is different from previous CR research in that the CE is applied at the network level with shared knowledge enabled by the REM. A new approach is introduced that allows the transformation of various types of REM information to be utilized by the CE for intelligent radio resource management and interference management. The beauty of the REM is that it enables CR to "look" through all layers of communication stacks and find the needed radio environmental information or prior knowledge from a single database. Therefore, the information access and processing time could be significantly reduced, which helps CR to make fast adaptation.

The second major contribution is the formalization of generic REM-enabled CE architecture and the development of a primitive yet flexible WRAN CE testbed together with other team members–Joseph Gaeddert and Lizdabel Morales. REM-CKL was proposed and implemented for the WRAN CE testbed. Scenario-driven testing was also proposed and employed to evaluate the performance of the WRAN CE. Preliminary testing results show that the WRAN CE can adapt up to one hundred times faster by using the REM-CKL algorithms than using the genetic algorithms when establishing forty new connections between the BS and CPEs. Fast adaptation is very important to insure that SUs do not interfere with PUs. The WRAN CE testbed will be used extensively at Virginia Tech to investigate a variety of problems in CR and cognitive wireless networks. It will probably take many years of research to fully gauge the best refinements and benefits of this CE testbed.

The third contribution is the development of link-level and network-level spectrum-sharing CR simulation platform using the MATLAB® and network simulator (NS-2), respectively. Mechanisms for disseminating REM information to the network nodes are proposed and it was found that exploiting the MPR flooding enables a reasonable REM dissemination overhead to support ad hoc CR networks. Analytical and simulation results show that the overhead of REM dissemination in ad hoc wireless networks via MPR flooding can be significantly reduced by orders of magnitude than using plain flooding. The benefits of exploiting the Global REM were quantitatively evaluated with link-level and network-level simulations. When using the Global REM, thirty 802.11-like SU radio nodes (moving randomly in an area of 1000 meters by 1000 meters) generate on the average about 10 dB less interference to the PU nodes compared to that when only Local REMs were in use. The overall network utility of spectrum-sharing networks (consisting of twenty 802.11-like PU nodes and twenty REM-CR nodes) in dense urban environment is increased by about 100% by exploiting the Global REM.

Last, but not the least, this research offers many insights into CR and REM. First of all, situation-awareness and learning capability are two key defining features of CR. Compared to CR, traditional radios are "memory-less" since they cannot learn from past experience. For CR, the cognition capability relies on three types of memory: radio environmental information base, knowledge base, and experience base (case library). These three inter-correlated memories are indispensable to a strong CE. In addition, CR must keep updating these memories and retaining the useful information throughout its cognition cycle and life cycle. A well-designed REM will integrate these memories for CE to access (including update and query). The capability and the level of situation-awareness greatly impact the effectiveness and efficiency of other cognition functionalities, such as reasoning, learning, planning, and decision-making. The more the REM information is exploited by the CE, the higher level situation awareness and better adaptation can be achieved. Secondly, leveraging Global and Local REMs presents a practical, flexible, and cost-efficient way to implement CR networks. The REM-based CR is also a future-proof approach to dynamic spectrum management because that it allows regulators or service providers to modify or change their rules or policies simply by updating the REMs accordingly. Since the REM is a comprehensive database, it can be stored inexpensively (with storage devices that obey Moore's law). Even a low-cost/low-complexity radio device could obtain cognitive functionality by referencing a well-developed REM. Thirdly, leveraging REM-based network support and node collaboration through REM-CCL is another important strategy for the development of low-cost/large-scale CR networks. Network support and node collaboration can dramatically relax the requirements on a CR device and improve the reliability of CR networks. The REM can be disseminated efficiently in both infrastructure-based networks and ad hoc CR networks. When fully exploited, the REM can improve the efficiency of network operation and reduce the overhead of cognitive wireless networks. To function well, the CE requires feedback from other nodes. Disseminating the REM among radio nodes can be employed as a mechanism for CR nodes to know the effects of their adaptations on radio environment (e.g., the variation of interference temperature sensed by the other nodes), which is critical for implementing learning algorithms.

In summary, the ultimate goal of employing REMs in CR networks is to put prior knowledge and collective intelligence to work. This research shows that REM is a viable, cost-efficient approach to developing CRs and cognitive wireless networks with significant potential in various applications (such as dynamic spectrum access and sharing networks, public safety or military radios, and emergency communications).

8.3 Future Research Recommendations

Many open research issues remain to be investigated to fulfill the expected potential of REM-enabled CR and cognitive wireless networks. This section discusses future research issues and possible directions. Applying REMs to cognitive wireless networks is an interesting inter-disciplinary research problem. Database design, signal processing, wireless communication, networking, and artificial intelligence all come into play to fully explore the potential of REM-enabled CR networks. The REM itself also presents many interesting research issues such as database management and memory management. Some recommendations on future research directions are summarized as follows.

(1) Investigate effective decision fusion schemes and inference engines for REM-CKL. One potential improvement to REM-CKL could be realized by combining the artificial neural network with the CKL module for case or knowledge adaptation and fusion, which might be exploited to deal with the extreme scenarios (or really challenging scenarios) where little past experience or prior knowledge is available. It could also be interesting to

investigate on applying the game theory or graph theory to the REM-enabled CR networks. This investigation could be carried out in the next phase of the 802.22 WRAN CE development project.

(2) Investigate potential improvements on performance metric and utility function for the WRAN CE. Since the metric and utility function used in current WRAN BS CE testbed is defined in an ad hoc approach, they may not reflect the true quality of WRAN systems. Comparing with other metrics or utility functions and refining the metric or utility function for WRAN CE is an interesting and important research area for the next phase of CE development.

(3) Compare the complexity between different CE algorithms by using profiling tools (like OProfile or other similar tools) in terms of the number of basic operations such as "adds", "multiplies", and "memory allocations" instead of the CPU run time.

(4) Research mobility support for cognitive WRANs and 802.16e/h WiMAX by employing the REM-enabled CRs. The REM can also be viewed as a natural, but major evolution of radio resource management used in today's commercial wireless networks. REM-enabled CR presents a smooth evolutionary path from the legacy radio. REM has great potential in bridging heterogeneous wireless communication networks (such as WPAN, WLAN, WiMAX, WRAN, 3G, and 4G systems) to support seamless cooperative CR networks. In addition, the performance gain and the mitigation of hidden node problem due to using the Global REM need to be fully investigated and quantified in future research.

(5) Integrate the REM into OSSIE for developing CR. Note that OSSIE is an open source version of the software communications architecture created at Virginia Tech. Some initial work on this front has begun with the integration of the REM and OSSIE for the *Smart Radio Challenge 2007* sponsored by the SDR Forum [82]. Implementing the CE algorithms with specific hardware platforms such as Universal Software Radio Peripheral (USRP) is also a future work.

(6) Research ontology to be utilized by CR for negotiation. "The ultimate cognitive radio will be able to autonomously negotiate and propose entirely new optimized protocols for use in

the networking environment" [83]. Just as language is important for us human beings to exchange ideas, ontology is important for CRs to efficiently collaborate with each other.

(7) Standardize the REM and its APIs to CE for widespread applications and compatibility. If the REM and APIs have standard formats, the REM will be better accepted by the CR community and it will be more capable of coordinating different systems and service providers. The REM database itself could become a product or service to the wireless service providers, end users, and spectrum regulators.

Appendix A: Waveforms in the TV/ISM/UNII Bands

In this section, the well-known waveforms (including both signal and interference) in 802.11 WLAN and 802.22 WRAN systems are discussed and modeled for detection or identification.

Signals in VHF/UHF TV Broadcast Bands

In TV broadcasting bands (54–862 MHz),[20] the primary services are TV broadcasting and FCC Part 74 Low Power Auxiliary Station devices, e.g., wireless microphones, wireless intercoms, and so on, and PLMRS (Private Land Mobile Radio Service). The goal of 802.22 is a global standard, capable of use in different regulatory domains where different TV technologies are used (NTSC, PAL, SECAM, ATSC-8VSB, DVB-T). Table A.1 lists VHF/UHF TV band signals coexisting with IEEE 802.22 WRAN systems. Wireless microphones typically use FM modulation. Digital modulation may also be used. See Table A.2 for typical parameters for wireless microphone.

Table A.1: Summary of VHF/UHF TV Signals

		Countries	Standard	Frequencies	Bandwidth	Color carrier	Audio carrier
Analog	Vestigial Side Band (VSB)	US, Canada, Japan, South Korea, Taiwan, etc	NTSC M	54–746 MHz (Japan 90–770 MHz)	6 MHz channel: 4.2 MHz video, 250kHz audio	3.580 MHz above video carrier	4.5 MHz above video carrier
	Phase Alternating Line (PAL)	Australia, Brazil, China, Denmark, Finland, Great Britain, India	PAL B	48–798 MHz (New Zealand 44–798 MHz, Australia 45–806 MHz)	7 MHz channel: 5.0 MHz video, 250 kHz audio	4.434 MHz above video carrier	5.5 MHz above video carrier
			PAL H	47–798 MHz	8 MHz channel: 5.0 MHz video, 250 kHz audio	4.434 MHz above video carrier	5.5 MHz above video carrier
			PAL N	54–806 MHz	6 MHz channel: 4.2 MHz video, 250 kHz audio	3.582 MHz above video carrier	4.5 MHz above video carrier

[20] 47–910 MHz with IEEE 802.22 PAR (Project Authorization Request) modification

	Sequential Color with Memory (SECAM)	France, Germany, Iraq, North Korea, the former Soviet Union	SECAM B	47–798 MHz	7 MHz channel: 5.0 MHz video, 250 kHz audio	N/A	5.5 MHz above video carrier
			SECAM D, K, K1, L	470–790 MHz	8 MHz channel: 6.0 MHz video, 250 kHz audio	N/A	6.5 MHz above video carrier
						Pilot	
Digital	Vestigial Side Band	North America	ATSC	54–746 MHz	6 MHz channel	11.3 dB below the average data signal power	
	Orthogonal Frequency Division Multiplexing	Europe	DVB-T	48–798 MHz	7 or 8 MHz channel	N/A	
		China	TDS-OFDM	48–798 MHz	7 or 8 MHz channel		
		Japan	ISDB-T	54–746 MHz	6 MHz channel		

Table A.2: Typical Parameters for Wireless Microphones

Wireless Microphone Parameter	Value
Operating Frequency	54–72, 76–88, 174–216, 470–488, 488–494 (except Hawaii), 494–608, and 614–806 MHz
Output Power Limit (Conducted)	54–72, 76–88, and 174–216 MHz: 50 mW 470–608 and 614–806 MHz: 250 mW
Occupied Bandwidth Limit	200 kHz
Modulation	Any type of modulation is possible but is subject to the Occupied Bandwidth Limit. The Maximum Deviation is 75 kHz if FM is used. Typically use FM modulation is used. Digital modulation may also be used.

Signals in 5 GHz UNII Band

Table A.3: List of 5 GHz UNII Band Signals (Interferers to IEEE 802.11a WLAN)

Signal Type	Key Features	Note
Radar	High power pulse	various frequency in different countries
Penetrating WLAN	OFDM	known OFDM training symbols/pilot sub-carriers/cyclic prefix known MAC frame structure self-coherent signal features
Medical Device	Various features	sensitive to RF interference

Signals in 2.4 GHz ISM Band

Table A.4: List of 2.4 GHz ISM Band Signals (Interferers to IEEE 802.11b/g WLAN)

Type of Interferers	Key Characteristics	Differentiable and/or Exploitable Features
Bluetooth	FHSS: 1600 hops/second TDD: 625μs Tx/625 μs Rx 1Mbps, 1MHz channel spacing GFSK with time-bandwidth product BT=0.5 Modulation index: 0.28–0.35 3 power classes: Class 1/2/3: P_{max} = 20/4/0 dBm In most cases, 0 dBm (1 mW) is used. Range: 10 cm–10 m for Class 3, ~100 m for Class 1	GFSK Frequency hopping TDD framing rate =1/3 redundant coding blocks Spatial Coherence
Microwave Oven	~ 2.45GHz pulsed CW Consists of narrow less than 1 MHz wide spikes, sweeping wildly in frequency due to the circulators built into the ovens The higher power spikes were mostly concentrated in the upper half of the band between 2450 and 2485 MHz. EIRP: 16–33dBm	Narrowband, pulsed CW Unit-specific power spectral density signature Active period is about 8 ms (out of 20 ms of main power cycle at 50 Hz, or 16.66 ms at 60Hz)
Interpenetrating (adjacent) 802.11b	1Mbps DBPSK-DSSS; 2Mbps DQPSK-DSSS 5.5Mbps,11Mbps DQPSK-CCK TDD; CSMA/CA	known BPSK DSSS/CCK preamble known MAC frame structure Spatial Coherence
Interpenetrating (adjacent) 802.11g	1–11Mbps DSSS/CCK; 6/9/12/18/24/36/54Mbps BPSK/QPSK/16QAM/64QAM OFDM TDD, 25MHz nominal channel spacing CSMA/CA	known OFDM training symbols/pilot sub-carriers/cyclic prefix known MAC frame structure self-coherent signal features
Cordless Phone VoWiFi Phone	FHSS/DSSS Detailed specifications could be vender dependent	802.11 features (VoWiFi) Spatial Coherence
Active RFID	For WLAN-based RFID, use the same waveform as WLAN signal, e.g., DSSS	802.11 features
ZigBee IEEE 802.15.4 Devices	O-QPSK modulation; 250 kb/s raw data rate 16 channel in 2.4GHz band channel spacing: 5MHz	Low emission power and low duty ratio

Appendix B: Mathematical Models for Signals in the TV/ISM/UNII Bands

This section summarizes the mathematical models for some signals in the TV/ISM/UNII bands.

(1) Microwave Oven Leakage (MWOL) Model (extended AM-FM model [Zhao 05a])

The microwave oven leakage emission can be modeled as

$$i(t) = I_0 U(V(t)) \exp\left\{ j2\pi \int_{-\infty}^{t} [f_d(u) + f_{\max} V(u)] du \right\} \qquad \text{(B-1)}$$

where

$$V(t) = \begin{cases} \cos(2\pi f_v t) & \textbf{transformer type} \\ |\cos(2\pi f_v t)| & \textbf{switching type} \\ \cos(2\pi f_v t)\cos(2\pi f_s t) & \textbf{inverter type I} \\ |\cos(2\pi f_v t)\cos(2\pi f_s t)| & \textbf{inverter type II} \end{cases} ; \; U(V) = \begin{cases} V, & for\ V \ge V_0 \\ 0, & for\ V < V_0 \end{cases} ;$$

$$f_d(t) = f_0 + f_w \sin(2\pi t / T_w)$$

where f_0 and f_w are initial MWOL carrier frequency and the maximum MWO frequency wander, respectively, and T_w is the frequency wander period, e.g., due to the MWO's periodic stirrer. I_0 and $f_{\max}$ are the maximum observed MWOL amplitude and the maximum frequency deviation for the FM modulation, respectively, and $V(t)$ is the normalized driving voltage for AM modulation.

(2) Bluetooth Signal Model

The Bluetooth (GFSK) signal, $s(t)$, can be represented by the following equation:

$$s(t) = \sqrt{\frac{2Es}{T}} \cos(2\pi f_c t + \Phi(t;I) + \varphi_0) \qquad \text{(B-2)}$$

with the following definition. Es is the energy of the signal; T is the symbol duration (1 μs for Bluetooth); f_c is the carrier frequency (~2.4 GHz for Bluetooth); φ_0 is the initial phase of the carrier; $\Phi(t;I)$ represents the time-varying phase of the carrier, which is defined as

$$\Phi(t;I) = 2\pi h \sum_{k=-\infty}^{n} I_k q(t-kT), \qquad nT \le t \le (n+1)T$$

I_k is the data bits, either +1 or -1; and h is the modulation index, and determines how far apart these two frequencies are spaced. For Bluetooth modeling and simulation in this document, the modulation index has a value of 0.32. Correspondingly, the peak frequency deviation (f_d) is 160 kHz.

q(t) is the so-called phase shaping pulse. The waveform of *q(t)* may be represented in general as the integral of the Gaussian frequency shaping pulse *g(t)*. The Gaussian low pass filter has the following impulse response *g(t)*:

$$g(t) = \{Q[2\pi B(t-3T/2)/\sqrt{\ln 2}] - Q[2\pi B(t-5T/2)/\sqrt{\ln 2}]\}/(2T)$$

where $Q(t) = \int_t^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2} dx$ is the so-called error function.

(3) DSSS PAM Signal

The 802.11 WLAN DSSS beacon signal can be modeled as a PAM waveform as

$$S_{ana}(t) = \sum_n d_{sym}(n) h_{sym}(t - nT_{sym}) \qquad \text{(B-3)}$$

where $\{d_{sym}(n)\}$ is the baseband symbol sequence, T_{sym}= 1 μs is the nominal symbol period, and $h_{sym}(t)$ is the data symbol shaping, i.e., the pulse modulated by the baseband data sequence,

$$h_{sym}(t) = \sum_{m=0}^{10} C_{chp}(m) h_{chp}(t - mT_{chp})$$

where C_{chp} is the 11-chip Barker code sequence, T_{chp} = 1/11 μs is the nominal chip period, and $h_{chp}(t)$ is the DSSS chip shaping, i.e., the pulse modulated by the spread data sequence.

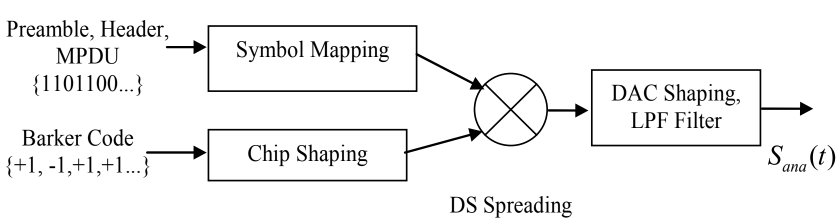


Figure C-1: Model for WLAN Beacon Signal Generation

If the DSSS signal is subject to RF carrier frequency offset by

$$\omega = 2\pi\Delta f$$

then, $d_{sym}(n)$ should be modified slightly, by frequency shifting $e^{j\omega nT_{sym}}$, which yields

$$S_{ana}(t) = \sum_{n} S_{sym}(n) h_{sym}(t - nT_{sym}) e^{j\omega(t-nT_{sym})}$$

$$S_{sym}(n) = d_{sym}(n) e^{j\omega nT_{sym}}$$

With such a Pulse Amplitude Modulation (PAM) model, the analog output signal $S_{ana}(nT_{ana})$ can be derived through (essentially) the frequency domain operations as follows:

$$D_{sym}(k) = FFT\{d_{sym}(n), N_{sym\_per\_dat}\}$$

$$S_{ana}(k) = H_{sym}(k) D_{sym}(\mathrm{mod}(k, N_{sym\_per\_dat}))$$

$$S_{ana}(nT_{ana}) = IFFT\ \{S_{ana}(k), N_{ana\_per\_dat}\}$$

where $N_{sym\_per\_dat}$ and $N_{ana\_per\_dat}$ are the number of data symbols and "analog" samples in the simulation interval, respectively. The data symbols $d_{sym}(n)$ are zero-valued over the unmodulated segments of the data interval, and are BPSK (long preamble, 1 Mbps PHY) or mixed BPSK-QPSK valued (short preamble, 2 Mbps PHY) over the modulated data segment. T_{ana} is the time interval between analog samples at the output of AP transmitter.

(4) FM (wireless microphone, cordless phone) signal

The frequency modulation (FM) signal can be modeled as

$$S_{FM}(t) = A\cos[\omega_c t + \beta_{FM} \sin \omega_m t] \qquad \text{(B-4)}$$

where β_{FM} is the frequency modulation index, ω_c is the carrier frequency, ω_m is the frequency of modulating signal, and A is the amplitude of the carrier.

Bibliography

[1] J. Mitola III and G. Q. Maguire Jr., "Cognitive Radio: Making Software Radios More Personal," *IEEE Personal Communications*, vol. 6, no. 4, pp.13–18, Aug. 1999.

[2] J., Mitola III, "Cognitive Radio-An Integrated Agent Architecture for Software Defined Radio," Ph.D. dissertation, Royal Institute of Technology (KTH), Stockholm, Sweden, 2000.

[3] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, Feb. 2005, pp. 201–220.

[4] F. K. Jondral, "Software-Defined Radio–Basics and Evolution to Cognitive Radio," *EURASIP Journal on Wireless Communications and Networking*, pp. 275–283, March 2005.

[5] J. H. Reed and C. W. Bostian, "Understanding the Issues in Software Defined Cognitive Radio," *Tutorial for 2005 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Network* (DySPAN 2005), Baltimore, MD, Nov. 2005.

[6] *In the Matter of Facilitating Opportunities for Flexible, Efficient, and Reliable Spectrum Use Employing Cognitive Radio Technologies, Authorization and Use of Software defined Radios*, Federal Communication Committee (FCC) NPRM 03-322, Dec. 30, 2003.

[7] S. Mangold, A. Jarosch, and C. Monney, "Cognitive Radio – Trends and Research Challenges," Swisscom Comtec Magazine, pp. 24–27, May 2005.

[8] B. Fette, *Cognitive Radio Technology*, Elsevier/Newnes, 2006.

[9] I. Poole, "What Exactly is Cognitive Radio?" *Communications Engineer*, vol. 3, no. 5, Oct.-Nov. 2005, pp. 42–43.

[10] Christian J. Rieser, "Biologically Inspired Cognitive Radio Engine Model Utilizing Distributed Genetic Algorithms for Secure and Robust Wireless Communications and Networking," Ph.D. Dissertation, Virginia Tech, 2004.

[11] Y. Zhao, B. Le, and J. H. Reed, "Network Support – The Radio Environment Map", in *Cognitive Radio Technology*, B. Fette, Ed., pp. 337–363, Elsevier/Newnes, 2006.

[12] J. S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, Second Edition, Pearson Education, 2003.

[13] http://www.2pass.co.uk/awareness.htm#SAdefinition

[14] J. H. Reed, C. Dietrich, J. Gaeddert, K. Kim, R. Menon, L. Morales, and Y. Zhao, "Development of a cognitive engine and analysis of WRAN cognitive radio algorithms," Mobile and Portable Radio Research Group (MPRG) Technical Report, Virginia Tech, Dec. 2005.

[15] http://www.wireless-world-research.org/index.html

[16] *In the matter of Establishment of an Interference Temperature Metric to Quantify and Manage Interference and to Expand Available Unlicensed Operation in Certain Fixed, Mobile and Satellite Frequency Bands*, FCC NOI and NPRM 03-289, Nov. 28, 2003.

[17] J. Bravo, H. Kopeck, R. Tai, J. Velasco, and D. Wong, "FCC Spectrum Policy: Reforming Policy to Incorporate Emerging Technologies," Project Report, UCLA School of Public Policy and Social Research, Mar. 2004.

[18] S. Shankar N, C. Corderio, and K. Challapali, "Spectrum Agile Radios: Utilization and Sensing Architectures," in *Proc. 2005 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Network (DySPAN2005)*, Baltimore, MD, Nov. 2005, pp. 160–169.

[19] W. Krenik and A. Batra, "Cognitive Radio Techniques for Wide Area Networks," in *Proc. of the 42nd Design Automation Conference*, Anaheim, CA, June 13–17, 2005, pp. 409–412.

[20] C. W. Bostian, (Jan., 2006). "An Opportunity to Build a Large Scale Cognitive Wireless Network," [online] Available: http://www.cwt.vt.edu/research/cognitiveradio/presentations.html

[21] BBN Technologies, "The XG Vision Request for Comments (Version 2.0)," 2004. [online] Available: http://www.ir.bbn.com/projects/xmac/index.html

[22] *Draft Standard Definitions and Concepts for Spectrum Management and Advanced Radio Technologies, Next Generation Radio and Spectrum Management*, Committee of the IEEE Communications Society and the Electromagnetic Compatibility Society, Feb. 15, 2006.

[23] M. McHenry, "Dynamic Spectrum Sharing," *Presentation to IEEE Communications Society*, January 25, 2005.

[24] M. Kifer, A. Bernstein, and P. M. Lewis, *Database Systems: An Application-oriented Approach*, Pearson Education, 2005.

[25] E. E. Azzouz and A. K. Nandi, "Procedure for Automatic Recognition of Analogue and Digital Modulations," *IEE Proceedings–Communications*, vol. 143, no. 5, pp. 259–266, Oct. 1996.

[26] M. Lu, X. Xiao, L. Li, "Source Separation Based Modulation recognition of Cochannel Signals," in *Proc. International Conference on Communication Technology*, vol. 2, Oct. 1998.

[27] A. Nandi and E. E. Azzouz, "Algorithms for Automatic Modulation Recognition of Communication Signals," *IEEE Trans. on Communications*, vol. 46, no. 4, pp. 431–436, April, 1998.

[28] H. Yoshioka, Y. Shirato, I. Toyoda, and M. Umehira, "A Fast Modulation Recognition Technique Using Nearest Neighbor Rules with Optimized Threshold for Modulation Classification in Rayleigh Fading Channels," in *Proc. 5th International Symposium on Wireless Personal Multimedia Communications*, vol. 3, Oct. 2002, pp. 1049–1052.

[29] J. Lopatka and R. Bukowski, "A Use of Instantaneous Frequency Estimators for Radio Signals Identification," in *Proc. IEEE AFRICON 1999*, vol. 2, pp.1139–1142.

[30] B. G. Agee, S. V. Schell, and W. A. Gardner, "Spectral Self-Coherence Restoral: a New Approach to Blind Adaptive Signal Extraction Using Antenna Arrays," *Proceedings of the IEEE*, vol.78, no. 4, April 1990, pp.753–767.

[31] B. G. Agee and D. L. Young, "Blind Capture and Geolocation of General Spatially Self-Coherent Waveforms Using Multiplatform SCORE," in *Conference Record Twenty-Fourth Asilomar Conference on Signals, Systems and Computers*, vol. 1, pp. 33–38, Nov. 1990.

[32] W. A. Gardner (Editor), *Cyclostationarity in Communications and Signal Processing*, IEEE Press, 1994.

[33] B. G. Agee, "Fast Acquisition of Burst and Transient Signals Using a Predictive Adaptive Beamformer," in *Proc. IEEE Military Communications Conference*, Oct. 1989, vol.2, pp. 347–352.

[34] M. Vossiek, L. Wiebking, P. Gulden, J. Wieghardt, C. Hoffmann, and P. Heide, “Wireless Local Positioning,” *IEEE Microwave Magazine*, vol. 4, no. 4, Dec. 2003, pp. 77–86.

[35] O. Hilsenrath and M. Wax, “Radio transmitter location finding for wireless communication network services and management,” U.S. Patent 6,026,304, Feb. 2000.

[36] M. Wax and O. Hilsenrath, “Signature matching for location determination in wireless communication systems,” U.S. Patent 6,108.557, Aug. 2000.

[37] T. H. Clausen, G. Hansen, L. Christensen, and G. Behrmann, “The Optimized Link State Routing Protocol, Evaluation through Experiments and Simulation,” in *Proc. IEEE Symposium on Wireless Personal Mobile Communications*, Sept. 2001.

[38] B. Krenik and C. Panasik, “The Potential for Unlicensed Wide Area Networks,” Wireless Advanced Architectures Group, Texas Instruments White Paper, Oct. 2004.

[39] http://www.fcc.gov/mb/databases/cdbs/

[40] C. Corderio, K. Challapali, D. Birru, and S. Shankar N, “IEEE 802.22: The First Worldwide Wireless Standard Based on Cognitive Radio,” in *Proc. 2005 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Network*, Baltimore, MD, Nov., 2005, pp. 328–337.

[41] C.-J. Kim, H. S. Kim, and J. Laskar, “WRAN PHY/MAC Proposal for TDD/FDD,” doc.: IEEE 802.22-05/0109r0, Nov. 7, 2005.

[42] J. M. Smith, “Adaptive Cognition Enhanced Radio Teams (ACERT),” (presentation, May, 2005). [Online] Available: http://www.darpa.mil/ipto/solicitations/open/05-37_PIP.htm

[43] SDRC’s Hybrid MANET Backbone Network, White Paper, San Diego Research Center, [Online] www.sdrcinc.com.

[44] C. R. Aguayo Gonzales, J. Gaeddert, K. Kim, K. K. Bae, L. Morales, M. Robert, Y. Zhao, C. Dietrich, and J. H. Reed, “Design and Implementation of an Open-Source Software-Defined Cognitive Radio Testbed,” unpublished.

[45] T. S. Rappaport, *Wireless Communications Principles and Practice*, Prentice Hall, 1996.

[46] G. Bauer, R. Bose, and R. Jakoby, "Three-Dimensional Interference Investigations for LMDS Networks Using an Urban Database," *IEEE Trans. on Antennas and Propagation*, vol. 53, no. 8, part 1, pp. 2464–2470, Aug. 2005.

[47] T. Connolly and C. E. Begg, *Database Systems: A practical Approach to Design, Implementation, and Management*, Fourth Edition, Addison Wesley, 2005.

[48] *Functional Requirements for the 802.22 WRAN*, IEEE 802.22-05/0007r46, Sept. 2005.

[49] *Draft Standard for Wireless Regional Area Networks Part 22: Cognitive Wireless RAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications: Policies and Procedures for Operation in the TV Bands*, IEEE P802.22 Draft Standard (D0.1).

[50] Y. Zhao, B. G. Agee, and J. H. Reed, "Simulation and Measurement of Microwave Oven Leakage for 802.11 WLAN Interference Management," in *Proc. IEEE 2005 International Symposium on Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications*, Beijing, China, Aug. 8–12, 2005, pp. 1575–1578.

[51] http://en.wikipedia.org/wiki/Kurtosis.

[52] A. Fehske, J. Gaeddert, and J. H. Reed, "A New Approach to Signal Classification Using Spectral Correlation and Neural Networks," in *Proc. 2005 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Network*, Baltimore, MD, Nov. 2005, pp. 144–150.

[53] http://www.darpa.mil/ato/solicit/WANN/index.htm

[54] R. Ramanathan, "Challenges: A Radically New Architecture for Next Generation Mobile Ad-hoc Networks," in *Proc. 11th Annual International Conference on Mobile Computing and Networking (Mobicom)*, Cologne, Germany, 2005, pp. 132–139.

[55] Y. Zhao, B. G. Agee, and J. H. Reed, "Collaborative Synchronization for Macrodiverse Exploitation of Conventional 802.11 Enterprise Networks," *Poster for 2005 MPRG Wireless Personal Communications Symposium*, Blacksburg, VA, June 2005.

[56] The Network Simulator (NS-2). [online] Available: http://www.isi.edu/nsnam/ns/

[57] S. M. Kay, *Statistical Signal Processing–Estimation Theory*, Prentice Hall, 1993.

[58] *Office of Engineering and Technology Announces Projected Schedule for Proceeding on Unlicensed Operation in the TV Broadcast Bands*, FCC Public Notice, ET Docket No. 04-186, Sept. 2006.

[59] R. Chen and J. Park, "Ensuring Trustworthy Spectrum Sensing in Cognitive Radio Networks," in *Proc. 1st IEEE Workshop on Networking Technologies for Software Defined Radio Networks*, Sept. 2006, Reston, VA.

[60] C. S. Krishnamoorthy and S. Rajeev, *Artificial Intelligence and Expert Systems for Engineers*, CRC Press, 1996.

[61] D. Raymond, I. Burbey, Y. Zhao, S. Midkiff, and C. P. Koelling, "Impact of Mobility Models on Simulated Ad Hoc Network Performance," in *Proc. 9th International Symposium on Wireless Personal Multimedia Communications (WPMC)*, pp. 398–402, Sept. 2006, San Diego, CA.

[62] F. Bai and N. Sadagopan, "The IMPORTANT Framework for Analyzing the Impact of Mobility on Performance of Routing for Ad Hoc Networks," *Ad Hoc Networks Journal - Elsevier Science*, vol. 1, pp. 383–403, 2003.

[63] J. Gaeddert, K. Kim, R. Menon, L. Morales, Y. Zhao, K. K. Bae, and J. H. Reed "Applying artificial intelligence to the development of a cognitive radio engine," Mobile and Portable Radio Research Group (MPRG) Technical Report, Virginia Tech, June 2006.

[64] M. Negnevitsky, *Artificial Intelligence: A Guide to Intelligent Systems*, Pearson Education, 2002.

[65] T. Clancy and B. Walker, "Predictive Dynamic Spectrum Access," in *Proc. 2006 Software Defined Radio Forum Technical Conference*, Nov. 2006, Orlando, Florida.

[66] L. D. Xu, "Case-based reasoning: A major paradigm of artificial intelligence," *IEEE Potentials*, vol. Dec 1994–Jan 1995, pp. 10–13.

[67] S. K. Pal and S. C. K. Shiu, *Foundations of Soft Case-Based Reasoning*, John Wiley & Sons, 2004.

[68] D. Niyato and E. Hossain, "A Queuing-Theoretic and Optimization-based Model for Radio Resource Management in IEEE 802.16 Broadband Wireless Networks," *IEEE Trans. on Computers*, vol. 55, no. 11, pp. 1473–1488, Nov. 2006.

[69] P. Jacquet, A. Laouiti, P. Minet, and L. Viennot, "Performance Analysis of OLSR Multipoint Relay Flooding in Two Ad Hoc Wireless Network Models," Research Report-4260, INRIA, Sept. 2001, *RSRCP journal special issue on Mobility and Internet*.

[70] http://masimum.dif.um.es/?Software:UM-OLSR

[71] T. Clausen and P. Jacquet, "Optimized Link State Routing Protocol (OLSR)," IETF RFC 3626, Oct. 2003.

[72] Y. Zhao, L. Morales, J. Gaeddert, K. K. Bae, J. Um, and J. H. Reed, "Applying Radio Environment Maps to Cognitive WRAN Systems," in *Proc. of the Second IEEE International Symposium on Dynamic Spectrum Access Networks* (DySPAN 2007), April 17–20, 2007, Dublin, Ireland.

[73] Y. Zhao, J. Gaeddert, K. K. Bae, and J. H. Reed, "Radio Environment Map-Enabled Situation-Aware Cognitive Radio Learning Algorithms," in *Proc. of Software Defined Radio (SDR) Technical Conference*, Nov. 13–17, 2006, Orlando, FL.

[74] Y. Zhao, J. H. Reed, S. Mao, and K. K. Bae, "Overhead Analysis for REM-Enabled CR Networks," in *Proc. of the First IEEE Workshop on Networking Technologies for Software Defined Radio Networks*, Sept. 25, 2006, Reston, VA

[75] P. Marshall, "DARPA Progress in Spectrally Adaptive Radio Development," *Presented at Software Defined Radio Forum Technical Conference 2006*, Nov. 13–17, 2006, Orlando, FL.

[76] Y. Zhao, J. Gaeddert, L. Morales, K. K. Bae, and J. H. Reed, "Development of Radio Environment Map Enabled Case- and Knowledge-Based Learning Algorithms for IEEE 802.22 WRAN Cognitive Engines," submitted to *the Second International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM 2007)*

[77] A. Sahai and D. Cabric, "Spectrum Sensing–Fundamental Limits and Practical Challenges," *Tutorial for 2005 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Network*, Baltimore, MD, Nov. 2005.

[78] http://www.usgs.gov/

[79] M. Mohammad, "Cellular diagnostic systems using hidden Markov models," Ph.D. dissertation, Virginia Tech, 2006.

[80] P. Marshall, "XG Communications Program Information Briefing," Presentation to the Semantic Web Applications for National Security (SWANS) Conference, April 2005.

[81] D. Simone, "802.11k makes WLANs measure up," in *Network World*, Mar. 29, 2004.

[82] P. Balister, C. R. Aguayo Gonzalez, D. Cormier, J. D. Gaeddert, S. M. Shajedul Hasan, K. Lee, S. Sayed, H. I. Volos, and C. Dietrich, "CIREN: Cognitively Intrepid Radio Emergency Network," Proposal for *SDR Forum Smart Radio Challenge*, Mobile and Portable Radio Research Group (MPRG), Virginia Tech, 2006.

[83] T. Weingart, D. C. Sicker, and D. Grunwald, "Cross-Layer Optimization for Adaptive Wireless Systems," manuscript submitted to *Journal on Advances in Multimedia*.

[84] M. S. Bazaraa, H. D. Sherali, and C. M. Shetty, *Nonlinear Programming: Theory and Algorithms*, Second edition, John Wiley & Sons, Inc., New York, NY, 1993.

[85] M. S. Bazaraa, J. J. Jarvis, and H. D. Sherali, *Linear Programming and Network Flows*, Third edition, John Wiley & Sons, Inc., New York, NY, 2005.

[86] http://en.wikipedia.org/wiki/Local_search_(optimization)

[87] W. A. Gardner, *Statistical Spectral Analysis: A Nonprobabilistic Theory*, Prentice Hall, Englewood Cliffs, NJ, 1987.

[88] N. P. Padhy, *Artificial Intelligence and Intelligent Systems*, Oxford University Press, 2005.

[89] K. Kim, I. A. Akbar, K. K. Bae, J. Um, C. M. Spooner, and J. H. Reed, "Cyclostationary Approaches to Signal Detection and Classification in Cognitive Radio," in *Proc. of the Second IEEE International Symposium on Dynamic Spectrum Access Networks* (DySPAN 2007), April 17–20, 2007, Dublin, Ireland.

[90] R. Jain, *The Art of Computer Systems Performance Analysis: Techniques for Experimental Design, Measurement, Simulation, and Modeling*, John Wiley & Sons, 1991.

[91] J. Gaeddert, K. Kim, R. Menon, L. Morales, Y. Zhao, K. K. Bae, and J. H. Reed, "Development of a Cognitive Engine and Analysis of WRAN Cognitive Radio Algorithms," Mobile and Portable Radio Research Group (MPRG) Technical Report, Virginia Tech, Dec. 2006.

[92] P. Marshall and S. Tekinay, Workshop Announcement: *2006 Workshop on Real-Time Knowledge Processing for Wireless Network Communications*, Stanford University, March 29, 2006. [online] Available: http://www.knowledgebasednetworking.org/

[93] T. W. Rondeau and C. W. Bostian, “Cognitive Techniques: Physical and Link Layers,” in *Cognitive Radio Technology*, B. Fette, ed., Elsevier/Newnes, 2006.

[94] T. W. Rondeau, C. J. Rieser, T. M. Gallagher, and C. W. Bostian, “Online Modeling of Wireless Channels with Hidden Markov Models and Channel Impulse Responses for Cognitive Radios,” in 2004 IEEE MTT-S International Microwave Symposium Digest, pp. 739–742, vol. 2, Fort Worth, TX, 2004.

[95] J. Gaeddert, L. Morales, and Y. Zhao, 802.22 Cognitive Engine Simulator Users Manual, unpublished internal technical document, Mobile and Portable Radio Research Group (MPRG), Virginia Tech, 2006–2007.

[96] M. Xiao, N. B. Shroff, and E.K.P. Chong, “A Utility-Based Power-Control Scheme in Wireless Cellular Systems,” *IEEE /ACM Trans. on Networking*, vol. 11, no.2, pp. 210–221, April 2003.

[97] Y. Zhao and J. H. Reed, “Radio Environment Map Enabled Cognitive Radios,” 2006 *Wireless@Virginia Tech Wireless Personal Communications Symposium*, June 7–9, 2006, Blacksburg, VA.

[98] J. M. Cioffi, “A Multicarrier Primer,” in *ANSI T1E1.4 Committee Contribution*, 91–157, Boca Raton, Nov., 1991.

Vita

Youping Zhao made his final defense on May 8, 2007. He received his B.S. and M.S. degrees in Electrical Engineering from Tsinghua University, Beijing, China, in 1994 and 1996, respectively. Prior to his Ph.D. study at Mobile and Portable Radio Research Group (MPRG), Bradley Department of Electrical and Computer Engineering, Virginia Tech, he had been employed by China Unicom, Nanovation Technologies, and LinkAir Communications. He has research and/or industry experience in the areas of RF transceiver design, radio channel sounder development, (indoor) radio propagation measurement and characterization, 2G/3G wireless communication systems design, integration, simulation, testing, and standardization, field testing on broadband wireless access systems (such as LMDS), and digital signal processing. He has more than 20 publications in the general area of wireless communications. His current research interests are development and exploitation of radio environment map and cognitive radio for various applications (such as dynamic spectrum access and sharing, public safety, and cognitive vehicles), advanced signal processing, cross-layer design and optimization, software defined radio, and cognitive wireless networking technologies.