AIN SHAMS UNIVERSITY
FACULTY OF ENGINEERING
CAIRO – EGYPT
Electronics and Communications Engineering Department

Adaptation Engine for Cognitive Radio Systems based on Meta-Heuristic Techniques

Dissertation submitted to the Faculty of the Engineering – Ain-Shams University in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Electrical Engineering

submitted by

Eng. Ramy Ahmed Fathy Mahmoud
Electronics and Communications Eng. Dept.
Faculty of Engineering - Ain Shams University

supervised by

Prof. Dr. Abdelhalim Zekry
Professor in the Electronics and Communications Eng. Dept.
Faculty of Engineering - Ain Shams University (ASU)
Cairo, Egypt

Dr. Ahmed Abd-Elhafez
Communications Eng. Dept.
Military Technical College (MTC)
Cairo, Egypt

Cairo 2013

AIN SHAMS UNIVERSITY
FACULTY OF ENGINEERING
CAIRO - EGYPT

Examiners Committee

Name : **Ramy Ahmed Fathy Mahmoud**
Thesis : **Adaptation Engine for Cognitive Radio Systems based on Meta-Heuristic Techniques**
Degree: **Doctor of Philosophy in Electrical Engineering**

Title, Name and Affiliation	Signature
1. Prof. Christian Gontrand Electronics Department INSA-LYON University, Villeurbanne, France	……………..
2. Prof. Hadya Elhennawy Electronics and Communication Eng. Dept. Ain Shams University, Cairo, Egypt	
3. Prof. Abdelhalim Zekry Electronics and Communication Eng. Dept. Ain Shams University, Cairo, Egypt	

Date: 31/07/2013

STATEMENT

This dissertation is submitted to Ain Shams University in partial fulfillment of the degree of Doctor of Philosophy in Electrical Engineering.

The work included in this dissertation was carried out by the author in the department of Electronics and Communications Engineering, Ain Shams University.

No part of this dissertation has been submitted for a degree or a qualification at any other university or institute.

Name : Ramy Ahmed Fathy Mahmoud
Signature :
Date : 31/07/2013

Abstract

Adaptation Engine for Cognitive Radio Systems based on Meta-Heuristic Techniques

This research aims at contributing to the problem of decision-making in Cognitive Radio Systems (CRS); where optimization of specific Cognitive Radio (CR) physical layer parameters is targeted, in order to minimize the communication link BER at the lowest possible transmitted terminals' EIRP levels. Moreover, this thesis mainly focuses on developing an Adaptation Engine that achieves the aforementioned objectives in order to establish a reliable communication link, with the least terminals' power consumption and minimum possible interference on other neighboring communicating radio systems. Applying cognition to radio systems is not an easy task. The problem is that there is currently no universal widely-accepted definition for that terminology. Accordingly, this poses some difficulties as to specify the necessary CR adaptation architecture components that enable the radio from attaining adaptive behavior.

Hence, attempting to close that gap, this work initially introduces a formal rigorous model of CR inspired from cognitive sciences. Identifying the nature of cognition is crucial for laying down a rigorous theoretical model for CR. Two aspects are needed to be considered when it comes to specifying cognitive behavior. One is the functional specification of cognition, and the other is the architectural specification needed for attaining cognitive behavior. By developing a novel computational formal model based on a modified form of Turing Machines, the peculiar nature of the radio's cognitive properties as inspired from cognitive sciences, and cognitive neurosciences is modeled, and hence reflected in the required adaptation functionalities.

The Adaptation Engine is designed to respond to varying operating contexts which account for varying provisioned services under varying environmental impairments, represented by dynamic noise plus interference levels at different frequency bands. However, its performance is ratified against the operational and efficiency requirements of two of state of the art use cases in the industry; namely, the efficient utilization of the spectrum through Dynamic Spectrum Access (DSA), and Public Protection and Disaster Relief (PPDR) communication systems. In the later case, first responders in disaster scenarios need to have a secured, robust, and reliable communication system that can reach the compromised areas in case there is damage in its underlying infrastructure. Cognitive Radio Systems (CRS) could provide an ultimate solution to such situations. With the ability to adapt to varying levels of stimuli, and intelligently adapt its operating parameters to satisfy the aforementioned objectives; the adaptation function of CR is one fundamental

aspect necessary for the functionality of many CR use cases, like DSA and PPDR. The Adaptation Engine varies the radio operating parameters assuming an underlying Software Defined Radio (SDR) architecture that provides the ability of the radio to change its waveform according to the optimized parameter set achieved during the optimization process.

This thesis also presents a novel architecture, design, and implementation of the Adaptation Engine employing Genetic Algorithms (GA) as core meta-heuristics optimization techniques for the adaptation process. GA is an optimization method that mimics natural evolution. Optimization is based on the development of the population comprising a certain number of chromosomes. The chromosomes represent a possible solution set for the optimization problem; which could be maximization or a minimization for a specific objective function. The population size indicates the number of parallel solutions that would be tried in parallel to reach towards the optimum/sub-optimum solution. The development of the population is regulated by means of two genetic operators; namely, crossover and mutation.

GA has been widely used in the development of Adaptation Engines. However, it has been criticized for its slow dynamic response times. Accordingly Real-coded Genetic Algorithm (RGA) – a specific type of GA – has been implemented, to address this problem. RGA alleviates many of the disadvantages of conventional Binary-coded Genetic Algorithm (BGA) based engines, employed often in the CR adaptation literature, like the slow convergence and dynamic response times. Employing RGA based AE, as a core meta-heuristic technique; enables the radio to provide a multitude of applications and services including high data rate and bandwidth hungry applications like video calls and VOD services, and it does indeed satisfy the operational and efficiency constraints of DSA and PPDR use cases.

It is the first time to our knowledge that RGA has been used to carry out the adaptation process in CRS. RGA has the advantage of producing accurate and reliable solutions with reasonable dynamic response times depending on the radio's operating frequency spectrum span and data rate of the service provisioned. Using single objective optimization with a special power limiting algorithm, rather than using multi-objective optimization, the Adaptation Engine is operated to minimize the communication link BER at the lowest possible transmitted terminals' EIRP levels.

Experimental results show that RGA based implementations attain superior performance in terms of faster dynamic engine response times and better engine reliability compared to BGA based implementations. In addition BGA is shown to produce misleading results in the optimization problem investigated, unless it is used in a multi-objective optimization setup where the minimization of the transmitted EIRP levels is included as a secondary objective.

Acknowledgments

I would like to express my deepest gratitude to my true mentor and friend professor Zekry for his support and mentorship during my whole post graduate studies. For over 10 years, Prof. Zekry, through his endless endeavors and scientific contributions, assisted me in every aspect of conducting research. From ideas inception to implementation and development, Prof. Zekry taught us the essence of becoming a researcher. I am very lucky to work under his supervision, and for that I am most grateful. Prof. Zekry has been the cornerstone and key success factor of this work. With close follow-up, insightful critics, strategic thinking; Prof. Zekry is the role model for any professorship. Thank you professor for the effort you have done and all the true support you have willingly given for the accomplishment of this project. Without you, we wouldn't have been standing here today, and we definitely wouldn't have accomplished what we've today accomplished.

I would also like to thank Dr. Ahmed AbdelHafez for being an important success factor of this project. With close follow-up, constant supervision, and proof-readings; Dr. Ahmed was a true assistance for me along the way. He gave plenty of time for discussions, and technical assistance; and for that I am most grateful.

My gratitude also goes to Eng. Ismaiil Elghitany for his continuous support and critical discussions which triggered more intuitive questions and more practical concerns. I would also like to thank the Spectrum Monitoring team at NTRA for all the support given during my research to conduct the lab trials and experimentation.

A special acknowledgement to my father, my true mentor and source of inspiration; whom I consider my third supervisor. With his guidance and support, proof-listening, and critical discussions in every aspect of this work, he was a great help and supporter during the difficult phases of the project.

I thank my mother, brother, and my wife for their prayers and support during my work. I apologize for all the long nights and weekends, and holidays which I missed. But at the end, I can only say to my wife, proudly,

.. Dear.. Thanks to you.. I made it.

Dedication

To my family

Table of Contents

1. Background and Problem Statement 17
   1.1 Research Drivers 18
      1.1.1 Efficient Utilization of the Spectrum 19
      1.1.2 Public Protection and Disaster Relief (PPDR) 21
   1.2 Historical Roots of the Problem and its Description 22
   1.3 Research Overview and Contributions 25
      1.3.1 Formal Modeling of CR 25
      1.3.2 Adaptation Engine Design 26
   1.4 Dissertation Organization 27
2. Formal Theoretical Modeling 28
   2.1 Former Cognition Cycles 31
      2.1.1 Analysis 33
      2.1.2 Additional Blocks Needed 34
   2.2 Current CR Definitions 34
      2.2.1 Partially Overlapping Technologies 39
      2.2.2 Discussion 39
   2.3 Nature of Cognition and Modularity of the Mind 40
      2.3.1 Functional Requirements of Cognitive Behavior 41
      2.3.2 Modularity 42
      2.3.3 Parallel Distributed Processing 42
      2.3.4 Evolutionary Nature of Cognition 43
      2.3.5 Subsumption Architecture 43
   2.4 Reference Theoretical Framework (RTF) 44
      2.4.1 Computational Representation Understanding of Mind (CRUM) 44
      2.4.2 Cognitive Neuroscience 45
      2.4.3 Framework 46
   2.5 Novel Cognition Cycle 47
   2.6 Intelligence and Cognition 49
   2.7 Theoretical Computational Modeling 55
      2.7.1 Turing Machine (TM) 56

2.7.2 Multitape Turing Machine (MTM) 56
2.7.3 Universal Turing Machine (UTM) 56
2.8 A Novel Formal Theoretical Model for CR 57
2.8.1 Novel Computational Model – Universal Multitape Turing Machine (UMTM) 57
2.8.2 Novel Formal Cognition Cycle Model 58
2.8.3 Modeling Evolution 59
2.8.4 Formal Cognitive Radio Model 60
2.9 Model Generality and Openness 61
2.10 Summary 61
3. Adaptation Engine based on Meta-Heuristic Techniques 63
3.1 Operational and Efficiency Requirements of Efficient Spectrum Utilization Use Cases 64
3.2 Operational and Efficiency Requirements of PPDR Use Cases 65
3.3 Adaptation through Meta-Heuristics 67
3.3.1 Genetic Algorithms (GA) 68
3.3.2 Particle Swarm Optimization (PSO) 71
3.3.3 No Free Lunch Theorems (NFL) 72
3.4 CRE Previous Work 73
3.4.1 Discussion 75
3.5 Proposed CRE Structure Design and Key Differences 76
3.6 Ideal Generic Adaptation Engine Architecture (IGAEA) 77
3.6.1 Invoker Algorithm 80
3.7 Adaptation Engine Architecture Based on Genetic Algorithms – First Generation Architecture 81
3.7.1 Engine Method of Work 82
3.8 System Model of Cognitive Radio Systems and the Cognitive Radio Adaptation Cycle 85
3.8.1 Link Drop 90
3.8.2 Operating Frequency Band Unavailability 91
3.8.3 Real-coded Genetic Algorithm (RGA) 92
3.9 Implementation 96
3.9.1 Single Objective Optimization (SOO) 97

3.9.2 Power Limiting Algorithm (PLA) 101
3.10 Summary 101
4. Experimentation, Results, and Validation Procedures 103
4.1 Experimentation Procedures 103
4.2 Accuracy Assessment 107
4.3 Accuracy Validation 107
4.4 Performance Assessment 111
4.5 Performance Validation 117
4.6 Comparative Performance Validation 118
4.7 Comparative Assessment 124
4.8 Engine Control Parameters 125
4.9 Summary 125
5. Conclusion and Future Work 127
5.1 Conclusion 129
5.2 Summary of Contributions 129
5.3 Future Work 130
5.3.1 Invoker Design and Implementation 130
5.3.2 Multi-Objective Optimization Constructor 130
5.3.3 Multi-Objective Optimization (MOO) 130
Appendix 132
References 140

List of Figures

Figure 2.1 Mitola's Cognition Cycle in CR [21] 32
Figure 2.2 Haykin's Basic Cognition Cycle in CR 33
Figure 2.3 Novel Cognition Cycle for CR 48
Figure 2.4 Layered Reference Model of the Brain (LRMB) [61] 51
Figure 2.5 Classification of CPs in the LRMB Reference Model [61] 52
Figure 2.6 A Conceptual CR Functional Representation based on Formal Theoretical Model of CR: Red (Dark) colored blocks demonstrate the functionalities implemented in the Adaptation Engine 54
Figure 2.7 OODA loop incorporated into proposed Cognition Cycle 61
Figure 3.1 Dynamic Spectrum Access (DSA) use case [67] 65
Figure 3.2 Network coverage extension use case by means of CRS [11] 66
Figure 3.3 Pseudo code of Genetic Algorithms (GA) [68] 66
Figure 3.4 Crossover at a random crossover location 70
Figure 3.5 Mutation of a single site by flipping a randomly selected bit 70
Figure 3.6 Pseudo code of Particle Swarm Optimization (PSO) [68] 72
Figure 3.7 Ideal Generic Adaptation Engine Architecture (IGAEA) Based on Meta-Heuristic Techniques 79
Figure 3.8 AE Architecture Based on GA – First Generation Architecture 83
Figure 3.9 Cognitive Radio System (CRS) Model 87
Figure 3.10 Cognitive Radio Adaptation Cycle 88
Figure 3.11 Evolution of population in Genetic Algorithm (GA) 93
Figure 4.1 Test Cases Schematic Diagram for the AE Experimentation and Validation Procedures 105
Figure 4.2 BER of BPSK, and QPSK Modulation at Different Transmitted EIRP Power Levels for TC3 108
Figure 4.3 BER of 8-PSK Modulation at Different Transmitted EIRP Power Levels for TC3 109
Figure 4.4 BER of 16-PSK Modulation at Different Transmitted EIRP Power Levels for TC3 110

List of Tables

Table 4.1: RGA Based Engine Reliability Assessment at Different Selected Maximum Allowable EIRP 112
Table 4.2: RGA Based Engine Dynamic Response Time of *Test Case 1*, and *Test Case 2* (without PLA) 113
Table 4.3: RGA Based Engine Dynamic Response Time of *Test Case 3*, and *Test Case 4* (without PLA) 113
Table 4.4: RGA Based Engine Dynamic Response Time of *Test Case 5*, and *Test Case 6* (without PLA) 114
Table 4.5: RGA Based Engine Transmitted EIRP of *Test Case 1*, and *Test Case 2* (without PLA) 114
Table 4.6: RGA Based Engine Transmitted EIRP of *Test Case 3*, and *Test Case 4* (without PLA) 115
Table 4.7: RGA Based Engine Transmitted EIRP of *Test Case 5*, and *Test Case 6* (without PLA) 115
Table 4.8: RGA Based Engine Reliability and Response Time Assessment of the AE (with PLA) 116
Table 4.9: Reliability Assessment of BGA Based AE at Different Selected Maximum Allowable EIRP 119
Table 4.10: BGA Based Engine Dynamic Response Time of *Test Case 1*, and *Test Case 2* (without PLA) 119
Table 4.11: BGA Based Engine Dynamic Response Time of *Test Case 3*, and *Test Case 4* (without PLA) 120
Table 4.12: BGA Based Engine Dynamic Response Time of *Test Case 5*, and *Test Case 6* (without PLA) 120
Table 4.13: BGA Based Engine Transmitted EIRP of *Test Case 1*, and *Test Case 2* (without PLA) 121
Table 4.14: BGA Based Engine Transmitted EIRP of *Test Case 3*, and *Test Case 4* (without PLA) 121
Table 4.15: BGA Based Engine Transmitted EIRP of *Test Case 5*, and *Test Case 6* (without PLA) 122
Table 4.16: BGA Based Reliability and Response Time Assessment of the AE (with PLA) 123

List of Acronyms

ACO: Ant Colonization Optimization

AE: Adaptation Engine

AI: Artificial Intelligence

A. K. A.: Also Known As

AMPS: Advanced Mobile Phone Service

ANOVA: Analysis of Valiance

BCO: Bee Colonization Optimization

BER: Bit Error Rate

BGA: Binary-coded Genetic Algorithm

CBR: Case Based Reasoning

CDMA: Code Division Multiple Access

CRE: Cognitive Radio Engine

CR: Cognitive Radio

CRS: Cognitive Radio Systems

DSA: Dynamic Spectrum Access

DSP: Digital Signal Processor

EIRP: Effective Isotropic Radiated Power

FA: Firefly Algorithm

FCC: Federal Communications Commission

FDMA: Frequency Division Multiple Access

FM: Frequency Modulation

GA: Genetic Algorithm

GSM: Global System for Mobile Communications

IMT-Advanced: International Mobile Telecommunications-Advanced

ITU: International Telecommunication Union

ITU-R: International Telecommunication Union, Radiocommunication Sector

KB: Knowledge Base

LRMB: Layered Reference Model of the Brain

MAC: Media Access Control

MOO: Multi-Objective Optimization

MTM: Multitape Turing Machine

NTIA: National Telecommunications and Information Administration

OPS: Operating Parameter Set

PLA: Power Limiting Algorithm

PPDR: Public Protection and Disaster Relief

PSO: Particle Swarm Optimization

REM: Radio Environment Map

RGA: Real-coded Genetic Algorithm

RKRL: Radio Knowledge Representation Language

RSS: Received Signal Strength

RTPA: Real-Time Process Algebra

SA: Simulated Annealing

SDL: Specification and Description Language

SDR: Software Defined Radio

SOO: Single Objective Optimization

OFDMA: Orthogonal Frequency Division Multiple Access

TC: Test Case

TDMA: Time Division Multiple Access

TM: Turing Machine

UML: Unified Modeling Language

UMTM: Universal Multitape Turing Machine

UTM: Universal Turing Machine

List of Symbols

Q: Set of states of a Turing Machine

⊔: Blank symbol

Σ: Input alphabet not containing the blank symbol ⊔

Γ: Tape alphabet, where $\sqcup \in \Gamma$, and $\Sigma \subseteq \Gamma$

δ: Transition function of a Turing Machine

q_0 : Initial (start) state of a Turing Machine

q_{accept}: Accept state of a Turing Machine

q_{reject}: Reject state of a Turing Machine, where $q_{accept} \neq q_{reject}$

$\{\mathrm{L}, \mathrm{R}\}$: Set of head movement of a Turing Machine where L represents one step move to the left and R represents one step move to the right

$U(M; x)$: Universal Turing Machine, a generalization of a Turing Machine representing the description of the Turing Machine *M* along with its behavior to an input data *x* applied to its input

∀: 'for all' symbol

∃: 'there exists' symbol

ℂ: Cognition Set

P_c : Probability of cross over in a Genetic Algorithm

P_m : Probability of mutation in a Genetic Algorithm

$v_{m,n}$: Particle velocity in a Particle Swam Optimization algorithm

$x_{m,n}$: Particle variables in a Particle Swam Optimization algorithm

$\mathrm{r}_1, \mathrm{r}_2$: Independent uniform random numbers in a Particle Swam Optimization algorithm

Γ_1, Γ_2: Learning factors in a Particle Swam Optimization algorithm

$x^*_{m,n}$: Best local solution in a Particle Swam Optimization algorithm

$g^*_{m,n}$: Best global solution in a Particle Swam Optimization algorithm

N: Channel noise level

I: Co-channel interference levels

Pos^A: Position information of Cognitive Radio terminal A

Pos^B: Position information of Cognitive Radio terminal B

ν^A: Operating frequency of Cognitive Radio terminal A