DECLARATION

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged.

17 February 2012  AYMAN ABD EL-SALEH
P38294
ACKNOWLEDGEMENT

First and for most, all praises are due to Allah, the Almighty, the Most Gracious and the Most Merciful, on Whom ultimately we depend for sustenance, guidance and blessing.

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ABSTRACT

Cognitive radio (CR) users are envisioned as intelligent secondary users (SUs) armed with spectrum sensing capabilities to monitor licensees’ or primary users’ (PUs’) activities and opportunistically access unused channels. In cognitive radio networks (CRNs), cooperative spectrum sensing is performed with an essential aim of maximizing CRN throughput and also PU protection. However, these two objectives are unfortunately contradictory such as improving the PU detection through cooperation between SUs results in an increased relaying overhead. The main objective of this research work is to develop multi-objective evolutionary algorithms (MOEAs) based on genetic algorithms (GAs) for optimizing the performance of CRNs and CR by attaining a compromise between corresponding conflicting objectives according to predefined criteria. Three different CRN architectures, namely, hard decision fusion (HDF), soft data fusion (SDF), and hybrid SDF-HDF cluster-based CRNs have been proposed. The architectures satisfy distinct requirements of PU detection performance and overhead traffic. The SDF can be used when high PU detection performance is needed whereas the HDF is to be used when low overhead traffic is demanding. In contrast, the hybrid SDF-HDF is used when a balanced compromise between PU detection performance and overhead traffic is of interest. MOEAs based on GAs called single-objective GA (SOGA), bi-objective GA (BOGA), and multi-objective GA (MOGA) have been also developed as intelligent optimization systems for SDF, HDF, and hybrid SDF-HDF cluster-based CRNs, respectively. In addition, another MOGA has been developed to add in cognition and environment-awareness to CR systems. The MOGA-based decision engine evolves autonomously to return sub-optimal set of transmission parameters for the sensed wireless environment and under a predefined operational scenario resulted from the conflicting nature of corresponding objectives. Throughout this thesis, the CRN network deployments and CR system models are first proposed and their mathematical formalisms are derived, simulated, and analyzed to observe existing tradeoffs. Based on pre-simulation results, objective functions and their corresponding dependency relationships with design parameters for each proposed network or system have been then identified and formulated. These conflicting objectives are introduced as performance metrics for the corresponding MOEA. The performance of the GA-based system/engines is evaluated for different channel conditions and operating scenarios. Post-analyses and comparisons are finally carried out to verify the conceptual functionality and validate the obtained results. Simulation results of MOEAs of CRNs and CR systems show successful adaption in response to environmental and topological conditions. In SDF-based CRNs, the proposed SOGA achieves a fitness score of 10% higher than that of the best conventional SDF scheme given the same false alarm rate. The BOGA optimization system of HDF-based CRN achieves a fitness score improvement of 10% and 4% than when using static cooperation level and static sensing time, respectively. In hybrid SDF-HDF cluster-based CRN, the proposed MOGA optimization system, when using its optimal parameters, show a fitness score improvement of about 14.4% greater than that if the parameters are set to their maximum values and an improvement of about 69.3% when they are set to their minimum values. Finally, for CR systems, the simulation results confirm the effectiveness of the proposed MOGA decision engine since more than 80% of fitness score can always be achieved within the first 50 generations which is fast enough to meet real-time requirements.
Pengguna radio kognitif (CR) boleh dianggap sebagai pengguna sekunder (SU) cerdik yang memiliki kebolehan menderia spektrum bagi mengawas aktiviti pemilik lesen atau pengguna utama (PU) dan berpeluang untuk mengakses saluran-saluran yang tidak digunakan. Dalam rangkaian radio kognitif (CRN), penderiaan spektrum kerjasama dilaksana dengan matlamat penting bagi memaksimum truput dan juga perlindungan PU. Walaupun demikian, kedua-dua objektif tersebut malangnya saling bercanggahan seperti peningkatan pengesanan PU melalui kerjasama antara SU akan menghasilkan lebihan gegantian yang bertambah. Objektif utama kerja penyelidikan ini ialah membangunkan algoritma evolusi berbilang-objektif (MOEA) berasaskan algoritma genetik (GA) dalam mengoptimum prestasi CRN dan CR dengan mencapai kompromi antara objektif yang bercanggah yang sepadan mengikut kriteria yang telah dipratentukan. Tiga senibina CRN yang berbeza yang dinamakan CRN lakuran keputusan keras (HDF), CRN lakuran keputusan lembut (SDF) dan CRN berasaskan kelompok SF-HF hibrid telah dicadangkan. Senibina memenuhi keperluan nyata bagi prestasi pengesanan PU dan trafik lebihan. SDF boleh digunakan apabila prestasi pengesanan PU yang tinggi diperlukan sementara HDF digunakan apabila permintaan trafik lebihan adalah rendah. Sebaliknya, SDF-HDF digunakan apabila kompromi terimbang antara prestasi pengesanan PU dan lebihan trafik diminati. MOEA algoritma-algoritma genetik (GAs) yang dikenali sebagai GA objektif-tunggal (SOGA), GA dwiobjektif (BOGA) dan GA berbilang-objektif (MOGA) juga telah dibangunkan sebagai sistem pengoptimuman cerdik masing-masing bagi CRN SDF, HDF dan berasaskan kelompok SF-HF hibrid. Di samping itu, satu lagi MOGA telah dibina untuk menambah pecahan dan kesedaran persekitaran kepada sistem CR. Enjin keputusan berasaskan MOGA berkembang secara autonomi untuk mengembalikan set sub-optimum parameter penghantaran bagi persekitaran tanpa wayar yang diperlukan dan dalam senario operasi yang telah dipratentukan yang terhasil akibat keadaan bercanggahan objektif yang sepadan. Dalam keseluruhan tesis ini, pertama, pelaksanaan rangkaian CRN dan model sistem CR telah dicadangkan dan kemudiannya formalisasi matematik diterbit, disimulasi dan dianalisis untuk memerhatikan tolakansur yang wujud. Berdasarkan hasil prasimulasi, fungsi objektif dan hubungkait masing-masing dengan parameter rekabentuk bagi setiap rangkaian atau sistem yang dicadang telah dikenali dan disesuaikan. Enjin yang bercanggahan ini telah diperkenalkan sebagai metrik prestasi bagi MOEA yang sepadan. Prestasi sistem dan enjin berasaskan MOGA telah dipantau melalui perbandingan skor kecergasan bagi setiap topologi dan model sistem CR. Sistem pengoptimuman SOGA bagi CRN telah mencapai skor kecergasan 10% lebih baik berbanding skor terbaik bagi skema SDF lazim untuk kadar penggera salah yang sama. Sistem pengoptimuman BOGA bagi CRN berasaskan HDF mencapai peningkatan skor kecergasan 10% dan 4% masing-masing apabila menggunakan tahap kerjasama statik dan masa deria statik. Dalam CRN berasaskan kelompok SDF-HDF, sistem pengoptimuman MOGA yang dicadangkan menunjukkan peningkatan skor kecergasan sebanyak 14.4% apabila parameter optimumnya digunakan berbanding jika parameter disetkan pada nilai maksimum dan peningkatan di sekitar 69.3% apabila nilai minimum disetikan. Akhirnya, bagi sistem CR hasil simulasi
membuktikan keberkesanan enjin keputusan MOGA yang dicadangkan kerana lebih dari 80% skor kecerdasan sentiasa boleh dicapai dalam 50 generasi dan hal ini cukup pantas bagi memenuhi keperluan masa nyata.
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<tr>
<td>AAF</td>
<td>Amplify-and-Forward</td>
</tr>
<tr>
<td>ABC</td>
<td>Artificial Bee Colony</td>
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<tr>
<td>ACO</td>
<td>Ant Colony Optimization</td>
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<tr>
<td>ADC</td>
<td>Analog-to-Digital Converter</td>
</tr>
<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>AP</td>
<td>Access Point</td>
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<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
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<td>Bit Error Rate</td>
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<td>Balanced Mode</td>
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<td>Bi-Objective Fitness</td>
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<td>BOGA</td>
<td>Bi-Objective Genetic Algorithm</td>
</tr>
<tr>
<td>BS</td>
<td>Base Station</td>
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<tr>
<td>BWRC</td>
<td>Berkeley Wireless Research Centre</td>
</tr>
<tr>
<td>CCB</td>
<td>Control Channel Bandwidth</td>
</tr>
<tr>
<td>CES</td>
<td>Constant-Elasticity-of-Substitution</td>
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<tr>
<td>CFAR</td>
<td>Constant False Alarm Rate</td>
</tr>
<tr>
<td>CFD</td>
<td>Quantization Fidelity</td>
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<tr>
<td>CGA</td>
<td>Quantum Genetic Algorithm</td>
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<tr>
<td>CH</td>
<td>Cluster Header</td>
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<tr>
<td>CLT</td>
<td>Central Limit Theorem</td>
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<tr>
<td>CR</td>
<td>Cognitive Radio</td>
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<tr>
<td>CRM</td>
<td>Cognitive Resource Manager</td>
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<tr>
<td>CRN</td>
<td>Cognitive Radio Network</td>
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<tr>
<td>CSI</td>
<td>Channel State Information</td>
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</tbody>
</table>
CSS  Cooperative Spectrum Sensing
CWT  Centre for Wireless Telecommunications
DAF  Decode-and-Forward
DARPA  Defense Advanced Research Projects Agency
DC  Deflection Coefficient
DIMSUMnet  Dynamic Intelligent Management of Spectrum for Ubiquitous Mobile Network
DRiVE  Dynamic Radio for IP Services in Vehicular Environments
DSA  Dynamic Spectrum Access
EGC  Equal Gain Combination
EHF  Extra High Frequency
FC  Fusion Centre
FCC  Federal Communications Commission
FEC  Forward Error Correction
FFT  Fast Fourier Transform
GA  Genetic Algorithm
GSM  Global System for Mobile Communications
GUISM  Graphical User Interface Simulation Model
HDF  Hard Decision Fusion
HMM  Hidden Markov Model
IEEE  Institute of Electrical and Electronics Engineers
i.i.d.  Independent and Identically Distributed
ISM  Industrial, Scientific, and Medical Frequency Band
KPP  Key Performance Parameter
LAN  Local Area Network
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
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<tr>
<td>MCMC</td>
<td>Malaysian Communications and Multimedia Commission</td>
</tr>
<tr>
<td>MDC</td>
<td>Modified Deflection Coefficient</td>
</tr>
<tr>
<td>MIMO</td>
<td>Multiple-Input Multiple-Output</td>
</tr>
<tr>
<td>MOEA</td>
<td>Multi-Objective Evolutionary Algorithm</td>
</tr>
<tr>
<td>MOF</td>
<td>Multi-Objective Fitness</td>
</tr>
<tr>
<td>MOGA</td>
<td>Multi-Objective Genetic Algorithm</td>
</tr>
<tr>
<td>MOO</td>
<td>Multiple-Objective Optimization</td>
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<td>MRC</td>
<td>Maximal-Ratio Combining</td>
</tr>
<tr>
<td>NDC</td>
<td>Natural Deflection Coefficient</td>
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<tr>
<td>OCRA</td>
<td>OFDM-based Cognitive Radio</td>
</tr>
<tr>
<td>Ofcom</td>
<td>Office of Communications</td>
</tr>
<tr>
<td>OFDM</td>
<td>Orthogonal Frequency-Division Multiple</td>
</tr>
<tr>
<td>OFDMA</td>
<td>Orthogonal Frequency-Division Multiple Access</td>
</tr>
<tr>
<td>OSI</td>
<td>Open Systems Interconnection</td>
</tr>
<tr>
<td>PDA</td>
<td>Personal Digital Assistant</td>
</tr>
<tr>
<td>PDF</td>
<td>Probability Density Function</td>
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<tr>
<td>POD</td>
<td>Probability of Detection</td>
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<tr>
<td>PSD</td>
<td>Power Spectral Density</td>
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<tr>
<td>PSK</td>
<td>Phase Shift Keying</td>
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<tr>
<td>PSM</td>
<td>Power-Saving Mode</td>
</tr>
<tr>
<td>PSO</td>
<td>Particle Swarm Optimization</td>
</tr>
<tr>
<td>PU</td>
<td>Primary User</td>
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<tr>
<td>QAM</td>
<td>Quadrature Amplitude Modulation</td>
</tr>
<tr>
<td>QoS</td>
<td>Quality of Service</td>
</tr>
<tr>
<td>RCM</td>
<td>Reliable Communication Mode</td>
</tr>
<tr>
<td>Acronym</td>
<td>Full Form</td>
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<tr>
<td>RKRL</td>
<td>Radio Knowledge Representation Language</td>
</tr>
<tr>
<td>ROC</td>
<td>Receiver Operating Characteristics</td>
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<tr>
<td>SDF</td>
<td>Soft Data Fusion</td>
</tr>
<tr>
<td>SDR</td>
<td>Software Defined Radio</td>
</tr>
<tr>
<td>SEM</td>
<td>Spectrally-Efficient Mode</td>
</tr>
<tr>
<td>SINR</td>
<td>Signal to Interference and Noise Power</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal-to-Noise Ratio</td>
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<tr>
<td>SOF</td>
<td>Single-Objective Function</td>
</tr>
<tr>
<td>SOGA</td>
<td>Single-Objective Genetic Algorithm</td>
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<tr>
<td>SPTF</td>
<td>Spectrum Policy Task Force</td>
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<tr>
<td>SU</td>
<td>Secondary User</td>
</tr>
<tr>
<td>THR</td>
<td>CRN Throughput</td>
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<tr>
<td>TPC</td>
<td>Total Power Consumption</td>
</tr>
<tr>
<td>TS</td>
<td>Test Statistic</td>
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<tr>
<td>TSP</td>
<td>Travelling Salesman Problem</td>
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<tr>
<td>TVWS</td>
<td>TV While Space</td>
</tr>
<tr>
<td>UHF</td>
<td>Ultra High Frequency</td>
</tr>
<tr>
<td>UMTS</td>
<td>Universal Mobile Telecommunications System</td>
</tr>
<tr>
<td>UNII</td>
<td>Unlicensed National Information Infrastructure</td>
</tr>
<tr>
<td>UWB</td>
<td>Ultrawide Band</td>
</tr>
<tr>
<td>VHF</td>
<td>Very High Frequency</td>
</tr>
<tr>
<td>WLAN</td>
<td>Wireless Local Area Network</td>
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<tr>
<td>WRAN</td>
<td>Wireless Regional Area Network</td>
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<tr>
<td>XG</td>
<td>neXt Generation</td>
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</tbody>
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**LIST OF SYMBOLS**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>$\overline{P}_d$</td>
<td>Given probability of detection</td>
</tr>
<tr>
<td>$\overline{P}_f$</td>
<td>Given probability of false alarm</td>
</tr>
<tr>
<td>$\overline{\beta}$</td>
<td>Given threshold setting</td>
</tr>
<tr>
<td>$\sigma_S^2$</td>
<td>Variance of PU signal</td>
</tr>
<tr>
<td>$\sigma_{W,i}^2$</td>
<td>Variance of white noise of ith PU-SU link</td>
</tr>
<tr>
<td>$\sigma_i^2$</td>
<td>Variance of white noise of ith SU-CH link</td>
</tr>
<tr>
<td>$P_{R_i}$</td>
<td>Relay power of ith SU</td>
</tr>
<tr>
<td>$\bar{\mu}_0$</td>
<td>Means vector of all SU observations under $H_0$ hypothesis</td>
</tr>
<tr>
<td>$\bar{\mu}_1$</td>
<td>Means vector of all SU observations under $H_1$ hypothesis</td>
</tr>
<tr>
<td>$\bar{\omega}$</td>
<td>Weighting coefficients vector</td>
</tr>
<tr>
<td>$E(.)$</td>
<td>Expected value operator</td>
</tr>
<tr>
<td>$\text{var}(.)$</td>
<td>Variance operator</td>
</tr>
<tr>
<td>$Q_{f,j}$</td>
<td>CRN-noise probability of false alarm within the jth cluster</td>
</tr>
<tr>
<td>$Q_{d,j}$</td>
<td>CRN-noise probability of detection within the jth cluster</td>
</tr>
<tr>
<td>$Q(.)$</td>
<td>Q-function operator</td>
</tr>
<tr>
<td>$| \cdot |_n$</td>
<td>$n$-norm operator of a given vector</td>
</tr>
<tr>
<td>$\Sigma_{H_0}$</td>
<td>Covariance matrix under hypothesis $H_0$</td>
</tr>
<tr>
<td>$\Sigma_{H_1}$</td>
<td>Covariance matrix under hypothesis $H_1$</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Elasticity between the single-objective functions</td>
</tr>
<tr>
<td>$d_m^2$</td>
<td>Modified Deflection Coefficient (MDC)</td>
</tr>
</tbody>
</table>
$d_n^2$ Normal Deflection Coefficient

$R^n$ Normal Deflection Coefficient

$B$ Sensed bandwidth

$BW_{SU-FC\ link}$ Channel bandwidth of the SU-FC link

$C(t)$ Offspring population

$CCB_{\max}$ Maximum available control channel bandwidth

$CFD_{\max}$ Maximum possible fidelity

$diag(.)$ Diagonal operator maps vector elements to a diagonal matrix

$E_b$ Energy per bit

$elite$ Elitism rate

$F_{BLM}$ Objective function under balanced mode (BLM)

$F_{PSM}$ Objective function under power-saving mode (PSM)

$F_{RCM}$ Objective function under reliable communication mode (RCM)

$F_{SEM}$ Objective function under spectrally-efficient mode (SEM)

$F_{\text{re}use}$ Frequency reuse factor

$f_s$ Sampling frequency

$g_i$ Gain of $i^{th}$ PU-SU channel

$h_i$ Gain of $i^{th}$ SU-CH channel

$G_r$ CR receiving antenna gain

$G_t$ CR transmit antenna gain

$H_0$ Hypothesis of PU is absent

$H_1$ Hypothesis of PU is present

$j$ cluster index

$K$ Sensing time period
\( L_n \)  
Number of subcarriers  

\( m \)  
Number of cooperated SUs  

\( m_{opt} \)  
Optimal number of collaborated SUs  

\( M \)  
Total number of existing SU  

\( M_d \)  
Modulation index  

\( M_j \)  
Number of SUs into the \( j^{th} \) cluster  

\( \mathcal{N} \)  
Normal distribution  

\( n \)  
Number of single objective functions  

\( N \)  
Magnitude of the noise power in decibels  

\( N_0 \)  
Noise power spectral density  

\( nbits \)  
Total number of bits per chromosomes  

\( ngene \)  
Total number of generations  

\( N_{i} \)  
Noise of the \( i^{th} \) SU-FC Channel  

\( N_{\text{var}} \)  
Number of dimensions of the optimization problem  

\( P(H_0) \)  
Probability of the PU being inactive in a given band  

\( P(H_1) \)  
Probability of the PU being active in a given band  

\( P(t) \)  
Random population of the \( t^{th} \) generation  

\( P_c \)  
crossover rate  

\( P_d \)  
Probability of detection  

\( P_m \)  
Probability of missing detection  

\( P_f \)  
Probability of false alarm  

\( P_e \)  
Total probability of sensing error  

\( PL \)  
Path Loss  

\( \text{pops} \)  
Size of chromosomes population  

\( P_r \)  
Total power required to relay sensing measurements
\(Q_d\)  The CRN-wise probability of detection

\(Q_f\)  The CRN-wise probability of false alarm

\(R_0\)  CRN throughput under \(H_0\)

\(R_1\)  CRN throughput under \(H_1\)

\(R_b\)  Bit rate

\(R_n\)  Normalized CRN throughput

\(R_s\)  Symbol rate

\(S(f, \alpha)\)  Spectral correlation function

\(S[n]\)  PU discrete signal

\(\text{SINR}_{\text{max}}\)  Maximum score of SINR

\(\text{SNR}_i\)  SNR at the \(i^{th}\) SU receiver

\(T\)  Transpose operator of a vector

\(T_d\)  SU Data transmission time

\(T_f\)  Total frame duration

\(\text{THR}_{\text{max}}\)  Maximum achievable throughput of the CRN

\(\text{TPC}_{\text{max}}\)  Maximum power consumption

\(T_r\)  Total relay time from SU to BS through CH

\(T_s\)  Spectrum sensing time period

\(u\)  Number of quantization bits per sample

\(v\)  Number of bits per symbol

\(W\)  Transmission bandwidth

\(w_i\)  Weighting coefficient of the \(i^{th}\) class of objective functions

\(W[n]\)  The \(i^{th}\) SU-PU sensing channel discrete noise

\(X(f)\)  Auto-correlation function
\( X_i[n] \)  \hspace{1em} \text{Discrete received sensing measurement by the } i^{th} \text{ SU}

\( Y_i \)  \hspace{1em} \text{Energy estimate of received measurement by the } i^{th} \text{ SU}

\( Z_g \)  \hspace{1em} \text{Global decision constructed at the fusion centre}

\( Z_i \)  \hspace{1em} \text{Sensing decision made at the output of the decision maker of } i^{th} \text{ SU}

\( \alpha \)  \hspace{1em} \text{Cyclic frequency}

\( \beta \)  \hspace{1em} \text{Threshold value}

\( \zeta \)  \hspace{1em} \text{Spectral efficiency of a modulation scheme}
CHAPTER I

INTRODUCTION

1.1 BACKGROUND

In the past decade, cognitive radio (CR) has been proposed as an innovative paradigm for enabling efficient spectrum utilization, providing more reliable wireless services, mitigating harmful interference, and facilitating convergence for different wireless networks. CR systems are distinguished by distinct features include “awareness”, “sensing”, “learning”, and “adaptation” (Arslan 2007). Because of such attributes, CR could be used in niche applications such as emergency management, disaster recovery, fire services, search and rescue, crime prevention, and various military applications. In fact, today’s demands and future ambitions have convinced the researchers and developers that CR would drive the future of wireless communications. For instance, in emergency situations where certain areas might be out-of-service for cellular phones, if a cellular phone becomes cognitive enough, the CR user can then dial an emergency call by exploiting any existing radio infrastructure (such as satellite networks) and technologies (such as beamforming) to any nearby rescue unit. The CR technology aims, at its ultimate goals, to solve the so-called interoperability problem through realizing wireless networks that could have high level of coordination, cooperation, and compatibility. Aside from public safety applications, the development of CR technologies could generate huge revenue for governments and industry by, for example, permitting CR users or secondary users (SUs) to access unused TV broadcast bands. In fact, IEEE802.22 wireless regional area network (WRAN) will be the first worldwide CR-based standard for
opportunistic access of the (54-862 MHz) TV bands (Xiao & Hu 2009). Such efficient utilization of spectrum is critically important for progressive development of next generation wireless communications.

In the reminder of this chapter, current spectrum regulations and their emerging problems are briefly discussed. Then, an introduction to CR is formally introduced being a potential solution to overcome the problems of current spectrum regulations. As a critical function of CR, spectrum sensing is also explained in short. The preceding sections pave the road to the presented problem statement (and research motivation) of the thesis. Then, the research objectives, contributions, and overview of thesis organization are all stated.

1.1.1 Overview on Current Spectrum Regulations

Regulating spectrum was a consequence of the communication failures associated with the sinking of the Titanic in 1912 (FCC 2002a). Present communication technologies use a fixed frequency spectrum allocation approach where different frequency bands are exclusively assigned to different users and service providers by governmental agencies on a long-term basis and for large geographical regions. This traditional spectrum licensing has the advantage of offering adequate quality of service (QoS) for licensees due to reduced potential interference since every user uses his own dedicated band with no overlapping with neighbouring bands. However, with the rapid growth and ever-increasing demands for radio frequency services and applications, the problem of “spectrum scarcity” has become more severe since spectrum is a limited natural resource. With the existing regulatory policies of every country, most part of the spectrum is already allocated to licensed radio users, commonly named as primary users (PUs). This makes the national allocation charts very crowded as depicted, for example, in Malaysia Spectrum Allocation chart regulated by the Malaysian Communications and Multimedia Commission (MCMC) shown in Figure 1.1 (MCMC 2009). Similar allocation charts issued by equivalent regulatory bodies of other counties, such as the Federal Communications Commission (FCC) in the United States and the Office of Communications (Ofcom) in the United Kingdom, are also too crowded. Most of the frequency bands are regulated under the
so-called command-and-control scheme while some unlicensed bands are reserved for other purposes such as the industrial, scientific, and medical (ISM) frequency band. This ISM band can also be used for wireless communications but subject to interference since there is no control on accessing it.

Obviously, this rigid policy of fixed frequency allocation approach has led to an inefficient use of spectrum. Several short-term (snapshot) (Roberson et al. 2006; Roberson 2007; Chiang 2007) and long-term (spectrum observatory) (Petrin 2005; McHenry 2005; Bacchus et al. 2008) experimental measurements of spectrum occupancy have been carried out and their observations reveal that the spectrum is significantly underutilized. For example, a field spectrum-use measurement taken in New York City showed that the maximum total spectrum occupancy is only 13.1% from 30 MHz to 3 GHz (Roberson 2007). Figure 1.2 shows spectrum occupancy measurement of 0 to 6 GHz band conducted at Berkeley Wireless Research Centre (BWRC) (Yang 2004).

Figure 1.1 Malaysia Spectrum Allocations as issued by MCMC.

Source: MCMC 2009
This finding of “spectrum underutilization” has exposed the reality of spectrum scarcity; that is the allocated spectrum is not efficiently used at any location and at any given time. The FCC’s Spectrum Policy Task Force (SPTF) reported large temporal and geographical variations in the utilization of allocated radio spectrum report came to the conclusion that the existing spectrum rules and regulations that allocate discrete bands for different services and applications are no longer useful and functional (FCC 2002a). The report also highlighted the necessity to make use of today’s technology that is capable of enabling time-based usage of spectrum through dynamic spectrum access (DSA).

1.1.2 Cognitive Radio Overview

As a promising solution to the spectrum scarcity problem, CR has emerged as means of realizing DSA on an opportunistic basis. CR users can be thought of SUs that are allowed to use the licensed spectrum of PUs if the later ones are detected inactive. For example, the ongoing IEEE standardization on 802.22 WRAN is to exploit the underutilized TV spectrum based on CR technology. DSA techniques are now of great attention to the research community as it is anticipated to be good candidates to
replace the traditional approach of fixed spectrum allocation that is no longer able to cope up with user’s requirements of contemporary communication systems.

Although the term “cognitive radio” was first formulated by Joseph Mitolla III in 1990s (Mitola III & Maguire 1999; Mitola III 2000), there has been however no commonly agreed definition for CR. The reason behind this lies on that different researchers or institutes have distinct views on CR. Mitola described the CR as a decision-making layer at which “wireless personal digital assistants and the related networks were sufficiently computationally intelligent about radio resources, and related computer-to-computer communications, to detect user needs as a function of use context, and to provide radio resources and wireless services most appropriate to those needs” (Mitola III & Maguire 1999; Mitola III 2000). Later on, the term “cognitive radio” was defined by Haykin (2005) as follows: “Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind: highly reliable communication whenever and wherever needed; efficient utilization of the radio spectrum”. On the other hand, the US Federal Communications Commission (FCC) defined 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” (FCC 2003). However, some entities are actually in process of standardizing the CR-related concepts. In fact, FCC’s and Haykin’s views are simplified forms of Mitola’s vision where only radio spectrum circumstances are taken into account while making a decision on future transmission parameters. Thus, it is concluded that the original CR concept of Mitola has been reduced in scope to a radio that efficiently utilizes spectrum, looks for spectrum opportunities, and its adaptation process is limited to the physical layer (Wyglinski et al. 2010).
Since there are distinct definitions for CR as was mentioned, there are also different sets of cognitive capabilities and functions introduced by different researchers and organizations. To overcome this ambiguity of CR definitions and thus their corresponding capabilities, Simon Haykin’s definition of CR will be considered throughout this thesis. In addition to limiting the scope of Mitola's CR definition to an efficient spectrum utilization-oriented system, Haykin (2005) also modified the basic cognition cycle introduced by Mitola (1999). Surprisingly, according to ISI Web of Science, as of October 2011, Haykin’s article (2005) which was published in the *IEEE Journal on Selected Areas in Communications* in 2005 has been cited 1,661 times whereas the original Mitola’s article on CR (1999) has been cited 944 times only though it was published in 1999. Obviously, this is because Mitola’s full CR, which takes into account every possible observable parameter and uses a large set of adaptable parameters, is very much complex and not expected to be realized in the near future. The research community is more interested in spectrum-sensing CR due to its commercial and technical feasibility. A simple architecture of Haykin’s CR vision can be depicted in Figure 1.3. The CR system comprises an intelligent core that could interact periodically with surrounding wireless environment by processing certain set of observation parameters and formulating optimal set of transmission parameters whereby user’s requirements are also taken into account.

![Simple CR system architecture](image-url)
In comparison with CR, the traditional radio systems and wireless communication networks, starting from 1897 when Guglielmo Marconi devised the wireless telegraph and up to the current advances of third (wideband) and fourth (broadband) generations, are obviously very limited in terms of cognition functionality as their behaviours are mostly predefined by manufacturers and their performance cannot be autonomously improved as in the case of CR. With the emergence of CR technology, there should be consequent conceptual transitions (Haykin 2005) that can be briefly summarized in Table 1.1. As was clearly stated in (Mitola III & Maguire 1999), software defined radio (SDR) provides feasible platform for CR implementations. It is believed that CR will evolve from the present SDR infrastructure by incorporating more cognition attributes such as self-awareness, learning capability, and autonomous adaption. However, there are some other concerns that need to be clarified; for instance, one might ask why a PU should agree to allow a CR user to opportunistically access its licensed band? Reasons for such agreement might be concisely listed as (Wyglinski et al. 2010; Molisch 2011)

(i) **Regulatory policy**: the national regulator might mandate that specific bands can be accessed by CR users as long as they do not cause harmful interference to PUs.
(ii) **Profit**: PUs (license-holders) might be able to charge SUs (CR users).
(iii) **Emergency services**: in cases of emergency, CR-based services might make use of any existing PU infrastructure and bands.

In fact, a good analogy can be made between spectrum and country land; consider a house owner (PU) who has decided to leave the country (spectrum) for certain period, say on business trip. In this case, a question appears whether the owner should rent his house (licensed band) for a tenant (CR user) or simply leave it vacant. In this scenario, the house owner does not need to notify his developer (spectrum regulator) on this. Another scenario is when there are polices allow the developer to unconditionally make use of the house as soon as it was empty, perhaps to house a foreign visitor. The difference between the two scenarios lies on whether or not the intervention of regulatory body is appropriate. It basically depends on the “philosophy of spectrum ownership” of a country whether ownership means full property rights or limited property rights for PUs or license-holders.
Table 1.1 Associated changes with emergence of CR

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Required Change</th>
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<tbody>
<tr>
<td>Spectrum allocation</td>
<td>From static and centralized spectrum allocation to dynamic spectrum access.</td>
</tr>
<tr>
<td>Adaption requirement</td>
<td>From preset (and known) radio behavior to awareness of and adaptation to the environment by the radio.</td>
</tr>
<tr>
<td>Device centricity</td>
<td>From transmitter centricity to receiver centricity, whereby interference power rather than transmitter emission is regulated.</td>
</tr>
</tbody>
</table>

1.1.3 Spectrum Sensing Overview

With recent advances in signal processing, digital communication, and network architectures, new paradigms should be devised to replace conventional policies of spectrum management which were essentially limited by technology. CR is introduced as an innovative DSA solution aims for opportunistic access of temporally and spatially unused licensed frequency bands that are commonly defined as white spaces or spectrum holes (Haykin 2005). In order to support cognitive functionalities of CR systems, spectrum awareness is a crucial demand that allows the CR users to detect unused segments of spectrum, and it can be realized by means of spectrum sensing (Yucek & Arslan 2009; Cabric et al. 2004; Ghasemi & Sousa 2005; Mishra 2006), databases registry with environmental maps (Zhao et al. 2006; Min & Shin 2009; Kim et al. 2009; Kim et al. 2010; Bazerque & Giannakis 2010), or beacon signals (Wyglinski et al. 2010; Fitzek & Katz 2007; Hossain et al. 2009). Among these approaches, spectrum sensing is the only autonomous and flexible scheme that is based on real-time measurements of instant spectrum occupancy at a given location and therefore, making it more robust to environmental changes (Fitzek & Katz 2007).

In overlay approach of spectrum access (Hossain & Bhargava 2007), the spectrum sensing task to identify existing spectrum holes that can be temporarily used by CR users becomes extremely necessary in contrast to underlay-based spectrum access where CR users can access the whole PU band, not only spectrum holes, as long as its transmission is below a predefined power threshold (Hossain & Bhargava 2007). Due to hidden terminal problem and detection uncertainty (Ghasemi & Sousa 2005),
cooperative spectrum sensing (CSS) (Akyildiz et al. 2011; Yücek & Arslan 2009), where multiple CR users of specific geographical collaborate, is widely proposed as a key concept to improve PU detectability in cognitive radio networks (CRNs). CSS can be realized by means of centralized (Ganesan & Li 2005; Visotsky et al. 2005) or distributed (Tang 2005; Ahmed et al. 2006) architectures. Distributed sensing has an advantage in the sense that it does not require a backbone infrastructure. However, the concept of distributed cooperation where multiple CR terminals have to communicate among themselves might not be attractive to the CR goals and functionalities due to the increased cooperation overhead during the detection cycle. To reduce the cooperation overhead, there have been studies proposed where CR users might only share their 1-bit sensing decisions among themselves (Tang 2005). However, this approach has been proven to be inferior to soft/data fusion schemes (Ganesan & Li 2005; Visotsky et al. 2005). Also, distributed sensing performs poorly in shadowing environments and scenarios of hidden node problem (Krenik & Batra 2005) where CR users might not be able to receive sensing measurements or decisions from other neighbours, resulting in a sub-optimal knowledge of channel occupancy. Thus, centralized sensing can be considered as a good candidate that suits network-wide optimization though it requires infrastructural deployments (Hossain & Bhargava 2007).

Figure 1.4 shows simple deployment of CRN in conjunction with an existing PU network. The CRN consists of SU base station (SU-BS) and multiple geographically-scattered SUs that fall within the coverage of SU-BS (represented by the solid-line circle). Take note that the SU is a CR user and equivalently, SU-BS is a CR base station. SUs can collaborate with each other through their centralized SU-BS. The figure also shows a deployed PU network comprises a PU base station PU-BS and multiple PUs falling within the coverage area of PU-BS (shown as a dashed-line circle). PUs are license-holders and might be, for instance, TV users. Obviously, the PUs have the priority to access their allocated bands anytime whereas a SU is allowed to opportunistically access the PU channel if the later is declared absent. To obtain awareness on PU activities, all SUs perform spectrum sensing locally and then relay either their sensing decisions or sensing data to their corresponding centralized SU-BS at which these decisions or data will be combined by using a hard decision fusion
(HDF) scheme or a soft data fusion (SDF) scheme, respectively, implemented at a fusion centre (FC). The FC makes a global decision on the existence of PU and SU-BS will then instruct its corresponding SUs whether or not to use the sensed band based on that decision. This collaboration among SUs aims at reliable detection of PU in order to reduce potential interference to it. This sensing activity is a crucial task to enable success to CR technology since maintaining good QoS to PU is a must. Therefore, the sensing activity has to be periodically repeated to keep monitoring the PU availability using an appropriate duty cycle. The cooperative spectrum sensing is proposed to overcome the hidden terminal problem where local sensing by a single SU might fail to detect an active PU as a result of an existing obstacle shadowing the transmission of the PU-BS as shown on the link labelled as (1) in Figure 1.4. The cooperation between multiple SUs is also justified by being a means to have spatial diversity and mitigate degradation of detection performance due to potential poor quality of SU to SU-BS links as shown on the link labelled as (2) in the figure. This deployment of CRN represents a centralized architecture for spectrum sensing. In distribute architectures, the collaboration between SUs on sensing decisions or data is realized by means of ad-hoc networks.

Figure 1.4 Simple deployment of CRN in conjunction with existing PU network
1.2 PROBLEM STATEMENT

Since the license-holder or PU has the priority for unconstraint access of its allocated frequency band, the users’ collaboration in CSS-based CRNs is performed with an essential aim of maximizing spectral efficiency in one hand, but on the other hand, maintaining low level of potential interference to PU. However, these two objectives are unfortunately contradictory. This is because increasing the CRN throughput, to maximize the overall spectral efficiency, makes the PU less protected against possible SU interfering signals whereas too much unnecessary protection for PU limits the chances of CRN to conditionally access exiting spectrum holes. Thus, this contradiction necessitates an algorithm that could jointly optimize these two conflicting objectives so that a balanced compromise between them is attained.

Another issue needs to be addressed is on how to settle the detection-overhead tradeoff. In CRNs, the PU detection has to be maximized so that the PU becomes more protected from SU potential transmission. The PU detection performance can be significantly improved by means of cooperation among SUs. However, this cooperation results in an increased communication overhead due to the relaying activities between cooperated nodes. Thus, this SU cooperation improves the PU detection performance but at the same time it causes an increased overhead leads to wastage of spectral resources. This thesis handles this contradiction between the detection performance and overhead requirements through different potential CRN architectures that can be used for different operational conditions.

The third issue which will be addressed in this thesis is on the adaptability requirement of CR systems. A CR system is supposed to behave autonomously in response to environmental changes based on user requirements and/or performance priorities. To support the cognition capabilities of a CR system, an intelligent decision engine that could perform multiple optimization tasks for different design objectives should be implemented. Unfortunately, the contradiction is again expected and still a major concern. For example, if a CR system aims to transmit with high throughput and low error performance at the same time, a question appears here about how this CR system can optimize these two conflicting objectives simultaneously. Also, CR
system should be able to know the type of transmission (modulation) format that should be autonomously used in order to enhance the spectral efficiency which is the cornerstone objective of CR technology.

This thesis provides solutions to the three main issues mentioned above. Firstly, in order to jointly optimize the CRN throughput and PU protection, a Neyman-Pearson approach has been used to maximize the PU detection performance for constant CRN throughput. The detection performance is characterized by CRN-wise detection probability whereas the CRN throughput is formulated in terms of the CRN-wise false alarm probability. Thus, the confliction nature between the CRN throughput and PU protection is formulated as a constrained optimization problem of maximizing the CRN-wise probability of detection for a given CRN-wise false alarm probability. This optimization problem of maximizing the detection performance sets the motivation to look for potential CRN architectures that can satisfy this objective. Unfortunately, maximizing the detection performance, through cooperation, results in an increased communication overhead due to relaying activities among cooperated SUs.

In order to entertain the second issue mentioned above, three distinct CRN architectures have been proposed and developed to provide diverse options of deployments to satisfy different requirements of PU detection performance and communication overhead. These three architectures are for HDF-based CRNs, SDF-based CRNs, and hybrid SDF-HDF cluster based CRNs. The operational requirements at which each of these CRN architectures can be used are presented in Table 1.2. The proposed CRNs are based on centralized CSS-based architectures where SUs send their sensing decisions/data to a fusion centre located at a central BS. The proposed HDF-based CRNs can be used when low overhead communication is required while PU detection performance is moderate. On the other hand, SDF-based CRNs is used when high PU detection performance is needed despite an increased overhead. SDF-based CRNs show better PU detection performance than HDF-based CRNs since the measurements data carry more informative content than the 1-bit decisions of the HDF-based CRNs upon fusion. On the other hand, the HDF-based CRN requires lesser data to be reported from SUs to FC than SDF-based CRNs and therefore has a
reduced traffic overhead. The hybrid SDF-HDF cluster-based CRN can be used when balanced compromise of detection performance and traffic overhead is demanding. The three architectures employ multi-objective evolutionary algorithms (MOEAs) based on genetic algorithms (GAs) to optimize the performance metrics of CRNs. The third issue of adaption requirement for CR systems is also resolved by proposing a MOEA decision engine that could be envisioned as an intelligent core that processes sensed parameters and provides adequate transmission options under predefined conditions and design objectives.

<table>
<thead>
<tr>
<th>CRN architecture</th>
<th>PU detection performance</th>
<th>Traffic overhead condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>HDF-based CRN</td>
<td>Moderate detection performance</td>
<td>Low traffic overhead</td>
</tr>
<tr>
<td>SDF-based CRN</td>
<td>Excellent detection performance</td>
<td>High traffic overhead</td>
</tr>
<tr>
<td>Hybrid SDF-HDF Cluster-based CRN</td>
<td>Good detection performance</td>
<td>Moderate traffic overhead</td>
</tr>
</tbody>
</table>

1.3 RESEARCH OBJECTIVES AND SCOPE

The main objective of this research is to develop a set of MOEAs based on GAs for optimizing the performance of CR systems and CRNs and to attain a balanced compromise between corresponding conflicting objectives in accordance to user requirements, performance priorities, and/or environmental conditions. This set of MOEAs includes single-objective GA (SOGA), bi-objective GA (BOGA), and multi-objective GA (MOGA). The proposed single-, bi-, and multi-GA objectives are formulated based on pre-analyses carried out on each CR system and CRN architecture. In a nutshell, the specific objectives of this research are listed as follows:

(i) To develop a MOGA-assisted intelligent decision engine that realizes the cognition and adaption functionalities of CR systems and evaluates its performance under various transmission scenarios.

(ii) To design a BOGA-assisted HDF-based cooperative spectrum sensing scheme for low communication overhead in CRNs and evaluate its performance.
(iii) To devise a SOGA-assisted SDF-based cooperative spectrum sensing scheme for high detection performance in CRNs and evaluate the performance of the proposed scheme against other conventional SDF-based schemes.

(i) To propose a MOGA-assisted hybrid SDF-HDF cluster-based cooperative spectrum sensing scheme for balanced compromise between detection performance and traffic overhead in CRNs and analyze its performance under different operational modes.

As a research scope, this thesis presents a bottom-up approach as it begins with system-level development of CR nodes and then, it proceeds to a network-level deployment of CRNs with HDF-, SDF-, and hybrid SDF-HDF architectures. Figure 1.5 shows the research roadmap across the thesis chapters where CR systems, HDF-/SDF-based CRNs and hybrid SDF-HDF cluster-based CRNs are covered in Chapter III, IV and V, respectively. In this research, the concept of cross-layer design has been extended to multiple-objectives optimization (MOO) rather than the typical independent optimizations of single objectives of the cross-layer design which lead to non-optimal solutions. The work carried out in this research is performed through extensive computer simulations to prove the correct functionality of the proposed models as well as the validity of the obtainable results.

Figure 1.5  Bottom-up approach with coverage of thesis chapters.
1.4 RESEARCH CONTRIBUTIONS

The contributions of this research can be categorized into three distinct classes; analytical studies, formalisms, algorithms and tools. The details of these contributions can be addressed as follows:

(a) **Analytical studies:** In order to develop the objective function(s) for the proposed CRN deployments as well as for CR systems, several analytical studies and computer simulations have been performed. These analytical studies set a good foundation of presenting the interrelationships between multitudes of performance metrics and design parameters. These studies can be summarized in point form as follows:

(i) Performance metrics and Pareto-front analysis for CR systems.
(ii) Tradeoff analysis for HDF-based CRNs.
(iii) Comparative analysis for SDF-based CRNs.
(iv) Tradeoff analysis for hybrid HDF-SDF cluster-based CRNs.

(b) **Formalisms:** In this research, mathematical derivations for certain performance metrics, such as PU detectability performance, have been carried out. Also, complete single-, double-, and multi-objective formalisms for the proposed CRN deployments and CR systems have been developed as needed. These formalisms include the following outcomes:

(i) Multi-objective fitness function (MOF) for CR systems.
(ii) Bi-objective function (BOF) for HDF based CRNs.
(iii) Single-objective function (SOF) for SDF based CRNs.
(iv) Multi-objective function (MOF) for hybrid SDF-HDF cluster based CRNs.

(c) **Algorithms:** In this regard, GA-based optimization engines for CRN and CR systems have been developed. These algorithms have been configured to suit the optimization problems at hand and can be presented as follows:

(i) MOGA-based adaptive decision engine for CR systems.
(ii) BOGA-based optimization system for HDF-based CRNs.
(iii) SOGA-based weighting engine for linear SDF-based CRNs.
(iv) MOGA-based optimization system for hybrid SDF-HDF based CRNs.
(d) Tools: a graphical user interface simulation model (GUISM) is developed. It is a friendly interactive tool that allows the user to interact with a MOGA optimization system used for optimizing the MOF performance for a hybrid SDF-HDF cluster-based CRN. The developed tool allows the user to vary the CRN settings including the operational modes and search space of design parameters.

1.5 GENERAL METHODOLOGY

The research methodology followed in this thesis is depicted in Figure 1.6. In Chapter I, a literature review has been carried out to identify the problem statement and research objectives. Then, the same methodology, with minor variations, has been used in Chapter III, IV, and V for CR systems, HDF/SDF-based CRNs, and hybrid SDF-HDF cluster-based CRNs, respectively. The employed methodology begins by proposing the system architecture or network deployment for CR systems or CRN, respectively. The equivalent mathematical models of the proposed CR systems and CRNs are then developed. Pre-analysis of preliminary performance metrics are carried out to display the dependency relationships between the performance metrics and their corresponding design parameters. These analyses were necessary to identify the conflicting performance objectives that should be entertained when the design problems are formulated afterwards. Problem formulations and operational modes definitions are the cornerstone necessary for the GA implementations and frameworks.

The formulated problems for CR systems and CRNs are configured into GA-based frameworks. As shown in Figure 1.6, four MOEAs are developed in Chapter III, IV, and V. These MOEAs are MOGA-assisted decision engine for CR systems, BOGA-assisted HDF-based CRNs, SOGA-assisted SDF-based CRNs, and MOGA-assisted hybrid SDF-HDF cluster-based CRNs. The bi-objective and multi-objective functions of BOGA and MOGA systems are combined together into a unified formula that is used to evaluate the betterment of the GA chromosomes. These chromosomes are binary encoded to represent the decision variables of the formulated optimization problem. The binary encoding suits the discrete GA system and can significantly reduce the search space of decision variables when searching for optimal parameters.
The proposed MOEAs above are then evaluated through computer simulations and the corresponding convergence performance of SOGA, BOGA, MOGA systems is displayed and the obtainable solutions are recorded. Then, post-analysis is performed to verify the optimality of the solutions obtained by the GA optimizations and check whether or not these parameters provide the best operational performance taking the fitness score as performance criteria. Finally, concluding remarks are drawn and the research items are documented.

In Figure 1.6, the steps of thesis research methodology are mapped to their corresponding chapters at which they are conducted. Most of these steps are further explained and particularized in each chapter based on coverage and as needed. In addition, detection performance and communication overhead tradeoffs between SDF-based, HDF-based, and hybrid SDF-HDF cluster-based CRNs are also provided.

![Diagram of research methodology](image)

**Figure 1.6** General methodology of research
1.6 THESIS ORGANIZATION

This thesis is organized as follows. Chapter II provides structured background on CR concepts including, but not limited to, CR functions, spectrum sensing, cooperative spectrum sensing, and CRN architectures. Also, the GA concepts, mechanisms, operations, and parameters are all explained since the GA is the AI tool used in this research for optimizing the performance of the CR systems and CRNs. Chapter II also includes a survey in the literature on the applications of GAs on various CR aspects such as adaption, spectrum allocation, and scheduling.

In Chapter III, the development of MOEA-assisted intelligent decision engine is presented. The chapter begins by proposing the performance metrics of the CR decision engine and analyzing the dependency relationships between these metrics and their corresponding decision parameters (transmission parameters) to observe and identify the conflicting objectives. This analysis is then used to develop the objective functions that will be optimized by the MOEA-based decision engine under various operational modes.

In Chapter V, the proposed HDF-based and SDF-based CRNs deployments are presented. Then, the chapter provides equivalent mathematical models of the proposed CRNs and performance metrics (i.e. objectives) are also developed. Pre-analysis is performed to identify any existing conflicts between the proposed objectives. The chapter also presents the fitness functions that are introduced to the GA-assisted FC at the centralized BS. Evaluation and results discussions are also provided.

Chapter VI presents the proposed hybrid SDF-HDF cluster-based CRN. Various pre-analysis simulations were carried out to identify potential conflicting objectives. The proposed multi-objective fitness function is then introduced to the GA optimization system whose performance is evaluated under various operational modes and channel conditions. Finally post-analysis are conducted to verify the obtained results. In Chapter VII, the conclusions are drawn and suggested future works are listed.
CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, aspects of CR and, in particular, spectrum sensing are being discussed. The chapter begins with providing an overview on CR including a brief description of its evolution, capabilities, and potential applications. Then, various spectrum sensing elements are presented. These elements include local sensing techniques, sensing performance evaluation, sensing challenges and existing standards, cooperative spectrum sensing, decisions and data fusion schemes, and some other DSA issues. It also gives brief explanation on optimization and GA concepts. Finally, the chapter ends up with a survey on the previous research works of GA optimization for CR-based problems.

2.2 COGNITIVE RADIO TECHNOLOGY

In a research paper published in 1999, there was a significant juncture in wireless communications when J. Mitola introduced his terrific idea of CR as a result of his research at the KTH Royal Institute of Technology, University of Stockholm, Sweden (Mitola 1999). Mitola presented how CR could add in flexibility to personal wireless services using a new language named the radio knowledge representation language (RKRL). Then, he emphasized his idea further in his PhD thesis (Mitola 2000). In the United States, there have been several studied focusing on spectrum utilization carried out by organizations such as the Federal Communications Commission (FCC) and the
National Telecommunication and Information Administration (NTIA) as well as the
academies and researchers themselves. In 2002, the Spectrum-Policy Task Force
(SPTF) appointed by FCC published a report based on extensive studies of spectrum
usage (FCC 2002a). The report came to the conclusion that the existing spectrum rules
and regulations that allocate discrete bands for different services and applications are
no longer useful and functional. The report also highlighted the necessity to make use
of today’s technology that is capable of enabling time-based usage of spectrum
through dynamic spectrum access (DSA). Consequently, the research on CR has been
quickly focused on DSA and secondary usage of spectrum through many funded
projects. Among all those, the neXt Generation (XG) project funded by the US
Defense Advanced Research Projects Agency (DARPA) was a significant and
interesting research work focusing on spectrum management and secondary-usage
opportunities (DARPA 2003a, DRAPA 2003b). In addition, there have been other
strategies proposed in the literature for DSA such as spectrum pooling (Weiss &
Jondral 2004), the usage of virtual unlicensed spectrum based on CR approach
(CORVUS) (Broderson et al. 2004), the OFDM-based cognitive radio (OCRA)
network (Akyildiz & Li 2006), the European dynamic radio for IP services in
vehicular environments (DRiVE) (Xu et al. 2000) and dynamic intelligent
management of spectrum for ubiquitous mobile network (DIMSUMnet) (Buddhikot et
al. 2005).

Aside from that, there have been other research groups working on
standardizing CR and SDR technologies and architectures; one of which is the IEEE
802.22 group whose focus is on providing dynamic access to unused TV bands
(Cordeiro et al. 2005). The main framework of IEEE 802.22 is to investigate on
employing CR-based opportunistic access to the so-called TV while spaces (TVWSs)
since considerable segments of the VHF/UHF TV bands are largely underutilized. In
2004, the FCC already agreed to permit opportunistic to TV bands in the US (FCC
2004). The selection of TV bands in particular is due to its lower spectral utilization
than other PU networks such as cellular networks. FCC called for proposals from
industry for CR prototypes (FCC 2006). After comprehensive evaluations and tests
(FCC 2008), the FCC officially approved the opportunistic access of TVWSs (FCC
2009). Also, Ofcom, the spectrum regulatory body of UK has similar activities to that
of FCC. In 2009, Ofcom published a report on its proposal of CR access to TVWSs (Ofcom 2009). In fact, the IEEE 802.22 standard for *Wireless Regional Area Networks* (WRAN) is expected to be the first commercial CR-based deployment aiming at opportunistic access of unused and underused VHF/UHF TV bands between 54 and 862 MHz (Cordeiro et al. 2006).

### 2.2.1 Cognitive Radio Capabilities

As presented earlier, CRs are intelligent radios that use DSA techniques to improve spectral efficiency by opportunistically access unused bands (i.e. white spaces or spectrum holes). In order to realize such a dynamic access strategy, the CR node should possess specific cognitive capabilities and functions. Taking Haykin’s (2005) definition of CR into account, the CR cognition cycle can be envisioned as shown in Figure 2.1. This cognition cycle depicts the functions that any CR system should be capable of as well as the interrelationships between these functions (Akyildiz et al. 2006).

![Figure 2.1 Cognition cycle of CR](image)

The main and most critical function of CR is the process of detecting unused segments of spectrum in order to opportunistically use them (*spectrum sensing*). Once the white spaces are detected, the CR must then have the ability to select the right channel that suits its communication and quality-of-service (QoS) requirements.
(spectrum management). Since the CRs are given lower priority than license-holders, they should be able to terminate their transmission in case a licensed user (i.e. PU) suddenly becomes active and smoothly move to another unused channel (spectrum mobility). Also, In a CR network there should be a scheduling algorithm involved to assure that all CRs get fair opportunities on accessing the spectrum (spectrum sharing). Brief descriptions of CR functions are summarized in Table 2.1.

Based on the functions above, the CR can be further characterized by two functionalities; cognitive capability and reconfigureability (Haykin 2005). The cognitive capability indicates to the ability of the CR to obtain awareness on the surrounding environment (e.g. spectral occupancy, channel condition, etc) whereas the reconfigureability allows the CR system to autonomously adapts to the observed radio environment by dynamically programming its transmission parameters (transmit power, modulation scheme, and others).

<table>
<thead>
<tr>
<th>CR function</th>
<th>Function description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectrum sensing</td>
<td>Detecting unused spectrum and sharing the spectrum without harmful interference with other users.</td>
</tr>
<tr>
<td>Spectrum management</td>
<td>Capturing the best available spectrum to meet user communication requirements.</td>
</tr>
<tr>
<td>Spectrum mobility</td>
<td>Maintaining seamless communication requirements during the transition to better spectrum.</td>
</tr>
<tr>
<td>Spectrum sharing</td>
<td>Providing the fair spectrum scheduling method among coexisting CR users.</td>
</tr>
</tbody>
</table>

2.2.2 CR Potential Applications

The term “cognitive radio” is coined to describe a radio with intelligence. In contrast, to traditional radio systems, CR is capable of employing its radio in the most optimal way by observing its surrounding environment, learn about it, and use the learning outcomes to improve communication. Due to such attributes, CR can suit multitudes
of wireless applications that require a sort of intelligence. Some of these applications can be addressed as follows (Arslan 2007):

(i) **Resources optimization and QoS enhancement applications:** The limited wireless resources necessitate innovative solutions to optimize their usage and at the same time improve communication QoS. CR systems and networks can be interestingly used to optimize several resource aspects such as power consumption, spectrum utilization, software/hardware resources, and network infrastructure. In addition, the cognition feature of CR can be used to obtain awareness on surrounding environment and make use of it. For instance, awareness of channel fading properties, noise, available interference, capability of error correction can assist on suitable employment of modulation type and index, forward error correction (FEC) scheme, and interleaving length. Power optimization is a continuous objective, since the emergence of wireless communication technology, aiming at sustained and long-lasting connectivity. For instance, adaptive power control can be used based on awareness of channel and positions of mobile users for prioritizing tasks according to received power levels. With spectrum awareness, CR can enable multitudes of spectral tasks such as dynamic spectrum sensing, dynamic spectrum access, and dynamic spectrum management. In fact, dynamic spectrum management offers dynamic cognitive ruling, coordination, and synchronization required after sensing the spectrum and before accessing it and subject to PU unavailability. The utilization of software/hardware resources of individual nodes within a link can also be intelligently improved by CR. For instance, SDR-based CR applications can support upgrade of hardware through software alternation. This can help to reduce the needs for hardware replacement which in turn reduce manufacturing and labor costs. This configurability of SDR-based CR systems can realize convergence among different networks such as Global System for Mobile Communications (GSM) and Wireless Local Area Network (WLAN) in emergency situations (Arslan 2007).

(ii) **Interoperability enabling applications:** As mentioned above, CR can be used to realize ubiquitous connectivity for adaptive systems over heterogeneous networks, multiple bands, diverse geographical locations, and distinct policies and regulations of
spectrum. This concept of interoperability can find futile applications in public safety responders as well as military (Da Silva et al. 2004).

(iii) End user product/service specific applications: One of the CR sets of applications is the one entraining the direct needs of consumers. CR can be used for many service-specific products such as cell phones, personal digital assistants (PDAs), laptops, and fax machines. Many other CR applications include public safety, protection and security, climate change and disaster relief, fire services, crime prevention, traffic control, and medical applications (Arslan 2007).

2.3 SPECTRUM SENSING

DSA techniques are being widely proposed as a key solution that could resolve the spectrum scarcity versus spectrum underutilization dilemma. For wireless communications, it is commonly known that the range of frequencies between 10 MHz and 6 GHz is mostly used. While one might view this as a lot of resource, we should keep in mind that most of it has been already allocated to a variety of wireless technologies and services leading to a sort of spectrum scarcity. However, several experimental studies of spectrum occupancy have shown that the real cause of spectrum scarcity lies on that the exclusively allocated bands are not being efficiently utilized (Yang 2004; Roberson 2007).

As explained in section 1.1.3, spectrum sensing is a key requirement that CR has to be capable of in order to monitor PU activities. Reliable and efficient sensing scheme is crucially required to ensure low level of interference to PU while allowing SUs to utilize unused frequency bands. Various aspects of spectrum sensing are shown in Figure 2.2 and addressed in the following sections.

2.3.1 Local Spectrum Sensing Techniques

In local spectrum sensing, every CR user senses the spectrum locally and does its decision of PU availability by its own and without further communication with other
Figure 2.2  Elements of spectrum sensing
CR users in the vicinity. From a statistical point of view, sensing the spectrum is represented by a problem of binary hypothesis-testing:

\[ H_0: \text{PU is absent} \]
\[ H_1: \text{PU is present} \]

Under these two hypotheses, two important probabilities are defined and used as a key metric of sensing performance, namely, probability of detection \((P_d)\) and probability of false alarm \((P_f)\) which are, respectively, given by

\[ P_d = P(\text{Decision} = H_1 \mid H_1) \] \hspace{1cm} (2.1)
\[ P_f = P(\text{Decision} = H_1 \mid H_0) \] \hspace{1cm} (2.2)

In the literature, there have been several detection techniques that can be invoked in local spectrum sensing. In following section, some of these techniques are addressed.

**(i) Matched filter:** The matched filter is considered as an optimal detection scheme since it maximizes the signal-to-noise ratio (SNR) of the received signal in the presence of additive white Gaussian noise (AWGN). As shown in Figure 2.3 (a), the matched filter is realized by correlating an unknown received signal \(x(t)\) with a known signal (template) to detect the presence of the later in former. The test statistic (TS) is then compared with a predefined threshold \(\beta\) and a decision on the presence of PU us made. Matched filters are often employed in radar applications. In CR, however, the usage of matched filter is very much limited as it essentially requires knowledge of PU signal which not commonly available. Actually, spectrum sensing is defined as a detection process of unknown PU signals. When partial information of PU signal is known to the CR receiver, then, the match filter can still be used for coherent detection (Cabric et al. 2004). For instance, if the PU signal of interest is a digital TV signal, its pilot tone can be detected using a delay circuit. Then, this pilot will be then used as a template signal in the matched filter to detect any potential TV signal. Due to coherency, the matched filter requires less number of samples for a given \(P_d\) constraint (Sahai et al. 2004).
Figure 2.3 Realization of various detection techniques for spectrum sensing. (a) Matched filter, (b) Energy detection, (c) Cyclostationary detection, and (d) Wavelet detection.

However, the matched filter, unfortunately, lacks of feasibility as every CR user would require a dedicated receiver for every PU signal format leading to a demand for a bank of filters with higher cost.

(ii) **Energy detection**: Non-coherent detection can be realized through energy detection that is distinguished as a sub-optimal detection technique. The energy detector has been widely used in radiometry and can be implemented in a way similar to a spectrum analyzer as it measures the energy of the received signal to determine whether a PU exists or not. As depicted in Figure 2.3 (b), the received signal $x(t)$ is first sampled in a given time frame and passed through an fast Fourier transform (FFT) to get its frequency response $X(f)$ which is also windowed to obtain the in-band
spectrum $Y(f)$. Then, the signal energy is estimated and compared with a predefined threshold $\beta$ to decide $H_0$ or $H_1$. The main feature of energy detection is that it does not require any prior knowledge of PU waveform. This feature reflects ease on the implementation of the CR receiver employing energy detection. However, the energy detector might not be the choice in low SNR environments as it cannot detect the PU signal if its estimated energy is below the predefined threshold. In fact, selecting appropriate threshold is also challenging as it is solely susceptible to the variations of interference level and channel noise. It also cannot distinguish between SUs sharing the same band and the PU (Shankar et al. 2005).

(iii) Cyclostationary detection: if the autocorrelation of the PU signal is a periodic function of time, then, the signal is referred to as cyclostationary. With such a property, the PU can be detected even at very low SNR environments. The implementation of cyclostationary detection is shown in Figure 2.3 (c). The so-called spectral correlation function $S(f,\alpha)$ is computed by auto-correlating $X(f)$ where $\alpha$ is known as cyclic frequency (Hossain & Bhargava 2007). Then, cyclic frequency detector is used to extract the periodicity of the PU signal if any. The drawbacks of cyclostationary detection can be identified as its demand of partial knowledge of PU waveform as well as its high computational cost.

(iv) Wavelet detection: The wavelet technique can be used for PU detection over wideband channels as it offers adaption flexibility to dynamic environments (Tian & Giannakis 2006). The idea of this scheme lies on the power spectral characteristics of a train of consecutive sub-bands that construct the entire wideband where the spectral power is smooth within the sub-bands but changes abruptly of the sub-bands boundaries. As depicted in Figure 2.3 (d), the power spectral density (PSD) of $X(f)$ is computed and a wavelet transform is employed to locate the singularities of $S(f)$ by which the unused sub-bands can be identified. There are, however, drawback for this scheme such as the inability to perform well for spread spectrum signals and the demand for high sampling rate which increases the computational cost. Table 2.2 shows the pros and cons of the spectrum sensing techniques mentioned earlier. In this thesis, energy detection has been adopted due its simplicity and optimality for zero-mean PU signals.
Table 2.2 Comparison of various spectrum sensing techniques

<table>
<thead>
<tr>
<th>Spectrum sensing technique</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
</table>
| Matched filter             | 1. Optimal detection performance  
2. Low computational cost | 1. Requires a priori knowledge of the primary user  
2. Design for each kind of primary system signal |
| Energy detection           | 1. Does not need any a priori Information  
2. Low computational cost | 1. Cannot work with low SNR  
2. Cannot distinguish users sharing the same channel |
| Cyclostationary detection  | 1. Robust in low SNR  
2. Robust to interference | 1. Requires partial information of the primary user  
2. High computational cost |
| Wavelet detection          | 1. Effective for wideband signal | 1. Does not work for spread spectrum signals  
2. High computational cost |

Source: Chen & Prasad 2009

2.3.2 Performance Evaluation of Spectrum Sensing

The spectrum sensing is normally considered as a pure detection problem where the CR-assisted users have to scan a vast range of frequencies to observe available white spaces or holes that are temporarily and spatially available for transmission. The CR-assisted users are classified as secondary users (SUs) competing with primary users (PUs) who are obviously, Licensees, or alternatively, users of existing technologies on unlicensed bands (e.g., IEEE802.11a). The SUs are allowed to utilize the frequency bands of the PUs when they are not currently being used but they should willingly and quickly vacate the band once a PU has been detected. This fast vacation is necessary to avoid causing harmful interference to the PUs who should maintain ubiquitous and uninterrupted accessibility. Therefore, the SUs are required to periodically monitor the PUs activities using fast and reliable detection/sensing algorithms. In such algorithms, the two probabilities in equations (2.1) and (2.2) are of interest. $P_d$ is the probability of the sensing algorithm detecting the presence of a PU when it is active by discriminating its signal from noise. High $P_d$ is always required to ensure minimum level of interference to PUs. On the other hand, $P_f$ is defined as the probability of the
sensing algorithm is mistakenly detecting the presence of PUs while they are inactive. Low \( P_f \) should be targeted to offer more chances for SUs to use the sensed unused spectrum. Unfortunately, attaining simultaneous high \( P_d \) and low \( P_f \) is a challengeable problem as these two objectives are contradictory. To elaborate on this further, let us take into account the energy detection, as presented earlier, as a spectrum sensing scheme performed by a CR system. In fact, the energy detection has been found to be the optimal detection method for zero-mean PU signals although there are some limitations when SNR is below a certain level (Sahai et al. 2004). In energy detection, the energy of the received signal within a specific bandwidth over a specific observation time period is measured. The probability density functions (PDFs) of the received signal energy under \( H_0 \) and \( H_1 \) sensing hypotheses are shown in Figure 2.4. Then, Equations (2.1) and (2.2) can be particularized to energy detection scheme as

\[
P_d = P(Y > \beta|H_1) = \int_\beta^\infty f_1(Y) dY
\]

\[
P_f = P(Y > \beta|H_0) = \int_\beta^\infty f_0(Y) dY
\]

As can be extracted from Figure 2.4, the contradiction between the objectives of high \( P_d \) and low \( P_f \) can be graphically shown by shifting the threshold \( \beta \) of the energy detector right and left. Shifting \( \beta \) to the right minimizes \( P_f \) which is a good effect but it at the same time minimizes \( P_d \) which bad. On the other hand, shifting \( \beta \) to the left will maximize \( P_d \) but also maximizing \( P_f \). The joint pairs of \( (P_d, P_f) \) values are forming the so-called receiver operating characteristic (ROC) curve which is commonly used to evaluate the performance of spectrum sensing.

![Figure 2.4](image-url)  
**Figure 2.4**  Probability densities of received signal energy under \( H_0 \) and \( H_1 \) sensing hypotheses.
2.3.3 Detection Criteria of Primary User

In CR systems of SUs, spectrum sensing tasks are periodically performed to observe potential vacant bands by reliable monitoring of PUs activities. Thus, accurate detection of PUs is a crucial requirement for both parties; PUs and SUs. In fact, spectrum sensing is often considered as a pure signal detection problem. In this section, two different philosophies of exploiting the observed white spaces are presented and can addresses as follows:

(i) Neyman-Pearson criterion: In Neyman-Pearson approach, the decision protocol aims at maximizing $P_d$ for a given $P_f$ (Quan et al. 2008; Shen & Kwak 2009). Defining the probability of missed detection as $P_m = 1 - P_d$, the decision approach can also be formulated as to minimize $P_m$ for a given $P_f$. This scenario is called constant false alarm rate (CFAR) (Peh & Liang 2007). The philosophy of Neyman-Pearson criterion lies on minimizing potential interference to active PU while maintaining constant rate of accessing the unused spectrum. Mathematically, by setting $P_f$ in (2.4) to a fixed rate $\overline{P}_f$, thus

$$P_f = P(Y > \beta | H_0) = \int_{\beta}^{\infty} f_0(Y) dY = \overline{P}_f \quad (2.5)$$

Then, the threshold $\overline{\beta}$ for $\overline{P}_f$ can be expressed as

$$\overline{\beta} = func(\overline{P}_f) \quad (2.6)$$

where $func$ is a statistical function comprised of received PU signal properties. By substituting (2.6) into (2.3), then

$$P_d = P(Y > \overline{\beta} | H_1) = \int_{\overline{\beta}}^{\infty} f_1(Y) dY \quad (2.7)$$
(ii) **Mini-max criterion**: This criterion is more aggressive as it jointly takes into account PU as well as SU perspectives (Shen & Kwak 2009). This is because it minimizes the total sensing decision error probability defined as

\[ P_e = P(H_0) \cdot P_f + P(H_1) \cdot P_m \]  

(2.8)

where \( P(H_0) \) and \( P(H_1) \) denote the probabilities of PU under \( H_0 \) and \( H_1 \), respectively.

While the detector threshold in Neyman-Pearson criterion is set at a fixed level for a given \( P_f \), the detector threshold based on Mini-max approach is dynamically positioned according to the statistical properties of the PDFs under \( H_0 \) and \( H_1 \). For example, if the distance between the means of the two PDFs is far, the threshold might be set to be relatively large so that \( P_f \) can be minimized while still maintaining no miss detection of the PU signal. For simplicity, \( P_f \) and \( P_m \) might be assumed equal to obtain closed form expression for the detector threshold although this strict assumption might not be always acceptable (Shen & Kwak 2009).

### 2.3.4 Challenges of Spectrum Sensing

In this section, some of the challenges associated with spectrum sensing are briefly addressed.

(i) **Sensing time**: Designing the sensing slot for CR systems is one of the critical development tasks. The sensing activity is performed with a duty cycle or frame duration \( T_f \). This \( T_f \) is divided into two slots; the first slot \( T_s \) is allocated for spectrum sensing whereas the remaining slot \( (T_f - T_s) \) is used by the SU to access the unused licensed bands (Liang et al. 2008). However, the CR system, or SU, has to immediately vacate the licensed bands once an active PU has been declared by the next sensing exercise. Making \( T_s \) too short might result in poor detection of PU and will therefore cause harmful interference to it whereas using long \( T_s \) will limit the access time period of unused bands by SUs and then consequently reduces the total throughput of the CRN. Thus, designing \( T_s \) is one of the challengeable tasks of CR systems and adaptive solutions should be employed to dynamically set the sensing time based on wireless environmental conditions.
(ii) **Hardware requirements:** In CR systems, spectrum sensing can make use of the state-of-the-art solutions to support its functional requirements (Arslan 2007). Spectrum sensing requires high-rate samplers, large dynamic range analog-to-digital converters (ADCs), reconfigurable hardware, multiple antenna circuitry, and high-speed signal processors. For instance, in CRN, sensing nodes are required to scan a much wider band than conventional narrowband receivers. This calls for employment of high-rate processors to meet real-time requirements.

(iii) **Hidden primary user problem:** This problem occurs when the PU transmitter is shadowed from the SU receiver by any existing obstacles on the line-of-sight between them (Ghasemi & Sousa 2005) as has been depicted earlier in Figure 1.4. Failure of PU detection makes it less protected from interference and results quality degradation. Thus, spatial diversity solutions should be employed to improve the detectability of PU receivers. This diversity can be realized by means of collaboration among SUs as will be shown in Section 2.4.

(iv) **Spread spectrum primary users:** Spread spectrum-based PU signals are distinguished by their wide spanned bandwidth and low power levels. This low power level requires spectrum sensors of very high sensitivity so that the presence of PUs can be reliably identified. If partial knowledge on PU signal is available, feature detection-based sensors can be used as was proposed in (Roy et al. 2010).

### 2.3.5 Spectrum Sensing in Existing Wireless Standards

Some wireless technologies can be said to be partially cognitive in the sense that require some sort of spectrum sensing. For instance, the IEEE 802.11k standard which is an extension of IEEE 802.11 require some measurements through constructing reports of channel load and noise histogram at an access point by collecting channel data form mobiles nodes and measuring interference levels, respectively (Arslan 2007). Also, in the Bluetooth standard, new features are being introduced to allow the Bluetooth users to adaptively identify active transmissions in the ISM band such as, microwave ovens and cordless telephones, and avoid potential mutual interference (Arslan 2007). In addition, the IEEE 802.22 standard which is believed to be the first
real CR standard is featured by the ability to identify the unused TV bands and exploit
them for temporary access (Xiao & Hu 2009).

### 2.4 COOPERATIVE SPECTRUM SENSING

Due to the hidden terminal problem (Ghasemi & Sousa 2005), a CR user may fail to
identify active licensed users, or PUs, and will then access their channels and cause
interference to them. To overcome this problem, multiple CRs, or SUs, can cooperate
in a network to perform spectrum sensing. The concept of cooperative spectrum
sensing has been presented in Section 1.1.3 and graphically depicted in Figure 1.4.
This concept rests on that multiple CR users receive different versions of the same PU
signal through various transmission paths which realizes spatial diversity and improve
the PU detectability. These different versions of PU signals are then combined
through distributed or centralized architectures (Akyildiz et al. 2006) as will be seen
later. In comparison to local (non-cooperative) spectrum sensing, several recent
research works have shown that the cooperative sensing can significantly increase the
detection performance in fading environments (Ghasemi & Sousa 2005). However,
cooperative spectrum sensing requires efficient information exchange algorithms and
suffers from increased complexity. Table 2.3 tabulates the advantages and
disadvantages of local versus cooperative sensing schemes.

<table>
<thead>
<tr>
<th>Sensing Scheme</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local sensing</td>
<td>1. Computational and implementation simplicity.</td>
<td>1. Hidden node problem.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Multipath and shadowing.</td>
</tr>
<tr>
<td></td>
<td>2. Reduced sensing time.</td>
<td>2. Traffic overhead.</td>
</tr>
<tr>
<td></td>
<td>3. Shadowing effect and hidden node problems can be prevented.</td>
<td>3. The need for a control channel.</td>
</tr>
</tbody>
</table>

Source: Arslan 2007
As mentioned earlier, cooperative spectrum sensing can be implemented in two approaches: distributed or centralized architectures. These two approaches are explained in the following two sections.

2.4.1 Centralized Sensing Architecture

In centralized cooperative sensing architecture, unlicensed CR users, or SUs, sense the target PU channels and report the sensing results to a central unit at which a global decision on the spectrum access is made (Ganesan & Li 2005; Visotsky et al. 2005). This global decision of whether or not a PU is active is made by combining the sensing results from all SUs in the vicinity of the central unit which might be an access point (AP) as in Wireless LAN technology or base station (BS) as in cellular technology. Figure 1.4 shows the deployment of centralized CRN where all the SUs within the coverage area of the SU-BS report their sensing results to it. In terms of advantages, the centralized BS whose footprint may span several kilometres can afford optimal DSA solution as it offers optimization across network-wide information. On the other hand, the main disadvantage of the centralized approach is the requirement for backbone infrastructure (i.e. central BS). However, this infrastructural requirement can be mitigated by replacing the central BS by a master mobile node (Visotsky et al. 2005).

2.4.2 Distributed Sensing Architecture

In the distributed approach of cooperative spectrum sensing, unlicensed CR users, or SUs, exchange the sensing results among each other and the decision on the spectrum access by each unlicensed user is made locally (Tang 2005; Ahmed et al. 2006). The main advantage of distributed spectrum sensing is the on-fly ad-hoc set up of the network where no central BS is needed. However, the deployment of such distributed architecture would not be anticipated in the near future due to many challenges and drawbacks; since the distributed networks usually have comparatively smaller coverage area than centralized networks, the measurements received from multiple nearby SUs might not differ much and therefore, sensing measurements will be redundant and the spatial diversity gain will then be reduced. Consequently, this
reduction of spatial diversity will have negative effect on mitigating potential hidden terminal problems which results in sub-optimal knowledge of PU channel occupancy (Xiao & Hu 2009). Also, since sensing results are to be exchanged among neighbouring SUs, the distributed networks suffer from increased cooperation overhead. In addition, every CR node in the network is to process large amount of sensing measurements received from other SUs. Thus, every CR node should be armed with efficient processors and requires great computational resources (Hossain et al. 2009). Table 2.4 shows the pros and cons of centralized and distributed architectures for cooperative spectrum sensing in CRNs.

<table>
<thead>
<tr>
<th>Cooperation Architecture</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2. Hidden terminal problem can be greatly mitigated.</td>
<td></td>
</tr>
<tr>
<td>Distributed</td>
<td>1. Ad-hoc cooperation with no infrastructure needed.</td>
<td>1. Inability to achieve optimal DSA solutions.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Increased cooperation overhead.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. Each CR transceiver requires great computational resources.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. Susceptibility to hidden terminal problem.</td>
</tr>
</tbody>
</table>

### 2.5 FUSION SCHEMES FOR COOPERATIVE SPECTRUM SENSING

The cooperative spectrum sensing is realized by collecting sensing information from multiple SUs in the vicinity using centralized or distributed approach. The received sensing information of multiple SUs is combined at a central BS or at every SU’s receiver for the centralized or distributed architecture, respectively, to come out with a final decision on presence or absence of PU. The combining process of sensing information is commonly known as fusion (Varshney 1997). The fusion schemes can be classified as hard decision fusion (HDF) or soft data fusion (SDF) schemes. These
two schemes are presented in the next section with considering the centralized approach of cooperative spectrum sensing.

2.5.1 Hard Decision Fusion (HDF)

In HDF, every local sensor or SU senses the PU signal on the observed band, processes the potential PU signal received at its receiver, and makes its own decision on the presence or absence of the PU locally. Thus, every SU should have a built-in local spectrum sensing technique implemented at its receiver such as energy detection, feature detection, or wavelet detection. Then, the resultant binary decisions (0 or 1) from all SUs are sent to a central BS for fusion. This mechanism of hard decision fusion has been followed by many researchers (Ganesan & Li 2007; Liang et al. 2008; Zhang et al. 2008). Assuming that there are $N$ SUs within the coverage area of a BS, then, $k$-out-of-$N$ fusion rule is commonly used to combine the $N$ hard decisions of the $N$ corresponding SUs (Peh et al. 2009). In $k$-out-of-$N$ fusion rule, $k$ out of the $N$ SUs have to declare YES for the presence of PU in order for the global decision to be YES. Other HDF fusion rules such as OR- (i.e. 1-out-of-$N$) fusion rule and AND- (i.e. $N$-out-of-$N$) fusion rule have also been widely used in the literature (Ghasemi & Sousa 2005; Peh & Liang 2007; Sun et al. 2007). These hard fusion schemes have the advantage of reduced cooperation overhead as only one single bit needs to be reported to the BS from each SU as shown in Figure 2.5 (a). However, since the hard fusion process combines binary decisions only rather than combining sensing measurements, most of the sensing information content will be lost and therefore, the achievable detection performance is non-optimal or only sub-optimal.

2.5.2 Soft Data Fusion (SDF)

In contrast to HDF schemes, the SDF schemes require that every SU reports its sensing measurements as raw data to the BS. Thus, the SUs transceivers should not be armed with local detectors (e.g. energy detectors) and/or decision-making devices. These sensing measurements from all SUs which are received by the common receiver of the central BS will be aggregated and a detection algorithm is employed to process the data and come out with a global decision on the presence or absence of PU. Thus,
it is clear that the SUs in SDF scenario act as radio relays and have no processing units since only one single detector is needed at the common receiver of the central BS as shown in Figure 2.5 (b). Linear combination data fusion scheme was proposed in (Quan et al. 2008) and extended further in (Shen & Kwak 2009) where the received sensing measurements are first weighted and then aggregated based on maximizing the natural deflection coefficient (NDC) or modified deflection coefficient (MDC). Other SDF schemes include the maximal-ratio combining (MRC) (Ma & Li 2007) and equal gain combination (EGC) (Qi et al. 2009). These soft schemes show better detection performance than HDF schemes. However, the SDF schemes have the disadvantage of increased cooperation overhead due to the huge amount of sensing data reported from the SUs to the central BS. Some relay protocols such as Amplify-And-Forward (AAF) approach or Decode-And-Forward (DAF) approach (Molisch 2011) can be used to relay sensing measurements from the SUs to the fusion centre placed at the centralized BS (Shen & Kwak 2009).

![Diagram of HDF and SDF](image-url)
2.6 OTHER DYNAMIC SPECTRUM (DSA) ASPECTS

This section provides some other DSA aspects such as the potential CR operating bands, Spectrum Sharing Techniques and the PU-SU and SU-SU cooperation behaviour.

2.6.1 CR Operating Bands

One of the main aspects for the feasibility of CR technology is the frequency bands at which a CR system operates. The potential CR access bands can be classified into two main categories, namely, licensed bands and unlicensed bands. These two categories can be presented as follows:

(i) Licensed bands: These bands are defined as frequency bands assigned exclusively to licensees such as the Global System for Mobile Communications (GSM) bands and Universal Mobile Telecommunications System (UMTS) in cellular technology and the TV bands in TV broadcasting. With the emergence of spectrum sensing techniques, CR can scan the spectrum and temporarily access the bands declared as not in use. The first realizable CRN is the 802.22 WRAN which uses the unused (54-862 MHz) TV bands (Xiao & Hu 2009). Making use of these licensed unused bands requires rapid vacation once the licence holder returns and therefore spectrum sensing is a crucial requirement for the success of CR technology. In addition, spectrum mobility is also important as it offers smooth transition from one band to another.

(ii) Unlicensed bands: The unlicensed bands are segments of spectrum allocated for unconstrained access by any device with no licence or complicated ownership rules involved. These bands include the the 2.4 GHz Industrial, Scientific and Medical (ISM) band used by IEEE 802.11 b/g/n and Bluetooth devices, the 5 GHz Unlicensed National Information Infrastructure (UNII) band used by IEEE 802.11a standard, and the 60 GHz Extra High Frequency (EHF) band used for short-range communications (Arslan 2007). Utilising such unlicensed bands is more challengeable than accessing licensed bands since any device of any public services can freely access the
unlicensed band at any time and therefore, CR operating on the same band becomes more susceptible to interference.

2.6.2 Spectrum Sharing Techniques

In general, two spectrum sensing techniques can be distinguished and known as overlay and underlay spectrum sharing (Cabric et al. 2006).

(i) Overlay spectrum sharing: As shown in Figure 2.6 (a), unused portions of spectrum (i.e. spectrum holes) are utilized by overlay systems through the employment of spectrum sensing and adaptive allocation. This approach is characterized by its ability to enhance spectral efficiency. Sufficient guard intervals should be introduced to suppress possible power leakage from SU bands to PU bands and mitigate harmful interference to the high priority PUs (Berthold & Jondral 2005). Obviously, CR systems are envisioned as overlay systems that use spectrum sensing and adaptive allocation to improve spectral efficiency while avoiding harmful interference to license holders.

(ii) Underlay spectrum sharing: In underlay systems, the transmitted power levels are restricted to be below the noise floor (Menon et al. 2005) or predefined power spectral density mask (Cabric et al. 2006) while using ultrawide band (UWB) (FCC 2002b) as shown in Figure 2.6 (b). As a matter of fact, it is practically not possible to ensure absolutely no interference to PUs. Thus, underlay systems makes use of this fact by tolerating non-harmful interference rather than not accepting interference at all. Figure 2.6 (b) shows the coexistence between PUs and underlay UWB systems. The transmit power of the underlay UWB is low enough to be felt as a slight rise on the noise floor. Although UWB underlay systems can noticeably improve the spectrum occupancy, such systems are limited to short-range communications due to their restricted transmit power level. Hence, the exploration on overlay techniques would be more attractive to the research community and industry due to relatively unrestricted power levels compared to underlay techniques.
2.6.3 Cooperation Behaviour

For both centralized and distributed approaches of cooperative sensing, the PU may or may not choose to cooperate with the central BS or individual SUs, respectively. However, this PU-SU sort of cooperation is not feasibly anticipated without providing benefits to PUs as returns for tolerating potential and, hopefully, non-harmful interference from SUs (Hossain & Bhargava 2007). On the other hand, SU-SU cooperation is highly needed to improve the detection performance by supplying spatial diversity. In centralized cooperative sensing, the SU-SU cooperation
is performed through the central SU-BS whereas in distributed sensing, the SU-SU cooperation is conducted directly in an ad-hoc fashion. In fact, the SU-SU cooperation is not limited to the uplink operations (i.e. spectrum sensing) only but also extended to the downlink transmission where channel and power allocation algorithms are needed for spectrum sharing.

2.7 OPTIMIZATION

Optimization deals with the problem of finding solutions over a given set of choices to optimize certain criteria (Gen & Cheng 2000). This optimization problem might be of single-objective or multi-objective in accordance to the number of criteria to be optimized. To solve optimization problems using computers, the problem at hand should be first mathematically formulated. Then, this mathematical model is used by an optimization algorithm to find the best (global) optima (maxima/minima) rather than suboptimal (local) maxima/minima (Haupt & Haupt 2004). Advanced numerical methods are often used for problem optimization. However, as the difficulty level of a given problem increases, the conventional numerical methods cannot be used. Iterative random-search methods such as evolutionary algorithms can be the best choice for such complicated problems.

2.7.1 Types of Optimization Problems

(i) Parametric problems: In this type of problems, parameters are the decision variables to be optimized. These optimization problems can be further categorized into constrained and unconstrained problems. The problem constraints might be design conditions, initial boundaries or quality demands. A constrained single-objective optimization problem is usually written in the following form (Gen & Cheng 2000):

$$\max z = f(\bar{x})$$

subject to  
$$g_i(\bar{x}) \leq 0, \quad i = 1, 2, \ldots, m$$

(2.9)
where $\bar{x} \in \mathbb{R}^n$ is a vector of $n$ decision variables, $f(\bar{x})$ is an objective function, $g_i(\bar{x}) \leq 0$ is the $i^{th}$ constraint of $m$ total constraints form the feasible search space. This feasible search space, denoted as $S$, is defined as:

$$S = \{ \bar{x} \in \mathbb{R}^n | g_i(\bar{x}) \leq 0, i = 1, 2, ..., m, \bar{x} \geq 0 \} \quad (2.10)$$

As an example of parametric optimization problems, the problem of array antenna design is considered (Haupt & Haupt 2004). The optimization problem of (2.9) can be minimizing total sidelobe levels in the antenna pattern and the parameters of $\bar{x} \in \mathbb{R}^n$ are the $n$ array amplitude weights.

(ii) **Combinatorial problems**: Combinatorial optimization problems are characterized by a finite set of feasible solutions. These optimization problems can, for instance, be relative or absolute ordering problems (Todd 1997). A common example of combinatorial problems is the travelling salesman problem (TSP) where a salesman travelling between a limited set of cities and returning to the start city covering the shortest distance. Another practical example would be the ordering of jobs in a manufacturing or production line. With very large but number of feasible solutions, it is too hard to obtain the optimal solution by simple enumeration (Gen & Cheng 2000). It is very common to solve such hard problems using a heuristic search algorithm such as GA.

2.7.2 Multi-Objective Optimization

Multi-objective problems appear when there are multiple conflicting objectives to be optimized simultaneously. In such a case, there does not necessarily exist a solution that is best with respect to all objectives because of incommensurability and confliction among objectives (Gen & Cheng 2000). A solution might be optimal for one objective but sup-optimal or even poor for another. Therefore, there is usually a set of solutions for a given multiple-objective function which cannot simply be with each other. These solutions are commonly called *nondominated solutions* or *Pareto front solutions* (Gen & Cheng 2000). For such solutions, no improvement is possibly
achieved in any objective without sacrificing at least one of the other objective functions.

To explain the concept of multiobjective optimization together with Pareto solutions, consider the following optimization problem (Haupt & Haupt 2004)

$$
\begin{align*}
\min f_1 &= x_1 + x_2^2 + x_3 + \sqrt{x_4} \\
\min f_2 &= \frac{1}{x_1} + \frac{1}{x_2^2} + \sqrt{x_3} + \frac{1}{x_4}
\end{align*}
$$

subject to \( 1 \leq x_n \leq 2, \quad n = 1, 2, \ldots, 4 \) (2.11)

Obviously, these two objectives are in agreement on the variable \( x_3 \) but not on the variables \( x_1, x_2, \) and \( x_4 \). By plotting \( f_1 \) against \( f_2 \) for \( 10^3 \) random combinations of \( x_1, x_2, x_3, \) and \( x_4 \), the blue markers shown in Figure 2.7. By plotting other \( 10^6 \) random combinations the green region, often called feasible region, is defined. This feasible region represents all possible or obtainable solutions for the problem of equation (2.11). Among these solutions are the optimal solutions that jointly minimize \( f_1 \) and \( f_2 \). These solutions are located on the south-western boundary of the feasible region and are forming the red curve in Figure 2.7. This red curve is defined by the Pareto front solutions or sometimes called as Pareto optimal solutions. The solutions near to the lower end of the Pareto front are good in minimizing \( f_2 \) but they are not good in minimizing \( f_1 \). In contrast, the solutions near to the upper end of the Pareto front are good in minimizing \( f_1 \) but poor in minimizing \( f_2 \). Thus, these solutions cannot be further improved in any direction. Below the Pareto front is the infeasible region as no solutions can be found therein. The point that is the minimum of each independent functions (\( \min f_1, \min f_2 \)) is located within the infeasible region in the plot. Thus, the main aim of multiobjective optimization is to find the Pareto front solutions rather than finding the optimal solutions of independent objectives. Multiobjective optimization can often be found in design, modelling and planning of many complex real systems in the areas of industrial production, urban transportation, energy distribution, and many more.
2.7.3 Multi-Objective Approaches

One of the issues arising in solving multi-objective optimization problems is how to assign a numerical single value for the overall multi-objective function in terms of its dependent objectives and corresponding variables. In comparison with a single-objective problem in (2.11), the multiple-objective optimization problem of $q$ objectives can be represented formally as follows:

$$
\max \{z_1 = f_1(\bar{x}), z_2 = f_2(\bar{x}), \ldots, z_q = f_q(\bar{x})\}
$$

subject to \ $g_i(\bar{x}) \leq 0, \quad i = 1, 2, \ldots, m$

(2.12)

From solutions techniques point of view, several methods are utilized to reduce multiple objectives to a single objective and then solve the optimization problem using mathematical programming tools. To realize this aim, preferences on individual objectives have to be first identified and numerically expressed so that the multiple objective functions can be put into a scalar single multiobjective function. In
the next two items, several approaches to combine multiple objective functions into one overall utility function are briefly explained (Chung 1994).

(i) **Weighted-sum approach**: In this approach, optimization preferences are expressed by weighting coefficients assigned to individual single-objective functions. The weighted-sum technique applied on the problem of (2.12) can be represented as follows:

\[
\max z(\bar{x}) = \sum_{k=1}^{q} \omega_k f_k(\bar{x})
\]

\[
\text{subject to } \bar{x} \in S
\]

where \(\omega_k\) the individual weighting coefficient of the kth objective which is interpreted as the relative emphasis of its corresponding objective compared to other objectives. Practically, \(f_k(\bar{x})\) is often normalized to prevent the utility function \(z(\bar{x})\) being much sensitive to high-score objectives and less sensitive to low-score objectives. Therefore, the condition \(\|\bar{\omega}\| = 1\) is usually implemented where \(\bar{\omega} = [\omega_1, \omega_2, \ldots, \omega_q]\) and \(\|\|\) is 1-norm operator of a given vector. Different settings of \(\bar{\omega}\) helps to tradeoff corresponding objectives based on system requirements or user needs.

(ii) **Linear-logarithmic approach**: The linear-logarithmic utility function is formulated by additive terms of logarithmic functions representing the individual objectives. Unlike the weighted-sum utility, the linear-logarithmic formulation helps to improve the optimization performance when optima at the extreme edges by providing convexity to the optimization curve so that this problem can be mitigated. The mathematical representation of linear-logarithmic utility function is expressed as:

\[
\max \ln\{z(\bar{x})\} = \sum_{k=1}^{q} \omega_k \ln\{f_k(\bar{x})\}
\]

\[
\text{subject to } \bar{x} \in S
\]

Obviously, this formulation is very much similar to the weighted-sum one but with incorporating logarithmic addition instead of linear addition.
(iii) **Constant-elasticity-of-substitution (CES) approach:** As the name implies, this approach is established by developing a constant which indicates to a dependency measure among corresponding objective functions. The utility function of this approach is expressed as follows:

\[
\max z(\bar{x}) = \left( \sum_{k=1}^{q} \omega_k (f_k(\bar{x}))^{-\rho} \right)^{-1/\rho}
\]

subject to \( \bar{x} \in S \)  

where \( \rho = (1 - \sigma)/\sigma \) and \( \sigma \) is the elasticity between the single-objective functions. However, this formulation might not be really feasible for adaptive optimization which involves individual objectives traded-off due to the usage of constant value of elasticity for all objectives.

### 2.8 GENETIC ALGORITHMS (GAs)

Genetic Algorithms (GAs) are evolutionary algorithms well-known as powerful and broadly applicable stochastic search and optimization techniques. The GA framework was first proposed by Holland (1975) and further investigated by De Jong’s doctoral dissertation (1975). However, more interest was generated when Goldberg published his famous book in 1989 which has become a standard text for GAs (Goldberg 1989). Within less than a decade since Goldberg’s book, GAs have been widely applied in many engineering fields.

#### 2.8.1 GA Concepts and Terminology

GAs can be often classified into two main types; binary and continuous (Haupt & Haupt 2004). In this section, the binary GA is presented and explained. However, the overall idea remains the same for continuous GA with some modifications.

In binary GA, solutions are represented by binary strings (chromosomes) evolve in a manner similar to the genetic growth (Gen & Cheng 2000). A population of strings \( P(t) \) at the \( t^{th} \) iteration (generation) is randomly initialized giving a diverse
range of possible solutions (candidates). Each binary string consists of one or more variables (traits) encoded by equal or possibly unequal number of bits (genes). The binary-coding search space (genotype) is then accurately decoded to a solution space (phenotype) based on one-to-one mapping to ensure no trivial solutions. Each of these possible solutions is evaluated and given a fitness score. The selection operator is then invoked to select the more fit chromosomes (individuals) from the parent population. This is, in Darwinian terms, performing a ‘survival of the fittest’ operation on the population. The selected population then forms the basis of a mating pool and undergoes stochastic transformations by means of genetic operations to form new individuals. The genetic operators are: crossover, which creates new offspring strings by combining parts (alleles) from two parent individuals, and mutation, which creates new individuals by randomly making changes in the genes of a single individual to encourage diversity. It is worth to notice that genetic operators (crossover and mutation) perform essentially a blind search whereas selection operators provide the driving force to hopefully steer the genetic search toward the desirable region of the solution space.

2.8.2 Mechanism of GA

In this section, the operational mechanism of GA is presented. Figure 2.8 shows an explanatory flowchart of GA mechanism. The algorithm begins by initialization of random population \( P(t) \) which represent a set of possible solutions maintained within a predefined search space. The population fitness is then evaluated and the fittest \( \zeta \) \(*pops\) chromosomes are identified and stored as \( P_\zeta(t) \), where \( \zeta \) is the elitism ratio and \( pops \) is the population size. The elitism was first introduced by DeJong (1975) and used to force the GA to retain a number of the best chromosomes at every generation which might be destroyed by subsequent operations. The main GA operations; selection, crossover, and mutation, are then performed. The population of the new individuals (children) resulting from selection, crossover and mutation are called offspring population and denoted as \( C(t) \). Once \( C(t) \) is formed, a new population \( P(t + 1) \) is constructed by combining \( C(t) \) with the fittest chromosomes of the parent population; \( P_\zeta(t) \). The fitness of \( P(t + 1) \) is evaluated and a stopping criterion is checked to decide whether or not to terminate the optimization algorithm. The
stopping criterion might be a predefined number of generations, a predefined fitness threshold, or when no noticeable improvement is observed over a predefined number of generations. If the stopping criterion is met, the algorithm is terminated and the optimal solution is extracted from $P(t + 1)$. Otherwise, $P(t)$ will be updated with $P(t + 1)$ individuals and the GA evolutionary processes are recycled again as shown. The GA mechanism ensures converges to better set of solutions which hopefully includes an optimal solution to the problem at hand.

2.8.3 GA Components

In this section, the main components of which the GA is constructed and controlled. These components are briefly explained and further details can be found in (Goldberg 1989; Gen & Cheng 2000; Haupt & Haupt 2004). However, in order to briefly, yet
sufficiently, explain these components, the subsequent sections are associated with an exemplary optimization problem.

(i) Decision variables and fitness functions: The GA begins by defining the given optimization problem and its corresponding decision variables. The optimization problem might be a maximization or minimization problem based on its physical interpretation. The defined problem is formulated as a fitness function which might be a mathematical function or a game. Fitness scores are calculated by frequent evaluations of the fitness function at different sets of input decision variables. Each set of decision variables forms a chromosome. If the chromosome has $N_{\text{var}}$ variables given by $p_1, p_2, \ldots, p_{N_{\text{var}}}$ in an $N_{\text{var}}$-dimensional optimization problem, then the chromosome is written as a vector of $N_{\text{var}}$ elements,

$$\text{Chromosome} = [p_1, p_2, p_3, \ldots, p_{N_{\text{var}}}] \quad (2.16)$$

To efficiently associate the theory with practical application, an optimization problem depicted in Figure 2.9 and mathematically expressed in (2.17) is presented as

$$\begin{align*}
\max f(x, y) &= e^{-2(x^2+y^2)^2} + 2e^{-1000((x-0.5)^2+y^2)^2} + 3e^{-1000((x-0.8)^2+y^2)^2} \\
\text{subject to} \quad &-1 \leq x, y \leq 1
\end{align*} \quad (2.17)$$

Obviously, this fitness function is a 2-Dimensional constrained problem that can be solved by finding $(x_{\text{opt}}, y_{\text{opt}})$ at which $f(x, y)$ is maximized. As can be seen in Figure 2.9, the problem has global maxima as well as local maxima. The decision variables represent any $\{x, y\}$ pair and equation (2.16) can therefore be written as

$$\text{Chromosome} = [x, y] \quad (2.18)$$

(ii) Variable encoding and decoding: Binary encoding was historically considered since Holland’s time and therefore, most following works have been using binary encodings due to the well-developed and binary-based theories and mechanisms (Mitchell 1996). On the other hand, GAs with real and integer encodings were also
used (Wright 1991; Lin et al. 1992; Thomas et al. 1995). However, there have been no rigorous guidelines for predicting which encoding scheme will work better for a given application. In binary GA, the decision variables are represented in binary. Thus, stable encoding and decoding processes are required to map the decimal range of decision variables to a binary range and vice versa, respectively. Assume that each decision variable in decimal is encoded into an \( n_{genes} \) bits string, then, each chromosome as in (2.16) will be consisted of \( N_{var} \times n_{genes} \) bits. Taking the given problem at (2.17) into account with using 16-bit string per variable, a chromosome of 32 bits is generated.

(iii) Population of chromosomes: After the fitness function and its corresponding decision variables are all identified, the GA initialized by randomly generating a group of chromosomes called population. Each chromosome (of \( N_{var} \) decision variables) in the population represents a possible solution to the given problem. This initial population of \( p_{ops} \) chromosomes (potential solutions) is shown in Figure 2.9 as black markers. The chromosomes of the initial population will undergo GA operations to produce new chromosomes with hopefully better fitness values. Other alternatives than random initial population is the uniform population, where chromosomes are uniformly distributed across the search space, and complementary sampling, where half the population is randomly generated and the second half is the complementary chromosomes of the first half (Haupt & Haupt 2004).

(iv) Chromosome selection: Once the initial population is generated, certain ones of its chromosomes are selected for mating. The main purpose of selection is to choose the fittest individuals of every population for reproduction in hopes that their offspring will have better fitness. To achieve this purpose, several selection schemes were proposed in the literature and again, it could be worth to say that there are no clear guidelines to know which selection scheme works best for which application. To maintain the best chromosomes of every population, elitism strategy is often used (DeJong 1975). With \( p_{ops} \) being the population size of \( P(t) \), the elitist (fittest ever) \( \xi \) \( *p_{ops} \) chromosomes are transferred straight away to the next population. Thus, the selection process aims at selecting the good chromosomes from which \( (1 - \xi) \) \( *p_{ops} \) new chromosomes are generated and are to replace the discarded chromosomes.
Common selection schemes include roulette wheel selection (Holland 1975), tournament selection (Goldberg et al. 1989), steady-state reproduction (Whitley 1989; Syswerda 1989), ($\mu + \lambda$)-selection (Bäck 1994), and ranking and scaling (Gen & Cheng 2000). However, the roulette wheel selection scheme is the most well-known scheme that can be ideally suit many optimization problems.

(v) Genetic operators: As mentioned earlier, the essential genetic operators of GA are crossover and mutation. These two operators are briefly explained herein.

(a) Crossover: Crossover is the process of creating offspring from the parent chromosomes chosen during the previous chromosome selection process. The crossover operator is the main exploration force of a given search space and it is realized by random manipulation of genetic contents. Commonly, two parent chromosomes undergo crossover operation to produce two offspring or children. In single point crossover, a crossover point is randomly selected between the first and last bits of the parents’ chromosomes; parent$_1$ and parent$_2$. Then, two offspring, offspring$_1$ and offspring$_2$, are constructed by swapping the binary portions of parent$_1$
and parent\textsubscript{2} around the crossover point. Assume that parent\textsubscript{1} and parent\textsubscript{2} are 0011100010 101110 and 1001001101 100011, respectively, with a crossover point randomly selected. After crossover, offspring\textsubscript{1} and offspring\textsubscript{2} will be 0011100010\textcolor{red}{100011} and 1001001101\textcolor{red}{101110}, respectively. This mating process continues to generate random crossover points used to exchange the binary portions of the \((1 – \zeta) \ast \textit{pops}\) parent chromosomes and generate \((1 – \zeta) \ast \textit{pops}\) new chromosomes or offspring which forms the population \(C(t)\) in Figure 2.8. Single point crossover might not be efficient when dealing with long strings. Other crossover alternatives include two-point crossover (Eshelman et al. 1989) and uniform crossover (Syswerda 1989). As was the case for the selection process, choosing the right crossover scheme is still an open research question and the best that one can do is to set-and-test certain schemes for the given problem to indentify the optimal scheme that can facilitate the GA convergence.

(b) **Mutation**: In mutation, certain percentage of the bits in a population of chromosomes is altered. Mutation is an evolutionary process that helps to further explore the given search space. It also prevents premature convergence to local optima. In single bit mutation, an arbitrary bit is probably complemented (i.e. 0 → 1 and 1 → 0). For instance, the chromosome 0011100010\textcolor{red}{100011} obtained upon the crossover operation above becomes 0010\textcolor{red}{100010}00011 if mutation is randomly made on the 4\textsuperscript{th} bit of the original chromosome. Mutation points are randomly selected from the population matrix. Mutation is a very critical process as using a high mutation rate transforms the GA into a pure random search mechanism whereas low rates cause premature convergence to sub-optimal solutions. Adaptive mutation rates where mutation rate vary as the generations progress can also be used (Fogarty 1989; Back et al. 1993). Fogarty claimed that variable mutation rate works better than constant mutation rate when certain control is made on the generation of initial population whereas no much difference if the initial population is randomly generated. However, no general conclusions can be made since his results were performed on a specific optimization problem.

(vi) **GA control parameters**: One of the important questions when implementing GA for a given optimization problem is how to set its control parameters such as
population size, crossover rate, and mutation rate. Unfortunately, these parameters are nonlinearly dependent on one another and therefore, they cannot be optimized independently. There have been many research studies trying to answer this question although their conclusions don’t really tally with each other. These conflicts are due to the usage of different research methodology and suite of benchmarking functions.

De Jong (1975) carried out an early experimental study to analyze the effect of varying the control parameters on GA online and offline performance. The online performance is defined as the average fitness of all chromosomes formed in all generations where as the offline performance is defined by the fitness estimate of the best chromosome for each generation. De Jong made use of a particular suite of benchmarking functions to evaluate the GA performance over different settings of control parameters. He found out that there are always specific values of control parameters that produce good online and offline performance and they are as stated in Table 2.5. De Jong’s functions have been widely used in the literature for evaluation of evolutionary algorithms. Grefenstette (1986) came out with an interesting approach when he optimized the GA parameters by another GA. The results obtained in this method can be said to be more reliable than those obtained from experimental studies. Grefenstette’s setting of GA control parameters is as mentioned in Table 2.5. Another comprehensive experiment was conducted by Schaffer et al. (1989) who spent more than a year of CPU time on systematic testing of a large set of parameter combinations and his finding of optimal set of GA control parameters is addressed in Table 2.5. However, all above studies as well as other recent literature studies focus on searching for optimal parameter settings for specific sets of benchmarking functions. Thus, the parameter values of each setting will most likely differ when applied on different optimization problems and/or real-world engineering problems.

<table>
<thead>
<tr>
<th>GA Control parameters</th>
<th>(De Jong 1975)</th>
<th>(Grefenstette 1986)</th>
<th>(Schaffer et al. 1989)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>50-100</td>
<td>30</td>
<td>20-30</td>
</tr>
<tr>
<td>Crossover rate</td>
<td>0.60</td>
<td>0.95</td>
<td>0.75-0.95</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>0.001</td>
<td>0.01</td>
<td>0.005-0.01</td>
</tr>
</tbody>
</table>
(vii) **Algorithm convergence**: To observe the convergence of a GA, a performance metric should be used. The most common approach of evaluating the convergence performance is to calculate the maximum (best) fitness in each population as well as the mean (average) fitness of all chromosomes of each population. Figure 2.10 displays the GA performance over 100 generations. It is clear that the GA can find the global maxima of Figure 2.9 within less than 50 generations. The GA termination criteria can be a predefined number of generations, a predefined fitness threshold, or when no noticeable improvement is observed over a predefined number of generations. Other researchers prefer to use the number of fitness evaluations rather than number of GA generations (Nickabadi et al. 2011).

![Figure 2.10 GA performance over 100 generations of optimizing equation (2.17)](image)

**2.9 PREVIOUS WORK OF EVOLUTIONARY ALGORITHMS FOR CR**

For the past few decades, the area of artificial intelligence (AI) is being receiving a great attention by the scientific research community. In the context of CR, several AI techniques have been proposed and implemented for different fields and applications of CR systems and networks. These AI techniques include, but not limited to, evolutionary algorithms such as genetic algorithms (GAs), neural networks (NNs), fuzzy control, game theory, knowledge-based Reasoning, and case-based reasoning (Fette 2009). In this section, a survey on GA-based research works of CR is presented.
The first GA-based implementation of CR framework was carried out at the Centre for Wireless Telecommunications (CWT) of Virginia Tech when Rieser and Rondeau developed a testbed of a CR system that could adapt reliably in disaster and emergency situations of communications environments (Rieser 2004; Rieser et al. 2004; Rondeau et al. 2004a). They successfully originated the employment of genetic algorithms as an intelligent core, namely, BioCR, to embed cognition to the CR engine that helps on tuning “knobs” based on measuring “meters”. The experimental results of his research show that the developed engine is able to reformulate new transmission waveform to avoid interference from existing co-channel interferer as in (Rondeau et al. 2004a). However, the adaption performance of his developed system showed limitations being unable to respond appropriately due to sensitivity issues as well as instability of obtained solutions. His research also lacks of clear definitions and control of performance objectives due to unavailability of fitness functions and proper ranking of single objectives, respectively.

Due to dynamic wireless environments, CR systems should be able to support time-varying Quality-of-Service (QoS) requirements rather than being limited to frequency adaption. (Rondeau et al. 2004b; Rondeau 2007) extends the research works in (Rieser 2004; Rieser et al. 2004; Rondeau et al. 2004a) by developing various operational strategies represented by corresponding fitness functions and employed GA-based engine to choose the best strategy that suits the user’s requirements and/or environmental conditions. Rondeau also developed a wireless channel imitated by Hidden Markov Model (HMM) trained by genetic algorithm. This imitated model is used to assist the GA-based CR engine to automatically rank the single objectives that construct the overall fitness function. In (Mähönen et al. 2006), a Cognitive Resource Manger (CRM) is proposed as a cross-layer multi-functional optimizer supported by a toolbox of a set of enabling optimization methods that allows for analyzing multi-dimensional problems. The toolbox of the CRM considers the use of GA as one of potential candidates applicable for optimizing specific types of objectives. However, it was not really obvious how the right technique will be automatically chosen by CRM for a given requirement. Hauris (2007) adopted the use of GA in CR system for autonomous vehicle communications where Key Performance Parameters (KPPs) were proposed and used to constitute a Fitness Measure (FM) that
is then used to guide the random processes of the GA. Unfortunately, this research work does not add much beyond the conceptual framework of (Rieser 2004; Rieser et al. 2004) where the only difference is a new set of proposed performance objectives. The research work in (De Baynast et al. 2008) uses the CRM architecture proposed in (Mähönen et al. 2006) for cross-layer optimization of different performance objectives related to the three Media Layers of the Open Systems Interconnection (OSI) model; the Physical, Data Link, and Network Layers. The GA of the CR toolbox was invoked as an iterative methodology to find the optimal parameters of corresponding layers based on acknowledgement signals without knowledge of network state information. However, issues such as the constraints of overall network capacity need to be investigated.

In (Newman et al. 2007a; Newman et al. 2007b), Newman presented a significant contribution to the use of GA for CR. In his research, he derived an analytical relationship between input parameters, or meters, and output parameters, or knobs. The meters-knobs relationships were implemented into a GA-based wireless multi-carrier transceiver. This research presents a good step towards the successful employment of GA for CR systems though the setting of ranking multiplicands was not clearly investigated. The researchers in (Chen & Wyglinski 2009a; Chen & Wyglinski 2009b) followed a similar framework to that presented in (Newman et al. 2007a; Newman et al. 2007b) but the scope of their work was extended to a distributive CRN at which each CR node share its local measurements with other nodes through overhead channels. In fact, their research work combines distributed resource allocation with cross-layer design techniques to satisfy different operational requirements. However, the choice of allocating specific segments of spectrum, as overhead channels, to exchange data seems painful a bit especially in the context of CR where the main concern is to efficiently use the available resources.

Other research works on the problem of resource allocation is presented in (Ngo 2009; Zhao et al. 2009). In (Ngo 2009), GA was used to optimally share out the available radio frequency bands of an Orthogonal Frequency-Division Multiple Access- (OFDMA-) based CR multicast network. A subcarrier and power allocation GA-based scheme is invoked at a centralized base station to maximize the design goal
under constraints of interference threshold at the primary user’s frequency bands. The researchers in (Zhao et al. 2009) proposed three distinct methodologies realized by mapping the elements of channel assignment matrix to the chromosomes of GA, Quantum GA (CGA), or to the positions of Particle Swarm Optimization (PSO), respectively. They showed that their proposed algorithms can outperform the conventional colour sensitive graph colouring algorithm. Recently, there have been some other applications for GAs on CR different fields such as GA-based framework for opportunistic radio (Chantaraskul & Moessner 2010), joint beamforming and power control in multiple-input multiple-output- (MIMO-) based CRNs (Noori et al. 2010), and scheduling (Gözüpek & Alagöz 2011). Table 2.6 shows a summary of the GA-based CR applications and their corresponding research works.

<table>
<thead>
<tr>
<th>CR research fields</th>
<th>Related CR research works</th>
</tr>
</thead>
<tbody>
<tr>
<td>− Adaptive communications for CR systems (software simulation)</td>
<td>− Rieser (2004); Rieser et al. (2004); Rondeau et al. (2004a); Rondeau et al. (2004b); Rondeau (2007); Mähönen et al. (2006); Hauris (2007); De Baynast et al. (2008); Newman et al. (2007a); Newman et al. (2007b); Chen &amp; Wyglinski (2009a); Chen &amp; Wyglinski (2009b); Chantaraskul &amp; Moessner (2010)</td>
</tr>
<tr>
<td>− Adaptive communications for CR systems (hardware testbed)</td>
<td>− Rieser (2004); Rieser et al. (2004); Rondeau et al. (2004a); Rondeau et al. (2004b); Rondeau (2007); Chantaraskul &amp; Moessner (2010)</td>
</tr>
<tr>
<td>− CR channel modelling</td>
<td>− Rieser (2004); Rieser et al. (2004); Rondeau et al. (2004a); Rondeau et al. (2004b)</td>
</tr>
<tr>
<td>− Resource and/or subcarrier allocation</td>
<td>− Ngo (2009); Zhao et al. (2009)</td>
</tr>
<tr>
<td>− Beamforming and/or power control</td>
<td>− Noori et al. (2010)</td>
</tr>
<tr>
<td>− Scheduling</td>
<td>− Gözüpek &amp; Alagöz (2011)</td>
</tr>
</tbody>
</table>

It is clear that most of research works have been focused on the field of adaptive communications for CR systems whereas the research community is lesser focused on other fields such as beamforming, power control, and scheduling. In addition, it is also obvious that, to the best of my knowledge, there has been no work done on the field of GA employment for optimizing the performance or coordination.
of cooperative spectrum sensing. Thus, this thesis presents the novelty of employing GAs for optimizing different CRN structures as well as CR systems with improved features.

2.10 SUMMARY

This chapter reviews many related aspects of cognitive radio, spectrum sensing, and related solutions. It begins with an introductory background to CR capabilities and potential applications in various engineering fields. The spectrum sensing is presented in details as a key concept to realize dynamic spectrum solutions such as CR. The evaluation procedure of detection performance is also explained. The common challenges to realize efficient sensing schemes are reviewed. The local spectrum sensing schemes are then extended to cooperative architectures and common fusion approached of sensing data and sensing decisions are introduced as well as some other DSA aspects. After providing the previous CR and spectrum sensing concepts, the chapter proceeds to deliver brief background on the GA mechanism and associated operators and parameters. Finally, a review on the literature of GA applications on CR research fields is presented. This includes employing GAs for adaptive CR systems, channel modelling, resource allocation, beamforming and scheduling. This chapter is considered as a cornerstone reference that cover most of the research methods and components used on the following chapters.
CHAPTER III

MOGA-ASSISTED DECISION ENGINE FOR CR SYSTEMS

3.1 INTRODUCTION

In a CRN, a CR node should be able to autonomously adapt to surrounding environmental conditions by means of configurable parameters or “knobs”. This chapter presents a realization of a CR system by incorporating a GA decision engine on it. The research methodology followed in this chapter is as outlined in Chapter I. Various steps are implicitly explained within the text to improve the chapter readability. This chapter begins with introducing the motivation towards the modulation scheme proposed for CR systems and problem formulation. The, the CR system development, performance evaluation, and sensitivity analysis is presented.

3.2 PROBLEM FORMULATION

To develop a CR system, the main challenge is to propose a cognition entity that maps the CR input parameters to its output parameters based on predefined performance objectives. For a system to be cognitive, it should be aware of the surrounding wireless conditions and able to autonomously adapt to a certain transmission mode that optimizes the overall performance of the system. This awareness of channel condition is realized by defining the CR inputs as environmentally sensed parameters which are used in conjunction with predefined radio objectives to determine an optimal setting of transmission parameters. A simplified crucial diagram of the cognition components of a CR system is depicted in Figure 3.1. In the next sections, a
detailed explanation of the proposed environmental parameters, transmission parameters and interrelated performance objective functions are presented.

3.2.1 Proposed Elements of CR System

In this section, a detailed presentation of the proposed environmental parameters, transmission parameters, and corresponding objective functions of a CR system is provided. In fact, the proposed parameters are chosen to characterize the operational parameters of a CR transceiver carefully. These parameters should not be redundant to avoid unreasonable emphasis on a certain adaption direction as well as to reduce unnecessary computational complexity. This applies for the proposed objective functions as well.

(i) Transmission parameters: Environmental parameters are responsible of enabling the CR system to alert to the surrounding environment so that the QoS of the system is maximized. This information is periodically sensed by external sensors and can be better classified as CR system dials. Table 3.1 displays the type of environment parameters implemented in this research work.
Table 3.1 Proposed environmental parameters

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Received power</td>
<td>$P_r$</td>
<td>Power estimation of the received signal.</td>
</tr>
<tr>
<td>Noise power</td>
<td>$N$</td>
<td>Magnitude in decibels of the noise power</td>
</tr>
<tr>
<td>Path Loss</td>
<td>$PL$</td>
<td>Amount of signal power degradation due to the channel path characteristics.</td>
</tr>
</tbody>
</table>

A brief justification on selecting these parameters is presented herein. Just as in any communication system, the received power ($P_r$) estimation is an important parameter which provides information to the CR receiver about the channel condition. Together with the noise power ($N$), the received power determines the signal-to-noise (SNR) ratio used as an indicator that helps the CR transceiver to make a decision on the modulation scheme that should be used. For example, if the SNR estimate is good, a modulation scheme with high index can be used whereas if the SNR is too low, binary signalling might be the choice of transmission. When the received power is measured, the noise power should be first sensed in order to determine the SNR. The noise power sensing can be done by sending beacons with known power between to cooperative CR nodes and observe the degradation occurred at the receiving node. The noise power estimate will be then shared with all CR system in the vicinity through dedicated control channels. The path loss ($PL$) is the decrement in the signal power strength as it travels through space. This decrement may be due to free-space loss, refraction, reflection, diffraction, and absorption. A Similar mechanism to that of the noise power sensing can be followed to sense the path loss as well. These informative feedbacks realize a sort of intelligence which is highly needed at the CR transceiver to optimize its performance objectives and for making decisions on the transmission parameters should be used.

(ii) Transmission parameters: The transmission parameters are envisioned as system knobs that can adapt based on the measured readings of environmental parameters dials and under the instruction of predefined objective functions. In the context of optimization, they can also be defined as decision variables that need to be determined based on prescribed optimization procedure. The transmission parameters characterize the transmission style of the CR system and realize its cognition functionality. In this
work, the proposed transmission parameters with their corresponding symbols and description are tabulated in Table 3.2. It is assumed that each CR system owns a unique set of these parameters but every CR can independently adapt to a certain transmission scenario based on its local observation.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmit power</td>
<td>$P_t$</td>
<td>Raw transmission power of the CR system.</td>
</tr>
<tr>
<td>Modulation index</td>
<td>$M$</td>
<td>The constellation size in $M$-ary signaling.</td>
</tr>
<tr>
<td>Symbol rate</td>
<td>$R_s$</td>
<td>Number of symbols per second.</td>
</tr>
</tbody>
</table>

Indeed, one cannot imagine that the CR system can create infinite number of transmission choices due to infeasibility reasons. Thus, the transmission choices should be limited a finite set of transition options with considerable diversity. To achieve this goal, a distinct discrete range or *search space* for each transmission parameter should be first defined. This search space is introduced as a pool of potential solutions to the intelligent core (i.e. the GA decision engine) in Figure 3.1. The intelligent core performs its optimization activity to come out with the best optimal combination of transmission parameters based on tradeoffs of predefined CR objectives.

In this work, the proposed discrete range of each parameter in Table 3.2 is as follows: The range of transmit power ($P_t$) varies from 10 dBm to 25 dBm with 1 dBm incremental step size. The modulation index ($M$) is chosen to be any of eight possible values \{2, 4, 8, 32, 64, 128, 256, 512\}. Practically, phase shift keying (PSK) is commonly used for low modulation indices (i.e. when $M$ equals to or less than 8) whereas quadrature amplitude modulation (QAM) is used for higher orders. Thus, the proposed modulation schemes used in this research are 2-PSK (or BPSK), 4-PSK, 8-PSK, 32-QAM, 64-QAM, 128-QAM, 256-QAM, and 512-QAM. The 16-QAM has been excluded as it approximately provides the same error performance of 8-PSK as can be seen later. The proposed choices of modulation schemes (i.e. types plus indices) offer modulation diversity needed for the CR adaption requirement. The
symbol rate \( (R_s) \) in kilo symbols per second (ksp) used in this research ranges from 125 ksp to 1Msps with an incremental step of 125 ksp.

(iii) **Objective Functions:** The intelligent core of a CR system is the optimization engine which returns optimized solutions or setting for the transmission parameters based on the sensed environmental parameters under the control of predefined performance objectives. These objectives are defined as formalisms that map every set of environmental parameters to a mirrored set of transmission parameters, and they should reflect a satisfactory representation of CR system metrics, requirements, and functionalities. For example, minimizing BER is a quality metric whereas maximizing spectral efficiency is a performance requirement in a sense. The CR system, being cognitive, should be able to find the optimal setting of transmission parameters which optimize such objectives simultaneously. In this research, the proposed objectives of a CR system are listed in Table 3.3. The intelligent core is responsible to achieve a compromise between these objectives based on predefined tradeoff requirements.

<table>
<thead>
<tr>
<th>Objective Name</th>
<th>Description</th>
<th>Related parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimize bit error rate</td>
<td>To improve the overall BER of the transmission environment</td>
<td>{ P_t, M }</td>
</tr>
<tr>
<td>Minimize power consumption</td>
<td>To decrease the amount of power consumed by the system</td>
<td>{ P_t, M, R_s }</td>
</tr>
<tr>
<td>Maximize spectral Efficiency</td>
<td>To maximizing the usage of spectrum.</td>
<td>{ M, R_s }</td>
</tr>
</tbody>
</table>

The proposed objectives in Table 3.3 can also be thought of a mix of quality and quantity objectives. Minimizing bit error rate is a common aim of any communication system to assure good QoS and it is very much dependent on the modulation scheme used as well the channel condition. Also, for a CR transceiver, minimizing power consumption is a critical objective to ensure long life battery life. The CR system uses power to transmit its signal as well as to supply the computational and optimization processes of its intelligent core. Last but not least, maximizing the spectral efficiency is an essential requirement for any CR system since the whole idea of CR is how to use the bandwidth efficiently. It is a key
objective to achieve high data rates required when large amount of data needs to be transmitted such as when sending audio/video streaming.

The catalysts that construct these objectives are the transmission parameters listed earlier where each objective is a function of certain set of parameters as shown in Table 3.3. These dependencies of objectives on corresponding parameters can be traced by analyzing the mathematical representation of each objective. The first objective \( f_i \) which is to minimize BER \( (f_{\text{min\_BER}}) \) is mathematically expressed as follows

\[
 f_1 = f_{\text{min\_BER}} = 1 - \frac{\log(0.5)}{\log(BER)}
\]  

(3.1)

where BER is the probability of bit error for a given modulation scheme. Equation (3.1) is the so-called fitness function of the minimizing BER objective. It is formulated to obtain a range between 0 and 1. Take note that the higher the better for this objective since it has been complemented to change it from a minimization problem to a corresponding maximization problem. The log base 10 is taken for BER as well as the worst BER case of 0.5 to provide a linear scale based on the exponent. The BER is calculated for M-ary PSK (MPSK) and M-ary QAM (MQAM) of the modulation indices earlier and can be expressed as (Sklar 2001)

\[
 BER_{\text{BPSK}} = Q\left( \sqrt{\frac{2E_b}{N_0}} \right), \; M = 2
\]  

(3.2)

\[
 BER_{\text{MPSK}} \approx \left( \frac{2}{k} \right) Q\left( \sqrt{\frac{2kE_b}{N_0}} \sin\left( \frac{\pi}{M} \right) \right), \; M > 2
\]  

(3.3)

\[
 BER_{\text{MQAM}} \approx \left( \frac{2 \left( 1 - L^{-1} \right)}{\log_2 L} \right) Q\left( \sqrt{\frac{3 \log_2 L}{L^2 - 1}} \frac{2E_b}{N_0} \right)
\]  

(3.4)
where $k$ is the number of bits per symbol, $k = \log_2(M)$, $E_b/N_0$ is the bit energy-to-noise power spectral density ratio, and $L = \sqrt{M}$. The $E_b/N_0$ can be further expressed in terms of the received signal power, $P_r$, as follows

$$\frac{E_b}{N_0} = \frac{W}{R_b} \frac{P_r}{N}$$  \hspace{1cm} (3.5)$$

where $W$ is transmission bandwidth, $R_b$ is the bit rate, and $N$ is the noise power. For MSPK and MQAM, the spectral efficiency is given by $R_b/W = \log_2(M)$. Also, the received power, $P_r$, can be expressed as

$$P_r = G_t G_r \frac{P_i}{PL}$$  \hspace{1cm} (3.6)$$

where $G_t$ is the CR transmit antenna gain, $G_r$ is the CR receiving antenna gain, and $PL$ is the path loss. Thus, (3.5) can be re-written as

$$\frac{E_b}{N_0} = \frac{P_i}{kN} \frac{G_t G_r}{PL}$$  \hspace{1cm} (3.7)$$

Equations (3.6) and (3.7) play an important mapping role between the environmental parameters $P_r$ and $N$ as inputs to the intelligent core of the CR system with $P_t$ and $M$ as output transmission parameters.

For the objective of minimizing-power consumption, all contributing factors to the power usage should be included. The proposed contributing factors in this work are, of course, the transmit power as well as the power consumption as a result of increased complexity when higher orders of modulation or higher symbols rates are used. To normalize the score of this objective to fall within the range from 0 to 1, the transmit power, modulation index and symbol rate are all divided by their maximum proposed values. This normalization is needed to have fair comparisons between different objectives by preventing an objective with a range of higher values to
dominate over another objective of a range of smaller values. The fitness function of the minimizing power consumption objective can be written as

\[
f_2 = f_{\text{min\_power}} = \alpha \left( 1 - \frac{P}{P_{\text{max}}} \right) + \gamma \left( 1 - \frac{\log_2 (M)}{\log_2 (M_{\text{max}})} \right) + \lambda \left( 1 - \frac{R_s}{R_{s_{\text{max}}}} \right)
\]  

(3.8)

where \(\alpha, \gamma,\) and \(\lambda\) are arbitrary weighting coefficients. For maximizing the spectral efficiency objective, the main contributing parameters are the symbol rate and the order of the modulation scheme used. The spectral efficiency increases by maximizing these two parameters at a fixed transmission bandwidth. This is true for bandwidth-limited systems such as MPSK and MQAM non-orthogonal signalling (Sklar 2001). The fitness function of the maximizing spectral efficiency objective can be simply written as

\[
f_3 = f_{\text{max\_spectral\_efficiency}} = \frac{\log_2 (M) \times R_s}{\log_2 (M_{\text{max}}) \times R_{s_{\text{max}}}}
\]  

(3.9)

To cope up, these objective functions are developed by dividing the variable score to its maximum possible value to attain a normalized range falls within (0, 1). The justification behind this normalization is to prevent the optimization trend being attracted to the objectives of relatively large magnitudes. It is also worth to notice that each of the three objective functions \(\{f_1, f, f_3\}\) is mathematically formed to be a maximization problem by transforming any \(f_i\) minimization objective to an equivalent \((1 - f_i)\) maximization objective, where \(i = 1, 2,\) or 3.

3.2.2 Observation of Conflicting Objectives

The proposed objective functions listed in Table 3.3 forms the radio objectives of the CR system which characterize the mutual relationships between the environmental and transmission parameters. These objective functions are used to drive the adaptive CR system to an optimal transmission mode at which the QoS and overall performance is maximized. Unfortunately, a certain objective of the proposed ones
might conflict with another. For instance, using a higher modulation index for a specific modulation scheme increases the throughput or spectral efficiency of the CR system, but at the same time, it consequently increases the BER. Also, increasing the transmit power reduces the BER and therefore, the objective function of minimizing BER improves. But instantaneously, this increment of transmit power increases the power consumption and hence, the objective function of minimizing the power consumption degrades.

Figure 3.2 shows the error performance of MPSK and MQAM in AWGN environment obtained from Equations (3.2) to (3.4). As a matter of fact, the error performance degrades as the modulation index $M$ increases. Definitely, increasing the modulation index means that the number of constellations increases and consequently, the distances between these constellations decrease which lead to higher probability of errors due to overlapping the detection/decision regions of the corresponding symbols. Figure 3.3 maps the corresponding environmental parameters of {$P_r$, $PL$, $N$} represented by {$E_b/N_0$, $M$} to their related scores in the fitness function of the minimizing-BER objective.

![Figure 3.2 Error performance of MPSK and MQAM schemes.](image-url)
Figure 3.3 confirms the superiority of low-order modulation schemes, such as 2-PSK, over high-order modulation schemes in satisfying the objective/fitness function of the minimizing-BER. However, high order modulation schemes have better spectral efficiency since higher number of bits-per-symbol can be enclosed. This tradeoff between quality (i.e. BER) and quantity (i.e. throughput) is one of the challengeable issues of CR systems. This variety of schemes with different modulation indices realizes the modulation diversity which will allows the CR system to be able to adapt to more operational and transmission choices based on the current environmental situation. Figure 3.4 shows the influence of increasing the level of transmitting power, which lead to an increase in the received power level represented by $E_b/N_0$, in the objective function of minimizing-power consumption. It is clear that either increasing the transmitting power or modulation index leads to decrement in this objective function. Figure 3.5 also shows degradation in the objective scores of minimizing power consumption as a result of increasing the symbol rate. The results in Figure 3.4 and Figure 3.5 follow equation (3.8) with $\alpha = \gamma = \lambda = 1/3$. 
Figure 3.4  Fitness of minimizing-power consumption objective versus $E_b/N_0$ for various MPSK and MQAM schemes.

Figure 3.5  Fitness of minimizing-power consumption objective versus symbol rate for various MPSK and MQAM schemes.
Figure 3.6 depicts the effect of varying the symbol rate as well as the modulation index of MPSK and MQAM schemes in the objective function of maximizing the spectral efficiency. The simulation results in this figure follow the simple relationship in (3.9). Of course, increasing either one, the symbol rate or modulation index, results in better scores of the mentioned objective. More emphasis on this objective should be given when large amount of data needs to be transmitted with high rates such as in multimedia video/audio applications.

Obviously, there exist contradictory relationships among these individual objectives when varying their corresponding parameters. These conflicting trends of the proposed objectives observed in Figure 3.3 to Figure 3.6 are graphically summarized in Figure 3.7. Remember that $f_1 = f_{\text{min\_BER}}$, $f_2 = f_{\text{min\_power\_consumption}}$, and $f_3 = f_{\text{max\_spectral\_efficiency}}$. As can be seen, increasing $P_t$ results in increasing $f_1$ but decreasing $f_2$, increasing $M$ results in decreasing $f_1$ and $f_2$ but increasing $f_3$, and finally, increasing $R_s$ leads to deceasing $f_2$ but increasing $f_3$. Thus, optimization schemes should be employed to search for the best combination of transmission parameters which satisfies a balanced compromise between such conflicting objectives.

Figure 3.6 Fitness of maximizing-spectral efficiency objective versus symbol rate for various MPSK and MQAM schemes.
As mentioned in Section 2.7.2, the obtainable solutions of optimizing conflicting objectives are commonly called as Pareto-front solutions, or non-dominated solutions. In fact, these solutions are non-optimal under any arbitrary one single objective as no improvement can be further achieved in any direction. Figure 3.8 shows a Pareto-front tradeoff between minimizing BER and minimizing power consumption labelled on x- and y-axis, respectively. The Pareto-front solutions are those located on the nearest curve to the right-upper corner which represents joint maximization of both objectives. It is clear that the Pareto-front occurs at the 2-PSK curve. However, the 2-PSK performs poorly in comparison to, for instance, 256-QAM, if the objective of maximizing spectral efficiency is involved. This observation of confliction among various objectives calls for the use of an innovative optimization scheme to be implemented into the intelligent core of the CR system to autonomously find the Pareto-front solutions (i.e. transmission parameters) for different channel conditions.
Figure 3.8  Pareto-front tradeoff between minimizing-power consumption versus minimizing-BER objectives for various MPSK and MQAM schemes.

In this research work, a naturally-inspired optimization algorithm, namely, genetic algorithm is employed to add in the cognition functionality to the intelligent core of the CR system.

3.3 SYSTEM DEVELOPMENT

This research work presents the idea of using multi-objective genetic algorithm (MOGA) decision engine as an intelligent core for CR systems. The following sections provide insight explanation on the proposed CR system and its functionality.

3.3.1 System Architecture

The proposed architecture of the MOGA-based CR system is depicted in Figure 3.9. The CR system extracts data of channel condition via its environmental parameters and passes them to a multi-objective decision maker. The decision maker fits the environmental parameters into their corresponding objective functions and passes them to the GA optimization engine. The tuner of CR transmission scenario is used to assign
a distinct weighting coefficient for each radio objective. These different weighting coefficients are used to vary the priority level among radio objectives where the largest weighting coefficient is allocated for the objective of highest priority. The other benefit of using these weighting coefficients is to convert the multiple objective functions into one single multi-objective function through the weighted-sum approach explained in section 2.7.3. Without loss of generality, the sensed environmental parameters together with the weighting coefficients assigned to the three radio objectives of Equations (3.1), (3.8), and (3.9) construct the multi-objective fitness function on which the GA optimization engine works to find a Pareto-front solution set of transmission parameters. This multi-objective fitness function, \( F \), can be expressed using the weighted-sum approach as follows

\[
F = \sum_{i=1}^{n} \omega_i \times f_i \\
\text{subject to } \sum_{i=1}^{n} \omega_i = 1 \\
\text{and } \omega_i \geq 0
\]  
(3.10)

where \( n \) is the number of proposed single objective functions (i.e. \( n = 3 \)).

Figure 3.9 Proposed MOGA-base CR system architecture
3.3.2 CR Transmission Modes

The weighted-sum approach used to combine the individual single objective functions into one scalar multi-objective function suits the adaptability requirement of CR systems well as it is envisioned as a flexible yet efficient mechanism to steer the optimization process towards the objective of highest priority by assigning it a higher weight. The weighted-sum approach is also useful to model the conflicting objectives into a single formalism allowing the GA-based intelligent code to return a Pareto-front solution that maximizes this aggregated fitness function. Thus, performance tradeoffs can be readily performed by adjusting the weighting coefficients of the individual objectives. The tuner of CR transmission mode in Figure 3.9 is seen as a weighting system enabling a means of prioritization to rank the relative importance of each objective in comparison to others. Thus, the trend of the aggregated multi-objective function can be easily steered by simple tuning of the weighting vector. For the proposed three individual objectives in (3.1) to (3.8), the multi-objective function in (3.9) becomes

\[ F = \omega_1 \times f_1 + \omega_2 \times f_2 + \omega_3 \times f_3 \]  

(3.10)

In this research work, three distinct CR transmission modes or scenarios are defined by assigning a relatively higher weight to the fitness function of a specific objective and lower weights for others. In addition, another mode is introduced by fair distribution of weights among the three objectives. The resulting four modes are named and listed as in Table 3.4. The reliable communication mode is defined and used when a reduced error probability is of demand such as in emergency or disaster cases. This requires more emphasis to be focused on the objective of minimizing bit error rate. The CR user can switch to the power-saving mode when the battery of his device declares low power status. This scenario aims to minimizing transmitting power for the benefit of long battery power sustainability. The spectrally-efficient mode can be used when large amount of data need to be transmitted such as in video streaming. To realize each of the preceding transmission modes, a weight of 80% is arbitrarily assigned to the objective of highest priority whereas the other objectives share the remaining 20% weight. Other weighting distributions are still feasible. Finally, the balanced mode is
introduced when fairness among all objectives is needed. This mode can be realized by assigning equal weights for all single objectives as shown in Table 3.4. Each multiobjective function (MOF) in the table is obtained by plugging in the corresponding weighting vector into equation (3.10).

Table 3.4 Definition of CR transmission modes

<table>
<thead>
<tr>
<th>Transmission Mode</th>
<th>Weighting Vector</th>
<th>Corresponding MOF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reliable communication mode (RCM)</td>
<td>[0.8 0.1 0.1]</td>
<td>$F_{RCM}$</td>
</tr>
<tr>
<td>Power-saving mode (PSM)</td>
<td>[0.1 0.8 0.1]</td>
<td>$F_{PSM}$</td>
</tr>
<tr>
<td>Spectrally-efficient mode (SEM)</td>
<td>[0.1 0.1 0.8]</td>
<td>$F_{SEM}$</td>
</tr>
<tr>
<td>Balanced mode (BLM)</td>
<td>[1/3 1/3 1/3]</td>
<td>$F_{BLM}$</td>
</tr>
</tbody>
</table>

3.3.3 GA Configuration

In this section, the optimization problem of obtaining the transmission parameters, which maximize the CR multi-objective fitness function defined in (3.10), is configured into a GA framework. The GA mechanism explained in section 2.2.2 is now employed for the purpose of maximizing the CR multi-objective function. Here, it is worth to say that most of the GA operations are actually independent of the problem given in terms of configuration. However, specific settings of GA parameters show better convergence performance than others. Unfortunately, there is no rule-of-thumb to determine this optimal setting of GA parameters in advance. This optimal setting is achieved through a set-and-test approach.

For a given optimization problem, the essential challenge lies on how to represent this problem in a GA formalism. More specifically, an efficient way of how a GA chromosome can represent a potential solution for the problem given should be developed. The process of constructing a meaningful chromosome is commonly known as chromosome encoding. Due to the almost discrete nature of the CR adaption problem, a binary GA is invoked. Each chromosome in a binary GA population represents a potential solution of transmission parameters set. The three transmission parameters introduced in Table 3.2 are encoded as shown in Figure 3.10. The proposed
ranges or types of these parameters have been already presented in section 3.3.1. The range of transmit power from 10 dBm to 25 dBm is represented by four bits \(\{b_0, b_1, b_2, b_3\}\) which offers \(2^4\) possible values within this range. Eight modulation schemes, namely, 2-PSK, 4-PSK, 8-PSK, 32-QAM, 64-QAM, 128-QAM, 256-QAM, 512-QAM are used and encoded using the 3 subsequent bits \(\{b_4, b_5, b_6\}\). Different combinations of the string \(\{b_4, b_5, b_6\}\) are mapped to the \(2^3 = 8\) possible modulation schemes mentioned above. The \(2^3\) possible combinations of the string \(\{b_7, b_8, b_9\}\) are mapped to the range of symbol rate varying from 125 kbps to 1Mbps with an increment of 125 kbps. Thus, each chromosome of the randomly-generated GA population consists of ten bits which results in \(2^{10}\) possible solutions each of which constructs a potential setting for the transmission parameters of the CR system.

To perform GA operations on a population of chromosomes, each chromosome should be first evaluated to estimate its fitness score. This can be done by decoding all strings (traits) of bits (genes) to their respective transmission parameters and feed them into the multi-objective function for evaluation. Finer power/rate resolution and more modulation schemes can be used by extending the chromosome length. However, this extension might also require larger population size and consequently, the computational complexity increases. Careful selection of chromosome length should be always maintained to attain satisfactory convergence performance for such a real-time application.

Figure 3.10 Chromosome encoding of CR transmission parameters
3.4 PERFORMANCE EVALUATION

This section presents computer simulations of the developed MOGA-based CR system performance under various transmission modes. The convergence performance as well as the obtainable transmission parameters after GA optimization is shown. The convergence performance is described by the number of generations needed to find the Pareto-front solutions. These obtained solutions are analyzed in correspondence to the belonging CR transmission modes to verify the correct functionality of the proposed system.

3.4.1 Simulation Parameters and GA Operators

As has been mentioned earlier, there is no rule-of-thumb to choose the best combination of GA operators and parameters for a given optimization problem. Thus, the GA parameters used in this research are of standard settings suggested in the literature (De Jong 1975; Grefenstette 1986; Schaffer et al. 1989) with minor variations as a result of observations realized by plug-and-test experiments. The initial GA population of 20 chromosomes is randomly generated. Each chromosome has a length of 10 bits as explained in section 3.4.3. Roulette wheel selection, Two-point crossover with a rate of 95%, and bit-flip mutation with a rate of 0.001 are appropriately implemented. An elitism rate of 10% is kept to maintain the best solutions in every parent population. The evolutionary optimization process of GA is terminated after 100 generations and the best chromosome in the last population is extracted, decoded, and displayed as a Pareto-front solution which achieves a well-balanced compromise between the conflicting objectives.

3.4.2 Performance Evaluation of MOGA-based CR Systems

In this section, the performance of the MOGA-based CR system is simulated under the four transmission modes proposed in Table 3.4. For each mode, the obtained solution after terminating the GA evolutionary processes is analyzed to verify its adequate satisfaction of the CR system requirements under this mode.
(i) MOGA-based CR system performance under reliable communication mode (RCM): Under this transmission mode, more emphasis is placed on the objective of minimizing-BER to realize a scenario of reliable transmission and reception. The performance of the MOGA-based CR system is depicted in Figure 3.11. The simulation graph shows the progress of multi-objective fitness (MOF) function under RCM (i.e. $F_{RCM}$) as the number of generations goes on. The mean fitness shown in the graph is the average of chromosome fitness scores across the whole population in every generation whereas the maximum fitness represents the best chromosome fitness found in the population in every generation. This MOF score versus number generations is a common practise to evaluate the performance of GA convergence towards the Pareto-front solution for the problem given. Figure 3.11 shows the online performance obtained by running the MOGA-based CR system for a given set of environmental parameters. The maximum achievable fitness is 0.8608 obtained within the first 45 generations which is said to be fast enough to meet real-time requirements. The Pareto-front solution obtained for transmission parameters’ setting under RCM returns a transmit power of 22 dBm, a modulation scheme of 2-PSK, and a symbol rate of 125 k symbol per second (ksps). The transmission parameters are tabulated in Table 3.5 for further comparison and analysis with other transmission parameters obtained under other transmission modes.

Figure 3.11  MOF score versus number of generations under RCM.
(ii) MOGA-based CR system performance under power-saving mode (PSM): The convergence performance of the MOGA-based CR system under PSM is shown in Figure 3.12. The simulation graph presents the incremental progresses of mean (average) and maximum (best) fitness with the number of generations. The maximum achievable fitness under this mode is 0.8120 captured after 32 generations. As tabulated in Table 3.5 for PSM, the Pareto-front solution observed after upon terminating the algorithm after 100 generations returns a transmit power of 11 dBm, a modulation scheme of 2-PSK, and a symbol rate of 125 ksp.

![Figure 3.12 MOF score versus number of generations under PSM.](image)

(iii) MOGA-based CR system performance under spectrally-efficient mode (SEM): When large amount of data needs to be sent or relayed while maintaining high spectral efficiency, the weighting coefficients of the MOF function are distributed such that maximizing spectral efficiency is prioritized. As presented in Table 3.5, the obtained Pareto-front transmission parameters are a transmit power of 11 dBm, a modulation scheme of 512-QAM, and a symbol rate of 1000 k symbol per second (i.e. 1 Msps). The results are obtained after premature convergence of only 10 generations scoring a normalized MOF value of 0.89. Obviously, the fast convergence speed is always preferable since the MOGA-based CR system works in real-time condition.
(iv) MOGA-based CR system performance under balanced mode (BLM): In BLM, the three single objective functions constructing the MOF are all given equal weights. This scenario might be utilized by the MOGA-based CR system in cases where no particular operational plan exists or when the system requires no major attraction in favour of a specific objective in comparison with other objectives. The convergence performance of the system is shown in Figure 3.14 and Figure 3.15. It is observed that two potential solutions can be obtained in different runs each of which is of 100 generations. The convergence performance of the MOGA-based CR system under BLM for the first obtainable solution is shown in Figure 3.14 with a maximal achievable MOF of 0.6334 found after 26 generations. Figure 3.15 shows another potential solution obtained after 13 generations only scoring a maximum achievable MOF of 0.6089. The decoded transmission parameters observed at these two obtainable Pareto-front solutions are both tabulated in Table 3.5. In fact, the simulation results obtained across all transmission modes are recorded for online performance with 100 generations at maximum. Thus, it is likely to have more than one unique solution with this small number of iterations.
Figure 3.14  MOF score versus number of generations under BLM (Solution 1).

Figure 3.15  MOF score versus number of generations under BLM (Solution 2).
3.4.3 Discussion of Results

In this section, the obtainable Pareto-front solutions of transmission parameters under RCM, PSM, SEM, and BLM shown in Figure 3.11 to Figure 3.15 are summarized and discussed. Here, it is worth to remind again on the suggested ranges of transmission parameters that are from 10 dBm to 25 dBm for $P_t$, all the possibilities from 2 to 8 for $M$ of PSK and from 32 to 512 for $M$ of QAM, and from 125 kbps to 1000 kbps with incremental step of 125 kbps for $R_s$.

Table 3.5 Summary of simulation results of CR system performance

<table>
<thead>
<tr>
<th>Transmission Mode</th>
<th>Pareto-front Solution</th>
<th>Convergence Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_t$ (dBm)</td>
<td>$M$</td>
</tr>
<tr>
<td>RCM</td>
<td>22</td>
<td>2</td>
</tr>
<tr>
<td>PSM</td>
<td>11</td>
<td>2</td>
</tr>
<tr>
<td>SEM</td>
<td>11</td>
<td>512</td>
</tr>
<tr>
<td>BLM</td>
<td>11, 18</td>
<td>512</td>
</tr>
</tbody>
</table>

Under RCM, the dominating priority is placed on the objective minimizing BER. Thus, the transmission parameters which determines the modulation scheme used in response to the instantaneous environmental parameters should return a low order modulation index because of their superior error performance. In addition, this transmission mode requires the CR system to transmit with a relatively high power to enhance the detectability of signals at the receiving nodes and to be able to face and overcome potential channel fades and path losses so that a reliable communication can be assured. The transmission parameters obtained from Figure 3.11 and tabulated in Table 3.5 show a transmit power of 22 dBm under RCM. As expected, and considering the available power range, the selected power suits the RCM requirement since it is large enough to ensure good receivable power at receiving nodes. Also, the MOGA-based intelligent core of the CR system has selected 2-PSK as a modulation scheme to be used. This selection is also adequate since such a low order modulation scheme can offer good error performance since the receiving node will have to distinguish between regions of lesser number of constellation points. The symbol rate
returned is 125 ksp s and this also anticipated in RCM since higher rates will result in unnecessary higher power consumption. From Pareto-front point of view, the obtained solution is definitely sub-optimal. This can be observed by the selected transmit power being 22 dBm not 25 dBm. However, this is the best compromise that can be agreed with among the three proposed conflicting objectives.

The obtained transmission parameters under PSM are as shown in Table 3.5. Under this scenario, the power consumption should be minimized. The transmit power selected by the MOGA-based decision engine returns a low 11 dBm level of transmit power. This proves the correct functionality of the CR system employing MOGA. Also, the modulation scheme selected is 2-PSK which also ensures low power consumption, and finally, the symbol rate found by the evolutionary processes of MOGA is only 125 ksp s which again minimizes the objective of minimizing-power consumption.

When the MOGA-based CR system is being under SEM, the highest priority objective is to achieve high spectral efficiency so that more date can be sent out in shorter time frames. Assuming a fixed allowable bandwidth such as in non-orthogonal signalling of PSK and QAM, the optimization problems can be said to be maximizing the achievable throughput of the CR system; that is maximizing it data rate. The simulation results of the CR system shows that the MOGA intelligent core returns a symbol rate is 1000 ksp s with 512-QAM modulation scheme. Obviously, these parameters of high symbol rate and high modulation index allow the CR system to transmit as a rate of 9 Mbps.

Under BLM, the MOGA intelligent core of the CR system returns two possible solutions when it runs online for 100 generations. The corresponding transmission parameters of these two solutions are tabulated as shown in Table 3.5. It can be observed that in the first Pareto front solution, the MOGA returns low \( P_t \) and high \( \{ M, R_s \} \) whereas in the second solution, average \( P_t \) and low \( \{ M, R_s \} \) is returned. Take note that the Pareto-front includes more than one unique solution as can be seen in Figure 2.7. Interestingly, the returned values of transmission solutions under BLM has a sort of complementary or water-filling relationship between the transmit power
on one side and the symbol rate and modulation index on the other side. Also, since all objectives enjoy fairness, the MOGA works freely to return any possible solution that maximizes the MOF score within the proposed number of generations.

3.5 ADAPTIVE VERSUS STATIC TRANSMISSION PARAMETERS OF MOGA-BASED CR SYSTEM

To prove the effectiveness of the proposed adaptive MOGA-based CR system, the sub-optimality of the obtained Pareto-front solutions under the RCM, PSM, and SEM is verified. The followed verification procedure compares the MOGA-based CR system whose transmission parameters are fully adaptive, as presented earlier, with the same system but with static setting of transmission parameters. The semi-adaption property of the CR system is realized by selecting one transmission parameter each time and set it to a static value and compare it with a fully adaptive CR system under different transmission modes. The performance metric considered in the comparisons is the maximum MOF. The maximum MOF achieved in every experiment of testing the transmit power, the modulation index, and the symbol rate is extracted and tabulated in Tables 3.6, 3.7, and 3.8, respectively. The total number of simulation experiments for the three parameters with one adaptive and three static settings under four the transmission modes is 48. However, only the MOF values are extracted and tabulated into the corresponding tables as below.

Table 3.6 presents the MOF scores of the MOGA-based CR system with adaptive transmit power as well as with three static values set at 15 dBm, 18 dBm, and 25 dBm under the proposed transmission modes. The sensitivity of a transmission parameter is defined as the dynamic range or change amount of the achievable MOF when varying the setting of this transmission parameter. It is clear that the achievable MOF of the CR system under PSM shows high sensitivity to the setting of transmit power in comparison to other transmission modes. This is basically expected since in PSM, a high weighting coefficient is placed on the objective function of minimizing-power consumption. Thus, varying the transmit power level results in a considerable change on the MOF score. Under RCM, SEM and BLM, the transmit power has no major effect since it receives a reduced weight and therefore, lesser effect.

Table 3.6 Effect of varying the setting of CR transmit power
Next, the effect of modulation index on the MOF score is shown in Table 3.7. The modulation index has been set to be adaptive and then static at 4, 64, and 256. It is clear that changing the modulation index has a major effect on the MOF score under RCM, PSM and SEM. This is because the modulation index is playing an important role on minimizing BER under RCM, minimizing power consumption under PSM, and maximizing spectral efficiency under SEM. The effect of the modulation index under BLM is overwhelmed by the other transmission parameters.

Finally, the symbol rate is set to be adaptive and then static at 250 ksps, 500 ksps, and 875 ksps. As seen in Table 3.8, it is observed that the MOF score is said to be sensitive under PSM and SEM. This sensitivity can be justified by stating that the symbol rate has a major effect on the objective of maximizing spectral efficiency which is the most prioritized objective under PSM as well as under SEM whereas it is overwhelmed by the transmit power and modulation index under RCM and BLM.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Maximum MOF Score under Transmission Mode (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_t )</td>
<td>RCM</td>
</tr>
<tr>
<td>Adaptive</td>
<td>86.08</td>
</tr>
<tr>
<td>15 dBm</td>
<td>85.18</td>
</tr>
<tr>
<td>18 dBm</td>
<td>85.03</td>
</tr>
<tr>
<td>25 dBm</td>
<td>82.54</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>Low</td>
</tr>
</tbody>
</table>

Table 3.7 Effect of varying the setting of CR modulation index

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Maximum MOF Score under Transmission Mode (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( M )</td>
<td>RCM</td>
</tr>
<tr>
<td>Adaptive</td>
<td>86.08</td>
</tr>
<tr>
<td>4</td>
<td>84.57</td>
</tr>
<tr>
<td>64</td>
<td>72.46</td>
</tr>
<tr>
<td>256</td>
<td>66.11</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>High</td>
</tr>
</tbody>
</table>

Table 3.8 Effect of varying the setting of CR symbol rate
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Maximum MOF Score under Transmission Mode (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_s$</td>
<td></td>
</tr>
<tr>
<td>Adaptive</td>
<td>86.08</td>
</tr>
<tr>
<td>250 kbps</td>
<td>82.27</td>
</tr>
<tr>
<td>500 kbps</td>
<td>84.35</td>
</tr>
<tr>
<td>875 kbps</td>
<td>83.35</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>Low</td>
</tr>
</tbody>
</table>

The simulation results CR system under different transmission scenarios prove that the achievable MOF score of the fully adaptive MOGA-based approach is always the highest when compared to semi-adaptive configuration where certain transmission parameters are arbitrarily set to static values. At these maximized MOF scores, the corresponding transmission parameters are the Pareto-front or sub-optimal solutions at which a balanced compromise among the conflicting objectives is attained. The proposed MOGA-based CR systems realizes the cognition functionality by sensing the environmental parameters represented by noise power, received signal strength, and channel path loss and then, adapting to a certain set of transmission parameters based on transmission requirements or user preferences.

3.6 SUMMARY

In this chapter, a CR system with its environmental and transmission parameters as well as objective functions is proposed. The proposed environmental parameters are the received power, noise power, and path loss estimation whereas the transmission parameters are transmission power, the modulation scheme, and the symbol rate. The objective functions that formulate the relationships between these parameters are also proposed. Then, an analytical simulation study was carried out to show the contradictory nature of the proposed objectives. These conflicting objectives are then aggregated into one overall multi-objective function through the use of variable weighting coefficients that can be adjusted to define distinct transmission scenarios. The selection among these transmission scenarios is assumed to be based on the user preferences or possibly according to environmental conditions. These distinct transmission modes are the reliable communication mode (RCM), the power-saving
mode (PSM), the spectrally-efficient mode (SEM) and the balanced mode (BLM). The proposed MOGA decision engine is developed to be able to optimize the transmission parameters, for a given set of sensed environmental parameters, which can satisfy the requirements of the predefined transmission mode. The performance of the proposed MOGA system is evaluated and verified under the proposed transmission modes. It is shown that the proposed MOGA decision engine is able to search for and find the sub-optimal or Pareto-front solutions of transmission solutions within the first 50 evolutionary generations. This convergence speed makes the proposed MOGA decision engine feasible for such a real-time application. Under RCM, PSM, or SEM transmission modes, the proposed MOGA engine achieves a MOF score of more than 80%. This MOF score is a considerable achievement since it represents a compromise between several conflicting objectives. A lower MOF score of more than 60% is achieved when BLM transmission mode is used due to increased level of contradiction occurred when weighting coefficients are uniform assigned to the confliction objectives. Finally, sensitivity analyses have been carried out to prove the effectiveness of the proposed inclusion of the transmission parameters in the overall multi-objective performance.
CHAPTER IV

BOGA-ASSISTED HDF- BASED AND SOGA-ASSISTED SDF-BASED
COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO
NETWORKS

4.1 INTRODUCTION

In spectrum-sensing CRNs, several CR users collaborate together and share their information on PU activities. This collaboration can be realized by centralized or distributed means. In this research, a centralized architecture has been used due to its reduced communication overhead in comparison to distributed architectures. This chapter presents the employment of GAs for optimizing the performance of (hard decision fusion-) HDF- and (soft data fusion) SDF-based CRNs. For each of these two fusion approaches, the corresponding optimization problem is identified and formulated as an objective function(s) on which GA works, the GA-based optimization system is evaluated, and the obtainable solutions are analyzed to judge on the effectiveness of the proposed methodology. For HDF-based CRN, a bi-objective genetic algorithm (BOGA) is used whereas a single-objective genetic algorithm (SOGA) is used.

4.2 GENERIC CRN MODEL AND FUSION SCHEMES

Spectrum sensing is normally considered as a pure detection problem where the CR-assisted users have to scan a vast range of frequencies to observe available ‘white spaces’ or ‘holes’ that are temporarily and spatially available for transmission. The CR-assisted users are classified as secondary users (SUs) with lower access priority
than primary users (PUs) who are obviously, Licensees, or alternatively, users of existing technologies on unlicensed bands (e.g. IEEE802.11a).

The CRN deployment can be simply envisioned as was shown in Figure 1.3. From a functional perspective, CRN can also be seen as a network of two levels where the main activity on the first link (i.e. PU-SU link) is sensing whereas the main activity on the second link (i.e. SU-FC link) is relaying, as shown in Figure 4.1. Take note that the information to be relayed from SUs to FC differs in nature based on whether HDF or SDF scheme is employed at FC. In HDF-based CRNs, relaying of sensing decisions is to be conducted whereas relaying of sensing measurements is to be done in SDF-based CRNs as was shown in Figure 2.5. Detailed models for HDF- and SDF-based CRNs will be presented in section 4.3 and 4.4, respectively. In fact, there is a sensing-overhead tradeoff when using HDF- or SDF-based CRNs. HDF-based CRNs have lesser communication overhead since only individual 1-bit decisions are to be relayed from SUs to FC. However, making a decision at the SU stage leads to a loss of sensing information content which results in a reduced detection performance at the FC stage. On the other hand, SDF-based CRNs show better detection performance at the FC since sensing data from all SUs are combined but at the same time, heavy traffic overhead occurs on the SU-FC links due to the huge amount of data to be relayed from SUs to FC. These two approaches of fusion in CRNs are considered and related objective function(s) are proposed as fitness function(s) for GA.

![Figure 4.1](image)  
**Figure 4.1**  Simplified CRN model with its main activities.
4.3 BOGA-ASSISTED HDF-BASED COOPERATIVE SPECTRUM SENSING

In CRN, SUs are allowed to utilize the frequency bands of PUs when these bands are not currently being used. However, the SUs should willingly and quickly vacate the band once a PU has been detected. This fast vacation is necessary to avoid causing harmful interference to the PUs who should maintain ubiquitous and uninterrupted accessibility. Therefore, the SUs are required to periodically monitor the PUs activities using fast and reliable detection/sensing algorithms. In such algorithms, the PU(s) detection probability ($P_d$) and false alarm probability ($P_f$) measured at the SU or FC stage will be of interest. These two probabilities are directly related to the interference introduced to PU and the throughput of SU network, respectively. Higher probability of detection should always be targeted to make the PU more protected against SU interference whereas lower false alarm probability must be the main aim if the throughput of SU network or CRN needs to be maximized. Unfortunately, these two probabilities are inversely correlated as increasing the probability of detection leads to decreasing the probability of false alarm and vice versa, as shown in section 2.3.1. This conflicting nature leads to conflicting behaviour between objective of protecting PU and the objective of maximizing CRN throughput.

In this research, a CRN based on WRAN system deployment has been proposed. Each frame in WRAN consists of a sensing time slot plus a data transmission slot. Longer sensing time offers higher probability of detection and therefore, better PU detection. However, this long sensing time results in a reduction on the remaining time fraction that can be used for data transmission and hence it degrades the achievable throughput of CRN. This fundamental tradeoff among the conflicting objectives of maximizing PU protecting and maximizing SU accessibility requires an intelligent mechanism to formulate a sensing time duration that can jointly sub-optimize these two objectives.

Also, the fusion process at FC is performed by combining the individual sensing decisions from all existing SUs in the vicinity of the base station at which the FC is located. However, since the local sensing decision taken at every SU is very
much dependent on the corresponding SNR at the SU receiver, it is likely to obtain unreliable sensing decisions when the SNR of received signal is low. These unreliable decisions affect the overall detection performance at the FC stage upon combining them. This is because the inclusion of SUs with low SNR measures will contribute negatively on creating the final sensing decision. Therefore, again, the intelligent mechanism suggested above for finding the optimal sensing time should also be able to determine the cooperation level between $N$ existing SUs. The cooperation level is defined as the $k$-out-of-$N$ SUs with the highest SNRs that should collaborate to produce a reliable global sensing decision at the FC.

Thus, a GA-based intelligent mechanism is used to find a pair of sensing time and cooperation level that optimize the performance of cooperative sensing in HDF-based CRNs. This is the scope of research work in Section 4.3. The performance metrics used in this architecture are the PU protection as well as the CRN throughput. Thus, the proposed GA mechanism works on optimizing these two objectives and it is therefore termed as bi-objective genetic algorithm (BOGA).

### 4.3.1 HDF-based CRN System Model

The main attribute of the proposed HDF-based CRN is that the sensing measurement at every SU is locally processed to come out with an individual sensing decision. The resultant individual decisions from all SUs are then forwarded to the FC at which all decisions are aggregated to produce one global sensing decision on the availability of PU in a given band. The mathematical model of the deployed HDF-based CRN is graphically represented in Figure 4.2. The PU-SU link can be any of $M$ links from the PU to $M$ existing SUs whereas the SU-FC link can be any of the $M$ links from the SUs to the FC. The channel noise and gain of the $i$th PU-SU link is $W_i$ and $g_i$, respectively, where $i = 1, 2, \ldots, M$. $X_i[n]$ is the $n$th sample of the received sensing measurement at $SU_i$, $Y_i$ is the energy estimate of received measurement within $SU_i$, and $Z_i$ the sensing decision made at the output of the decision maker (DM) to be sent to FC. The global decision constructed at FC is denoted as $Z_g$. In order to achieve a synchronized sensing, relaying, and decision making processes, all SUs are assumed to monitor the PU activities within the same sensing time slot ($T_s$).
4.3.2 Energy Detection Model for Channel Sensing

In HDF-based CRNs, a local spectrum sensing method is used at the receiver of every SU. Local spectrum sensing can be realized by means of matched filter, energy detection, or cyclostationary feature detection. A detailed comparison between these different spectrum sensing techniques is presented in section 2.3.1. In this work, energy detector is employed due its fast processing speed in comparison to cyclostationary detection and also due to the practical assumption that the CR/SU system has no knowledge on the PU signal format as in the case of match filters. The potential two hypotheses of the received PU signal at SU$_i$ are defined as follows

\[ H_0: X_i[n] = W_i[n]; \quad \text{PU is absent} \]  \hspace{1cm} (4.1)
\[ H_1: X_i[n] = g_i S[n] + W_i[n]; \quad \text{PU is present} \]  \hspace{1cm} (4.2)

where \( n = 1, 2, \ldots, K \), and \( K = T_s f_s \) where \( T_s \) is the sensing time and \( f_s \) is the Nyquist sampling frequency. Take note that \( K \) is the number of samples of the received PU signal and it can be rewritten as \( K = 2 T_s B \) where \( B \) is the sensed bandwidth of interest.
$S[n]$ is the PU signal which is assumed to be independent and identically distributed (i.i.d.) Gaussian random process with zero mean and variance, i.e., $S[n] \sim \mathcal{N}(0, \sigma_S^2)$, and $W_i[n]$ is the $i^{th}$ sensing channel noise which is assumed to be additive white Gaussian with zero mean and variance $\sigma_{W_i}^2$, i.e., $W_i[n] \sim \mathcal{N}(0, \sigma_{W_i}^2)$. All these variances are collected into the vector $\mathbf{\sigma}_w = [\sigma_{w1}^2, \sigma_{w2}^2, ..., \sigma_{wM}^2]^T$, where $T$ is the transpose of the vector and the sampled signals received at the $M$ SUs are collected into the vector $\mathbf{X} = [X_1, X_2, ..., X_M]^T$. The channel gains of the PU-SU $\{g_i\}$ are assumed to be constant over each sensing period. Using the energy detector implemented at the receiver of every SU, the energy contents $Y_i$ of the sampled received signals $X_i[n]$ can be estimated as

$$Y_i = \sum_{n=1}^{K} |X_i[n]|^2 \tag{4.3}$$

The energy estimates $\{Y_i\}$ of all $M$ SUs are then compared with a local decision maker (DM) to come out with a local hard decision on PU availability. Next, all the individual decisions $\{Z_i\}$ are forwarded to the FC at which HDF scheme is employed to construct a global decision on PU availability. The energy estimate obtained from (4.3), $Y_i$, has a chi-square distribution with $K$ degrees of freedom with $K\sigma_w^2$ mean and $2K\sigma_w^4$ variance under $H_0$, and $K(\sigma_w^2 + \sigma_S^2)$ mean and $2K(\sigma_w^2 + \sigma_S^2)^2$ variance under $H_1$. Since low SNR environment is proposed at the receiver of every SU where $\text{SNR}_i = \frac{|g_i^2|\sigma_S^2}{\sigma_{w,i}^2}$, large number of samples should be used (e.g. $K \geq 100$) in order to improve the PU detectability. According to the central-limit theorem, chi-square distribution can be approximated by a Gaussian distribution when large number of samples is used. Thus, $Y_i$ under $H_0$ and $H_1$ can be statistically described as $(Y_i|H_0) \sim \mathcal{M}(K\sigma_w^2, 2K\sigma_w^4)$ and $(Y_i|H_0) \sim \mathcal{M}(K(\sigma_w^2 + |g_i|^2)|\sigma_S^2), 2K(\sigma_w^2 + |g_i|^2)|\sigma_S^2)^2)$, respectively. The detection probability ($P_d$) and false alarm probability ($P_f$) are defined as the probabilities that the sensing SU algorithm detects a PU under $H_0$ and $H_1$, respectively. Hence, the energy detector performance can be characterized by a resulting pair of $(P_f, P_d)$ defined as
\[ P_{f,i} = P(Y_i > \beta_i \mid H_0) = Q \left( \frac{\beta_i - K \sigma_{w,i}^2}{\sqrt{2K} \sigma_{w,i}^4} \right) \]  \hspace{1cm} (4.4) \\

\[ P_{d,i} = P(Y_i > \beta_i \mid H_1) = Q \left( \frac{\beta_i - K \left( \sigma_{w,i}^2 + g_i^2 \sigma_s^2 \right)}{\sqrt{2K} \left( \sigma_{w,i}^2 + g_i^2 \sigma_s^2 \right)^2} \right) \]  \hspace{1cm} (4.5) \\

where \( Q(x) = \int_{x}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt \) and \( \beta_i \) is the DM threshold of the \( i^{th} \) SU that tests the energy statistic \( Y_i \). For a given false alarm rate \( (\bar{P}_{f,i}) \), the threshold \( \beta_i \) is independent of the PU statistics. Thus, by expressing \( \beta_i \) in terms of \( P_{f,i} \) from (4.4) and substituting into (4.5) we can write

\[ P_{d,i} = Q \left( \frac{Q^{-1} (\bar{P}_{f,i}) \sqrt{2K} \sigma_{w,i}^4 + K \sigma_{w,i}^2 - K \left( \sigma_{w,i}^2 + g_i^2 \sigma_s^2 \right)}{\sqrt{2K} \left( \sigma_{w,i}^2 + g_i^2 \sigma_s^2 \right)^2} \right) \]  \\

Then,

\[ P_{d,i} = Q \left( \frac{Q^{-1} (\bar{P}_{f,i}) \sqrt{2K} \sigma_{w,i}^4 - K g_i^2 \sigma_s^2}{\sqrt{2K} \sigma_{w,i}^2 + g_i^2 \sigma_s^2} \right) \]  \hspace{1cm} (4.6) \\

Similarly, for a given probability of detection \( (\bar{P}_{d,i}) \), the false alarm probability can be expressed as

\[ P_{f,i} = Q \left( \frac{Q^{-1} (\bar{P}_{d,i}) \sqrt{2K} \sigma_{w,i}^4 + K \left( \sigma_{w,i}^2 + g_i^2 \sigma_s^2 \right)^2 - K \sigma_{w,i}^2}{\sqrt{2K} \sigma_{w,i}^4} \right) \]  \\

Then,

\[ P_{f,i} = Q \left( \frac{Q^{-1} (\bar{P}_{d,i}) \sqrt{2K} \left( \sigma_{w,i}^2 + g_i^2 \sigma_s^2 \right)^2 + K g_i^2 \sigma_s^2}{\sqrt{2K} \sigma_{w,i}^4} \right) \]  \hspace{1cm} (4.7)
The two equations (4.6) and (4.7) represent the sensing decision probabilities at every SU in the network. Thus, these equations characterize the probabilities of the resultant individual binary decisions at each SU receiver where the relationship of all possible realizations of \((P_{d,i}, P_{f,i})\) pairs define the so-called receiver operating characteristics (ROC) curve.

### 4.3.3 CRN-wise HDF Decision Probabilities

In HDF-based cooperative spectrum sensing, the resultant binary decisions from all SUs are forwarded to the corresponding FC for aggregation purpose. At the SUs base station, all local sensing decisions are combined and merged into one final decision using Chair-Varshney fusion schemes (Chair & Varshney 1986; Varshney 1997). In HDF, The FC of the central BS uses \(k\)-out-of-\(N\) rule where a global decision that the PU is present if \(k\) or more individual decisions declare YES on the availability of PU, otherwise, FC makes a decision that the PU is absent. Using \(k\)-out-of-\(N\) rule and assuming that all decisions are independent, the network-wise probability of detection \((Q_d)\) and probability of false alarm \((Q_f)\) can be expressed as

\[
Q_d = \sum_{i=k}^{N} \binom{N}{i} P_{d,i}^i (1-P_{d,i})^{N-i}
\]

(4.8)

\[
Q_f = \sum_{i=k}^{N} \binom{N}{i} P_{f,i}^i (1-P_{f,i})^{N-i}
\]

(4.9)

where \(\binom{N}{i} = \frac{N!}{i! \times (N-i)!}\). When \(k = 1\), the 1-out-of-\(N\) HDF rule is commonly named as an OR-rule whereas if \(k = N\), the \(N\)-out-of-\(N\) HDF rule is known as AND-rule. In OR-rule, the final decision on the presence of a PU will be positive if at least one of the \(N\) collaborating SUs detects this PU. In AND-rule fusion scheme, all collaborating \(N\) SUs should declare the presence of a PU in order for the final decision to be positive. Figure 4.3 shows a realization for \(k\)-out-of-\(N\) rule where \(N = 5\) and \(k = 1, 2, \ldots, 5\). Assuming that all individual probabilities are identical, it is clear that when \(k = 1\), i.e. OR-rule, the global probability of detection is the highest for any given individual probability of detection. Similar finding can be observed if the probability
of false alarm is taken into account. In this research work, the OR-rule has been implemented at the FC for combining the individual binary decisions sent from collaborating SUs. The CRN-wise detection and false alarm probabilities under OR-rule can be mathematically simplified from (4.8) and (4.9) as

\[ Q_d = 1 - \prod_{i=1}^{N} (1 - P_{d,i}) \]  
(4.10)

\[ Q_f = 1 - \prod_{i=1}^{N} (1 - P_{f,i}) \]  
(4.11)

Thus, by plugging the individual probabilities in (4.6) and (4.7) into (4.10) and (4.11), respectively, the CRN-wise probabilities can be written as

\begin{align*}
Q_d &= 1 - \prod_{i=1}^{N} \left( 1 - Q \left( \frac{Q^{-1}(\overline{P}_{d,i}) - K \frac{2^k \sigma_{w,i}^2}{\sigma_s^2}}{2K \left( \sigma_{w,i}^2 + \left| g_{ij} \right|^2 \sigma_s^2 \right)^2} \right) \right) \\
Q_f &= 1 - \prod_{i=1}^{N} \left( 1 - Q \left( \frac{Q^{-1}(\overline{P}_{f,i}) - K \frac{2^k \sigma_{w,i}^2}{\sigma_s^2}}{2K \left( \sigma_{w,i}^2 + \left| g_{ij} \right|^2 \sigma_s^2 \right)^2} \right) \right)
\end{align*}

(4.12)

(4.13)

Figure 4.3 Realization of k-out-of-N HDF rule for \( N = 5 \).
4.3.4 PU Protection-SU Throughput Tradeoff in HDF-based CRNs

In this section, the tradeoff problem of maximizing PU protection while maximizing the SU network throughput is analyzed. In fact, these two objectives are directly linked to the conflicting objectives of maximizing the CRN-wise probability of detection and minimizing CRN-wise probability of false alarm, respectively. Since the later objectives are conflicting each other, thus, the former ones are also so. Under Neyman-Pearson criterion, the threshold can be dynamically set based on a given probability of false alarm. Therefore, equation (4.12) is used in this research to characterize the CRN-wise probability of detection and by maximizing which the PU becomes more protected.

By inspecting the CRN-wise probability of detection in Equation (4.12), it can be observed that this probability depends on the number of samples, $K$, as well as the total number of collaborating SUs, $N$. But since $K = 2T_s B$ where $T_s$ is the sensing time and $B$ is the sensed bandwidth which is assumed to be fixed, it is concluded that the CRN-wise probability of detection depends on the two parameters; sensing time and number of collaborating SUs. Figure 4.4 shows the CRN-wise probability of detection when the sensing time varies from zero to maximum frame duration ($T_f$) where $T_f = 1000$ $\mu$s and $N$ is set to 1 SU. Thus, $Q_d = P_{d,i} = P_d$. As expected, the probability of detection increases with increasing the sensing time since more samples can be collected from the received PU signal. The conflict of maximizing probability of detection while minimizing the probability of false alarm is also shown. When the probability of false alarm, $P_f$, equals to 0.4, the higher probability of detection can be achieved and vice versa. On the other hand, Figure 4.5 shows interesting finding of how the CRN-wise probability of detection varies as the number of collaborated SUs increases. As can be seen, the maximum probability of detection is achieved by collaboration of certain number of SUs rather than the collaboration of all SUs in the network. As shown, when the total number of SUs, $N$, is 50, 100, 150 and 200, the maximum fitness is achieved by collaboration of 10, 19, 27 and 34, respectively. The simulation is carried out by adjusting the channel conditions to obtain different random SNR values between -15 dB to -25 dB at the receivers of the $N$ SUs. The algorithm sorts the SUs based on their SNR values in a descending order.
Figure 4.4  Probability of detection versus sensing time at different probabilities of false alarm.

Figure 4.5  Probability of detection versus number of collaborating SUs for different total number of SUs.
A comparison between the optimum (maximum) versus overall probability of detection for $N = 25, 50, \ldots, 200$ SUs is depicted in Figure 4.6. The optimum probability of detection is obtained by collaboration of certain number of SUs whereas the overall probability of detection is calculated when all existing SUs are taken into account. It is clear that not all sensing decisions from existing SUs should be considered during fusion as this will degrade the CRN-wise probability of detection. This observation can be justified by stating that the SUs with low SNR values at their receivers will contribute negatively on the global sensing decision if their individual sensing decisions are taken into account. Thus, an intelligent algorithm should be used to select the number of SUs whose decisions should be involved in fusion out of the total number of existing SUs in the network.

![Figure 4.6 Optimal versus overall probability of detection for different number of SUs.](image)

Figure 4.6  Optional versus overall probability of detection for different number of SUs.

Now, the objective of maximizing the throughput SU is discussed. Take note that the sensing activity has a periodic time of $T_f$ where $T_f$ is the total frame time and it is defined as $T_f = T_s + T_d$ where $T_s$ is the sensing time and $T_d$ is the remaining time slot used for data transmission. In fact, there are two cases in which a SU might operate on a PU’s licensed band (Liang et al. 2008); the first is when the PU is inactive and the
SU successfully declare that there is no PU. In this case, the normalized throughput, $R_0$, of the WRAN system is represented as

$$R_0 = P(H_0) \left( \frac{T_f - T_s}{T_f} \right) \left( 1 - Q_f \right)$$  \hspace{1cm} (4.14)$$

where $P(H_0)$ is the probability that the PU is inactive in the frequency band being sensed. The other case is when the PU is active but the SUs fail to detect it. The normalized throughput, $R_1$, is then given by

$$R_1 = P(H_1) \left( \frac{T_f - T_s}{T_f} \right) \left( 1 - Q_d \right)$$  \hspace{1cm} (4.15)$$

where $P(H_1)$ is the probability of the PU being active in the frequency band of interest. Obviously, $P(H_0) + P(H_1) = 1$. Since $Q_d >> Q_f$ and with assumption that $P(H_1) << P(H_0)$, then, $R_0 >> R_1$. Thus the total normalized throughput of the SU network, $R_n$, can be simplified as

$$R_n = \left( \frac{T_f - T_s}{T_f} \right) \left( 1 - \overline{Q}_f \right)$$  \hspace{1cm} (4.16)$$

For a given CRN-wise probability of false alarm and frame duration, the SU throughput decreases with increasing the sensing time. This is because increasing the sensing time results in a reduction on the remaining time for data transmission and therefore reduces the SU network throughput as shown in Figure 4.7. The simulation results in Figure 4.4 and Figure 4.7 show the contradiction between the objectives of maximizing the CRN-wise probability of detection and maximizing the throughput of CRN. As the sensing time increases, the PU becomes more protected since the probability of detection increases. However, increasing the sensing time results in a reduction of the available time for SU access and thus it reduces the CRN throughput. This tradeoff between these two objectives again calls for employment of an intelligent code that can provide a joint optimization of sensing time and cooperation level so that a compromise between these two objectives is attained.
4.3.5 Problem Formulation for BOGA Optimization

The PU protection-SU throughput tradeoff observed in the preceding section is now formulated. As have been shown in Figure 4.4 to 4.7, both the CRN-wise probability of detection as well as the CRN throughput are very much dependent on the sensing time as well as the cooperation level between existing SUs. Thus, a bi-objective function that combines these two objectives can be formed as

\[ F(T_s, m) = C_1 \times Q_d(T_s, m) + C_2 \times R_n(T_s, m) \]  \hspace{1cm} (4.18)

where \( Q_d(T_s, m) \) and \( R_n(T_s, m) \) are given by Equations (4.12) and (4.16), respectively. \( C_1 \) and \( C_2 \) are arbitrary constants and \( C_1 + C_2 = 1 \). Since \( Q_d(T_s, m) \in (0,1) \) and \( R_n(T_s, m) \in (0,1) \), thus, bi-objective function \( F(T_s, m) \in (0,1) \).

The PU protection-SU throughput tradeoff can be formed as an optimization problem with two decision variables and three constraints as follows
This formed bi-objective function can be solved by finding the optimal pair of sensing time and cooperation level at which this bi-objective function is maximized. This optimization problem is configured into a GA framework whose chromosomes represent the two decision variables; $T_s$ and $m$. The concept of encoding the GA chromosomes is very much similar to the one explained in section 3.3.3 with minor modifications such as the number of decision variables and the number of bits used to encode each variable.

### 4.3.6 Performance Evaluation of BOGA-assisted HDF-based Optimization System

This optimization problem defined in equation (4.19) is introduced as a constraint fitness function for a GA framework. Figure 4.8 shows the convergence performance of the implemented BOGA for HDF-based system. The system runs for any given set of channel conditions and number of existing SUs and return the optimal $(T_s, m)$ pair which maximizes the bi-objective fitness function. The number of bits per chromosome is set to 20 which give a search space of $2^{20}$ potential solutions. The time frame and total number of existing users have been introduced as 1000 $\mu$s and 200, respectively. Two-point crossover scheme with a rate of 0.95 and bit flip with a rate of 0.01 are used. The population size and the elitism percentage are set to 20 and 10%, respectively. The system is run for 100 generations and the best and average fitness obtained in every population is displayed in Figure 4.8. The last population formed after terminating the system is inspected and the best chromosomes are decoded to obtain the sensing time and cooperation level decision variables. The maximum fitness achieved is about 0.73 captured within the first 30 generations. The optimal $(T_s, m)$ pair for the results obtained has been found to be (256 $\mu$s, 26 SUs) which are 25.6% and 13% of the frame duration and total number of SUs, respectively.
4.3.7 Results and Discussion

In this section, the sub-optimality of the obtained results in the previous section is verified. In fact, the obtained decision variables of $T_s$ and $m$ are correlated to the channel condition characterized by the SNR values at the SU receivers. Thus, the BOGA convergence performance as well as the sub-optimal results obtained is related to the SNR distribution at the SU receivers. Figure 4.9 shows the bi-objective fitness function (BOF) achieved when $m = 1$, $m = m_{opt}$ and $n = N$, where $N$ is the total number of existing SUs and $m_{opt}$ is the optimal number of collaborating SUs obtained in section 4.3.6 (i.e. $m_{opt} = 26$). The BOF is drawn for all possible CRN-wise probability false alarm scores. It is clear that the maximum BOF is achieved when the system uses the optimal number of collaborating SUs rather than including the sensing decisions of all SUs. Similar result is shown in Figure 4.10 when BOF is plotted versus CRN-wise probability of false alarm at different setting of sensing times. Again, it is clear that the maximum BOF is attained when the optimal sensing time is used in comparison to 1% and 50% of the total frame time duration. The observations of Figure 4.9 and 4.10 have been found valid for any arbitrary $T_s$ and $m$ values.
Figure 4.9  
Bi-objective Fitness versus CRN-wise probability of false alarm at different number of collaborating SUs.

Figure 4.10  
Bi-objective Fitness versus CRN-wise probability of false alarm at different settings of sensing time.
Take note that the optimal sensing time and the optimal cooperation level have been used in Figure 4.9 and Figure 4.10, respectively. In Figure 4.9, the simulation results show that the best achievable BOF score when using the optimal cooperation level is improved by more than 10% in comparison to the best achievable BOF score when all existing SUs are included. On the other hand, the best achievable BOF score when using the optimal sensing time improves by about 4% higher than the case when the sensing time is set to half of its frame time duration. Similar trends can be found when using other static settings of sensing time and cooperation level since the problem is a unimodal optimization problem for the same channel condition.

4.4 SOGA-ASSISTED SDF-BASED COOPERATIVE SPECTRUM SENSING

In CRNs, incumbent awareness and interference prevention are partially-realized as part of MAC and PHY layers by means of cooperative spectrum sensing which is used to alleviate the so-called hidden terminal problem in shadowing environments (Ghasemi & Sousa 2005). Cooperative spectrum sensing can be deployed as hard-decision fusion (HDF) schemes (Zhang et al. 2008) or soft-data fusion (SDF) schemes (Quan et al. 2008; Shen & Kwak 2009). The SDF schemes are superior to the HDF ones in terms of the detection performance whereas the HDF schemes outperform the SDF ones when the traffic overhead is taken into account. As has been shown in section 4.3, in HDF, the local sensors (or SUs’ receivers) make their own judgements on the presence of a PU and their corresponding resultant 1-bit decisions are sent to a central BS for fusion. These hard fusion schemes have the advantage of reduced traffic overhead as only one single bit needs to be reported to the FC/BS from each SU. However, HDF schemes suffer from a reduced detection performance due to the content loss of sensing information upon the decision making process. In contrast, the SDF schemes require the local sensors to report their measurements as raw data to the FC/BS at which, this data will be aggregated to construct a final decision on the presence of PU. The soft schemes show better detection performance than HDF schemes (Ma, J. & Li, Y. G. 2007). In (Quan et al. 2008; Shen & Kwak 2009), linear SDF-based cooperative spectrum sensing was proposed and the optimal weighting coefficients vector of all CR systems in the network was derived by maximizing the deflection coefficient (DC). The DC provides a good measure of the detection
performance because it characterizes the variance-normalized distance between the centers of the two conditional PDFs of the global test static. However, the DC-based methods provide sub-optimal solutions leading to some performance degradation. In this section, we propose to use single objective genetic algorithm (SOGA) is proposed to optimize the detection performance of SDF-based cooperative spectrum sensing. The proposed scheme lies on optimizing the weighting coefficients vector used in a linear SDF-based framework. The detection performance of the proposed GA-assisted SDF-based scheme is compared with other conventional SDF schemes as well as the OR-logic HDF scheme.

### 4.4.1 SDF-based CRN System Model

The system model of linear SDF-based cooperative spectrum sensing is shown in Figure 4.11 where $M$ SUs in the network send their statistical measurement data to a common fusion centre (FC). Each SU in the network serves as a relay as it receives a distinct version of probable PU transmission and then forwards it to FC.
In Figure 4.11 above, the FC receives the SUs signals and performs linear weighted SDF to combine the individual measurements and concludes a final decision on the availability of PU.

4.4.2 Characterization of PU-SU and SU-FC Link

(i) Characterization of PU-SU Link: The sensing task at any arbitrary SU is the same binary hypothesis test expressed in (4.1) and (4.2). In this section, the same PU-SU channel parameters and PU signal statistical properties of the HDF model are used again in this SDF model. To clear potential confusion and ensure continuity, these characteristics are briefly re-mentioned herein. \( S[n] \) is the PU signal whose statistical properties are similarly defined as \( S[n] \sim \mathcal{N}(0, \sigma_s^2) \), and \( W_i[n] \) is the \( i^{th} \) sensing channel noise which is characterized as \( W_i[n] \sim \mathcal{N}(0, \sigma_{w_i}^2) \). The variances of PU-SU paths are collected into the vector \( \mathbf{\sigma_w} = [\sigma_{w1}^2, \sigma_{w2}^2, \ldots, \sigma_{WM}^2]^{T} \) where \( T \) is the transpose of the vector. \( \{g_i\} \) is the channel gains of the PU-SU paths which is assumed to be constant over each sensing period; this can be justified by assuming slow-fading nature over these links where the delay requirement is short in comparison to the channel coherence time is a quasi-static scenario (Hossain & Bhargava 2007). \( X_i[n] \) is the received sampled signal at the \( i^{th} \) SU receiver and the sampled signals received at the \( M \) SUs are collected into the vector \( \mathbf{\hat{X}} = [X_1, X_2, \ldots, X_M]^{T} \).

(ii) Characterization of SU-FC Link: In SDF-based architectures, no decision making processes are to be performed at SUs stage. Instead, the \( M \) SUs relay their individual sensing data or measurements of PU signal availability to the corresponding FC/BS through a dedicated control channel in an orthogonal manner. Each relay will simply act in an amplify-and-forward (AAF) manner. The justification of using AAF instead of the less complexity decode-and-forward (DAF) scheme is referred to its ability to improve the detection performance by employing some signal processing techniques at the FC. The channel noises \( \{N_i\} \) of the SU-FC paths are assumed to be zero mean and spatially uncorrelated.
additive white Gaussian with variances \( \{ \delta_i^2 \} \) which are collected into the vector 
\[ \delta = [\delta_1^2, \delta_2^2, \ldots, \delta_m^2]^T. \] Then, the signal received at FC from the \( i^{th} \) SU will be

\[ Y_i[n] = \sqrt{P_{R_i}} h_i X_i[n] + N_i[n] \quad (4.20) \]

where \( P_{R_i} \) is the transmit power of the \( i^{th} \) relay and \( h_i \) is the amplitude channel gain of the \( i^{th} \) SU-FC path. The use of AWGN model here is justified by the slow-changing nature of the channels between the \( M \) SUs and their corresponding FC. Now, by considering the binary hypotheses in (4.1) and (4.2), the received signal at the FC can be expressed as

\[ Y_i[n|H_0] = \sqrt{P_{R_i}} h_i W_i[n] + N_i[n] = u_0[n] \quad (4.21) \]

\[ Y_i[n|H_1] = \sqrt{P_{R_i}} h_i g_i S_i[n] + \sqrt{P_{R_i}} h_i W_i[n] + N_i[n] = \sqrt{P_{R_i}} h_i g_i S_i[n] + u_0[n] \quad (4.22) \]

where \( u_0[n|H_0] \sim \mathcal{M}(0, \sigma_{0,i}^2) \sim \mathcal{M}(0, P_{R_i} | h_i|^2 \sigma_{w,i}^2 + \delta_i^2) \) and \( Y_i[n|H_1] \sim \mathcal{M}(0, \sigma_{1,i}^2) \sim \mathcal{M}(0, P_{R_i} | g_i|^2 |h_i|^2 \sigma_{s,i}^2 + \sigma_{0,i}^2). \) In a Matrix form, the received signals at the FC through the control channel under \( H_0 \) and \( H_1 \), respectively, can be written as

\[ Y[n|H_0] = \begin{bmatrix} \sqrt{P_{R_1}} h_1 & 0 & \ldots & 0 \\ 0 & \sqrt{P_{R_2}} h_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \sqrt{P_{R_M}} h_M \end{bmatrix} \begin{bmatrix} W_1[n] \\ \vdots \\ W_M[n] \end{bmatrix} + \begin{bmatrix} N_1[n] \\ \vdots \\ N_M[n] \end{bmatrix} \quad (4.23) \]

\[ Y[n|H_1] = \begin{bmatrix} \sqrt{P_{R_1}} g_1 h_1 & 0 & \ldots & 0 \\ 0 & \sqrt{P_{R_2}} g_2 h_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \sqrt{P_{R_M}} g_M h_M \end{bmatrix} \begin{bmatrix} S_1[n] \\ \vdots \\ S_M[n] \end{bmatrix} + \begin{bmatrix} u_0_1[n] \\ \vdots \\ u_0_M[n] \end{bmatrix} \quad (4.24) \]
At the FC, each received sequence $Y_i[n]$ will be individually averaged and squared using a separate energy detector to estimate its own energy as shown in Figure 4.11. Thus, the estimated energy collected by the $i^{th}$ SU all the way to the FC is

$$Z_i = \sum_{n=0}^{K-1} |Y_i[n]|^2 ; \quad i = 1, 2, \ldots, M \quad (4.25)$$

By denoting $\{Z_{0,i}\} = \{Z_i|H_0\}$ and $\{Z_{1,i}\} = \{Z_i|H_1\}$, the two sets of test statistics can be written as $\tilde{Z}_0 = [Z_{0,1}, Z_{0,2} \ldots Z_{0,M}]^T$ and $\tilde{Z}_1 = [Z_{1,1}, Z_{1,2} \ldots Z_{1,M}]^T$. For a large number of samples, the central limit theorem (CLT) approximates each test statistic into the vectors $\tilde{Z}_0$ and $\tilde{Z}_1$ to be normally distributed with mean and variance given by

$$E(Z_i | H_0) = K \sigma_{0,i}^2 = K(P_{R_i} | h_i |^2 \sigma_{w_i}^2 + \delta_i^2) = \mu_{0,i} \quad (4.26)$$

$$\text{var}(Z_i | H_0) = 2K \sigma_{0,i}^4 = 2K(P_{R_i} | h_i |^2 \sigma_{w_i}^2 + \delta_i^2)^2 \quad (4.27)$$

$$E(Z_i | H_1) = K \sigma_{1,i}^2 = K(P_{R_i} | g_i |^2 | h_i |^2 \sigma_S^2 + \sigma_{0,i}^2) = \mu_{1,i} \quad (4.28)$$

$$\text{var}(Z_i | H_1) = 2K \sigma_{1,i}^4 = 2K(P_{R_i} | g_i |^2 | h_i |^2 \sigma_S^2 + \sigma_{0,i}^2)^2 \quad (4.29)$$

where $\mu_0 = [\mu_{0,1}, \mu_{0,2}, \ldots, \mu_{0,M}]^T$ and $\mu_1 = [\mu_{1,1}, \mu_{1,2}, \ldots, \mu_{1,M}]^T$. Assume that $\theta_i = K P_{R_i} | g_i |^2 | h_i |^2 \sigma_S^2$ and $\bar{\theta} = [\theta_1, \theta_2, \ldots, \theta_M]^T$, consequently, it can be conclude that $\mu_{1,i} = \mu_{0,i} + \theta_i$ and $\bar{\mu}_i = \bar{\mu}_0 + \bar{\theta}$.

Next, all the individual test statistics $\{Z_i\}$ are used to linearly formulate the resultant test statistic of the $j^{th}$ cluster, $Z_j$, which can be expressed as

$$Z = \sum_{i=1}^{M} \omega_i Z_i = \bar{\omega}^T \bar{Z} \quad (4.30)$$
where \( \tilde{\omega} = [\omega_1, \omega_2, \ldots, \omega_M]^T \) is the weighting coefficients vector; \( \omega_i \geq 0 \). Since \( \{Z_i\} \) are all normal random variables, their linear combination represented by the test statistic \( Z \) in (4.30) will also be normally distributed with statistical properties formulated as

\[
E(Z \mid H_0) = \sum_{i=1}^{M} \omega_i K(P_{Ri} \mid h_i)^2 \sigma_{wi}^2 + \delta_i^2 = \sum_{i=1}^{M} \omega_i K\sigma_{0,i}^2 \\
= \sum_{i=1}^{M} \omega_i \mu_{0,i} = \tilde{\omega}^T \tilde{\mu}_0
\]

(4.31)

\[
E(Z \mid H_1) = \sum_{i=1}^{M} \omega_i K(P_{Ri} \mid g_i)^2 h_i^2 \sigma_S^2 + \sigma_{0,i}^2 \\
= \sum_{i=1}^{M} \omega_i K\sigma_{1,i}^2 = \sum_{i=1}^{M} \omega_i \mu_{1,i} = \tilde{\omega}^T \tilde{\mu}_1
\]

(4.32)

\[
\text{var}(Z \mid H_0) = \sum_{i=1}^{M} 2\omega_i^2 K(\sigma_{0,i}^2 + \delta_i^2)^2 \\
= \sum_{i=1}^{M} 2\omega_i^2 K(P_{Ri} \mid h_i)^2 \sigma_{wi}^2 + \delta_i^2)^2 = \tilde{\omega}^T \sum_{H_0} \tilde{\omega}
\]

(4.33)

\[
\text{var}(Z \mid H_1) = \sum_{i=1}^{M} 2\omega_i^2 K(\sigma_{1,i}^2 + \sigma_{0,i}^2)^2 \\
= \sum_{i=1}^{M} 2\omega_i^2 K(P_{Ri} \mid g_i)^2 \sigma_S^2 + \sigma_{0,i}^2)^2 = \tilde{\omega}^T \sum_{H_1} \tilde{\omega}
\]

(4.34)

where the covariance matrices in equations (4.33) and (4.34) are defined as

\[
\sum_{H_0} = \text{diag}(2K\sigma_{0,i}^4) \quad \text{and} \quad \sum_{H_1} = \text{diag}(2K(P_{Ri} \mid g_i)^2 \sigma_S^2 + \sigma_{0,i}^2)^2)
\]

where \( \text{diag}(\cdot) \) is a square diagonal matrix with the elements of a given vector on the diagonal.

### 4.4.3 CRN-wise SDF Decision Probabilities

At the FC, a global threshold \( (\beta) \) is employed into a decision making device that tests the likelihood ratio \( Z \geq_{H_0} \beta \). As such, the overall probability of detection \( (Q_d) \) and probability of false alarm \( (Q_f) \) for the cooperative \( M \) SUs at the FC can be written as
\[ Q_f = P(Z > \beta | H_0) = Q \left( \frac{\beta - E(Z | H_0)}{\sqrt{\text{var}(Z | H_0)}} \right) = Q \left( \frac{\beta - \tilde{\omega}^T \tilde{\mu}_0}{\sqrt{\tilde{\omega}^T \sum_{H_0} \tilde{\omega}}} \right) \quad (4.35) \]

\[ Q_d = P(Z > \beta | H_1) = Q \left( \frac{\beta - E(Z | H_1)}{\sqrt{\text{var}(Z | H_1)}} \right) = Q \left( \frac{\beta - \tilde{\omega}^T \tilde{\mu}_1}{\sqrt{\tilde{\omega}^T \sum_{H_1} \tilde{\omega}}} \right) \quad (4.36) \]

Then, for a given \( Q_d = \bar{Q}_d \), \( Q_f \) can be written as

\[ Q_f = Q \left( \frac{Q^{-1}(\bar{Q}_d) \sqrt{\tilde{\omega}^T \sum_{H_1} \tilde{\omega} + \tilde{\omega}^T \tilde{\omega} \tilde{\theta}}}{\sqrt{\tilde{\omega}^T \sum_{H_0} \tilde{\omega}}} \right) \quad (4.37) \]

Similarly, for a given \( Q_f = \bar{Q}_f \), \( Q_d \) can be expressed as

\[ Q_d = Q \left( \frac{Q^{-1}(\bar{Q}_f) \sqrt{\tilde{\omega}^T \sum_{H_0} \tilde{\omega} - \tilde{\omega}^T \tilde{\omega} \tilde{\theta}}}{\sqrt{\tilde{\omega}^T \sum_{H_1} \tilde{\omega}}} \right) \quad (4.38) \]

### 4.4.4 SDF-based Single-Objective Function

In CRNs, the probabilities of false alarm and detection have unique indications. Specifically, \((1 - Q_d)\) measures the probability of interference from SUs on the PUs. On the other hand, \(Q_f\) determines an upper bound on the spectrum efficiency, where a large \(P_f\) usually results in low spectrum utilization. This is because the SU is allowed to perform transmissions if and only if the PU is undetected under either \(H_0\) or \(H_1\). In this research work, the main aim is to protect the PU while maintaining a constant secondary spectrum access. This leads to the quantifiable objective of maximizing \(Q_d\) while meeting a certain requirement on \(Q_f\) (i.e. \(Q_f = \bar{Q}_f\)). Thus, equation (4.38) forms the detection performance criterion of the linear SDF-based sensing scheme. It is clear that \(Q_d\) is very much dependent on \(\tilde{\omega}\). Thus, the optimal weighting vector is defined as the one which maximizes \(Q_d\). However, if \(\tilde{\omega}^*\) is an
optimal solution which maximizes $Q_d$, there will be an unlimited number of optimal solutions of the form $\psi \tilde{\omega}^*$, where $\psi$ is any real scaling factor. Therefore, additional constraint is proposed to limit the number of optimal solutions and reduce the search space on which the GA works. The optimal weighting vector of the constraint optimization problem becomes

$$\tilde{\omega}^* = \arg \max_{\tilde{\omega}} Q_d(\tilde{\omega})$$

subject to: $\| \tilde{\omega} \|_2 = 1$

where $\| . \|_2$ in the constraint is the 2-norm of the vector $\tilde{\omega}$.

4.4.5 Conventional SDF Schemes

In this section, conventional schemes of optimizing the weighting vector in SDF-based CRNs. These schemes include the equal gain combination (EGC) and the maximal ratio combining (MRC), maximizing the normal deflection coefficient (NDC) or maximizing the modified deflection coefficient (MDC). The deflection coefficient is a measure of the detection performance formulated based on the distance between the centers of $H_0$ and $H_1$. The weighting vector $\tilde{\omega}$ in Figure 4.11 is optimized to maximize the probability of detection defined in (4.38) under EGC, MRC, NDC, and MDC schemes. These methods are then used to benchmark the proposed SOGA-assisted SDF-based cooperative sensing. Thus, closed form expressions for the weighting vector under the EGC, MRC, NDC, and MDC schemes should be derived and formulated.

(i) Equal gain combination- (EGC-) based weighting scheme: The EGC scheme is a weighting scheme similar to the one used in systems with multiple receive antennas. It does not require any channel state information (CSI), but still exhibits much better performance than the conventional HDF schemes. The individual weights assigned to the $M$ SUs signals at the FC in (4.38) are all equal and expressed by

$$\omega_i = \sqrt{\frac{1}{M}}$$

(4.40)
(ii) **Maximal-Ratio Combining (MRC) Based Weighting Scheme:** The weight coefficient assigned for a particular SU signal at a FC represents its contribution to the overall decision made. Thus, if a SU has a high PU SNR at its receiver that may lead to a correct detection on its own, it should be assigned a larger weighting coefficient. On the other hand, for those SUs experiencing deep fading or shadowing, their weights are decreased in order to reduce their negative contribution to the final decision. By maintaining \( \| \bar{\omega} \|_2 = 1 \), we can derive the individual weight for the \( i^{th} \) SU’s measurement as follows

\[
\sum_{i=1}^{M} SNR_i = SNR_f \Rightarrow \sum_{i=1}^{M} \frac{SNR_i}{SNR_f} = 1 = \sum_{i=1}^{M} \omega_i^2 \Rightarrow \omega_i^2 = \frac{SNR_i}{SNR_f}
\]

Thus,

\[
\omega_i = \sqrt{\frac{SNR_i}{SNR_f}}
\]

where \( SNR_i \) is the signal-to-noise ratio at the FC receiver estimated at the \( i^{th} \) SU. The weighting vector definition based on MRC as in (4.41) is supplied to (4.38) to optimize the CRN-wise probability of detection.

(iii) **Normal Deflection Coefficient (NDC) Maximization:** From (4.38), it is observable that the weighting vector \( \bar{\omega} \) is playing an important role in determining the overall detection and false alarm probabilities at the FC stage. In addition, equations (4.31) to (4.34) show that \( \bar{\omega} \) characterizes the PDFs of \( Z \) under \( H_0 \) and \( H_1 \). The statistical characterizations of these two PDFs can be used to mathematically define the detection performance objective, NDC maximization, as follows

\[
d_n^2 = \frac{\left[ E(Z_j \mid H_1) - E(Z_j \mid H_0) \right]^2}{\text{var}(Z_j \mid H_0)} = \frac{\left( \bar{\omega}^T K P_{\bar{\omega}} \mid g_i \mid h_i \mid \sigma^2 \right)^2}{\bar{\omega}^T \sum_{\bar{\omega}} \bar{\omega}} = \frac{\left( \bar{\omega}^T \bar{\omega} \right)^2}{\bar{\omega}^T \sum_{\bar{\omega}} \bar{\omega}}
\]

The NDC scheme provides a good measure of the detection performance because the \( \sum_{\bar{\omega}} \) covariance matrix under hypothesis \( H_0 \) is used to characterize the variance-
normalized distance between the centers of the two conditional PDFs of $Z_j$ under $H_0$ and $H_1$. Now, we set $d_a^2(\tilde{\omega})$ as our optimization target, optimal weight vector $\tilde{\omega}_{\text{opt, NDC}}$ that maximizes the distance is

$$
\tilde{\omega}_{\text{opt, NDC}} = \arg \max_{\tilde{\omega}} d_a^2(\tilde{\omega}) \quad (4.43)
$$

By solving the equation $\frac{\partial d_a^2(\tilde{\omega})}{\partial \tilde{\omega}} = 0$, we obtain $\tilde{\omega}_{\text{opt, NDC}} = \frac{\tilde{\omega}^T \sum_{H_0} \tilde{\omega}}{\tilde{\omega}^T \tilde{\omega}} \sum_{H_0}^{-1} \tilde{\theta}$, let $\alpha_{\text{NDC}}$ and by setting $\alpha_{\text{NDC}}$, which is a scalar, to one and normalizing each weighting coefficient, we obtain the optimal weighting vector as

$$
\tilde{\omega}^*_{\text{opt, NDC}} = \frac{\tilde{\omega}_{\text{opt, NDC}}}{\| \tilde{\omega}_{\text{opt, NDC}} \|} = \sum_{H_0}^{-1} \tilde{\theta} \quad (4.44)
$$

The justification of setting $\alpha_{\text{NDC}}$ to 1 is that $\alpha_{\text{NDC}}$ is a scalar value with no effect on $d_a^2$ in (4.42). This optimal weighting vector is the best that can push the centers of the two PDFs under $H_0$ and $H_1$ apart from each other and hence, maximizes the detection probability in (3.38). Then, by substituting the optimal weighting vector in (4.44) into (4.38) we obtain

$$
Q_\theta = Q \left( \frac{Q^T (\tilde{Q}_j) \sqrt{\tilde{\omega}^T \sum_{H_0}^{-1} \tilde{\omega} - \tilde{\omega}^T \sum_{H_0}^{-1} \tilde{\theta}}}{\sqrt{\tilde{\omega}^T \sum_{H_0}^{-2} \sum_{H_1} \tilde{\theta}}} \right) \quad (4.45)
$$

(iv) Modified Deflection Coefficient (MDC) Maximization: In this subsection, we investigate the maximization of MDC in order to find the optimal weights setting for the SDF at the FC. The MDC can be defined as

$$
\begin{align*}
d_m^2 &= \frac{[E(Z_j | H_1) - E(Z_j | H_0)]^2}{\text{var}(Z_j | H_1)} = \left( \tilde{\omega}^T K \mathbf{P}_\mathbf{R}_1 | g_1 |^2 \tilde{h}_1 |^2 \sigma_3^2 \right)^T \left( \tilde{\omega}^T \sum_{H_1} \tilde{\omega} \right) = \left( \tilde{\omega}^T \tilde{\theta} \right)^2 \left( \tilde{\omega}^T \sum_{H_1} \tilde{\omega} \right) \quad (4.46)
\end{align*}
$$
which employs the $\Sigma_{H1}$ covariance matrix under hypothesis $H_1$ to fulfill the task of variance-normalization. Obviously, $d^2_m$ can be obtained by simply replacing the $\Sigma_{H_0}$ covariance matrix in (4.42) with the $\Sigma_{H1}$ covariance matrix. The optimal weight vector $\tilde{\omega}_{opt, MDC}$ is then similarly defined as the one that maximizes the distance $d^2_m(\tilde{\omega})$

$$
\tilde{\omega}_{opt, MDC} = \arg \max_{\omega} d^2_m(\tilde{\omega})
$$

By solving the equation $\frac{\partial d^2_m(\tilde{\omega})}{\partial \tilde{\omega}} = 0$, we obtain $\tilde{\omega}_{opt, MDC} = \frac{\tilde{\omega}^T \sum_{H1} \tilde{\omega}}{\sum_{H1} \tilde{\omega}}$. Similarly, let $\frac{\tilde{\omega}^T \sum_{H1} \tilde{\omega}}{\sum_{H1} \tilde{\omega}} = \alpha_{MDM}$ which is a scalar and again by setting $\alpha_{MDM} = 1$ to ensure $\| \tilde{\omega} \|_2 = 1$ and normalizing each weighting co-efficient, we obtain the optimal weighting vector

$$
\tilde{\omega}^{*}_{opt, MDC} = \frac{\tilde{\omega}_{opt, MDC}}{\| \tilde{\omega}_{opt, MDC} \|} = \frac{\sum_{H1} \tilde{\omega}}{\tilde{\omega}}
$$

Again, this optimal weighting setting will be used to optimize the detection probability in (4.38). Similar to NDCM, by substituting the optimal weighting vector in (4.48) into (4.38) we obtain

$$
Q_d = Q\left(\frac{Q^{-1}(\tilde{Q}_{f})}{\sqrt{\tilde{\theta}^T \sum_{H1} \sum_{H0} \tilde{\omega} - \tilde{\theta}^T \sum_{H1} \tilde{\omega}}}\right)
$$

4.4.6 Performance Evaluation of SDF-based Schemes

In this section, the detection performance of the SDF-based NDC, MDC, MRC and EGC schemes as well as the OR-rule based HDF scheme is studied. The SU-FC channel bandwidth of the SDF-based schemes is also analyzed. The purpose of these explorative studies is to determine the parameters that significantly affect the CRN performance. The design parameters examined in this section include the setting of the
weighting coefficients vector as on the mentioned SDF schemes, the number of collaborating SUs in the network, the sensing time interval, and the quantization and modulation parameters used when relaying the sensing data/measurements from the SUs to the central FC/BS.

The default sensing time and sensed bandwidth are set as $T_s = 25 \mu s$ and $B = 6$ MHz, respectively, unless a change is mentioned. The relay transmit power is set to 12 dBm and the channel gains of the PU-SU and SU-FC links, $\{g_i\}$ and $\{h_i\}$, respectively, are normally distributed but remain constant within each sensing time interval $T_s$, as $T_s$ is sufficiently small. $\{g_i\}$ and $\{h_i\}$ are randomly-generated so that a low SNR environment at SU, and FC stages is realized (SNR < -10 dB). The simulation results are obtained for a certain number realizations of channel gains and noise variances.

In SDF, the SUs relay their sensing measurement data to the central FC/BS for fusion whereas HDF uses a different concept where the sensing measurement/data is locally processed at the SUs’ stage and 1-bit decisions will be then sent to the central FC. Figure 4.12 presents a comparison between the NDC-, MDC-, MRC- and EGC-based SDF schemes as well as the OR-rule based HDF. The detection performance is characterized by the ROC curve obtained by plotting the CRN-wise probability of detection ($Q_d$) for a given CRN-wise probability of false alarm ($Q_f$) as given in (4.38) based on the setting of weighting vector of each corresponding SDF scheme as mentioned in Section 4.4.5. The number of SUs in the vicinity is set to 20 (i.e. $M = 20$). It is clear that the NDC-based SDF scheme shows the best detection performance in comparison to MDC-, MRC- and EGC SDF schemes as well as the OR-rule based HDF scheme. The OR-rule scheme, as expected, is inferior to all other methods as it suffers from a significant loss of information content being a HDF process. The EGC SDF scheme shows better performance than the OR-rule HDF scheme but it is inferior to all other SDF schemes due to its fixed and equal weighting coefficients assigned to the energy measurements of the $M$ SUs at the corresponding FC. The MRC-based scheme shows better performance than the EGC one due to its adaptability. The MRC scheme assigns larger weights for the SUs with high SNRs and smaller weights for
those with low SNRs and therefore, it controls the contributions of each SU in the overall decision taken at the FC stage.

Figure 4.12 ROC performance comparison of cooperative spectrum sensing SDF and HDF schemes.

The simulation results in Figure 4.12 also show that the most promising SDF schemes are the NDC-based and MDC-based ones. The NDC scheme outperforms the MDC one with non-trivial difference. The detection performance of NDC is slightly better than that of MDC because the MDC scheme introduces estimates of the PU signal strength and test statistics into the estimated covariance matrix $\sum_{H_1}$ simultaneously in opposite to the covariance matrix $\sum_{H_0}$ in NDC which is exclusively defined by the test statistics only. Obviously, the elements of $\sum_{H_0}$ are smaller than those of $\sum_{H_1}$ in magnitude, and therefore, $d_n^2 > d_m^2$ based on (4.42) and (4.46), and $\vec{d}_{opt,NDC} > \vec{d}_{opt,MDC}$ as can be concluded from (4.44) and (4.48). By substituting these optimal vectors separately into (4.38) we obtained (4.45) and (4.49) which are the CRM-wise probability of detection for a given false alarm probability.
under NDC and MDC, respectively. By performing simple mathematical analysis on these two equations, it can be observed that detection probability under NDC is a bit higher than that of MDC. Thus, NDC-based scheme can be said to be the best SDF method and will be therefore used as a default SDF scheme for testing the effect of varying the number of collaborating SUs.

Next, we investigate the effect of varying the number of cooperative SUs in a CRN. The proposed NDC scheme is considered as it shows the best performance as has been presented above. Figure 4.13 shows the performance of the CRN at the FC stage represented by the ROC curve for different number of SUs; $M = 5, 10, 15,$ and 20. Obviously, the performance improves well when the number of cooperative users in the CRN increases. In fact, when $M = 5$, the ROC curve becomes closer to the line of no-discrimination (where there is no difference between the PU signal and noise) than that when $M = 20$. Thus, as $M$ increases, the separation between the hypotheses $H_0$ and $H_1$ increases and the performance of the ROC curve improves accordingly.

![Figure 4.13 ROC performance comparison of NDC-based SDF cooperative spectrum sensing at FC with different number of SUs per cluster.](image-url)
Figure 4.14 depicts some existing tradeoffs in the performance of SDF schemes. Consider that during every sensing interval, $T_s$, there are $K$ samples at each SU to be relayed to the FC over the SU-FC link. Suppose that all SUs relay their observations to the FC in an orthogonal manner and each SU quantizes the received signal samples with $u$ bits per sample, thus, the total number of relayed bits by each SU is then $uK$. Assume that the SUs cooperate with the corresponding FC using a potential multiple-ary QAM, say 16QAM, 32QAM, 64QAM, 128QAM, or 256QAM. Then, the channel bandwidth of the SU-FC link can be written as

$$BW_{SU-CH link} = \frac{R_b}{\xi} = \frac{uK}{\xi T_r} = \frac{2T_s B u}{\xi T_r}$$

(4.50)

where $R_b$ is the bit rate, $\xi$ is the spectral efficiency of the modulation scheme used (assume Nyquist minimum bandwidth), $T_r$ is the time required by each SU to relay its observation to the FC. The three surfaces sketched in Figure 4.14 show the estimated $BW_{SU-FC link}$ for different number of bits per QAM symbol ($v$) and number of bits per quantized sample ($u$) at different sensing times. The relay time, $T_r$, is set to 1 ms. It is clear that for a fixed sensing time, the minimum $BW_{SU-FC link}$ is achieved when a high-order modulation scheme and low number of quantization levels are jointly used. Thus, the first tradeoff appears here is that the good achievement of minimizing the bandwidth is disturbed by sacrificing the detection performance because of the poor signal representation when lesser number of quantization levels is used. Moreover, $BW_{SU-FC link}$ can also be minimized by reducing the sensing time, say from 30 $\mu$s to 10 $\mu$s, but then, the detection performance will also be degraded because of decreasing the number of samples captured to from the received PU signals at the SU receivers. Thus, a wise compromise between the performance and resources should be carefully considered.

To summarize, it can be concluded that the detection performance of CRN is very much dependent on the weighting scheme of the SUs’ contributions at the FC. As has been shown in Figure 4.12, different SDF schemes that use different weighting techniques have shown different scores of detection performance. Thus, a more reliable weighting scheme might be used to improve the detection performance.
further. There has been observed that increasing the number of collaborated SUs leads to an absolute improvement on the detection performance as shown in Figure 4.13. Thus, all existing SUs in the vicinity of a central BS/FC should be included in the cooperation exercise in order to improve the detection performance as much as possible. The same goes for the sensing time used to capture the samples of sensing data. Increasing the sensing time improves the detection performance but at the same time, it results in a bandwidth expansion of the dedicated control channel as depicted in Figure 4.14. Thus, in order to attain the best detection performance ever, all existing SUs in the network should be included in the cooperation processes. A careful selection of sensing time slot should be done to attain a compromise between throughput and sensing. Also, a suitable modulation index and number of quantization levels should be used at the SU stage in order to enhance the spectral efficiency when relaying the sensing data from the SUs to the FC while maintaining good error performance and fidelity.

Figure 4.14  Channel bandwidth of the SU-FC link as a function of number of bit per symbol and number of bits per sample at different sensing times.
In fact, great rooms for improvement in the detection performance can be achieved by employing a more effective weighting scheme at the FC. Since there is no tradeoff behaviour observed on the detection performance as a result of varying the sensing time and number of collaborating SUs, only the setting of weighting vector at the FC should be chosen as a design objective to improve the detection performance. This calls for a more innovative and probably intelligent scheme to search for the most optimal setting of weighting coefficients so that the PU can be perfectly detected and hence sufficiently protected.

4.4.7 Proposed SOGA-assisted SDF-based Optimization System

As mentioned in the preceding section. The CRN-wise detection performance is very much dependent on the setting of weighting coefficients at the FC. The weighting coefficients are shown in Figure 4.11 and are mathematically collected into the vector \( \omega = [\omega_1, \omega_2, ..., \omega_M]^T \). The objective of maximizing the CRN-wise probability of detection expressed in (4.38) can be realized by determining the optimal setting of this weighting vector. In this section, a single-objective genetic algorithm (SOGA) is proposed to search for the optimal values of weighting coefficients intelligently and autonomously. This research work is motivated by the fact that the conventional SDF methods such as NDC, MDC, MRC, and EGC are capable of providing sub-optimal settings of weighting coefficients which might not suffice when low SNR values are observed such as in deep fading environments.

The proposed SOGA-assisted SDF-based algorithm is explained in Table 4.1. A population of strings \( P(t) \) at generation \( t \) is randomly initialized giving a diverse range of possible solutions or potential weighting settings. Each binary string consists of \( M \) decision variables encoded by equal number of bits. The binary-coded search space is then accurately decoded to a solution space based on one-to-one mapping to ensure no trivial solutions. Each of these possible solutions is evaluated and given a fitness score based on equation (4.38). The selection operator is then invoked to select the fittest chromosomes from the parent population. In Darwinian terms, this performs a ‘survival of the fittest’ operation on every population. The selected parent population forms the basis of a mating pool and undergoes stochastic transformations
Table 4.1 Proposed SOGA-assisted SDF-based algorithm.

<table>
<thead>
<tr>
<th>Steps</th>
<th>Details of the Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Set ( t = 0 ) and randomly generate a population ( P(t) ) of ( pops ) chromosomes each of which is of ((M*nb\text{bits})) bits long, where ( M ) is the number of weighting coefficients (i.e. number of SUs in the network) and ( nb\text{bits} ) is the number of bits to represent each coefficient.</td>
</tr>
<tr>
<td>Step 2</td>
<td>Decode each chromosome in the random population into its corresponding weighting coefficients vector ( \tilde{\omega}<em>j = [\omega</em>{j1}, \omega_{j2}, ..., \omega_{jM}]^T ), where ( \omega_{ji} \in [0,1], i = 1, 2, ..., M ) and ( j = 1, 2, ..., pops ).</td>
</tr>
<tr>
<td>Step 3</td>
<td>Normalize the weighting coefficients vector through dividing ( \tilde{\omega}_j ) by its 2-norm such that ( \tilde{\omega}<em>j^* = \frac{\tilde{\omega}<em>j}{\left( \sum</em>{i=1}^{M} (\omega</em>{ji})^2 \right)^{1/2}} ) so that the constraint ( | \tilde{\omega}_j^* |_2 = 1 ) is satisfied.</td>
</tr>
<tr>
<td>Step 4</td>
<td>Compute the fitness score of every normalized decoded weighting vector, ( \tilde{\omega}_j^* ), and rank their corresponding chromosomes based on their fitness scores and identify the best ( \left\lfloor pops*elite \right\rfloor ) chromosomes, where ( elite ) is a parameter determines a fraction of ( pops ), i.e. ( elite \in [0,1] ), and ( \lfloor . \rfloor ) denotes floor operation.</td>
</tr>
<tr>
<td>Step 5</td>
<td>Update ( t = t + 1 ) and reproduce ( \left\lceil pops*(1-elite) \right\rceil ) new chromosomes (candidate solutions) through genetic algorithm operations; selection, crossover, and mutation, where ( \lceil . \rceil ) denotes ceiling operation.</td>
</tr>
<tr>
<td>Step 6</td>
<td>Construct new population ( P(t) ) by concatenating the newly ( \left\lceil pops*(1-elite) \right\rceil ) reproduced chromosomes with the best ( \left\lfloor pops*elite \right\rfloor ) found in ( P(t-1) ).</td>
</tr>
<tr>
<td>Step 7</td>
<td>Decode and normalize the chromosomes of the new population ( P(t) ) as in Step 2 and Step 3, respectively.</td>
</tr>
<tr>
<td>Step 8</td>
<td>Evaluate the fitness score of each candidate solution as in Step 4.</td>
</tr>
<tr>
<td>Step 9</td>
<td>If ( t ) is equal to a predefined number of generations (iterations), ( ng\text{ene} ), terminate the algorithm; otherwise go to Step 5.</td>
</tr>
</tbody>
</table>
by means of genetic operations to form new individuals. The population of the new individuals resulting from crossover and mutation are called offspring population $C(t)$. It is worth to notice that genetic operators perform essentially a blind search whereas selection operators provide the driving force to hopefully steer the genetic search toward the desirable region of the solution space. Once $C(t)$ is formed, a new population is formed, by combining $C(t)$ with the fittest chromosomes of the parent population, and re-evaluated. The evolutionary process continues and after several predefined number of generations, the algorithm converges to the best individual which hopefully represents an optimal solution to the problem of maximizing the CRN-wise probability of detection. In this algorithm, the initial population of chromosomes is randomly generated and each chromosome is decoded and normalized to satisfy the constraint in (4.39). As our objective is to maximize $Q_d$, we utilize it as the fitness function (i.e. $f(\omega) = Q_d(\omega)$) used to evaluate the quality of the chromosomes. The constraint in (4.39) is proposed to limit the number of optimal solutions and reduce the search space on which the GA works.

4.4.8 Performance Evaluation of SOGA-assisted SDF-based Optimization System

In this section, the convergence and detection performance of the proposed GA-assisted scheme are both evaluated. In order to choose an appropriate form of the algorithm to meet the nature of the given problem and to achieve more efficient evolutionary processes, the effect of various GA parameter settings has been analyzed using a set-and-test approach. The GA parameters and operators used in this simulation are set as follows: $pops = 30$, $P_c = 0.95$, and $P_m = 0.01$ as in for online applications; where $P_c$ is two-point crossover rate and $P_m$ is bit-flip mutation rate, $nbits = 6$, $elite = 0.1$, $ngene = 100$, and roulette wheel selection was used. The CR network simulation parameters are $M = 20$, $K = 150$, $\bar{P}_f = 0.25$, $P_{RI} = 12$ dBm, and \{g_i\}, \{h_i\} are randomly-generated so that low SNR environment at SU and FC receivers is realized (SNR < -10 dB). Notice that \{g_i\}, \{h_i\} are assumed to be constant over every sensing time period; this is justified by the slow-fading nature over the PU-
SU and SU-FC links where the delay requirement is short compared to the channel coherence time in the so-called quasi-static scenario.

For the same channel condition, the maximum $Q_d$ fitness of the best chromosome and the mean fitness of all chromosomes in every generation are both shown in Figure 4.15. It can be seen that the proposed SOGA-assisted scheme converges within the first 50 generations, which is so fast. This means that the computation complexity of the proposed scheme can meet the real-time requirements. The improvement achieved by the evolutionary processes of GA after 44 generations is about 12.75% which is a considerable gain. The recent population formed upon terminating the SOGA evolutionary processes is analyzed the best chromosome found in this population is extracted and used at the FC as the optimal weighting setting. The optimality claim of the obtained weighting setting is partially supported by the maximum CRN-wise probability of detection of 98.12% after which no more improvement can be gain in any direction with any more generations. The obtained setting is examined further in the next section.

![Convergence performance of SOGA-assisted SDF-based system.](image)

**Figure 4.15**  Convergence performance of SOGA-assisted SDF-based system.

### 4.4.9 Results and Discussion
In order to prove the optimality of the obtained setting of weighting coefficients using SOGA, the detection performance of SOGA-assisted scheme should be compared with other conventional SDF-based schemes, such as the ones presented in Section 4.4.5, as well as the OR-logic HDF scheme by plotting the ROC curve for each. The same optimal solution (optimal weighting vector) obtained from the GA operations in Figure 4.15 is used to evaluate the performance of the SOGA-assisted scheme in Figure 4.16. It can be seen that our proposed SOGA scheme outperforms all other conventional SDF and HDF schemes. This validates the effectiveness of the proposed GA-assisted SDF-based linear cooperative spectrum sensing scheme. Higher probability of detection induces more protection for PUs which is a crucial requirement in CRNs.

For a given false alarm probability of 0.1, the proposed SOGA-assisted SDF-based cooperative spectrum sensing scheme achieves an improvement of more than
10% in the detection performance in comparison to the best conventional SDF-based scheme (i.e. NDC). This makes the proposed algorithm very promising since it offers better PU protection. The other excellent feature of the proposed algorithm is the fast computational speed since the optimal weighting setting can be found within about 50 generations as has been shown in Figure 4.15. This fast processing time makes the proposed SOGA technique very promising in such a real-time application.

4.5 HDF and SDF TRADEOFFS IN CRNS

The HDF- and SDF-based cooperative spectrum sensing methods are distinguished from each other by the mechanism they use to monitor the PU activities. As presented earlier, the HDF-based schemes make local decisions at the SU’s stage and send their 1-bit individual decisions to the FC to construct a global decision whereas the SDF-based schemes do not make decisions at SUs but they else relay their raw sensing measurements to the FC at which linear weighted combination is performed to develop the global decision on PU availability. Thus, the proposed BOGA-assisted HDF-based and SOGA-assisted SDF-based cooperative spectrum sensing can now be compared. Although, the performance objectives for the two algorithms are assumed distinct, fair comparison can be made by specifying two general items that are the detection performance and traffic (or communication) overhead. In terms of detection performance, it has been observed in Figure 4.16 that any SDF-based scheme such as EGC, MRC, MDC, NDC, or the proposed SOGA scheme show higher CRN-wise probability of detection for given probability of false alarm than the OR-logic HDF-based scheme. For instance, for a given false alarm probability of 0.1, the worst SDF scheme (i.e. EGC) shows a detection probability of about 15% higher than that of the OR-logic HDF scheme. Thus, SDF-based schemes should be used to enhance the detection performance and perfectly protect the PU especially when the PU-SU and SU-FC links undergo deep fades and/or high noise levels.

On the other hand, in terms of traffic or communication overhead, the HDF-based schemes such as the OR-logic rule outperforms and of the conventional or proposed SDF-based schemes. This is because in HDF, the SUs process the data locally and send single decision bits to the FC whereas in SDF, the sensing data is sent
as it is (after quantization) and the global decision on PU availability is made at the FC. Consider a CRN of $M$ SUs in the vicinity of a FC/BS, $K$ samples of potential PU signal to be captured at each SU receiver, and $u$ quantization bits per sample used to relay the soft measurement in the SDF case. Let’s simply define the traffic overhead by the total number of bits reported from all SUs to the FC/BS. In HDF architecture, $M$ SUs report their $M$ binary decisions to the FC. Thus, any HDF scheme requires relay of $M$ bits from all SUs to the central FC/BS. In any SDF scheme, each of the $M$ SUs relays $K$ samples each of which is quantized using $u$ bits. Thus, the total number of relayed bits from all SUs to the FC is $uKM$. This makes the ratio of traffic overhead of HDF to SDF as $M$ to $uKM$ or simply as 1 to $uK$. Obviously, this shows that HDF requires very much lesser number of bits to be relayed from SUs to FC than SDF. Therefore, HDF schemes require lesser spectral and power resources than SDF schemes. Thus, HDF schemes should be used instead of SDF schemes when restrictions on power and spectral resources exist.

### 4.6 SUMMARY

This chapter presents the employment of GAs for optimizing the performance of HDF- and SDF-based CRNs. In HDF-based CRNs, a BOGA-assisted optimization system is developed to optimize the sensing time and SU cooperation level so that the proposed BOF is maximized. The BOF function combines the detection performance as well as the SU throughput into one single scalar function introduced to the BOGA system as a fitness function. The performance of the proposed BOGA system is evaluated and the solutions obtained are further analyzed to prove their sub-optimality in comparison to other potential settings. The simulation results show an improvement of 10% on the BOF score when using the optimal cooperation level than when using 100% cooperation level as well as improvement of 4% when using the optimal sensing time rather than setting the sensing period to half of its total frame duration. On the other hand, a SOGA-assisted optimization system is proposed and developed to optimize the detection performance in SDF-based CRNs. The SOGA is configured to optimize the weighting coefficient of the linear soft fusion process at the fusion centre of CRN. The solution of weighting coefficients obtained from the evolutionary processes of SOGA is then used to evaluate the ROC curve of the CRN-wise detection
performance. The proposed SOGA-assisted is compared with other conventional SDF schemes in the literature such as NDC, MDC, MRC and EGC as well as the OR-rule HDF scheme. For a given false alarm rate of 0.1, the proposed SOGA-assisted SDF-based cooperative spectrum sensing scheme achieves an improvement of more than 10% in the detection performance in comparison to the best conventional SDF-based scheme (i.e. NDC). Finally, the detection performance and traffic overhead in HDF- and SDF-based CRNs are discussed based on the obtained results to support the claim of proposing HDF-based CRN when low traffic overhead is needed and the SDF-based CRNs for cases where high detection performance is of interest.
CHAPTER V

MOGA-ASSISTED HYBRID SDF-HDF CLUSTER BASED COOPERATIVE SPECTRUM SENSING FOR COGNITIVE RADIO NETWORKS

5.1 INTRODUCTION

The chapter presents an extended architecture of cooperative spectrum sensing model for CRNs from HDF- and SDF-based CRNs presented in Chapter IV. This is realized by means of hybridization between SDF and HDF architectures in a cluster based deployment. This proposal is motivated by contradiction between the detection performance and communication overhead in the performance of HDF- and SDF-based CRNs. Since SDF-based CRNs show better detection performance than HDF-based CRNs whereas HDF-based CRNs require lesser relay overhead than SDF-based CRNs, the idea of proposing a hybrid SDF-HDF cluster based architecture that comes as a solution to achieve a compromised detection performance and communication overhead is explained. The research work carried out in this chapter begins with proposing several performance metrics that can be formulated as multi-objective function to be optimized by a multi-objective genetic algorithm MOGA system. The convergence performance of the proposed system is examined and the results obtained are analyzed to verify the functionality of the proposed MOGA optimization system.

5.2 HYBRID SDF-HDF CLUSTER BASED CRN SYSTEM MODEL

The proposed deployment of hybrid SDF-HDF cluster based CRNs is depicted in Figure 5.1. The hybridization between SDF and HDF schemes is realized by grouping the existing SUs within the vicinity of a central BS into multiple clusters. The sensing measurements from the SUs of each cluster are relayed to their corresponding cluster
header (CH) where an SDF scheme is performed. Then, the individual sensing decisions made at the CHs are forwarded to the central BS at which a HDF scheme is conducted to construct a global decision on PU availability. Clustering the existing SUs provides means of frequency reuse among CRN clusters and thus spectral resources can be more efficiently utilized. Figure 5.1 shows the proposed CRN deployment where each geographically-nearby $M$ SUs are grouped into a cluster governed by a CH and the $N$ CHs of the $N$ clusters report their decisions to a common BS. The use of a weighting vector in the linear SDF brings up the advantage of eliminating the need for finding optimal thresholds for the individual SU nodes and abstracting all into a single global threshold. Possible ways of optimizing the weighting vector have been presented in Chapter IV. A well-dedicated algorithm to choose the CH of each cluster can be found in (Van & Koo 2009). It is assumed that the instantaneous channel state information (CSI) of the reporting channel is available at each CH. In Figure 5.1, three main links can be distinguished; the primary user-secondary user (PU-SU) link, the secondary user-cluster header (SU-CH) link, and finally, the cluster header-fusion centre (CH-BS) link.

Figure 5.1 Detailed system model of the proposed hybrid SDF-HDF cluster-based cooperative spectrum sensing.
5.3 PERFORMANCE METRICS AND PARAMETERS

In this section, several performance metrics that characterize the overall qualitative and quantitative performance of cooperative spectrum sensing are proposed. These performance metrics include sensing metrics such as the global detectability of PU as well as other metrics of crosslayer parameters. The proposed architecture is claimed to be a more extended and realistic model that can consider several aspects at the SU, CH, and BS stages. The CRNs architectures being formed of intelligent and autonomous nodes should be able to satisfy multiple operational requirements rather than considering the detection performance only. For instance, the power consumption as well as the bandwidth utilization due to the relay of sensing measurements should be both minimized. Thus, this section presents several performance metrics formulated in a normalized manner such that they can be aggregated into a scalar multi-objective metric or function.

5.3.1 Proposed Objective Functions

The proposed multiple objective functions of the hybrid SDF-HDF cluster based CRN are now derived based on the system model shown in Figure 5.1. These proposed objectives are put in normalized forms so that no objective of high scores overwhelms others of low scores. The normalization procedure is necessary to provide about uniform distribution of scores for all proposed objectives within the (0, 1) range. Detailed explanations of the proposed objectives are now addressed.

(i) PU detection Probability: The probability of detecting the PU is one of the main metrics of cooperative spectrum sensing in CRNs. As shown in Figure 5.1, an SDF scheme is employed at the CH stage whereas a HDF scheme is used at the BS. Thus, the probability of detection at the \( j^{th} \) CH, \( Q_{d,j} \), is the same as the one expressed in Equation 4.38 mentioned in Section 4.4.3. Thus

\[
Q_{d,j} = Q \left( \frac{Q^{-1}(\bar{Q}_f) \sqrt{\sum_{h_0} \bar{\omega} - \bar{\omega}^T \bar{\theta}}}{\sqrt{\sum_{h_1} \bar{\omega}}} \right) \quad (5.1)
\]
In the CH-BS link, all CHs communicate with the central BS through a dedicated control channel in an orthogonal manner. The individual clusters’ decisions are forwarded from the $N$ CHs to the BS at which a final global decision is made based on a HDF OR-rule. The HDF is used to reduce the reporting traffic overhead from the $M$ SUs to the BS. In our proposed system model, it is assumed that the reporting channel of each CH-BS link is a binary symmetric channel (BSC) with a probability of reporting error, $P_{e,j}$ (Sun et al. 2007). Therefore, the overall probability of detection, $Q_d$, of the hybrid SDF-HDF cluster based CRN is given by

$$POD = Q_d = 1 - \prod_{j=1}^{N} [(1 - Q_{d,j})(1 - P_{e,j}) + Q_{d,j}P_{e,j}]$$

For simplicity, it is assumed that the BSCs of the CH-BS links are all identical and have the same probability of reporting error, i.e. $P_{e,j} = P_e$. The objective of this metric is to maximize POD.

(ii) Relay probability of error: In the proposed model shown in Figure 5.1, any $i^{th}$ SU relays its sensing measurements to the $j^{th}$ CH. For simplicity, it is assumed that all SUs within a given cluster use an $M$-ary QAM scheme with the same modulation index, $M_d$, when relaying their measurements to their corresponding CH. Thus, the relay probability of error, denoted as BER, is expressed as

$$BER = \frac{2^*\left(1 - \sqrt{M_d}\right)}{\log_2\sqrt{M_d}} \phi\left(\frac{3\log_2\sqrt{M_d} 2^* E_b}{(M_d - 1) N_0}\right)$$

where $E_b/N_0$ is bit energy per noise power spectral density. The objective of this metric is to minimize BER.

(iii) Control Channel Bandwidth: The bandwidth of the control channel is an important design metric since the spectral resources is the main concern that has led to the emergence of CR technology. Thus, this metric should be included as a key parameter when designing a CRN. Assume that the SUs relay their measurements to their corresponding CH using orthogonal frequency division multiple access
(OFDMA) manner with $L_n$ subcarriers. For simplicity, it is assumed that the number of subcarriers used by each SU is the same. The normalized control channel bandwidth (CCB) is then written as

$$
CCB = \frac{(2T_s B)u L_n \sum_{j=1}^{N} M_j}{(\log_2 M_d)^{F_r} F_{reuse} CCB_{max}}
$$

(5.4)

where $T_s$ is the sensing time duration, $B$ is the sensed bandwidth, $u$ is the number of quantization bits per sample, $M_j$ is the number of SUs into the $j^{th}$ cluster, $M_d$ is the $M$-ary modulation index, $T_r$ is the relay time, $F_{reuse}$ is the frequency reuse factor and $CCB_{max}$ is the maximum available control channel bandwidth. The objective of this metric is to minimize CCB.

(iv) CRN Throughput: The CRN throughput is proportional to the available time of SU opportunistic data transmission out of the total frame time duration. The normalized CRN throughput (THR) for a given frame time duration can be modified from equation (4.16) introduced by Liang et al. (2008) as follows

$$
THR = \frac{\left(\frac{T_f - (T_s + T_r)}{T_f}\right) (1 - Q_f)}{THR_{max}}
$$

(5.5)

where $THR_{max}$ is the maximum achievable throughput of the CRN. The sensing time period is assumed to be the same for all SUs. This is because varying the sensing time among SUs may result in synchronization issues that complicate the periodic sensing activity of the CRN. The objective of this metric is to maximize THR.

(v) Total Power Consumption: As in any communication system, the power consumption should be always minimized to allow long connectivity especially when limited power resources are available. The total power consumption of SUs in the network is due to the total transmission power used to relay the sensing measurements
from the SU transmitters all the way to the central BS through the corresponding FC. The normalized total power consumption (TPC) during the relay of sensing measurements can then be expressed as

\[
TPC = \frac{\sum_{j=1}^{N} \sum_{i=1}^{M_j} P_{r,j,i}}{TPC_{\text{max}}}
\]  

(5.6)

where \(P_{r,j,i}\) is the transmit power of the \(i^{th}\) SU in the \(j^{th}\) cluster and \(TPC_{\text{max}}\) is maximum power consumption. The objective of this metric is to minimize TPC.

(vi) **Signal to interference and noise ratio:** As the number of SUs per cluster increases, the mutual interference caused by the transmission of nearby SUs becomes a serious matter. In this metric, it is assumed that the interference effect at the receiver of a certain SU is limited to the SUs who exist within the same cluster only and not to be influenced by the transmission of SUs of neighbouring clusters. The normalized signal to interference and noise power (SINR) can be expressed as

\[
SINR = \frac{1}{SINR_{\text{max}}} \frac{\sum_{j=1}^{N} \sum_{i=1}^{M_j} P_{r,j,i}}{N_{j,i} + \sum_{k=1, k\neq i}^{M_i} P_{r,j,k}}
\]  

(5.7)

where \(SINR_{\text{max}}\) is the maximum possible score of SINR. The objective of this metric is to minimize SINR.

(vii) **Quantization fidelity of sensing measurements:** The collected samples of the sensing measurements at the SU receivers are quantized to a certain number of levels to reduce the amount of traffic overhead upon relaying the sensing measurements to the corresponding CHs. The number of quantization levels, and thus the number of quantization bits per sample \((u)\), has to be carefully selected. This is because using too many quantization levels results in bandwidth expansion whereas reducing the number of quantization levels will degrade the signal fidelity. The fidelity can be simply
thought of how much the quantized samples resemble their original signal (Sklar 2001). The normalized quantization fidelity (CFD) can be written as

\[
CFD = \frac{2^{2u}}{CDF_{max}}
\]

where \(CDF_{max}\) is the maximum possible fidelity. The objective of this metric is to maximize CFD.

### 5.3.2 Dependency Relationships of Performance Metrics

The performance metrics formulated in Equations (5.2) to (5.8) describe multiple objectives of the CRN that need to be jointly optimized. By inspecting the mentioned equations of the performance metrics, several dependent parameters can be distinguished. These parameters and their used symbols and descriptions are tabulated in Table 5.1. Each of these parameters may control more than one single performance metric as shown in Figure 5.2.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modulation index</td>
<td>(M_d)</td>
<td>Modulation index used to relay the measurements.</td>
</tr>
<tr>
<td>Sensing time</td>
<td>(T_s)</td>
<td>Time duration taken to perform spectrum sensing.</td>
</tr>
<tr>
<td>Probability of false alarm</td>
<td>(Q_f)</td>
<td>The CRN-wise probability of false alarm.</td>
</tr>
<tr>
<td>Relay power</td>
<td>(P_r)</td>
<td>Amount of power required to relay the measurements.</td>
</tr>
<tr>
<td>Number of SUs per cluster</td>
<td>(M)</td>
<td>Number of SUs in each cluster.</td>
</tr>
<tr>
<td>No of bits per sample</td>
<td>(u)</td>
<td>Number of quantization bits per sample.</td>
</tr>
<tr>
<td>Total relay time</td>
<td>(T_r)</td>
<td>Total relay time from SU to BS through CH.</td>
</tr>
</tbody>
</table>
Figure 5.2 Objective-parameter dependency relationships and their conflicting behaviour.

Figure 5.2 depicts the dependency relationships between the performance metrics and their corresponding parameters. By performing simple inspections for the performance metrics expressed in Equations (5.2) to (5.8), it can be observed that the same parameter may influence a given performance metric differently. This means that increase a certain parameter may improve a certain performance metric but at the same time, it may degrade another. The proposed performance metrics are shown in ellipses shaded in gray whereas the corresponding parameters are listed in the legend. These parameters use arrows of different colors connecting the performance metrics they are related to. On these arrows, (g) and (b) are labelled to indicate good and bad effect on the connected metrics as the related parameter increases, respectively. For instance, increasing the $M_d$ has a good effect on control channel bandwidth whereas it has a bad effect on the relay probability of error as can be observed by inspecting Equations (5.4) and (5.3), respectively. Also, increasing the sensing time $T_s$ improves the detection probability of PU (good effect) but at the same time it reduces the CRN throughput (bad effect) since remaining time for transmission is then decreased. The later effects can be confirmed by inspecting Equations (5.2) and (5.5), respectively. The same goes for all other parameters and their related performance metrics.
It is clear that the proposed objectives demonstrate a conflicting behavior which requires an intelligent system that is able to search for sub-optimal parameters at which a balanced compromise among these conflicting objectives can be achieved.

5.4 FORMULATION OF OPTIMIZATION PROBLEM

The intended objectives of the performance metrics expressed mathematically in equations (5.2) to (5.8) are now defined as shown in Table 5.2. All objective functions are formed as maximization problems. The original minimization problems of CCB, TPC, and BER are complemented into equivalent maximization problems. The design parameters (decision variables) that control each objective are also listed. These objectives are classified into four main classes according to their functionality. The forth class combines quality parameters of the relay process from the SUs to the BS through corresponding CHs.

Table 5.2 The proposed objective functions and their related parameters.

<table>
<thead>
<tr>
<th>$f_i$</th>
<th>Objective</th>
<th>Abbr.</th>
<th>Aim</th>
<th>Parameters</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>PU detection Probability</td>
<td>POD</td>
<td>Maximization</td>
<td>$f(T_s, Q, P_r, M)$</td>
<td>1</td>
</tr>
<tr>
<td>$f_2$</td>
<td>CRN Throughput</td>
<td>TRP</td>
<td>Maximization</td>
<td>$f(T_s, Q, T_r)$</td>
<td>2</td>
</tr>
<tr>
<td>$f_3$</td>
<td>Control Channel Bandwidth</td>
<td>1 - CCB</td>
<td>Maximization</td>
<td>$f(M_d, T_s, M, u, T_r)$</td>
<td>3</td>
</tr>
<tr>
<td>$f_4$</td>
<td>Total Power Consumption</td>
<td>1 - TPC</td>
<td>Maximization</td>
<td>$f(P_r)$</td>
<td></td>
</tr>
<tr>
<td>$f_5$</td>
<td>Quantization fidelity of measurements</td>
<td>QFD</td>
<td>Maximization</td>
<td>$f(u)$</td>
<td>4</td>
</tr>
<tr>
<td>$f_6$</td>
<td>Signal to interference and noise ratio</td>
<td>SINR</td>
<td>Maximization</td>
<td>$f(M)$</td>
<td></td>
</tr>
<tr>
<td>$f_7$</td>
<td>Relay probability of error</td>
<td>1 - BER</td>
<td>Maximization</td>
<td>$f(M_d)$</td>
<td></td>
</tr>
</tbody>
</table>
5.4.1 Aggregation of Multiple Objective Functions

These multiple objective functions shown in Table 5.2 are aggregated into one multi-objective. As explained in section 2.7.3, the aggregation of multiple objectives is realized using the weighted-sum utility function or using the linear logarithmic utility function expressed in equation (2.13) and (2.14), respectively. Both approaches are used in the proposed work. In fact, the weighted-sum approach is the default option since it shows better performance whereas the linear logarithmic approach is used when the optima (maxima or minima) is found at extreme edges. Since the obtainable parameters after the optimization processes are expected to be Pareto-front or sub-optimal solutions, it is therefore less likely to find these solutions at extreme edges. The seven objective functions listed in Table 5.2 can be formed using the weighted-sum approach as follows

\[ f_{\text{multi-objective}} = \sum_{i=1}^{C} w_i f_i \]

\[ = w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 \]  

(5.9)

where \( f'_4 = (f_4 + f_5 + f_6 + f_7)/4 \), \( C \) is the number of objective classes (i.e. \( C = 4 \)) and \( w_i \) is the weighting coefficient of the \( i^{th} \) class (or objective). Similarly, the objective functions can be aggregated using the linear logarithmic utility function as follows

\[ \ln(f_{\text{multi-objective}}) = \sum_{i=1}^{C} w_i \ln(f_i) \]

\[ = w_1 \ln(f_1) + w_2 \ln(f_2) + w_3 \ln(f_3) + w_4 \ln(f_4') \]  

(5.10)

5.4.2 CRN Operational Modes

The aggregation procedure realized using the weighted-sum or linear logarithmic utility functions provides a unique feature that can benefit the cognition requirement of CRN as well as the CR systems. This cognition is allows the optimization process to be steered towards a specific objective according to the operational requirements
and/or user demands. The rational priority of each objective in comparison to other objectives is set by assigning a distinct weighting coefficient as shown in Equations (5.9) and (5.10). In this research work, six operational modes of the CRN have been defined by adjusting the weighting coefficients of the individual functions that constitute the overall multi-objective function as shown in Table 5.3. The high licensee protection mode is defined by assigning higher weight to the objective of maximizing the CRN-wise probability of PU detection. Increasing the detectability of existing PU(s) helps to make this PU(s) more protected from potential SU transmission. The low bandwidth mode is realized by allocating higher weighting coefficient to the objective of minimizing the control channel bandwidth. The CRN may switch to this operational mode in the case of limited spectral resources. The multimedia mode is formulated by putting more focus on the objective of maximizing the CRN throughput. The CRN may work with this mode when there is a demand to transmit large amount of data such as in video/audio multimedia applications. The high quality mode is constructed by assigning higher weight to the objective functions of class four as shown in Table 5.2. This operational mode ensures low-error relaying process with minimal power consumption, high quantization fidelity, and low potential interference due to other neighbouring SU transmissions. The balanced mode is formed by allocating equal weighting coefficients for each objective. In addition, a customised mode is defined by setting the weighting coefficients to any other constants \(c_1, c_2, c_3, c_4\) according to user needs or operational requirements. The objective which is receiving more emphasis is arbitrarily allocated 70% whereas other objectives would share the other remaining 30%.

Table 5.3 Proposed operational modes and their corresponding weighting coefficients.

<table>
<thead>
<tr>
<th>Operational Mode</th>
<th>Weighting coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>High licensee protection mode</td>
<td>0.7 0.1 0.1 0.1</td>
</tr>
<tr>
<td>Multimedia mode</td>
<td>0.1 0.7 0.1 0.1</td>
</tr>
<tr>
<td>Low bandwidth mode</td>
<td>0.1 0.1 0.7 0.1</td>
</tr>
<tr>
<td>High quality mode</td>
<td>0.1 0.1 0.1 0.7</td>
</tr>
<tr>
<td>Balanced mode</td>
<td>0.25 0.25 0.25 0.25</td>
</tr>
<tr>
<td>Customized mode</td>
<td>(c_1) (c_2) (c_3) (c_4)</td>
</tr>
</tbody>
</table>
The proposed MOGA-assisted SDF-HDF cluster based cooperative spectrum sensing is developed to optimize the multi-objective function stated in equation (5.9) or (5.10). Each of these aggregated multi-objective functions combines multiple objectives into one scalar function that represent the overall performance of the hybrid SDF-HDF cluster based CRN with distinct versions. These versions are formed by manipulating the weighting coefficients of the single objectives according to operational conditions and/or user preferences. The schematic architecture of the proposed MOGA optimization system is shown in Figure 5.3. The system receives the sensing measurements from SU nodes, measures the channel conditions, and adjusts its objective priorities according to the setting of weighting coefficients. The system is then runs its biologically-inspired evolutionary processes to search for the Pareto-from solutions of design parameters at which the multiobjective function is optimized under the selected operational mode. Finally, the system returns the design parameters shown as outputs from the MOGA optimization system in the figure. The symbols used to denote these parameters and their description are tabulated in Table 5.1. Take note that the obtainable parameters represent sub-optimal solutions since the overall multi-objective function is comprised of several conflicting objectives.

Figure 5.3 Proposed MOGA optimization system and its I/Os.
5.5.1 Chromosome Encoding

The design parameters shown in Figure 5.3 and described in Table 5.1 are encoded into the chromosomes of the proposed MOGA hybrid SDF-HDF cluster based optimization system. The chromosome is comprised of 7 decision variables and it has a length of 38 bits in total as shown in Figure 5.4. This chromosome length results in a search space of $2^{38}$ potential solutions. The selection of number of bits to represent a certain decision variable depends on the discrete range of values for that variable. Binary GA is developed due to the discrete nature of the optimization problem and to reduce the search space of potential solutions. The MOGA optimization system is initialized by defining the discrete range for each decision variable. Three bits are used to represent eight possible modulation indices and another three bits are used to represent eight permutations of quantization bits. Four bits are used to realize sixteen possible power levels and another four bits used to represent sixteen possible clustering plan. Also, eight bits are used to represent 256 possible sensing time choices, eight bits are used to represent a discrete range of 256 values for the false alarm rate, and eight bits used to encode 256 possible relay time slots. The mini-max values for each of these decision variables or design parameters should be supplied to the system before running it. For instance, the modulation index may vary as 16, 32, ..., 2048 QAM. The sensing time and relay time should also be defined in terms of the available frame duration. The number of bits per samples that determine the number of quantization bits per each sensing sample should also be defined. The same goes for all other design parameters. Choosing the range should be done carefully to realize a feasible range. For example, the false alarm rate may theoretically vary from 0 to 1. However, it is not practically feasible to consider this range during the optimization process. Thus, the false alarm rate has been constrained to be limited to the (0, 0.1) range. This is because a false alarm rate of 1 means that the CRN cannot access the available white spaces at all. The same requirement is found when designing the sensing time slot. Theoretically, the sensing time vary from zero up to the total frame duration. However, setting the sensing time to zero, by the MOGA optimization system, results in eliminating the sensing process whereas setting it to the total frame duration means that no secondary spectrum access by CRN is possible. Therefore range of sensing time should be chosen carefully to avoid such extreme cases.
5.5.2 Development of GUI Simulation Model (GUISM)

In this research work, a graphical user interface simulation model (GUISM) has been developed in order to realize a friendly interactive tool user interface that helps the user to choose the operational mode of the MOGA optimization system, select the aggregation approach and utility functions, setting the range of decision variables, and setting the genetic algorithm parameters. The GUISM is depicted in Figure 5.5. It contains three input panels which allow the user to interact with GUISM. The first panel allows the user to choose the utility function to be either weighted sum or linear logarithmic function. The second panel provides means to realize as static or dynamic channel conditions by using “With Twister” or “Without Twister”, respectively. The third panel allows the user to choose any of the six operational modes defined in Table 5.3. If the user chooses the customized mode, four input boxes are provided to enter the weighting coefficients of the four classes in Table 5.2, respectively. The user can also set the minimum and maximum values that define the range of each design parameter. Also, the user is able to set the total number of SUs in the system, the total number of generation, the total frame duration and the twister state if a static channel is considered. The GUISM is then run by clicking on the START button. After the MOGA optimization system is terminated upon exceeding the predefined total number of generations, the optimal design parameters will be shown in the static boxes in the same GUISM as shown. Other observations can be shown also in the GUISM including the value of the multi-objective functions, the generation index at which the maximum score of the multi-objective function is achieved, and the time taken by CPU to perform the optimization process in second. The best and average multi-objective fitness function scores versus generations will also be plotted in the upper...
part of GUIM. The fitness versus generation graphs in GUIM can be saved using the “Save Figure” button below the graph box. If the user wishes to clear the results displayed in GUIM including the setting and the optimal results as well as the GUIM graph, the user can simply click on the CLEER button. The GUIM can be closed by pressing the CLOSE button.

![GUIM](image)

**Figure 5.5**  GUIM for MOGA optimization system.

### 5.6 PERFORMANCE EVALUATION

In this section, the GUIM is used to show the convergence performance of the proposed hybrid SDF-HDF cluster based CRN. The system is initialized by selecting the utility function to be used for aggregation of objectives and the channel condition
as well as the operational mode. Also, the range of each decision variable and the GA parameters are supplied. The GUIISM is set to 100 existing SUs, total number of generations of 600, and total frame duration of 100 microseconds. The system is then run to observe the graph of fitness versus number of generations. The optimal parameters panel show the obtainable parameters after terminating the evolutionary processes of the system. Figure 5.6 show the settings as well as the obtained results under the high quality mode taken arbitrarily.

Figure 5.6 GUlSM simulation results under high quality mode.
The convergence performance is shown on the upper fitness versus generation’s graph. It is noticed that the obtainable sub-optimal solution is obtained after 158 generations scoring a maximum fitness of about 0.88 (or 88%). The obtainable parameters are modulation index $M_d = 16$, $u = 8$ quantization bits per sample, sensing time $T_s = 7.262$ microseconds, relay time $T_r = 9.133$ microseconds, relay power $P_r = 0.316$ dBm, false alarm rate $Q_f = 0.05$, and number of clusters $N = 7$ of about equal number of SUs. Under the chosen high quality operational mode, the optimization process is steered towards prioritizing the forth class of objectives in Table 5.2 that is to minimize the power consumption, maximize the quantization fidelity, minimizing the signal to interference and noise ratio, and minimizing the relay error rate. However, the dependent parameters of these conflicting objectives may conflict among each other as well as with objectives of other classes. For example, increasing the number of quantization levels results in increasing the quantization bits which improves the quantization fidelity but it causes increment on the control channel bandwidth. Also minimizing the power consumption can be achieved by reducing the transmission power of the SUs when relaying their sensing measurements to their corresponding CH. However, reducing the transmission power has the bad effect of degrading the CRN-wise probability of detection as has been shown in Figure 5.2. Therefore, the obtainable parameters are not expected to be the optimal parameters at their extreme values that solely maximize the class of objectives with the highest priority. Instead, the obtainable solutions are only sub-optimal values that can realize compromises between the conflicting intra and inter classes of objectives. By inspecting the values of obtainable parameters, the lowest modulation index of 16 is chosen since high relay quality is demanded. The highest number of quantization bits of 8 is also used to improve the quantization fidelity. A low sub-optimal transmission power of 0.316 dBm is acceptable to reduce the power consumption. The other parameters are selected to attain a balanced compromises based on the weighting coefficients assigned to the respective objectives. In fact, the obtainable solutions of design parameters should be judged by relating them to the respective objectives due to the contradictory natures of these objectives. The right way to prove the sub-optimality of the obtainable solutions is to evaluate their collective impact on the overall aggregated multi-objective fitness function. The simulation results of all operational modes are discussed on the next section.
5.7 RESULTS AND DISCUSSION

In this section, the obtained solutions of design parameters under different operational modes are analyzed to prove their sub-optimality in comparison to other potential settings of design parameters. Table 5.4 summarizes the MOF scores with different settings of the design parameters under related operational modes. Under the high licensee protection mode, the sensing time is set to be adaptive and encoded in the MOGA chromosomes or static with three different static values of $10 \, \mu s$, $1 \, \mu s$, and $0.1 \, \mu s$. The MOF scores at these different sensing time settings are captured and tabulated as shown in the table.

Table 5.4 MOF scores at different parameter settings under related operational mode.

<table>
<thead>
<tr>
<th>Design parameter</th>
<th>Parameter setting</th>
<th>Operational mode</th>
<th>MOF score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensing time ($\mu s$)</td>
<td>Adaptive</td>
<td>High licensee protection</td>
<td>0.8338</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td></td>
<td>0.7520</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td></td>
<td>0.5923</td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td></td>
<td>0.4805</td>
</tr>
<tr>
<td>Relay time ($\mu s$)</td>
<td>Adaptive</td>
<td>Multimedia</td>
<td>0.8863</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td></td>
<td>0.8085</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td></td>
<td>0.8705</td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td></td>
<td>0.8734</td>
</tr>
<tr>
<td>Modulation index</td>
<td>Adaptive</td>
<td>Low control channel bandwidth</td>
<td>0.9170</td>
</tr>
<tr>
<td></td>
<td>2048</td>
<td></td>
<td>0.8894</td>
</tr>
<tr>
<td></td>
<td>32</td>
<td></td>
<td>0.8681</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td></td>
<td>0.8887</td>
</tr>
<tr>
<td>Quantization bits</td>
<td>Adaptive</td>
<td>High quality</td>
<td>0.8798</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td></td>
<td>0.8558</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td></td>
<td>0.8061</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td></td>
<td>0.7345</td>
</tr>
<tr>
<td>Relay power (dBm)</td>
<td>Adaptive</td>
<td>Balanced</td>
<td>0.8321</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td></td>
<td>0.7512</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td></td>
<td>0.7658</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td></td>
<td>0.7234</td>
</tr>
</tbody>
</table>
It is clear that the adaptive sensing time achieves the highest MOF score in comparison to all other static values of sensing time. This proves the inclusion sensitivity of this parameter in the design problem. The sensing time is a key parameter that controls the detection performance which the performance metric of the highest priority under the high licensee protection operational mode. The obtained results show that setting the sensing time to a static value results in degradation on the overall MOF score. This result proves the effectiveness of the sensing time being an adaptive decision variable on the design problem.

The same observation has been found on other design parameters under their related operational modes. The adaptive relay time achieves the highest MOF under the multimedia mode. In fact, increasing the relay time leads to a reduction on the time figure remaining for data transmission. However, setting this parameter to a static low value of, say, 0.1 $\mu$s does not work fine on maximizing the overall MOF score. This proves the inclusion of the relay time as an adaptive design parameter. Similar observations are found for the modulation index under the low control channel bandwidth mode, the number of quantization bits under the high quality mode, and relay power under the balanced mode. The obtained results validate the proposed chromosome representation of the MOGA optimization system as setting any of the decision variables to static values cause degradation on the overall MOF score.

The obtainable sets of design parameters under the five operational modes; the high licensee protection mode, the low bandwidth mode, the multimedia mode, the high quality mode, and the balanced mode, are extracted from the GUISM after termination. The five maximum achievable multi-objective fitness (MOF) scores obtained at the five corresponding parameter sets are averaged and graphically represented on the first bar as shown in Figure 5.7. Similarly, the average MOF values under the five operational modes is also calculated at special parameter settings such as when all design parameters are set to be at their minimum values, maximum values, and mid-range or median values. The calculated average MOF scores obtained at these parameter settings are also graphically represented in bars as shown in Figure 5.7.
It can be observed that when the parameters are set to their sub-optimal values obtained by GUISM, the average MOF scores 0.883 which is higher than the average MOF obtained at any other setting. The average MOF scores under mid-range, maximum, minimum values of design parameters are 0.552, 0.739, and 0.19, respectively. Thus, the MOF can be significantly maximized when using the sub-optimal solutions for the hybrid SDF-HDF cluster based CRN which are obtained by GUISM. This experimental analysis provides a collective and comprehensive assessment on the effectiveness of the obtainable sub-optimal design parameters obtained by GUISM under various operational modes. The GUISM realizes the MOGA optimization system that works on optimizing the design parameters of the proposed hybrid SDF-HDF cluster based cooperative spectrum sensing. The achievable average MOF with the sub-optimal parameters can be calculated to be 14.4% greater than the best MOF score obtained when using the maximum values of the design parameters and 69.3% higher than the worst MOF score obtained when using the minimum values of the design parameters.
5.8 SDF-SDF, HDF-HDF, AND SDF-HDF TRADEOFFS IN CRNs

In CRNs, maximizing detection performance and minimizing communication overhead are the main two conflicting objectives. This contradiction calls for innovative solutions that can balance between these two objectives in an autonomous manner. The CRN being intelligent cognitive nets should be able to satisfy different requirements based on channel conditions or users’ preferences. In this section, the existing tradeoff between these conflicting objectives is addressed through three possible architectures of SDF-SDF, HDF-HDF, and SDF-HDF cluster based CRNs. Although clustering was only proposed for proposed SDF-HDF architecture in this chapter, it is here extended to SDF-SDF and HDF-HDF CRN architectures to present fair comparisons of detection performance and relaying overhead. Figure 5.8 depicts the front-end detection performance of different combinations of SDF and HDF schemes as well as SDF-SDF and HDF-HDF cluster-based scenarios.

Figure 5.8 Detection performance of various combinations of SDF- and HDF-based CRNs.
In fact, the only possible CRN scenarios are SDF-SDF, SDF-HDF, and HDF-HDF. The HDF-SDF is unrealizable because once the sensing information content is lost by hard fusion, this content cannot be retrieved or softened anymore. For the purpose of illustration, the SDF schemes used in this section are NDC, MRC, and EGC whereas the OR-rule is used as a HDF scheme. However, the SOGA-assisted scheme proposed in chapter IV can be used here as well. The MDC scheme has been excluded as it almost has the same detection performance as NDC. As expected, the SDF-SDF (NDC-NDC) cooperative sensing scenario shows the best detection performance among all other scenarios as demonstrated in Figure 5.8. However, being an SDF-SDF scenario, the NDC-NDC has the drawback of increased traffic overhead. On the other hand, the hybrid SDF-HDF (NDC-OR) cluster-based cooperative sensing scenario has a superior detection performance comparing to all other SDF-SDF (except NDC-NDC scenario), HDF-HDF, and SDF-HDF combinations. The interesting finding here is that although the SDF-SDF combinations of MRC-MRC and EGC-EGC use soft fusion in both SU-CH and CH-BS stages, these two combinations still unable to outperform the proposed SDF-HDF (NDC-OR) scenario which uses hard fusion in the CH-BS stage.

One may intuitively say that applying SDF in two successive links should result in better performance than applying SDF followed by HDF in these two links. However, the improved performance of SDF-HDF (NDC-OR) over the two SDF-SDF scenarios, MRC-MRC and EGC-EGC, is justified by the degradation occurred in SDF-HDF (NDC-OR), due to the utilization of OR-rule fusion scheme in the CH-BS link, is compensated by the superior performance of NDC so that the overall performance of the NDC-OR scenario outperforms the ones of MRC-MRC and EGC-EGC combinations. The advantage of using HDF instead of SDF at the CH-BS link is the reduced traffic overhead especially when the number of clusters is comparable. The MRC-MRC and EGC-EGC have better performance than MRC-OR and EGC-OR, respectively, which is again due to using the OR-rule HDF in the CH-BS stage. Finally, the HDF-HDF (OR-OR) has the worst detection performance as comparing to all other combinations but it has the unique advantage of minimum traffic overhead. Thus, the SDF-HDF CRN architecture can be said to be a good compromise between
improving the detection performance (by using SDF) and reducing the traffic overhead (by using HDF).

Table 5.5 presents a traffic overhead analysis for the three general possible scenarios; SDF-SDF, SDF-HDF, and HDF-HDF. SDF might be NDC, MRC, or even EGC whereas OR- rule is used as HDF. Assume that a quantization process is applied whenever an SDF scheme is used to reduce the transmission bandwidth. Each SU in a particular cluster needs to transmit $u \times K$ bits in the case of SDF and only one single bit in the case of HDF to the corresponding CH. Now, recall that the overhead traffic is defined as the total number of bits that need to be reported from all SUs all the way to the BS through CHs. The overhead ratio in the SU-CH links is $(u \times K) : (u \times K) : 1$ for SDF-SDF, SDF-HDF, and HDF-HDF scenarios, respectively, whereas in the CH-BS links, it is $(u \times K \times M) : 1 : 1$ for SDF-SDF, SDF-HDF, and HDF-HDF scenarios, respectively. Considering the SDF-HDF scenario, there is an increment of $(u \times K)$ times comparing to HDF-HDF in the SU-CH links and a reduction of $(u \times K \times M)$ times comparing to SDF-SDF in the CH-BS links. It is clear that the amount of overhead reduction when comparing to SDF-SDF is $M$ times greater than the amount of overhead increment when comparing to HDF-HDF. In addition, when the number of clusters $N$ is large, using SDF-SDF will lead to increase this number $u \times K \times M$ times greater than $N$. Strictly speaking, the HDF-HDF scenario offers the lowest ever overhead traffic, but unfortunately, the detection performance of HDF scheme is not as good as the SDF one. Thus, the SDF-HDF scenario presents an excellent and balanced compromise between maximizing the detection performance and minimizing the overhead traffic conflicting objectives.

<table>
<thead>
<tr>
<th>Hybrid Scenario</th>
<th>Number of bits transmitted over $M \times N$ SU-CH links</th>
<th>Number of bits transmitted over $N$ CH-BS links</th>
</tr>
</thead>
<tbody>
<tr>
<td>SDF-SDF Scenario</td>
<td>$u \times K \times M \times N$</td>
<td>$u \times K \times M \times N$</td>
</tr>
<tr>
<td>SDF-HDF Scenario</td>
<td>$u \times K \times M \times N$</td>
<td>$N$</td>
</tr>
<tr>
<td>HDF-HDF Scenario</td>
<td>$M \times N$</td>
<td>$N$</td>
</tr>
</tbody>
</table>
5.9 SUMMARY

This chapter extends the SDF- and HDF-based CRNs proposed in chapter IV to a hybrid SDF-HDF cluster-based CRN architecture. Several performance metrics are proposed to construct the overall multi-objective fitness function of the whole network from the SUs all the way to the central FC/BS through corresponding CHs. The contradiction between the proposed single objective functions is observed. The CRN design parameters are then identified and the single objective functions are aggregated into one overall multi-objective function after being weighted using appropriate weighting coefficients. The CRN operational modes associated with the distinct settings of the weighting coefficients are also identified. A MOGA optimization system is then developed to optimize the CRN design parameters so that the overall MOF function is maximized. GUISM is also developed that allow the user to interact with the proposed MOGA optimization system and observe its convergence performance as well as the returned solutions after exceeding the predefined total number of generations. The obtainable design parameters under various operational modes are analysed to prove the effectiveness of their inclusion as adaptive parameters in the design problem. The optimal parameters can score an average MOF value of 0.883 which is 14.4% greater than the best MOF score obtained when using the maximum values of the design parameters and 69.3% higher than the worst MOF score obtained when using the minimum values of the design parameters. SDF-SDF, HDF-HDF, and SDF-HDF detection performance and traffic overhead tradeoffs are finally discussed based on the obtained simulation results. The analyses support the claim of proposing the hybrid SDF-HDF cluster based CRN architecture for a compromised detection performance and traffic overhead.
CHAPTER VI

CONCLUSIONS AND FUTURE WORK

6.1 CONCLUSIONS

Nowadays, there is a common agreement among research community in academia as well as in industry on that the conventional exclusive allocation of spectral resources for different technologies is no more feasible. This agreement is originated from the continuously increasing demand for operating frequency bands to support new emerging technologies. Recent empirical studies have shown that the scarcity of spectrum is not really caused due to limited nature resource, but instead, it is a result of the current inefficient allocation schemes since most of the frequency bands are significantly underutilized. To tackle this issue, DSA schemes are being proposed to replace the current static allocation schemes that are no more able to cope up with the state of the art technologies and applications. CR is widely envisioned as means of realizing DSA solutions and provides opportunities to enhance spectrum efficiency. CR systems are adaptive wireless nodes act autonomously based on their awareness of the surrounding environment. Therefore, the CR systems should employ an intelligent core that is able to process the environmental information and adapts its transmission accordingly. On the other hand, this awareness requires the CR nodes to be armed with spectrum sensing capabilities. Cooperative spectrum sensing is established among several CR nodes in a CRN to improve the PU detection performance. However, this cooperation between CR nodes results in communication overhead due to relaying activities of sensing data and decisions. Unfortunately, the two objectives of maximizing detection performance and minimizing communication overhead are contradictory. Thus, an intelligent optimization system should be used to compromise
between these two conflicting objectives. As mentioned in the research objectives in Section 1.3, this thesis proposes MOEAs as intelligent autonomous cores for CR systems as per objective (i) and as optimization systems for HDF-, SDF-, and hybrid SDF-HDF cluster-based CRNs as per objective (ii), (iii), and (iv), respectively. The novelty of this thesis lies on the proposed hybrid SDF-HDF cluster based CRN architecture as a solution that realizes a balanced compromise between the conflicting objectives of maximizing the detection performance while minimizing the communication overhead. In addition, the thesis novelty is reflected on the employment of MOEAs of different objectives for CR systems and CRNs. The proposed MOEAs developments for CR systems and CRNs and their corresponding findings are all summarized in the following sections.

6.1.1 MOEA for CR Systems

In Chapter III, a particular MOEA called MOGA is developed as an intelligent core or decision engine of a CR system that is able to adapt its transmission parameters in response to a set of sensed environmental parameters based on given performance objectives. The proposed environmental parameters of the CR system are the received power, the noise power, and the path loss estimation whereas the transmission parameters are the transmission power, the modulation scheme, and the symbol rate. The objective functions that formulate the relationships between these I/O parameters are also proposed. Then, an analytical simulation study was carried out to show the contradictory nature of the proposed objectives. These conflicting objectives are aggregated into one overall multi-objective function through the use of variable weighting coefficients that can be adjusted to define distinct transmission scenarios for the CR system. These distinct transmission modes are the reliable communication mode (RCM), the power-saving mode (PSM), the spectrally-efficient mode (SEM) and the balanced mode (BLM).

The proposed MOGA decision engine is developed to be able to adaptively optimize the transmission parameters in such a way it can satisfy the requirements of the predefined transmission mode. The performance of the proposed MOGA system is evaluated and validated under the proposed transmission modes. It is shown that the
proposed MOGA decision engine is able to search for and find the sub-optimal or the so-called Pareto-front solutions of transmission solutions within the first 50 evolutionary generations. This convergence speed makes the proposed MOGA decision engine feasible for such a real-time application. Under RCM, PSM, or SEM transmission modes, the proposed MOGA engine achieves a MOF score of more than 80%. This MOF score is a considerable achievement since it represents a compromise between several conflicting objectives. A lower MOF score of more than 60% is achieved when BLM transmission mode is used due to increased level of contradiction occurred when weighting coefficients are uniform assigned to the confliction objectives. Sensitivity analyses have been carried out to prove the effectiveness of the proposed inclusion of the transmission parameters in the overall multi-objective performance metric. It was shown that by triggering the MOGA decision engine to adaptively optimize its transmission parameters, higher MOF values can be scored than when setting its parameters to static values. Thus, these analyses confirm the validity of including the proposed transmission parameters as decision variables in the CR optimization problem. However, more environmental and transmission parameters can be identified, formulated and optimized by the proposed MOGA decision engine to improve its cognition capabilities and awareness of the surrounding environment.

### 6.1.2 MOEAs for CRNs

Three distinct CRN architectures are proposed to resolve the contradiction between the detection performance and communication overhead in cooperative spectrum sensing. Chapter IV presents HDF- and SDF-based CRN architectures whereas Chapter V extends the CRN architectures in Chapter IV to a hybrid SDF-HDF cluster based one. The motivation of proposing these CRN architectures is to provide choice diversity of detection performance and communications overhead. The proposed HDF-based CRN is distinguished by its reduced communication overhead whereas the other proposed SDF-based CRN show better PU detection performance. This performance contradiction between HDF- and SDF-based CRN is settled by proposing a hybrid SDF-HDF cluster based CRN architecture. This hybrid architecture provides a balanced compromise between the conflicting objectives of maximizing the detection performance while minimizing the communication overhead. Tradeoff
analyses on these two objectives in HDF-, SDF-, hybrid SDF-HDF CRN architectures are supplied in Chapter IV and V.

For HDF-based CRN architectures, a BOGA-assisted optimization system is proposed and developed to jointly optimize the sensing time and SU cooperation level so that the proposed BOF is maximized. The BOF function combines the detection performance as well as the SU throughput into one single scalar function introduced to the BOGA system as a fitness function. The performance of the proposed BOGA system is evaluated and the solutions obtained are further analyzed to prove their sub-optimality in comparison to other potential settings. The simulation results show an improvement of 10% on the best achievable BOF score when using the optimal cooperation level than when using 100% cooperation level as well as an improvement of 4% when using the optimal sensing time than when setting the sensing period to half of its total frame duration.

On the other hand, a SOGA-assisted optimization system is proposed and developed to optimize the detection performance in SDF-based CRNs. The SOGA is configured to optimize the weighting coefficient of the linear soft fusion process at the fusion centre of CRN. The solution of weighting coefficients obtained from the evolutionary processes of SOGA is then used to evaluate the ROC curve of the CRN-wise detection performance. The proposed SOGA-assisted is compared with other conventional SDF schemes in the literature such as NDC, MDC, MRC and EGC as well as the OR-rule HDF scheme. For a given false alarm rate of 0.1, the proposed SOGA-assisted SDF-based cooperative spectrum sensing scheme achieves an improvement of more than 10% in the detection performance in comparison to the best conventional SDF-based scheme (i.e. NDC). Finally, the detection performance and traffic overhead in HDF- and SDF-based CRNs are discussed based on the obtained results to support the claim of proposing HDF-based CRN when low traffic overhead is needed and the SDF-based CRNs for cases where high detection performance is of interest.

In Chapter IV, the proposed hybrid SDF-HDF cluster-based CRN architecture is presented. Several performance metrics are proposed to construct the overall multi-
objective fitness function of the whole network from the SUs all the way to the central FC/BS through corresponding CHs. The contradiction between the proposed single objective functions is first analyzed. The CRN design parameters are then identified and the single objective functions are aggregated into one overall multi-objective function after being weighted using appropriate weighting coefficients. The CRN operational modes associated with distinct settings of the weighting coefficients are also formulated. A MOGA optimization system is then developed to optimize the CRN design parameters so that the overall MOF function is maximized. GUISM is also developed that allow the user to interact with the proposed MOGA optimization system and observe its convergence performance as well as the returned solutions after exceeding a predefined number of generations. The obtainable design parameters under various operational modes are analysed to prove the effectiveness of their inclusion as adaptive parameters in the design problem. The optimal parameters can score an average MOF value of 0.883 which is 14.4% greater than the best MOF score obtained when using the maximum values of the design parameters and 69.3% higher than the worst MOF score obtained when using the minimum values of the design parameters. SDF-SDF, HDF-HDF, and SDF-HDF detection performance and traffic overhead tradeoffs are finally discussed based on the obtained simulation results. The analyses support the claim of proposing the hybrid SDF-HDF cluster based CRN architecture for a compromised detection performance and traffic overhead.

In conclusion, all the objectives of this thesis defined in chapter I have been achieved. Although the proposed MOEAs can successfully realize intelligent cores for CRs and optimization systems for CRNs of different architectures, there are still several open problems need to be addressed in order to further extend and improve the results presented in this thesis. Among the main limitations of this research work is the lack of knowledge on how a certain CRN with a specific architecture such as an HDF-based one can be cognitively switched to another hybrid SDF-HDF cluster-based architecture with least possible change of infrastructure and in a seamless manner. In fact, further investigation should be carried out on the correlation of the proposed parameters and their corresponding search spaces. These limitations and other ones are recommended as a future work in the next section.
6.2 FUTURE WORK

This section summarizes some recommendations and potential research directions suggested as a future work to extend the achievements and improve the results presented in this thesis. These summaries include the followings:

(i) To facilitate the interoperability and convergence of the proposed different HDF-, SDF-, and hybrid SDF-HDF CRNs, an interesting research direction can be found in looking into practical ways of evolvable networks that can adapt its functionalities and activities using the same infrastructure. For instance, the idea lies on the technology that can be used to configure a specific infrastructure to work as SDF- or HDF-based architectures based on channel conditions or operator/user requirements.

(ii) More design parameters are performance metrics can be included as decision variables and objective functions, respectively, for CR systems as well as HDF-, SDF-, and hybrid SDF-HDF CRN architectures.

(iii) In this research, it is assumed that a transmission mode is chosen through tuning the weighting coefficients assigned to the individual objectives by the CR user. However, it would be worth to explore the possibility of mapping these weighting coefficients directly to certain environmental circumstances or device operating conditions.

(iv) The relaying scheme used by the SUs in this research is the amplify-and-forward scheme. It would be of interest to explore the possibility of employing other relaying schemes such as decode-and-forward scheme.

(v) In the proposed hybrid SDF-HDF cluster based CRN architecture, the MOGA optimization system searches for the optimal modulation index, transmission power, sensing time, relay time, modulation scheme, and quantization levels which are shared by all SUs. However, this work can be extended to search for a distinct set of parameters for each SU. This would definitely improve the
overall performance of the network with the penalty of hugely increased overhead.

(vi) In this research, standard settings of GA parameters have been used in all proposed MOEA optimization systems. However, commonly, there has been no rule-of-thumb on the best set of parameters that optimize the convergence performance of the GA system. The conventional procedure of selecting the GA parameter for a formulated optimization problem used to be the set-and-test approach of extensive experiments. This approach requires long time and unnecessary effort with uncertainty on whether or not the set of parameters found is the optimal set ever. This work can be extended to consider employing a hierarchical formalism of two GA layers where the first GA works to search for the optimal set of parameters that can be then used by the second GA for the given optimization problem.

(vii) It is also worth to consider other biologically-inspired optimization algorithms such as particle swarm optimization (PSO), ant colony optimization (ACO), or artificial bee colony (ABC) algorithm that may show better convergence performance with possibly lesser number of parameters to be set.
REFERENCES


LIST OF PUBLICATIONS

Journal Papers


Proceeding Papers


Other Presentations/Workshops/Seminars
