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CERTIFICAN

Que la tesis "Study and Development of Advanced Meta-Heuristic Approaches for Resource Allocation in Intelligent Communication Systems", presentada por D. Javier Del Ser Lorente y realizada en el Departamento de Teoría de la Señal y Comunicaciones bajo nuestra dirección, reúne méritos suficientes para optar al grado de Doctor, por lo que puede procederse a su depósito y lectura.

Alcalá de Henares, Abril 2013.

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Fdo.: Dr. D. José Antonio Portilla Figueras

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D. Javier Del Ser Lorente ha realizado en el Departamento de Teoría de la Señal y Comunicaciones y bajo la dirección del Dr. D. Sancho Salcedo Sanz y del Dr. D. José Antonio Portilla Figueras, la tesis doctoral titulada "Study and Development of Advanced Meta-Heuristic Approaches for Resource Allocation in Intelligent Communication Systems", cumpliéndose todos los requisitos para la tramitación que conduce a su posterior lectura.

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Dpto. de Teoría de la Señal y Comunicaciones

Doctorado en Tecnologías de la Información y las Comunicaciones

Memoria de Tesis Doctoral

Study and Development of Advanced Meta-Heuristic Approaches for Resource Allocation in Intelligent Communication Systems

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Abril 2013

Borbolitantzat ta Gangarritantzat, bihotzez

Abstract

The starting point of this dissertation lies on the concept of intelligent radio systems, which brings together all those communication systems capable of adapting their operations - via the optimized management of their available radio resources - to both the status of the physical medium through which the information is sent and possible restrictions imposed by the user, operator, or application at hand. The reasons for the implementation and deployment of this kind of systems are manyfold and diverse: as to mention, the mobility of the devices incorporating this adaptive functionality (ranging from people to vehicles of any kind) lead to amplitude fluctuations and eventually, deep fades in the signal power received at the destination front-end, with particular emphasis on wireless transmission mediums. Furthermore, the ecosystem of applications using wireless communication systems require an increasingly demanding quality of service by the equally growing size of the underlying networks supporting multiple and concurrent multimedia communications. Both factors determine significantly the allocation of radio resources (such as frequency, time or power) between users and applications, so they must be taken into consideration when optimally managing such resources.

Although the advent of the so-called transmission adaptability dates back to the early nineties, the interest in intelligent radio systems has gained momentum in the last decade, mainly due to the crystallization of new technological trends in regulatory radio spectrum policies. Many studies have indeed shown that in recent years the inefficiency of allocation and resource exploitation strategies traditionally imposed throughout the World: the exclusive allocation and operation of certain "licensed" frequency bands by operators, and the arbitrary use of "unlicensed" spectral bands by operators and private users. To date the coexistence of both policies in the international regulatory framework has sown a fertile substrate for the rapid growth and development of wireless communication systems at both technical and application levels. However, the release of the so-called "digital dividend" (i.e. the UHF band between 790 and 862 MHz) has revealed numerous shortcomings of this regulatory framework, which call for the adoption of alternative mixed regulatory schemes. In addition, several measurement campaigns carried out in different countries (e.g. USA, United Kingdom and Finland) have unanimously concluded that although the licensed spectrum is considered a scarce and valued resource, a large portion is not utilized or when used, is done in short periods of intense use or bursts.

In this context, cognitive radio stands emerges as a radio communication paradigm that can provide a flexible and practical technological response to the need for a more flexible and dynamic access to radio spectrum. Conceived as the most technologically advanced form of intelligent communication systems, cognitive radio devices are capable of monitoring the status of different spectral bands, determining their occupancy level, and opportunistically and autonomously adapting their radio

parameters for the best use of the spectrum band at hand. The adaptability of radio resources and the development of algorithms for their efficient management lie consequently at the heart of current and future radio communication standards.

This being exposed, this dissertation aims at shedding light on the applicability of novel meta-heuristic techniques for the optimization of the allocation of resources in intelligent communication systems. Inspired by the observation of physical phenomena and social behaviors in the Nature, these techniques are known to efficiently balance the tradeoff between computational complexity and the quality of the generated solutions, which is deemed of utmost relevance in view of the growing scales of communication networks. Specifically, three are the scenarios where meta-heuristics are exemplified as efficient algorithmic means for the management of radio resources:

- The first scenario focuses on radio communication downlinks where a base station transmits information to several distant user through a single frequency-wide orthogonally multiplexed transmit signal. The establishment of limits on the perceived transmission rate for each user and the insertion of a second base station as an unlicensed transmitter on the band in question yields a constrained optimization problem, which is efficiently solved by the novel meta-heuristic Harmony Search algorithm. This contribution also includes an innovative greedy repair procedure that accounts for the fulfillment of the produced solutions with respect to the imposed transmission rates by user.
- The second stage addresses a dynamic channel allocation problem in cognitive radio networks, where Harmony Search is again employed for the allocation of frequency channels in the links between nodes under an error rate minimization criteria. The novelty of this contribution lies not only in the adaptation of the Harmony Search optimization technique itself to this particular scenario, but also in the tailored design of this algorithm for distributed network topologies, in an attempt at balancing the localized complexity featured by their centralized counterpart.
- The third scenario goes beyond meta-heuristics to span the contributions of the Thesis towards another branch in the field of Soft Computing: fuzzy logic. Specifically, this contribution proposes a novel selection scheme for spectrum sensing methods according to a set of heuristic rules that can be made by experts or learnt from previous actions and their results. Fuzzy logic eases the joint consideration of several parameters of relevance to the selection process (e.g. detection probability or the available computation time), hence overriding the necessity for defining a precise mathematical model for the process itself.

In summary, this dissertation takes a technical step towards the adoption of meta-heuristic techniques – and by extension, Soft Computing methods – for the management of radio resources in intelligent communication systems.

Resumen

Esta tesis doctoral adopta como punto de partida el concepto de radio inteligente, el cual agrupa todos aquellos sistemas de comunicación capaces de adaptar su funcionamiento – mediante la gestión optimizada de sus recursos radio – tanto a las condiciones del medio físico por el que transmiten la información como a restricciones impuestas por el usuario, operador, o aplicación que los utilizan. Los motivos para la implementación y despliegue de sistemas inteligentes de comunicación son varios y diversos: por un lado, la movilidad de los dispositivos que incorporan esta funcionalidad (abarcando desde personas hasta vehículos de toda clase) dan lugar a fluctuaciones y, ocasionalmente, profundos desvanecimientos de potencia en la señal recibida en la interfaz destino, con particular énfasis en los medios de transmisión inalámbrica. Por otro lado, el ecosistema de aplicaciones multimedia que utilizan este tipo de sistemas demanda requisitos de calidad de servicio cada vez más exigentes por las igualmente crecientes dimensiones de las redes de comunicación que los soportan. Ambos factores condicionan significativamente la asignación de recursos radio tales como frecuencia, tiempo o potencia entre los usuarios y aplicaciones que los explotan, por lo que deben ser tenidos en consideración a la hora de gestionar óptimamente dichos recursos.

Aunque el auge investigador de los denominados interfaces adaptativos de comunicación datan de comienzos de la década de los noventa, el interés en la radio inteligente ha resurgido en los últimos años debido, fundamentalmente, a la cristalización de nuevas corrientes tecnológicas en las políticas regulatorias del espectro radioeléctrico. Son múltiples los estudios que han evidenciado la ineficiencia de las estrategias de asignación y explotación de recursos espectrales tradicionalmente implantadas a nivel mundial: la asignación de derechos exclusivos de explotación de bandas frecuenciales por parte de determinados operadores (bandas “licenciadas”), y la explotación de bandas espectrales de manera arbitraria por parte de operadores y usuarios particulares (bandas “no licenciadas”). Hasta la fecha la coexistencia de ambas políticas en el marco regulatorio internacional ha sembrado un sustrato fértil para el florecimiento y desarrollo vertiginoso de los sistemas de comunicación inalámbrica tanto a nivel técnico como aplicativo. Sin embargo, la liberación del denominado “dividendo digital” (banda UHF entre 790 y 862 MHz) ha revelado numerosas carencias de este marco mixto de regulación que sugieren la adopción de marcos regulatorios alternativos. Además, varias campañas de medidas llevadas a cabo en diferentes países (e.g. EEUU, Gran Bretaña o Finlandia) concluyen unánimemente que, si bien el espectro licenciado es considerado como un bien escaso y apreciado, una gran parte del mismo no se emplea de manera continuada, y cuando se utiliza, se hace en períodos cortos de utilización intensa o ráfagas.

En este contexto, la denominada radio cognitiva se erige en un paradigma de comunicaciones radio capaz de proporcionar una respuesta tecnológica ágil y práctica

a la necesidad de flexibilizar y dinamizar el acceso al espectro radioeléctrico. Concebidos como la forma más tecnológicamente avanzada de los sistemas inteligentes de comunicación radio, los dispositivos de radio cognitiva tienen la capacidad de monitorizar bandas espectrales, determinar su grado de utilización y adaptar sus parámetros radio de manera oportunista y autónoma para el mejor aprovechamiento de la banda en cuestión. La adaptabilidad de los recursos radio y el desarrollo de algoritmos que los gestionen de manera eficiente juegan, por tanto, un papel de máxima relevancia en las comunicaciones radio del presente y futuro.

Esta tesis doctoral tiene por objetivo demostrar la aplicabilidad de nuevas técnicas meta-heurísticas de optimización a la asignación de recursos en sistemas de radio inteligente. Inspiradas en la observación de fenómenos físicos y comportamientos de la Naturaleza, estas técnicas son bien conocidas por equilibrar eficientemente el compromiso entre complejidad computacional y la calidad de las soluciones generadas, balance de gran trascendencia habida cuenta de las crecientes escalas de las redes de comunicación. Específicamente, son tres los escenarios donde se paraboliza la meta-heurística al servicio de la gestión de recursos radio:

- El primer escenario se centra en enlaces descendentes donde una estación base transmite a varios usuarios multiplexando la información de cada uno de ellos en una misma señal transmitida mediante el uso de portadoras ortogonales. La imposición de límites en la tasa de transmisión a recibir por cada usuario y la introducción de una segunda estación base a modo de usuario no licenciado en la banda en cuestión da lugar a un problema de optimización con restricciones, resuelto de manera eficiente mediante el algoritmo meta-heurístico búsqueda por harmonía. Esta contribución también incluye un innovador proceso voraz de reparación que permite compatibilizar las soluciones producidas con las tasas de transmisión impuestas por usuario.
- El segundo escenario aborda el problema de la asignación dinámica de canales en redes basadas en radio cognitiva, donde la búsqueda por harmonía es empleada para la asignación de canales en frecuencia a los enlaces entre nodos bajo criterios de minimización de su tasa de error promedio. La novedad de esta contribución radica tanto en la aplicación de esta meta-heurística de optimización en sí, como en el diseño del algoritmo para su funcionamiento en topologías distribuidas, orientadas éstas últimas a balancear la complejidad localizada característica de los sistemas centralizados.
- El tercer escenario bordea lateralmente la meta-heurística considerando, en su lugar, una rama relacionada en el ámbito del *Soft Computing* para su aplicación a escenarios de radio inteligente: la lógica difusa. En concreto, se propone un esquema novedoso de selección del método de sensorización espectral según un juego de reglas heurísticas que pueden ser formuladas por expertos o por la propia experiencia del selector. La lógica difusa facilita la consideración conjunta de varios parámetros relevantes para el proceso de selección (e.g. probabilidad de detección o tiempo de cómputo disponible) sin la necesidad de definir un modelo matemático preciso y objetivo para dicho proceso.

En resumen, esta tesis supone un avance científico-técnico hacia la adopción de herramientas meta-heurísticas – y por extensión, de *Soft Computing* – en la gestión de recursos radio de los futuros sistemas inteligentes de comunicación.

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More than ten years ago I decided to focus my professional career on research, mainly motivated by the fact that I love digging into new fields (well, frankly speaking almost all my daily routine revolves around research). I seldom ask myself why to opt for this instead of any other less health-demanding dedication; I am constantly involved in so many things that my mind often diverges to more urgent and ground-touching matters. Nevertheless, I eagerly believe that devotion to research reduces to a two-fold rationale: passion for the undiscovered and rewardless satisfaction. I feel passionately keen on investigating new things, which certainly satisfies me upon new achievements. However, my motivation has been mainly ignited by many people that, in one way or another, have made this Thesis become true. I'm not good at expressing feelings in viva voce, so here is my most sincere attempt at acknowledging all such individuals.

Contrarily to the majority of Theses I've come through so far, this section will not start by shedding lots of deserved gratitude over my supervisors. I'm sure they will tolerate it. My strongest support during this difficult period has been the loving memory of my mother, to whom I owe not only the existence itself, but also my tenacious commitment to always do and perform my best in every single endeavour. Amatxo, eskerrik asko bihotz-bihotzez!

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I am known to be quite lost in thoughts, and prone to brain-scattering in the most unexpected moments. Since the time of this writing is not an exception, I apologize in advance for any oversight.

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List of Acronyms and Symbols

MIMO	Multiple Input Multiple Output
GSM	Global System for Mobile Communications
GPRS	General Packet Radio Service
UMTS	Universal Mobile Telecommunications System
LTE	Long Term Evolution
IEEE	Institute of Electrical and Electronics Engineers
$\mathcal{A}$	Adaptation strategy
$f_{\mathcal{A}}(\cdot)$	Resource allocation criterium in strategy $\mathcal{A}$
QoS	Quality of Service
$\mathcal{P}$	Operators operational policy
M2M	Machine to Machine
FPGA	Field Programmable Gate Array
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency-Division Multiple Access
$\mathbf{X}$	Decision variable vector
$\boldsymbol{\mathcal{X}}$	Alphabet of a decision variable vector
$X(k)$	Component or entry of a decision variable vector
$\mathcal{X}$	Alphabet of a component of a decision variable vector
$f(\cdot)$	Fitness function
$g(\mathbf{X})$	Generic constraint
G	Upper or lower limit for $g(\mathbf{X})$
$\mathbb{R}$	Set of all real numbers
$\mathbb{R}^+$	Set of real positive numbers
$\mathbb{R}^K$	Cartesian product of K copies of $\mathbb{R}$
$h_i^\flat(\mathbf{X})$	Equivalent aggregate equality constraint
$N_c^=$	Number of $h_i^\flat(\mathbf{X})$
$h_i^\sharp(\mathbf{X})$	Equivalent aggregate inequality constraint
$N_c^<$	Number of $h_i^\sharp(\mathbf{X})$
$\mapsto$	Mapping between domains
$\boldsymbol{\mathcal{X}}^*$	Set of optimum solutions
$\mathbb{N}$	Set of all natural numbers
$\mathbb{N}^+$	Set of natural positive numbers
$\mathbb{N}^K$	Cartesian product of K copies of $\mathbb{N}$
$\mathbf{X}^\surd$	Repaired decision variable vector

HS	Harmony Search
GA	Genetic Algorithm
DE	Differential Evolution
EDA	Estimation of Distribution Algorithm
Ψ_{GA}	Population size of a GA
P_c	Crossover probability (GA)
P_m	Mutation probability (GA)
LLE	Linear Linkage Encoding
μ	DE weighting factor
P_c^{DE}	Crossover probability (DE)
F_n	n-th tonal frequency
HM	Harmony Memory
Ψ	Size of HM
∂_n	MIDI number for F_n
$\mathbf{X}(\psi)$	ψ-th harmony vector
$X(\psi, k)$	k-th note of $\mathbf{X}(\psi)$
HMCR	Harmony Memory Considering Rate
φ	HMCR probability
PAR	Pitch Adjusting Rate
ϑ	PAR probability
RSR	Random Selection Rate
ε	RSR probability
$\rightsquigarrow$	Assignment in a meta-heuristic operator
ω_{HMCR}	Auxiliary variable for the HMCR operator
η	Pitch bandwidth
ω_{PAR}	Auxiliary variable for the PAR operator
ISI	Inter Symbol Interference
DVB	Digital Video Broadcasting
DAB	Digital Audio Broadcasting
DMT	Discrete Multi Tone
ADSL	Asymmetric Digital Subscriber Line
DFT	Discrete Fourier Transform
TDMA	Time Division Multiple Access
FDMA	Frequency Division Multiple Access
WRAN	Wireless Regional Area Network
iDFT	Inverse Discrete Fourier Transform
ADSL	Asymmetric Digital Subscriber Line
B	Overall transmission bandwidth
N	Number of frequency subcarriers (or channels, depending on the context)
Δf	Spacing between consecutive subcarriers
f_c	Central frequency
T_m	Delay spread of a wireless communication channel
T_s	OFDM symbol time
N_{cp}	Length of the cyclic prefix
$a \mod b$	Modulo operator between dividend a and divisor b
$\odot$	Circular convolution
D/A	Digital-to-Analog conversion
A/D	Analog-to-Digital conversion

MAC	Medium Access Control
PAPR	Peak-to-Average Power Ratio
$\Omega(n)$	User index assigned to subcarrier n
$P(n)$	Power allocated to subcarrier n
K	Number of users/nodes in a multiuser communication setup
PBS	Primary Base Station
SBS	Secondary Base Station
$H_{f,k}(n)$	Frequency response of user k in subcarrier n
$\vartriangle$	Subindex for belonging to PBS
$\blacktriangle$	Subindex for belonging to SBS
$R_{\vartriangle}^{min}(k)$	Lower rate limit for PBS user k
$R_{\blacktriangle}^{max}(k)$	Upper rate limit for SBS user k
AWGN	Additive White Gaussian Noise
SNR	Signal to Noise Ratio
N_0	Noise spectral density
$\mathbf{SOL}(\psi)$	Same as $\mathbf{X}(\psi)$, differently denoted for context
$\widehat{P}_{\vartriangle}(\psi, n)$	New mutated power assigned to subcarrier n in the ψ-th solution vector
η	DE amplifying factor
$RC(\mathbf{SOL}(\psi))$	Rate compliancy metric for solution vector $\mathbf{SOL}(\psi)$
$\mathbb{I}[\cdot]$	Indicator function
$\mathcal{K}_{\vartriangle}^{ur}(\psi)$	Set of under-rated PBS users in solution vector $\mathbf{SOL}(\psi)$
$\mathcal{K}_{\blacktriangle}^{or}(\psi)$	Set of over-rated SBS users in solution vector $\mathbf{SOL}(\psi)$
$\mathcal{I}$	Overall number of iterations
$\mathcal{I}_g$	Number of iterations for a greedy repair procedure
ITU	International Telecommunication Union
φ_s	Starting value for a progression imposed on the HMCR operator
ϑ_e	Ending value for a progression imposed on the PAR operator
$\text{sgn}(x)$	Sign function
$\mathcal{L}(m_{\mathcal{L}}, \varpi_{\mathcal{L}})$	Levy distribution with location $m_{\mathcal{L}}$ and scale $\varpi_{\mathcal{L}}$
IMT	International Mobile Telecommunication
ISM	Industrial, Scientific and Medical
BER	Bit Error Rate
QAM	Quadrature Amplitude Modulation
$\mathcal{Q}$	QAM constellation size
$\mathcal{F}(k)$	Available channel set at user k
$\mathcal{F}^T$	Total set of available channels in a network
$\mathcal{F}(k,j)$	Available channel set for the link from node k to node j
$F(k,j)$	Channel assigned to the link connecting node k to j
R_c	Connectivity radius [m]
R_*	Interference radius [m]
d_{kj}	Distance between node k and j [m]
$P(k)$	Power transmitted by user k
$\Phi(k,n)$	Power penalty for node k at channel n
$\xi(k,n)$	Number of outgoing links in channel n from node k
$P(k,n)$	Power emitted by node k at channel n
$\text{unique}\{\cdot\}$	Number of different elements within the set in its argument
L_{kj}	Power loss factor in the link from node k to node j
a	Power attenuation exponent

ξ^T	Number of communication links existing in a network
$\times$	Result of a cartesian product between sets
$F(\psi, k, j)$	Channel assigned to the link from node k to j in solution vector ψ
$\mathcal{I}_p$	Number of iterations for a perturbation procedure
β	Amplifying factor for $\mathcal{I}_p$
σ^2	Noise variance
$\mathcal{I}_c$	Solution broadcasting period for island approaches
Υ	Number of bits circulated in a naïve island algorithm [bits]
$\mathcal{N}(k)$	Number of neighbors of node k
ρ	Probability controlling the dissemination of solutions in island algorithms
LSA	Licensed Shared Access

CHAPTER 1

INTRODUCTION

"Of course motivation is not permanent. Neither is bathing;
but it is something you should do on a regular basis."

- Zig Ziglar

Since the advent of digital communications in the early beginning of the XX century, the humankind has witnessed a technological race aimed at the derivation of new communication protocols and techniques subject to ever-growing demands and requirements for ubiquity, throughput, latency, flexibility and/or energy efficiency. This race has been so far held up by technical milestones of ground-breaking impact at both scientific and industrial levels, which are exemplified by the multiple antenna technology that gave birth to the MIMO (Multiple Input Multiple Output) technology in the late nineties, or the rediscovery of sparse linear block error correcting codes motivated by new sophisticated yet practical algorithmic approaches for performing inference in graphical models. Many additional evidences of this technological evolution in digital communications arise in many other baseline areas such as distributed transmission, cryptography, software-defined radio interfaces, power control, cellular network architectures and multiple user communications. This series of successive (in some cases, even contemporary) key achievements has given rise to the wide portfolio of standards utilized in the majority of wireless and wired communication systems, ranging from resilience-based industrial sensor ecosystems to the newest generations of cellular networks.

Besides the aforementioned set of punctual yet disruptive technical accomplishments, a cardinal component that has traditionally reinforced the competitiveness of emerging communication systems lies on the so-called *adaptability*, widely understood as the capability of a given communication system to dynamically and preemptively set the value of its operational parameters depending on the status of the radio electric medium, side conditions and/or constraints. As opposed to their static counterparts, adaptive communication schemes dynamically adjust (in terms of cardinality, amount and share) the available resources in order to better match, under a certain fitness criterium, the opportunities enabled by the communication medium at hand or incumbent policies established aside by relevant agents in the communication process (e.g. network operators). This adaptive strategy finds its roots in the variability of the communication channel (with particular emphasis on the wireless case), as well as on the dynamic nature of the constraints imposed by the user, operator or by any other stakeholder involved in the communication process. From a technological standpoint, the rationale behind adaptability in modern communication systems hinges on a twofold argument: 1) the heterogeneity of requirements imposed by different applications (e.g. from delay sensitiveness in voice transmission to

reliability in email transfer); and 2) the coexistence of different radio interfaces in the same communication device, as can be currently noted in modern cellular devices equipped with GSM, GPRS, UMTS, LTE, Bluetooth and IEEE 802.11 functionalities. Thus, adaptability of radio interfaces based on different – and possibly, conflicting – criteria is deemed of utmost operational importance for the development and deployment of future communication standards.

At this point an insightful question remains at the concept of *resource* in a communication system. From a general perspective, by resource it is meant any asset that can be exploited so as to yield some measure of benefit for the process at hand. When contextualized to digital communication procedures, the reader may straightforwardly map *asset* to any radio electric variable that may impact on the performance of the communication process itself. Many examples stem immediately from this mapping, split in different domains not only related to the physical layer (from transmission bandwidth to power, rate or constellation depth), but also to upper layers (route, time slot) or even constituent parts of the transmitter device (e.g. available silicon space in reconfigurable hardware interfaces).

In adaptive communication systems, knowledge of the transmitter with respect to the current status of the channel is generally captured by means of the so-called *feedback* channel depicted in Figure 1.1. Through this channel the estimated and predicted information $\mathbf{Z}$ on the channel status is forwarded from the receiver to the transmitter. This information – either in digital or analog form – conveys some notion of the forward link status (e.g. received power, interference level), which is exploited by the transmitter to adapt the transmission parameters for the forward link. Clearly the stringency of the feedback channel – in terms of latency or error rate reflected in $\tilde{\mathbf{Z}}$ – drives the efficiency of the adaptability of the communication process.

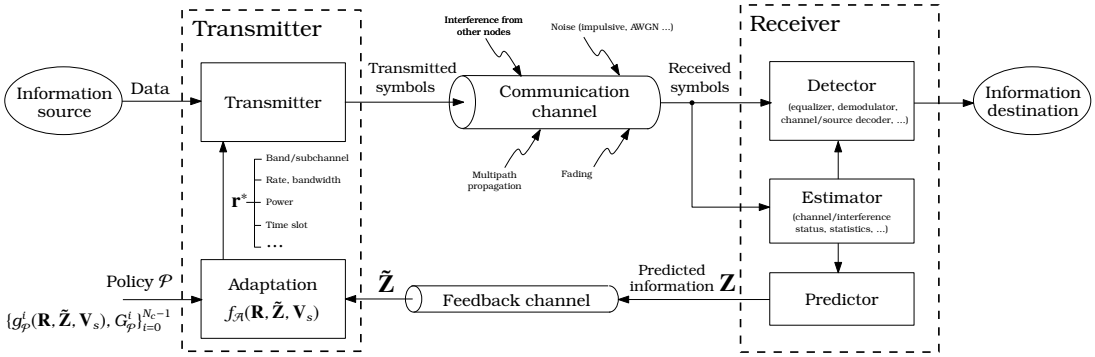


Figure 1.1: Generic single-user adaptive communication system based on a feedback channel.

From a historical standpoint, a closer study on radio frequency adaptability for communication systems reveal that it dates back to 1948, when Claude E. Shannon published his landmark manuscript “A Mathematical Theory of Communication” [1]. Besides the renowned mathematical foundations describing and analytically assessing the performance of any digital communication system, Shannon derived the so-called Water-Filling approach to adapt the distribution of the transmission power to the status of any additive white Gaussian noise vector channel fed back to the transmitter, contribution that upholds nowadays in a plethora of more involved communication paradigms. Subsequent early contributions gravitated on different theoretical and practical aspects of limited feedback channels for adaptive communications

[2]-[6]. Later, Slepian and Wolf stated in [7] their famous theorem for the optimum allocation of distributed compression rates for two or more correlated data streams that are to be sent to a central receiver, which further spans the adaptability of the transmitter to the compression or source coding of multiterminal correlated sources. Surprisingly, it was not until mid-nineties when adaptive transmission with feedback from the transmitter was not put in practice, mainly for mobile communications [8]-[10], local and wide area wireless networking [11]-[13] and power-constrained sensor networks [14, 15].

Nowadays adaptation has become a *sine qua non* in the development and implementation of most of the current communication standards, to the extent of unchaining a new research trend aimed at one capability beyond adaptability: cognition. Still relatively far from its practical maturity, but grounded on the scarcity and inefficient use of spectrum resources evidenced in a plethora of empirical studies [16]-[18], cognitive radio systems are able to obtain knowledge of their operational and geographical environment, established policies and its internal state, to dynamically and autonomously adjust its operational parameters and protocols according to the obtained knowledge in order to achieve predefined objectives, and to learn from the obtained results [19]. In cognitive radio interfaces, adaptability in transmission is further complemented with the potentiality of the transmitter to learn from previous resource allocation stages, as well as by the capability of the transmitter to autonomously monitor the variables (e.g. spectrum occupancy) driving the adaptation process itself. Cognitive networks are, by virtue of cognition, enhanced in terms of resiliency, self-organizability and interoperability, thus providing a new and powerful radio substrate where to deploy new services and applications for a variety of industry verticals such as smart energy grids [20] and industry automation [21].

This Thesis focuses on what are hereafter coined as *intelligent* systems, proposed terminology to refer to all communication schemes where adaptive resource management takes a crucial role in the process of data communication.

1.1 Motivation

Before delving into the rationale behind the research scope of this Thesis, a brief yet stimulating mathematical observation must be first made. In connection to Figure 1.1, let $\mathbf{R}$ denote the variable vector representing the available communication resources managed by a certain adaptation strategy $\mathcal{A}$. The adaptive transmitter will then seek the optimum $\mathbf{R}^*$ under a fitness function $f_A(\mathbf{R}, \tilde{\mathbf{Z}}, \mathbf{V}_s)$ that quantifies the performance indicator to be maximized (e.g. rate, spectral efficiency) or minimized (e.g. transmit power, latency). This optimization problem may also include operational, user- or operator-side constraints representing e.g. upper bounds on the transmit power to be allocated, QoS (Quality of Service) levels per user involved in the setup, or any other limiting factor alike. If sketched as a single mathematical statement, adaptive resource allocation in intelligent systems can be formulated as

$$\underset{\mathbf{R}}{\text{Optimize}} \quad f_A(\mathbf{R}, \tilde{\mathbf{Z}}, \mathbf{V}_s), \tag{1.1}$$

$$\text{subject to} \quad g^i_{\mathcal{P}}(\mathbf{R}, \tilde{\mathbf{Z}}, \mathbf{V}_s) \gtreqless G^i_{\mathcal{P}}, \ i = 0, \ldots, N_c - 1, \tag{1.2}$$

$$R(k) \in \mathcal{R}(k), \ k = 0, \ldots, K - 1, \tag{1.3}$$

i.e. as a conventional mathematical optimization problem where Expression (1.2) denotes the N_c equality or inequality constraints corresponding to the aforementioned operational, user-

or operator-defined policy $\mathcal{P}$. Expression (1.3) establishes the support for the variables $\mathbf{R} \triangleq \{R(k)\}_{k=0}^{K-1}$ representing the resources to be allocated. It is of utmost importance to note that the above formulation implicitly assumes that the data required to evaluate $f_A(\cdot)$ (i.e. not only the variables $\mathbf{R}$ themselves, but also the predicted variables $\tilde{\mathbf{Z}}$ fed back from the receiver or any other set of involved static variables $\mathbf{V}_s$) are set available as *a priori* information for the adaptive resource management stage. Put differently, adaptability in intelligent communication systems considers the estimation of other variables and parameters involved in the evaluation of its fitness function $f_A(\cdot)$ as a necessary yet external processing stage.

Having said this, the inherent challenges and issues arising from the efficient solving of optimization problems may also apply in the context of intelligent communication systems. In fact, scalability and performance of current resource allocation approaches are being lately put to question due to several aspects of diverse nature:

- A total traffic increase by a factor of several hundreds has been predicted for the next decade by a number of studies based on extrapolations from past figures. In large numbers, these figures bespeak a 10 times increase in broadband mobile users and 50-100 times higher traffic per subscriber [22]. Accordingly, the achievable throughput per user has to be risen significantly, yielding a rough estimation of 10 times increase in average and peak data rate. In fact, according to a recent report by Cisco [23], traffic from wireless devices will exceed traffic from wired devices by 2014, resulting in a 61% percent share of the traffic originated by Wi-Fi and mobile devices by 2016. This envisaged explosion of traffic and users in wireless and mobile communication networks implies new optimization paradigms of increased complexity, ranging from the guarantee of fairness between users in the allocation of shared radio resources to the adequate management of latency to reduce response times and a better support for a multitude of QoS requirements originating from different services. These paradigms are expected to get even more involved in light of the upsurge of new wireless communication devices such as M2M (Machine-to-Machine) systems, smart TV sets and video game consoles, among others.

- The scales of the electronic equipment and devices supporting future communication networks are foreseen to break the so-called Moore's law, in part due to the provision of adaptability and intelligence to radio interfaces. This technological effort towards more involved electronics must be properly bolstered by efficient allocation algorithms operating on both hardware (e.g. placing and routing tool chains in Field Programmable Gate Array – FPGA – based architectures) and radio resources. However, uncertainty has been lately entered the debate on the proficiency of existing optimization solvers to face the predicted complexity of such allocation algorithms.

- New traffic consumption patterns have stemmed from the uprising of social networks, mobile conferencing and video distribution platforms. Indeed, as has been predicted in several reports (see e.g. Figure 1.2), video on demand will become increasingly important in years to come, whereas TV content provision through Internet also generates a substantial amount of data traffic on mobile networks. This predicted change in the traffic consumption habits also hinders the provision and allocation of radio resources due to the need for high processing throughput and the establishment of stringent constraints in terms of reliability against channel errors, end-to-end delay and energy efficiency.

- Current spectrum management strategies are not suitable nor efficient to meet the envisioned demands of wireless communication networks. Such strategies rely on regulations

dating back more than 30 years ago, when spectrum bands were statically allocated in their majority to fixed radio services. However, measurement campaigns have concluded that such strategies not only lack of enough flexibility to accommodate new and future services, but also under-utilize large portions of spectrum in both time and spatial domains. As the mobile telecommunication market is estimated to grow exponentially in the period 2010-2020 in terms of number of user and aggregate rate demands, this fact calls for the urgent development of cognitive systems capable of identifying and exploiting spectrum opportunities without jeopardizing transmissions from other users.

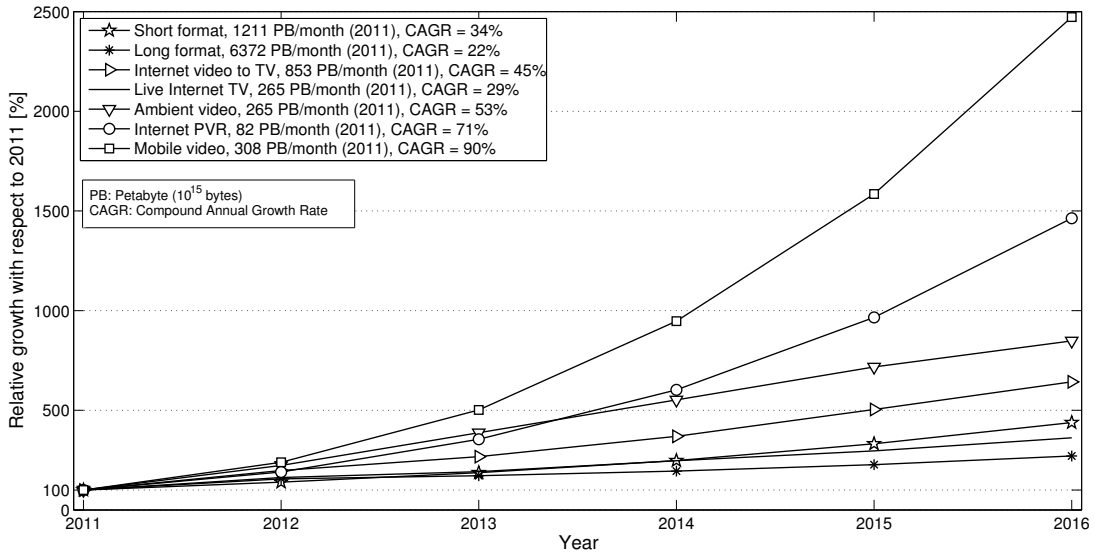


Figure 1.2: Forecasts for the globally consumed Internet video in the period 2011-2016. All mobile video conveyed through cellular data networks is expected to experiment the highest cumulative growth (data extracted from [23]).

Bearing all the above evidences in mind, current resource allocation solutions for adaptive communication systems will undoubtedly undergo potentially severe computational pitfalls in the near future. In practice, one could resort to exhaustive search techniques to solve the optimization problem characterizing a given resource allocation criterium when 1) the scales of the problem (given by the dimensionality of $\mathbf{R}$) are small enough; 2) the fitness function $f_{\mathcal{A}}(\cdot)$ is *well-behaved* (i.e. convex, continuous and differentiable, allowing for derivative-based analytical solvers); and 3) the computation of the fitness function is not too costly in machine time. However, traditional numerical optimization approaches have so far not paid enough attention to complexity issues, but have instead focused on purely asymptotical convergence and optimality results. In general, a non-convex problem is difficult to tackle by means of numerical approaches, since the computational effort required to solve such problems increases prohibitively fast with the dimensions of the problem. In short, complexity can be thought of as the intrinsic feature of non-convex problems rather than a drawback of existing numerical optimization techniques.

As a consequence of both non-convexity and high dimensionality in optimization problems, it results mandatory to resort to black-box optimization techniques where only the values – and the (sub)gradients, if available – of the objective and the constraints at a point can be

computed. In this line of reasoning, meta-heuristics have historically emerged as efficient algorithmic means to address optimization problems with uncertain convexity and unmanageable dimensionality by traditional optimization tools. Formally speaking, meta-heuristics can be defined as Soft Computing methods that optimizes a given problem by iteratively refining a candidate solution with regard to a given measure of quality through the use of specialized stochastically-driven operators. Interestingly, meta-heuristics make no assumptions about the optimization problem at hand (neither convexity nor differentiability), and have been shown to efficiently explore search spaces of large dimensionality. Indeed, meta-heuristics fall within the field of direct search or derivative-free optimization, because among the usually unavailable pieces of information is the derivative of the fitness function $f_A(\cdot)$, on which many analytical optimization methods usually rely. As a byproduct, meta-heuristics do not guarantee optimality of the produced solution, but only ensures that the likelihood of being trapped in local optima is deeply decreased along iterations.

The above reasons being stated, the application of meta-heuristic algorithms in the context of radio resource allocation paradigms in intelligent communication systems constitutes the raison d'être of this doctoral Thesis. The search efficiency, robustness and light computational burden featured by this class of approximate solvers suit perfectly the needs and requirements demanded by current and future communication standards when allocating the available radio resources under severe operational constraints.

1.2 General and Specific Objectives

This Thesis will thoroughly delve into the possibilities to apply meta-heuristic algorithms for the efficient solving of optimization paradigms arising from the radio resource allocation process in intelligent communication systems. Therefore, this study is arranged from an exemplificative approach, i.e. several instances of such optimization problems will be analyzed, put in context with respect to their related state of the art, and approached via meta-heuristics. Specifically, the following setups will be henceforth analyzed:

- The first targeted setup addresses a Orthogonal Frequency Division Multiple Access (OFDMA) downlink. In the considered setup a primary base station forwards information to a set of distant receivers by using a single OFDM waveform, whereas a secondary base station – subject to stringent per-user rate constraints – interferes with the former by sending information from users to the same set of destinations. Power and user allocation at both base stations will be jointly performed by a hybrid meta-heuristic algorithm so as to maximize the overall throughput of the setup while satisfying, at the same time, the imposed rate constraints.
- The second scenario considered in this Thesis gravitates on the spectrum channel allocation problem, where each compounding node of a intelligent radio network is assigned a frequency channel for transmission over a given outgoing link, based on optimizing an overall network performance metric dependant on the level of interference among nearby nodes. In this context, genetically-inspired algorithms have been extensively used so far for solving this optimization problem in a computationally-efficient manner. This Thesis proposes the application of alternative meta-heuristic algorithms to this problem under centralized and distributed network topologies.

- A side yet closely related contribution spans this Thesis beyond meta-heuristics to another Soft Computing area: Fuzzy logic. To be concise, a novel rule-based decision-making system will be investigated for the selection of methods to obtain knowledge of spectrum availability in intelligent communication systems equipped with cognitive radio capabilities. The proposed scheme selects the methods to obtain knowledge of spectrum availability between control channels, databases and spectrum sensing based on the specific requirements of the frequency band at hand. The developed decision-making system considers realistic frequency bands and spectrum sharing scenarios, including bands with primary allocation to mobile service where the operator governs the spectrum use, bands with co-primary or secondary allocation to mobile service where the primary users have to be protected from harmful interference, and finally license-exempt bands, where different systems coexist in uncontrolled interference conditions.

As outlined above, the first two analyzed scenarios ground on the formulation of a resource allocation procedure as a conventional optimization problem subject to a set of constraints. By contrast, the contribution of the third studied case lies not only on the particular practical approach proposed for decision making in cognitive radio systems, but also on the exemplification of fuzzy reasoning as another field within Soft Computing with a clear impact on the performance of intelligent communication networks. Remarkable is also the fact that the selection of spectrum sensing method may be regarded as a necessary task for triggering the subsequent allocation of hardware and software resources in the transmitter frontend, observation that connects this decision-making stage to the main topic of the Thesis.

1.3 Methodology

The methodology followed in this Thesis is based on an analytical, applied quantitative procedure starting from the high-level formulation of every research problem on which the Thesis is built. On this purpose, all available conceptual (concepts and theories) and empirical (earlier similar studies) literature related to the scenario at hand has been thoroughly collected and examined. This procedure has permitted to identify what data and other materials are meaningful to contextualize and put in value the problem at hand. Next, the problem itself is modelled and described in mathematical notation; this second stage eases the identification of further variables and parameters to be considered in the definition of the problem itself. The methodology proceeds by examining the particularities of such a mathematical formulation, and by designing meta-heuristic algorithms specially suited to balance the trade-off between optimality and complexity when solving the problem at hand. This stage may include different versions of the algorithms (e.g. distributed, centralized, computational relaxations, and other distinctive factors alike) that complement the proposed algorithm.

In what concerns to the evaluation and validation of the proposed heuristics, numerical computer simulations have been carried out to yield a number of averaged performance indicators that permit to assess the optimality and computational burden incurred by the algorithms. This simulative procedure is well-known in the design of communication systems as the Monte Carlo method [24], which essentially reduces to the use of random sampling for inferring numerical results. Where available, performance bounds will be properly argued, derived and established as simulative benchmarks. Comparisons to other existing algorithms – if any – will be also presented and discussed in detail.

1.4 Structure of the Thesis and Notation Generalities

This Thesis is clearly organized in three different thematic tracks as remarked (bold line) in Figure 1.3. The first, embodied in Chapter 3, addresses the power and subchannel problem in OFDMA based intelligent communication systems, whereas Chapter 4 delves into spectrum channel allocation in intelligent systems, respectively. Both chapters are complemented by Chapter 2 which, if needed (dashed line in the Figure), provides the reader with the fundamentals on optimization and meta-heuristics necessary to make the document self-contained. Next, Chapter 5 concentrates on the side contribution of this Thesis, focused on the application of approximate reasoning techniques to the selection of spectrum sensing techniques in cognitive radio systems. Each of these Chapters also includes a literature review of the recent activity around the problem considered therein. Finally, Chapter 6 concludes this Thesis by drawing the main conclusions and outlining several further related lines of research, some of which are being pursued at the time of writing. The the scientific publications derived from this work are enumerated and classified in Appendix A. In any case, this Thesis outline is merely a proposal for a coordinated and effective understanding of this report; any other criterium for the reading order can be followed at will.

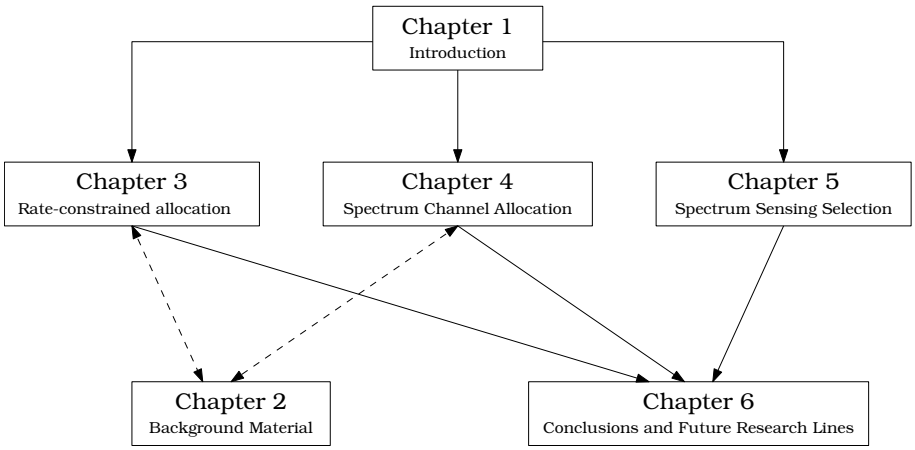


Figure 1.3: Flow diagram representing the structure of the Thesis. Dashed arrow lines indicate that the reading of the destination chapter is optional.

The following mathematical notation will be hereafter adopted: vectors will be denoted in capitalized bold font (e.g. $\mathbf{X}$), whereas sets will be typeset in calligraphic case (e.g. $\mathcal{X}$), except for the sets $\mathbb{N}$ and $\mathbb{R}$ of integer and real numbers, respectively. When unfolded, the elements of a given vector will be enclosed within brackets and enumerated by parenthesized indices, e.g. $\mathbf{X} = \{X(0), \ldots, X(K-1)\}$ or $\mathbf{X} = \{X(k)\}_{k=0}^{K-1}$. As can be noted from the previous convention, zero-based indexing will be always assumed for all enumerative variables and parameters. Unless otherwise stated, Greek letters will be utilized for denoting user-defined parameters for the proposed algorithms. In any case, acronyms and symbols are compiled at the beginning of this document for the reader's reference.

CHAPTER 2

BACKGROUND MATERIAL

"Any sufficiently advanced technology is indistinguishable from magic."

- Arthur C. Clarke

As has been highlighted in Chapter 1, this Thesis builds upon the formulation and solving of optimization problems, understood as the mathematical statement that poses the criteria and constraints driving the allocation of radio resources in intelligent communication systems. Optimization problems by themselves rigorously capture and model all the particularities of the resource allocation problem at hand, and eases the identification and selection of solving techniques specifically tailored to such particularities. As the foundation for most of the investigations compiled in this report, this chapter formally introduces the basic concepts of optimization problems and describes a brief taxonomy of its different variants. The scope is then focused on practical problem solving techniques, stressing on some of the most pertinent state-of-the-art meta-heuristic approaches. For the sake of the thematic coherence of this chapter, the basics on approximate reasoning methods and fuzzy logics in connection to the third scenario under study will be included in Chapter 5.

Before proceeding further, it is important to point out that this chapter does not intend to be a rigorous and exhaustive encyclopedia of optimization theory and methods. A plethora of bibliographic references can be found in the literature deeply delving into the roots of this topic, along with a thorough revision of several analytical methods widely used on this purpose. Instead, the contents here exposed aim at briefly discussing on different practical approaches used for solving continuous and discrete optimization problems, with particular emphasis on those applied to resource allocation in communication systems. In the interest of further details the reader is referred to [25, 26] and the seminal book by Boyd and Vandenberghe [27].

2.1 Fundamentals of Optimization Problems

The starting point of this Thesis resides in the general conception of an optimization problem, which can be defined as the discovery of the best alternative within a given search space with the most cost-effective or highest achievable performance under the given constraints, by maximizing desired factors and minimizing undesired ones. As such, the mathematical formulation of a given optimization problem permits to properly model any scenario where a decision on the values for certain design variables is not clear and can not be intuitively made.

Specifically, the aim is to infer the best value for a (set of) decision variables based on 1) the maximization or minimization of a certain function numerically quantifying the fitness of any given solution; and 2) the fulfillment of a series of restrictions or constraints bounding the range of values permitted for such variables. Formally, an optimization problem is defined as to find the best solution

$$\mathbf{X}^* \triangleq \{X(0), \ldots, X(K-1)\} \in \mathfrak{X},$$

with $\mathfrak{X}$ denoting the search space for $\mathbf{X}$, such that it fulfills

$$\underset{\mathbf{X}\in\mathfrak{X}}{\text{Optimize}} \quad f(\mathbf{X}), \tag{2.1}$$

$$\text{subject to} \quad g_i(\mathbf{X}) \gtreqless G_i, \ i = 0, \ldots, N_c - 1, \tag{2.2}$$

where $f : \mathfrak{X} \mapsto \mathbb{R}$ is called the objective or *fitness* function, and $\{g_i(\cdot), G_i\}$ define the N_c constraints imposed on the problem formulation and which restricts the search space $\mathfrak{X}$ to a certain *feasible* subspace. In the above formulation, $\mathbf{X}^*$ denotes the solution of the problem, which simultaneously meets the N_c constraints and provides the best value of $f(\cdot)$ among $\mathfrak{X}$. The problem space $\mathfrak{X}$ is the set of all elements $\mathbf{X}$ which can be the solution of the problem at hand. If the elements of $\mathfrak{X}$ are composed of multiple variables (i.e. if $K > 1$), they are often referred to as *decision variables*. An exemplifying practical case would be a child's rectangular play yard to be built next to a house subject to a given number of available fencing meters. Here the problem can be formulated as the estimation of the dimensions of the three (i.e. $\mathfrak{X} = \mathbb{R}^3$) sides of the child's playpen (decision variables $\mathbf{X} = \{X(0), X(1), X(2)\}$) so as to achieve a maximum area (fitness function $f(\mathbf{X})$). Obviously, the fact that the fencing length $g_i(\mathbf{X})$ is bounded to a certain maximum value G_i imposes a stringent constraint on the problem.

In other words, an optimization problem aims at achieving an optimum decision on the values for a set of decision variables to maximize (e.g. power saving, speed, time, efficiency) or minimize (correspondingly, money, time, risk or error, among others) a given fitness function, always taking into account the imposed constraints for which no any possible value for the decision variables is possible. Some restrictions may represent a certain limitation whose impact on the variable alphabet $\mathfrak{X}$ can not be described in analytical form (*implicit* constraint), whereas other may alternatively correspond to *explicit* constraints posed by the context in which the problem is formulated. Yet another type of constraints may apply depending on the specific implementation context where the problem is to be solved (e.g. lack of numerical precision for real numbers in computers). In the majority of cases the constraints can be rearranged in a set of equalities and inequalities, namely,

$$h_i^{\flat}(\mathbf{X}) < 0, \qquad i = 0, \ldots, N_c^{=} - 1, \tag{2.3}$$

$$h_i^{\sharp}(\mathbf{X}) = 0, \qquad i = 0, \ldots, N_c^{<} - 1, \tag{2.4}$$

based on which the following classification for the produced solutions can be established:

- A feasible solution will be any vector $\mathbf{X} \in \mathfrak{X}$ satisfying the $N_c^{=} + N_c^{<}$ imposed constraints.
- A global optimum solution will denote the feasible vector $\mathbf{X}$ that provides, among all feasible vectors in $\mathfrak{X}$, the best value for the fitness function $f(\cdot)$. Formally, when dealing with minimization problems $\mathbf{X}^{\heartsuit} \in \mathfrak{X}$ will be a global minimum if $f(\mathbf{X}^{\heartsuit}) \leq f(\mathbf{X})$ for all $\mathbf{X} \in \mathfrak{X}$. Two important aspects must be emphasized at this point: optimality requires feasibility (the converse does not hold), and optimality does not imply uniqueness, i.e. there may be more than one global optimum (even infinite in some cases).

- A local optimum is an optimum of only a subset of $\mathcal{X}$. Mathematically speaking, a feasible solution vector $\mathbf{X}^{\wp} \in \mathcal{X}$ will be a local minimum if there exists an open neighboring set $\mathcal{N}_{\mathbf{X}^{\wp}}$ of $\mathbf{X}^{\wp}$ such that $f(\mathbf{X}^{\wp}) \leq f(\mathbf{X})\ \forall \mathbf{X} \in \mathcal{N}_{\mathbf{X}^{\wp}}$. It should be noted that even a simple one-dimensional function $f : \mathcal{X} \mapsto \mathbb{R}$ can have more than one global maximum, multiple global minima, or even both in its domain $\mathcal{X}$ (Figure 2.1). In this case, the correct solution of such an optimization problem would then be given by a set $\mathcal{X}^* \subseteq \mathcal{X}$ comprising all globally optimum inputs in $\mathcal{X}$ rather than a single optimum. Depending on the problem at hand, one single solution of such a set may suffice.

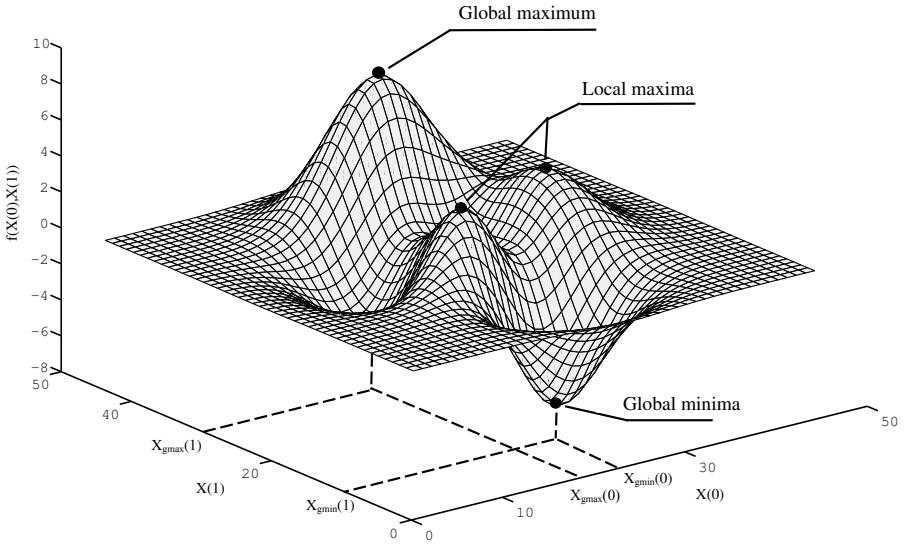


Figure 2.1: Example of a two-dimensional (i.e. $|\mathcal{X}| = 2$) function $f(\mathbf{X})$ with multiple local optima and isolated global optima $\mathbf{X}_{gmax} = \{X_{gmax}(0), X_{gmax}(1)\}$ and $\mathbf{X}_{gmin} = \{X_{gmin}(0), X_{gmin}(1)\}$.

- A near-optimum solution refers to a feasible solution whose fitness value is *potentially* close to that of the optimum solution. It is interesting to gauge the term "potentiality" in this definition of near-optimality. Some of the problem-solving techniques later described are inherently suboptimum by nature, as they are based on approximative methods attempting at approaching regions of $\mathcal{X}$ with progressively better fitness values. For instance, the well-known Newton-Raphson method is deemed an open method due to the fact that its convergence to global optima is not guaranteed when dealing with functions with multiple roots, around inflection points or in regions with near-zero slope [28]. Therefore, the degree of optimality of a given solver (and therefore, of its produced solutions) depends roughly on its capability to efficiently explore the search space $\mathcal{X}$.

2.2 Continuous and Discrete Optimization Problems

Also referred to as *numerical* optimization, continuous optimization is the class of optimization problems where $\mathcal{X}$ is a subset of the K-length extension $\mathbb{R}^K$ of the set of real numbers, i.e. $\mathcal{X} \subseteq \mathbb{R}^K$. The term "continuous" refers to the continuous decision variables $\{X(k)\}_{k=0}^{K-1}$, thus it has nothing to do with the continuous or discrete nature of the fitness function $f(\cdot)$. Dealing with real-valued search spaces $\mathcal{X}$ comes along with several drawbacks. Specifically:

- The dimensionality of the search space is infinite, which complicates significantly the time taken to produce a solution of satisfactory quality. Furthermore, the application of enumerative approaches (e.g. exhaustive search) is not possible in these cases. This complexity gets even more involved when $\mathcal{X}$ becomes bounded by a collection of constraints, in particular when the optimum lies on the search space boundary (i.e. is not an interior point). In this context, intense research activity is devoted towards dealing with the specific issues of constrained optimization (most notably, convex optimization). Simplistic approaches for unconstrained optimization can be applied as well to handle multiply-constrained problems by e.g. imposing penalties in the value of the fitness function when the solution at hand does not meet the requirements at hand.

- The complexity incurred by the infinite cardinality of the search space $\mathcal{X}$ may increase due to the existence of multi-modality in the fitness landscape. Taken from the field of statistics, multi-modality refers to the presence of several localized peaks in $f(\cdot)$ corresponding to either local or global optima. In the first case, the optimization algorithm utilized for its solving should avoid premature convergence to such local optima, whereas in the second the presence of several solutions with equal optimum fitness arises the issue of how an algorithm can locate – if required – all the global optima.

- Side issues appear when dealing with continuous problems, specially in applications where the precision of the solution plays a crucial role (e.g. control of critical infrastructures or avionics). Quantization is always finite in practical systems and must be designed with care and caution. So must operate the search techniques involved in these systems.

Luckily, most realistic fitness functions are relatively smooth and well-behaved. This paves the way for a flurry of optimum and suboptimum methods of optimization approaches that benefit from this smoothness when handling continuous-valued variables (e.g. gradient descent methods), in contrast to discrete search spaces where such techniques are not directly applicable. This fact has led to the traditional – and well-founded – belief that continuous problems can be often solved easier and faster than their discrete counterparts. For the organizational sake, it is convenient to first catalog such problems depending on the linearity and convexity of the fitness function $f(\cdot)$ and the associated constraints:

- Linear programming covers all such optimization problems where the fitness $f(\cdot)$ itself and the constraints $\{h_i^\flat(\cdot)\}$ and $\{h_i^\sharp(\cdot)\}$ are linear combinations of the entries in $\mathbf{X}$, i.e.

$$f(\mathbf{X}) = \sum_{k=0}^{K-1} w_f(k) \cdot X(k), \quad h_i^\flat(\mathbf{X}) = \sum_{k=0}^{K-1} w_g^i(k) \cdot X(k), \quad h_i^\sharp(\mathbf{X}) = \sum_{k=0}^{K-1} w_h^i(k) \cdot X(k),$$

  where $\{w_f(k), w_g^i(k), w_h^i(k)\}$ denote the linear coefficients establishing the aforementioned linearity. This first category can be regarded as a particular form of non-linear programming, a wider class of optimization problems where one or several of the above functions may not hold a linear relation with respect to $\mathbf{X}$. However, the linearity imposed in the functions involved in the problem formulation allows for certain computationally-efficient solving methods such as the simplex algorithm, which is known to be quite efficient and can guarantee to find the global optimum if proper pivoting approaches are used for cycling avoidance [29]. Another family of good solvers exploiting the linearity in the formulation of the optimization problem hinges on combining the advantages of the simplex algorithm with the geometry of the ellipsoid algorithm, giving rise to the so-called

interior point methods [30]. For instance, the interior-point algorithm by Karmarkar [31] cuts through the interior of the feasible region to reach an optimal solution by using transformations from projective geometry to determine the direction for movement. Both algorithmic families are known to perform well in terms of optimality and computational efficiency for a wide span of linear programming problems related to the allocation of resources in communication systems (e.g. see [32, 33] and references therein).

- From a more general standpoint, convex optimization refers to all such problems where the functions $f(\cdot)$, $\{h_i^\flat(\cdot)\}$ and $\{h_i^\sharp(\cdot)\}$ are convex, i.e. $\mathcal{X}$ is a closed convex set and the functions themselves are convex on $\mathbb{R}^K$. As in linear programming, the convexity of these functions paves the way to a number of efficient solving techniques, which benefit from the fact that a convex problem lacks of local optima, thus the global optimality of the produced solutions is always guaranteed. Furthermore, the convexity of the problem allows for powerful convex analysis tools, leading to necessary and sufficient conditions for optimality, a duality theory generalizing that for linear programming, and effective computational methods such as the method of Lagrange multipliers, least squares, quadratic programming and all its variants, geometric programming and semi-definite programming, among many others. Besides, linearity can be regarded as a special case of convexity, thus the above techniques and algorithms are also applicable to generally convex problem formulations. As for their application to resource allocation, recent works have resorted to convex relaxation methods so as to exploit the inherent benefits of the aforementioned algorithms [34]. Besides, several cardinal problems mostly arising from power allocation in frequency-selective channels are theoretically – and optimally – solved via Lagrange multipliers [1].

On the other hand, discrete, *combinatorial* or *integer programming* problems deal with decision variables $\mathbf{X}$ restricted to assume only discrete values, e.g. $\mathcal{X} \subseteq \mathbb{N}^K$. Combinatorial problems possess very different characteristics with respect to those of their continuous counterparts. Some of them are beneficial at the design step of the problem, as modeling with integer variables is useful represent certain discrete quantities, logical requirements, fixed costs, sequencing and scheduling requirements, as well as many other problem aspects. In what relates to radio resource allocation, while e.g. the power is in essence a continuous-valued decision variable playing its role in the underlying problem, other parameters such as frequency subchannels or time slots are naturally modelled by means of integer variables.

However, the downside of the identified modelling potentiality of integer programming problems is their computational complexity and scalability with as few as a couple of dozens of variables. Most real problems with more than a hundred variables (such as those emerging in avionics scheduling problems [35]) are not easily solvable unless they show specific exploitable structure. To efficiently deal with this unmanageable complexity, the most straightforward manner to solve an integer programming problem relies on 1) removing the constraint that $\mathbf{X}$ is an integer vector (i.e. relaxing the problem); 2) solving the corresponding relaxed continuous optimization problem by any of the aforementioned methods; and 3) rounding the components of the solution vector $\mathbf{X}^*$ corresponding to the relaxed formulation of the original integer programming problem. Unfortunately, not only may this relaxed solution not be optimum in a global sense, but it may also not be even feasible with respect to other imposed constraints.

Fortunately, there exists a variety of algorithms that can be used to exactly solve integer linear programs. Among the most renowned approaches it is worth to highlight the cutting-

plane method, which hinges on solving a linear relaxation of the original problem and by then adding linear constraints that drive the solution towards being integer without excluding any integer feasible points [36]. Also of relevance are the so-called branch-and-bound algorithms which, inspired from the divide-and-conquer principle, systematically enumerates and discards candidate solutions by resorting to upper and lower estimated bounds of the fitness being optimized [37]. Hybrid schemes embedding cutting-plane and branch-and-bound techniques [38] or the former with interior point methods [39] have also been proposed in the research community. Not less noteworthy is dynamic programming, another technique often used in integer programming which exploits the underlying substructure of the problem to break it down into smaller subproblems that can be recursively solved to optimality [40].

2.3 Derivative-Free Optimization and Meta-heuristics

Interestingly for the rationale of this Thesis, all the above problem-solving methods were originally developed for known and tractable fitness functions whose optimum can not be calculated analytically. Furthermore, other approximative approaches for iteratively solving optimization problems as the ones above enumerated rely on first and second order derivatives (e.g. gradient and Hessian) for guiding their progression to the global optima, which may not be applicable in practical optimization paradigms of uncertain differentiability. This observation unveils a severe shortcoming of the above tools that becomes particularly relevant in view of 1) the ever-growing involvedness of mathematical models representing setups in disciplines and fields related to communication systems; and 2) the abundance of legacy codes for such models, which are often protected and kept unavailable for the optimization practitioner (see Figure 2.2).

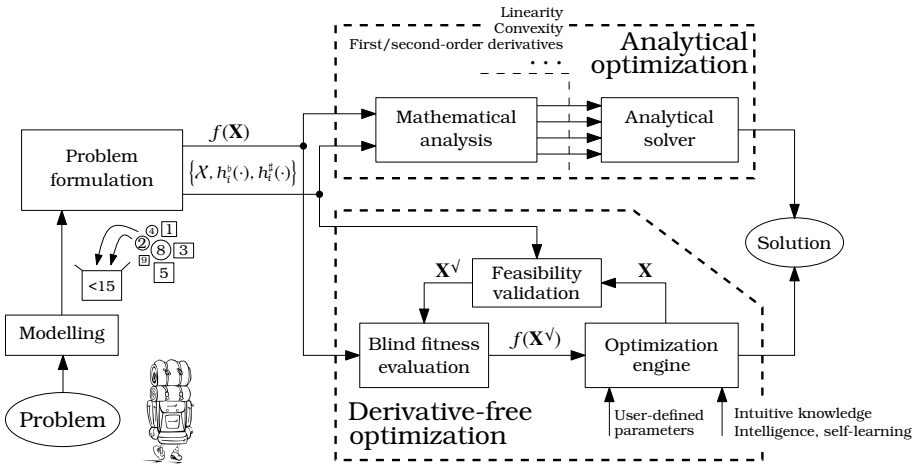


Figure 2.2: Block diagram elucidating the derivative-free optimization strategy.

This noted deficiency buttresses the rationale for which *derivative-free* or *black-box* approaches have recently gained momentum in the research community. This terminology refers to all such optimization algorithms requiring only the availability of fitness function values, but no derivative information nor any further assumption on the linearity, convexity or decomposability of the problem at hand. Although they are in general slower than derivative-based optimization methods, derivative-free techniques are flexible and do not demand sophisticated

mathematical reformulations not even relaxations of the problem that often hinder the development of practical systems implementing such problem solving techniques. More interestingly, in some yet frequent cases it becomes computationally impractical to compute an optimum solution in the global sense, hence one has to settle for a good (but not necessarily optimum) solution. Near-optimality is efficiently targeted by derivative-free methods of known scalability when facing optimization problems of high dimensionality.

Within this class of computationally-efficient derivative-free optimization schemes, meta-heuristic techniques have come into sight for efficiently tacking this type of *involved* optimization paradigms. Meta-heuristics can be thought of as intelligent self-learning algorithms stemming from the study and mimicking of intelligent processes and behaviours occurring in diverse disciplines. An insightful definition by Stützle [41] is adopted in this Thesis as the factual interpretation of meta-heuristics:

> *"Meta-heuristics are typically high-level strategies which guide an underlying, more problem specific heuristic, to increase their performance. The main goal is to avoid the disadvantages of iterative improvement and, in particular, multiple descent by allowing the local search to escape from local optima. This is achieved by either allowing worsening moves or generating new starting solutions for the local search in a more intelligent way than just providing random initial solutions. Many of the methods can be interpreted as introducing a bias such that high quality solutions are produced quickly. This bias can be of various forms and can be cast as descent bias (based on the objective function), memory bias (based on previously made decisions) or experience bias (based on prior performance). Many of the meta-heuristic approaches rely on probabilistic decisions made during the search. But, the main difference to pure random search is that in meta-heuristic algorithms randomness is not used blindly but in an intelligent, biased form."*

In many cases (especially when large-scale problems are considered), meta-heuristics are deemed one of the most efficient alternatives to seek and determine a near-optimum solution without relying on exact yet computationally-demanding algorithms, and by overcoming the major drawback of local search algorithms, i.e. getting trapped in biased local regions far from the sought global solution. Indeed, on the latter lies one of the main design challenges of modern meta-heuristic methods: to avoid local optima so as to get global optima, which can be achieved by exploring the whole search space through the use of intelligent stochastically-driven operators. Furthermore, meta-heuristics are not problem-specific, but may make use of domain-specific knowledge in the form of local methods that are controlled by the upper level meta-heuristic strategy.

In order to enhance the overall search performance of any given meta-heuristic it is of utmost importance to balance the tradeoff between two important related aspects: diversification and intensification. On one hand, diversification refers to a form of randomization added to the deterministic components driving the algorithm operation in order to explore the search space in a diverse manner, while intensification stands for the improvement of existing partial solutions to the problem by exploring the vicinity of such solutions in the region space (e.g. by means of elitism mechanisms). If diversification is strong enough, a great number of zones of the search space may be loosely explored, which will reduce the convergence rate of the algorithm. By

contrast, if diversification is kept low in the algorithm design, there is a significant risk of leaving a fraction of the solution space unexplored or even producing far-from-optimal solutions due to trapping in local optima. An appropriate intensification is carried out by means of exploiting the knowledge acquired from past solutions, and by properly fine-tuning the parameters that control the performance of the algorithm for a particular problem so as to enhance its convergence properties. Having said this, the main difference among existing meta-heuristics concerns 1) the way diversification and intensification are mutually balanced in the algorithm thread (see Figure 2.3); 2) the search path they follow; and/or 3) the observed phenomena that inspires the algorithm design.

Another characteristic of meta-heuristic algorithms is the distinction between memory usage versus memoryless methods is the definition of population-based and single-point search-based strategies. In contrast to single-point search-based algorithms in which a unique solution is generated at each iteration, population-based meta-heuristic algorithms maintain a set of solutions (i.e. population) which evolve at each iteration. Therefore, populated-based algorithms provide an efficient and natural way for exploring the search space and obtaining an acceptable solution. Algorithms working on single solutions are also referred to as *trajectory* methods, and encompass global and local search-based meta-heuristics such as Simulated Annealing [42], Tabu Search [43, 44], Iterated Local Search [45] and Variable Neighborhood Search [46]. Interestingly, Memetic Algorithms [47, 48] blend several concepts from these two working strategies in order to balance the diversification and intensification of their search procedure.

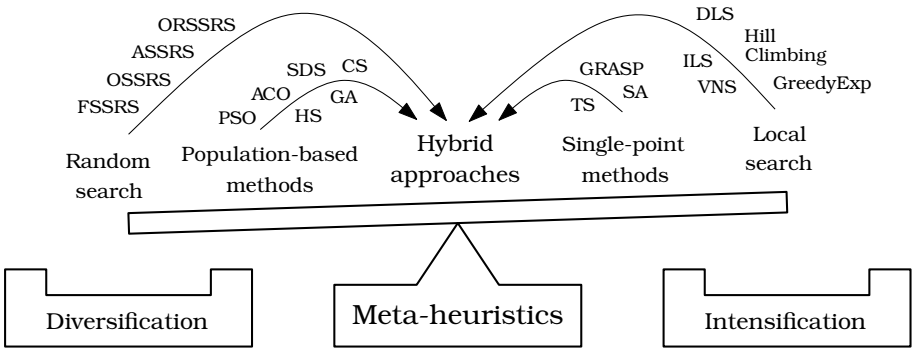


Figure 2.3: Graphical representation of the tradeoff between intensification and diversification and the relative positioning of different meta-heuristics.

Another taxonomical yet more intuitive perspective for classifying meta-heuristics can be taken if it is noticed that a good number of algorithms are actually inspired by natural phenomena and have been developed by mimicking the intelligence characteristics of biological and physical agents. This broad category includes, among others, the evolutionary algorithms (EA), which includes a whole family of techniques based on concepts borrowed from natural evolution and survival of the fittest individuals in Nature. Likewise, Ant Colonies Optimization [49] are based on the social behavior of ants, whereas Artificial Immune System algorithms [50] focus on imitating the behavior of the immune system in animals. In this same line of research, Particle Swarm Optimization approaches [51] are in essence elegant algorithms specially well-suited for continuous optimization problems. They imitate the behavior of birds flocks or fish schools. There have been more research activity on bio-inspired meta-heuristics, with approaches such as Artificial Bee Colony [52], which imitates the bees behavior when locating and bring food to the hive, as well as other recently proposed techniques such as the Gravitational Search

Algorithm [53], inspired by the law of the gravity; the Invasive Weed Optimization Algorithm [54], based on weed growth and their invasive properties; the Hunting Search [55], based on how group of animals hunt; the Biogeography-Based Optimization algorithm [56], based on the geographical distribution of living organisms; optimization based on virus infection [57], on colonies of bacteria [58, 59] or the so-called Cuckoo search approach [60], built upon the reproduction and breeding of the cuckoo bird.

There exist other meta-heuristic optimization approaches not straightforwardly classifiable as bio-inspired approaches; instead, they are based on alternative concepts or processes that make them worth to be considered in this literature review. For instance, Simulated Annealing is a well-known meta-heuristic based on the process of annealing in metallic materials. It consists of heating a substance and then cooling it down slowly, until a final strong molecular structure is obtained. This process can be artificially simulated in order to solve optimization problems. There are several variants of this algorithm such as Simulated Quenching [61], etc. Another recently proposed meta-heuristic is the Harmony Search (HS) algorithm [62], which has been successfully applied to numerous optimization problems in the last few years. As will be later detailed, HS inspires from the improvisation process of musicians, i.e. the process by which the musicians (who may have never played together before) refine, through variation and check, their individually improvised notes, resulting in an aesthetic harmony, played by the entirety of musicians in the orchestra. Other modern heuristics recently proposed for optimization problems include, among others, the Teaching-Learning-Based optimization [63], based on the process of teaching-learning produced by different teachers in a class of students; the Society and Civilization algorithm [64], which simulates the social behavior of humans; the Imperialist Competitive Algorithm [65], which makes optimization based on imperial-colonies competition; the Artificial Chemical Reaction Optimization Algorithm [66], based on different types of chemical reactions (synthesis, decomposition, redox, etc.); or the Electromagnetic-like algorithm [67, 68], based on physics of electrically charged particles, repelling and attracting each other in a multidimensional space. Some of the above referred approaches have been also extended to multi-objective optimization problems with success [69].

2.3.1 Genetic Algorithms and Evolutionary Computation

Pioneered and developed by J. Holland in the late sixties [70], Genetic Algorithms (GA) constitute a specific class of meta-heuristic optimization techniques based on conceiving the Darwinist natural evolution of species [71] as an effective strategy to find near-optimum solutions to a given problem. In essence, this near-optimality is attained by mimicking the adaptive character of natural evolution through the artificial emulation – in the form of an algorithm – of the processes involved therein. This class of algorithms can be framed within the more general category of Evolutionary Computation, which gained momentum in the research community by virtue of the seminal findings on Evolution Strategies by Rechenberg [72] and Schwefel [73] (later surveyed in [74]), and thereby stimulated evolution-based schemes such as Evolutionary Programming [75], Differential Evolution (DE) [76] and Estimation of Distribution Algorithms (EDA) [77]. This stirred flurry of evolutionary techniques have motivated their widely acknowledged consideration as one of the most prominent research lines in Artificial Intelligence and Soft Computing to date.

In general, a genetic algorithm (and in general, all evolutionary techniques) utilize a set of Ψ_{GA} individuals, each representing, under an encoding strategy, a possible solution to the

problem at hand. These individuals undergo successively applied operations that emulate different processes springing from the natural evolution, such as crossover, inheritance, mutation and selection. The encoding strategy and operators themselves discriminate one given evolutionary technique from another. For instance, Evolutionary Strategies have traditionally dealt with real-valued solution encodings, although variants for discrete problems can be found in the literature. On the other hand, genetic approaches are mainly associated with integer-encoded populations, but it has been shown to render a satisfactory performance in many continuous-variable problems by partly redefining their constituent operators [78]. This section will condense the basics of the canonical form of Genetic Algorithms [79], which has served as the reference benchmark for a plethora of new population meta-heuristics reported ever since. For a complete and comprehensive outlook on genetic algorithms, the reader is referred to the landmark bibliography on this matter available in [80]–[83].

2.3.1.1 Encoding Strategies

As mentioned previously, Genetic Algorithms operate on a set or population of Ψ_{GA} candidate solutions (often denoted as *individuals*, *chromosomes* or *phenotypes*), which are evolved along iterations or *generations* toward progressively better solutions. Each of such candidate solutions is further composed by several entries or *genes*, whose values can be mutated and altered within a given allowed vocabulary or *allele* set. In general, Genetic Algorithms consider encoding strategies where the genes can take on integer values, particularly binary values. Nonetheless, continuous-valued encodings can be also approached by genetically-inspired algorithms by simply redesigning their operators, yielding the more general case of evolutionary computation and evolution strategies mentioned before.

In general, the values taken by each of the genes (i.e. the set of alleles for each constituent gene of a given chromosome) do not depend on the alleles corresponding to any other gene, hence being correlated exclusively through the fitness of the problem under consideration. However, some special strategies feature structural rules that impose rigidness and intra-correlation in the alleles corresponding to different genes, as exemplified by grouping [84, 85], permutation and Dandelion [86] encoding techniques for clustering, ordering and tree-based problems, respectively. The existence of these encoding constraints implies the need for modified genetic operators tailored to deal with these encoding particularities and, in most of the cases, the addition of side repair techniques aimed at belatedly reconstructing the encoding integrity of chromosomes through the evolved population. From this observation it can be easily inferred that the proper selection of an encoding strategy results to be crucial for ensuring the near-optimality not only of a genetic algorithm, but in general of any search meta-heuristic. To this end, several properties of the selected encoding approach must be carefully analyzed and contrasted with those of the problem to be tackled, namely:

- The most evident among such properties lies on the so-called encoding redundancy, i.e. the capability of the encoding scheme to entirely yet univocally represent the search space or more optimally, the set of feasible solutions for the problem. For instance, it is well understood that the aforementioned grouping schemes result appropriate for clustering problems where the order between elements in a given group is deemed irrelevant. When this is not the case, however, other representations such as the Linear Linkage Encoding

(LLE [87]) have been shown to minimize the inherent redundancy of conventional grouping techniques.

- Secondly, it is desirable that the encoding strategy not only represents the solution space in its entirety, but also that the encoding itself favours the generation of *good* individuals with high probability. As will be later shown, selection and mutation operators in Genetic Algorithms are stochastically driven by means of probabilistic parameters. In this context, genetic algorithms should adopt solution encoding strategies capable of representing distinctive features for the best individuals in the search space – which can be identified beforehand in the majority of the cases – with its stochastic procedure, in such a way that best individuals would possess, at large, higher chances to be generated.

- Feasibility should be also taken into consideration when designing the encoding approach for any genetic algorithm. Unfortunately, it results very difficult in practice to embed this characteristic in the encoding design, thus bringing into play repair procedures that account for the avoidance of unfeasible chromosomes in the evolutionary process. Repair methods abound and are sharply problem-specific, yet it is common practice to impose a high degree of *locality* so as to maintain as much similarity as possible between the original and the repaired chromosome. These tactics permit to keep the search intelligence of Genetic Algorithms without impacting decisively on their convergence properties.

- It should be noted that the encoding strategy may not be itself regarded as the explicit representation of solutions to a certain paradigm, but is instead a mere artificial representation aimed at easing the derivation and iterative application of different genetic operators. Accordingly, the evaluation of the fitness for any given encoded individual may require a more straightforward, less operatively-optimized representation. This conversion between encodings must be performed in a computationally light fashion; otherwise, the benefits stemming from a good choice of the encoding strategy become outgained by the execution time taken for its reversal to an fitness-evaluation-ready format.

- Finally, locality and distance distortion are also relevant when designing a representation suited for a given problem structure. The locality of an encoding strategy describes how well neighboring phenotypes correspond to neighboring genotypes, whereas distance distortion describes how well the phenotypic distance structure is preserved when individuals mapped by means of a solution encoding are mapped to fitness-ready representations. For instance, Gray encoding has perfect locality when dealing with binary representations of integer genes, as opposed to the conventional binary encoding, with known locality issues arising from the so-called Hamming cliff [88]. Crossover operators, besides, complicate the structure of the problem and its solving complexity by changing the distance distributions between individuals. Assessing and quantifying these two important properties among different solution encoding schemes has recently gained momentum in the research community due to the enormous difficulty arising from the derivation of proper distance measurements in certain search spaces.

2.3.1.2 Genetic Operators

There are basically two different types of genetic operators: explorative and exploitative. The first class is embodied in the canonical form of a Genetic Algorithm by the mutation and crossover

operators, whereas the second builds on selection methods. All these operators are sequentially applied to the population at every generation of the algorithm, in the following order:

A. The objective of the selection operator is to produce an entirely new set of individuals by choosing chromosomes from the original population, in such a way that those featuring a better fitness (in terms of $f(\cdot)$) are selected with high probability. Such potential survivors in the selection process are usually referred to as *parents* in the specialized jargon. Therefore, the selection of parent chromosomes or individuals is usually biased towards those of high fitness: a chromosome with better fitness value is more likely to become a parent than an unfit one. In this context, the so-called *selection pressure* becomes relevant as it represents the ratio between the probability that the fittest individual of the population is selected to be a parent and the probability that an average member is instead selected. Intuitively, a high selection pressure will result in a fast convergence of the population towards a solution, but at the cost of reducing dramatically the explorative capability of the algorithm. Since balancing this tradeoff is specially critical in optimization problems of combinatorial nature, a compromise between diversification and intensification is usually met by the algorithm designer.

   The above being said, very diverse selection methods have been proposed, among which the following outstand as the most frequently utilized:

   - Roulette-wheel: this stochastically-driven technique establishes the probability of being selected as a parent corresponding to the original chromosomes proportionally to their fitness values. To this end, a conceptualized roulette wheel is divided in as many sectors as the size of the population, with angular widths proportional to the fitness values. Specifically, if $f(\mathbf{X}(i))$ denotes the fitness value of individual $\mathbf{X}(i)$ in an Ψ_{GA}-sized population, its probability p_i of being selected is given by

   $$p_i = \frac{f(\mathbf{X}(i))}{\sum_{j=0}^{\Psi_{\text{GA}}-1} f(\mathbf{X}(j))}, \tag{2.5}$$

     with $i \in \{0, \ldots, K-1\}$. Subsequently, as many balls as the number of parents to be selected are spined on this unevenly sectionized roulette, and the pockets where the balls eventually fall will indicate those chromosomes selected for parenthood. This analogy is put into algorithmic practice by drawing as many outcomes from a uniform distribution from the $[0, 1]$ interval as the number of desired parents.
   - Stochastic universal sampling: the roulette-wheel explained above may result in a population saturated by its fittest members when their fitness values are extremely unbalanced. To avoid this, stochastic universal sampling uses a single random value to sample all the population by at evenly spaced intervals. This permits that the worst members of the population (according to their fitness) can be chosen for subsequent operations. Besides the evidently enhanced fairness of this method with respect to other fitness-proportional approaches, stochastic universal sampling imprints a higher diversifying behaviour at the selection stage.
   - Tournament: in this case, parents are selected by repeatedly selecting the best individual of a randomly chosen subset of the original population. As opposed to their above counterparts, selection pressure can be easily tailored in the tournament method by simply adjusting the tournament size, e.g. if the tournament size (namely,

the size of the randomly drawn subsets) is set to a high value, unfit individuals will be selected with small probability.

Despite the above methods being the most frequently used, many other selection operators have been reported, most stemming from other disciplines such as the entropy-Boltzmann selection, based on entropy and importance sampling methods in Monte Carlo simulation [89] or the so-called geometric selection, where the probability of selecting the best individual is given by the statistical geometric distribution [90].

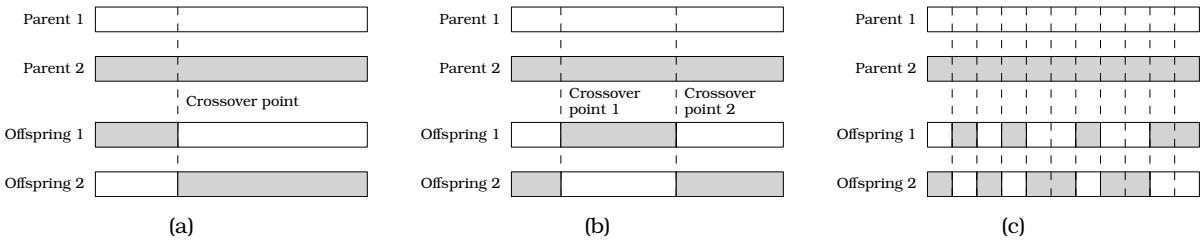


Figure 2.4: (a) Single-point crossover; (b) two-point crossover; (c) uniform crossover.

B. Once the selection operator has produced a set of parent chromosomes, these selected individuals are pairwise grouped under a certain fixed crossover probability P_c, which asymptotically establishes the fraction of selected chromosomes that will participate in the recombination or *mating* process. Each of such pairs will generate one or several offsprings by exchanging their genotypes. The ultimate goal of this operator is to improve the fitness of offsprings by virtue of the inheritance of genetic characteristics from their parents, which have been previously selected based on the potentiality of their fitness values. Many methods for the recombination and inheritance of genotypes from the parents to the offsprings have been proposed so far, to mention (Figure 2.4):

   - Single-point crossover: both parent chromosomes are cut at a certain point taken at random over the length of the genotype. Beyond this point the data from both parents is swapped, giving rise to a pair of offsprings each having two segments.
   - Two-point crossover: the procedure is similar to its single-point correlative, the difference being that in this case, two points are selected at random, and it is the genotype between the two points what is swapped between the parent individuals, rendering two offsprings. This is a particular case of the so-called N-point crossover, which generalizes this swapping approach for the exchange and inheritance of genotypes between generations.
   - Uniform crossover: unlike any point crossover, the uniform crossover exchanges genotypes at the gene level rather than at a segment level. To this end, a mixing ratio – usually set to $1/2$ – is utilized as a probabilistic threshold on which to base the exchange of every single gene. This mating strategy has been empirically shown to be more explorative than other segment-wise exploitative approaches [91], which makes it interesting for problems characterized for a specially acute multi-modality.

   As in the selection operators, many other alternatives for genetic recombination abound in the literature, such as hierarchical [92], multiple parent [93], reduced surrogate [94] and shuffle [95] crossovers, among others. Many studies have gravitated on empirically

assessing the performance of the prevailing portfolio of crossover operators by resorting to intensive simulations on known test functions [96, 97].

C. Mutation: this last operator introduces, under a certain probability P_m, some controlled yet random modifications in the offsprings produced as a result of the above crossover operator. The aim of this operator is to prevent the algorithm search from getting trapped in local optima; indeed, by introducing subtle modifications in the genotype of offsprings the search path *jumps* between different regions of the solution space, thus reinforcing the explorative behavior of the algorithm without compromising the potentiality of the specific solutions discovered in previous generations. Again, different mutational approaches are nowadays utilized, such as bit flipping (inversion of the value of the chosen gene in binary-encoded genetic algorithms), gene swapping (exchange of the values for two genes within a given offspring), boundary mutation (replacement of the value of the chosen gene with either the upper or lower bound for that gene, only used for integer and float encodings) or probabilistic mutation (a realization of a random variable is summed to a given real-encoded gene as an additive noise). In all these cases the mutation operator can be adapted so as to increase the probability that the amount of the mutation will be close to zero as the algorithm evolves, which is usually done by decreasing the value of P_m as the number of generations of the algorithm increases. This progression reduces the stagnation of the population in the early stages of the algorithm, deferring the fine-grained tuning of the produced solution for the later stages.

As shown in Figure 2.5, the canonical genetic algorithm implements all the above sequence of operators in an iterative fashion. The algorithm starts by initializing the population of chromosomes (in general, uniformly at random, although initialization strategies exploiting a prior knowledge on the landscape of the search may be adopted), followed by the fitness evaluation of all the initialized individuals. The algorithm then iterates by performing selection, crossover and mutation over the set of successively-refined individuals. Elitism may be imposed in the algorithm design as a means to grant the privilege to the best chromosomes to be unaltered between generations, i.e. the best chromosome survives from iteration to iteration. This iterative procedure is repeated until a certain stopping criterium is met (e.g. convergence flattening or maximum number of generations).

2.3.1.3 Modern Evolutionary Meta-heuristics

A number of new evolutionary techniques have recently emerged as powerful and innovative alternatives with respect to traditional techniques emanating from evolutionary computation, and have been successfully applied to a wide variety of optimization problems in several disciplines. One of such innovative schemes is Differential Evolution (DE [76]), where the offspring generation is based on four different individuals $\{\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3, \mathbf{X}_P\}$ selected from the population at random. A new offspring $\mathbf{X}_{off}$ is produced, gene by gene and under a probabilistic threshold P_c^{DE}, as

$$X_{off}(k) = X_3(k) + \mu \cdot (X_1(k) - X_2(k)), \tag{2.6}$$

with $k = 0, \ldots, K-1$ and $\mu \in [0, 1]$ is a real-valued weighting factor that controls the impact of the differential term in the generation of the offspring. This offspring is then compared to $\mathbf{X}_P$, and the best among this recombined individual and $\mathbf{X}_P$ is kept in the population. This

procedure is sequentially repeated so that all individuals in the original population have acted as the parent individual $\mathbf{X}_P$.

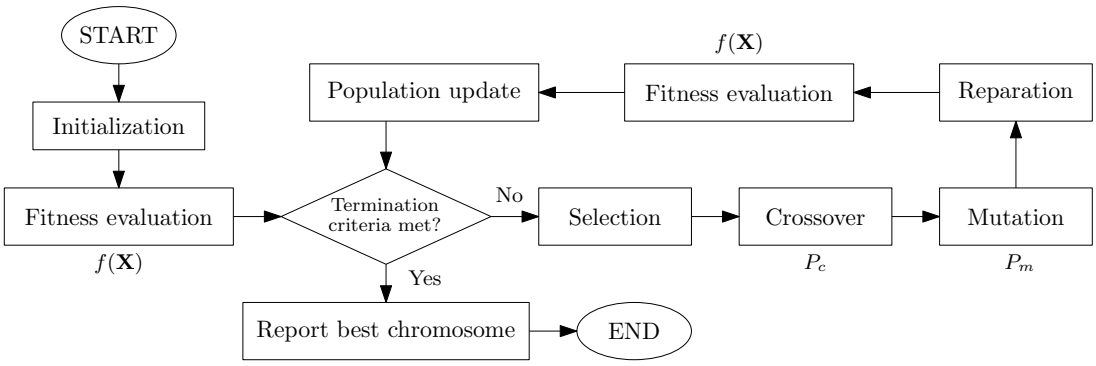


Figure 2.5: Block diagram of a generic GA.

On the other hand, the Estimation of Distribution Algorithm differs significantly from other evolutionary techniques in the fact that an EDA generates new chromosome populations generation after generation by sampling explicitly expressed probabilistic distributions (modelled by means of Bayesian networks, multivariate models or any other technique), which are computed based on the selected individuals from the previous generation. The principal advantages featured by EDA over its genetic counterpart lies on the lack of need for tuning multiple parameters for properly guiding the search process, as well as the implicitness of probabilistic model that permits to easily tackle optimization problems with strong interactions within the genotype components (also known as *epistasis* [98]).

2.3.2 Harmony Search

Most of the algorithmic background of this Thesis will gravitate on the Harmony Search (HS) algorithm, which is a relatively new population-based meta-heuristic that has shown to render excellent results for continuous and combinatorial problems and applications such as tour routing [99], Sudoku puzzle solving [100], water network design [101], dam operation [102], vehicle routing [103], multicast routing [104], multiuser detection [105, 106] and design of radar codes [107], among many others. First coined in [62], a comprehensive literature survey on different application fields to which this meta-heuristic algorithm has been applied so far can be found in [108] (under review at the time of writing and available on demand).

Operationally, HS mimics the behavior of a music orchestra when aiming at composing the most harmonious melody, as measured by aesthetic standards. To be concise, the aesthetic quality of the sound played by any given musical instrument is set by three different yet related quantities:

- Pitch, which stands fora subjective psycho-acoustical attribute of sound, usually measured in terms of a frequency scale.
- Timbre, tone quality or color, which articulates on five different attributes: the range between tonal and noisy characters, the spectral envelope, the time envelope (rise, duration,

and decay), the changes in spectral envelope (formant-glide) and fundamental frequency (micro-intonation), and the prefix or onset.

- Amplitude or loudness of the waveforms, which denotes a psychological perception closely related to the physical strength of the sound.

Pitch occurs to be the most relevant feature when addressing aesthetics in the composition of harmonies, since the pitch adjustment reduces, in fact, to a change the frequency. It is important to highlight that different notes have different frequencies. For example, the "RE", "FA" and "LA" notes in the conventional Latin notation style have fundamental frequencies of 294, 349 and 440 Hz. In music theory, pitch is usually represented as a numerical scale (a linear pitch space) where each frequency F_n (in Hz) is mapped to a MIDI number ∂_n using

$$\partial_n = 69 + 12 \cdot \log_2\left(\frac{F_n}{440}\right), \tag{2.7}$$

yielding MIDI numbers of 62, 65 and 69 for "RE", "FA" and "LA" notes. On this scale, an octave covers 12 units and semitones correspond to one-unit steps, which leads to a 2:1 ratio between the frequencies of two notes being an octave apart, i.e. the frequency of a note doubles (halves) when it is risen (lowered) a full octave. In this context, the aesthetic measure, yet being subjective as in any other perceptual or sensory-emotional concept, is known to rely mainly on the frequency ratios between the played notes. For instance, two notes playing one octave apart (i.e. a MIDI gap of 12) sound pleasantly, and so do other simple ratios such as 3:4 or 2:3. Contrarily, MIDI gaps of 7 semitones (e.g. "DO" and "SI") have been found to be dissonant.

Bearing the above basics on harmony aesthetics in mind, HS imitates a musician's improvisation process when intending to produce a piece of music with aesthetically perfect harmony. When comparing the improvisation process of musicians with optimization methods, one can realize that each musician corresponds to a decision variable; the musical instrument's pitch range refers to the alphabet of the decision variable; the musical harmony improvised at a certain time corresponds to a solution vector at a given iteration; and audience's aesthetic impression links to the fitness function of the optimization problem at hand. In a similar way to how musicians improve the melody – through variation and check – time after time, the HS algorithm progressively enhances the fitness of the solution vector in an iterative fashion. Each musician corresponds to an attribute of a given candidate solution picked from the problem solution domain, whereas each instrument's pitch and range corresponds to the bounds and constraints imposed on the decision variable.

2.3.2.1 Harmony Search Operators

HS is a population-based algorithm; it hence maintains a set of Ψ solutions or Harmony Memory (HM), similar to the population of chromosomes in genetic approaches. As such, an estimation of the optimum solution is achieved at every iteration by applying a set of optimization operators to the HM, which springs a new harmony vector every time. Notwithstanding this evident similarity, the rationale for the advantages of HS with respect to genetic algorithms lies on the fact that HS combines concepts from population-based meta-heuristics with subtle, yet important, modifications (e.g. polygamy), jointly with principles springing from evolutionary computation (i.e. new solutions evolve from previous versions of themselves, based on the

application of global-search and local-search operators). This synergy is generally able to better balance the trade-off between the explorative and exploitative behavior of the HS heuristics with respect to classical genetic operators.

Figure 2.6 illustrates the flow diagram of the HS algorithm, which can be summarized in four steps: (i) initialization of the HM; (ii) improvisation of a new harmony; (iii) update the HM with the new generated harmony if its fitness improves that of the worst currently in the HM; and (iv) returning to step (ii) until a termination criteria is satisfied. The improvisation procedure is mainly controlled by two different probabilistic operators, which are sequentially applied to each note so as to produce a new set of improvised harmonies or candidate solutions:

- The Harmony Memory Considering Rate (HMCR) sets the probability $\varphi \in [0, 1]$ that the new value for a certain note is drawn uniformly from the values of this same note in all the remaining melodies. Otherwise (i.e. with a probability $1 - \varphi$), the new value are randomly chosen from their alphabet $\mathcal{X}$. This case is commonly referred to as *random consideration* and increases the diversity of the solutions towards optimality; however, some contributions leave the random consideration as a third, separated operator (Random Selection Rate, RSR) with its own probabilistic parameter ε. Following the notation introduced in this chapter, if the HM is denoted as $\{\mathbf{X}(\psi)\}_{\psi=0}^{\Psi-1}$, with $\mathbf{X}(\psi) \triangleq \{X(\psi, 0), X(\psi, 1), \ldots, X(\psi, K-1)\}$ being the ψ-th harmony of the HM, and K the number of notes, then
$$\varphi \triangleq Pr\{X(\psi, k) \rightsquigarrow \omega_{\text{HMCR}}\}, \tag{2.8}$$
where ω_{HMCR} is a discrete random variable uniformly distributed in $\{X(\psi, 0), \ldots, X(\psi, k-1), X(\psi, k+1), \ldots, X(\psi, K-1)\}$. It results insightful to stress on the fact that this operator operates note by note in the HM, i.e. the above operation is repeated for every $k \in \{0, \ldots, K-1\}$ and $\psi \in \{0, \ldots, \Psi-1\}$.

- The Pitch Adjusting Rate (PAR) poses the probability $\vartheta \in [0, 1]$ that the new value $\widehat{X}(\psi, k)$ for a given note value $X(\psi, k)$ is computed via a controlled random perturbation, i.e.
$$\vartheta \triangleq Pr\left\{X(\psi, k) \rightsquigarrow \widehat{X}(\psi, k)\right\}, \tag{2.9}$$
where
$$\widehat{X}(\psi, k) = \begin{cases} \omega_{\text{PAR}} & \text{if } |\mathcal{X}| < \infty, \\ x_{old} + \eta \cdot z & \text{otherwise,} \end{cases} \tag{2.10}$$
with $\eta \in \mathbb{R}^+$ representing the pitch bandwidth, and z being drawn from an uniform distribution with support $[-1, 1]$. A low pitch adjusting rate with a narrow bandwidth may restrict the diversification of the algorithm within a small search subspace and consequently, decrease the convergence rate of the overall solver. On the other hand, a high pitch adjusting rate with a high value of ω_x may force the algorithm to unnecessarily escape from areas with potentially near-optimal solutions. As for the case of discrete alphabets, ω_{PAR} is a random binary variable with equal probability of taking the neighboring values on $X(\psi, k)$ in $\mathcal{X}$. In order to boost the performance of this operator, the alphabet $\mathcal{X}$ is usually sorted under some vicinity ordering criterium, in general based on the characteristics of the metric $f(\cdot)$ defining the problem at hand. Again, it should be emphasized that this operator operates note-wise on the constituent harmonies of the HM.

By analyzing these parameters in detail, it can be intuitively inferred the way in which the HS algorithm balances diversification and intensification. While both HMCR and PAR control

the diversification of the search procedure, the pitch adjustment driven by ϑ can be regarded as a locally refining procedure operating on the solutions just before the evaluation of their fitness. On the other hand, the complementary randomization procedure executed with probability $1-\varphi$ in the HMCR operator permits to explore regions of the search space far apart from each other. The intensification in the HS algorithm is mainly embedded in the HMCR operator, which sets the degree of elitism, i.e. the amount of solutions from the HM to be kept for subsequent generation. If φ is set to a low value, the algorithm will converge slowly to a potentially optimum solution. By contrast, a high value of φ will favour the intensification based on the knowledge contained in the HM, but at the risk of trapping the algorithm into local optima.

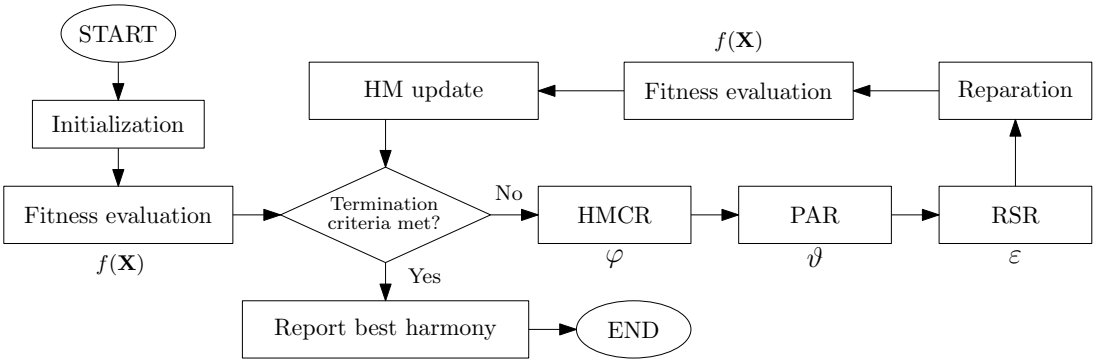


Figure 2.6: Block diagram of a generic HS algorithm.

Even though a perfect algorithm that renders the best performance in all optimization schemes does not exist (in line with the statements of the so-called *No Free Lunch Theorem* [109]), the HS algorithm has shown a great potential and efficiency in comparison with other meta-heuristic methods. Similarly to other related population-based algorithms, the HS relies on a group of solutions that can be simultaneously exploited for improving the efficiency of the algorithm. However, Genetic Algorithms consider only two vectors (referred to as *parents*) for generating a new solution or offspring, whereas HS takes into account, on a probabilistic basis, all the existing solutions (melodies) in the harmony memory. Besides, it independently operates on each constituent variable (*note*) of a solution vector (*melody*), to which stochastic operators for fine-tuning and randomization are applied. As opposed to gradient-search techniques, the convergence rate of HS and the quality of its produced solutions are not dramatically affected by the initialized values of the constituent melodies in the harmony memory. Another remarkable strength of HS hinges on the simplicity of the structure and operators of HS algorithm, which makes it flexible for its combination with other techniques [110] and its implementation in parallel hardware architectures.

2.3.2.2 Improved Variations of the HS Algorithm

A number of recent publications incorporate some modification to the original HS algorithm in [62] with no specifically targeted application scenario. Such variations include 1) alternative initialization procedures for the HM; 2) variable parameters for the improvisation procedure; 3) options for handling constraints when generating new harmonies; 4) different criteria for filtering and selecting new harmonies for the HM; 5) distinct termination criteria; and finally

6) modifications in the structure of the algorithm by adding or removing blocks or hybridizing it with other existing heuristics. Reviews on the existing HS flavours abound in the literature, e.g. [111] and references therein. A research work exemplifying different HS modifications can be found in [112], where an algorithm hybridizing HS and a local Hill Climbing approach is proposed in order to better balance between diversification and intensification of the search procedure in an attempt at guaranteeing the fine-tuning of the new harmonies and the avoidance of getting stuck in local optima. In addition, a global-best Particle Swarm Optimization approach is further aggregated to the hybrid solver so as to achieve a best convergence rate than that that rendered by the HMCR operator. Other considerations and adjustments performed in [112] to the original HS algorithm include novel repair methods for maintaining the feasibility of the solutions in the HM at both initialization and runtime of the hybrid heuristic, as well as a modification of the PAR procedure under which only pitch adjustments improving the quality of the produced solutions are accepted.

In order to cope with realistic design situations, Geem proposed a novel derivative for discrete design variables based on the HS algorithm [114]. In this work HS can ultimately find the optimal solution or near-optimal solutions by the help of the stochastic derivative for discrete variables. Based on the contents of the HM at a given iteration of the algorithm, the stochastic derivative for discrete variables provides the algorithm with information on the probability of selecting optimal values, which in general increases progressively along the iterations. While the traditional calculus-based derivative generates information on the search direction and step size for a function of continuous variables, the stochastic derivative utilized in this work computes the probabilistic trend of the algorithm to select a certain discrete point based on multiple vectors stored in the HM for a function of discrete variables.

To conclude with, an interesting contribution has focused on deriving a new version of this algorithm from a simple yet intuitive mathematical analysis on its exploratory behavior [115]. In this work Das *et al* analytically show that the standard deviation of the naive HS algorithm computed over the harmony memory can be used as a proportionality factor for adaptively controlling the bandwidth η in Expression (2.10). This approach introduces no additional complexity in the original HS framework, and is simulatively shown to outperform other HS variants and well-known evolutionary counterparts.

Chapter 3

Resource Allocation in Rate-Constrained Orthogonal Multicarrier Downlink Systems

"Human development is a form of chronological unfairness, since late-comers are able to profit by the labors of their predecessors without paying the same price."

- Alexander Herzen

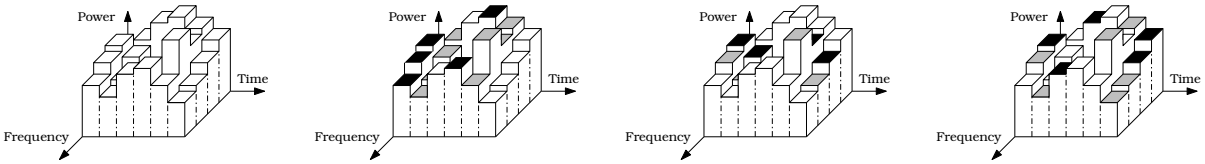
This chapter elaborates on the first application scenario where the applicability of metaheuristic algorithms to resource allocation is doubtlessly evidenced in the context of intelligent networks. The underlying radio access technique hinges on the so-called orthogonal multicarrier modulation, which support high-rate data transmissions and enhanced robustness over frequency-selective fading channels. When utilized in a single-user scenario, this radio interface essentially divides the available transmission bandwidth in a number of orthogonal narrowband spectrum channels (which are commonly referred to as *subcarriers* in the related literature), such that the information to be transmitted is split through all such channels [116]. The number of subcarriers is selected so that the information transmitted therethrough experiments flat (i.e. non-selective) fading, which can be achieved if the effective bandwidth of such subcarriers is set below the coherence bandwidth of the communication channel at hand. In such a case, multicarrier modulations can be shown to be very robust against the inter-symbol interference (ISI) characterizing high-rate wireless communications over multi-path channels. This robustness against distortions and fades induced by the channel has motivated the adoption of multicarrier modulation in a plenty of wireless communication standards, ranging from the IEEE 802.11 specification for wireless local area networks [117] to the last generations of LTE standards for cellular networking [118, Chapter 5] and a number of digital multimedia broadcasting services (e.g. DVB-T and DAB [119]). Also remarkable is the adoption of multicarrier modulations in protocols and standards for wired communications, as exemplified by the Discrete Multi Tone (DMT) scheme in Asymmetric Digital Subscriber Line (ADSL [120]).

As a byproduct of this enhanced resiliency against dispersive channel effects, several technological drawbacks jeopardized the adoption of multicarrier modulation since their advent in the late sixties [121], epitomized by the increased complexity derived from the huge oscillator and modulator banks required for its implementation. It was not until the reformulation of

the Discrete Fourier Transform (DFT) in [122] and subsequently achieved advances towards alleviating both the complexity and price of DFT processors when the interest in Orthogonal Frequency Division Multiplexing (OFDM) ignited and unchained a flurry of scientific activity, later crystalized in the plethora of aforementioned communication standards having adopted this technology.

When shifting to a multiple-user communication scenario, OFDM allows several users to employ different subcarriers for transmission which, if properly configured, entails an increased efficiency of the available radio resources. The possibilities to implement this shared use of subcarriers abound, depending on the domain on which the sharing is established [123, Chapter 5]. To begin with, and in reference to Figure 3.1, one of such possibilities is to allocate the entire spectrum band (i.e. all subcarriers) to a given user during a certain time slot, giving rise to the so-called OFDM Time Division Multiple Access (OFDM-TDMA). Likewise, OFDM Frequency Division Multiple Access (OFDM-FDMA) dedicates certain fixed subcarriers to each user statistically along time. However, in both cases the delay associated to the access of any user to the pool of shared time (OFDM-TDMA) or frequency (OFDM-FDMA) resources may be excessive when the number of users is large. To refrain from this inherent issue of time and frequency division multiplexing, Orthogonal Frequency Division Multiple Access (OFDMA [124]) combines the previous both multiple access approaches by assigning a subset of subcarriers to every user, in a similar fashion to OFDM-FDMA. However, the allocation of subcarriers to users may change between successive time slots by virtue of the orthogonality between subcarriers. Despite their evident differences, all these three OFDM multiple access schemes are nowadays utilized in several standardized radio interfaces such as IEEE 802.16 (WiMAX), where both OFDM-TDMA and OFDMA have been adopted for communications in the 2-11 GHz band [125].

From the theoretical perspective, OFDMA can be shown to be the optimum multiple access scheme for multiple-user multicarrier downlinks with independent decoding. Indeed, when K users transmit information to K distant receivers through an OFDMA downlink, maximizing the overall throughput of the system is solved by allocating each subcarrier to the user with highest corresponding channel gain, followed by a power per carrier distribution based on the well-known Water-Filling algorithm [126]. These advantages have motivated the adoption of OFDMA as the *de facto* radio interface of several avantgarde communication standards such the emerging standard for Wireless Regional Area Network (WRAN) using white spaces in the TV band (IEEE 802.22 [127]).



(a) OFDM (b) OFDM-TDMA (c) OFDM-FDMA (d) OFDMA

Figure 3.1: Resource allocation grid corresponding to different single- and multiuser multicarrier schemes. Black, gray and white colors in the assigned slots □ correspond to three different users.

However, when imposing additional constraints such as maximum and/or minimum rates per user (either for enforcing fairness in the exploitation of the resources or for implementing QoS contractual policies), the optimization problem driving the allocation of resources in OFDMA scenarios lacks of any analytical solution. As a workaround to solve this issue, most of

the related literature has so far resorted to heuristic algorithms in order to obtain near-optimum but feasible solutions at an affordable computational effort. Among them, intense research activity has been lately conducted towards the application of well-known evolutionary approaches (e.g. genetic algorithms [128, 129, 130, 131], swarm intelligence [132, 133] and Ant Colony Optimization [134]) to the allocation of radio resources in OFDMA downlinks.

This chapter takes a step further by extending a baseline OFDMA downlink scenario consisting of a K-user OFDMA downlink subject to per-user rate constraints with a *secondary* interfering OFDMA transmission to the same set of K distant receivers. Coexistence of users belonging to different OFDMA downlinks is permitted at a given frequency subchannel. More stringent rate constraints are also imposed to the secondary transmitter in order to minimize the excess interference at the primary OFDMA downlink, since secondary users are in general granted less transmission bandwidth than their primary counterparts. The proper selection of these rate limits, jointly with the aforementioned spectral coexistence, lay the basis for a intelligent multicarrier communication setup. To efficiently perform power and subcarrier allocation in this cognitive scheme, an iterative algorithm is designed based on the hybridization of the HS algorithm described in Section 2.3.2) with Differential Evolution (DE) inspired heuristics, similarly to other recently reported hybrid approaches, see e.g. [135, 136, 137]. The designed approach further incorporates a greedy procedure to account for the feasibility of the generated solutions. To the knowledge of the author of this Thesis, and despite its practical applicability, the use of the hybrid evolutionary techniques to this particular rate-constrained dual OFDMA scenario is completely novel in the research community.

The rest of the chapter is structured as follows: for the sake of integrity and to ensure the self-containedness of the chapter, Sections 3.1 and 3.2 sketch the fundamentals of OFDM when employed in single-user and multiple-user scenarios, along with a brief yet detailed insight on the activity carried out around resource allocation for this technology. Next, Section 3.3 elaborates on the system model and poses the underlying resource allocation optimization problem. Section 3.4 details the proposed hybrid HS-DE algorithmic approach, jointly with the greedy repair method. Finally, Section 3.5 discusses the obtained experimental results.

3.1 Foundations of OFDM Systems

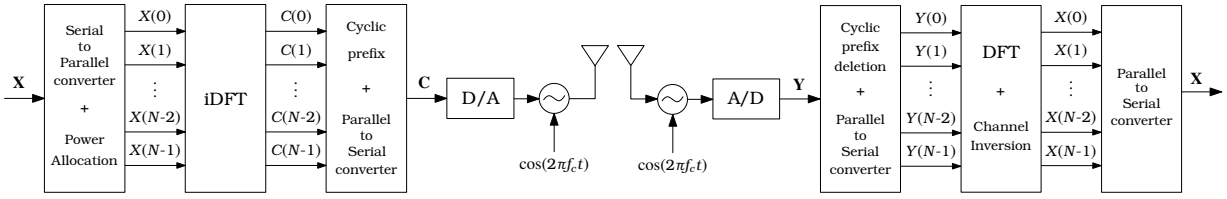
As aforementioned in the introduction to this chapter, OFDM divides a communication channel with available transmission bandwidth B and central frequency f_c in N orthogonal subcarriers with individual bandwidth $\Delta f \triangleq B/N$, each of which is allocated a subcarrier $n \in \{0, \ldots, N-1\}$ [138]. In its discrete formulation depicted in Figure 3.2.a, the OFDM modulator receives, as an input, an information sequence[1] of N complex-valued symbols[2] $\mathbf{X} = \{X(n)\}_{n=0}^{N-1}$, which are first parallelized and processed through an inverse Discrete Fourier Transform (iDFT) to yield the N iDFT coefficients $\mathbf{C} = \{C(n)\}_{n=0}^{N-1}$ corresponding to $\mathbf{X}$. Note that as argued later, conceptually the power associated to the complex symbol $X(n)$ results to be the power allocated to subcarrier n. Therefore, the power per subcarrier allocation procedure is usually applied to the constituent symbols of the parallelized $\mathbf{X}$ prior to the iDFT stage.

[1] This sequence could be the result of chopping an input sequence of infinite length in blocks of length N.

[2] This complex nature of the input symbols comes from a previous baseband modulation applied to the actual information symbols from the user. Since this Thesis will not address bit-loading aspects, this modulation will be set fixed and hence irrelevant for previous derivations.

Such coefficients $\mathbf{C}$ comprise the OFDM *symbol*, which is next added a cyclic prefix to avoid the interference between successive OFDM symbols transmitted over time-dispersive communication channels. These channels are characterized by the so-called *maximum delay spread* T_m, which can be interpreted as the maximum difference between the time of arrival of the earliest significant multipath component (typically the line-of-sight component, if any) and the time of arrival of the latest multipath component. To avoid overlapping between OFDM symbols, every symbol $\mathbf{X}$ itself must be enlarged with $N_{cp} \geq T_m/T_s$ additional components, where T_s denotes the time taken to process and transmit one single OFDM symbol. On this purpose, the extended OFDM symbol $\tilde{\mathbf{C}}$ is built by preceding $\mathbf{C}$ with a copy of its last N_{cp} entries, i.e.

$$\tilde{\mathbf{C}} \triangleq \{C(N-N_{cp}), C(N-N_{cp}+1), \ldots, C(N-1), C(0), C(1), \ldots, C(N-1)\}. \tag{3.1}$$



(a) Transmitter. (b) Receiver.

Figure 3.2: Block diagram of a generic single-user OFDM transmitter and its corresponding receiver.

The reason behind this particular choice of components for padding the OFDM symbol lies on the fact that it allows the linear convolution of a frequency-selective multipath channel to be modelled as circular convolution, which in turn may be transformed to the frequency domain using a discrete Fourier transform. Mathematically speaking, let $\mathbf{h}_t \triangleq \{H_t(l)\}_{l=0}^{L_c-1}$ represent the set of L_c time coefficients (i.e. sampled impulse response) characterizing the channel at hand. The received signal $\mathbf{Y} = \{Y(n)\}_{n=0}^{N-1}$ will be then given by

$$Y(n) = \sum_{l=0}^{L_c-1} h_t(l) \cdot \tilde{X}(n-l), \quad n = 0, \ldots, N-1, \tag{3.2}$$

which, since $\tilde{C}(n-l) = \tilde{C}((n-l) \mod N)$, reduces to a circular convolution. Simple calculus based on the properties of the DFT leads to [139, Section 1.5]

$$DFT[\mathbf{Y}] = DFT[\mathbf{C}] \odot DFT[\mathbf{h}_t], \tag{3.3}$$

where $\odot$ denotes componentwise multiplication. The rationale follows if one notices, from the modulator depicted in Figure 3.2.b, that $DFT[\mathbf{C}] = DFT\,[iDFT[\mathbf{X}]] = \mathbf{X}$. In words: after demodulation, the received signal is composed by a replica of the original information sequence $\mathbf{X}$, symbol-wise scaled by the channel coefficients $\mathbf{H}_f = \{H_f(n)\}_{n=0}^{N-1} \triangleq DFT[\mathbf{h}_t]$. Thus, a multipath channel is converted into several scalar parallel *subchannels* in the frequency domain, which simplifies the receiver design considerably. Additional benefits of cyclic prefixing arise from the estimation of the channel characteristics, since only the scalar coefficients corresponding to each subchannel must be estimated and separately inverted on the received demodulated symbols so as to recover the original symbols $\mathbf{X}$. This tailored selection of the cyclic prefix also brings about other side benefits, such as the lack of need for a pulse-shaping filter, and the reduced sensitivity to time synchronization issues.

In what relates to the scope of this Thesis, radio resource allocation for OFDM systems can be better understood if the modulation and demodulation procedures explained above are visually arranged in the time-frequency grid depicted in Figure 3.1.a. In this grid every axis corresponds to a domain, to be allocated under a given resource management criterium, i.e. time slots, spectrum subcarriers and assigned power per subcarrier. In other words, every depicted vertical bar stands for the power allocated to every subcarrier at a certain time slot. In the context of single-user OFDM communication scenarios, the formulation of the most straightforward resource allocation problem targets the maximization of the amount of information that can be transferred via OFDM modulation through a communication channel.

To further unfold this first allocation problem, let the communication channel be reduced to a set of parallel N subchannels, in light of the findings on the entire signal processing chain exposed previously. For each of such subchannels Additive White Gaussian noise (AWGN) will be assumed with a constant spectral density equal to N_0 (watts per hertz) and a Gaussian distribution of amplitude. Thermal and electrical noise from amplifiers and other signal processing stages in the receiver frontend exhibit white Gaussian noise properties, allowing them to be modelled accurately with the AWGN model. Most other noise and interference sources also fit in the AWGN model due to the fact that OFDM signals are characterized by flat spectral density shapes provided that the number of subcarriers N is large enough with respect to the transmission bandwidth B. Following this model, at each subcarrier $n \in \{0, \ldots, N-1\}$ the symbol $X(n) \in \mathbf{X}$ is transmitted with power $P(n)$, being $H_f(n)$ the frequency response of the channel at the n-th subcarrier bin. Since power is a limited resource, the total power available at the transmitter will be denoted by P^{max}. Having said this, Shannon's Theory dictates that the capacity $\mathcal{C}(n)$ of any of these N parallel AWGN channels is given as

$$\mathcal{C}(n) \triangleq \Delta f \log_2\left(1 + \frac{P(n)|H_f(n)|^2}{N_0 \Delta f}\right), \tag{3.4}$$

measured in bits per transmitted symbol. The overall capacity of this channel model (and hence, that theoretically achievable by means of the OFDM scheme) can be then computed by solving

$$\underset{P(0),\ldots,P(N-1)}{\text{Maximize}} \quad \mathcal{C} \triangleq \sum_{n=0}^{N-1} \mathcal{C}(n) = \sum_{n=0}^{N-1} \Delta f \log_2\left(1 + \frac{P(n)|H_f(n)|^2}{N_0 \Delta f}\right), \tag{3.5}$$

$$\text{subject to} \quad \sum_{n=0}^{N-1} P(n) \leq P^{max}, \tag{3.6}$$

$$P(n) \geq 0, \; n = 0, \ldots, N-1, \tag{3.7}$$

which, indeed, reduces to a resource allocation problem with the power per subcarrier $\mathbf{P} = \{P(n)\}_{n=0}^{N-1}$ as the optimization variable. This problem belongs to the class of convex optimization problems where a convex objective function is to be minimized subject to a convex constraint set. Thus, it can be solved by using Lagrange multipliers [140], yielding the optimal power distribution policy $\{P^*(0), P^*(1), \ldots, P^*(N-1)\}$ given by

$$P^*(n) = \begin{cases} 0 & \text{if } \frac{N_0 \Delta f}{|H_f(n)|^2} \geq \upsilon, \\ \upsilon - \frac{N_0 \Delta f}{|H_f(n)|^2} & \text{if } \frac{N_0 \Delta f}{|H_f(n)|^2} < \upsilon, \end{cases} \tag{3.8}$$

where υ is a constant that establishes the maximum power up to which each subcarrier is *filled* with energy depending on its corresponding baseline level $N_0 \Delta f / |H_f(n)|^2$. This theoretical

result, referred to as the *Water-Filling* algorithm in the research community, poses a reference benchmark system to which to assess and compare the performance of distinct power assignment policies. At this point it is important to emphasize that the significance of the water-filling approach in the design of practical OFDM systems must be understood with caution, as the optimum power policy derived therefrom may involve that

$$\mathcal{C}^*(n) \triangleq \Delta f \log_2\left(1 + \frac{P^*(n)|H_f(n)|^2}{N_0 \Delta f}\right) \notin \mathbb{N}, \tag{3.9}$$

i.e. a non-integer maximum capacity per subcarrier $\mathcal{C}_i^*$. From a practical perspective, this means that the baseband modulator preprocessing the symbols $\mathbf{X}$ would require a constellation with infinite number of points to realize any given value of $\mathcal{C}^*(n)$. Source and channel coding would eventually allow for non-integer values of this optimum capacity, but would still lack of enough granularity to cope with any channel status. This is the basis for the upsurge of research activity around *bit-loading* schemes, which denote all such practical power allocation algorithms focused on maximizing the overall transmission rate subject the values of $\mathcal{C}(n)$ being integer, in contrast to the above classical water-filling result where no constraints are set on the capacity per subcarrier. In this field many practical algorithms have been proposed, among which the ones presented in [141, 142, 143, 144] can be deemed as pivotal with respect to the majority of adaptive bit-loading approaches published so far in the literature.

3.2 OFDM in Multiuser Systems: OFDMA

When utilized in the context of communication scenarios involving several users, their corresponding information sequences are separated and multiplexed in both time and frequency domain to yield a series of OFDM symbols (i.e. OFDMA symbols) simultaneously conveying the information from all users. The subcarriers in which B is divided and the OFDM symbol period are the resource allocation units of finest granularity. Hence, users are assigned different units or *slots* in time and frequency domain under a certain resource allocation strategy. Therefore, an OFDMA transmitter utilizes a subcarrier allocation and assignment function instead of the serial-to-parallel conversion used in OFDM systems to split the single user's stream into a set a parallel low-rate streams. This procedure is graphically illustrated in Figure 3.3, where a downlink transmission system is considered with K users – each equipped with a single antenna – and N subcarriers. The total transmit power is again constrained to P^{max}. For user k on subcarrier n, the channel gain is denoted by $H_{f,k}(n)$.

When compared to an OFDM-TDMA system which, as mentioned in the introduction of this chapter, allocates the entire OFDM symbol to one user at a given time (i.e. $K = N$), an OFDMA system reduces the granularity in the radio resource allocation mechanism, and this improves the efficiency of the medium access control (MAC) protocol. In addition, an OFDMA system can exploit the available power P^{max} more efficiently than a OFDM-TDMA system. Indeed, focusing on the uplink case, an OFDMA system concentrates the power available in the user terminal on the group of subcarrier allocated to this user terminal, whereas a OFDM-TDMA system distributes it over the entire channel bandwidth B. In an OFDMA system which allocates $M < N$ carriers to each user, the power gain with respect to OFDM-TDMA on the uplink scenario can be shown to be $10 \log_{10}(N/M)$ dB, which leads to a significant extension of the cell range. Similar gains can also be achieved on the downlink by allocating more power to subcarriers assigned

to distant users. These rendered operational benefits outgain several technical drawbacks common to all multicarrier schemes, e.g. higher sensitivity to frequency offsets and phase noise, and the Peak-to-Average Power Ratio (PAPR) problem. In regards to the latter, since each sample at the output of the iDFT is the sum of M independent variables it is asymptotically Gaussian, which leads to high envelope variations. This high PAPR value can unchain undesired nonlinearities and distortions in the output of any given linear amplifier in the transmission frontend.

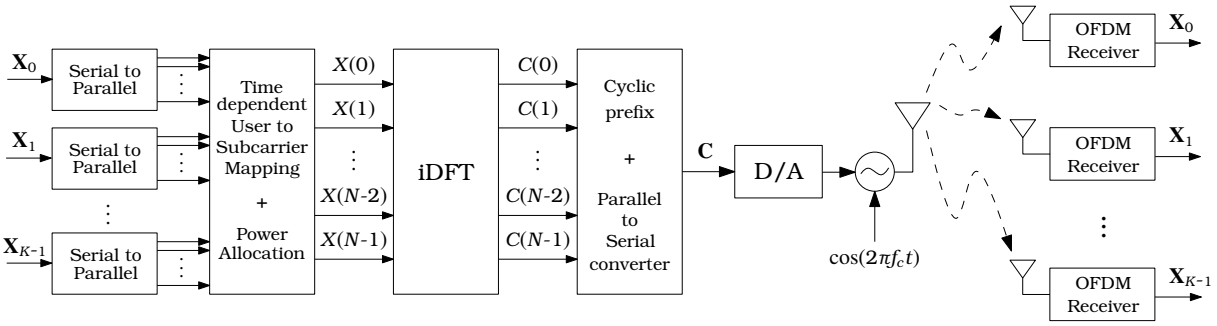


Figure 3.3: Block diagram of a generic multiuser OFDMA downlink.

Delving into the technical grounds of these multiuser schemes, OFDMA based transmission rely on the so-called *multiuser diversity*, concept first tackled for uplink systems in the seminal work by Knopp and Humblet [145]. It should be set clear, as argued previously for the single-user case, that broadband signals often experience frequency-selective fading due to the time dispersion of the transmitted signals in bandwidth-limited channels. OFDMA allows different users to transmit over different portions of the broadband spectrum, hence perceiving effectively different channel gains at a given frequency channel. As a consequence, a deeply faded channel for one user may still be favorable to others. In other words, certain subcarriers that are in deep fade for some users are not necessarily bad for others since the user channel fading characteristics $|H_{f,k}(n)|^2$ are uncorrelated for different $k \in \{0, \ldots, K-1\}$. Hence, the selection of good subcarriers for one user may not necessarily block other users from accessing their good subcarriers. This motivates the need for developing resource allocation mechanisms that exploit multiuser diversity to assign an active user its best subcarriers, and hence increase the efficiency of channel utilization. In practice, multiuser diversity in OFDMA systems usually assign each of the available N subcarriers to the user that will potentially best exploit the frequency subchannel at hand. Quantitatively, the application of this strategy results in a performance gap – in terms of overall achieved transmission rate – with respect to any other random user-to-subcarrier policy (see [146] for an insightful information-theoretic analysis).

An additional observation of crucial importance for the scope of this Thesis can be drawn from the above introduction to multiuser diversity in OFDMA systems: the central role of the user-to-subchannel assignment in the performance of such systems. Since sharing between users enters the picture, radio resources in OFDMA systems become even more stringently limited than in their single-user counterparts, with particular stress on the available transmission power P^{max} and bandwidth B. Under this premise, it is of utmost importance to dynamically allocate resources in such a way that the potential capacity offered by the communication channel is exploited to its maximum. For that to be achieved, multiuser diversity mechanisms such as the one described above are to be utilized jointly with power allocation algorithms matched to the dynamics to the communication channel, which can be both regarded as particular forms

or instances of adaptive resource allocation procedures.

As aforementioned in the introduction of this chapter, in absence of any other side constraint the maximization of the overall rate of an OFDMA downlink can be theoretically solved by a sequential approach consisting of two interrelated stages. First, subcarriers are assigned to the users with best effective channel response (i.e. higher value of $|H_{f,k}(n)|^2$) at the frequency at hand. Next, once all subcarriers have been properly mapped to users, power allocation via the water-filling scheme in Expression (3.9) is performed over the set of effective channel responses. Notwithstanding the optimality of this resource management strategy when applied to the unconstrained rate-maximization problem, side constraints are often added to the problem formulation so as to account for operational factors such as contracted QoS guarantees. Therefore, the above sequential strategy may not be optimum under this perspective. This lack of optimality gets even more acute when the naive OFDMA downlink scenario in Figure 3.3 is complicated with interfering communications in the same transmission band B, paradigm that goes in line with the concept of intelligent communication networks outlined in Chapter 1. When this is the case, the resulting formulation unveils a mixed integer programming problem with multiple inequality constraints given by

$$\underset{\{\{P_k(n)\}_{k=0}^{K-1}\}_{n=0}^{N-1}}{\text{Optimize}} \quad U(\cdot), \tag{3.10}$$

$$\text{subject to} \quad \sum_{k=0}^{K-1}\sum_{n=0}^{N-1} P_k(n) \leq P^{max}, \tag{3.11}$$

where $P_k(n)$ is the power allocated by user $k \in \{0,\ldots,K-1\}$ to subcarrier $n \in \{0,\ldots,N-1\}$, and $U(\cdot)$ represents a *utility* function that will strictly depend on the target criterium imposed to assess the performance of the OFDMA system at hand. Two different approaches are usually considered on this purpose: to maximize the overall transmitted throughput (usually referred to as rate-adaptive transmission), or to minimize the overall power consumption subject to rate per user guarantees (correspondingly, margin-adaptive transmission). In both cases, the above formulation is redundantly made more explicit by including a N-length vector variable $\mathbf{\Omega} \triangleq \{\Omega(n)\}_{n=0}^{N-1}$ indicating to which user each subcarrier is allocated. In this case, the power vector variable is redefined to $\mathbf{P} \triangleq \{P(n)\}_{n=0}^{N-1}$, as the user assignment is uniquely indicated by $\mathbf{\Omega}$.

From the algorithmic point of view, the above problem has been tackled in the literature under two different strategies: the first one aims at efficiently finding an optimum solution by jointly allocating all the radio resources involved in the problem (at least $\mathbf{P}$ and $\mathbf{\Omega}$, with possible extensions to bit-loading), at a significant penalty in computational complexity. Some contributions adopting this strategy can be found in [147, 148, 149, 150] and references there included. On the contrary, suboptimum resource allocation algorithms for OFDMA systems allocate the available resources in a separate, sequential fashion. This suboptimum approach has been so far assimilated in a number of research works resorting to different combinations of greedy (e.g. Levin-Campello, Hungarian), water-filling and ad-hoc designed low-complexity heuristics in [151, 152, 153, 154].

3.3 System Model under Consideration

The dual OFDMA radio downlink under consideration in this chapter falls within the wide class of OFDMA networks featuring complex resource allocation problems for which ad-hoc approxi-

mate heuristics must be devised. As depicted in Figure 3.4, a primary base station (PBS) transmits information from K users to their corresponding destinations through a OFDMA downlink with N equally spaced subcarriers, central frequency f_c, overall transmission bandwidth B and total transmit power $P_{\triangle}^{max}$. Only one user is allowed to occupy every subcarrier. In this scenario a secondary base station (correspondingly, SBS) sends data from another set of K users to the same K destinations by establishing a secondary OFDMA downlink with identical bandwidth support $[f_c - B/2, f_c + B/2]$, same number of subcarriers N and total transmit power $P_{\blacktriangle}^{max}$. As assumed for the PBS, the SBS allocates only one user to each subcarrier, but simultaneous coexistence of a primary and a secondary user is permitted at a given spectrum subchannel.

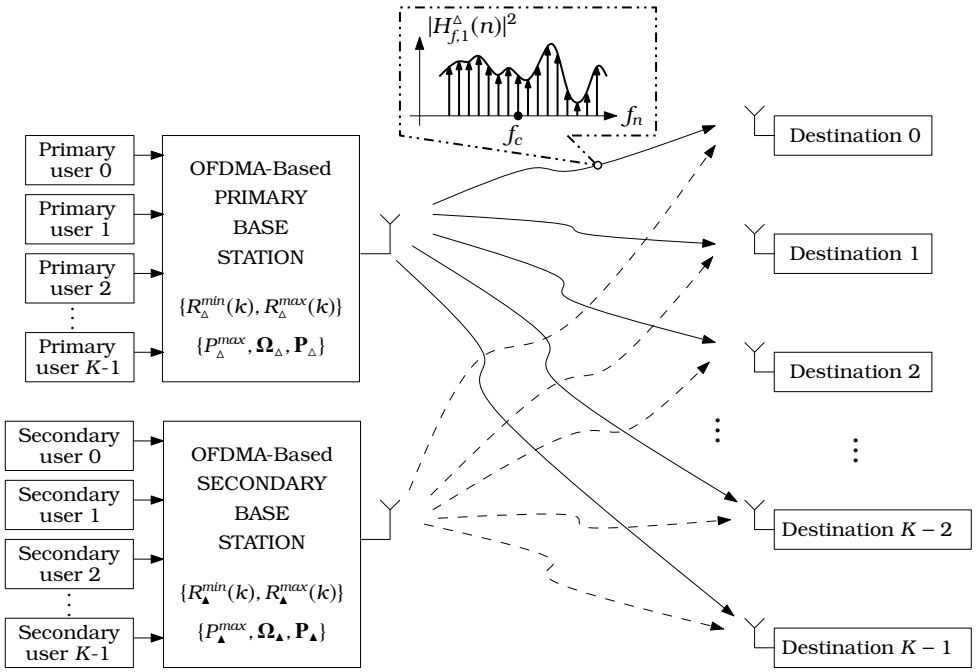


Figure 3.4: Block diagram of the proposed OFDMA downlink scenario.

Let $H_{f,k}^{\triangle}(n)$ (respectively, $h_{f,k}^{\blacktriangle}(n)$) denote the channel gain experienced by the k-th primary (respectively, secondary) user in subcarrier $n \in \{0, \ldots, N-1\}$. Indices $\triangle$ and $\blacktriangle$ will be hereafter utilized for those system parameters corresponding to the PBS and the SBS, respectively. Following this notation, let $P_{\triangle}(n)$ (respectively, $P_{\blacktriangle}(n)$) be the power assigned to subcarrier n at the PBS (respectively, SBS). By defining the user index to which the n-th subcarrier is allocated at the PBS as $\Omega_{\triangle}(n) \in \{0, \ldots, K-1\}$, and assuming Gaussian signalling at the SBS, the theoretical rate delivered by the PBS to the k-th destination is given by [1]

$$R_{\triangle}(k) = \sum_{\substack{n=0 \\ \Omega_{\triangle}(n)=k}}^{N-1} \Delta f \log_2 \left(1 + \frac{P_{\triangle}(n)|H_{f,k}^{\triangle}(n)|^2}{N_0 \Delta f + P_{\blacktriangle}(n)|H_{f,k}^{\blacktriangle}(n)|^2} \right), \tag{3.12}$$

where N_0 represents the power spectral density of the Additive White Gaussian Noise (AWGN) assumed at each receiver frontend. As often assumed in most related works (e.g. see [155] and references therein), the interference of the secondary base station is included in the above expression as an additional Gaussian noise in the corresponding subchannel. Likewise, a similar expression can be obtained for the theoretical rate of SBS by simply substituting $\triangle$ for

▲ in the above formula. The rate-constrained optimization problem can be then formulated as

$$\underset{\mathbf{\Omega}_{\triangle},\mathbf{\Omega}_{\blacktriangle},\mathbf{P}_{\triangle},\mathbf{P}_{\blacktriangle}}{\text{Maximize}} \quad R^T \triangleq \sum_{k=0}^{K-1}(R_{\triangle}(k)+R_{\blacktriangle}(k)), \tag{3.13}$$

$$\text{subject to} \quad \sum_{n=0}^{N-1} P_{\triangle}(n) = P_{\triangle}^{max}, \tag{3.14}$$

$$\sum_{n=0}^{N-1} P_{\blacktriangle}(n) = P_{\blacktriangle}^{max}, \tag{3.15}$$

$$R_{\triangle}^{min}(k) \leq R_{\triangle}(k) \leq R_{\triangle}^{max}(k), \tag{3.16}$$

$$R_{\blacktriangle}^{min}(k) \leq R_{\blacktriangle}(k) \leq R_{\blacktriangle}^{max}(k), \tag{3.17}$$

where $\mathbf{\Omega}_{\triangle} \triangleq \{\Omega_{\triangle}(n)\}_{n=0}^{N-1}$, $\mathbf{P}_{\triangle} \triangleq \{P_{\triangle}(n)\}_{n=0}^{N-1}$, and $\{R_{\triangle}^{min}(k), R_{\triangle}^{max}(k)\}$ and $\{R_{\blacktriangle}^{min}(k), R_{\blacktriangle}^{max}(k)\}$ represent lower and upper bounds on the maximum rate of user k in the PBS and SBS OFDMA downlinks, respectively. Therefore, the interest lies in finding the optimum power and subcarrier allocation policies at both primary and secondary base stations such that the overall throughput of the setup is maximized and the imposed rate constraints are fulfilled. Note that since throughput maximization is sought, no control on the total transmission power $P_{\triangle}^{max}$ and $P_{\blacktriangle}^{max}$ is considered, so base stations are assumed to operate always at maximum transmit power.

It is also important to note that perfect Channel State Information (CSI) is assumed for the algorithms next described, which can be obtained by virtue of e.g. feedback channels sending channel estimates computed at high operational signal to noise ratio sent from each distant receiver to both base stations. This involves that the above coefficients $H_{f,k}^{\triangle}(n)$ and $H_{f,k}^{\blacktriangle}(n)$ are known perfectly at the base stations and therefore, do not impact, in terms of achievable capacity, the end-to-end performance of the system posed in Expression (3.12). Nevertheless, it should be emphasized that the forthcoming algorithmic formulations accommodate any possible source of uncertainty impacting on such a expression, not only the accuracy in the channel estimates, but also the performance gap to the ultimate capacity featured by distinct channel codes and/or modulators (the so-called *SNR gap* [156]) or side implementation-related effects such as quantization aspects in the channel estimation.

3.4 Proposed Joint Subcarrier and Power Allocation Algorithm

To efficiently tackle the optimization problem in Expressions (3.13) through (3.17), this Thesis proposes a novel hybrid heuristic technique inspired in the HS algorithm, which has been described in its seminal form in Section 2.3.2. As mentioned in the previous section, the proposed scheme seeks the optimum user-to-subcarrier mapping variable vectors $\{\mathbf{\Omega}_{\triangle}, \mathbf{\Omega}_{\blacktriangle}\}$ and power distributions $\{\mathbf{P}_{\triangle}, \mathbf{P}_{\blacktriangle}\}$ that maximize the overall metric in expression (3.13). To this end, the algorithm iterates on a set of Ψ candidate solutions

$$\{\mathbf{SOL}(\psi)\}_{\psi=0}^{\Psi-1} \triangleq \{\mathbf{\Omega}_{\triangle}(\psi), \mathbf{\Omega}_{\blacktriangle}(\psi), \mathbf{P}_{\triangle}(\psi), \mathbf{P}_{\blacktriangle}(\psi)\}_{\psi=0}^{\Psi-1}, \tag{3.18}$$

each of which is progressively refined and evaluated in terms of both the aforementioned overall metric and the fulfillment of the imposed per-user rate constraints. Note that the refinement of the user-to-subcarrier mappings $\mathbf{\Omega}_{\triangle}(\psi) = \{\Omega_{\triangle}(\psi, n)\}_{n=0}^{N-1}$ and $\mathbf{\Omega}_{\blacktriangle}(\psi) = \{\Omega_{\blacktriangle}(\psi, n)\}_{n=0}^{N-1}$ entails

a discrete-variable optimization problem which can be tackled by means of the original HS algorithm, i.e. by means of the adaptation of the two operational processes controlling the operational procedure of this heuristic: the Harmony Memory Considering Rate (HMCR), which is driven by the probabilistic parameter $\varphi \in [0, 1]$, and the Pitch Adjusting Rate (PAR), which is controlled by $\vartheta \in [0, 1]$. Such operators are defined in the context of the problem at hand as:

- HMCR: the corresponding parameter φ establishes the probability that the new allocated user to a given subcarrier is uniformly drawn from the values of the same subcarrier allocation taken in all the other $\Psi - 1$ candidate solutions, e.g. $\varphi \triangleq Pr\{\Omega_{\triangle}(\psi, n) \rightsquigarrow \omega_{\text{HMCR}}\}$, where ω_{HMCR} is a discrete random variable uniformly distributed in the set

$$\{\Omega_{\triangle}(0, n), \ldots, \Omega_{\triangle}(\psi - 1, n), \Omega_{\triangle}(\psi + 1, n), \ldots, \Omega_{\triangle}(\Psi - 1, n)\},$$

  with $\psi \in \{0, \ldots, \Psi - 1\}$. At this point it is relevant to point out that this first description of the algorithm assumes that φ and the forthcoming ϑ are kept statically fixed along the running horizon of the algorithm. However, a number of studies (e.g. [157]) have shown that a progression established on both probabilistic parameters enhances both the convergence speed of the heuristic algorithm and the quality of the provided solution. This is the rationale for adopting, in this study, the novel logarithmic progression later described in Section 3.5.

- PAR: the real-valued parameter ϑ sets the probability that the new value of a given subcarrier allocation $\Omega_{\triangle}(\psi, n)$ is picked from its neighboring values in the alphabet $\{0, \ldots, K-1\}$ sorted in increasing order of the power of the corresponding downlink channel gain $|H^{\triangle}_{f,k}(n)|^2$. The rationale behind sorting the alphabet as a function of the channel gain lies on the fact that as explained in Section 3.2, in absence of interference and rate constraints the subcarrier allocation that maximizes the throughput reduces to finding the user with highest channel gain at every frequency subchannel.

On the other hand, for the allocation of the overall power budget $P^{max}_{\triangle}$ and $P^{max}_{\blacktriangle}$ along subcarriers (i.e. the refinement of $\mathbf{P}_{\triangle}(\psi)$ and $\mathbf{P}_{\blacktriangle}(\psi)$), the HMCR procedure works analogously to the subcarrier allocation case, i.e. the power allocated to a certain subcarrier evolves based on φ and the values taken by such allocated power among the Ψ candidates. However, a different strategy is adopted for the PAR process by utilizing a DE approach. As such, every time the PAR process is to be applied on the power allocated to a certain subcarrier, say $P_{\triangle}(\psi, n)$, its new refined value, hereafter denoted by the *hat* superscript (e.g. $\widehat{P}_{\triangle}(\psi, n)$), is computed as

$$\widehat{P}_{\triangle}(\psi, n) = \begin{cases} P_{\triangle}(\psi, n) + \eta \cdot z \cdot (P_{\triangle}(\psi_{\circ}, n) - P_{\triangle}(\psi_{\bullet}, n)) & \text{with probability } \vartheta, \\ P_{\triangle}(\psi, n) & \text{with probability } 1 - \vartheta, \end{cases} \tag{3.19}$$

where $\eta \in \mathbb{R}^+$, and z is a realization of a continuous random variable $\mathcal{Z}$ following an arbitrary probability density distribution $f_{\mathcal{Z}}(z)$ with support $(-\infty, +\infty)$ (further details are provided in Section 3.5). Besides, $\psi_{\circ}$ and $\psi_{\bullet}$ are discrete random variables drawn from the range $\{0, \ldots, \psi - 1, \psi + 1, \ldots, \Psi\}$. The particular differences with respect to the naive DE in [76] lie on the amplification of the so-called *differential variation*: in the above equation, both the factor η and the realization z control a random amplifying perturbation of the difference between individuals in the harmony memory.

In order to satisfy the power budget available at each base station, the entries of every newly generated power allocation candidate $\widehat{\mathbf{P}}_{\triangle}(\psi) \triangleq \{\widehat{P}_{\triangle}(\psi, n)\}_{n=0}^{N-1}$ (respectively, $\widehat{\mathbf{P}}_{\blacktriangle}(\psi)$) are normalized

to sum $P_{\triangle}^{max}$ (respectively, $P_{\blacktriangle}^{max}$), i.e. $\sum_{n=0}^{N-1} \widehat{P}_{\triangle}(\psi, n) = P_{\triangle}^{max}$ for $\psi \in \{0, \ldots, \Psi - 1\}$. It is also important to emphasize that, although the power budget in Expressions (3.14) and (3.15) is satisfied by this particular hybrid procedure, an additional greedy algorithm is required so as to account for the imposed rate constraints, which is later explained in Subsection 3.4.1.

The evaluation of the fitness for each generated candidate $\mathbf{SOL}(\psi)$ is performed hierarchically in two separated steps. A first metric $RC(\cdot)$ for checking the Rate Compliancy of each generated candidate is built by computing its associated per-user rates $R_{\triangle}(\psi, k)$ and $R_{\blacktriangle}(\psi, k)$ based on Expression (3.12), and by sequentially comparing the obtained rates with the corresponding rate constraints $R_{\triangle}^{min}(k)$, $R_{\triangle}^{max}(k)$, $R_{\blacktriangle}^{min}(k)$ and $R_{\blacktriangle}^{max}(k)$. Namely:

$$RC(\mathbf{SOL}(\psi)) \triangleq \frac{\sum\limits_{\delta \in \{\triangle, \blacktriangle\}} \sum\limits_{k=0}^{K-1} \mathbb{I}\left[R_{\delta}(\psi, k) \geq R_{\delta}^{min}(k)\right] + \mathbb{I}\left[R_{\delta}(\psi, k) \leq R_{\delta}^{max}(k)\right]}{4K}, \tag{3.20}$$

where $\psi \in \{0, \ldots, \Psi - 1\}$ and $\mathbb{I}[\cdot]$ denotes an indicator function taking value 1 if its argument is true and 0 otherwise. This metric is upper bounded by 1, value corresponding to a fully rate-compliant proposed candidate. Once $RC(\cdot)$ is computed for all the newly generated Ψ candidates, they are sorted in decreasing order of their metric value. Then, the evaluation of the overall throughput metric R^T in expression (3.13) permits to sort – again in decreasing order – those candidates sharing the same value of $RC(\cdot)$. Based on this adopted strategy, the proposed algorithm grants priority to those candidates fulfilling as many rate constraints as possible, whereas the maximization of the overall throughput R^T is the criteria to sort candidates with identical rate compliancy.

3.4.1 Greedy Frequency Reallocation Procedure

Regarding the optimization problem posed in expressions (3.13) to (3.17), the iteratively generated candidate solutions must fulfill the imposed rate constraints

$$\{R_{\triangle}^{min}(k), R_{\triangle}^{max}(k), R_{\blacktriangle}^{min}(k), R_{\blacktriangle}^{max}(k)\}_{k=0}^{K-1}.$$

On this purpose, the proposed resource allocation scheme incorporates a greedy subcarrier reallocation procedure that attempts at iteratively repairing the set of already built candidates $\{\mathbf{SOL}(\psi)\}_{\psi=0}^{\Psi-1}$. Despite the simplicity of this local search method, it turns out to be an effective repairing technique at a reduced computational cost for the optimization problem at hand.

The greedy procedure is divided in 4 different steps, which are sequentially applied to each proposed solution $\mathbf{SOL}(\psi)$, with $\psi \in \{0, \ldots, \Psi - 1\}$. The first two steps handle those candidate solutions that violate any of the imposed *lower* rate constraints for either the primary (step 1) or the secondary base station (step 2). In both steps the greedy algorithm works in a similar fashion: once the set of users violating their lower rate constraint has been identified, the algorithm reassigns subcarriers from the *best* user (i.e. the user with highest rate margin above its upper limit) to such under-rated users. On the other hand, steps 3 and 4 of the greedy procedure handles candidate solutions whose any of the associated rates per user is above its corresponding upper constraint. In this case, subcarriers allotted to such over-rated users are reassigned to the user with lowest rate margin in the candidate solution at hand. These 4 steps are sequentially applied to the ^{o}Psi candidate solutions $\{\mathbf{SOL}(\psi)\}_{\psi=0}^{\Psi-1}$ for a maximum of $\mathcal{I}_g$ iterations.

Let us be more precise by denoting as $\mathcal{N}_{\triangle}(k)$ the set of subchannels associated to user $k \in \{0, \ldots, K-1\}$ at the primary base station, i.e. n belongs to $\mathcal{N}_{\triangle}(k)$ if $\Omega_{\triangle}(n) = k$. With this definition, the first step of the proposed greedy repair technique is described as follows:

1.1. Identify the set of currently under-rated users as

$$\mathcal{K}_{\triangle}^{ur}(\psi) \triangleq \{k : R_{\triangle}(\psi, k) < R_{\triangle}^{min}(k)\}.$$

1.2. Find the *best* user k^* satisfying

$$R_{\triangle}(\psi, k^*) - R_{\triangle}^{max}(k^*) > R_{\triangle}(\psi, k) - R_{\triangle}^{max}(k) \quad \forall k \in \{0, \ldots, K-1\}.$$

1.3. Sort the set $\mathcal{N}_L^{k^*}$ in decreasing order of the corresponding channel gain $|H_{f,k}^{\triangle}(n)|^2$, with $n \in \mathcal{N}_{\triangle}(k^*)$. This produces the sorted set $\widetilde{\mathcal{N}}_{\triangle}(k^*)$.

1.4. For each under-rated user $k \in \mathcal{K}_{\triangle}^{ur}(\psi)$, allocate the first subchannel in $\widetilde{\mathcal{N}}_{\triangle}(k^*)$ to under-rated user k by setting the associated entry of $\mathbf{\Omega}_{\triangle}(\psi)$ to k. Once this is done, delete such first subchannel from the set $\widetilde{\mathcal{N}}_{\triangle}(k^*)$. This is repeated until all under-rated users have been processed or the set $\widetilde{\mathcal{N}}_{\triangle}(k^*)$ has been emptied.

Similarly, step 2 operates on the candidate solution for the secondary base station by replacing $\triangle$ with $\blacktriangle$ in the above sequence of operations. As for the repair of over-rated candidate solutions (steps 3 and 4), the procedure works as follows:

3.1. Identify the set of currently over-rated users as

$$\mathcal{K}_{\triangle}^{or}(\psi) \triangleq \{k : R_{\triangle}(\psi, k) > R_{\triangle}^{max}(k)\}.$$

3.2. Find the *worst* user $k^{\dagger}$ satisfying

$$R_{\triangle}(\psi, k^{\dagger}) - R_{\triangle}^{min}(k^{\dagger}) < R_{\triangle}(\psi, k) - R_{\triangle}^{min}(k) \quad \forall k \in \{0, \ldots, K-1\}.$$

3.3. For each over-rated user $k \in \mathcal{K}_{\triangle}^{or}(\psi)$, sort the corresponding set $\mathcal{N}_{\triangle}(k)$ in decreasing order of the corresponding channel gain $|H_{f,k}^{\triangle}(n)|^2$, with $n \in \mathcal{N}_{\triangle}(k)$. Then, the first subchannel in the sorted set is reallocated to the worst user $k^{\dagger}$ by setting the associated entry of $\mathbf{\Omega}_{\triangle}(\psi)$ to $k^{\dagger}$. This is repeated until all over-rated users have been processed.

It is important to emphasize that the above described procedures essentially hinge on a similar subcarrier exchanging policy based on the imposed minimum and maximum rate constraints. Although this approach would intuitively be outperformed by a combined power and subcarrier reallocation technique, the proposed greedy method suffices for achieving a satisfactory statistical performance at a very reduced penalty in computational load, as the simulation results in Section 3.5 clearly show.

Once this greedy repair method is inserted into the overall resource allocation algorithm, the resulting operational thread – along with the parameters driving the behavior of the underlying heuristic hybrid search procedure – is described in Figure 3.5.

- **REQUIRE**: K, N, Δf, N_0, $H^{\triangle}_{f,k}(n)$,$H^{\blacktriangle}_{f,k}(n)$, $P^{max}_{\triangle}$, $P^{max}_{\blacktriangle}$, $R^{min}_{\triangle}(k)$, $R^{max}_{\triangle}(k)$, $R^{min}_{\blacktriangle}(k)$, $R^{max}_{\blacktriangle}(k)$.
- **SET**: Ψ, φ, ϑ, η, $f_{\mathbb{Z}}(z)$, $\mathcal{I}$, $\mathcal{I}_g$.
- **INITIALIZE** Ψ candidate vectors $\{\mathbf{SOL}(\psi)\}_{\psi=0}^{\Psi-1}$ at random, denote them as $\{\mathbf{SOL}^{(0)}(\psi)\}_{\psi=0}^{\Psi-1}$, and normalize the allocated power at each generated candidate to fulfill the power budget in Expressions (3.14) and (3.15).
- **REPAIR** each of the randomly-generated candidates by means of the greedy procedure detailed in Subsection 3.4.1.
- **EVALUATE** and store the rate-compliancy metric $RC(\cdot)$ and the associated overall throughput R^T in expression (3.13) for each *repaired* randomly-generated candidate.

FOR $i = 1$ to $i = \mathcal{I}$

- Apply HMCR and PAR processes (driven by φ and ϑ) to each compounding entry of $\mathbf{\Omega}_{\triangle}(\psi)$ and $\mathbf{\Omega}_{\blacktriangle}(\psi)$.
- Apply HMCR and PAR processes (driven again by φ and ϑ) to each compounding entry of $\mathbf{P}_{\triangle}(\psi)$ and $\mathbf{P}_{\blacktriangle}(\psi)$. In this power allocation, the PAR is based on the differential approach in Expression (3.19) with selected parameters η and $f_{\mathbb{Z}}(z)$.
- Detect and repair each non-rate-compliant candidate by executing the greedy frequency reallocation procedure detailed in Subsection 3.4.1 for $\mathcal{I}_g$ iterations. This produces a set of Ψ refined candidates $\{\mathbf{SOL}^{(i)}(\psi)\}_{\psi=0}^{\Psi-1}$ at iteration i.
- Compute the rate-compliancy metric $RC(\cdot)$ and the overall throughput corresponding to each refined candidate $\{\mathbf{SOL}^{(i)}(\psi)\}_{\psi=0}^{\Psi-1}$.
- Concatenate the candidate set from iteration $i-1$, i.e. $\{\mathbf{SOL}^{(i-1)}(\psi)\}_{\psi=0}^{\Psi-1}$, with that in the present i-th iteration, along with their associated metric values.
- Sort the overall 2Ψ-sized set of candidates in increasing order of the rate-compliancy metric $RC(\cdot)$.
- For each group of candidates with equal value of $RC(\cdot)$, sort them in increasing order of their overall throughput R^T.
- Filter and label the first M candidates as $\{\mathbf{SOL}^{(i)}(\psi)\}_{\psi=0}^{\Psi-1}$, among which $\mathbf{SOL}^{(i)}(1)$ will be the best candidate solution produced at iteration i.

END FOR

Figure 3.5: Proposed heuristic resource allocation algorithm.

3.5 Simulation Results

Three sets of computer experiments have been carried out by considering: 1) a single-base-station scenario in absence of rate constraints; 2) a single-base-station scenario with rate constraints set beforehand; and 3) a cognitive two-base-stations OFDMA downlink scenario including per-user rate constraints. It is important to point out that as has been shown in Section 3.2, the optimum resource allocation is known for the first scenario (i.e. best-user subcarrier allocation followed by classical Water-Filling), thus it allows verifying the behavior of the algorithm in a well-known setup. All simulations have been executed on a Core 2 processor running at 2.66 GHz with 3.45 Gb of available RAM memory.

The first simulated system consists of $K = 10$ users utilizing $N = 30$ subcarriers equally spaced on a bandwidth of $B = 1.5$ MHz around the central frequency $f_c = 2.1$ GHz. The total power of the single base station is set to 1 Watt, whereas the OFDMA symbol time is fixed to $T_s = 66.67$ μs. The *Extended Vehicular A* C channel model [158] has been selected, which specifies a Doppler frequency of 70 Hz (corresponding to a relative speed of 36 Km/h) and a r.m.s. delay spread of 357 ns. The noise spectral density N_0 is kept fixed to -30 dBm. As for

the parameters of the proposed hybrid allocation algorithm, the size of the pool of iteratively refined candidate solutions and the maximum number of iterations are set to $M = 80$ and $\mathcal{I} = 150$. As mentioned before, no rate constraint will be imposed, thus the greedy method in Subsection 3.4.1 will not be required in this first simulation set. A logarithmic progression is further established on the probabilistic parameters φ and ϑ controlling the HMCR and PAR refining processes. The reason for this is that this progression has been found – via numerical simulations – to enhance both the convergence speed of the heuristic algorithm and the quality of the provided solution. If i denotes the iteration index and subindexes s and e stands for *starting* and *ending* values of the parameter at hand, such progression is given, for $i \in \{1, \ldots, \mathcal{I}\}$ and the HMCR parameter, by

$$\varphi(i) = \varphi_s \left[1 - \Upsilon(\varphi_s, \varphi_e) \left(\frac{\log(i-1)}{\Theta(\varphi_s, \varphi_e, \zeta) \log(\mathcal{I}-1)} \right)^{\frac{1}{\zeta}} \right], \tag{3.21}$$

where $\zeta \in \mathbb{R}^+$ is an arbitrary positive parameter that tunes the convexity of $\varphi(i)$ in the range $[\varphi_s, \varphi_e]$,

$$\Upsilon(\varphi_s, \varphi_e) \triangleq \operatorname{sgn}(\varphi_s - \varphi_e), \tag{3.22}$$

$$\Theta(\varphi_s, \varphi_e, \zeta) \triangleq \left[\Upsilon(\varphi_s, \varphi_e) \left(1 - \frac{\varphi_e}{\varphi_s} \right) \right]^{-\zeta}, \tag{3.23}$$

and $\operatorname{sgn}(x) = +1$ if $x \geq 0$ and -1 otherwise. Observe that once starting and ending values have been set, the convexity of the parameter at hand is exclusively controlled through the real-valued parameter ζ, as exemplified in Figure 3.6.

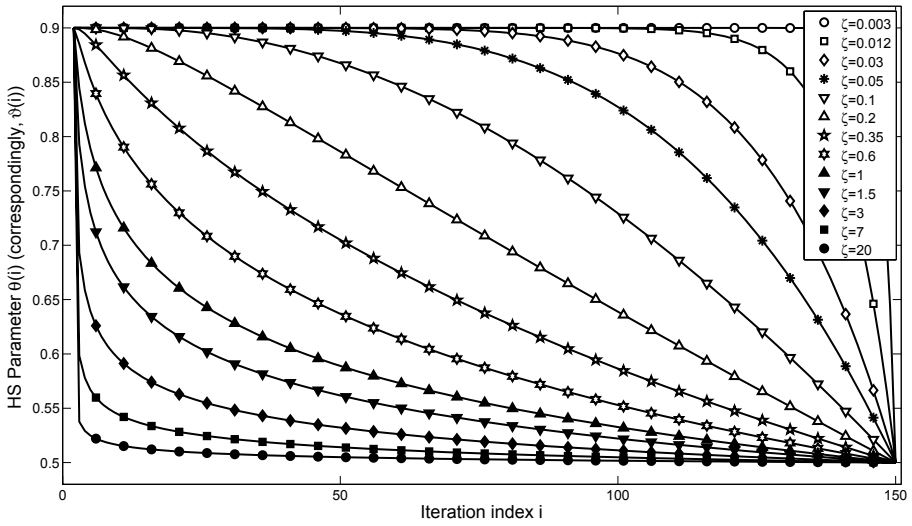


Figure 3.6: Example of the logarithmic progression imposed in the parameters of the proposed hybrid resource allocation approach.

Based on this definition and on a preliminary simulation-based study (not shown for the sake of brevity), the simulations presented heretofore utilize $\{\varphi_s, \varphi_e, \vartheta_s, \vartheta_e\} = \{0.9, 0.5, 0.01, 0.05\}$ and $\zeta = 0.2$. Finally, the PAR process for the power allocation over subcarriers given in expression (3.19) is driven by $\eta = 1$ and $f_{\mathcal{Z}}(z) = \mathcal{L}(0, 0.5)$, where $\mathcal{L}(0, \varpi_L)$ stands for the mirrored Lévy

distribution[3] with location and scale parameters equal to 0 and $\varpi_{\mathcal{L}}$, respectively. The reason behind selecting the Lévy distribution for $f_{\mathcal{Z}}(z)$ lies on the fact that the proposed algorithm for power allocation essentially hybridizes Harmony Search with a random walk procedure, for which escaping from local optima through the PAR randomization of each candidate $P_{\triangle}(\psi, n)$ (respectively, $P_{\blacktriangle}(\psi, n)$) becomes critical. On this purpose, it is important to note that the Lévy distribution has an infinite mean and infinite variance with a heavy tail, which may generate any differential step size[4].

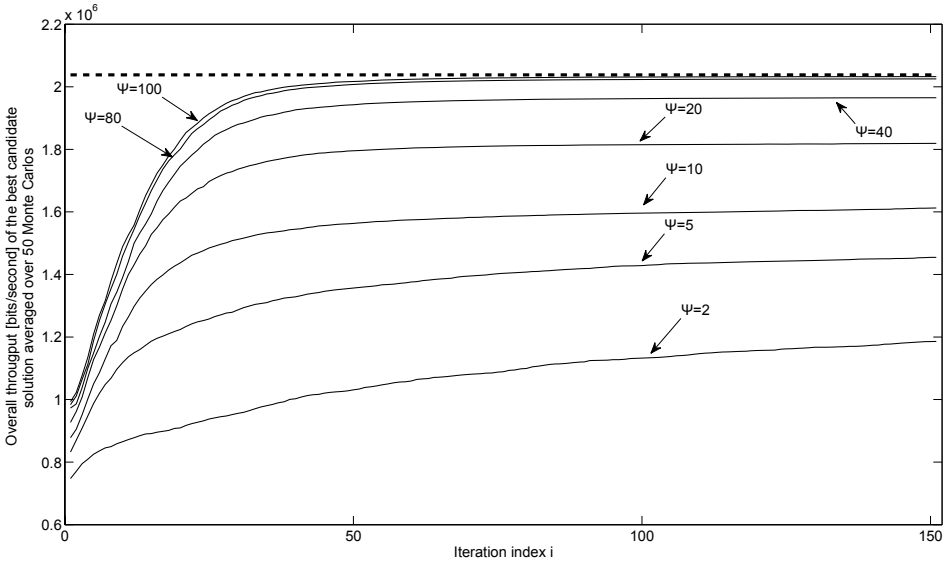


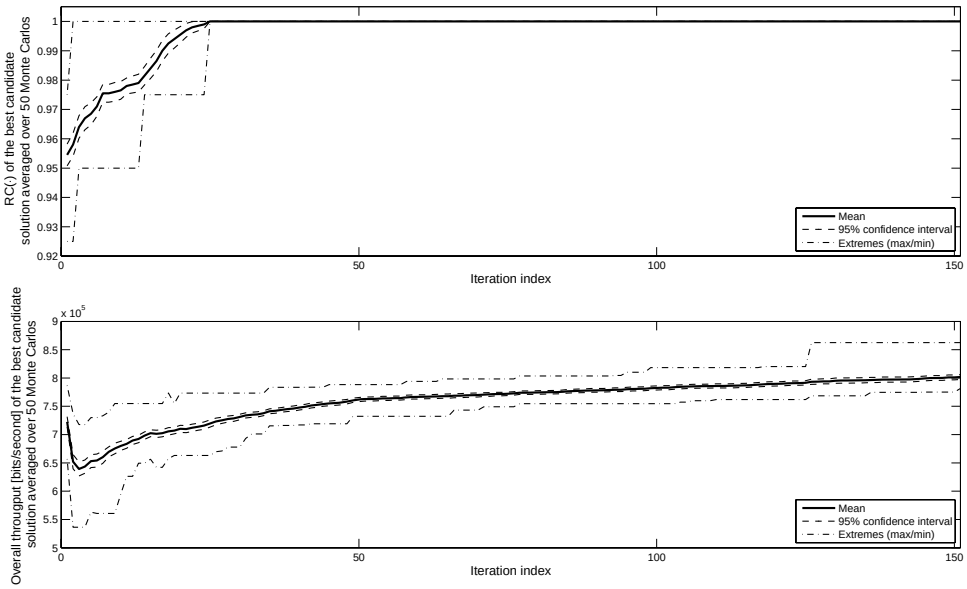
Figure 3.7: Overall throughput of the best candidate solution along iterations, averaged over 50 executions of the algorithm over a fixed channel realization.

With all the above parameters, Figure 3.7 depicts the overall throughput R_T – averaged over 50 executions of the algorithm over a fixed realization of the *Extended Vehicular A* ITU channel model – as a function of the iteration index i and the candidate memory size $\Psi \in \{2, 5, 10, 20, 40, 80, 100\}$. The maximum achievable throughput is also included as an horizontal asymptote for comparison. The obtained average computation times per execution of the algorithm are 3.66 ($\Psi = 2$), 8.77 ($\Psi = 5$), 17.37 ($\Psi = 10$), 36.99 ($\Psi = 20$), 80.34 ($\Psi = 40$), 194.69 ($\Psi = 80$) and 265.41 seconds ($\Psi = 100$). As expected, the higher Ψ is, the better the algorithm behaves with respect to the aforementioned maximum throughput. However, for $\Psi = 100$ the improvement in performance with respect to $\Psi = 80$ is outgained by the associated increase in computational load. Based on this observation, Ψ is hereafter set to 80.

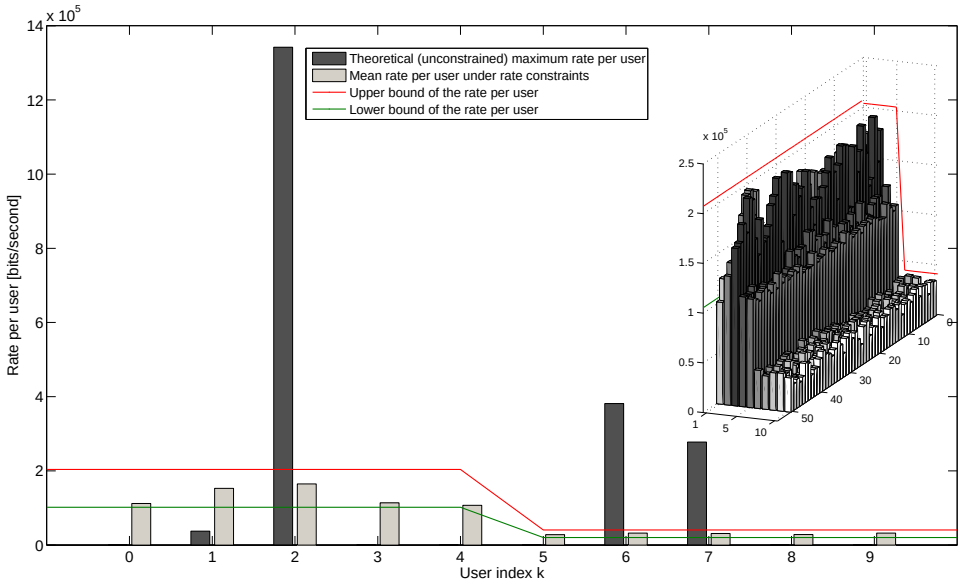
In order to address the second simulated scenario, rate constraints are added to the above setup. Specifically, the first $K/2$ users will have a minimum rate constraint fixed to 5% of the maximum overall achievable throughput R_{WF}^{T} in absence of rate constraints, whereas the rate associated to the other $K/2$ users will be lower bounded by 1% of the aforementioned overall throughput. On the other hand, the maximum rate per user is kept fixed to 10% for the first $K/2$ users and 2% for the last $K/2$ users. Notice that since no secondary base station is considered

[3] A *mirrored* Lévy distribution extends its support to $(-\infty, +\infty)$ by imposing an even symmetry on the standard Lévy probability density function.

[4] As a matter of fact, this particularity of the Lévy distribution has been recently exploited in emerging combinatorial heuristics such as the Cuckoo Search [60].



(a)



(b)

Figure 3.8: (a) Progression of the $RC(\cdot)$ (top) and sum-rate metrics (bottom) of the best candidate rendered along iterations; (b) average rates per user for the constrained scenario (light gray bars) as compared with those corresponding to a Water-Filling allocation (dark gray bars). Plots have been obtained by averaging 50 executions of the algorithm over a fixed channel realization.

at this point, the rate-compliancy metric $RC(\cdot)$ reduces to

$$RC(\mathbf{SOL}(\psi)) \triangleq \frac{\sum_{k=0}^{K-1} \mathbb{I}\left[R_{\Delta}(\psi,k) \geq R_{\Delta}^{min}(k)\right] + \mathbb{I}\left[R_{\Delta}(\psi,k) \leq R_{\Delta}^{max}(k)\right]}{2K}. \tag{3.24}$$

It is also important to note that in this case the fulfillment of the imposed rate constraints depends roughly on the available power and the set of channel gains derived from the realization

of the ITU channel model. Therefore, it is not possible to guarantee that a feasible solution exists for a set of per-user rate constraints and a given channel realization. Nevertheless, the proposed algorithm attempts to find such power and subcarrier allocation vectors with higher rate compliancy and, secondarily, with higher overall throughput. To this end, the greedy repair method detailed in Subsection 3.4.1 is applied for $\mathcal{I}_g = 10$ iterations. The rest of parameters defining the communication scenario and the proposed algorithm are kept the same as in the first simulated case.

The simulation results for this second study are summarized in Figures 3.8.a and 3.8.b. In the first plot, the evolution of $RC(\mathbf{SOL}(1))$ and the overall throughput R^T defined in expression (3.13) – both averaged over 50 executions of the algorithm over a realization of the ITU channel model – is plotted as a function of the iteration index. Also are included dashed lines corresponding to the 95% confidence interval for the obtained results as a means to indicate the reliability of the estimate for the average performance. This reliability is further guaranteed based on the results of a t-test with 49 degrees of freedom over the obtained results, which renders a p-value of 1 at all iterations. Interestingly, as opposed to the strict increasing behavior of the rate compliancy metric (upper plot), the overall throughput metric R^T degrades in the first few iterations. The reason being that the criteria of the proposed algorithm is to prioritize the fulfillment of the imposed rate constraints over the maximization of the sum-rate metric. However, the value of the rate-compliancy metric $RC(\cdot)$ gets very close to its maximum value 1 in the first iteration, which evidences the good performance of the proposed greedy repair approach even if it is applied on candidate solutions generated at random. On the other hand, the obtained allocated rates per user $R_{\triangle}(k)$ when utilizing the proposed scheme (light gray bars in Figure 3.8.b) do meet all the imposed rate constraints, as opposed to the rate allocation based on maximum channel gain and Water-Filling (dark gray bars), which is optimum in absence of constraints. As for the average computation time per execution of the algorithm, its value increases up to 380.87 seconds (2.54 seconds per iteration on average), mainly due to the incorporation of the greedy repair approach to the algorithm thread.

Table 3.1: Imposed rate constraints – relative to the theoretical maximum overall throughput R^T_{WF} of the corresponding OFDMA downlink – utilized for the third set of simulations.

	Constraint	$0 \leq k \leq \lfloor (K-1)/2 \rfloor$	$\lfloor (K-1)/2 \rfloor < k \leq K-1$	R^T_{WF} [bits/second]
PBS	$R^{min}_{L,k}$	2%	1%	2038136.37
	$R^{max}_{L,k}$	10%	2.5%	
SBS	$R^{min}_{U,k}$	0.01%	0.04%	2179722.84
	$R^{max}_{U,k}$	1%	1%	

Finally, the third simulated scenario is composed of the dual base station scenario thoroughly described in Section 3.3. Output power is set to 1 Watt for both primary ($P^{max}_{\triangle}$) and secondary ($P^{max}_{\blacktriangle}$) base stations, whereas rate constraints – relative to the theoretical maximum sum-rate achievable at each OFDMA downlink in absence of interferences and rate constraints – are defined in Table 3.1. The values for all the operational parameters of the proposed allocation procedure are kept identical to those of the second simulation set, except for the maximum number of iterations $\mathcal{I} = 300$. The rate compliancy metric $RC(\cdot)$ is now determined by Expression (3.20). Analogously to the previously discussed results, Figures 3.9.a and 3.9.b summarize the obtained results by averaging over 50 executions of the algorithm over a realization of the

Extended Vehicular A ITU vehicular channel model. In this case, the average computation time augmentates to 751.13 seconds (approximately 5 seconds per iteration) due to the greedy repair procedure operating twice on this dual base station setup. Similar conclusions hold for this third scenario; both the rate compliancy (Figure 3.9.a, top) and the overall throughput metric (Figure 3.9.a, bottom) are simultaneously maximized, whereas the average rates per user are kept within the imposed rate limits at both PBS and SBS (Figure 3.9.b).

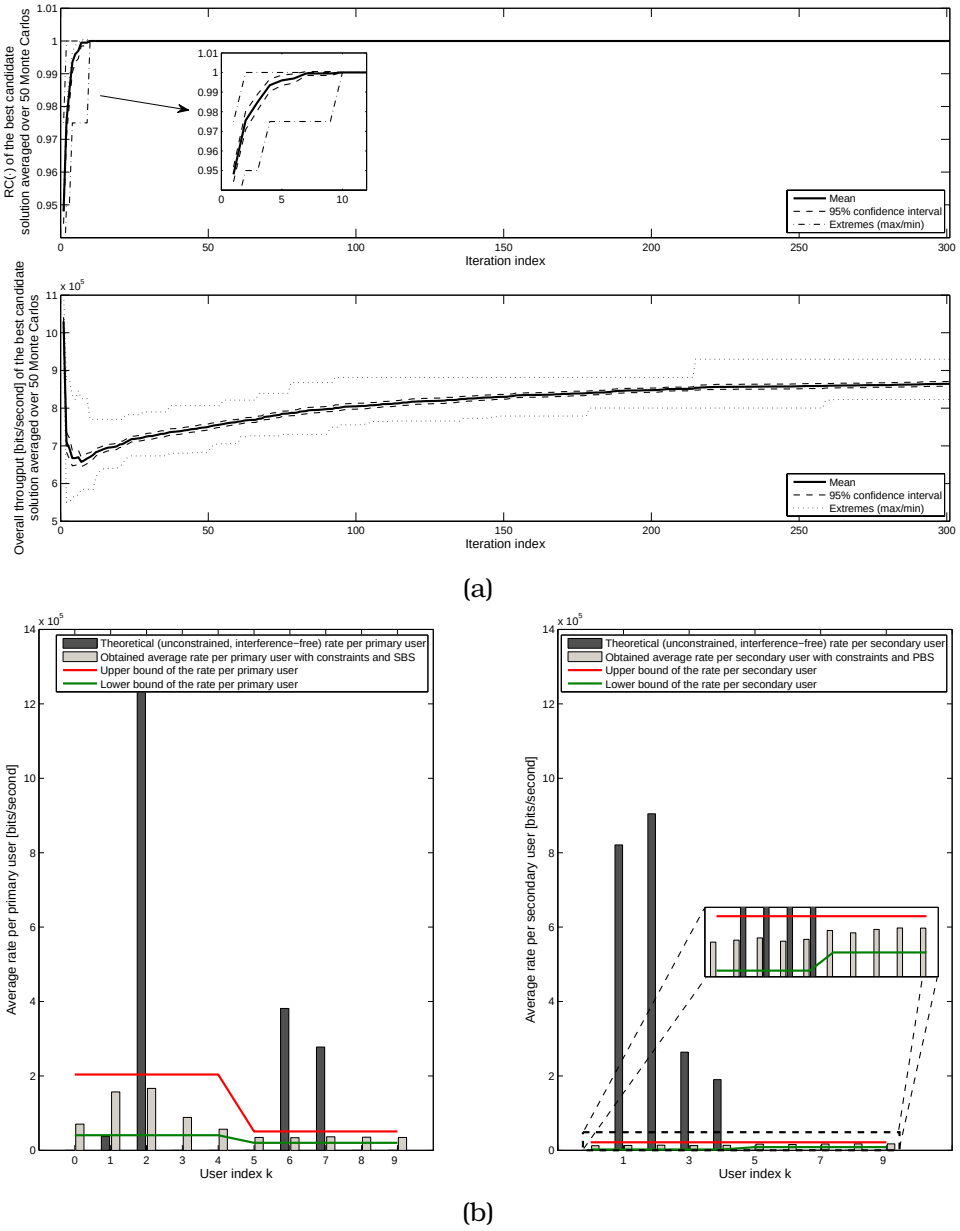


Figure 3.9: (a) Progression of the $RC(\cdot)$ (top) and sum-rate metrics (bottom) of the best candidate rendered by the proposed resource allocation algorithm when applied on the dual-base station scenario; (b) average rates per user for the primary (left) and secondary (right) base station, along with those corresponding to an optimum Water-Filling allocation in absence of rate limits and interference between base stations (dark gray bars). All plots have been obtained by averaging 50 executions of the algorithm over a fixed channel realization.

CHAPTER 4

CENTRALIZED AND DISTRIBUTED SPECTRUM ASSIGNMENT IN COGNITIVE RADIO NETWORKS

"I do not think that the wireless waves I have discovered will have any practical application."

- Heinrich Rudolf Hertz

Following the storyline on resource allocation meta-heuristic algorithms begun in the preceding chapter, the scope is now focused exclusively on the frequency spectrum as a natural limited radio resource urgently demanding flexible methods and techniques for its efficient management in the near future. The rationale for this imperative need departs from the sharp growth experienced by the society in the need for ubiquity, mobility and wireless connectivity at both personal (e.g. Bluetooth), local (WIFI) and metropolitan areas (e.g. WiMAX, 3G and 4G). This proliferation of communication systems has stimulated the series of forecasts for the future mobile telecommunication market published in [159], where sharp increases are predicted for this sector in terms of per-user and aggregate data rates within the time span 2010-2020, resulting in an ever-growing spectrum demand in the near future [18].

In this context, current wireless communications operate on spectrum bands that are statically allocated to different radio services, ranging from mobile to fixed, broadcast and satellite systems. This allocation is regulated by government or state agencies, which concede – often by means of auctions – the license to operate in different bands under fixed spectrum allocation policies. Thereby, a fundamental problem to be encountered by future wireless systems is where to find suitable carrier frequencies and bandwidths for operation, because most of the spectrum bands are already allocated. On this purpose, new spectrum identifications were made for International Mobile Telecommunication (IMT) systems at the World Radiocommunication Conference (WRC-07) of the International Telecommunication Union Radiocommunication Sector (ITU-R) [18]. Unfortunately, such spectrum identification happened to be lower than the actual estimated spectrum demand, and got even more involved by subsequent field studies putting in evidence the partial utilization of large portions of already allocated spectrum. In summary: new advanced spectrum management approaches are urgently needed in order to satisfy the demand of future wireless services.

From the technical perspective, spectrum sharing techniques that allow different systems to coexist on the same scarcely-available spectrum band will be important in the development of future wireless systems. As such, cognitive radio techniques have recently emerged by

offering huge potential to optimize the spectrum usage. As defined in the introduction of this Thesis, cognitive radio systems can be aware of the spectrum use in their surrounding environment, make decisions on the transmission channels according to the channel availability information, and further improve their performance by employing intelligent radio resource allocation techniques with learning capabilities. By virtue of these capabilities, cognitive radio techniques are indeed expected to be major building blocks in future mobile communication systems. This expectation has motivated an upsurge of research studies focused on analyzing cognitive radio operations and functionalities in *cognitive radio networks*, which refer to those networks composed of nodes with cognitive radio interfaces.

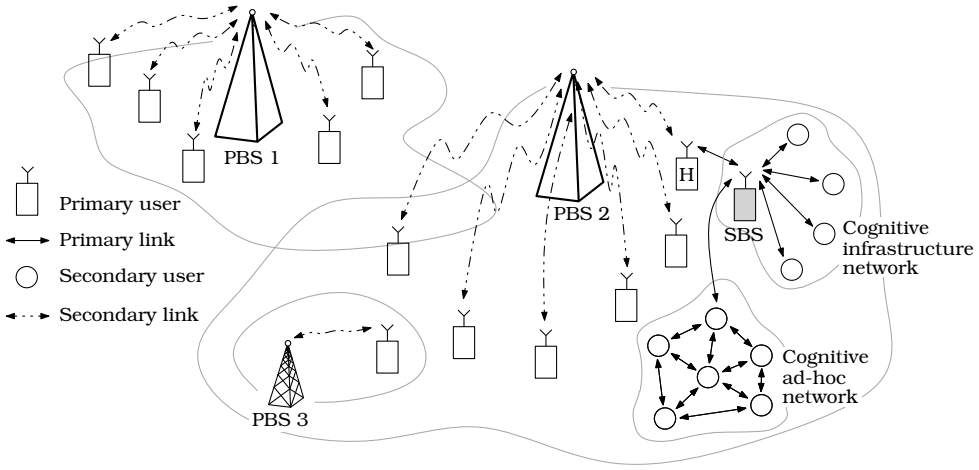


Figure 4.1: Topologies for cognitive radio networks co-located with primary transmissions.

An interesting interplay arises in cognitive radio networks between the interference among nodes and the performance criterium under which the spectrum is allocated. This interplay builds upon the difference between *primary* and *secondary* users; while the first refer to all those users with privileged access to a certain licensed spectrum, the second have, in general, no license for accessing spectrum bands. Instead, they resort to cognitive radio techniques so as to opportunistically and temporally access the licensed spectrum, under the condition that transmissions between primary users are not severely affected. Consequently, in reference to Figure 4.1 the network topology embracing both primary and secondary users can be further broken down into:

- Primary networks, which comprise all such network nodes connected to wireless network infrastructures possessing assigned licenses to operate on certain spectrum bands, such as GSM, UMTS or TV broadcasting. As such, primary base stations will denote all such infrastructure equipment holding a spectrum license thanks to which they communicate with primary users. Therefore, primary base stations lack of any spectrum sharing functionality with secondary users.

- Secondary networks, which gathers all such devices with no access to licensed spectrum and who, therefore, need to resort to cognitive radio functionalities to communicate to other secondary peers in an ad-hoc fashion or to secondary base stations. The latter enables one-hop communication between secondary users by coordinating the spectrum usage over their coverage area. To this end, secondary base stations may incorporate

spectrum sensing methods or side information fed from licensed operators so as to detect and ultimately minimize the interference on primary transmissions. Contrarily, ad-hoc cognitive networking may be implemented in non-regulated frequency bands such as the industrial, scientific and medical (ISM) radio bands.

- Hybrid nodes, which refer to those nodes acting as primary and secondary users in the network setup at hand. Despite the scarce contributions dealing with this class of hybrid devices, it is envisaged that the progressive implementation of multiple radio access techniques in wireless devices (for instance, the coexistence of cellular and WLAN interfaces in the latest generations of smart phones) will enable new resource allocation paradigms on cognitive radio networks due to the need for adequate priority policies for the managed secondary data flows at hybrid nodes.

- Spectrum servers (also referred to as spectrum *brokers*), which may be used for coordinating the spectrum usage among nearby secondary networks, i.e. as a replacement for the primary base station in those cases where spectrum information is not distributed by licensed operators, but rather through an intermediate stakeholder.

All in all, interference plays a major role in cognitive radio networks, which is in general approached via spectrum allocation techniques. As a consequence, the development of techniques for obtaining knowledge about the spectrum occupancy and adapting to this acquired information is currently a trendy research topic undergoing intense activity within the scientific community. As the operational environment for cognitive radio systems is predicted to be highly dynamic and versatile, such techniques need to be applicable to a wide variety of situations and conditions. Therefore, the time scales for adaptations in the dynamic and complex operational environment with conflicting requirements will be compressed. As a result, traditional numerical methods might not guarantee attaining optimum solutions to underlying optimization problems in a fast and scalable fashion. Consequently, the design goal becomes to find good enough solutions at a reduced computational complexity.

In order to address this performance-complexity tradeoff in cognitive radio systems, heuristic algorithms have recently attracted great attention, mainly motivated by their experience-based operation methodology and self-learning capabilities that render near-optimum solutions at a significantly reduced computational cost. A plethora of cognitive radio related optimization problems have benefited from the application of heuristic approaches. For instance, in [128, 160] genetically-inspired evolutionary algorithms have been applied to the simultaneous multi-objective optimization of throughput, Bit Error Rate (BER) and interference level in point-to-point cognitive radio communications. Rate and power allocation in multiuser Orthogonal Frequency Division Multiplexing (OFDM) systems was optimized via a heuristic successive user integration algorithm in [149], which follows a series of previous contributions (e.g. [161, 162]) on resource allocation heuristic techniques for this particular OFDM scenario. Fuzzy logic was also proven to be an efficient approach for distributed cooperative spectrum sensing [163], dynamic bandwidth allocation [164], cross-layer design [165] and reconfiguration [166]. Synergy between heuristics and resource allocation in cognitive radio systems is also evidenced by contributions on the application of Particle Swarm Optimization [167] and Simulated Annealing [168] to this communication paradigm. At this point it is worth noting that despite spectrum allocation in cognitive radio networks has so far been tackled under similar assumptions to the traditional channel assignment paradigm (i.e. how to properly select channels of fixed bandwidth from a set of available channels), the majority of related contributions published so far

have widely regarded the frequency spectrum as a discrete resource. This assumption helps alleviating the inherent complexity derived from a fully-continuous model.

Among the above examples where heuristics have been shown to be profitable for cognitive radio systems, the scope is hereafter focused on the spectrum channel allocation problem where transmission channels for the links in a secondary cognitive radio network are allotted to each node based on optimizing an overall network performance metric, while simultaneously minimizing the amount of interference among nearby nodes. Given its numerical intractability as the network size increases, this optimization paradigm has been traditionally tackled by means of swarm intelligence [169]-[172] and in the majority of cases, via genetically-inspired optimization approaches [173]-[179]. This chapter takes a step further by elaborating on a novel spectrum allocation technique based on the HS meta-heuristic algorithm. For the particular spectrum channel allocation scenario considered herein, a cognitive radio network model is introduced to which both centralized and distributed optimization procedures will be applied. Numerical results carried out for a wide range of network scenarios will verify that the proposed HS-based optimization scheme outperforms genetic algorithmic approaches, specially when the size of the network increases.

The rest of the chapter is organized as follows: Section 4.1 presents the adopted model for our cognitive radio network and poses the spectrum allocation optimization problem, whereas Section 4.2 elaborates on the centralized and distributed HS heuristic optimization procedure tailored for the problem at hand. Finally, Section 4.3 discusses intensive numerical results obtained for several network instances.

4.1 System Model under Study

The cognitive radio network model under consideration is depicted in Figure 4.2.a, which consists of K nodes capable of operating on multiple frequency channels. Each node $k \in \{0, \ldots, K-1\}$ operates on a subset of locally-available frequency channels $\mathcal{F}(k) \subseteq \mathcal{F}^T$, where $\mathcal{F}^T \triangleq \{0, \ldots, N-1\}$ indexes the set of channels in which the overall spectrum band is divided (with cardinality $|\mathcal{F}^T| \geq |\mathcal{F}(k)| \ \forall k$). In this scenario every node is assumed to communicate with any other node located within a circular range R_c [m] via full-duplex links, i.e. the link from node k to node j may be assigned a different channel $F(k,j)$ than that from j to k, namely $F(j,k)$. Based on this rationale, every pair of directional links between node k and j may use $\mathcal{F}(k,j) \triangleq \mathcal{F}(k) \cap \mathcal{F}(j)$ possible spectrum channels, where $F(k,j) \in \mathcal{F}(k,j)$. Furthermore, any link outgoing from node k interferes on any link incoming at node j provided that the following two conditions simultaneously hold: 1) the distance d_{kj} from node k to node j is within a circular range of radius $R_* \geq R_c$ [m]; and 2) both links utilize the same frequency channel.

As for the criterion adopted to optimally allocate the frequency channels between every pair of connected nodes in the network, options proliferate in the literature, addressing from interference minimization to fairness, energy efficiency, delay, connectivity or even economical profit (see [180] for a thorough review). Without loss of generality and extendability to other metrics, this Thesis will consider the minimization of the overall Bit Error Rate (BER) obtained by the compounding nodes in the cognitive network. It should be noted that this metric is directly linked to the effective throughput attained by such nodes when particularized to an specific communication protocol. Therefore, if nodes are assumed to employ uncoded Q-ary

QAM modulation with Gray mapping, the analytical approximation for the BER derived in [181] can be utilized as an analytical approximation for the effective BER at every node. Again, it should be emphasized that the forthcoming formulation for the spectrum assignment problem accommodates any other assumption for the utilized modulation and coding schemes, even tabulated error rate measurements.

Regarding the transmitted power per node $P(k)$, it is assumed to be constant (i.e. no power control is considered) and linearly split over all different spectrum channels utilized by node k. Besides, a power penalty loss per link function $0 < \Phi(k,n) \leq 1$ accounts for the number of outgoing links from node k with same assigned channel $n \in \mathcal{F}(k)$, which will be hereafter denoted as $\Im(k,n)$. Mathematically,

$$P(k,n) = \frac{P(k)\Phi(k,n)}{\text{unique}\{\mathcal{F}(k,j) : d_{kj} \leq R_c\}}, \tag{4.1}$$

where $P(k,n)$ denotes the available transmit power per link at node k and channel n, and unique$\{\cdot\}$ returns the number of different elements within the set in its argument. An illustrative example of this power allocation for $\Phi(k,n) = 1/\Im(k,n)$ is plotted in Figure 4.2.b. Each link is subject to a power loss factor L_{kj} proportional to $1/d_{kj}^a$, where a denotes the power attenuation exponent. Additive White Gaussian Noise (AWGN) with variance σ^2 is also considered.

If ξ^T stands for the number of communication links existing in the above network model, the spectrum channel allocation problem reduces to finding the ξ^T-length set of channel assignments $\mathbf{F} \triangleq \{F(k,j)\}$ ($\forall k,j$ such that a communication link from k to j exists, with $F(k,j) \in \mathcal{F}(k,j)$) that minimizes the overall BER averaged over all the ξ^T links. By resorting to the analytical BER approximation of [181], this optimization problem can be expressed as

$$\underset{\mathbf{F}\in\mathcal{F}^{\times}}{\text{Minimize}} \quad \sum_{k=1}^{K} \sum_{\substack{j\neq k \\ d_{kj}\leq R_c}} 0.2 \exp\left[-\frac{1.6P(k,F(k,j))L_{kj}(Q-1)^{-1}}{\sigma^2 + \sum\limits_{\substack{i\neq j,k \\ d_{ij}\leq R_*}} P(i,F(k,j))L_{ij}} \right], \tag{4.2}$$

$$\text{subject to} \quad F(k,j) \in \mathcal{F}(k,j) \quad k,j \in \{0,\ldots,K-1\}, \tag{4.3}$$

$$P(k) = P^{max}, \quad k \in \{0,\ldots,K-1\}, \tag{4.4}$$

where $\mathcal{F}^{\times}$ denotes the Cartesian product of all available channel sets per link $\mathcal{F}(k,j)$, and the denominator in the exponent corresponds to the additive noise variance plus the power from other interfering nodes under the assumption of Gaussian signalling. As opposed to previous related works (e.g. [178]) assuming binary interference model, coexistence of links with same origin but different destination nodes is allowed on a certain spectrum channel. Having said this, the posed problem can be regarded as that of optimum spectrum allocation in *underlay* cognitive radio networks.

4.2 Proposed Heuristic Spectrum Allocation Technique

In a similar manner to the problem tackled in Chapter 3, the meta-heuristic HS algorithm is adapted to efficiently obtain the channel assignment vector $\mathbf{F}$ under the fitness minimization criteria of Expression (4.2). Specifically, the Ψ-sized memory of harmonies is encoded as

$\{\mathbf{SOL}(\psi)\}_{\psi=0}^{\Psi-1} \triangleq \{\mathbf{F}(\psi)\}_{\psi=0}^{\Psi-1}$, where each $\mathbf{F}(\psi)$ is built by serializing $F(k,j)$ first through k. In other words, the first component of $\mathbf{F}(\psi)$ corresponds to the lowest value of j such that $d_{1j} \leq R_c$, followed by the next value of j until the whole neighborhood of node $k = 1$ has been explored. Then the same procedure is repeated with $k = 2$, and so forth. Following the notation introduced in [62] and adopted throughout this Thesis, a possible solution vector $\mathbf{F}(\psi)$ is referred to as *harmony* whereas, by an slight abuse in the notation, *note* denotes any of its compounding entries $F(\psi, k, j)$, with $\psi \in \{0, \ldots, \Psi - 1\}$ and both k and j are drawn from the set $\{0, \ldots, K-1\}$.

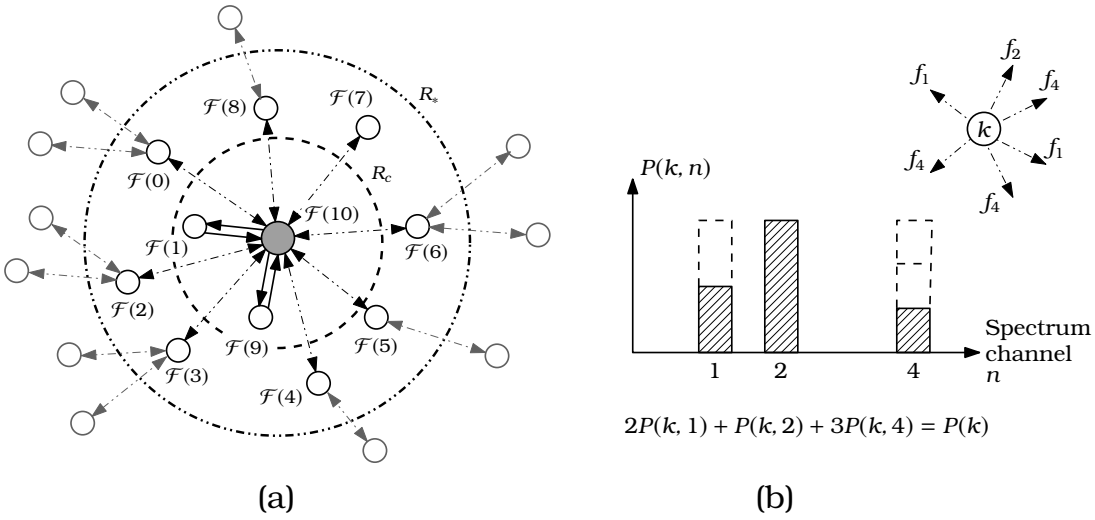


Figure 4.2: (a) Signal model assumed for the considered cognitive wireless network. Here, bold and dash-dotted lines stand for communication and potentially interfering links, respectively; (b) example, for a generic node $k \in \{0, \ldots, K-1\}$), of the local power assignment per link given by Expression (4.1).

The so-encoded constituent harmonies $\{\mathbf{F}(\psi)\}_{\psi=0}^{\Psi-1}$ are iteratively refined by means of intelligent combinations and mutations of the constituent channel assignments $F(\psi, k, j)$, implemented by the HMCR and PAR processes of the HS algorithm as follows:

- HMCR: the corresponding parameter φ establishes the probability that the new allocated spectrum channel to a given (k,j) link is uniformly drawn from the spectrum channel values of the same (k,j) link taken in all the other $\Psi - 1$ candidate solutions, e.g. $\varphi \triangleq Pr\{F(\psi, k, j) \rightsquigarrow \omega_{\text{HMCR}}\}$, where ω_{HMCR} is a discrete random variable uniformly distributed in the set

$$\{F(0, k, j), \ldots, F(\psi - 1, k, j), F(\psi + 1, k, j), \ldots, F(\Psi - 1, k, j)\},$$

  with $\psi \in \{0, \ldots, \Psi - 1\}$. In this case three different numerical progressions are considered for the values taken by the parameters governing the PAR and HMCR processes. This strategy permits to differently trade explorative for exploitative behavior of the allocation algorithm through iterations $i \in \{1, \ldots, \mathcal{I}\}$. Namely:

  - Constant: the HS parameter at hand is kept fixed to a constant value over the iterations of the algorithm, e.g. for the HMCR $\varphi(i) = \varphi \; \forall i \in \{1, \ldots, \mathcal{I}\}$. This corresponds to the standard implementation of the algorithm .

  - Linear: as first proposed in [157], in this case the value of the HS parameter increases (or decreases) linearly with the iteration index i. By denoting starting and ending values of the considered parameters with subindexes s and e, respectively, the linear progression is given, for $i = 1, \ldots, \mathcal{I}$, by

$$\varphi(i) = \varphi_s + \frac{\varphi_e - \varphi_s}{\mathcal{I} - 1}(i - 1), \tag{4.5}$$

    where, for the pitch adjustment rate, φ should be replaced by ϑ.
  - Logarithmic: in this third case the progression is set logarithmic, as explained in Chapter 3, Expressions (3.21) to (3.23).

- PAR: the parameter ϑ acts as a fine adjusting rate of the note vocabulary by defining the probability that the new note value for a given note $F(\psi, k, j)$ is picked from its neighbor value in the alphabet $\mathcal{F}(k, j)$. As opposed to the alphabet sorting in Chapter 3, in this case the neighboring relationship between spectrum channels in $\mathcal{F}(k, j)$ hinges on a natural increasing ordering of their indices, thus serving as an arbitrarily random perturbation for the progression of the algorithm.

The successive application of these two procedures generate a new set of potential Ψ candidates. Based on this new set, the harmony memory is updated whenever any of such Ψ new improvised candidates or *harmonies* at a given iteration sounds *better* – under the fitness criterion of Expression (4.2) – than any of the Ψ harmonies remaining from the previous iteration. This procedure iterates until $\mathcal{I}$ attempts or iterations are completed. The flow diagram of the centralized version of the HS algorithm is depicted in Figure 4.3.a, and consists of 3 steps:

A. The initialization process is only executed at the first iteration. At this point, since no *a priori* knowledge of the solution is assumed the harmony notes, the entries $F(\psi, k, j)$ of $\mathbf{F}(\psi)$ for $\psi \in \{0, \ldots, \Psi - 1\}$) are filled with values picked randomly from the corresponding alphabet $\mathcal{F}(k, j)$. The iteration counter is set to $i = 1$.

B. In the improvisation procedure, both the harmony memory considering rate and the pitch adjusting rate (driven by real-valued parameters $\varphi(i)$ and $\vartheta(i)$) are sequentially applied to each note $F(\psi, k, j)$. As a result, a new set of Ψ improvised harmonies or candidate channel assignments is produced.

C. At each iteration the quality evaluation of the improvised harmony memory is made based on the fitness function in Expression (4.2). Based on such metric values and the Ψ remaining from the previous iteration, the Ψ harmonies with *best* (lowest) metric are stored in the harmony memory. If $i < \mathcal{I}$, the algorithm iterates by setting $i = i + 1$ and by returning to step B. Otherwise, the algorithm stops and the best channel assignment is given by $\mathbf{F}(0)$ (i.e. $F(\psi, k, j)$ for $\psi = 0$), provided that the Ψ harmonies conforming the harmony memory are arranged in ascending order of their associated metric.

Additionally, a perturbation criterium is inserted within the iterative process so as to escape from local minima. Before proceeding to the next iteration, the algorithm checks whether the best candidate channel assignment has not changed during a certain number $\mathcal{I}_p$ of consecutive iterations. If so, the algorithm randomly resets the $\Psi - 1$ harmonies with *worse* (higher) metric. Every time this perturbation technique is applied, $\mathcal{I}_p$ is increased to $\beta\mathcal{I}_p$, where β is a fixed value in the range $\mathbb{R}[1, \infty)$.

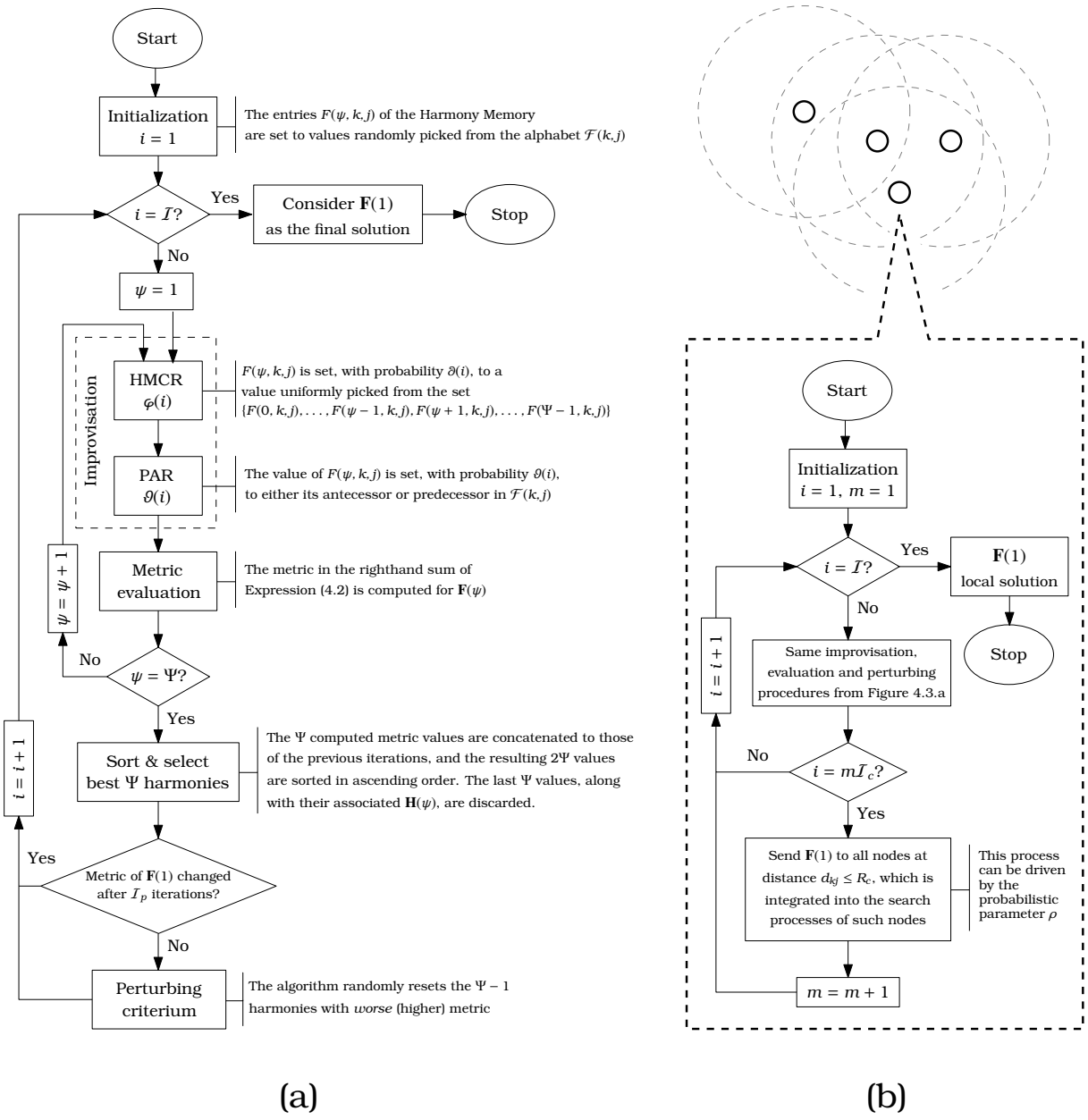


Figure 4.3: Flow diagram of (a) the centralized HS algorithm; (b) the distributed HS algorithm. In these figures, i denotes iteration index.

4.2.1 Distributed HS Channel Allocation Scheme

As can be intuitively inferred from its above description, the derived channel allocation algorithm operates in a centralized fashion, i.e. all nodes in the network forward their estimated channel gains L_{kj} and the detected set of available channels $\mathcal{F}(k)$ to a central receiver, which executes the above algorithmic procedure and sends back the optimized channel assignments $F(k, j)$. Unfortunately, this centralized strategy implies a high complexity for the central receiver which may not be particularly suitable for the scenario where all nodes are equal to each other (sensors emitting in the ISM band, for instance). In this specific scenario, the computational burden due

to the resource algorithm being run in one of the nodes could rapidly deplete the battery and dramatically shorten the lifetime of the node at hand. Therefore it is deemed essential to devise a distributed implementation of the centralized HS channel allocation procedure that permits to average its computational complexity over all the nodes of the network.

In order to reduce this asymmetry in the use of the computational resources in the network an island approach is proposed. In a general island heuristic solver, the overall population is divided in sub-populations or islands that interact with each other through the exchange or migration of individuals between islands. This migration is performed according to a migration policy, which consists of a migration interval (i.e. the number of generations between migrations) and a migration topology, which establishes where individuals migrate. In the setup under study, by assuming perfect a priori knowledge of the network parameters (e.g. inter-node distances, available channels per link $\mathcal{F}(k,j)$ and noise variance σ^2) at all nodes, each constituent node of the network executes a separate instance of the HS algorithm (as was adopted in [128] for genetically-inspired allocation techniques) with a reduced population size Ψ_{ISLAND} with respect to its centralized counterpart. As for the migration policy, every $\mathcal{I}_c$ iterations ($1 < \mathcal{I}_c < \mathcal{I}$) each node broadcasts its best candidate channel assignment to all nodes at distance less than or equal to R_c. This approach requires communicating a total of Υ bits over an assumed separate control network, which is given by

$$\Upsilon = \left\lfloor \frac{\mathcal{I}}{\mathcal{I}_c} \right\rfloor \sum_{k=1}^{K} \mathcal{N}(k) \sum_{\substack{i,j \\ d_{ij} \leq R_c}} \log_2 |\mathcal{F}(i,j)| \quad \text{[bits]}, \tag{4.6}$$

where $\mathcal{N}(k)$ denotes the number of communication links outgoing from node k. In order to reduce the transmission overhead through the control underlay network, an alternate broadcasting approach will be also considered by 1) allowing best candidate diffusion only when its metric has changed within the last $\mathcal{I}_c$-length period; and 2) by utilizing a novel parameter $\rho \in [0, 1]$ that establishes the probability of disseminating the best candidate harmony through a given link. Section 4.3 will elaborate on how to optimally set the value of this new probabilistic parameter ρ. It is also noteworthy to remark that the island approach also eases the process of synchronizing the allocated set of frequency channels over all the compounding nodes in the network, as this procedure is inherently embedded in the migration policy.

4.3 Numerical Results

In order to assess the performance of the proposed HS allocation procedure, intensive simulations have been carried out for both the centralized and distributed versions of the algorithm. In the first set of simulations, the focus is placed on assessing the scalability of the centralized allocation procedure in 7 networks of increasing size generated at random. Therefore, nodes are randomly spread over a square grid of variable size where, in all cases, communication and interference radius are set to $R_c = 250$ and $R_* = 500$ [m], respectively.

As explained in Section 4.1, the set of available frequency bands at a certain node may differ from those at another node in the network. In order to model this diversity of available frequency bands, each node operates on a subset of frequency channels $\mathcal{F}(k)$ ($k = 0, \ldots, K-1$) uniformly drawn from $\mathcal{F}^T$, where $\mathcal{F}^{min} \leq |\mathcal{F}(k)| \leq \mathcal{F}^{max}$. This uniform distribution of available

channels at the compounding nodes of the network may reflect worst-case application scenarios where there is no relationship between the physical location of nodes and their set of available frequency channels, e.g. when dealing with spatially uncorrelated colored interferers. Also note that in already existing wireless technologies such as 802.11a, 802.11h or 802.15.4 (in the 2.4GHz band), the overall number of spectrum channels $|\mathcal{F}^T|$ is fixed to 12, 23 and 16, respectively. However, this work will consider $|\mathcal{F}^T|$ as an additional factor to vary the overall complexity of the simulated scenarios, hence its value will be made arbitrary yet increasing with the size of the network.

Table 4.1: Parameters of the 7 simulated cognitive radio networks.

#	Grid size	K	$[\|\mathcal{F}^T\|, \mathcal{F}^{min}, \mathcal{F}^{max}]$	σ	$\overline{\mathcal{N}}$	$\|\mathcal{F}^{\times}\|$	Opt. Metric
1	500	5	[6, 2, 4]	$2 \cdot 10^{-3}$	2	64	$3.741 \cdot 10^{-4}$
2	850	10	[10, 3, 5]	$1 \cdot 10^{-3}$	1.8	2304	$4.833 \cdot 10^{-5}$
3	900	15	[12, 4, 6]	$1 \cdot 10^{-3}$	1.733	$2.36 \cdot 10^{6}$	$9.598 \cdot 10^{-5}$
4	1000	20	[15, 4, 8]	$7.5 \cdot 10^{-4}$	3.2	$1.94 \cdot 10^{23}$	$2.041 \cdot 10^{-8}$
5	1170	25	[20, 4, 10]	$5 \cdot 10^{-4}$	2.8	$4.36 \cdot 10^{25}$	$4.742 \cdot 10^{-5}$
6	2100	50	[30, 6, 12]	$2.5 \cdot 10^{-4}$	2.76	$8.06 \cdot 10^{52}$	$2.293 \cdot 10^{-6}$
7	2300	75	[30, 8, 14]	$2.5 \cdot 10^{-4}$	3.093	$7.66 \cdot 10^{133}$	$1.266 \cdot 10^{-129}$

Two conditions must be necessarily met in order to enable communication between node k and j: 1) both nodes must be in range of each other, i.e. $d_{kj} \leq R_c$; and 2) they must have at least one available band in common, i.e. $\mathcal{F}(k) \cap \mathcal{F}(j) \neq \emptyset$. Once the above two conditions are fulfilled, effective communication between nodes will depend on the available power budget $P(k, n)$ for the transmitting node i and channel n, as well as on the number of neighboring nodes sharing band n with such a node. In this context, the transmission power per node equals $P(k) = 1\ \forall k$. Likewise, the power penalty function $\Phi(k, n)$ is chosen to be $1/\Im(k, n)$, where $\Im(k, n)$ denotes the number of outgoing links from k to different destinations with same assigned channel n. Since $\Im(k, n)$ depends on every generated candidate channel assignment $\mathbf{F}(\psi)$, so do $\Psi(k, n)$ and $P(k, n)$ accordingly, as Expression (4.1) and Figure 4.2.b clearly reflect. This procedure allows for a simple local power allocation method between simultaneous communications held over the same frequency channel at a given node, although the proposed channel allocation algorithm also accommodates any other more sophisticated approach such as considering power allocation as part of the allocation procedure.

In all the simulated scenarios the modulation order is set to $Q = 4$ (4-QAM). As for the proportionality of L_{kj} with respect to the intra-node distance d_{kj}, the power attenuation exponent is set to $a = 4$, and the proportionality constant is chosen so as to render a mean power loss of 22 dB averaged over a R_c-radius circular area[1]. Table 4.1 summarizes the parameters characterizing each simulated scenario where, following the notation of Expression (4.6), $\overline{\mathcal{N}}$ denotes the average number of possible linkable neighbors per node. In such a table the optimum metric has been computed through exhaustive metric evaluation over the entire set $\mathcal{F}^{\times}$ (scenarios 1 to 3) or by averaging the best metric rendered by 10 executions of the HS algorithm with linear progression of the parameters after $25 \cdot 10^5$ iterations[2] (scenarios 4 to 7).

[1] A lower bound on the intra-node distance d_{kj} of 20 meters has also been imposed in the simulated network.

[2] Due to the high dimensionality of the allocation problem (column $|\mathcal{F}^{\times}|$ in Table 4.1), the metric obtained through

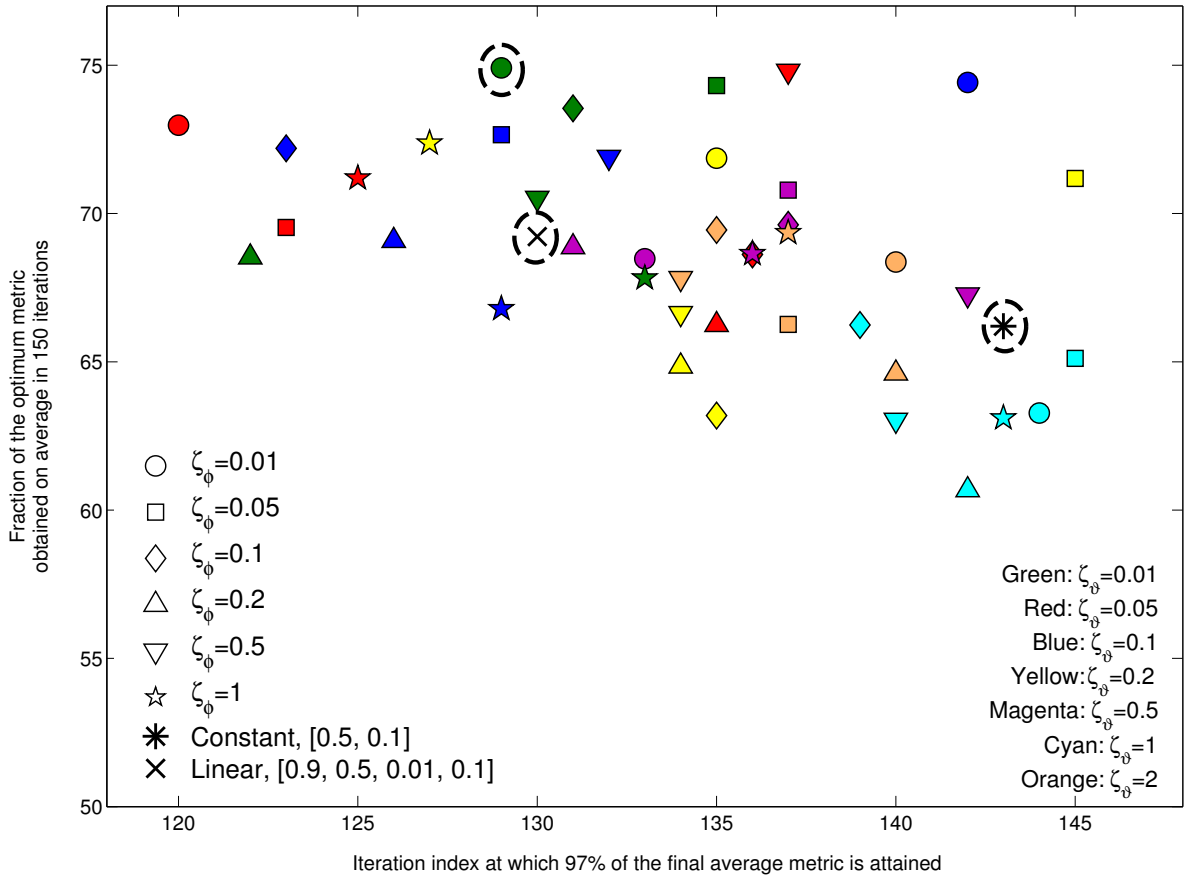


Figure 4.4: Results for the simulation-based study of the performance of the *centralized* HS spectrum allocation algorithm. The horizontal axis measures the convergence *speed* of the algorithm (e.g. leftmost points correspond to fast-converging configurations), whereas the vertical axis reflects the accuracy of the utilized algorithm with respect to the optimum metric in Table 4.1 (bottommost points stand for configurations approaching the optimum metric after 150 iterations). Selected configurations have been circled with a dashed line.

A simulation-based study has been previously performed to shed light on the performance of the considered different progression schemes of the parameters ruling the proposed algorithm. Focusing on scenario 5, Figure 4.4 summarizes the results of such study for $\Psi = 20$, $\mathcal{I} = 150$, $\mathcal{I}_p = 10$ and $\beta = 2$. In this plot, the horizontal axis stands for the iteration index where the metric – averaged over 100 executions of the algorithm – is at 97% of the best average metric produced after 150 iterations. In other words, the horizontal axis can be understood as a quantifiable metric of the convergence rate of the allocation procedure at hand. The vertical axis, however, represents the percentage of the optimum metric (rightmost column in Table 4.1) obtained on average in 150 iterations, i.e. the vertical axis stands for the accuracy of the algorithm with respect to the best achievable value of the metric shown in the righthand part of Expression (4.2). In this plot each marker corresponds to a simulated progression of the HS parameters (constant, linear or logarithmic), as can be read in the included legend. Therefore, markers located in the upper-left part of the plot would belong to *good* configurations of the HS

long simulation is referred to as *optimum* metric even though there is no guarantee that the global optimum is asymptotically attained by the proposed heuristics.

parameter progression (fast convergence rate and produced metric value close to the optimum one), whereas those located in the lower-right area of the plot would correspond to *bad* configurations (slow convergence to metric values far from their optimum). It should also be observed that although the logarithmic case has been simulated for a range of $[\zeta_\varphi, \zeta_\vartheta]$ combinations, the values selected for $[\varphi, \vartheta] = [0.5, 0.1]$ (constant) and $[\varphi_s, \varphi_e, \vartheta_s, \vartheta_e] = [0.9, 0.5, 0.01, 0.1]$ (linear and logarithmic) have been chosen based on a separate simulation-based analysis.

As expected, the constant progression ($*$) is outperformed, in terms of best balancing the tradeoff between accuracy and convergence rate of the algorithm, by the linear ($\times$) and most of the simulated logarithmic progression cases. Based on these results, the benchmark hereafter considers 4 different algorithms: 1) HS with constant parameters $[\varphi, \vartheta] = [0.5, 0.1]$; 2) HS with linear parameter progression using $[\varphi_s, \varphi_e, \vartheta_s, \vartheta_e] = [0.9, 0.5, 0.01, 0.1]$; 3) HS with logarithmic parameter progression given by $[\zeta_\varphi, \zeta_\vartheta] = [0.01, 0.01]$ and identical $[\varphi_s, \varphi_e, \vartheta_s, \vartheta_e]$ as in the linear case; and 4) a standard Genetic Algorithm (GA), which employs[3] a population of $\Psi_{\text{GA}} = 20$ *chromosomes* with an elite pool size of 10 individuals, a Roulette-Wheel selection process with an uniform crossover rate of $P_c = 0.7$, and a mutation probability of $P_m = 0.2$. At this point it should be pointed out that the spectrum allocation problem considered in this chapter has so far been tackled mostly by means of genetically-inspired approaches [173]-[179]. For this reason it is fair to compare the performance of the proposed HS allocation procedure with that of the GA technique. In this context, setting $\Psi_{\text{GA}} = \Psi$ ensures a fair comparison in terms of equal number of metric evaluations per iteration.

Having said this, Table 4.2 lists the Monte Carlo results of the aforementioned 4 algorithms for the 7 simulated scenarios. Before proceeding with the analysis of this table, it must be noted that since HS hinges on a intelligent albeit random search procedure, the results of multiple executions of the algorithm over a given network must be viewed statistically. Thus, the metric achieved along iterations is a $\mathcal{I}$-dimensional random variable. Consequently, the table includes, for each simulated case and scenario, the mean and standard deviation of the random variable corresponding to the metric attained after $\mathcal{I}$ iterations, along with the minimum value taken by this random variable within 100 executions of the algorithm. At this point it is important to remark that a Wilcoxon two-sided rank sum test has been performed over all possible experiment pairs in the listed set of performed experiments. This non-parametric statistical hypothesis test has verified that the medians of the simulated experiments are statistically different to each other with a confidence level of 95%. As opposed to the conventionally used Student's t-test, the Wilcoxon rank sum test does not assume any Gaussianity on the distribution of the tested experiments. Consequently, this test provides an analytical insight on the significance of the number of performed simulations without requiring any side assumption on the statistical nature of the samples themselves.

Back to Table 4.2, the HS allocation procedure along with the logarithmic progression of its operational parameters is shown to outperform any other simulated approach in all terms (mean, minimum and standard deviation), specially when the dimensions of the underlying optimization problem (given by $|\mathcal{F}^\times|$ in Table 4.1) increase. Noteworthy is also the fact that when considering the naive version of both GA and HS algorithms applied to the problem at hand (i.e. by imposing no progression on the parameters governing such heuristics), the dominance of HS over GA still holds for this first centralized scenario. Based on these observations, one can conclude that the proposed centralized HS allocation procedure with logarithmic progression

[3]The GA parameters have been selected based also on a simulation-based study.

Table 4.2: Monte Carlo numerical results for centralized spectrum allocation algorithms.

#	$\mathcal{T}$	Value	GA	HS, constant	HS, linear	HS, logarithmic
1	50	Mean	$3.741 \cdot 10^{-4}$	$3.741 \cdot 10^{-4}$	$3.741 \cdot 10^{-4}$	$3.741 \cdot 10^{-4}$
		Min	$3.741 \cdot 10^{-4}$	$3.741 \cdot 10^{-4}$	$3.741 \cdot 10^{-4}$	$3.741 \cdot 10^{-4}$
		Std	0	0	0	0
2	50	Mean	$4.833 \cdot 10^{-5}$	$4.833 \cdot 10^{-5}$	$4.833 \cdot 10^{-5}$	$4.833 \cdot 10^{-5}$
		Min	$4.833 \cdot 10^{-5}$	$4.833 \cdot 10^{-5}$	$4.833 \cdot 10^{-5}$	$4.833 \cdot 10^{-5}$
		Std	0	0	0	0
3	100	Mean	$9.620 \cdot 10^{-5}$	$9.655 \cdot 10^{-5}$	$9.599 \cdot 10^{-5}$	$9.599 \cdot 10^{-5}$
		Min	$9.598 \cdot 10^{-5}$	$9.598 \cdot 10^{-5}$	$9.598 \cdot 10^{-5}$	$9.598 \cdot 10^{-5}$
		Std	$2.164 \cdot 10^{-6}$	$3.743 \cdot 10^{-6}$	$6.792 \cdot 10^{-7}$	$4.81 \cdot 10^{-7}$
4	1000	Mean	$3.497 \cdot 10^{-5}$	$8.896 \cdot 10^{-6}$	$1.154 \cdot 10^{-6}$	$3.779 \cdot 10^{-7}$
		Min	$1.11 \cdot 10^{-6}$	$3.745 \cdot 10^{-7}$	$2.578 \cdot 10^{-8}$	$2.041 \cdot 10^{-8}$
		Std	$2.651 \cdot 10^{-5}$	$7.688 \cdot 10^{-6}$	$1.445 \cdot 10^{-6}$	$4.503 \cdot 10^{-7}$
5	150	Mean	$8.589 \cdot 10^{-5}$	$7.163 \cdot 10^{-5}$	$6.851 \cdot 10^{-5}$	$6.33 \cdot 10^{-5}$
		Min	$4.765 \cdot 10^{-5}$	$4.763 \cdot 10^{-5}$	$4.742 \cdot 10^{-5}$	$4.742 \cdot 10^{-5}$
		Std	$5.914 \cdot 10^{-5}$	$2.925 \cdot 10^{-6}$	$2.755 \cdot 10^{-6}$	$2.216 \cdot 10^{-7}$
6	1500	Mean	$1.898 \cdot 10^{-4}$	$3.65 \cdot 10^{-5}$	$3.988 \cdot 10^{-6}$	$3.245 \cdot 10^{-6}$
		Min	$4.09 \cdot 10^{-5}$	$4.838 \cdot 10^{-6}$	$2.293 \cdot 10^{-6}$	$2.293 \cdot 10^{-6}$
		Std	$8.124 \cdot 10^{-5}$	$2.286 \cdot 10^{-5}$	$5.14 \cdot 10^{-6}$	$2.557 \cdot 10^{-6}$
7	2000	Mean	$1.65 \cdot 10^{-4}$	$3.228 \cdot 10^{-5}$	$7.906 \cdot 10^{-9}$	$1.838 \cdot 10^{-10}$
		Min	$1.354 \cdot 10^{-5}$	$2.818 \cdot 10^{-6}$	$1.113 \cdot 10^{-82}$	$1.266 \cdot 10^{-129}$
		Std	$9.635 \cdot 10^{-5}$	$2.461 \cdot 10^{-5}$	$1.711 \cdot 10^{-8}$	$7.694 \cdot 10^{-10}$

of the parameters is specially suitable for large-scale applications where the number of nodes and/or available spectrum channels is notably high, which is in turn of increasing interest in the related literature [182, 183].

The second set of simulations performed in this study considers the distributed implementation of the proposed HS approach with $\mathcal{I} = 150$, $\Psi_{\text{ISLAND}} = 10$ and a broadcasting period equal to $\mathcal{I}_c = 5$. The discussion concentrates on scenario 5, although the conclusions extracted from this second study have been proven to be extensible to the rest of considered scenarios. The application of the perturbing criteria is no longer needed in the distributed approach of the algorithm, since sharing the best candidate among nearby nodes suffices for each instance of the HS allocation approach to escape from local minima[4]. Therefore, in what follows $\mathcal{I}_p$ will be set to ∞.

Analogously to the previous centralized allocation scheme, a simulation-based study is first performed to quantitative estimate the convergence rate and accuracy of different progression schemes of the HS parameters $[\varphi(i), \vartheta(i)]$ in the distributed allocation setup. The lower and upper limits are set as before, i.e. $[\varphi, \vartheta] = [0.5, 0.1]$ (constant) and $[\varphi_s, \varphi_e, \vartheta_s, \vartheta_e] = [0.9, 0.5, 0.01, 0.1]$ (linear and logarithmic). The results are depicted in Figure 4.5, for which the best metric attained after $\mathcal{I}$ iterations has been averaged over all nodes existing in the network

[4]This conclusion holds for highly-connected networks, since it is clear that for the distributed case, the need for a local perturbing technique at a given node depends on its number of neighbors.

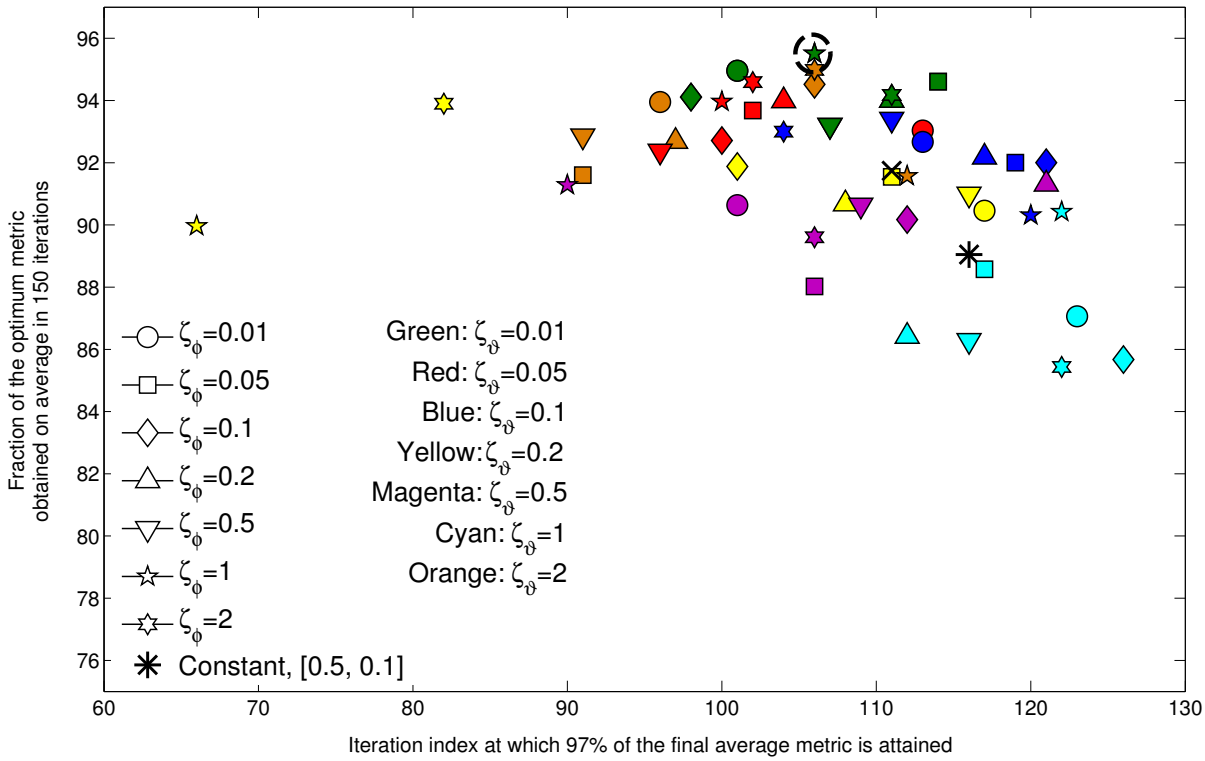


Figure 4.5: Simulation-based study of the performance of the *distributed* HS spectrum allocation algorithm. As in Figure 4.4, the horizontal axis quantifies the convergence rate, whereas the vertical axis reflects accuracy. The selected configuration has been circled with a dashed line.

and 20 different executions of the algorithm. As expected, the convergence of the distributed configurations (represented in the horizontal axis) is in general faster than its centralized counterparts. Most remarkably, a higher percentage of the optimum metric is achieved by virtue of the collaborative operation of the island-like HS allocation algorithm. The best performance – again, in what relates to the tradeoff between accuracy and convergence speed – is obtained by imposing a logarithmic progression of the HS parameters, with $[\zeta_\varphi, \zeta_\vartheta] = [1, 0.01]$.

Based on these results, Figure 4.6 depicts the value of the metric in Expression (4.2) along iterations, averaged over all the compounding nodes and 20 executions of the HS allocation algorithm on scenario 5. The plot includes results for 1) a genetically-inspired island-like distributed spectrum allocation approach with simulation-based optimized crossover and mutation rates $[P_c, P_m] = [0.7, 0.2]$ (red); 2) HS allocation approach with constant (green), linear (blue) and logarithmic (magenta) progression of the parameters; and 3) HS with logarithmic progression of the parameters, but incorporating the aforementioned probability ρ of disseminating the best candidate harmony through any outgoing link (brown). To properly set its value, one should intuitively infer that nodes with low number of communication links should have a high probability of broadcasting their best candidate vector in order to effectively enhance the overall performance of the network. Based on this rationale, in the simulations ρ is adaptively set, for each node $k \in \{0, \ldots, K-1\}$ satisfying $\mathcal{N}(k) > 0$, as

$$\rho \triangleq \rho(k) = \frac{1}{1 + \mathcal{N}(k)}, \tag{4.7}$$

where as defined before, $\mathcal{N}(k)$ denotes the number of links outgoing from node k.

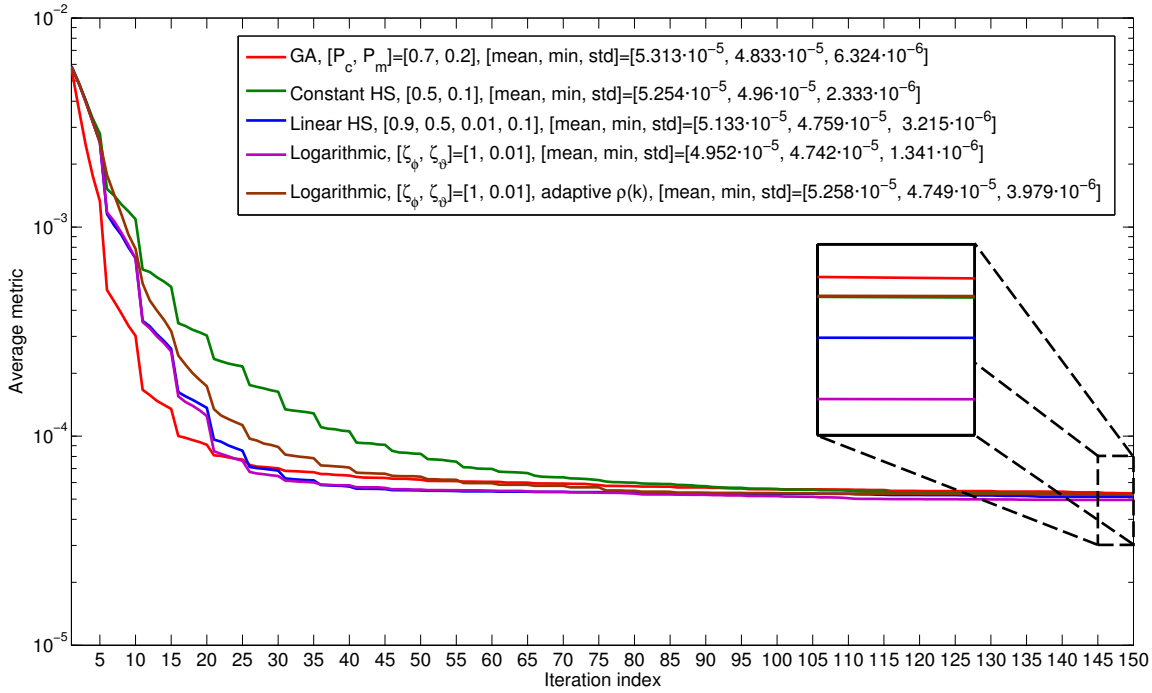


Figure 4.6: Average metric versus iteration index of the *distributed* (island) spectrum allocation algorithm for GA, HS with distinct progression of its parameters, and the adaptive probability $\rho(k)$ defined in Expression (4.7).

Also included are in the legend the mean, minimum average metric and standard deviation of the random variable representing the value of the metric after $\mathcal{I} = 150$ iterations. Several interesting observations can be made in this plot: first, despite its faster convergence rate, the GA based distributed allocation procedure is statistically outperformed by the results corresponding to any of its HS counterparts, which may due to the more exploitative behavior of the former. By inserting the adaptive probability $\rho(k)$ the mean, minimum metric and the standard deviation after $\mathcal{I}$ iterations is still kept below those of the GA approach. On the other hand, for this simulated scenario the average number Υ of broadcasted bits defined in Expression (4.6) is decreased from $178.863 \cdot 10^3$ (no adaptive probability or, equivalently, $\rho(k) = 1\ \forall k$) to $11.498 \cdot 10^3$ average bits per execution of the algorithm. Consequently, a control traffic saving of 93.572% is obtained at a slight performance degradation, which nevertheless keeps the statistical performance metrics below those of the GA approach used heretofore. This last result is particularly interesting for applications characterized by underlay control networks with stringently constrained communication resources, as well as for cases where it is imperative to reduce the data processing at the node to its minimum (e.g. wireless sensor networks).

CHAPTER 5

SPECTRUM SENSING SELECTION FOR COGNITIVE RADIO SYSTEMS

"Where observation is concerned, chance favors only the prepared mind."

- L. Pasteur

The third scenario where Soft Computing techniques will be shown to render profitable computational benefits focuses specifically on mobile communication systems which, as almost any other wireless communication network, have experienced a sharp growth during the last decade. Indeed, mobile communication systems have reached worldwide deployment with constantly increasing numbers of users and ever-growing data rates. New generations of these systems have evolved dramatically to provide improved capabilities so as to offer a diverse set of services ranging from voice transmission and short message delivery services to highly data-intensive communications. In this context, advanced techniques have been developed and taken into use to satisfy the growing user demand in terms of per user and aggregate data rates. One of the key factors in the success of mobile communication systems was the fact that spectrum had been made available in time for the new generations of systems with increasing spectrum requirements (see [17] for details). Indeed, spectrum has traditionally been the key asset of an operator to offer connectivity and services. Consequently, mobile communication systems have been planned to exploit their spectrum assignments with high spectral efficiencies and spectrum occupancies.

While the requirements of the end user for wireless traffic have been increasing in a continuous fashion, the radio spectrum has become a limited resource, as elucidated by recent spectrum identifications for the mobile service [17, 18]. In fact, the availability of new spectrum for sole primary allocation to mobile service is by itself challenging, due to the lack of unallocated spectrum support. Thus, new radio spectrum made available for mobile communication systems is likely to be shared with other systems, which calls for the development of efficient spectrum sharing techniques such as those offered by cognitive radio systems. As outlined in Chapter 1 of this dissertation, cognitive radio systems are expected to provide several benefits such as an improved efficiency of the spectrum use, as well as an increased flexibility and potential for new mobile applications [184].

When it comes to optimizing the use of resources in mobile communications with increased users' requirements, another emerging paradigm hinges on establishing opportunistic networks that are governed by an operator and created on demand [185]. In reference to Figure 5.1, these

networks can be thought of as temporary extensions of the infrastructure including cognitive management systems, aimed at managing the usage of resources and coordinate with the infrastructure. Inherent capabilities of such cognitive management systems are, among others, self-management and learning mechanisms [185]. An important aspect to be tackled when creating an opportunistic network is to select the participant nodes and the communications resources, particularly the spectrum to be used [186].

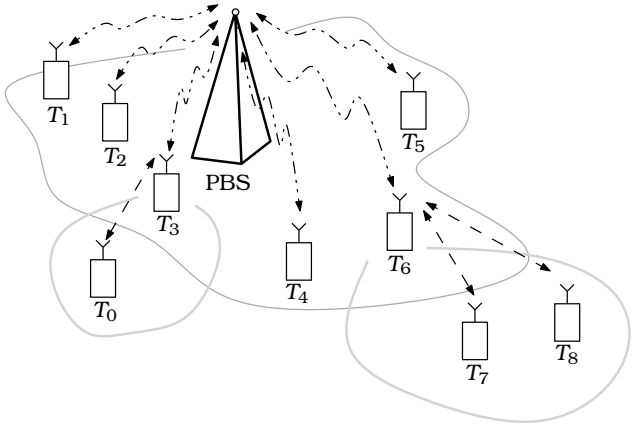


Figure 5.1: Example of opportunistic coverage extension. The primary base station (PBS) owned by a mobile operator extends its coverage area to provide service to terminals T_0, T_7 and T_8.

Since future mobile communication systems with cognitive and opportunistic characteristics – such as the aforementioned opportunistic networks – are expected to possess capabilities for intelligent decision making and learning, heuristics have emerged as an appealing research line in the related literature for their application through distinct processing stages involved in the cognitive cycle, e.g. [163, 187, 188, 189] and references therein. For different systems to operate on the same spectrum band, it is of utmost importance that they have accurate knowledge of the current status of the spectrum utilization. The methods to obtain knowledge of spectrum availability commonly studied in the research include spectrum sensing techniques, databases and control channels [190]. It is likely that different methods will be required in different spectrum bands due to the distinct spectrum sharing conditions resulting from the different systems and regulatory conditions on the bands. Such a heterogeneity in the utilized methods to obtain knowledge of spectrum availability can be exemplified by the spectrum sharing challenges of wireless networks on the so-called TV white spaces [191], where spectrum availability detection is implemented by means of databases with geolocation. By contrast, spectrum sensing is used instead for the detection of primary networks and other coexisting secondary networks.

Despite the substantial amount of work on the individual methods to obtain knowledge of spectrum availability existing in the research literature, the selection of the methods themselves has received so far very scarce attention. This observation gets even more relevant due to the fact that the spectrum sensing related literature is particularly vast, and has originated so far a flurry of sensing methods with different capabilities and requirements (e.g. [192, 193] and related bibliography there included). Optimal spectrum sensing frameworks for optimizing certain parameters of spectrum sensing techniques have been developed in [194, 195]. However, notwithstanding its operational relevance in future cognitive radio systems, the selection of the techniques itself has been set in a lower research priority level until recently [196], where a

spectrum sensing selection strategy is presented to guarantee a required performance level at the lowest signal to noise ratio while satisfying regulatory requirements.

On the other hand, an inherent capability of any cognitive radio system (and, in general, of any cognitive cycle) is the ability to learn from the results obtained [19]. Learning aims at improving the system performance by using stored information of its previous actions and their results [184]. Learning techniques for cognitive systems have been discussed thoroughly in the literature, e.g. [187, 188, 197]. Early work on learning for cognitive radio systems [188] included the learning of *where* and *when* other radios will be transmitting. An overview of learning in cognitive systems is presented in [187], where learning of context information and user preferences was used to build knowledge on network capabilities. Likewise, learning in channel selection for cognitive radio systems was studied in [197], where the channel selection was done by predicting future idle times in different channels, and by choosing the channel with the longest predicted idle time. Learning was introduced to the system to identify the traffic types on the different channels, and to select the prediction method based on this information. Furthermore, the selection of the spectrum bands can take advantage of the statistical modeling of the spectrum occupancy of different bands as done in [198], where analytical spectrum occupancy models are validated with real-life measurements.

This chapter deals with the selection of spectrum for opportunistic networks with cognitive management systems, with a focus on the selection of the methods to obtain knowledge about the current spectrum availability for cognitive radio systems. Despite its intrinsic technical interest above argued, no previous work on the adaptive selection of different spectrum detection methods in opportunistic networks has been reported in the literature. To be concise, the chapter presents a novel adaptive decision-making system with a learning mechanism for the selection of spectrum availability detection methods in opportunistic networks, which considers realistic spectrum sharing scenarios for mobile communication systems and specifically, opportunistic networks on different spectrum bands. Computer simulations will be run to shed light on the outperforming behavior of the proposed decision-making scheme with respect to traditional fixed spectrum sensing schemes in situations where the operational conditions (i.e. signal-to-noise ratio - SNR, target quality of the detection procedure, speed, complexity and availability of a priori information of the signals to be detected) are dynamic.

The chapter is organized as follows: first, opportunistic networks with cognitive management systems and spectrum sharing scenarios for mobile communication systems are described in Section 5.1. The proposed adaptive decision making system with learning capability is introduced in Section 5.2. Finally, Section 5.3 shows results of the performance evaluation for the decision making system.

5.1 Opportunistic Networks and Spectrum Sharing for Mobile Systems

As attested in the previous section, the adoption of opportunistic networking principles in mobile communication systems can help in optimizing the exploitation of the available radio resources. This section delves into the concept of opportunistic networks, with an emphasis on the phases of opportunistic network life-cycle and application scenarios. The spectrum sharing scenarios for mobile communication systems with opportunistic networks in different types of real-life spectrum bands are also discussed.

5.1.1 Opportunistic Networks with Cognitive Management Systems

Opportunistic networks [199] are temporary, localized network segments that are governed by the radio access network operator, which provides resources, policies, and knowledge on profiles and context. Opportunistic networks are thus local and temporary coordinated extensions of the mobile communication network infrastructure. Opportunistic networks include cognitive management systems to manage the resource usage and coordinate with the infrastructure. Due to the fact that they are operator-governed, the life cycle of opportunistic networks consists of the following phases [199]: 1) Suitability determination: the operator assesses the convenience of setting up a new opportunistic network by discovering new nodes and/or finding spectrum opportunities; 2) Creation: a feasible configuration for the opportunistic network is selected including the selection of e.g. participant nodes and spectrum; 3) Maintenance: quality of service (QoS) of the data flows in the opportunistic network are monitored and controlled, and corrective actions are performed on demand to maintain the network operations; and 4) Termination: resources are reallocated when the opportunistic network is released.

Opportunistic networks can be established in different deployment scenarios as discussed in [199]. As an example, the opportunistic network can be established in a situation where a given device cannot connect to the network operator's infrastructure due to the lack of coverage or mismatch in the available radio access technologies. In this hypothesized coverage extension situation depicted in Figure 5.1, the opportunistic network is established to create a link between the initial device and the infrastructure by using a device that has connection to both. Another example is the opportunistic capacity extension, where a device cannot access the operator infrastructure due to the congestion of the available resources at the serving access node. In this case, the access is redirected through an opportunistic network to avoid the congested network segment. Coverage extension and capacity extension in future mobile communication networks have been considered by using relaying in a number of works [200]. Moreover, an opportunistic network could be established in a disaster situation to recover network operations.

5.1.2 Spectrum Bands and Sharing Scenarios for Mobile Communication Systems

Mobile communication systems with opportunistic networks can be established in different types of spectrum bands. In fact, the selection of the spectrum band for the opportunistic network is an important step in the creation of the opportunistic network [185, 186]. Following the Radio Regulations of the ITU-R [201], operator governed opportunistic networks may be established in the following types of spectrum bands:

- Bands with primary allocation to mobile service;
- Bands with co-primary allocation to mobile service;
- Bands with secondary allocation to mobile service; and
- License-exempt bands.

Table 5.1 provides an example of different types of spectrum bands for opportunistic networks and their assumed characteristics. Based on the table, it is clear that the opportunistic

Table 5.1: Example spectrum bands for opportunistic networks and their assumed characteristics.

	MOBILE (primary service)	MOBILE (co-primary service with other radiocommunication services)	Mobile (secondary service)	License-exempt (ISM)
Example frequency band(s)	925-960 MHz/885-915 MHz	2.3-2.4 GHz	470-790 MHz	2.40-2.4835 GHz
Licensing	Typically requires a license	May require a license (decided by regulator). Licensed shared access (LSA) is likely.	May or may not require a license (decided by regulator)	No license required.
Status of opportunistic network	Primary user in the band and operator decides internally its resource use among opportunistic network and normal operations.	Opportunistic network is co-primary user and has to share with primary users. Opportunistic network has to ensure that primary user remains free from harmful interference.	Opportunistic network is secondary user. It has to share with primary users and other secondary users.	Opportunistic network has no priority status as all uses have equal status and have to obey power limits.
Reliability	Operator controls the interference scenarios internally. No interference from other services.	Potentially interference from primary users. Potentially interference from other secondary users.	Potentially interference from primary users.	High likelihood to suffer from harmful interference as there is no protection from harmful interference and no coordination among users.
Potential spectrum availability detection methods	System internal control channels	Databases	Databases, spectrum sensing	Spectrum sensing, knowledge gathered to databases during operations
Range	Wide coverage is possible	Wide coverage is possible depending on the licensed shared access rules.	Restricted by the requirement to protect primary service	Highly restricted by the transmission power limits
Cost	Typically high cost to acquire a license	May involve license costs	May or may not involve costs	Free of charge

network will have a different status and thus face a different spectrum sharing scenario depending on the selected spectrum band. For instance, on a band with primary allocation to mobile service (case 1) and written in capitals in Table 5.1, the operator governs the use of the spectrum band and can internally decide on the resource allocation between the opportunistic network and the normal infrastructure network. The spectrum sharing scenario and the resulting interference scenario are fully controlled by the operator with advanced interference mitigation techniques available in the mobile communication networks. On a band with co-primary allocation to mobile service (case 2), the operator wishing to deploy the opportunistic network has to ensure that other primary users (i.e. other radio communication services) remain free from harmful interference. This is most likely implemented with licensed shared access (LSA) rights and consulting a database. Then, the operator can establish the opportunistic network on the

band similarly as in case 1 with primary allocation to mobile. The opportunistic network has a primary status in its area defined by the LSA license and can use its internal control channels to coordinate between the opportunistic network and the infrastructure network.

On a band with secondary allocation to mobile service (case 3) and written in normal characters in Table 5.1, the opportunistic network has lower priority compared to the primary spectrum user and has to guarantee that the primary user does not suffer from harmful interference from the opportunistic network. The secondary user cannot claim protection from harmful interference from stations of the primary service. Moreover, spectrum sharing between several secondary users, i.e. opportunistic network(s) and others that have secondary spectrum allocation, may yield another problem as they share the same spectrum. An example of this is the TV white space in the 470-790 MHz band where the opportunistic network has to protect the TV broadcasting service and other primary systems and share the spectrum also with other secondary users. In a license-free spectrum band corresponding to case 4, all spectrum users including the opportunistic network can equally access the band but are not protected from harmful interference resulting in an uncontrolled interference conditions. The users have to obey the regulatory constraints set for the use of the band, but in general the constraints only limit e.g. the transmission power levels. Thus, there is a high probability of harmful interference to the opportunistic networks resulting from the other uncoordinated spectrum users.

Based on the above rationale, the selection of the spectrum band for the opportunistic network is an essential step and should consider the requirements of the opportunistic network for a given application scenario, as well as the different capabilities offered by the different types of spectrum bands under consideration. The availability of the spectrum can differ significantly over time and location. To efficiently check the availability of the specific spectrum, the selection of the method to obtain knowledge of the spectrum availability is deemed an essential step, which is discussed in depth in the next section.

5.2 Proposed Decision-making System for the Selection of Spectrum Sensing Methods

For the creation of an opportunistic network on a selected spectrum band, the availability of the spectrum needs to be examined and assessed. To this end, there is a wide range of different techniques to obtain information on the spectrum availability, such as control channels, databases and spectrum sensing techniques [184], each of which features highly different capabilities and requirements. Thus, it is of utmost importance to use a proper method for each situation. An adaptive decision-making system is hereafter proposed for the efficient, autonomous and intelligent selection of spectrum availability detection methods in opportunistic networks.

5.2.1 General Overview of the Proposed Decision-making System

A general overview of the adaptive decision-making system is presented in Figure 5.2. First, the spectrum band is selected for the opportunistic network. The next step is to select the proper method to obtain knowledge of spectrum availability for the given spectrum band between

the three general classes of spectrum availability detection methods, namely control channels, databases, and spectrum sensing techniques. Depending on the selected spectrum band, different detection methods result to be more appropriate. On bands with primary allocation to mobile service, the operator assigns the resources to the opportunistic network using its internal control channels. There is no need to worry about primary users.

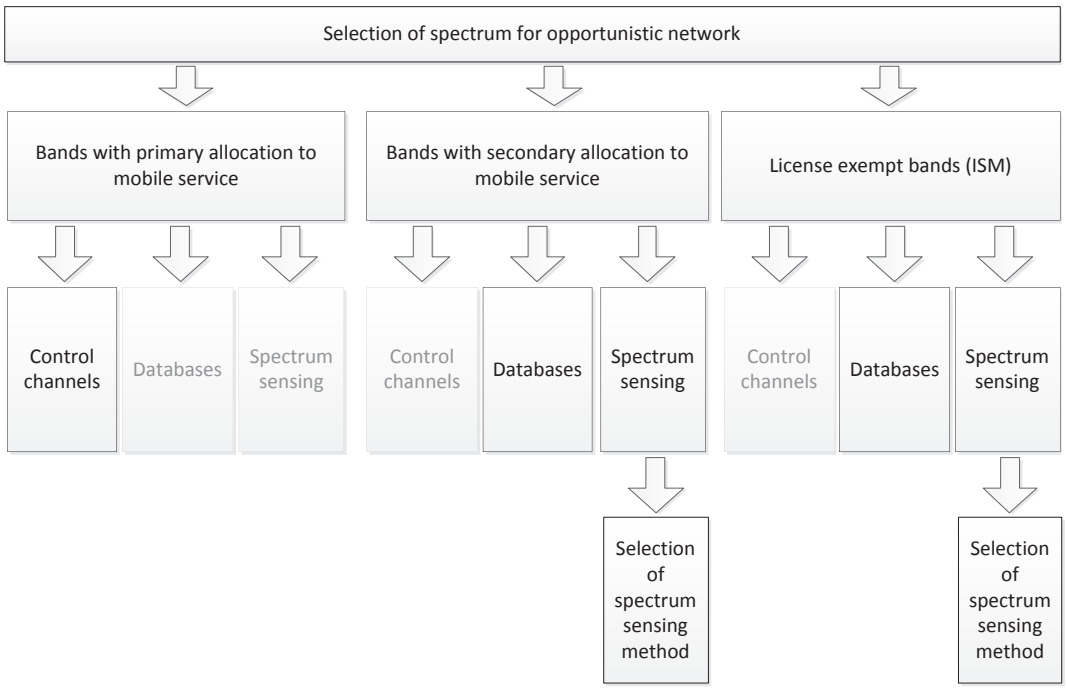


Figure 5.2: Proposed decision-making system for selecting spectrum availability detection methods.

On bands with co-primary allocation to mobile service, the opportunistic network has to ensure that it does not interfere with the primary systems. A key to protect the primary users from harmful interference is to use the proper methods to obtain knowledge of the current status of spectrum use. There can be regulator set requirements for the co-primary system to gain access to the spectrum band by acquiring licensed shared access (LSA) rights which can enforce the mobile systems to use certain predetermined methods to obtain knowledge of spectrum availability such as the database approach.

On bands with secondary allocation to mobile, the opportunistic network has to ensure that primary systems in the band remain free from harmful interference. As an example, the use of a database can be set as mandatory for devices operating on TV white spaces. Moreover, there may be several secondary users sharing the spectrum band. Thereby, knowledge of their spectrum use may also be needed to coordinate its usage. Thus, the selection of methods to obtain knowledge of spectrum availability will take place twice in the bands with secondary allocation to mobile. Typically the regulator is not going to decide which method should be used to facilitate the sharing between multiple secondary users, but the decision-making system should instead decide it.

Finally, on license-exempt bands there is no requirement to use a specific method and the other spectrum users are not requested to inform about their spectrum use. Thus, the

remaining way to obtain knowledge of the current spectrum use is to resort to spectrum sensing techniques. The spectrum sensing results can be stored into a database during the operations of the opportunistic network and this information can be used in the future in addition to the instantaneous spectrum sensing results. If spectrum sensing is selected as the spectrum availability detection method, the actual spectrum sensing method needs to be selected next.

5.2.2 Rule-based decision-making system for spectrum sensing technique selection

Spectrum sensing is the most widely studied detection method for spectrum availability in the research literature. If used as the method for identifying available spectrum opportunities on the bands, an important step is to select the actual sensing method and its parameters from the wealth of available methods. Indeed, spectrum sensing techniques possess different performances, requirements, and capabilities. Here relevant concepts related to spectrum sensing are presented, including different spectrum sensing techniques and their assumed capabilities, along with a simple decision-making system to select among different techniques.

5.2.2.1 Considered Spectrum Sensing Techniques

The goal of spectrum sensing is to identify whether a given frequency channel is occupied or vacant by observing the characteristics of the received radio signal. Five different spectrum sensing approaches – whose characteristics are summarized in Table 5.2 – will be addressed in this chapter. The approach presented here does not intend to be exhaustive in terms of the considered spectrum sensing methods, their classification or assumptions, but rather acts as the starting point as these are the only earlier work on the selection of the sensing techniques in the research literature:

- The first spectrum sensing method considered here, the energy detection, estimates the received signal energy by summing up the energy from the received signal and by comparing the result to a threshold which is determined based on the noise level. Energy detection is simple and fast, and does not require any a priori information; however, it is sensitive to threshold setting and cannot operate at low SNRs.
- The second of the spectrum sensing techniques considered here, the correlation detection, uses a stored version of the signal type and correlates the received signal with such stored version. The correlation detection has good detection performance and can operate fast but requires a priori information about the signal waveforms to be sensed, though.
- The third sensing scheme, the feature detection, hinges on the property that modulated signals contain cyclostationary features as opposed to the noise in the channel. These properties inherent to modulated signals can thus be exploited to differentiate the signals from noise. There are various types of feature detection algorithms. Here an exemplifying feature detection method is adopted, which calculates the covariance matrix of the received signal vector and based on the characteristics of this matrix, decides on the presence or absence of signal. As such, this detection method does not require a priori information and has better detection performance than energy detection, but at the cost of a higher computational complexity. However, there are also different spectrum

sensing algorithms that could fall under the category of feature detection with different characteristics regarding e.g. requirements on a priori information and operational SNR.

- Matched filtering, as the fourth considered spectrum sensing method, renders a very good detection performance and fast operations, but it requires much a priori information about the signal types including the precise waveform of the signal to be sensed. It is a coherent detection technique that correlates the unknown received signal with a known signal and compares the result to a threshold. Matched filtering is closely related to correlation detection, but is more complex. The implementation of matched filtering is very complex since a separate receiver is needed for each signal type. Thus the requirements and the complexity of the matched filtering are very high.

- Finally, cooperative spectrum sensing can be used to improve the sensing reliability by performing spectrum sensing at several nodes at the same time and making collaborative decisions on the availability of spectrum. Here cooperative energy detection is considered, which requires exchange of information between nodes and thus increases the complexity.

The performance of spectrum sensing is usually assessed by means of the so-called Receiver Operating Characteristics (ROC), which capture the relations of two interrelated key parameters in any decision process: the probability of detection and the probability of false alarm. The probability of detection denotes the probability that the spectrum sensing algorithm correctly detects the presence of a signal when there is actually a signal. On the other hand, the probability of false alarm presents the probability that the spectrum sensing algorithm erroneously detects the presence of the signal when in fact there is no signal. While the target is to obtain a high probability of detection and a low probability of false alarm, they cannot be achieved at the same time due to their interrelations. Therefore, a trade-off must be met.

Different spectrum sensing methods have different ROC curves for a given SNR. The higher the probability of detection for a given probability of false alarm, the more reliable the detection is, which is desirable for cognitive radio operations to protect other systems. On the other hand for a fixed requirement on the probability of detection, the different spectrum sensing methods have different probabilities of false alarm and it is desirable to have lower probability of false alarm offering better system performance as the spectrum availabilities are being wasted less. For instance, there are closed form expressions for the ROC of energy detection in Additive White Gaussian Noise (AWGN) and Rayleigh fading channels (e.g. [202]). With a better sensing technique, it is possible to reduce the probability of false alarm for the same requirement in terms of the probability of detection, yielding an improved overall system performance. Thus, the selection of the proper spectrum sensing method influences the performance of the system.

5.2.2.2 Fuzzy Rule-based Decision-making System

Based on the assumed characteristics of the spectrum sensing methods discussed above, a simple fuzzy rule-based decision making system is derived for the selection of the spectrum sensing method. The basic principle of the use of fuzzy decision making finds its roots on traditional methods from fuzzy logic [203]. Fuzzy logic is particularly attractive for the selection of spectrum sensing techniques as it allows the modeling and processing of very different types of information in a simple and human-understandable way. Fuzzy decision making resembles

Table 5.2: Considered spectrum sensing methods and their assumed characteristics.

	Energy detection	Correlation detection	Feature detection	Matched filtering	Cooperative energy detection
Speed of operations	Fast	Fast	Slow	Fast	Fast if exchange of information between cooperative sensing nodes is not considered
Performance	Limited detection performance	Can provide good probability of detection	Can provide good probability of detection	Can provide very good probability of detection	Limited performance but better than single node energy detection
Complexity	Low complexity	Medium complexity	Medium complexity	Complexity is very high as separate receivers are needed for different signals	Sensing algorithm has low complexity. Cooperative sensing is complex as control data exchange is required between cooperative nodes.
Operational SNR	Does not work at low SNRs	Can work at a wide range of SNRs	Does not work at low SNRs	Can work at a wide range of SNRs	Does not work at low SNRs
Requirement for a priori information	No a priori information required about signals to be sensed. Only noise power estimate required	Requires a priori information about signals to be sensed	No a priori information required about signals to be sensed	Requires full knowledge of signal waveform (e.g. bandwidth, modulation, frame format)	No a priori information required about signals to be sensed. Only noise power estimates at different cooperative sensing nodes required

human thinking, allows for fast operations as it does not require iterations, and does not experience unexpected outcomes as they are determined beforehand when building the model. It has been considered to be suitable for compromise-centric decision making with conflicting requirements. The selection of spectrum sensing techniques consists of conflicting requirements and different types of information for the decision making, which lay the basis for a promising application area for fuzzy logic.

The novel rule-based decision-making system is presented in Figure 5.3. Four input parame-

ters are considered for the selection of the spectrum sensing method: 1) required probability of detection; 2) operational SNR; 3) available time for performing the detection; and 4) available a priori information. It should be noted that any other input parameters could be also used such as the probability of false alarm. However, for the sake of simplicity the number of input parameters is restricted to four to avoid a too complex decision making system to begin with. The input parameters are first fuzzified from measurable values to fuzzy linguistic variables by using input membership functions. The fuzzy values are then fed into a rulebase consisting of IF-THEN clauses that represent the mappings between the inputs and outputs of the decision making. The output from the fuzzy reasoning is next mapped to real-world data (i.e. the selected spectrum sensing method) by using output membership functions. The decision making method can be implemented without fuzzy logic but it has been used here to ease possible modifications to the decision making and the inclusion of learning later on.

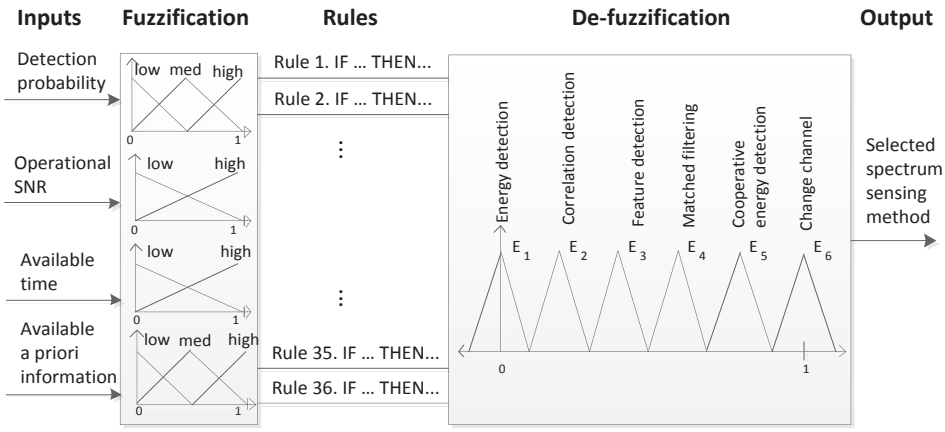


Figure 5.3: Fuzzy decision-making system for the selection of spectrum sensing methods.

Two of the input parameters (the operational SNR and the available time) are assigned two input membership functions: low and high. On the other hand, the requirement for detection probability and the available a priori information are assigned three input membership functions: low, medium or high. The output is the selected spectrum sensing method from the considered classes of energy detection, correlation detection, feature detection, matched filtering, and cooperative energy detection. If none of the spectrum sensing methods can be applied in the scenario at hand, the output is set to "change the channel". The decision-making method opts for the least complex spectrum sensing method that meets the requirements and operational conditions. The complexity level associated to each of the spectrum sensing methods is assumed to be, starting from the least complex method and in ascending order: 1) energy detection; 2) correlation detection; 3) feature detection; 4) matched filtering; and 5) cooperative energy detection. The rules for implementing the decision making summarized in Table 5.3 have been developed based on the assumed characteristics of the different spectrum sensing methods, which are presented in Table 5.2.

The proposed fuzzy decision-making system has several benefits. It is a one-shot method and does not iterate, thus it operates very fast. Likewise there are no unexpected outcomes from the decision-making system, since all the possible outputs are determined beforehand when the rules are developed. It should be also noted that there are various classifications for spectrum sensing methods and several variants of spectrum sensing methods inside the different

Table 5.3: Rulebase for the selection of the spectrum sensing method.

Rule	Inputs			Output
1	IF	(Detection probability is low) and (SNR is low) and (Time is low) and (Info is low)	THEN	(Output is Change channel)
2	IF	(Detection probability is low) and (SNR is low) and (Time is low) and (Info is med)	THEN	(Output is Correlation detection)
3	IF	(Detection probability is low) and (SNR is low) and (Time is low) and (Info is high)	THEN	(Output is Correlation detection)
4	IF	(Detection probability is low) and (SNR is low) and (Time is high) and (Info is low)	THEN	(Output is Feature detection)
5	IF	(Detection probability is low) and (SNR is low) and (Time is high) and (Info is med)	THEN	(Output is Correlation detection)
6	IF	(Detection probability is low) and (SNR is low) and (Time is high) and (Info is high)	THEN	(Output is Correlation detection)
7	IF	(Detection probability is low) and (SNR is high) and (Time is low) and (Info is low)	THEN	(Output is Energy detection)
8	IF	(Detection probability is low) and (SNR is high) and (Time is low) and (Info is med)	THEN	(Output is Energy detection)
9	IF	(Detection probability is low) and (SNR is high) and (Time is low) and (Info is high)	THEN	(Output is Energy detection)
10	IF	(Detection probability is low) and (SNR is high) and (Time is high) and (Info is low)	THEN	(Output is Energy detection)
11	IF	(Detection probability is low) and (SNR is high) and (Time is high) and (Info is med)	THEN	(Output is Energy detection)
12	IF	(Detection probability is low) and (SNR is high) and (Time is high) and (Info is high)	THEN	(Output is Energy detection)
13	IF	(Detection probability is med) and (SNR is low) and (Time is low) and (Info is low)	THEN	(Output is Change channel)
14	IF	(Detection probability is med) and (SNR is low) and (Time is low) and (Info is med)	THEN	(Output is Correlation detection)
15	IF	(Detection probability is med) and (SNR is low) and (Time is low) and (Info is high)	THEN	(Output is Correlation detection)
16	IF	(Detection probability is med) and (SNR is low) and (Time is high) and (Info is low)	THEN	(Output is Change channel)
17	IF	(Detection probability is med) and (SNR is low) and (Time is high) and (Info is med)	THEN	(Output is Correlation detection)
18	IF	(Detection probability is med) and (SNR is low) and (Time is high) and (Info is high)	THEN	(Output is Correlation detection)
19	IF	(Detection probability is med) and (SNR is high) and (Time is low) and (Info is low)	THEN	(Output is Cooperative energy detection)
20	IF	(Detection probability is med) and (SNR is high) and (Time is low) and (Info is med)	THEN	(Output is Correlation detection)
21	IF	(Detection probability is med) and (SNR is high) and (Time is low) and (Info is high)	THEN	(Output is Correlation detection)
22	IF	(Detection probability is med) and (SNR is high) and (Time is high) and (Info is low)	THEN	(Output is Feature detection)
23	IF	(Detection probability is med) and (SNR is high) and (Time is high) and (Info is med)	THEN	(Output is Correlation detection)
24	IF	(Detection probability is med) and (SNR is high) and (Time is high) and (Info is high)	THEN	(Output is Correlation detection)
25	IF	(Detection probability is high) and (SNR is low) and (Time is low) and (Info is low)	THEN	(Output is Change channel)
26	IF	(Detection probability is high) and (SNR is low) and (Time is low) and (Info is med)	THEN	(Output is Change channel)
27	IF	(Detection probability is high) and (SNR is low) and (Time is low) and (Info is high)	THEN	(Output is Matched filter)
28	IF	(Detection probability is high) and (SNR is low) and (Time is high) and (Info is low)	THEN	(Output is Change channel)
29	IF	(Detection probability is high) and (SNR is low) and (Time is high) and (Info is med)	THEN	(Output is Change channel)
30	IF	(Detection probability is high) and (SNR is low) and (Time is high) and (Info is high)	THEN	(Output is Matched filter)
31	IF	(Detection probability is high) and (SNR is high) and (Time is low) and (Info is low)	THEN	(Output is Change channel)
32	IF	(Detection probability is high) and (SNR is high) and (Time is low) and (Info is med)	THEN	(Output is Correlation detection)
33	IF	(Detection probability is high) and (SNR is high) and (Time is low) and (Info is high)	THEN	(Output is Correlation detection)
34	IF	(Detection probability is high) and (SNR is high) and (Time is high) and (Info is low)	THEN	(Output is Feature detection)
35	IF	(Detection probability is high) and (SNR is high) and (Time is high) and (Info is med)	THEN	(Output is Correlation detection)
36	IF	(Detection probability is high) and (SNR is high) and (Time is high) and (Info is high)	THEN	(Output is Correlation detection)

classifications with different capabilities. The scope of this chapter focuses on presenting a very rough classification addressing a limited set of sensing methods, thus addressing the aforementioned variants for future work. However, the fuzzy decision making system is very flexible, and consequently changes in the underlying assumptions on the spectrum sensing methods are straightforward to be accommodated and included in the process by simply changing the outputs of the corresponding rules. This allows the decision making system to be easily adjusted to different spectrum sensing methods.

5.2.2.3 Inclusion of a Learning Mechanism

Learning is an important part of the cognitive radio system to enhance its performance by using stored information of its previous actions and their results. When learning is incorporated to the system, two components are further needed [203]: a process monitor and an adaptation mechanism. The process monitor is a method used for evaluating the performance of the decision-making system in order to find out potential weaknesses, miss-behaviors, or potential for improvements. The adaptation mechanism processes information passed by the process monitor so as to update and adapt the decision-making system to changing situations. Figure 5.4 (left) illustrates a general learning mechanism based on performance evaluation of the target system and adaptation of the decision making system accordingly. Likewise, Figure 5.4 (right) shows an example of how the learning mechanism can be applied to the adaptive decision-making system for spectrum availability detection.

In the adaptive decision-making system for obtaining knowledge of spectrum availability in opportunistic networks here proposed, a learning mechanism can be introduced in order to modify the output parameters or the rule-base of the decision-making system. Learning may be

used to trigger the need for selecting other spectrum band for the opportunistic network. For example, if the operational conditions of the opportunistic network on the currently selected spectrum band start to degrade severely, the learning mechanism could identify the change in the performance and make changes to the decision-making system. Likewise, a change in the regulatory situation could change either the communication quality due to changing interference scenarios or the requirements for sharing a given spectrum band, which could trigger the need for adaptations in the decision-making system, e.g. in the decision-making rules for selecting the spectrum band. This update can be done by changing the shapes or values of the output or input membership functions: for instance, a change in the policies in terms of the required probability of detection can be implemented in the fuzzy decision-making system by changing locations and shapes of the input membership functions for this parameter. A change in the characteristics of a spectrum sensing method can be implemented with a change in the corresponding rule.

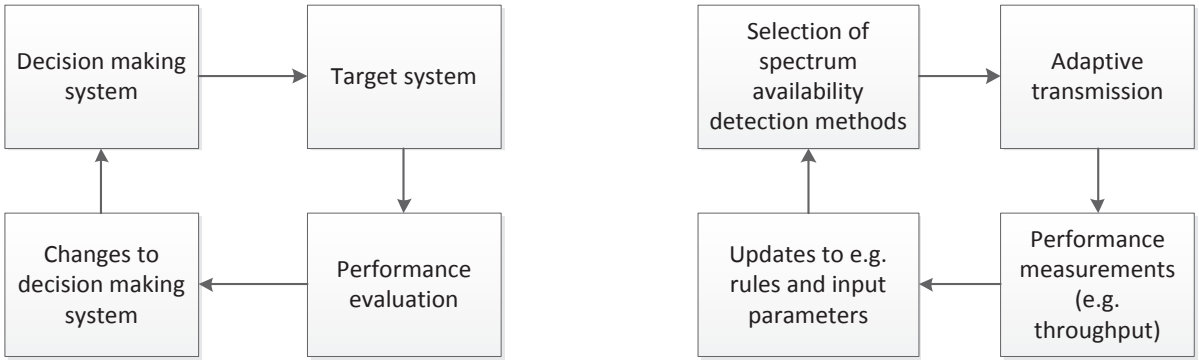


Figure 5.4: General learning mechanism (left), and learning mechanism applied to spectrum availability detection (right).

Furthermore, an interesting scenario could take place without a specific learning mechanism. The system performance could be improved by collecting and processing the sensed information to extract knowledge of the prevailing signals. This information could add up to the knowledge of the system as *a priori* information about the signals to be sensed, which allows the decision-making system to select a better sensing technique requiring *a priori* information, ultimately leading to an enhanced detection and thus, an improvement of the overall system performance.

5.3 Performance Evaluation

In order to check the performance of the developed decision-making system, an opportunistic coverage extension scenario is considered. A given device is located out of the coverage of a given infrastructure network and thus, an opportunistic network is created to serve the device. Here, a device does not have access to the infrastructure network while another device is in the coverage area of the infrastructure base station and provides connectivity to the other device. In this scenario, the devices are assumed to be closely located, and the QoS requirements of the considered application are assumed to be loose. Therefore, a band with low guarantee of protection against interference from other users can be selected. The power limits associated

with the license-exempt ISM bands can be fulfilled in the given scenario since the nodes of the opportunistic network are closely located. Thus the license-exempt ISM band from Table 5.1 is selected, which is free of charge, does not require a license for operations, and can still satisfy the requirements posed by the given application. The most potential method for spectrum availability detection on the ISM band is spectrum sensing. The specific spectrum sensing method is selected by means of the fuzzy decision-making system presented in Section 5.2.2.2.

The performance of the proposed fuzzy decision-making system for selecting among spectrum sensing methods is first inspected by assessing the proportions of the different outcomes of the decision making with different input parameter distributions. To evaluate the proportions of the different outcomes, the rules resulting in a given output from the rulebase are selected and weighted with the probabilities of the occurrence of the rules. In addition, the success rate of the decision-making is calculated by comparing it to a situation where the decision-making is not used but a single spectrum sensing method is always used instead. The success is evaluated as the percentage of occasions where a given sensing technique is applicable with certain input parameter distributions, but may not be the best one at hand.

Table 5.4: Input parameter sets for the fuzzy decision-making system.

		Input parameter set 1	Input parameter set 2	Input parameter set 3	Input parameter set 4
Detection probability	low	33.3%	100%	100%	100%
	medium	33.3%	0%	0%	0%
	high	33.3%	0%	0%	0%
Operational SNR	low	50%	50%	20%	50%
	high	50%	50%	80%	50%
Available time	low	50%	0%	0%	0%
	high	50%	100%	100%	100%
Available a priori information	low	33.3%	100%	100%	50%
	medium	33.3%	0%	0%	50%
	high	33.3%	0%	0%	0%

The four input parameter sets presented in Table 5.4 are considered in the simulations. In the table, percentage values represent the proportion of inputs that fall under a given input membership category (i.e. “low”, “medium” or “high”), depending on the input parameter. The input parameter set 1 describes the situation where all input values are equally likely. Input parameter sets 2 and 3 describe a typical setting for ISM band where the required probability of detection is low, there is much time available but no a priori information about the other signals. The difference between the input parameter sets 2 and 3 is the assumption on the operational SNR. Input parameter set 2 assumes that in 50% of the occasions the operational SNR is high and 50% low. Input parameter set 3 assumes that in 20% of the occasions the operational SNR is low and 80% high, which means that in this situation the other users are located closer to the opportunistic network than in the input parameter set 2. Finally, input parameter set 4 is modified from input parameter set 2 to reflect a situation where the opportunistic network has operated on the ISM band for some time and stored sensing information to a database and processed this information to extract a priori knowledge of the underlying signals. This knowledge adds up to available a priori information about the signals, and thus the input parameter set for available a priori information has been changed such that in 50% of the occasions there is a “medium” level of a priori information.

Having posed the above scenarios, Table 5.5 presents the proportions of the outcomes from the decision making with each of such input parameter sets. Specifically, the percentages shown in the table represent how often each of the sensing methods is selected as output from the decision making. The results verify that the selected spectrum sensing methods depend heavily on the input parameter distributions; this fact can be made intuitively clear if the reader notices that the decisions between the different methods are based on a limited number of key input parameters which differ between different spectrum sensing methods.

Table 5.5: Proportions of different outcomes from the fuzzy decision-making system and the success rates of individual sensing techniques with different input parameter sets.

		Input parameter set 1	Input parameter set 2	Input parameter set 3	Input parameter set 4
Energy detection	Proportion of outcomes	16.7%	50%	80%	50%
	Success rate	16.7%	50%	80%	50%
Correlation detection	Proportion of outcomes	44.5%	0%	0%	25%
	Success rate	55.6%	0%	0%	50%
Feature detection	Proportion of outcomes	8.3%	50%	20%	25%
	Success rate	19.5%	50%	20%	25%
Matched filtering	Proportion of outcomes	5.6%	0%	0%	0%
	Success rate	33.4%	0%	0%	0%
Cooperative energy detection	Proportion of outcomes	2.7%	0%	0%	0%
	Success rate	33.3%	50%	80%	50%
Change channel	Proportion of outcomes	22.2%	0%	0%	0%
	Success rate	100%	100%	100%	100%

Table 5.5 also presents the success rates of the individual spectrum sensing methods with the different input parameter sets. The success rates evince the percentage of occasions where each of the sensing methods alone is successful with the given input parameter sets. Therefore, this corresponds to the situation where the spectrum sensing method is kept fixed, so the percentage shows how often the fixed sensing method is actually applicable. In fact, the results show that the success rates of the individual spectrum sensing methods are rather low, which means that most of the time, keeping the spectrum sensing method fixed results in failure. The proposed adaptive decision-making system can select the most proper spectrum sensing method for each situation, and thus the opportunities are not wasted compared to keeping the sensing method fixed. The results indicate that the proposed fuzzy decision-making system can improve the success rate significantly. Remarkably, the success rate of “Change channel” is always 100% which is not a desirable situation, since no action is taken but a new channel needs to be selected.

CHAPTER 6

CONCLUDING REMARKS AND FUTURE RESEARCH LINES

"A conclusion is the place where you got tired of thinking."

- Harold Fricklestein

This Thesis has delved into the application of avant-garde meta-heuristic algorithms to the allocation of radio resources in intelligent communication systems. Built on an exemplificative methodology, the contributions springing from this research have verified that meta-heuristics can algorithmically buttress resource allocation procedures of involved complexity and undergoing stringent operational constraints. By virtue of their simplicity and derivative-free operating mode, meta-heuristics are shown to be a suitable tool for those cases where the formulation of the problem beneath complex resource allocation paradigms is not straightforwardly tractable using mathematical optimization, but instead calls for approximative solvers trading optimality for an alleviated complexity.

From the outcomes of the research activity developed within this Thesis, several relevant conclusions can be drawn as summarized in what follows:

- Chapter 3 has presented a novel iterative resource allocation algorithm for cognitive OFDMA networks where both a primary and a secondary base station communicate with a set of K distant destinations subject to per-user rate constraints. The proposed heuristic hybridizes subcarrier assignment based on the Harmony Search algorithm with power allocation based on a Differential Evolution approach. Fulfillment of the imposed rate bounds per user is performed via a greedy subcarrier exchange technique. Computer simulations performed for the *Extended Vehicular A* ITU channel model have shown that the proposed method is capable of efficiently maximizing the overall throughput of both base stations while simultaneously satisfying the established rate constraints per user.

- Chapter 4 has described a novel spectrum allocation algorithm for wireless cognitive radio networks based on the HS algorithm. Specifically, the chapter has thoroughly described both centralized and distributed implementations of this algorithm specifically tailored for the problem at hand. Further emphasis is placed on a novel adaptive probabilistic distributed allocation technique that permits to alleviate the amount of exchanged control traffic required between nearby nodes in the distributed implementation of the proposed approach. The performance of this HS-based algorithm has been compared to that of its genetic counterpart, the latter having been shown to be outperformed by the first when

simulated over networks of increasing size. As for the proposed distributed allocation technique, further simulation results verify that huge control traffic savings are obtained by virtue of the proposed novel adaptive probabilistic procedure, at a negligible performance degradation with respect to a conventional island-like scheme.

- Finally, Chapter 5 has elaborated on a novel adaptive decision-making system for the selection of methods to obtain knowledge of spectrum availability for mobile communication systems. The proposed decision-making system has been applied to operator-governed opportunistic networks that are local and temporary extensions of the infrastructure network. They can be established on different types of spectrum bands covering all valid real-life spectrum bands such as bands with primary allocation to mobile service, bands with co-primary allocation to mobile service, bands with secondary allocation to mobile service, and license-exempt bands. In this envisaged scenario different methods to obtain knowledge of spectrum availability are applicable to different spectrum bands, which is an important facilitator for spectrum sharing of different systems in the same spectrum band but has not been tackled in the research literature in the past. The developed decision-making system first selects the proper method to obtain knowledge of spectrum availability for the given spectrum band from control channels, databases and spectrum sensing. The decision making system further includes a simple rule-based system for the selection of specific spectrum sensing techniques between matched filtering, correlation detection, feature detection, energy detection and cooperative sensing, provided that spectrum sensing has been selected as the detection method. The decision-making system is further improved by introducing a learning mechanism. The obtained results from computer simulations have shown the performance gains of the proposed approach with respect to fixed spectrum sensing schemes when the operational constraints are particularly dynamic.

The research results summarized in this dissertation have been presented at several international conferences and published/submitted to renowned scientific journals. In particular, 5 papers have been published or submitted for publication in international journals, and 4 contributions have been presented in congresses and workshops. In addition, collaborations with other research lines have given rise to an additional publication record of 2 patents, 2 guest editorials, 6 contributions to books (including 2 edited books), 27 articles in international refereed journals, 45 contributions to international conferences and 8 presentations at national symposiums. A thorough compendium of these publications has been made available in Appendix A.

6.1 Future Directions

In light of the promising results obtained in this work, we plan to conduct future research on novel directions mainly aimed at circumventing practical limitations of the proposed spectrum allocation algorithm when applied to more realistic scenarios. Such research lines can be summarized as follows:

- As for Chapter 3, bit-loading was explicitly set apart from the problem definition in Expression (3.13), grounded on the fact that bit-loading functionalities are often not available in

already deployed systems. A natural extension of the developed algorithm would consider the inclusion of this additional resource in both the formulation of the problem and the structure of the algorithm designed for its efficient resolution.

- In what relates to Chapter 4, the PAR probabilistic operator in Section 4.2 essentially embodies a random perturbation technique, since there is no criteria imposed on the alphabet of the underlying set of channels so as to claim that when applied, the PAR process leads to a candidate solution with better fitness value. Although this PAR operator suffices for escaping from local minima, the overall convergence of the allocation algorithm can be boosted if the PAR process is supplied with information on the already allocated resources (e.g. locally available frequency channels and/or power distribution), and redesigned accordingly.

- Again for Chapter 4, it is foreseen that the linear power penalty function $\Psi(k, n)$ might incorporate the power allocated to each outgoing link over a certain spectrum channel as another optimization parameter of the proposed allocation procedure. By jointly optimizing power and channel allocation one may further enhance the error rate performance of the setup for a given overall power budget $\sum_{k=0}^{K-1} P(k)$. However, this optimization problem requires specific local search procedures whose design and application to the distributed spectrum allocation problem will be investigated in the future.

- In reference to Chapter 5, future research will gravitate on considering new input parameters for the adaptive decision-making system therein presented. Learning mechanisms will be elaborated further so as to adjust the rules of the rule-based decision making system. Accordingly, a closer look will be taken at classification of the spectrum sensing methods and the more detailed variants of the spectrum sensing methods and their associated parameters inside the general classes of spectrum sensing methods considered so far. As the assumed characteristics for the different spectrum sensing methods have been coarse, it may be useful to go into a more accurate characterization. In addition, the imperfections of the spectrum sensing methods and their influence on the system performance will be investigated in detail.

- In regards to the overall scope of the Thesis, an interesting extension of the developed resource allocation algorithms emerges if the focus of the optimization spans to upper layers of the protocol stack. In particular, when routing is considered as another resource to be optimized, cross-layer optimization (understood as the joint consideration of physical, link network and transport protocol layers as a single and unified resource pool without strict boundaries in between) has been thoroughly shown to render substantial gains in the end-to-end performance of stringently constrained communication systems. In this context, route allocation in infrastructure-based traffic offloading setups can be modelled as a tree-like topology optimization problem, for which the application of the meta-heuristic algorithms tackled in this Thesis along with solution encoding strategies well suited for this particular network topology (e.g. Dandelion encoding [86]) is expected to lay an algorithmic substrate with which to solve a plethora of optimization paradigms in a computationally efficient manner.

APPENDIX A

LIST OF PUBLICATIONS

"Advice is judged by results, not by intentions."

- Cicero

The research work developed in this Thesis has given rise to a number of scientific publications in journals and specialized conferences in the field. In particular, the specific thematic line of the dissertation has been tackled in 5 journal articles (3 already published) and 4 contributions in international conferences with IEEE® patronage.

Articles in refereed international journals:

1. J. Del Ser, M. Matinmikko, S. Gil-López and M. Mustonen, "Centralized and Distributed Spectrum Channel Assignment in Cognitive Wireless Networks: A Harmony Search approach" *Applied Soft Computing*, Vol. 12, N. 2, pp. 921-930, February 2012 (JCR: 2.612).
2. J. Del Ser, M. N. Bilbao, S. Gil-López, M. Matinmikko, S. Salcedo-Sanz, "Iterative Power and Subcarrier Allocation in Rate-Constrained OFDMA Downlink Systems based on Harmony Search Heuristics", *Engineering Applications of Artificial Intelligence*, Vol. 24, N. 5, pp. 748-756, August 2011 (JCR: 1.665).
3. M. Matinmikko, J. Del Ser, T. Rauma, M. Mustonen, "Fuzzy-logic based Framework for Spectrum Availability Assessment in Cognitive Radio Systems", submitted to *IEEE Journal on Selected Areas in Communications - Cognitive Radio Series*, October 2012 (JCR: 3.413).
4. T. Chen, M. Matinmikko, J. Del Ser, J. Zhang, "Energy Efficient Spectrum Access in Cognitive Wireless Access Networks", *Journal of Green Engineering*, Vol. 2, Issue 4, July 2012.
5. J. Del Ser, M. Matinmikko, S. Salcedo-Sanz, J. A. Portilla-Figueras, "Dandelion-encoded Heuristics for Joint Power, Spectrum and Topology Optimization in Operator-Governed Networks under Opportunistic Traffic Offloading", to be submitted to *Expert Systems with Applications*, May 2013 (JCR: 2.203).

International conference proceedings:

1. M. Matinmikko, M. Mustonen, T. Rauma, J. Del Ser, "Decision-Making System for Obtaining Spectrum Availability Information in Opportunistic Networks", *International Conference on Cognitive Radio and Advanced Spectrum Management* (CogART), 2011.

2. J. Del Ser, M. N. Bilbao, S. Gil-López, M. Matinmikko, S. Salcedo-Sanz, "Resource Allocation in Rate-limited OFDMA Systems: A Hybrid Heuristic Approach", *IEEE/ITG Workshop on Smart Antennas*, pp. 1–5, Aachen, Germany, February 2011.
3. M. Matinmikko, T. Rauma, M. Mustonen, J. Del Ser, "Architecture and Approach for Obtaining Spectrum Availability Information", *IEEE Vehicular Technology Conference* (Spring), pp. 1–5, Budapest, Hungary, May 2011.
4. J. Del Ser, M. Matinmikko, S. Gil-López, M. Mustonen, "A Novel Harmony Search based Spectrum Allocation Technique for Cognitive Radio Networks", *IEEE International Symposium on Wireless Communication Systems* (ISWCS), pp. 233–237, York, UK, September 2010.

Besides the above publications strictly related to this Thesis, other studies have been carried out in parallel, yielding the following list of scientific outcomes, most of which share the same computational basis as the one underneath this Thesis: the application of meta-heuristic and other Soft Computing techniques to problems arising in diverse disciplines and fields:

Patents:

1. S. Salcedo-Sanz, C. Casanova Mateo, J. A. Portilla-Figueras, S. Gil-López, J. Del Ser, "Dispositivo y Método de Predicción de Heladas y Nieblas Locales basado en Computación Neuronal con Selección de Características", *Spanish Patent Application* #P201130514 (March 2011).
2. D. Dominguez Bonini, M. Campo, B. Perez, M. Sánchez, J. Del Ser, P. Prieto, "Transceiver System for UHF-TV Channel Operation", *European Patent application* #10382165.8 (June 2010).

Editorials:

1. P. Chatzimisios, C. Verikoukis, I. Santamaria, M. Laddomada, J. Del Ser, O. Hoffmann, "Editorial: Recent Advances in Mobile Lightweight Wireless Systems", *EURASIP Journal on Wireless Communications and Networking*, to appear, 2013 (JCR: 0.87).
2. S. Gil-López, S. Salcedo-Sanz, J. Del Ser, "Editorial: Soft Computing Approaches for the Design of Wireless Communications Systems", *Applied Soft Computing*, January 2012 (JCR: 2.612).

Books and book chapters:

1. J. Del Ser, "Recent Advances on Meta-Heuristics and Their Application to Real Scenarios", Intech Publishers, ISBN: 978-953-51-0913-6, 2013.
2. J. Del Ser, "Recent Advances on Video Coding", Intech Publishers, ISBN: 978-953-51-0913-6, 2011.
3. I. Unanue, I. Urteaga, J. Del Ser, R. Husemann, V. Roesler, A. Rodriguez, P. Sánchez, "A Tutorial on H.264/SVC Scalable Video Coding and Its Tradeoff between Quality, Coding Efficiency and Performance", contributed chapter to the book entitled "Recent Advances on Video Coding", Intech Publishers, ISBN: 978-953-307-1404-0, 2011.

4. J. Del Ser, M. Mendicute, P. M. Crespo, S. Gil-López, I. Olabarrieta, "Joint Source-Channel-Network Decoding and Blind Estimation of Correlated Sensors using Concatenated Zigzag Codes", *Springer Lecture Notes in Computer Science*, Vol. 5793, pp. 30-41, ISBN: 978-3-642-04382-6, 2009.
5. J. Del Ser, J. García-Frías, D. Manjarres, P. M. Crespo, I. Olabarrieta, "Single LDGM Codes for Iterative Data Fusion over the Multiple Access Channel", 3rd *International Workshop on Multiple Access Communications* (MACOM), published in *Springer Lecture Notes in Computer Science*, Volume 6235/2010, pp. 47–57, 2010.
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Articles in refereed international journals:

1. H. Sarvanko, M. Matinmikko, J. Del Ser, M. Mustonen, "Spectrum Band and Channel Selection Scheme for Multi-RAT Systems with Heterogeneous Traffic", submitted to *Transactions on Emerging Telecommunications Technologies*, January 2013 (JCR: 0.454).
2. U. Kretzschmar, A. Astarloa, J. Jiménez, M. Garay, J. Del Ser, "Compact and Fast Fault Injection System for Robustness Measurements on SRAM Based FPGAs", submitted to *IEEE Transactions on Industrial Electronics*, November 2012 (JCR: 5.16).
3. D. Manjarrés, I. Landa-Torres, S. Gil-López, J. Del Ser, M. N. Bilbao, S. Salcedo-Sanz, Z. W. Geem, "A Survey on Applications of the Harmony Search Algorithm", submitted for its publication in *Engineering Applications of Artificial Intelligence*, November 2012 (JCR: 1.665).
4. M. Hernáez, P. M. Crespo, J. Del Ser, "A Decode-and-Forward Scheme for Multihop Wireless Networks", submitted to *IEEE Wireless Communication Letters*, March 2013.
5. M. N. Bilbao, S. Gil-López, J. Del Ser, S. Salcedo-Sanz, M. Sánchez-Ponte, A. Arana-Castro, "Novel Hybrid Heuristics for an Extension of the Dynamic Relay Deployment Problem over Disaster Areas", submitted to *TOP*, May 2012 (JCR: 0.765).
6. S. Salcedo-Sanz, L. E. Agustín-Blas, A. Portilla-Figueras, J. Del Ser, L. Cuadra, "A Novel Grouping Genetic Algorithm for Fuzzy Clustering Problems", submitted to *Fuzzy Optimization and Decision Making*, January 2012 (JCR: 1.488).
7. S. Salcedo-Sanz, A. Pastor-Sánchez, D. Manjarrés, J. Del Ser, J. A. Portilla-Figueras, S. Gil-López, "Optimum One-way Urban Traffic Reconfiguration using a Multi-Objective Harmony Search Approach", *Expert Systems with Applications*, accepted, in press, corrected proof, Available online 29 December 2012 (JCR: 2.203).
8. I. Landa-Torres, D. Manjarrés, S. Salcedo-Sanz, J. Del Ser, S. Gil-López, "A Multi-objective Grouping Harmony Search Algorithm for the Optimal Distribution of 24-hour Medical Emergency Units", *Expert Systems with Applications*, Vol. 40, N. 6, pp. 2343–2349, May 2013 (JCR: 2.203).
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12. S. P. Shariatpanahi, B. H. Khalaj, H. Shah-Mansouri, J. Del Ser, "Analysis of Quantization Effects on the Performance of Cooperative MIMO Techniques in Wireless Networks", *EURASIP Journal on Wireless Communications and Networking* 2012, 2012:290, September 2012 (JCR: 0.87).
13. S. Gil-López, J. Del Ser, S. Salcedo-Sanz, A. M. Pérez-Bellido, J. M. Cabero and J. A. Portilla-Figueras, "A Hybrid Harmony Search Algorithm for the Spread Spectrum Radar Polyphase Codes Design Problem", *Expert Systems with Applications*, Volume 39, Issue 12, pp. 11089–11093, September 2012 (JCR: 2.203).
14. I. Landa-Torres, J. Del Ser, S. Salcedo-Sanz, S. Gil-López, J. A. Portilla-Figueras, O. Alonso-Garrido, "A Comparative Study of Two Hybrid Grouping Evolutionary Techniques for the Capacitated P-median Problem", *Computers & Operations Research*, Vol. 39, N. 9, pp. 2214–2222, September 2012 (JCR: 1.720).
15. L. E. Agustin-Blas, S. Salcedo-Sanz, S. Jiménez-Fernández, L. Carro-Calvo, J. Del Ser, J. A. Portilla-Figueras, "A New Grouping Genetic Algorithm for Clustering Problems", *Expert Systems with Applications*, vol. 39, no. 10, pp. 9695–9703, August 2012 (JCR: 2.203).
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17. I. Landa-Torres, S. Gil-López, J. Del Ser, S. Salcedo-Sanz, D. Manjarrés, J. A. Portilla-Figueras, "Efficient Citywide Planning of Open WiFi Access Networks using Novel Grouping Harmony Search Heuristics", *Engineering Applications of Artificial Intelligence*, in press, June 2012 (JCR: 1.665).
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2. S. Salcedo-Sanz, J. Del Ser, S. Gil-López, I. Landa-Torres, J. A. Portilla-Figueras, "The Coral Reefs Optimization Algorithm: Simulating a Reef Formation for Solving Hard Optimization Problems", *International Conference on Applied Stochastic Models and Data Analysis*, Mataró, Spain, June 2013.
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4. M. N. Bilbao, D. Gallo-Marazuela, S. Salcedo-Sanz, J. Del Ser, C. Casanova-Mateo, "A Meta-Heuristic Approach for the Optimal Deployment of Aerial Firefighting Fleets based on Predictive Fire Risk Estimations", *International Conference on Applied Stochastic Models and Data Analysis*, Mataró, Spain, June 2013.
5. U. Kretzschmar, A. Astarloa, J. Lázaro, M. Garay, J. Del Ser, "Robustness of Different TMR Granularities in Shared Wishbone Architectures on SRAM FPGA", emphInternational Conference on ReConFigurable Computing and FPGAs (ReConFig), Cancún, Mexico, December 2012.

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