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THEME

Optimisation de l'Utilisation du Spectre par les Techniques de la Radio Cognitive dans les Systèmes de Communication Sans Fil

By
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DEDICATION

I dedicate the fruit of this modest work and all the efforts made in order to accomplish it

To our master and the greatest teacher our prophet Muhammad "peace be upon him".

To my dear parents, for their unconditional love, support, and guidance in all my study paths "God bless them"

I hope that their dream was achieved.

To my brothers and sisters who were supportive and gave me the strength to go ahead.

Sayhia Tidjani

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Abstract— *The major challenge in the new emerging technologies like IoT and 5G is the obtention of available and enough spectrum resources for their transmissions. Hence, it becomes necessary to optimize the actual spectrum utilization that is relying on the static spectrum allocation, by introducing the dynamic attribution of this scarce resource. CRNs are expected to tackle this issue by enabling the coexistence of secondary users with primary users via heterogeneous wireless architectures and dynamic spectrum access techniques. In this work, two main CR aspects are studied and evaluated. First, spectrum observatory and real database collection were performed to recognize the spectrum behavior and investigate the spectrum availability, for the integration of CR opportunistic networks. These measurements were achieved in cooperation with the ANF- Algeria, between January and February 2020, in two areas, one urban in the North in Constantine, and another rural in the south in Ouargla. The results of these measurement campaigns reveal low resource occupancy, lower than 30.27%, by comparing the occupied instants of each frequency band to its total number of samples, for both areas. In another hand, the impact of the spectrum observatory on the spectrum management strategy preferences is studied. Second, a low complexity spectrum prediction and preallocation system based on an optimized NN model for CR-IoT users is presented. The Bayesian Optimization algorithm was used for the optimization and evaluation of two NN prediction architectures, which are trained on a real spectral occupancy dataset, then compared. Very efficient results have been obtained, high prediction accuracy of 93.5%, a regression coefficient of 0.98, and a reduced MSE of 0.0013. Results show that the considered scheme is efficient in predicting the occupancy rates of different bands within the IoT spectrum resources.*

Keywords— *Bayesian Optimization; Cognitive Radio; Cognitive Radio Internet of Things; Measurement Campaign; Occupancy statistics; Spectrum Management; Spectrum Observatory; spectrum prediction; TDNN & NARX.*

ملخص — يتمثل التحدي الرئيسي في التقنيات الناشئة الجديدة مثل إنترنت الأشياء والجيل الخامس في الحصول على موارد طيف متاحة وكافية لعمليات الإرسال الخاصة بها. ومن هنا، يصبح من الضروري تحسين الاستخدام الحالي للطيف الذي يعتمد على التوزيع الثابت للطيف، من خلال إدخال الإسناد الديناميكي لهذا المورد النادر. حيث يُنْتَظَر من ال CRNs معالجة هذه المشكلة من خلال تمكين التعايش بين SUs مع PUs عبر البنى اللاسلكية غير المتجانسة وتقنيات الوصول الديناميكي إلى الطيف. في هذا العمل، تمت دراسة وتقييم جانبين رئيسيين من جوانب ال CR. أولاً، تم إجراء مرصد الطيف و جمع قواعد البيانات الحقيقية للتعرف على سلوك الطيف والتحقق من مدى توفر الطيف ، من أجل إنشاء شبكات CR الانتهازية .تمت هذه القياسات بالتعاون مع الوكالة الوطنية للترددات، بين شهري جانفي و فيفري 2020، في منطقتين، واحدة حضرية في الشمال في قسنطينة، وأخرى ريفية في الجنوب في ورقلة. تكشف نتائج حملات القياس هذه عن استعمال منخفض للموارد الراديوية، أقل من 30.27٪، بمقارنة اللحظات المشغولة لكل نطاق تردد بإجمالي عدد عيناته، لكلا المنطقتين. ومن ناحية أخرى، تمت دراسة تأثير مرصد الطيف على إعدادات إستراتيجية إدارة الطيف. ثانيًا، يتم تقديم نظام تنبؤ بالطيف منخفض التعقيد ونظام للتخصيص المسبق بناءً على نموذج NN محسن لمستخدمي CR-IoT. تم استخدام خوارزمية BO لتحسين وتقييم تصميمي NN للتنبؤ ، والتي يتم تدريبها على مجموعة بيانات إشغال طيفي حقيقية ، ثم مقارنتها. تم الحصول على نتائج جد فعالة ودقة تنبؤ عالية بلغت 93.5٪ ومعامل انحدار 0.98 و MSE منخفض قدره 0.0013. تظهر النتائج أن التصميم المدروس فعال في التنبؤ بمعدلات شغل النطاقات المختلفة داخل موارد طيف إنترنت الأشياء.

الكلمات المفتاحية — BO ؛ الراديو المعرفي؛ راديو إنترنت الأشياء المعرفي ؛ حملة القياس؛ إحصاءات الاستعمال ؛ إدارة الطيف؛ مرصد الطيف؛ التنبؤ بالطيف؛ TDNN و NARX.

Résumé— *Le défi majeur des nouvelles technologies émergentes comme l'IoT et la 5G est l'obtention de ressources spectrales disponibles et suffisantes pour leurs transmissions. Par conséquent, il devient nécessaire d'optimiser l'utilisation actuelle du spectre qui repose sur l'attribution statique du spectre, en introduisant l'attribution dynamique de cette ressource rare. Les CRN sont envisagés pour résoudre ce problème en permettant la coexistence des utilisateurs secondaires avec les utilisateurs primaires via des architectures sans fil hétérogènes et des techniques d'accès dynamique au spectre. Dans ce travail, deux aspects principaux de la RC sont étudiés et évalués. Tout d'abord, une scrutation du spectre et une collecte de bases de données réelles ont été réalisées pour reconnaître le comportement du spectre et étudier la disponibilité du spectre, pour l'intégration de réseaux opportunistes de la RC. Ces mesures ont été réalisées en coopération avec l'ANF, entre janvier et février 2020, dans deux zones, l'une urbaine au Nord à Constantine, et l'autre rurale au Sud à Ouargla. Les résultats de ces campagnes de mesures révèlent une faible occupation des ressources spectrales, inférieure à 30,27 %, en comparant les instants occupés de chaque bande de fréquence à son nombre total d'échantillons, pour les deux zones. D'autre part, l'impact du scrutation du spectre sur les préférences en matière de stratégie de gestion du spectre est étudiée. Deuxièmement, un système de prédiction et de préallocation de spectre de faible complexité basé sur un modèle NN optimisé, pour les utilisateurs CR-IoT est présenté. L'algorithme d'Optimisation Bayésienne a été utilisé pour l'optimisation et l'évaluation de deux architectures de prédiction NN, qui sont entraînées sur un ensemble de données d'occupation spectrale réelle, puis comparées. Des résultats très efficaces ont été obtenus, un taux de prédiction élevé de 93,5 %, un coefficient de régression de 0,98 et une MSE réduite de 0,0013. Les résultats montrent que le schéma considéré est efficace pour prédire les taux d'occupation des différentes bandes au sein des ressources spectrales de l'IoT.*

Mots clés— *Optimisation Bayésienne; Radio cognitive; Radio cognitive Internet des objets ; Campagne de mesures; Statistiques d'occupation; Gestion du spectre ; Scrutation du spectre ; Prédiction du spectre ; TDNN et NARX.*

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List of Abbreviations

2D-FPM	2D Frequent Pattern Mining Algorithm
3GPP	3G Partnership Project
AI	Artificial Intelligence
ACF	Autocorrelation Function
ANN	Artificial Neural Network
AR	Autoregressive
ARMA	Auto Regressive Moving Average
ARIMA	Auto-Regressive Integrated Moving Average model
API	Application Programming Interfaces
AWGN	Additive White Gaussian Noise
BIF	Bayesian Inference
BPNN	Backpropagation Neural Network
CE	Cognitive Engine
CR	Cognitive Radio
CRN	Cognitive Radio Network
CSI	Channel State Information
CUP	Cognitive Users with Prediction capability
DECT	Digital Enhanced Cordless Telecommunications
DDCA	Distributed Dynamic Channel Assignment
DLA	Deep Learning Algorithms
DNN	Deep Neural Network
DSA	Dynamic Spectrum Access
DSP	Digital Signal Processor
DVB-T	Digital Video Broadcast-Terrestrial
ITU	International Telecommunication Union
ED	Energy Detection
EM	Expectation Maximization
EMA	Exponential Moving Average
ERNN	Elman Recurrent Neural Network
EWMA	Exponential Weighted Moving Average
FC	Fusion Center
FCC	Federal Communications Commission
FEC	Forward Error Correction
FFT	Fast Fourier Transform
FH	Frequency Hopping
FMS	Frequency Monitor System
FS	Fixed-link Service
FPGA	Field-Programmable Gate Arrays
GA	Genetic Algorithm
GPP	General-Purpose Processors
HBMM	Hidden Bivariate Markov Model
HMM	Hidden Markov Model
IoT	Internet of Things
IUT	International Union of Telecommunications

LCSS	Low-Cost Spectrum Sensors
LM	Levenberg-Marquardt
LMR	Land Mobile Radio
LP	Linear Prediction
LPs	Local Predictors
LSTM	Long Short-Term Memory
MA	Moving Average
MF	Matched Filter
ML	Machine Learning
MLPN	Multi-layer Linear Perceptron Network
MMP	Markov Model Prediction
M2M	Machine to Machine
MS	Mobile Service
MSE	Mean Squared Error
NSHMM	Non-Stationary Hidden Markov Model
OFDMA	Orthogonal Frequency Division Multiple Access
PMP	Pattern Mining Prediction
POMDP	Partially Observable Markov Decision Process
PU	Primary User
QoS	Quality of Service
RBW	Resolution Bandwidth
RF	Radio Frequency
RMSRE	Root-Mean-Squared Relative Error
RNN	Recurrent Neural Network
SCC	Squared Correlation Coefficient
SA	Spectrum allocation
SDR	Software Defined Radio
SG	Smart Grid
SGCN	Smart Grid Communication Network
SNR	Signal To Noise Ratio
SO	Spectrum Occupancy
SU	Secondary User
SVM	Support Vector Machine
SS	Spectrum Sensing
UWB	Ultra-Wide-Band
UAVs	Unmanned Aerial Vehicles
VMM	Variable Length Markov Model
WLAN	Wireless Local Area Network
TH	Time Hopping
$\boldsymbol{H_0}$	is a null hypothesis
$\boldsymbol{H_1}$	is an alternative hypothesis that indicates the presence of the PU
$\boldsymbol{h}$	is the amplitude gain of the channel
$\boldsymbol{\sigma^2}$	Variance of the additive white gaussian noise
$\boldsymbol{T_n}$	is the symbol time duration.
$\boldsymbol{\tau}$	is the shift in the known signal.
$\boldsymbol{T_{MFD}}$	The test statistic of the MF detector
$\boldsymbol{\lambda_{\mathrm{MFD}}}$	Threshold of the MF detector
$\boldsymbol{T_{ED}}$	The test statistic of the energy detector

$\boldsymbol{\lambda_{ED}}$	Threshold of the energy detector
N_0	the time period of the received signal $Y[t]$
δ	cyclic frequency
$\boldsymbol{R_y^{\delta}(\tau)}$	represents the Autocorrelation Function
$m_y(n)$	the mean of $Y[t]$
P_{rx}	is the received signal power
$\boldsymbol{P_r}$	s the radiated signal powe

INTRODUCTION

Introduction

A. Overview

In the near future, significant growth in connected and wireless devices is expected; due to the emergence and the fast development of new technologies and applications, such as the Internet of Things (IoT), 5G, 6G, vehicular networks, sensor networks, smart grid control networks, and medical wearable and embedded wireless devices. Hereby, increasing demand for unlicensed bandwidth is fateful.

Conventional wireless paradigms are characterized by static spectrum allocation policies, where governmental agencies assign spectrum to licensed holders on a long-term basis and for large geographical regions. Cognitive Radio Networks (CRNs) are envisioned to change this trend by enabling the coexistence of unlicensed secondary users (SUs) and licensed primary users (PUs), via heterogeneous wireless architectures and dynamic spectrum access techniques [1].

Radio frequency Spectrum, as a natural resource is finite, and it is continuously in shortage due to the intervention of several factors:

1) The irreversible proliferation of wireless communication norms and standards;
2) The multiplication in the number of communication systems and technologies;
3) The increasing number of users and wireless devices;
4) The growing and competing demand for bandwidth.

All these factors are aggravated by the fixed spectrum allocation policy that attributes a static frequency band for every communication norm (GSM, 3G, LTE, WIFI, TV band, …). Hence, they all lead to a scarcity of available radio resources.

Looking at the current spectrum allocation chart, the spectrum seems full and it cannot support upcoming volumes of wireless devices and mobile data traffic (see Figure 1). However, later studies have revealed that a large range of the spectrum is idle (not occupied all the time or anywhere). Moreover, a study carried out by the Federal Communications Commission (FCC) has found that the use of frequency spectrum is not uniform according to the hours of the day and the geographical position; some frequency bands can be overloaded while others remain unused [2].

As a result, we can say that the problem is the utilization efficiency of the spectrum and not the scarcity of the spectrum.

Therefore, spectrum utilization needs to be intelligently managed and dynamically attributed for maximum benefits, hence the idea of CR.

According to the FCC, a cognitive radio is "***a radio that can change its transmitter parameters based on the environment in which it operates***". Such a radio automatically detects available channels in the spectrum, then accordingly changes its transmission or reception parameters to accommodate more concurrent wireless systems in one band, and in a specific location.

Moreover, a CR engine is that can be programmed and configured dynamically in order to exploit the best wireless channels (free or underutilized, suitable characteristics) in its vicinity for its transmissions, to prevent interference with licensed users, and spectrum congestion.

CR is the technology that allows the dynamic spectrum management of radio resources, opportunistic and dynamic spectrum access, high data rate transmissions, and high-speed internet and multimedia services, ... The CR intelligent system is the solution to treat the actual problem of spectrum scarcity or in other words, the spectrum inefficient utilization problem.

A CR user should, first, be aware of its surrounding radio users (PUs), in addition to their spectrum activity, access mode, and wave propagation characteristics. Second, it is claimed to have prior knowledge about the geographical location radio characteristics, and its relevant occupancy statistics. This process is known as awareness, and it is achievable via the sensing operation.

Besides, CR devices have the capability to exploit one or more spectrum dimensions by sensing the available opportunities in frequency, time, code, angle, or space.

B. Thesis issue

As we deduced before, the real problem that stands against the deployment of the new wireless systems, and the improvement of internet speed and transmission data rates, is not, really, the spectrum scarcity but in fact, it is the way of using this precious resource.

Accordingly, this thesis attempts to solve the following problem:

How can we optimize the utilization of spectrum resources using cognitive radio techniques for wireless communication systems?

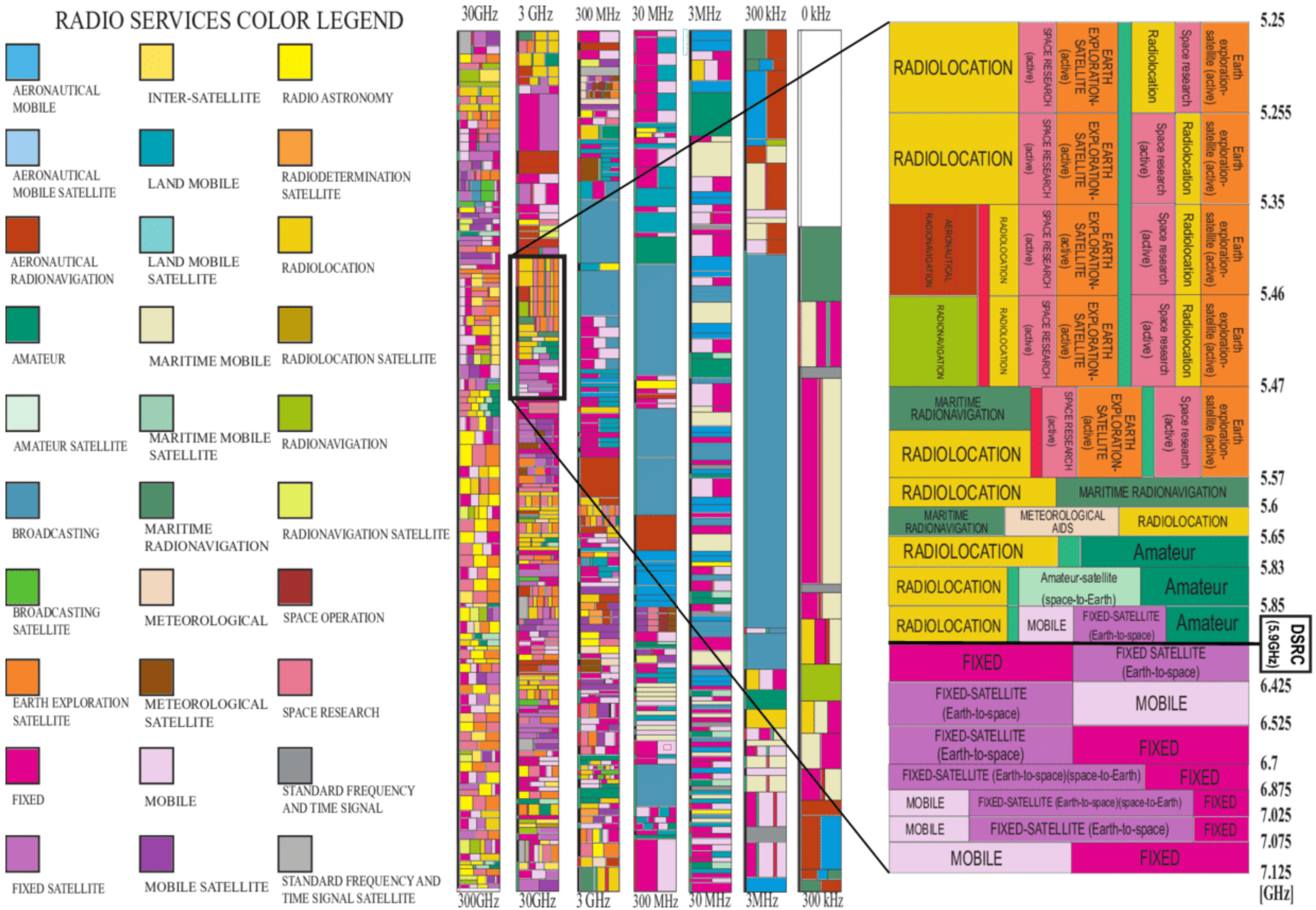


Figure 1. Example of Static spectrum allocation [3].

C. Hypotheses

In order to solve the problem of this work, we should investigate the following proposals/hypotheses:

Hypothesis 1:

All of the relevant spectrum surveys around the world stated that the spectrum is not fully utilized and that only around 30% of spectrum resources were effectively occupied.

Hence, we propose this hypothesis: “The occupancy percentage of the radio spectrum in Algeria is similar to that in other parts of the world”

Hypothesis 2:

Spectrum observatory procedure and setup parameters can affect the whole spectrum management system.

Hypothesis 3:

Spectrum prediction is one of the core CR functions, which participates in the optimization of spectrum utilization in wireless communication systems. In the literature, many prediction methods, like the Markov model, SVM, linear prediction methods, …, and machine learning, have been applied and evaluated.

Neural networks (NNs) have approved their major capabilities in many tasks related to learning from examples, parameters adaptation and modeling, decision making, and prediction. Therefore, it is the best choice for solving the spectrum prediction issue in CRNs.

D. Proposed workflow

To prove the previously presented hypothesis, and to solve the core problem of this thesis, we propose the following workflow. Where we emphasized on sensing and prediction functions for this.

a. Database collection and statistical analysis

In the aim of collecting a real spectrum occupancy database, we launched two measurement campaigns in two locations in Algeria. One urban in the north in Constantine, and another rural located in the south in Ouargla. The spectrum observatory was in cooperation with the “Agence Nationale des Fréquences” (ANF) – Algeria.

The measurements are performed over the mobile communication frequency bands (2G, 3G, 4G), and the DVB-T (digital television) band.

We provide detailed statistics (numerical and graphical results), and we calculate the overall occupancy rates of the selected spectrum bands, of both areas. Then, we study the impact of spectrum observatory parameters on the management strategy preferences.

The objective of these measurement campaigns is first, to investigate the spectrum occupancy in specific areas in Algeria. Second, to validate our hypothesis about the occupancy rates and the Primary Users (PUs) spectral behavior in Algeria. Third, to show the importance of a spectrum observatory over a spectrum management strategy.

b. Proposed prediction algorithm

The key CR specific feature that made it act as anticipated, is its prior knowledge of the spectrum occupancy status. This prior knowledge can be ensured via the spectrum prediction function.

In this thesis, we emphasize on this function for the optimization of spectrum utilization for CR-IoT devices and also the new wireless communication systems. We propose an NN-based spectrum predictor, and study the forecasting performances of this last, then compare it with other networks and relevant works. The simulation results are presented in chapter 4.

E. Study challenges

Nevertheless, we encountered several challenges both before and after the data collection. Where in order to continue the measurement campaigns, we had to get authorization from the general direction of the ANF Algeria, and this process took us two years to get the required permission. Additionally, after the setup of the measurement tasks, we faced a problem in the extraction of the data. The “Scorpio” integrated software produces very long (extended) data files in Rich Text Format (.rtf) formats only, which is not functional. Therefore, we had to convert hundreds of very long RTF files to excel format in order to exploit them in the preparation and preprocessing of the dataset using MATLAB.

From another hand, the training of multiple NN structures is a delicate process, and it needs enormous time to get the results, especially using an optimization algorithm. This is why we required a high processing and capacity workstation to get the target results. However, we were obliged to reduce the training dataset and the optimization time to be able to perform the required simulations.

F. Originality of the thesis

This thesis includes three original axes;

- *Originality of the proposed thematic:* Cognitive radio as a promising technology for the future wireless communication systems is a new concept and initially studied in in the Telecommunication field in Algeria via this work.
- *Originality of the collected data:* spectrum occupancy measurement and statistics are the first of their kind in Algeria, and had not been studied before.
- *Originality of the proposed prediction method:* the proposed NN predictors are multichannel multidimensional, low complexity, and optimized spectrum prediction algorithms.

G. The software employed in this thesis

- *Scorpio:* employed for programing the measurement tasks, setting up the sampling parameters, data arranging, and data files extraction (".rtf" format).
- *Matlab:* used for data preparation and preprocessing, acquisition of statistical and graphical results, NN predictors programming and training, and the training of the optimization algorithm.

H. Thesis Organization

This thesis is composed of four chapters; the first chapter presents the state of the art for both the "spectrum measurement" and the "spectrum prediction methods in CRNs". Chapter 2 provides the main definitions of the CR concept, its main functions, and its applications. In another hand, the third chapter illustrates the spectrum measurement campaigns, the employed equipment and software, the database collection, and statistical results, and studies the effect of the measurement parameters over spectrum management strategy choices. Chapter 4 presents our proposed prediction algorithm, simulation results, discussion of the obtained results, and comparison with the state of the art. Finally, a summary of our solutions, contributions, and perspectives is presented in the conclusion.

CHAPTER 1

State of the art

Sections

1. ***INTRODUCTION***
2. ***SPECTRUM OCCUPANCY MEASUREMENTS STATE OF THE ART***
3. ***SPECTRUM PREDICTION STATE OF THE ART***
4. ***CONCLUSION***

Abstract- *The optimization of spectrum utilization using cognitive radio (CR) methods is one of the actual issues which takes a lot of attention through the latest research issues to overcome the spectrum scarcity problem. Spectrum occupancy measurement is the first step to recognize the spectrum behavior and to identify frequency bands that can be invested in the integration of new wireless CR opportunistic networks. Spectrum prediction is one of the most important CR functions to predict the channel state information. It is considered an effective way to reduce processing latency and energy consumption, manage spectrum access, and avoid spectrum collisions between licensed and unlicensed users. Spectral prediction methods are meanly divided into five categories, Pattern mining prediction, Bayesian-Inference, linear prediction methods, prediction methods based on the Markov model, and prediction methods based on Machine learning. This chapter will provide a review of the spectrum measurement's related works, in addition to an updated survey on the main spectrum prediction methods in Cognitive Radio Networks.*

Keywords- *Cognitive Radio; Linear Prediction; Machine learning; Markov Model; Measurement Campaigns; Pattern mining prediction; Spectrum Occupancy Measurements; Spectrum Prediction.*

1.1. Introduction

1.1.1. Background and Motivation

Before affirming the full-occupancy of the spectrum bands, and before heading to the application of new technologies such as 5G, and IoT in higher working frequencies, which is; costly, frequency waves are easily-interfered and short distances traveling, and mainly they are harmful to human bodies, …; it is important to know to what extent the licensed bands are temporally occupied.

In order to investigate the real spectrum occupancy rate, meaningful data about spectrum usage should be gathered via quantitative spectrum measurements. Spectrum measurements provide a detailed analysis of the radio environment in a specific area, they are defined as an empirical data collection conducted for specific scenarios (indoor/outdoor) to collect spectrum occupancy samples on pre-selected frequency bands [4]. Measurement campaigns give valuable information to regulators about the efficiency of the current use of the spectrum allocations [5]. The captured spectral, spatial, and temporal dependencies along with the utilization rates of frequency bands are statistically estimated, analyzed, and categorized to be invested in the proposition of new spectrum management and dynamic resource allocation strategies, which are useful in the incoming wireless communication systems that consider Cognitive Radio Dynamic Spectrum Access (CR-DSA) techniques.

Cognitive Radio is the promising technology for future wireless networks. Through its new and efficient functionalities of opportunistic access and intelligent management of radio resources, CR can solve the actual problem of spectrum scarcity. One of the main issues of CR is spectrum prediction, which is added to this engine to ensure a good Quality of Service (QoS) with safe access for Secondary Users (SUs), far from Primary Users' interferences caused by spectrum sensing delays, processing, and decision-making delays. Thus, spectrum prediction can be defined as the most feasible method for the integration of SUs. The goal of which is to forecast the channel state information by giving advanced results about channel occupancy (busy or free). Therefore, ideal exploitation of spectrum holes [6].

1.1.2. Chapter Organization

This chapter presents the state of the art of the two crucial issues of this thesis, which are spectrum occupancy measurements, and spectrum prediction in CR Networks (CRNs). Thereby, this chapter is addressing the literature review of some important long-term and short-term spectrum measurement campaigns, in addition to the relevant works regarding spectrum prediction algorithms that have been applied in CRNs. A conclusion that outlines the importance of spectrum monitoring in CRNs, highlights prediction-related issues, and discusses some perspectives, is provided in the last section.

1.2. Spectrum Occupancy Measurements State of the Art

A deep quantitative and comprehensive spectrum measurement study is an axial process required for the efficient deployment of a CRN. It quantifies and models the spectral activity of Primary Users (PUs) and categorizes frequency bands according to their occupancy rates. Moreover, it provides a detailed comprehension of the spectrum evolution in the three basic dimensions, (time, frequency, and space), in addition to the definition and classification of the spectrum opportunities in these dimensions.

In the literature, many studies have been done in this context [7]. They are divided into two categories, one for long-term spectrum measurements and another for short-term. Indeed, an efficient measurement campaign requires the provision of adequate material and software, in addition to a precise preparation of the measurement proceeding that should correspond to the International Union of Telecommunications (IUT)' spectrum monitoring regulations and answers to the geographical location characteristics of the area under test. The purpose of the measurement is to find how the scarce radio spectrum allocated to different services is utilized in a specific area and identify the bands that could be accessed for future opportunistic use due to their low or no active utilization.

1.2.1. Spectrum Measurements Regulations and Challenges

To determine the spectrum utilization and the potential for exploitation by Cognitive Radio technology, several important criteria must be considered including [8]:

A. Spectrum Band Characteristics

Every service operating band has its own application and its specific signal characteristics like modulation scheme; signal polarization; signal transmit power; Power Spectral Density (PSD) parameters (Variance, mean, amplitude); spatial characteristics of the signal; signal duration; resolution bandwidth (exp: 200kHz for GSM band, and 15kHz for the fourth-generation band); threshold; …. However, a measurement over a service band should consider these characteristics to have meaningful occupancy results.

B. Measurement System

The acquisition of accurate occupancy samples relies on the utilization of suitable measurement equipment that simulates all the spectrum monitoring conditions. Whereas surveying spectrum environment in a specific location requires omnidirectional or multidirectional broadband antennas to ensure the coverage of the whole area and the frequency range to be analyzed. A low noise amplifier for well signal detection and a low loss cable to prevent power loss. Additionally, the usage of a spectrum analyzer that has a frequency span within the surveyed spectrum band (UHF, VHF, SHF, …). This ensemble of devices is controlled via a computer and software designed specifically for the application [7]. Figure 1.1 shows the basic model of a spectrum occupancy measurement system. These components should be able to operate over a range of wide operating frequencies. Furthermore, high-speed processing units (Digital Signal Processors "DSPs") are needed for performing computationally demanding signal processing tasks with relatively low delay.

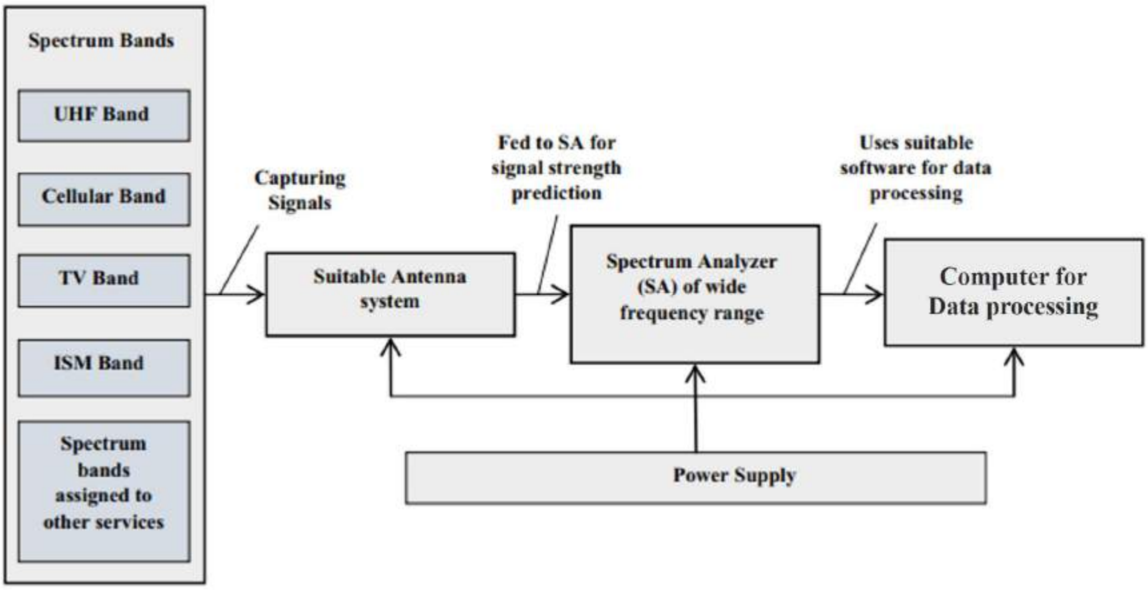


Figure 1.1. The basic model of spectrum occupancy measurement [7].

C. Localization Characteristics of the Surveyed Area

The previously cited criteria depend all on the area where the measurements will be performed. The nature of the area (urban, suburban, or rural); the position of the measurement system especially the antennas (indoor or outdoor, high or low altitude), the surrounding environment, if there are skyscrapers, high buildings, or natural obstacles (mountains, forests, …), or any sources of electromagnetic noise; the propagation space features (homogeneous or heterogeneous, selectivity, interferences, and signal mitigation); ...; and other characteristics are extremely important conditions for reliable spectrum observatory.

D. Sensing and Detection Tasks

- **Sensing method:** the selection of the sensing method is a critical issue; indeed, it depends on the measurement to be conducted, the available materials, the target advantages, and the avoidable/acceptable limitations. The simplest sensing method, from cost and complexity, utilized in most spectrum observatories around the world is Energy Detection (ED) method. It states that received signals with energy equal to or higher than a determined threshold are counted as active PUs, and vice versa, signals with energy less than that threshold are considered as spectrum holes which would be suitable for secondary usage [7].
- **Decision threshold:** the definition of the decision threshold is one of the most important tasks for spectrum sensing. Whereas it relies on the service band to be measured, the noise level in that band, and the radio environment characteristics in the area under investigation. The IUT has underlined a set of recommendations in this context stating the decision threshold to be from 5 dB to 10 dB above the noise level depending on the application.

1.2.2. Long-Term Spectrum Measurement Campaigns

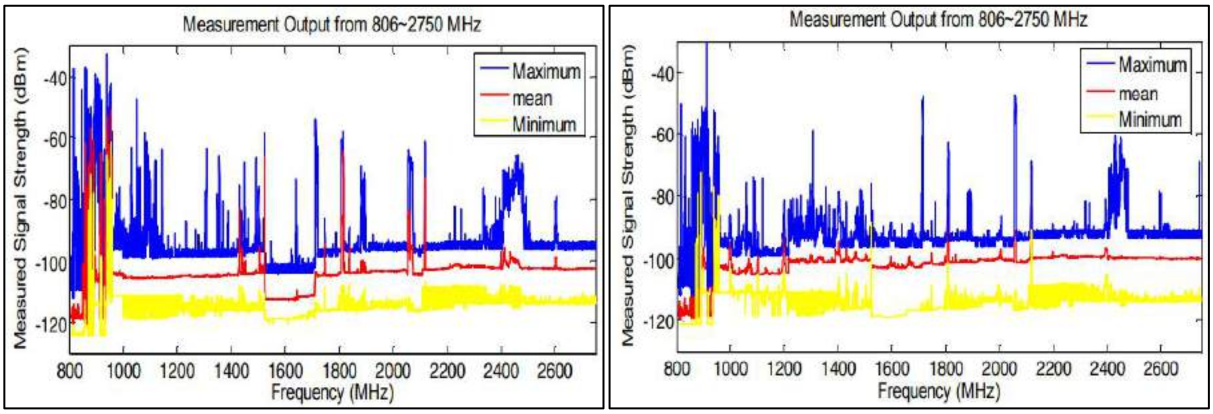
Long-term spectrum surveys are extended measurements that are achieved over months or even years. The goal of which is to accurately model the spectrum occupancy evolution at different times of the day, weekdays and weekends, holidays and special events, etc. [7], thus, realistic and accurate modeling of the investigated bands' activity. In addition, these works aim to inspect the radio environment to measure the real amount of spectrum being occupied by licensed users through the traditional fixed resource allocation policies, and to discover the spectrum white spaces and underused frequencies that must be reused appropriately. They believe that CR could bring significant gains in spectral usage. Future CR algorithms are expected to benefit from the findings of these studies for smart spectrum access, and intelligent sensing strategies. In the literature, a lot of long-term measurements have been done around the world. Below, some most cited measurement campaigns are presented.

A. New Zealand Long-Term Measurement Campaign

The New Zealand measurement campaign was conducted in 2007, over 12-weeks in outdoor and indoor environments in the Auckland urban city [9]. It covered the frequency span from 806MHz to 2750MHz. The measurement material included a dipole antenna (806 - 1000MHz) and a discone antenna (1000 - 2750MHz) connected to a Rohde & Schwarz ESVN40 Test Receiver, which was remotely controlled by a PC. The threshold was set to 5 dB above the mean noise power for each channel and the Resolution Bandwidth (RBW) to 120 kHz.

Based on the temporal occupancy of the spectrum, the authors in this study classified the spectral occupancy levels into three categories, namely black, grey, and white spaces. Statistical analysis of the measurement results indicated that the overall spectral usage in the (806 - 2750MHz) band is only about 6.2%, around 30% was for cellular Mobile Service (MS) bands that have had a significantly higher occupancy rate. Very little spectral activity has been recorded in the fixed link service (FS), radar, and satellite communications bands. A capture of the detected signal for the overall band is presented for each case, outdoor and indoor, in Figure 1.2.

The conclusion of this work was as follows, Point-to-point links and some mobile uplink channels are identified as the most probable candidates for future CR communications, and the authors proposed cooperative sensing as a perspective solution to mitigate various wireless channel effects.



(a) (b)

Figure 1.2. New Zealand spectrum occupancy measurement results (a) outdoor *and* (b) indoor [9].

B. Chicago Long-Term Measurement Campaign

Another long-term spectrum observatory was performed in Chicago at the Illinois Institute of Technology (IIT), which monitored the spectrum span from 30 to 6000 MHz for a unique duration of three years commencing from July 2007 [10]. In this work, three directional antennas connected to a pre-selector and a Rohde & Schwarz FSP-38 spectrum analyzer were employed, in addition to a computer that was controlling the entire operation. In order to acquire accurate sensing results, a dynamic threshold between 5 and 10 dB above the average noise floor has been opted. This paper also illustrated the noticeable effect in the (609 - 806 MHz) range due to the transition of TV band from analog to digital in 2009. Average occupancy over this entire band was found to be 18, 15, and 14 % for the years 2008, 2009, and 2010, respectively. Figure 1.3 shows the evolution of spectrum occupancy in the (450 - 465 MHz) land mobile radio (LMR) band for a period of around one year. In this figure, the authors indicated some special events (Thanksgiving and Holidays) to highlight the effect of these events on the PUs spectrum usage (usage intensity). In another hand, the estimated occupancy by band for 2010 is provided in Figure 1.4.

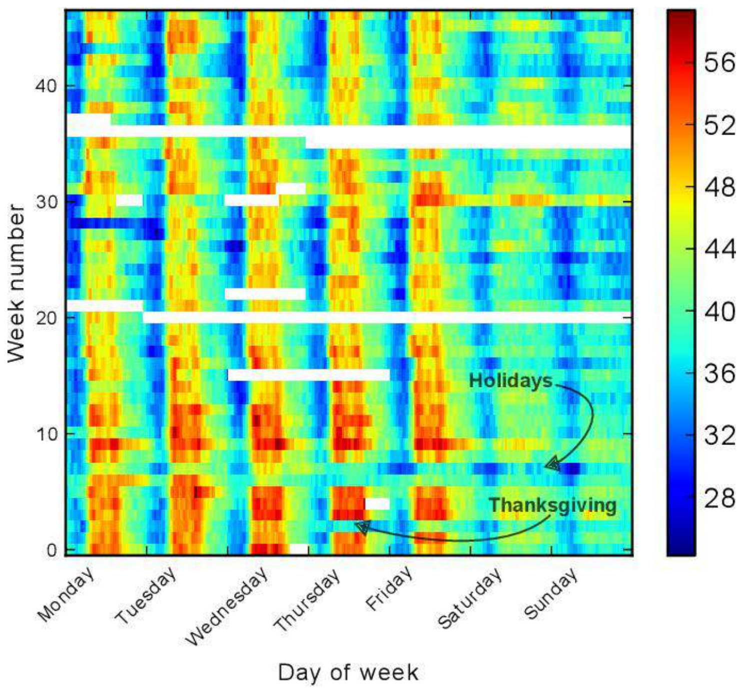


Figure 1.3. Week by week occupancy in the 450-465 MHz LMR band from November 9, 2008, to September 20, 2009 [10].

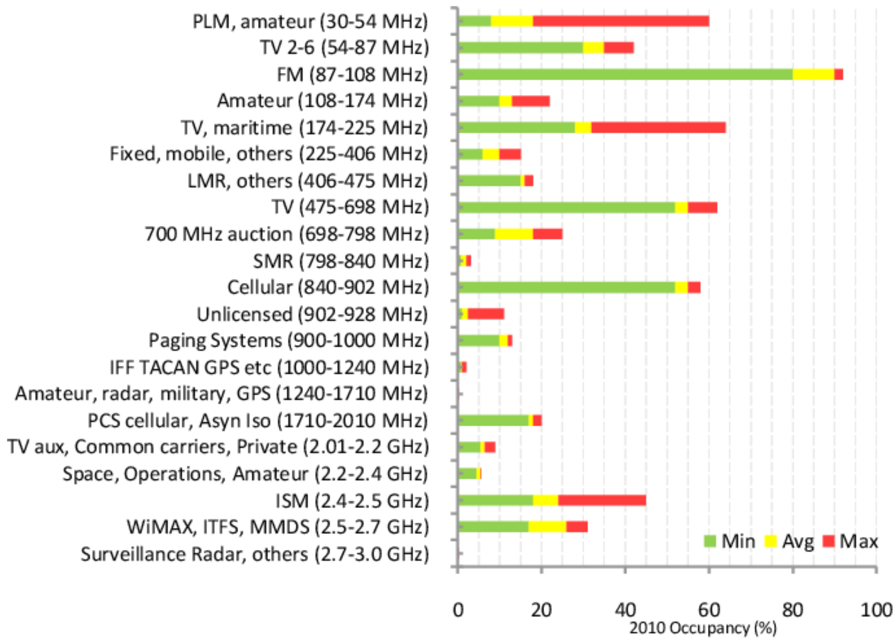


Figure 1.4. Estimated occupancy by band for 2010 (up to October). The average overall occupancy is 14% for 30-3000 MHz [10].

C. United Kingdom Long-Term Measurement Campaign

This study done by T. Harrold et al has been carried out in 2011, in Bristol, UK [11]. It surveys the indoor and outdoor spectrum occupancy via a set of long-term observations of six months in the range 300MHz – 4.9GHz. Two wideband discone antennas covering this range were used for signal capturing, connected to a spectrum analyzer with a 300kHz RBW for sampling, and a preamplifier to recover the signal attenuations, the system is illustrated in Figure 1.5. This work aims to inspect the short-term and long-term temporal variability of the channels' availability and to discover which channels might be suitable for CR use.

The spectrum occupancy results showed minimized activity overnight and at the weekend, and peak at around noon on working days. Moreover, it revealed that the broadcast TV band (470–862 MHz) and cellular band GSM 900/1800 MHz were always busy, and the frequencies above 2.5 GHz were mostly vacant.

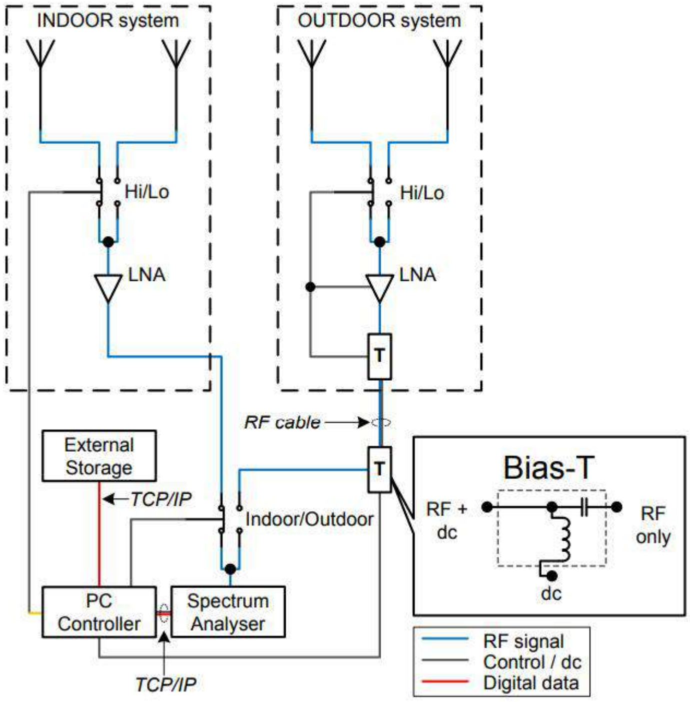


Figure 1.5. UK diagram of the measurement system [11].

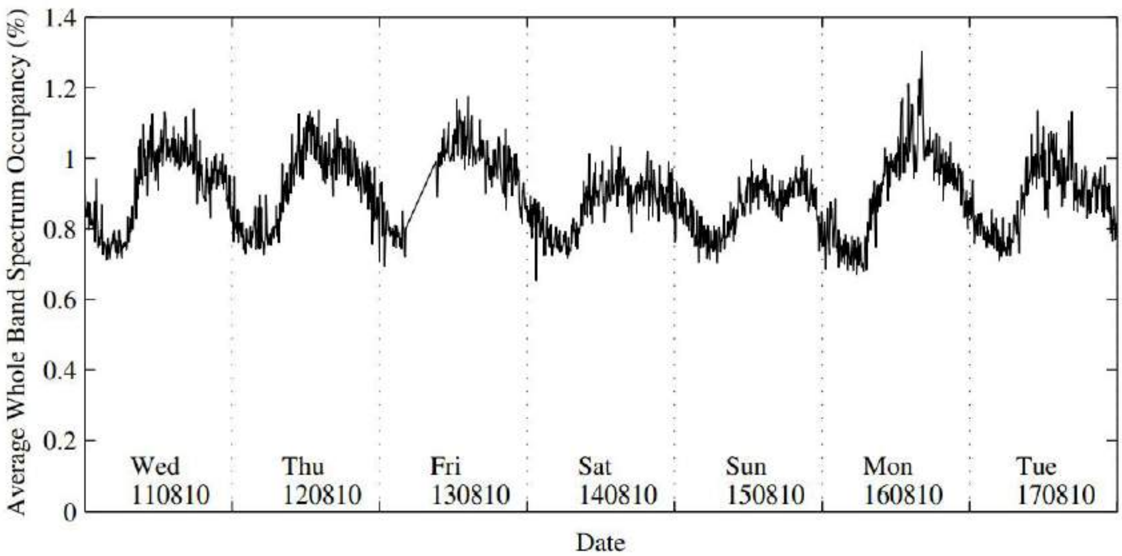


Figure 1.6. Mean occupancy of the whole observed band in the UK (from 11th, August to 18th, August 2011) [11].

D. Vietnam Long-Term Measurement Campaign

The paper [12] describes the measurement campaign performed in “Ho Chi Minh City and Long An province”, Vietnam, from October 2010 to February 2011. The measurements were in the frequency range from 20MHz to 3GHz, for 24h and over 4 months.

In this work, the utilized measurement devices consisted of a set of antennas, an “R&S EM550 VHF / UHF digital wideband receiver” (20 MHz - 3.6 GHz), and a server installed “R&S®ARGUS monitoring software”. The set of antennas, including (HE0166, HE3097, HE314A18, HF2149, and HF90210) that are switched depending on the measured band, is connected to the EM550 receiver via a switch matrix as shown in Figure 1.7. A threshold of 3dB above the minimum received signal power has been set for signal detection.

The experimental results of these spectrum analyses reveal that the spectral usage in the whole band for “Ho Chi Minh City and Long An province” is 13.74% and 11.19%, respectively, and that the highest occupancy band is the analog television band (470-806MHz) with 58%. The average spectrum occupancy for this area is compared to the occupancy of New York City over the defined frequency range in Figure 1.8.

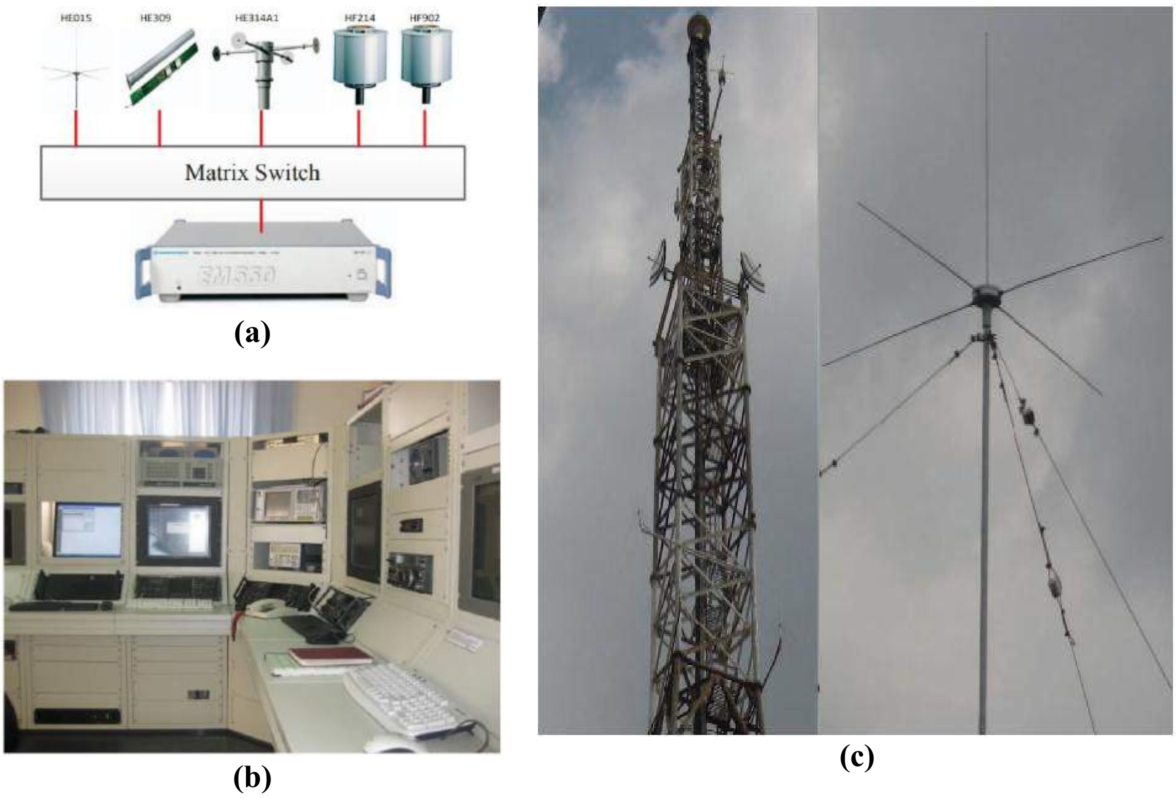


Figure 1.7. Vietnam spectrum measurement material, (a) & (b) The measurement system, and (c) The antenna system [12].

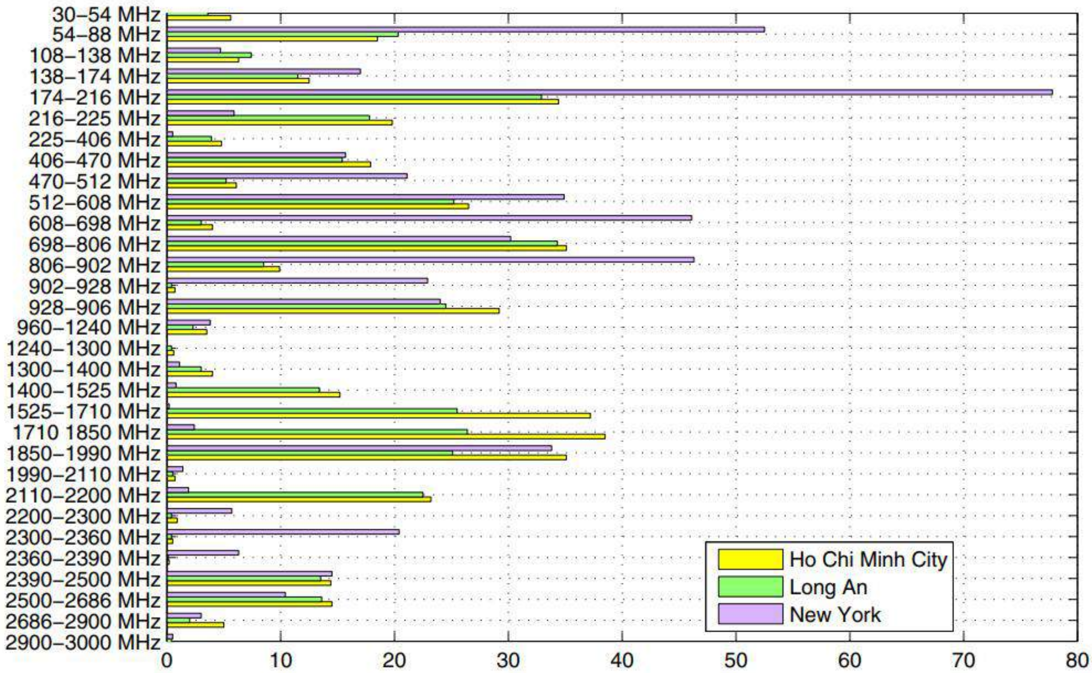


Figure 1.8. Average spectrum occupancy by band for Ho Chi Minh City vs. Long An vs. New York [12].

E. Turkey Long-Term Measurement Campaign

A multi-location long-term measurement campaign was presented in [13]. The study was fulfilled in three areas in Konya, Turkey, notice (Selçuklu, Karatay, and Meram) for six months, then it was published in 2019. It surveys the spectrum occupancy of the (25-3000MHz) frequency band, This band was divided into 30 subbands of 100 MHz each and analyzed using 199.6 kHz sampling frequency. The measurement system included four main elements that are a "Rigol DSA 1030 Spectrum Analyzer" (9 kHz – 3 GHz), an "AOR DA 3200 antenna" vertically polarized and covers (25 - 3000 MHZ) frequency range, an "AOR LNA 4000 low noise amplifier", and a laptop.

The obtained results for the three regions were examined, and it was determined that the spectrum below 1 GHz is excessively utilized, including the GSM downlink band that has had the heaviest activity, in contrast to the frequencies above 1GHz, where no transmission exists except for certain bands. In particular, the frequency ranges (230-470 MHz, 960-1700 MHz, and 2500-3000 MHz) were almost idle within the three measurement points.

The average occupancy ratios for Selçuklu, Karatay, and Meram were 5.12%, 4.46%, and 4.19%, correspondingly. Figure 1.9 presents the Band-by-band occupancy results of the three regions.

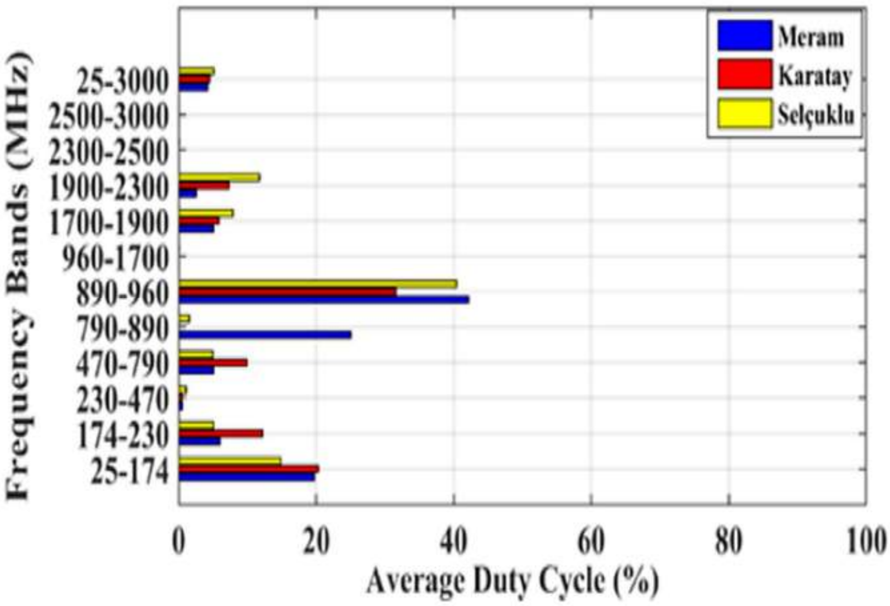


Figure 1.9. Band-by-band occupancy results of the three regions (Turkey) [13].

1.2.3. Short-Term Spectrum Measurements Campaigns

Short-term spectrum measurements are concise surveys that are accomplished in duration from hours to a few weeks. The goal of which is to estimate short-dependencies (by reducing sampling period and frequency) and to examine the utility of different sensing methods and other applications using the collected datasets.

The duration of a measurement campaign is decided according to, first, the objective of the measurements, second, the availability of the equipment and resources, and depending on the quality and capacity of the materials.

Until understanding how much spectrum is occupied? And how well is used? are there opportunities to integrate new users, new services, and new technologies? The occupancy and availability of different spectrum bands have been surveyed in many countries around the world like in Chicago [14], Singapore [15], Spain [16], Germany [11], Finland [17], [5], and few works in African and Arabian region have been done except those performed in South Africa [18], in Nigeria like [19], and in Morocco [20], … and as well as in Algeria via our work in presented in chapter 3. Under the title "spectrum measurement and analysis or spectrum survey for the implementation of a dynamic spectrum access system", these works have opened the perspectives for the new concept of cognitive radio and the development of its diverse applications. Table 1.1 summarizes the literature review of some short-duration measurement campaigns

Table 1.1. Summary of some related short-term measurement campaigns.

Spectrum survey	Location	Frequency band	Period	Threshold	Sweep time	Equipment and Software	Important results
McHenry et al., 2006 [14]	Chicago, IL	30 to 3000 MHz	2 days	Varies from one band to another Fixed in the same band	/	SSC-designed high linearity preselector, omnidirectional discone antenna, small log-periodic array (LPA) for frequencies > 1000 MHz	The overall usage for Chicago city is 17.4%
Islam et al., 2008 [15]	Singapore	80 MHz to 5.85 GHz	12 weekdays	6 dB above the noise floor	13.8 min	BiConiLog directional antenna (model 3149), E4407B Agilent's spectrum analyzer, Labview8.2	Average occupancy for the whole range of frequency = 4.54%
Chen et al., 2009 [21]	China	20MHz to 3GHz	1 week	(dynamic) 3 dB higher than the minimum signal value of the channel	75 sec	R&S EM550 super-heterodyne VHF/UHF Digital Wideband Receiver (20 MHz - 3.6 GHz)	High temporal / spectral / spatial correlation for the service congestion rate (SCR) series > 0.7, and high spectral correlation between Channel state information (CSI) series within the same service.
Valenta et al., 2009 [22]	France (Paris)	400 MHz to 6 GHz	12 weekdays	7 dB above the average noise floor	401 sec	Broadband logarithmic periodic antenna, spectrum analyzer, MATLAB	Spectrum usage in this band in a specific region is less than 5.3%. Comparison with the Czech Republic.
Xue et al., 2013 [23]	Beijing	450 to 2700 MHz	2 weeks	5 dB above the noise floor	0.42 sec	Omnidirectional BOGER DA-5000 broadband antenna (70MHz-3GHz), Agilent N9030A Spectrum Analyzer	The average spectral occupancy in Beijing is about 13.5%
Mehdawi et al., 2013 [24]	HULL-UK	180 to 2700 MHz	12 days	5 dB above the average received signal power	Auto (selected by the spectrum analyzer)	Bilog Antenna CBL 6143 (30-3000 MHz), Agilent E4407B spectrum analyzer, MATLAB	The average spectrum occupancy of the whole frequency range was 11.02 %

Spectrum survey	Location	Frequency band	Period	Threshold	Sweep time	Equipment and Software	Important results
Höyhtyä et al., 2015 [25]	Finland	2.3 – 2.4 MHz	2 weeks	Fixed to - 93 dBm	3 sec	Broadband omnidirectional and multi-polarized antenna (85-6000 MHz), CRFS RF eye receiving spectrum analyzer, data storage, and data transfer equipment	More than 90 % of the spectrum was shown to be idle in one specific measurement location in Turku, Finland. The 2.3 GHz band has potential for the LSA concept in Finland.
Ayeni et al., 2016 [19]	Nigeria	2.4 to 2.7 GHz	24 hours	10 dB above the noise floor	34.10 ms (Automatically selected by the spectrum analyzer)	Data storage device, data manipulation equipment (laptop), Agilent N9342C Handheld Spectrum Analyzer (HSA)	The investigated band is immensely underutilized with upper and lower occupancy values of 22.56% and 0% in urban and rural environments, respectively.
Cheema & Salous, 2019 [26]	UK	2.4GHz WLAN	20 min	10 dB above the noise floor	204.8 µsec	wideband omnidirectional discone antenna (1st setup), three commercial log-periodic vertically-polarized antennas (directional setup), sensing engine, and workstation.	omnidirectional and directional measurement setups: Gamma and lognormal distributions can model the idle state of a 2.4 GHz WLAN channel along with the generalized Pareto distribution.
Engiz & Rajab, 2021 [27]	Samsun - Turkey	700 to 2700 MHz	1 week	10 dB above the noise floor	/	RF Explorer 6G Combo spectrum analyzer, connected dongle to the laptop, MATLAB	The average occupancy of all services is 16.06%. 50% of locations' occupancies are below 20% for the LTE, and below 33% for GSM900 and UMTS2100.

1.3. Spectrum Prediction State of the art

Spectrum prediction is an essential function for the reduction of processing latency and energy consumption, the management of spectrum access, and the avoidance of spectrum collision between licensed (PUs) and unlicensed users (SUs). Currently, Spectrum prediction algorithms are adopted to be integrated into all new wireless devices that belong to the CR network.

In the literature, some relevant works have been done in the context of the classification and aggregation of the different methods of spectrum prediction in cognitive radio networks (CRNs). Where in [28] authors, in a comparative survey, classified Spectral prediction strategies according to their nature into three categories, regression analysis-based methods, spectrum prediction methods based on the Markov model, and third one based on machine learning. The papers in [29] & [30] surveyed and evaluated the state of the art of spectrum prediction in CRNs and summarized its major techniques and their applications, and addressed the relevant open research challenges. Furthermore, the basic spectrum hole prediction schemes were studied in [31], their theory and applicability in spectrum prediction and their advantages and shortcomings were highlighted, too. Then, the future research direction was discussed.

The objective of the following parts is to update the state of the art of spectrum prediction in CRNs, by providing another reading and diverse references more actual in this field.

1.3.1. Spectrum Prediction Methods in CRNs

In spectrum prediction, many approaches have been applied, and in our survey, these approaches were sorted into five categories, Pattern mining prediction (PMP), Bayesian-Inference-Based Prediction (BIF), linear prediction (LP) algorithms, Markov Model prediction (MMP) methods, and prediction methods based on Machine Learning (ML) [6].

A. Pattern Mining Prediction Methods

This kind of methods relies mainly on the continuous memorization of the past observations of spectrum energy samples, which are stocked in a matrix. Then, the prediction will be done according to the most frequent patterns. These prediction techniques that invest historical spectrum data to predict the next occupancy period are considered as time series prediction algorithms.

The 2D frequent pattern mining algorithm (2D-FPM) proposed in [32] presents a good example. Whereas authors represented the Channel State Information (CSI), over time, across channels, and for different wireless services, as a binary sequence of zeros and ones throughout a thresholding process. Furthermore, by extracting spectrum opportunities then drawing the data distribution, in addition to studying the temporal/spectral/spatial correlation of the CSI; spectral data can be memorized with sufficient information and thus it facilitates the prediction process. This prediction method, then, detects frequent patterns, which appear no less than 200 times throughout the CSI series in a set of channels. After that, it tries to find associations among these patterns, and finally, it builds a new prediction pattern to forecast the next states of channel occupancy.

B. Bayesian-Inference-Based Prediction (BIF)

Bayesian Inference (BIF) is an approach of inference where Bayes' rules are utilized to update the probability distribution of a hypothesis when additional evidence data is learned. In CRNs, a CR user can compute a prior probability distribution (also known as prior) of each system parameter θ (spectrum occupancy 0/1), denoted by P(θ), from experimental subjective assessments, before any data is taken into account. Through n time-slot spectrum sensing, some observed data $X = \{x_1, x_2, \dots, x_n\}$ are collected. Then the CR user computes a likelihood function of parameter θ, denoted by L($\theta|X$), as the probability of the observed data given that parameter. That is, L($\theta|X$) = P($X|\theta$). After acquiring the prior probability distribution and the likelihood function, BIF can be used to derive the posterior probability distribution of the system parameter θ conditioned on the data $X = \{x_1, x_2, \dots, x_n\}$. In BIF-based prediction, the CR user first derives the posterior probability distribution P($\theta|X$), illustrated in equation (1.1), according to Bayes' rule, and then uses the derived posterior to predict the data to be observed [29]:

$$\boldsymbol{P(\theta|X) = \frac{P(X|\theta).P(\theta)}{P(X)}} \quad \textbf{(1.1)}$$

Bayesian-based prediction techniques provide powerful and flexible tools to learn and adapt to the radio environment. SUs within the CRN, collect sensing information, and utilize statistical correlation, to infer possible future states of the primary user usage patterns. The algorithms perform well under both probabilistic and deterministic non-stochastic settings [4].

In [33], a BIF-based channel quality prediction scheme for CR networks was designed. In this approach, the authors utilized the Non-Stationary HMM (NSHMM) to model the spectrum sensing process, the model parameters were estimated via a BIF approach. These parameters carry the information about the next duration of the channel states and the sensing accuracy (detection accuracy and false alarm probability) of the SU. The channel quality was then predicted according to the inferred channel idle duration and sensing accuracy, and the channels are sorted in descending order according to the predicted quality to be exploited in improving available channels sensing and selection.

In another hand, authors in [34] proposed the BIF approach for spectrum status prediction. The Bayesian method was combined with an Exponential Weighted Moving Average (EWMA) prediction method as a hybrid approach. This approach performed better than Bayesian and EWMA standalone approaches. The novelty of this method is that it utilizes the conditional probability of (busy|idle) previous states to predict the probability of the next busy state.

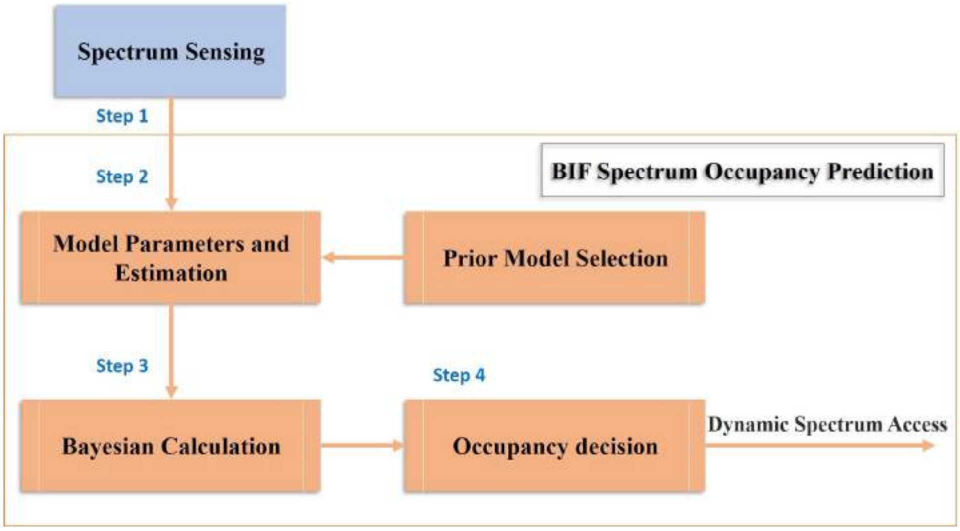


Figure 1.10. BIF Spectrum occupancy prediction flowchart [4].

C. Linear Prediction

Linear Prediction algorithms mainly include Moving Average (MA), autoregressive (AR), Auto Regressive Moving Average (ARMA), and Auto-Regressive Integrated Moving Average model (ARIMA). The Linear Prediction is widely utilized to deduce signal power also to predict spectrum in the time domain, due to its remarkable simplicity. Where future values are predicted as a linear function of previous samples [30].

The prediction methods based on (MA) present good performance in predicting the changing trend of the numerical sequence. The order-k MA predictor forecasts that the next value of a sequence is the average of the last k values in the sequence [35]. Z. Lin *et al*, in [36] proposed a prediction method based on Exponential Moving Average (EMA), by combining the EMA prediction and energy detection methods, which can predict the energy level in the frequency bands and enhance the spectrum sensing. Experiments show that this method can effectively reduce the spectrum sensing time end energy consumption and improve the efficiency of prediction [28]. AR models are commonly used to approximate discrete random processes. In this prediction approach, a CR user first estimates the model parameters, with Yule-Walker equations, maximum likelihood estimation, or other approaches. Then, it inputs the history of observations into the prediction rule and predicts the future state of the system [29]. However, these methods are mostly based on one-step prediction and do not improve the performance of AR models in multiple predictions. The problem of updating the regression coefficients with high complexity in the regression model cannot be effectively solved. Thus, the Markov model with a better prediction effect has been proposed [28].

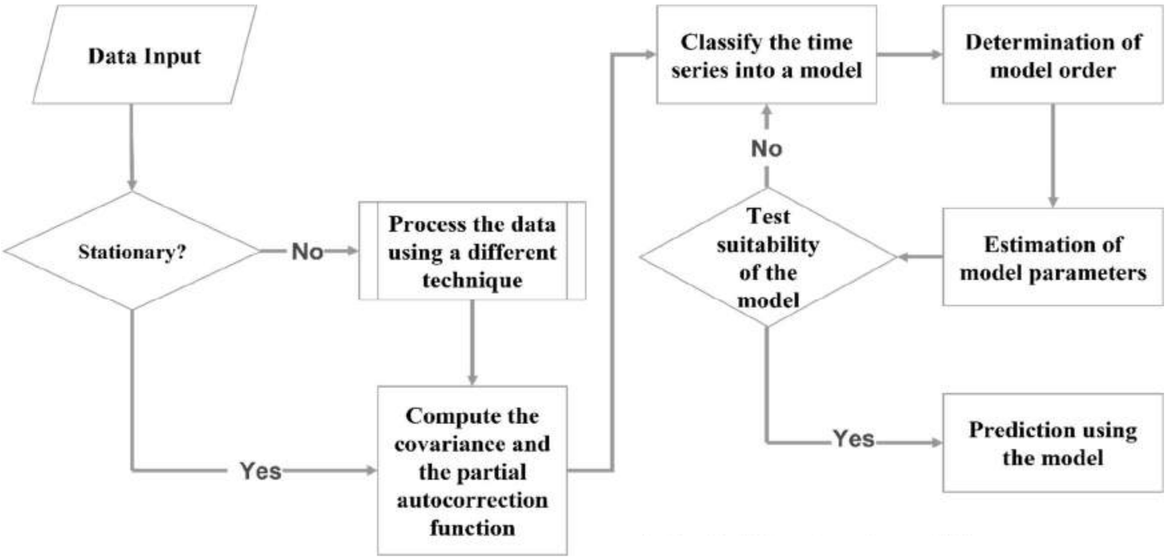


Figure 1.11. LP structure [30].

D. Prediction Method Based on Markov Model

Commonly used Markov Models (MMs) are the first-order MM, N-order MM, Hidden MM (HMM) stationary and non-stationary, Partially Observable Markov Decision Process (POMDP), Hidden Bivariate MM (HBMM), and Variable Length MM (VMM). The 1st-order MM is the simplest prediction method from its structure, a few estimation parameters, and prediction accuracy because it depends only on the relevant information about the present to predict the future state, not on the information of the distant past, which makes it a memory-less model [30]. It is also the most suitable model for forecasting time series. But its shortcoming is that it involves a decision delay which decreases the spectrum efficiency. In order to overcome this shortcoming, the authors proposed the N-order Markov model, which takes into account more historical information, but it is found that with the increase of order, complexity exponentially grows, which leads to the increase of the prediction delay of the model [28]. In [37], Z. Hong et al proposed a spectrum prediction method based on High-order Hidden Bivariate Markov Model, (H^2BMM), by supporting the advantages of high-order (consideration of more prior states) with the Hidden Bivariate HBMM (modeling multi-sub-states channel behavior) to predict channel states for stationary SU. Then they approached the advanced H^2BMM to take into account SUs' mobility by adjusting the training method of H^2BMM. To improve the performance of their approach, a comparison with the conventional HMM prediction approaches has been done under three main factors; transient state probability, prediction steps, and order of HBMM. Whereas H^2BMM achieved the best results compared with the conventional approaches. However, in a higher-prediction-steps, the prediction accuracy decreases for both. In addition, this method can extract the hidden correlation between adjacent observations (prior states) which increases the prediction accuracy. Furthermore, authors in [38] invested Non-Stationary Hidden Markov and Hidden Bivariate Markov Models to build a parallel (multi-channel) predictive spectrum sensing using real-time collected data (from the public safety frequency band). The model parameters have been estimated by the adaptive Expectation-Maximization (EM) Baum algorithm, in order to test the performances of the proposed method in a simple cognitive spectrum sharing scheme designed by the authors.

E. Prediction Method based on Machine Learning

a. Neural Networks

The Artificial Neural Network (ANN) is an artificial copy inspired from the human nervous system, introduced by the neurophysiologist W. McCulloch and the logician W. Pitts in 1943 [39]. ANN is a complex computational structure composed of nonlinear neurons which are arranged in layers (input, hidden layers, and an output layer), and highly interconnected using adaptive weights connections to report information from the previous layer to the next. Neurons are basically the processing elements that receive the weighted sum of their inputs and produce output via a nonlinear activation function [40]. In this way, ANNs are classified as nonlinear regression, discriminant, and data reduction models [40]. Thereby, it is considered as a mechanism to analyze large amounts of data and learn from data to find patterns and detect nonlinear relationships by learning from examples, then constructing an input-output mapping for the problem [41]. This makes it an easy learning and generalization model, but it needs a large amount of training data to ensure high accuracy prediction [28]. Figure 1.10 presents the general structure of a neural network with three hidden layers.

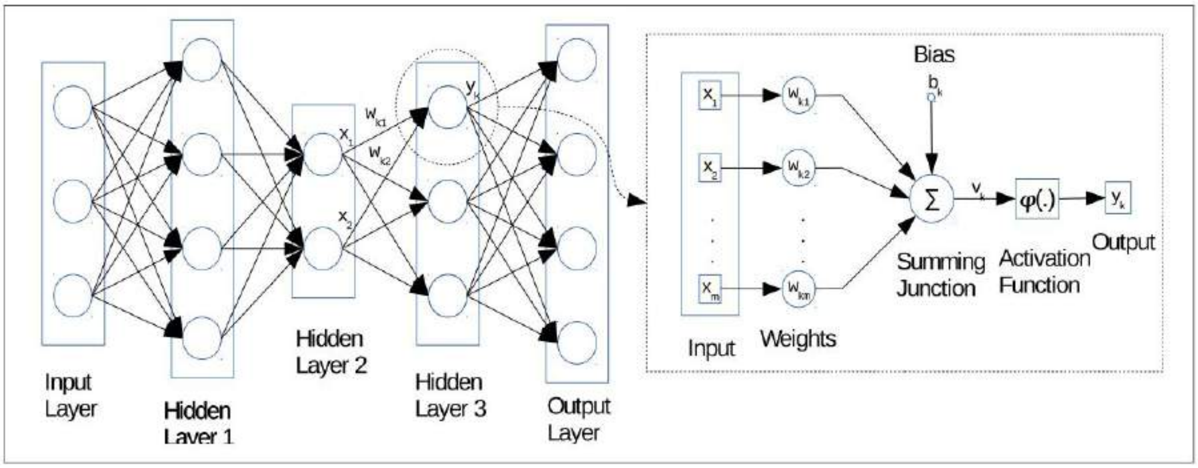


Figure 1.12. Example of a neural network with three hidden layers.

In the literature, the most common type of ANNs employed in spectrum prediction is the Multi-layer linear perceptron network (MLPN). MLPNs are linear combined layers of neurons, defer from its training method, it can be trained using several methods such as Backpropagation (BP), Genetic Algorithm (GA), or a combination of methods, depending on the size of the network and its application, to enhance the network performances [31]. In [42] and [43] authors used the (BPMLP) as a spectrum predictor to improve CR spectrum utilization and reduce sensing time and energy. The MLP predictor with BP algorithm is shown in Figure 1.11. In [42] authors evaluate the performance of the MLP predictor under Stationary and Non-Stationary traffic conditions for various traffic scenarios. Whereas the MLP predictor reached more than 60% of spectrum exploitation, it could discover more idle slots than a CR sensor device and it reduced around 51% of energy consumption. On another hand, authors in [43] proposed a system model for future wireless communication network (LTE- Advanced (5G)) based on the integration of Backpropagation trained Neural Network (BPNN) in Cognitive Users with Prediction (CUP) control units. The objective of which is to sense only channels predicted to be vacant via the prediction of the next state information. The system performances were evaluated in terms of the mean squared error.

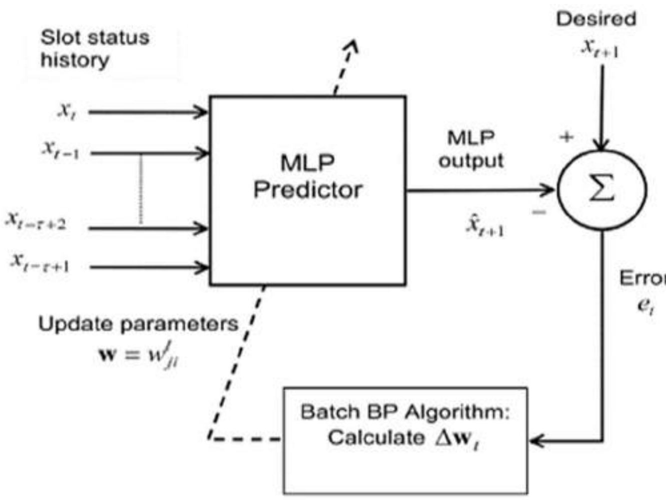


Figure 1.13. MLP predictor with BP training algorithm [42].

Backpropagation NN (BPNN) was proposed in [44] to compare the predictive accuracy of soft and hard decision models. Two model's historical spectrum information were utilized: real spectrum power values for a "soft decision", and channel status (0 or 1) for a hard decision. The authors studied the effect of variable decision thresholds on the predictive accuracy of the model. They proved that the "soft decision" model is better than the "hard decision" model in terms of accuracy.

In the reference [45], the Elman Recurrent Neural Network (ERNN) is introduced for cognition incorporation in Software Defined Radio (SDR). It exploits the inherent cyclostationary features of a primary user signal to predict the future spectrum evolution for one step ahead. The inputs of the ERNN predictor were the Radio Frequency (RF) spectrum samples that were modeled and decomposed as multivariate chaotic time series using EMA then simplified as trivariate RF time series. ERNN training is very delicate, thus, the authors applied Levenberg-Marquardt (LM) numerical method as a training algorithm. The algorithm is tested for the UMTS frequency band and obtained a very slight prediction error and good prediction results.

In [46] authors examined three predictive models, namely, Seasonal Auto-Regressive Integrated Moving Average (ARIMA), baseline method, and a TDNN, to measure their performances of predicting the next 50 time steps. They proved that the TDNN is better in terms of its reduced loss function and its ability to provide offline prediction rather than the ARIMA linear model which needs to be continuously trained to be able to forecast.

b. Support Vector Machine (SVM)

The SVM-based classifier is introduced by Vapnik in 1990. This type of classifiers is useful to solve discrimination and regression problems, function approximation, and detection of very weak signals. Based on Vapnik–Chervonenkis dimensional theory and structural risk minimization principle, SVM can tackle these problems and therefore can avoid over-fitting of empirical risk problems. The SVM is a non-parametric, nonlinear learning technique which means automatic selection of model parameters and high generalization ability which made it widely used in the fields of data mining and Spatio-temporal spectrum sensing problems. In addition, the SVM model is simple in structure and easy to train with small training data sets compared with NNs, but for large scale data sets, SVM performances decreases [28], [47]–[49].

Accordingly, SVM has been applied in cognitive radio issues by combining it with other conventional methods, like the Empirical Mode Decomposition (EMD) technique, to overcome or reduce some of their shortcomings, depending on the application [50]. EMD is very suitable to SVM model properties dealing with nonlinear and non-stationary signal analysis and time-frequency resolution better than Short Time Fourier Transform (STFT), Wigner-Ville distribution, and Wavelet transform. EMD decomposition capability makes any complicated signal appear as simpler frequency components with strong correlation, and thus easier to be analyzed [47].

To overcome the shortcomings of the Support Vector Regression (SVR), indicated in Table 1.2, the reference in [47] merged the EMD with the SVR method, which employs SVM, as a prediction algorithm called EMD-SVR. This algorithm invests the advantages of nonlinear and non-stationary signal decomposition with time-series forecasting using SVM capabilities. First, EMD decomposes the frequency spectrum series into several signal branches. Then, SVR is applied to each signal branch to perform spectrum prediction. Finally, the overall forecasting value is obtained as the sum of the partially predicted values. The EMD-SVR model was evaluated using the Mean Squared Error (MSE), Root-Mean-Squared Relative Error (RMSRE), and Squared Correlation Coefficient (SCC) as performance indices, then compared with AR and common SVR prediction methods. The EMD-SVR model provides much more accurate prediction results than the AR and common SVR models and can be useful for nonlinear, non-stationary, and strong complexity data prediction in a Frequency Monitor System (FMS). Table 1.2 shows some features and limitations of the SVR.

Table 1.2. Features and limitations of the SVR [47].

Features and Advantages	Limitations
▪ Dealing with nonlinear and non-stationary data (nonlinear prediction); ▪ Time-series forecasting; ▪ Guarantee global minima; ▪ Adaptive to complex systems.	▪ Neglects the inherent characteristics of time series; ▪ Imperfect detection of the local data tendency; ▪ Weak forecasting precision.

c. Deep Learning

Deep Learning Algorithms (DLA) were also applied to spectrum prediction in CR Networks (CRNs). Where Long Short-Term Memory (LSTM) takes a big part of actual works. LSTM is a specific Recurrent NN (RNN) structure that is considered an effective and suitable tool in classifying, processing, and making predictions dialing with time series data and their long-range dependencies more accurately than conventional RNNs. LSTM network can process a large number of diverse data dimensions, complex and nonlinear features, in addition to its property of selectively remembering patterns for long durations of time [51].

Mentioning the paper [51] that proposes a deep learning cooperative prediction model. In which SUs were not obliged to waste power and time for continuous Spectrum Sensing (SS). This task (SS) was attributed to distributed Low-Cost Spectrum Sensors (LCSS), which were deployed in different areas to provide the Local Predictors (LPs) by the temporal measurements, each LP unit represents an LSTM. A spatial fusion was applied then to the predicted results in the Fusion Center (FC).

While the authors in [52] solve the sub-band and power allocation problem in a multi-cell network. They proposed a Deep Neural Network (DNN) model, trained and tested using Genetic Algorithm (GA) generated datasets, to predict resource allocation solutions.

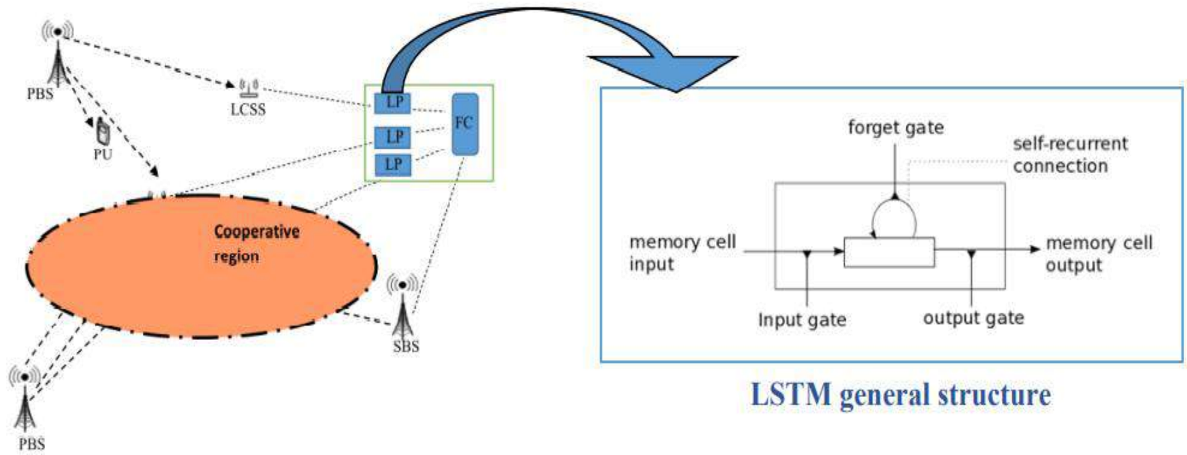


Figure 1.14. Cooperative spectrum prediction model [51].

However, in our work the model provides soft prediction results for multiple frequency channels and different areas, by considering the 3D parameters simultaneously (space, frequency, time). This makes it a multidimensional, and multiscale (soft) predictor and enhances its prediction accuracy and its efficiency. Whereas, most relevant works studied the prediction performance according to only one channel input dataset versus this actual work that presents an efficient algorithm to predict the occupancy state of 250 frequency channels simultaneously.

1.4. Conclusion

Throughout this first chapter, we have presented the state-of-the-art of spectrum measurements and spectrum prediction for CR concept.

In order to decide the best measurement parameters for the preparation of our database, and to select the suitable prediction algorithm for our specific study dependences; we have reviewed, investigated, and classified the different methods utilized in spectrum monitoring and forecasting. Where we have categorized spectrum measurement campaigns into two categories; short and long-term measurements. However, the prediction methods were sorted into five classes, depending on the prediction algorithm in use. Thereby, we motivated and positioned our work efficiently regarding the state-of-the-art of both topics.

Our measurement and prediction selections will be provided and extensively illustrated in the third and fourth chapters, respectively.

CHAPTER 2

Cognitive Radio

Sections

1. *INTRODUCTION*
2. *COGNITIVE RADIO*
3. *CR OPPORTUNITIES*
4. *CR FUNCTIONS*
5. *CR APPLICATIONS*
6. *CONCLUSION*

Abstract— *Conventional wireless paradigms are characterized by static spectrum allocation policies, where spectrum is assigned to licensed holders on a long-term basis, and for large geographical regions. CRNs are envisioned to change this trend by enabling the coexistence of SUs with PUs via heterogeneous wireless architectures and dynamic spectrum access techniques.*

Cognitive radio will improve spectrum utilization in wireless communication systems while accommodating the increasing amount of services and applications in wireless networks. A cognitive radio transceiver is able to adapt to the dynamic radio environment and the network parameters to maximize the utilization of the limited radio resources while providing flexibility in wireless access. The key features of a CR transceiver include awareness of the radio environment (in terms of spectrum usage, power spectral density of transmitted/received signals, wireless protocol signaling) and intelligence. This intelligence is achieved through learning for adaptive tuning of system parameters such as; transmit power, carrier frequency, modulation strategy (at the physical layer), and higher layer protocol parameters. Throughout this chapter, we will realize and inspect the main concept of CR and its related issues; History, vision, functions, and applications.

Keywords— *Cognitive Radio; Cognitive cycle; SDR; spectrum allocation, spectrum mobility; spectrum prediction; spectrum sensing; spectrum sharing.*

2.1. Introduction

2.1.1. Background and Motivation

The conventional static allocation policies of spectrum resources have been proven to successfully control interference among radio communication systems and simplify the design of hardware to operate at a typical and fixed range of frequencies. Nevertheless, the overwhelming proliferation of new operators and wireless technologies during the last years has resulted, under this inflexible regulatory regime, in a serious scarcity of usable radio frequencies. The traditional spectrum allocation strategy was once appropriate, but nowadays it has become obsolete, necessitating the development of new spectrum management paradigms to effectively exploit the precious radio resources [53].

Cognitive radio is believed to be a high-potential technology to address these issues. It refers to a category of devices that are aware of their surrounding radio environment and are intelligently capable of reconfiguring their own properties based on the current status of the spectrum with respect to spectrum traffic load, congestion situation, network topology, and wireless channel propagation.

This capability is particularly applicable to resolve heterogeneity, robustness, coexistence, and interference avoidance between licensed and unlicensed users. However, cognitive wireless networks are still in the early stages of research and development. There are several technical, economical, and regulatory challenges to be adopted, in order to deploy this technology. In addition, there are unique complexities in aspects of spectrum sensing, prediction, sharing, mobility, and management of this resource [54].

CR has been developed to improve the efficiency of spectrum usage to meet the increasing demand for frequency bandwidth, it allows channel sharing between licensed and unlicensed users without interruption via the dynamic spectrum access (DSA) for SUs [55].

2.1.2. Chapter Organization

Through this chapter, a detailed definition of the CR concept will be addressed. In Section 2, the CR history and definition are illustrated. Section 3, presents the core CR functions and the role of each function in the insurance of the right attribution of radio resources. Finally, a conclusion that summarizes the most important throughputs of the present chapter.

2.2. History of Cognitive Radio

Cognitive radio, as a concept, has been first introduced by Joseph Mitola in 1999 [56]. where artificial intelligence was used to control radios, allowing them to dynamically access the radio spectrum with the appropriate protocol, considering the context and usage information. However, a wide swath of contributions from many leaders in the field have participated in the appearance of this technology.

The history of CR returns to the research done on Distributed Dynamic Channel Assignment (DDCA) in the early 1990s. DDCA technology was applied in the military, and widely in ad hoc networks, to combat enemy threats and jamming.

Meanwhile, many research groups started being interested in a heterogeneous network when the 3rd Generation (3G) network and Wireless Local Area Network (WLAN) has been deployed and widely used. They believed that combining two networks brings better spectrum occupancy. Wireless network service operators were also interested in this mixed network in order to provide a cost efficient service because they face a rapid increase of data utilization rate. Thus, the 3G Partnership Project (3GPP) standard launched a study group about internetworking of WLANs.

By the end of 1990s, the usage of 2.4 GHz unlicensed band, protocols such as IEEE 802.11.x, and Bluetooth adopted dynamic techniques based on listening before talk strategies, along with Digital Enhanced Cordless Telecommunications (DECT) at 1.9 GHz, for indoor use. Moreover, the development of digital signal processing (DSP) techniques and digital filtering offered a typical transition from analog to digital processes.

In 1998, Randy H. Katz and Eric A. Brewer from the University of California could build a network system that allows Mobile Stations (MSs) to roam between different types of networks with the best possible connectivity and a minimum of disruption during handoffs.

After that, short-range networks such as Ultra-Wide-Band (UWB), ZigBee, and IoT emerged. These advanced researches and technologies cooperated in the occurrence of the CR.

At the beginning of 2000, there was a general consensus among research groups, standard groups, and regulation organizations that we should use the radio spectrum efficiently. CR became the most promising candidate to solve this problem by providing intelligently a higher spectrum occupancy to wireless network service providers and individual users [57].

In 2005, Simon Haykin [58] suggested new protocols that could be applied to DSA, and then it has been considered as cognitive radio.

In order to satisfy the requirement of the regulation organization, the standard groups such as the Institute of Electrical and Electronics Engineers (IEEE) 1900 committee, IEEE 802.22, and ITU-R started building working and study groups for defining spectrum management and Software Defined Radio (SDR) related concepts, standardization of CR policies, controlling the spectrum access, and analyzing the coexistence and/or the interference between operating radio systems. In this way, the development of SDR structures and virtual hardware has been a promising solution for the coexistence and interference, multi-standard, and multi-mode issues [59].

Within a few years later, CR was being deployed in the TV bands using devices that can exploit the 'white space' spectrum; a spectrum that is unoccupied in a particular geographical location [57].

These innovative and consecutive works have now made the research field mainstream over the last years forward the creation of an efficient CR technology.

2.3. Software Defined Radio (SDR)

The definition of SDR according to the International Telecommunication Union (ITU) [60] is summarized in:

"Software-defined radio (SDR) is a radio transmitter and/or receiver employing a technology that allows the RF operating parameters including, but not limited to, frequency range, modulation type, or output power to be set or altered by software, excluding changes to operating parameters which occur during the normal pre-installed and predetermined operation of a radio according to a system specification or standard."

The simplest definition of an SDR is a device in which the radio properties like carrier frequency, waveform, signal bandwidth, modulation, network access technique, and other transmission settings like cryptography, Forward Error Correction (FEC) coding, and source coding of voice, video, or data are defined by software without changes in the hardware components [61].

An SDR evolved from purely hardware-based equipment to a fully software-based system. It passed through three stages to becoming in its appropriate architecture applicable in the realization of cognition features for CRNs [61];

1) Hardware-driven radio: where Radio Frequency (RF) parameters are determined by hardware and cannot be changed without hardware changes;

2) Digital radio: A digital radio performs part of the signal processing or transmission digitally, but is not programmable in the field;
3) Software Defined Radio: All functions, modes, and applications can be configured and reconfigured by software.

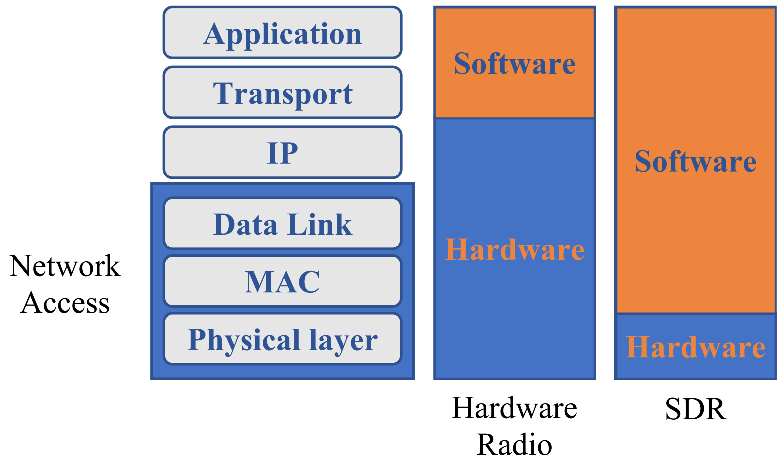


Figure 2.1. Evolution of a hardware radio into software defined radio.

The basic hardware architecture of a modern SDR may include mixtures of General-Purpose Processors (GPPs), Digital Signal Processors (DSPs), Field-Programmable Gate Arrays (FPGAs), and other computational resources, to include different modulation types. Whereas for the modern SDR software architectures, the Application Programming Interfaces (APIs) are defined for the major interfaces to ensure soft mobility across different hardware platforms and support a wide diversity of waveform applications [61].

2.4. Cognitive Radio Definitions

From the report of the ITU (REPORT ITU-R SM.2152)[60], CR was defined as follows: ***"A CR system is A radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives, and to learn from the results obtained."***

Joseph Mitola III and Gerald Q. Maguire have defined the functionality of CR for a new generation of communication systems based on software radios in the paper [56] as:

"***Cognitive radio agents may actively manipulate the protocol stack to adapt known etiquettes to better satisfy the user's needs. This transforms radio nodes from blind executors***

of predefined protocols to radio-domain-aware intelligent agents that search out ways to deliver the services the user wants even if that user does not know how to obtain them.”

CR is an emerging technology to realize wireless devices with cognition capabilities such as learning, sensing, awareness, and reasoning. Moreover, it has the capability of providing global seamless connectivity [59] and solving the cross-band coexistence and interference issues.

A CR device is an intelligent system that can sense, decide, and learn its surrounding radio environment occupancy, then recognize the available radio resource opportunities. It can adapt its usage context, and reconfigure its radio operating parameters dynamically and autonomously, in order to opportunistically access and transmit in these resources.

CR is a wireless communication technology that enables SUs to discover and access the spectrum holes in the licensed bands without interfering with PUs. According to the principles of CR, included in the IEEE 802.22 and IEEE 802.16 h, SUs can detect intelligently communication channels that are in use and those that are not occupied by PUs and can move to unused channels, like TV white spaces, to perform their communications at any time. Nevertheless, they must abandon the resources once a PU has occurred [2].

2.5. The Vision of Cognitive Radio

CR devices are anticipated to help you find people, things, and opportunities; translate languages; control your home and job tasks and complete them on time. They would capture the daily activities of their users and therefore they would have resources ready for you as well as your need.

Similarly, if a device was cognitive or smart, it could learn the available resources in locally accessible wireless networks and could interact with those networks in their functional protocols, so that it would have no confusion in finding the best wireless network for a video download or an online conference. Additionally, it could use frequencies and choose waveforms of any wireless network that minimize and avoid interference with existing radio communication systems [61].

CR is expected to bring together different technologies in one heterogeneous and coexistent network and manage them smartly to serve your digital life requirements immediately with the highest QoS. Furthermore, CR has been proposed to be the pioneering technology for future generations of wireless communication systems like 5G, 6G, and IoT.

2.6. Relation between CR and SDR

Until the development of CR technology, SDR has been mainly proposed to realize multi-mode and multi-standard wireless devices. Thus, the role of SDR in cognitive radios is very essential, which is the realization of cognition features (e.g. awareness, sensing, etc.) in cognitive radios [59].

In fact, one of the most prominent definitions of cognitive radio strongly supports the above argument: “A cognitive radio is an SDR that is aware of its environment, internal state, and location, and autonomously adjusts its operations to achieve designated objectives” [59].

Thereby, SDR's capabilities should support and correspond to three major applications to make it a cognitive radio [61]:

1) Spectrum management and optimizations;
2) Interface with a wide variety of networks and optimization of network resources;
3) Interface with a human and provide electromagnetic resources to aid the human in his activities.

SDR is able to offer the flexibility, reconfigurability, and portability features inherent in the adaptation aspect of cognitive radio.

2.7. Useful Concepts in CR

In CRNs, there exist important elements that participated in the accomplishment of the cognitive communications cycle, and that should be known before starting. Hereby, a simple definition of every element is provided below:

- **PUs:** are the users that have the priority in the usage of the assigned radio frequency spectrum. PUs are called also “licensed users”, they have the right to enter or quite the spectrum anytime and transmit within their pre-attributed transmission conditions.
- **SUs:** are the unlicensed users that use the spectrum in an opportunistic manner, using DSA techniques or by transmitting in the free frequency bands (white spaces).

A SU should respect some CR principles to benefit from the DSA and transmit within the PUs bands in coexistence:

1) Not harm other users of the spectrum (licensed and unlicensed users), overlay or underlay;
2) Add value to the user, operator, or owner who invested in the technology (share information);
3) Perform robustly and reliably in different environments and users’ requirements.

Figure 2.2 shows the DSA process, in frequency and time domains, performed by a SU by moving from one spectrum hole to another.

- **Licensed bands:** are fixed frequency bands allocated by the regulation bodies ("ITU", and Federal Communications Commission "FCC") for the different wireless networks (mobile communications, digital TV, WIFI, broadcasting, …). The users of these bands are licensed users (PUs).
- **spectrum holes:** A spectrum hole is a band of frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not being utilized by that user (idle) [43].

Spectrum bands are also classified according to their occupancy rate into three categories:

- **White spaces:** are spectrum bands only occupied by noise due to natural or artificial sources, no existence of RF interference, or frequency spans that are legally assigned to a specific system, however, that system does not employ the whole band for its communications, and just a part of this band is in use. An example of this kind is TV white spaces, which are the most targeted frequencies from SUs.
- **Gray spaces:** are frequency channels that are partially occupied in time. They present an opportunity for second use by other wireless devices.
- **Black spaces:** are the frequency sub-bands that are totally or mostly occupied in time. These sub-bands can be for example; downlink spectrum bands for mobile networks.

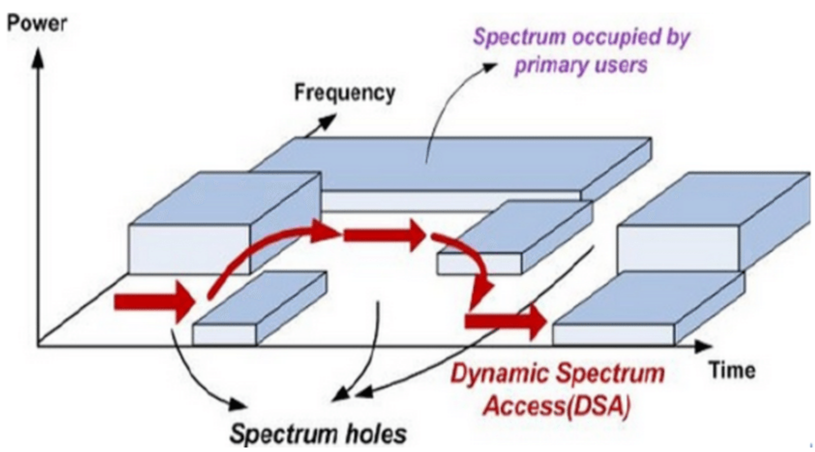


Figure 2.2. An example of dynamic spectrum access in CRNs.

2.8. Cognitive Radio Cycle

CR is an intelligent wireless communication system that is aware of its surrounding radio environment. So that, it can detect intelligently communication channels that are in use and those that are not.

According to the CR cycle, as shown in Figure 2.3, a CR intelligent system (transmitter/receiver) can be aware of its surrounding radio environment, by learning the spectrum frequencies using the spectrum sensing function, then analyzing the spectrum samples in frequency, and time dimensions. Thereby, it detects the presence of PUs and decides about the occupancy or vacancy of spectrum channels. After that, it sends the decision to the SDR unit to adapt and reconfigure its access parameters intelligently, and then switch to the appropriate career frequency, modulation type, and transmission power for efficient transmission in the radio interface.

Commonly, a set of attributes are expected from a CR system that makes it a Cognitive Engine (CE), and can be embodied in its CR cycle [62]:

1) Observation: gather information about the operating environment (propagation channel characteristics, mitigation, …), and characteristics of the radio (spectrum occupancy, …);
2) Reconfiguration: Change the transmission parameters of the radio according to the spectrum status and specifications;
3) Cognition: Understand the environment and capacity of the radio, awareness of geographic location, and local networks and their available services (awareness); make decisions regarding DSA, intelligent resources allocation, and sharing strategies for SUs (reasoning), and learn the impact of these actions on the performance of the radio, as well as the performance of the network in which the radio is embedded (learning).

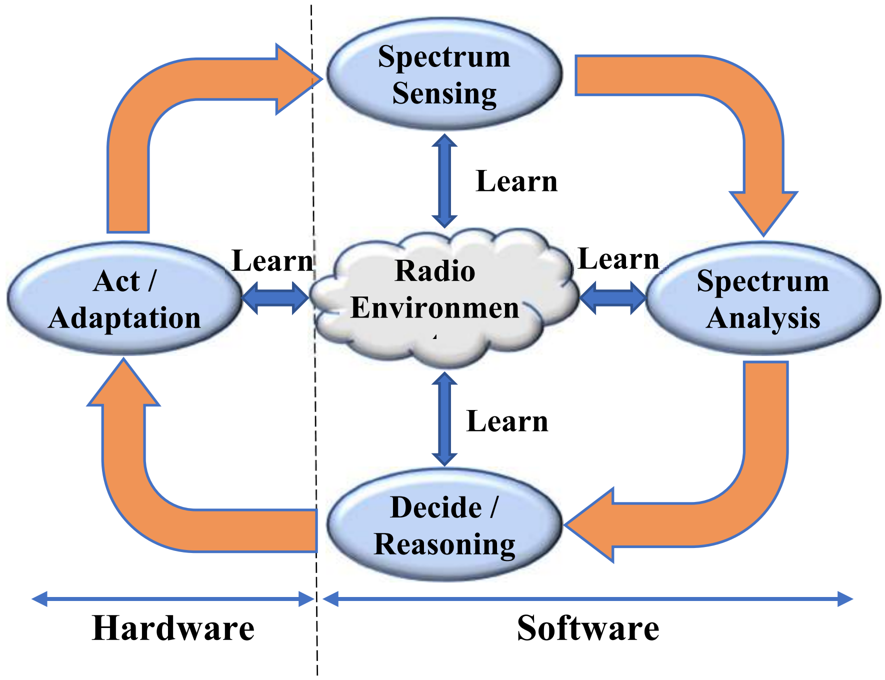


Figure 2.3. Simplified CR Cycle.

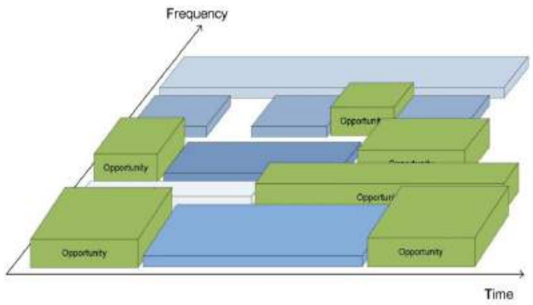
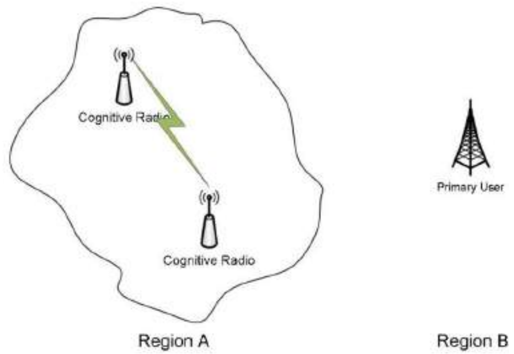
2.9. Multidimensional CR Opportunities

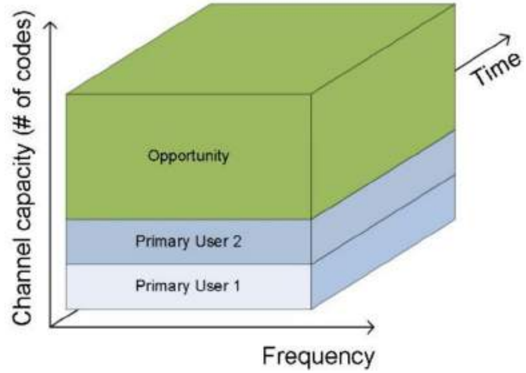
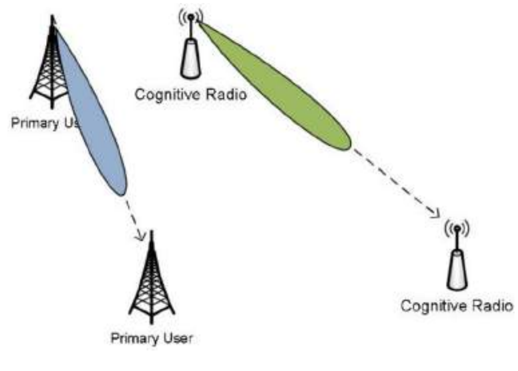
CR offers multiple opportunities in multiple dimensions for SUs to fully invest the unused and underused spectrum resources.

Radio spectrum opportunities can be sorted into five dimensions, where CUs can transmit their signals by sensing the following PUs signal characteristics; frequency domain, time domain, geographical space coordinates and distances, code, and the angle of the PU transmitted signal.

Table 2.1 illustrates the benefit of each radio spectrum space and transmission dimension for CR opportunistic users.

Table 2.1. Multi-dimensional Radio spectrum space and transmission opportunities [63].

Dimension	What needs to be sensed?	Comments	Illustrations
Frequency	Opportunity in the frequency domain.	Availability in part of the frequency spectrum. The available spectrum is devided into narrower chunks of bands. Spectrum oppurtunity in this dimension means that all the bands are not used simultaneously at the same time, *i.e.* some bands might be available for opportunistie usage.	
Time	Opportunity of a specific band in time.	This involves the availablity of a specific pat of the spectrum in time. In other words, the band is not continuously used. There will be times where it will be available for opportunistie usage.	

Dimension	What needs to be sensed?	Comments	Illustrations
Geographical space	Location (latitude, longitude, and elevation) and distance of primary users.	The spectruum can be available in some parts of the geaographical area while it is occupied in some other parts at a given time. This takes advantage of the propagation loss (path loss) in space. There measurement can be avoided by simply looking at the interference level. No interference means no primary user transmission in a local area. However, one needs to be careful because of hidden terminal problem.	
Code	The spreading code, Time Hopping (TH), or Frequency Hopping (FH) sequences used by the primary users. Also, the timing information is needed so that secondary users can synchronize their transmissions w.r.t. primary users. The synchronization estimation can be avoided with long and random code usage. However, partial interference in this case is unavoidable.	The spectruum over a wideband might be used at a given time through spread spectrum or frequency hopping. This does not mean that there is no availability over this band. Simultaneous transmission wihtout interfering with primary users would be possible in code domain with an orthogonal code with respect to codes that primary users are using. This requires the opportunity in code domain, *i.e.* not only delecting the usage of the spectrum, but also determining the used codes, and possibly multipath parameters as well.	

2.10. CR Functions

In the literature, the CR engine is meanly based on five issues to perform its functionalities and enable it to opportunistically use the spectrum. These functions are the core blocks that compose our proposed spectrum management scheme, which are; spectrum sensing, spectrum prediction, spectrum access, spectrum mobility, and spectrum sharing [6].

2.10.1. Spectrum Sensing

Spectrum sensing is the core function of a CRN. The goal of which is to detect the appearance of licensed users (PUs), via the continuous monitoring of their activity on the target frequency bands, and to determine PUs' occupancy status (free/busy) [64]. Spectrum sensing is a fundamental CR issue, regarding its functionality in ensuring awareness and sensitivity to changes in the radio frequency status for Cognitive Users (CUs). Furthermore, it provides meaningful information on the availability of usable bands and discovers accessible spectrum holes over a wide frequency range. Hence, it guarantees the right access guidance for SUs away from any harmful interferences to PUs.

A. Spectrum Sensing Methods

In the literature, there exist a lot of classifications for spectrum sensing methods; narrowband and wideband sensing methods, cooperative and noncooperative methods, classification based on the objective of sensing like opportunity detection-based methods, interference detection-based methods, and others.

In this thesis, we are interested in noncooperative narrowband opportunity detection-based methods, which are utilized for primary Transmitter detection.

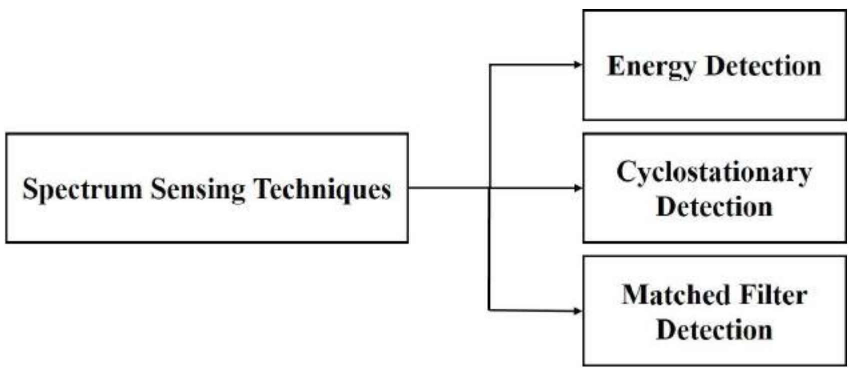


Figure 2.4. Narrowband spectrum sensing methods.

Narrowband spectrum sensing techniques allow SUs to decide on the presence or absence of the PUs over a specific frequency channel of interest. Figure 2.4 shows the narrowband spectrum sensing methods.

In the primary transmitter detection method primary users/signal detection is performed based on the received signal at the CU receiver. CUs should have the capability to determine if a signal from the primary transmitter is locally present in a certain band. A basic hypothesis model for transmitter detection that models the signal received by the CU in continuous time can be defined as follows:

$$\begin{aligned} &\boldsymbol{H_0}: \ \boldsymbol{y(t) = n(t)} &&; \boldsymbol{PU\ is\ absent} \\ &\boldsymbol{H_1}: \ \boldsymbol{y(t) = hs(t) + n(t)} &&; \boldsymbol{PU\ is\ present} \end{aligned} \qquad \textbf{(2.1)}$$

Where $y(t)$ is the signal received by the CU, $s(t)$ is the transmitted signal of the PU, $n(t)$ is an Additive White Gaussian Noise (AWGN) with zero-mean and a variance σ^2, and h is the amplitude gain of the channel. H_0 is a null hypothesis, which states that there is no licensed user signal in a certain spectrum band. On the other hand, H_1 is an alternative hypothesis, which indicates that there exists some primary user signal.

The most commonly employed spectrum sensing techniques for transmitter detection are energy detection, matched filtering, and cyclostationary detection.

a. Matched Filter Detection

One of the well-known techniques in the field of signal processing for identifying a known pattern from a received signal is matched filter detection. In the presence of additive stochastic noise, the Matched Filter (MF) is an optimal linear filter designed for maximizing the output Signal to Noise Ratio (SNR) of a given input signal [65].

The MF detection is applied only if the SU has a priori knowledge of the PU signal characteristics such as; modulation type, order, pulse shape, and packet format [66]. However, this operation consumes more power and has high complexity.

The PU transmitter sends its signal $s(t)$ along with a pilot stream signal $x_p(t)$ so that SUs receive them simultaneously, as shown in Figure 2.5.

The MF is equivalent to the convolution of the PU received signal $y(t)$ with the filter whose impulse response is the mirror and time-shifted version of a reference signal (the pilot stream) [67]. The filter response is a time-reversed and time-shifted version of the known signal $s(t)$. The operation of matched filter detection can be expressed as [66]:

$$y(t) * s(T_n - t + \tau) \tag{2.2}$$

where T_n is the symbol time duration and τ is the shift in the known signal.

The test statistic of the MF detector is determined using the following equation, where N denotes the number of received samples [68]:

$$T_{MFD} = \frac{1}{N}\sum_{t=-\infty}^{\infty} y(t) * x_p(t) \tag{2.3}$$

In order to decide whether the PU is present on the sensed band, this test statistic is then compared to a threshold λ_{MFD} to determine the sensing decision, that is:

$$T_{MFD} < \lambda_{\text{MFD}} \text{ , Primary user absent} \tag{2.4}$$

$$T_{MFD} \geq \lambda_{\text{MFD}} \text{ , Primary user present} \tag{2.5}$$

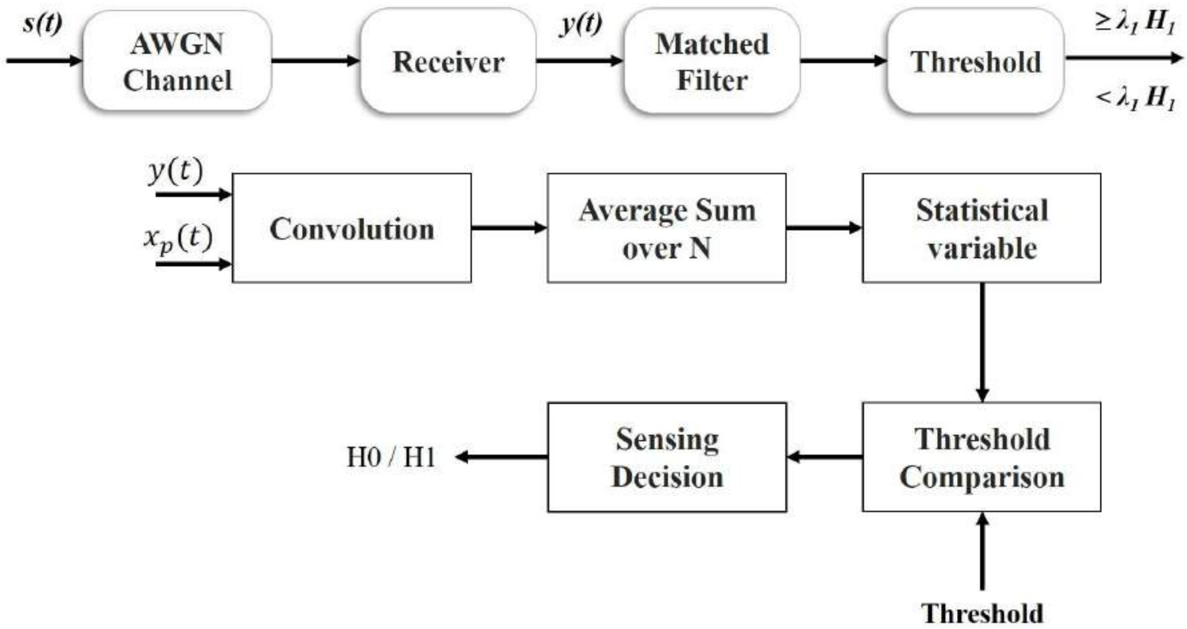


Figure 2.5. Matched filter detection for spectrum sensing [66], [69].

b. Energy Detection

The energy detection approach is the most straightforward that does not require prior knowledge of PU's signal characteristics. In comparison to other sensing approaches, this method has a lower implementation and computing complexity. When it is difficult for the SU to bring adequate information about the PU characteristics, matched filter detection is not a favorable choice. However, if the SU is given the AWGN power, energy detection becomes a better alternative for spectrum sensing [70].

Energy detection computes the energy of the samples and compares it to a threshold. If the energy is higher than this threshold, the PU signal is considered present; otherwise, the PU is considered absent [68]. The scheme in Figure 2.6, calculates the energy of the samples as the squared magnitude of the Fast Fourier Transform (FFT) averaged over the number of samples N. This is given by:

$$T_{ED} = \frac{1}{N}\sum_{n=1}^{N}(Y[nT])^2 \tag{2.6}$$

where N denotes the total number of received samples, and $Y[nT]$ denotes the received sample at nT, and T is the sampling time. The result of this computation is then compared to a predefined threshold to obtain the sensing decision.

$$T_{ED} < \lambda_{ED} \qquad \textbf{Primary User absent}, \tag{2.7}$$

and:

$$T_{ED} \geq \lambda_{ED} \qquad \textbf{Primary User present}, \tag{2.8}$$

where λ_{ED} denotes the threshold that depends on the noise variance. The selection of the threshold, which can be static or dynamic, dramatically affects the detection performance.

Energy detection is a reasonably simple technique that does not require any prior knowledge of the signal characteristics. However, it cannot distinguish between the noise samples and the signal samples, which makes it subject to high uncertainty. In addition, it has a low detection performance for low SNR values.

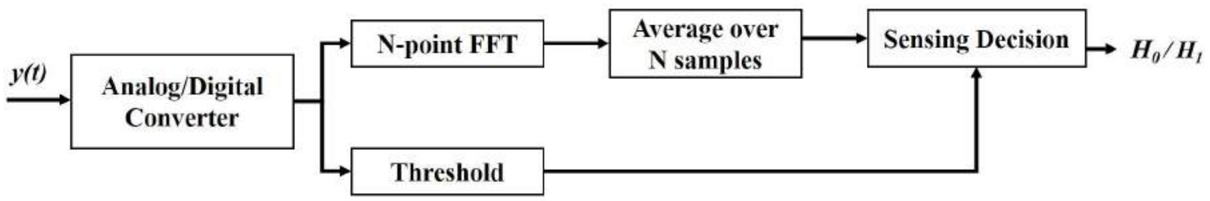


Figure 2.6. Block diagram of Energy Detection [68].

c. Cyclostationary Feature Detection

The statistical parameters of signal, such as modulation rate and carrier frequency, are periodic in nature and are considered cyclostationary features. If the mean and the Autocorrelation Function (ACF) of the received signal are periodic, then the signal is called a cyclostationary signal. The periodicity of the mean and ACF of a signal is utilized by cyclostationary features-based detectors to accomplish the sensing task. Mathematically, the periodicity of mean and ACF can be defined as [71]:

$$\boldsymbol{R_y^{\delta}(t,\tau) = R_y^{\delta}(t+N_0,\tau)} \quad \textbf{(2.9)}$$

$$\boldsymbol{m_y(t) = E[y(t)] = m_y(t+\tau)} \quad \textbf{(2.10)}$$

Therefore the main and ACF became as follows:

$$\boldsymbol{m_y(t) = \sum_{n=1}^{N-1}\left[y[t]e^{-j2\pi\delta t}\right]} \quad \textbf{(2.11)}$$

$$\boldsymbol{R_y^{\delta}(t,\tau) = E\left[y[t] * y[t+\tau]e^{j2\pi\delta t}\right]} \quad \textbf{(2.12)}$$

where E[.] represents the statistical expectation operator, N_0 represents the time period of the received signal $Y[t]$, τ represents the time offset, δ represents cyclic frequency. $R_y^{\delta}(\tau)$ represents the ACF, and $m_y(n)$ represents the mean of $Y[t]$.

Compared to the energy detection technique, the cyclostationary feature detection technique is less sensitive to noise uncertainty and, therefore, has less probability of false alarm. Further, this technique can detect low SNR signal values. The cyclostationary features-based approach provides better detection performance than the energy detector. This is because noise is stationary and has no correlation and be easily discriminated from the signal by calculating the spectral correlation function. The noise signals are uncorrelated and non-periodic in nature, so it is easy for cyclostationary detection to distinguish between the PU signal and noise as the PU signal exhibits periodic properties. This technique's major drawback is that it needs more power consumption, processing complexity, and sensing time. Figure 2.7 presents the block diagram of cyclostationary features-based techniques.

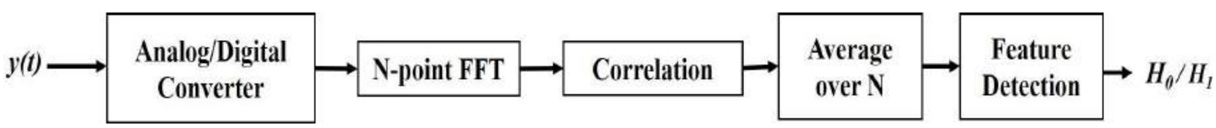


Figure 2.7. Block diagram of cyclostationary features-based techniques [68].

2.10.3. Spectrum Prediction

If the occupied or free status of the spectrum band can be predicted or inferred from current spectrum measurement data, then this approach would improve spectrum efficiency. This technique called Spectrum Inference/Prediction, it is a valuable tool to harness the spectrum effectively [72].

Spectrum prediction is one of the main CR functions. It is responsible for multistep ahead forecasting of the frequency channels occupancy rates. This enhances the ability to infer future states of PUs spectrum activity. Therefore, CUs can avoid interference with PUs, furthermore, they can select frequency channels that maximize their transmission rate and range.

Spectrum prediction is an invested function, whereas it is being merged with all other CR functions to optimize their sensing, allocation, sharing, or access performance. It gives fruitful results regarding its ability to reduce sensing, decision-making, and access delays, which achieves the vision and principles of DSA for SUs in CRNs. More details about spectrum prediction were given in the first chapter and in the fourth chapter too.

2.10.4. Spectrum Allocation

Spectrum allocation (SA) is the process of regulating the use of the electromagnetic spectrum and dividing it among various norms and services and as well to competing organizations and interests. In case of allocating a specific frequency band, SA can cause interference if the same frequency band is used for different and unregulated purposes. This regulation is controlled by various governmental and international organizations.

Nevertheless, spectrum allocation in CRN is the operation of attributing radio resources for SUs dynamically using Artificial Intelligence (AI) algorithms, by defining the idle frequency band to use, the channel bandwidth, the central frequency, the access technique, and the transmitting power to be handoff for each SU.

Therefore, advanced and intelligent radio resource allocation schemes are very essential to perform dynamic and efficient spectrum access among heterogeneous SUs requirements and to optimize the energy consumption of each individual SU in the network. Radio resource allocation schemes aim to ensure QoS guarantee, maximize the network lifetime, and reduce the inter-node and inter-network interferences.

2.10.5. Spectrum Sharing

Dynamic spectrum access is the new concept opposite of static frequency spectrum assignment and its management. Several secondary users can have access to the detected spectrum holes. However, the access of two or more secondary users to the same spectrum band results in collisions and contention. Spectrum sharing manages the spectrum usage among multiple secondary users to minimize harmful interference and collisions [73].

Spectrum sharing can be defined as a hierarchy scheduling of access priorities between primary licensed users and secondary unlicensed CR users. It is designed to maintain fair spectrum scheduling among secondary (unlicensed) users.

Within a spectrum sharing scheme, unlicensed SUs can access the radio resources dynamically, by making sure that the interference induced to licensed PUs is within the tolerable range; or by using the idle spectrum opportunistically without interfering PUs transmissions.

A. Spectrum Sharing Models of Dynamic Spectrum Access

There exist two famous topologies for SUs spectrum access, the overlay, and underlay approaches.

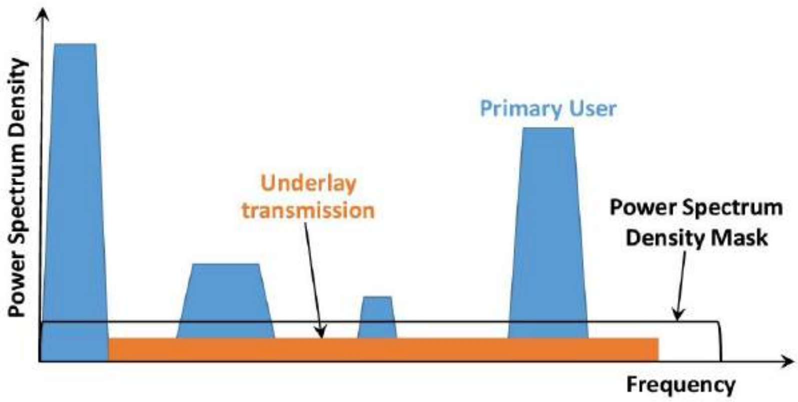
In spectrum overlay model, the CR device will have to identify the idle spectrum bands, which are not used by licensed systems at a given time and location, and use those idle bands dynamically. SUs in this topology can transmit with high transmission power to increase their rates for given spectrum opportunities within these bands. This model is presented in Figure 2.8 (a).

Whereas in spectrum underlay approach, the secondary CR users are allowed to transmit with low transmission power as in Ultra-Wideband (UWB) technology with no need for spectrum holes identification. SUs in this model can transmit simultaneously and coexist with PUs. However, they are not allowed to transmit with high transmission power even if the entire RF band is idle (not used by PUs). This model is presented in Figure 2.8 (b).

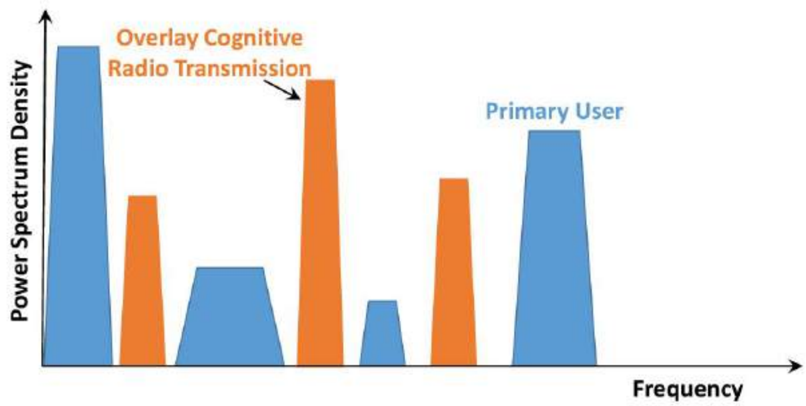
Moreover, the dynamic spectrum sharing by CR users in a given spectrum band can be categorized like in Figure 2.9 [74], that is:

a. **Horizontal sharing:** where CR users and primary users have equal opportunities to access the spectrum such as in wireless LAN operating in the ISM band at 2.4GHz. And in order to improve the overall system performance, CR users can choose the channels which have less traffics or less number of users. In this approach, CR users and primary users coexist in the system and use the bands simultaneously.

b. **Vertical sharing:** where CR users have less preference over the PUs, and thus CR users must vacate the spectrum as fast as possible once the licensed primary users are detected in the band. However, CR users can use the spectrum with potential whenever they detect the idle spectrum band. Moreover, in vertical sharing, the CR system needs an operator's assistant.



(a)



(b)

Figure 2.8. Spectrum (a) overlay and (b) underlay approaches.

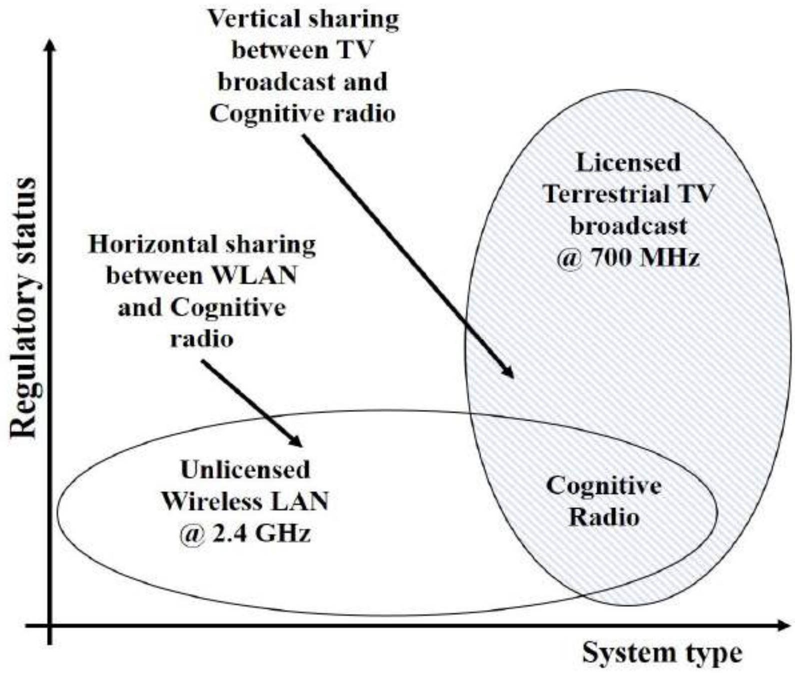


Figure 2.9. CR Spectrum Sharing Scheme: Vertical and Horizontal Sharing example [74].

2.10.6. Spectrum Mobility

After selecting an appropriate spectrum band, the secondary user commences communication. However, due to the dynamic nature of wireless environment, after a while, a primary user may start communicating in the selected band. In this case, the secondary user changes its operating band to avoid interference to the PUs. This handoff (between spectrum bands) performing the functionality of CR devices is called spectrum mobility [73].

Spectrum mobility is the function that ensures SUs switch from one spectrum hole to another, considering the characteristics of each frequency band to be accessed and all sharing protocols. When a PU suddenly appears, spectrum mobility provides seamless transmission, during the operating frequency and access mode switching for SUs, and adapts to fast-changing through communication environments [75].

Spectrum mobility depends essentially on the spectrum handoff and connection management sub-functions. Connection management ensures continuous SUs data transmission during the switch to a new spectrum hole.

2.11. CR Applications

CR technology promises several benefits toward the emerging wireless systems. It ensures an essential task for all new communication devices, no matter their diversity or their application field, that is the providence of spectrum resources for their transmissions. Some of the most interesting applications of the CR are cited below:

2.11.1. In Smart Grid (SG)

Traditional grid only transmits or distributes electric power without any form of automation. However, a SG optimizes energy efficiency by integrating the actions of suppliers and consumers in real-time by integrating information technology into the existing power grid [76].

A smart grid transforms the way power is generated, delivered, consumed, and billed. Adding intelligence throughout the newly networked grid increases grid reliability, improves demand handling and responsiveness, increases efficiency, better harnesses and integrates renewable/distributed energy sources, and potentially reduces costs for the provider and consumers. Cognitive-radio-based SG may offer many advantages such as bandwidth, distance, and cost, compared with other wireline/wireless technologies [77].

The SG has brought about new functionalities, solutions, and challenges. Some solutions proposed by SG networks include (1) reliable, secured, and efficient electric grid, (2) deployment and fusion of distributed resources and generation, (3) installation of smart metering and distribution automation, (4) installation of smart appliances and consumer devices, (5) advanced electricity storage and plug-in hybrid electric vehicles, (6) thermal-storage air conditioning, and (7) real-time information and control options. Some new functionalities of SG are, (1) control, e.g. advanced fault management control methods and the virtual power plant control technology and communication like; new multipath routing algorithms, smart metering, blind processing framework, and related communication technologies, (2) sensing, as synchrophasors or phasors measurement units and measurement, similar to digital smart meters, (3) security, for example, location-based security, integrated systems security, and Ortho code privacy mechanism, and (4) micro grids, pilots, and projects, that have been applied in Australia, Canada, Great Britain, USA, South Korea, Ireland, and Japan. Nonetheless, the Smart Grid Communication Network (SGCN) is a very crucial component in the realization of SG. The SGCN is intended as a low-cost, reliable, and secure communication infrastructure that meets the QoS requirements of SG. Though, the design and implementation of SGCN are very intimidating challenges. This is because SGCN is required to integrate different segments of a communications network with a huge number of heterogeneous elements distributed over large distances with dissimilar QoS requirements. Here are some examples of wireless technologies that have been proposed for the take-off of SG-ZigBee, IEEE 802.11ah (low Wi-Fi), IEEE802.11af (super Wi-Fi, or White-Fi), IEEE 802.22WRAN, IEEE 802.16-based network (WiMAX), cellular and satellite communications. Nonetheless, CR has been the preferred technology for SG environments. This is because of the enormous potential of improving spectral efficiency and transmission capacity through opportunistic spectrum utilization, in addition to the decreased implementation costs. The major benefits of CR technology for SG are the transmission of data over SG communication links with less communication latency and solving spectrum scarcity shortcomings in SG.

2.11.2. Cognitive-unmanned aerial vehicles

Another important area with growing CR interest is Unmanned Aerial Vehicles (UAVs) otherwise known as drones. UAVs are usually deployed in areas that are potentially too dangerous, highly risky, very expensive, or difficult for human activities. For example, earthquake-prone regions, warzones, and fire control, including tracking, and surveillance applications. Fundamentally, UAVs are built for surveillance and reconnaissance mission. As a result, they are usually equipped with sensors, cameras as well as communication equipment. However, the deployment of UAVs in the ISM band implies that they have to compete with other technologies, for example, Wi-Fi, Bluetooth, and IEEE 82.15.4-based technology for the available spectrum band. This leads to a scarcity of usable spectrum for this use. However, CR can mitigate the problem of spectrum scarcity through DSA techniques. As well as, improve channel capacity by opportunistic spectrum utilization for UAVs. Other benefits of applying CR for UAVs include (1) reduced energy consumption and delay, and (2) overlay deployment. Similarly, potential application areas of CR-UAVs include, (1) commercial drones, (2) traffic surveillance, (3) crop monitoring, (4) disaster management, (5) border patrolling, and (6) wildfire monitoring [76].

2.11.3. Cognitive-IoTs

IoT is a new paradigm introduced in the late 1990s. The IoT objective is to connect sets of anyone, anything, any service, and any network, anytime and anywhere. The huge research interest engendered by IoT in recent years is due to the values it promises to introduce. The IoT promises to create a world where things around us have the capabilities to distinguish between our likes, our wants, and our needs, and act, accordingly, without explicitly being trained. When IoT is fully implemented, it can provide solutions for a wide range of applications. Notably, smart and connected cities, mobile crowd sensing, and cyber-physical sensing, health care including; internet of e-health, glucose level sensing, and medical management. Further apps like traffic congestion, security, emergency services, logistics, and industrial control are developed too. However, some challenges of IoT that should be addressed in future research comprise; challenges associated with resource limitations and energy management, in addition to interoperability issues and legacy devices. Nevertheless, CR technology can solve these challenges for IoT applications by providing access to more bandwidth [76].

2.11.4. Cognitive-M2M

Machine to Machine (M2M) communication is a new communication paradigm similar to IoT. However, for IoT connected devices interact with each other and with humans, while in M2M communication, only machines are communicating together [78].

In addition, the main focus in M2M communications is connectivity. M2M interconnects intelligent machines in a digital network using diverse communication technologies to autonomously monitor and control machines without any human intervention. However, the full self-governing automation in M2M has given rise to several heterogeneous applications having entirely dissimilar capabilities and functionalities to leverage on advantages of M2M. Consequently, the number of devices taking part in M2M is massive.

According to a report by Ericsson, this number will rise to more than 50 billion devices by 2023. This geometric explosion necessitates huge improvement on existing access techniques to maintain QoS requirements of different applications running on millions of machines. Some challenges created by M2M technology include congestion and overload in the network, energy efficiency, heterogeneity, reliability, QoS, and ultra-scalable connectivity. To cater to millions of machines in M2M and to overcome challenges imposed by M2M there is a need for more spectrum. Accordingly, the authors in Reference [79] suggest the incorporation of CR technology in M2M. They argue that to prevent M2M devices from consuming more energy and degrading network performance and efficiency due to limited licensed spectrum a secondary spectrum is needed. However, developing techniques that would allow M2M to access and utilize primary spectrum as well as to opportunistically use the secondary spectrum remains an open issue in M2M. Nonetheless, when this is fully realized, M2M would find application in areas such as; smart metering, traffic monitoring, and e-health care. As well as cyber-physical production systems and industrial internet of things, as well as transportation [76].

2.11.5. Cognitive-5G networks

The 5G networking technology is a new communication network that is capable of providing higher data rates and higher capacity of data transmission. It is flexible to support various devices and services [80].

To fully realize the vision of 5G wireless network as intended, the actual wireless-based networks would have to improve several capabilities. Much of these new advancements should involve different techniques for accessing higher frequency ranges using the CR DSA and the deployment of massive antenna configurations. Similarly, device-to-device communications and ultradense structures should be incorporated. Nevertheless, the anticipated future of mobile technology is a networked society with unbounded and unlimited data rates. A network with access to infinite information and data sharing, which is everywhere, every time for everyone and everything. Consequently, the vision of 5G technology is to provide a network that supports, for example, 1000 times increased data volume per area, and 10 times increased numbers of connected devices. In addition, 10 to 100 times increased typical user data rates, 10 times extended battery life for low power massive machine communication devices, and five times reduced end-to-end latency. Accordingly, future advancements and solutions should be evolved by incorporating CR technology to address issues and challenges such as heterogeneous networks and coexistence, as well as the colocation of devices. Other needed improvements include the following; high-speed packets access, long-time evolution, Orthogonal Frequency Division Multiple Access (OFDMA), and scheduling [76].

Hence, addressing CR spectrum sharing and DSA techniques is a necessity for the efficient utilization of spectrum bands in 5G technology, and to overcome the spectrum shortage issues [80].

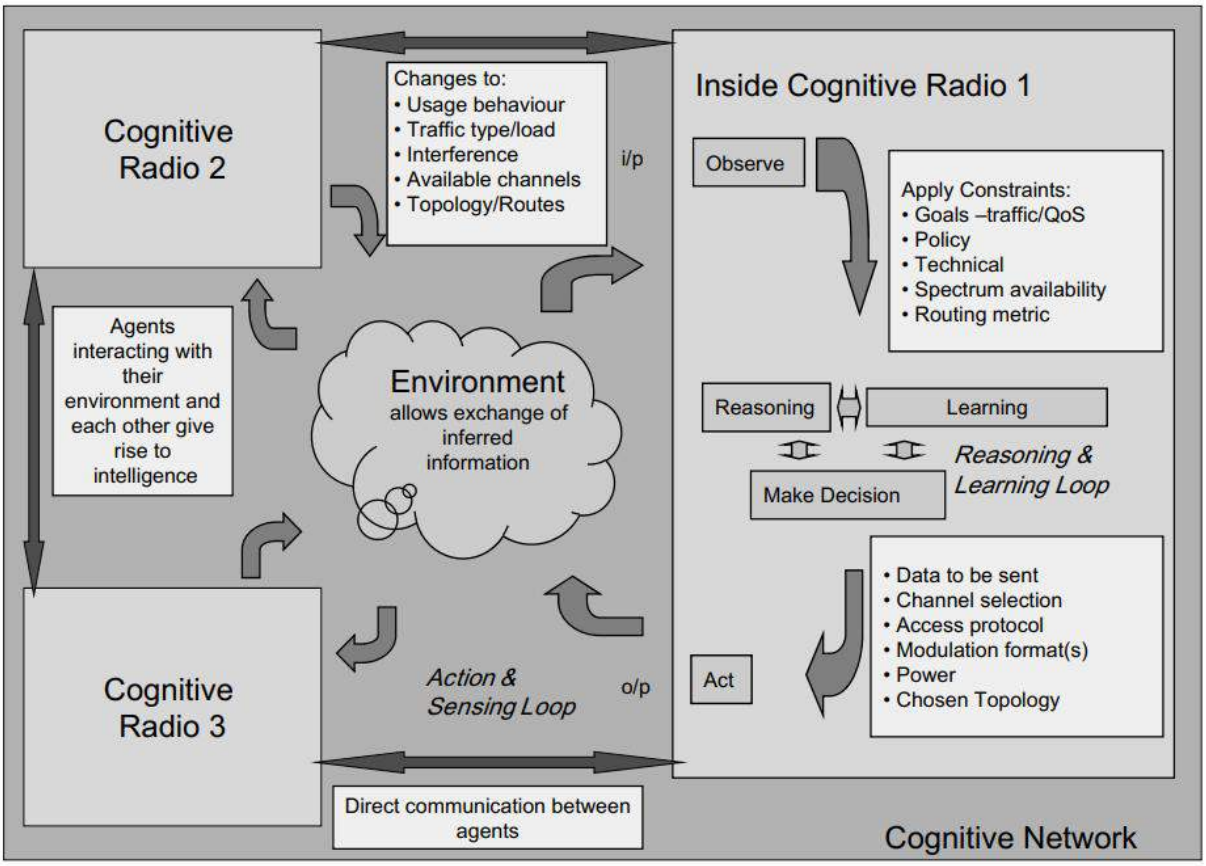


Figure 2.10. An example of an intelligent interactive CR system composed of three CR users/devices [57].

2.12. Conclusion

Throughout this chapter, we sought to surround the concept of cognitive radio, the most important CR issues, and CR applications.

In this way, the history of CR, its evolution from hardware to software defined radio-based CR, and the vision and definition of CR have been extensively illustrated. Moreover, the CR cycle and cognition behaviors of CUs, in addition to the CR main functions have been defined.

CRNs are designed to change the static resource attribution trend, by enabling the coexistence of SUs with PUs via heterogeneous wireless architectures and dynamic spectrum access techniques.

Cognitive radio is a technology that can provide a wide variety of intelligent behaviors and efficient perfections to wireless communication systems. It can enhance spectrum utilization and balance the traffic via the right exploitation and the intelligent reuse of spectrum white spaces and underutilized radio resources. Additionally, opportunistic access and intelligent spectrum allocation will optimize the spectral efficiency and the data transmission rates, due to the large frequency bandwidths offered by these CR techniques. CRNs can help to reduce the impact of interference through DSA and adaptive resource allocation. These were some of the several promises and potentials envisioned by the CR paradigm. Another benefit of the CR is to reuse lower frequency ranges for the new generation of wireless devices so that we prevent a lot of human diseases that are due to the high-frequency waves' propagation in the environment.

CHAPTER 3

Measurement campaign and data collection

Sections

1. ***INTRODUCTION***
2. ***MEASUREMENT SYSTEM***
3. ***METHODOLOGY FOR DATA COLLECTION AND ANALYSES***
4. ***SPECTRUM OCCUPANCY RESULTS, STATISTICS, AND DISCUSSION***
5. ***CONCLUSION***

Abstract— *This chapter describes a spectrum observatory performed outdoor in two locations in Algeria and highlights the importance of the spectrum observatory in the improvement of the spectrum management in cognitive radio networks (CRN). These measurements were achieved in conjunction with the ANF (Agence Nationale des Fréquences), between January and February 2020. It surveys second, third, and fourth-generation mobile networks and Digital Video Broadcast-Terrestrial (DVB-T) frequency bands. A comparative study of two measurement campaigns (in urban & rural locations) that were carried out via identical setup and equipment to obtain comparable results is presented. Additionally, Different statistics are imputed and 3D graphics of the spectrum occupancy are plotted to highlight the spectrum opportunities in this region. This work aims to analyze the radio environment in Algeria and identify frequency bands that could be invested for the integration of new wireless systems and Cognitive radio (CR) opportunistic networks. The evaluation of 15-weekday's measurement results reveals low resource occupation, lower than 30.27% for Constantine and 8.43% for Ouargla. The final part of the study inspects the effect of specific spectrum observatory features upon the management strategy parameters selection. An efficient CR spectrum management strategy is a strategy that achieves the safest SUs spectrum access to the highest availability rate channels with the minimum costs and risks. This can be reached via a meaningful spectrum observatory that makes the right decision rules for reliable sensing results.*

Keywords— *Cognitive radio; Measurement campaign; Spectrum management; Spectrum observatory; Spectrum occupancy measurements; Occupancy statistics.*

3.1. Introduction

3.1.1. Background and Motivation

New technologies' exponential evolution and expanded usage of advanced wireless devices and applications that require high operating data rates have doubled the spectrum scarcity problem. Due to the traditional policy of static spectrum allocation, the spectrum seems congested. In reality, a big percentage of frequency resources around the world is, most of the time, underutilized or completely unused, this is what most studies of spectrum measurements have revealed so far. The efforts devoted to the investment of these spectrum holes using cognitive dynamic mechanisms are still not effectively applied in most countries. However, Some associations in the US, UK, and Singapore developed new cognitive radio (CR) policies and devices to invest in TV white spaces, like “Whizepace Pte Ltd – Singapore – most than 5 years ago”, and others worked on transferring Wi-Fi users to the free 5-GHz Wi-Fi band like in [81]. Therefore, the challenge has been rose to propose new mechanisms for spectrum management via extended surveys and studies of the radio environment variation patterns. The new techniques and systems relying on CR that are being developed lately are standing essentially on the comprehensive analysis of spectrum behavior and the intelligent dealing with channel occupancy variability in time, frequency, and space to achieve an efficient spectrum allocation for unlicensed opportunistic spectrum users. The importance of a spectrum observatory is that it provides an interesting detection and characterization of the spectral holes in time and space [82] that is useful in the management of radio frequency resources. Technologies like M2M, IoT, smart grid networks, and urban connectivity based on Super Wi-Fi or TV white space spectrum communications require a deep spectrum status study for better reuse of spectrum opportunities.

3.1.2. The Importance of Spectrum Observatory in a Spectrum Management System

In the close future, spectrum resources will be used opportunistically via CR technology. This technology has been invested illegally during the last decade but actually, it will not stay without normalization. In our vision, as peer to other wireless technologies like mobile communication services (2G, 3G, 4G, …), the CR technology will be adopted by countries' regulatory bodies, and by their turn, they will attribute and allocate it to spectrum operators. In this way, the spectrum will be allocated in a licensed opportunistic manner. In our model, the management and handoff of radio resources for all operators will be supervised via one spectrum observatory and management system for each geographic area, and via dynamic sharing protocols, Secondary Users (SUs) will share the available channels. Finally, the system calculates the cost and the resource usage percentage for every operator. Figure 3.1 illustrates the role of the spectrum observatory and management system in a CRN.

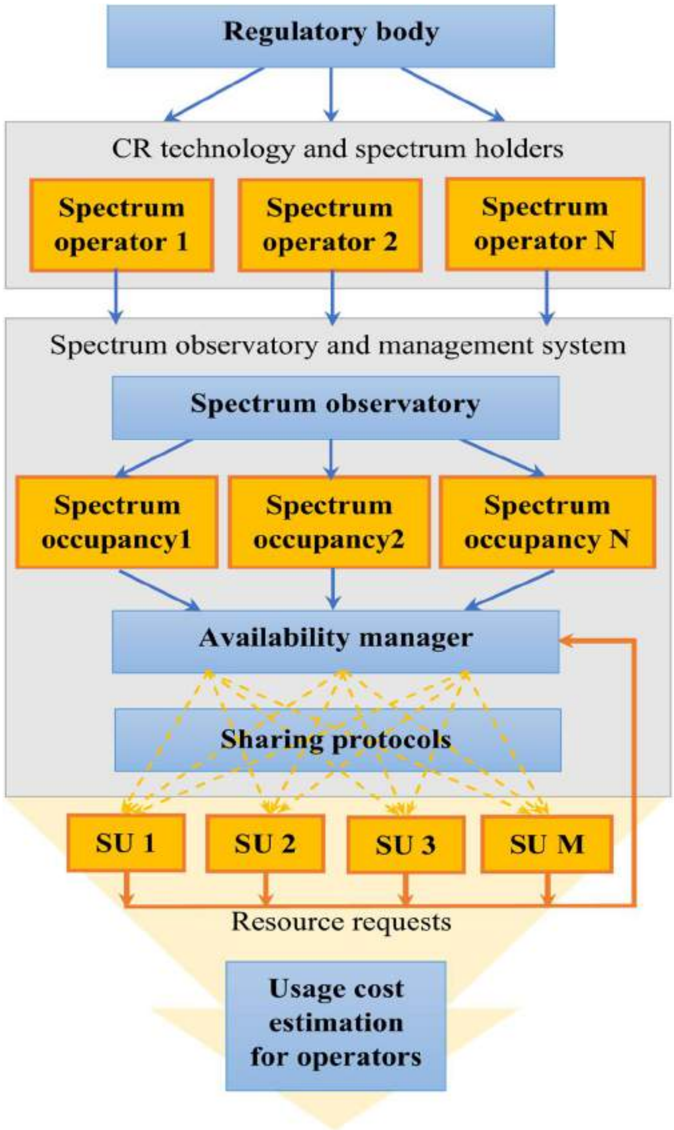


Figure 3.1. The role of the spectrum observatory and management system in a CRN.

A good management strategy is that ensures an accurate mobility mechanism, which guarantees safe transitions of SUs between available frequency bands and avoids interferences with Primary Users (PUs). A robust spectrum mobility algorithm can be achievable via an efficient spectrum allocation and sharing scheme. These latter functions are responsible for the dynamic attribution of the radio spectrum and the intelligent exploitation and sharing of radio resource opportunities for SUs. However, the allocation of spectrum resources without handoff delays requires prior knowledge of the channels' status, which is provided by the spectrum prediction process. A prediction algorithm relies essentially on the occupancy information acquired from a meaningful spectrum observatory that makes the right decision rules for reliable sensing results. Figure 3.2 shows the spectrum management functions gradation.

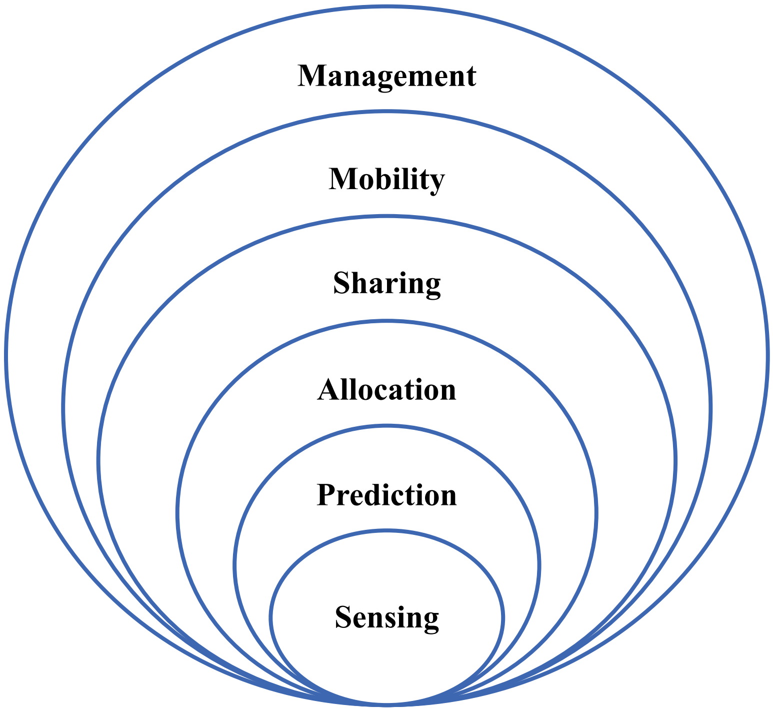


Figure 3.2. Spectrum management functions.

In a CR spectrum management system, a spectrum observatory has the responsibility of continuous spectrum monitoring, data gathering (database collection of spectrum characteristics and geo-localization information), estimation and evaluation of frequency bands occupancy status, and more. Its objective is to classify frequency channels according to their usage categories (idle, busy, underutilized, and highly utilized), and to extract relevant spectrum information and features for an accurate users detection, therefore, the modeling of the PUs activity. All this collected data will be then exploited in the training of prediction, allocation, and mobility algorithms for an efficient resource handoff for SUs and to reduce transmission costs. Figure 3.3 presents the proposed CR spectrum management scheme and highlights the position and the role of a spectrum observatory in this system.

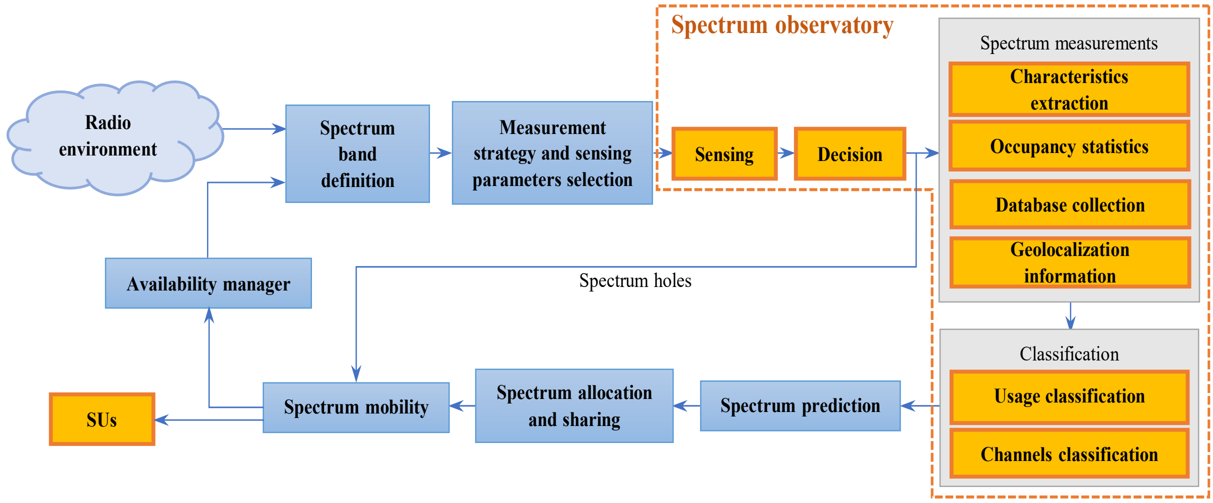


Figure 3.3. The proposed CR management system scheme.

3.1.3. Contribution of this Chapter

This chapter provides detailed spectrum scan statistics for every tiny channel for different spectrum bands. This measurement campaign aims to, first, highlight the importance of a spectrum observatory in a spectrum management system. Second, to study the spectrum occupancy behavior in specific geographic regions (urban and rural) by extracting the PUs activity in these areas, then to compare the results. Especially, to assess the potential of using CR or any other system based on the principle of dynamic spectrum allocation. Moreover, to build a real database that contains an updated spectrum occupancy scenario. This database is used next in solving diverse CR issues like spectrum sensing, prediction, allocation, sharing, and management. This contribution resides essentially in providing a recent and detailed spectrum occupancy survey of the actual mobile networks and DVB-T frequency bands and compares the results of the same measurements carried out in two different areas in Algeria, an urban area in Constantine and a rural area in Ouargla.

3.1.4. Chapter Organization

The rest of this chapter is organized as follows: Section 2 defines the measurement system, its technical characteristics, and key features, employed in this measurement campaign. Section 3 describes the considered data collection and analysis methodology in addition to the main parameters and settings of the measurement procedure. Spectrum occupancy statistical and graphical results are provided in Section 4, side-by-side with an investigation of the effect of the spectrum observatory on the management strategy selection. Finally, conclusions are summarized in Section 5.

3.2. Measurement System

Compared to the data collected otherwise, the actual data is collected using ANF professional signal monitoring system. Where the collection campaign of similar data requires hard work, to provide the required hardware “large span, wide range, multi-directional, and high sensitivity antenna” to cover all area directions, and a “spectrum analyzer”; especially to interface the hardware with the software using specific drivers. Then to build a “LabVIEW” or “MATLAB” corresponding diagram/model which catches the analyzed signal and processes it until getting the final useful frequency samples. This process may take a lot of time and complexity, appreciably, when dialing with long rang frequency span measurements in parallel and short-duration storage intervals.

In our measurements campaign, all these processes were summarized in one system “TCI 5093 Spectrum Processor” which can analyze and process multiple signals from different azimuths, with various spans and RBWs for diverse durations and sampling times. All these functions are done in parallel due to its important processing capabilities and its associated “Scorpio” software in addition to the “647D: V/U/SHF DF” Dual polarization multidirectional monitor and DF antenna array. The measurement system that we employed is shown in Figure 3.4.

(a) 647D Dual-Polarized (VHF/UHF/SHF) DF and multidirectional monitor antenna array.

(b) TCI 5093 Spectrum Processor and Receiver.

(c) PC with “Scorpio” monitoring software.

Figure 3.4. The used spectrum measurement equipment in both areas.

3.2.1. Antenna Technical Characteristics

- Antenna Model: the antenna model is 647D Dual-Polarized (VHF/UHF/SHF) DF (Direction Finder) and a multidirectional monitor antenna array. It consists of three major components; the antenna radome, the dual block converter module, and the POE (Power Over Ethernet) control interface module. Inside the radome are two DF antenna arrays (one is for the VHF/UHF band and the other is for the SHF band), a reference antenna, and a C-Band DF antenna switch unit. The 647 Dual-Polarized antenna generates three RF outputs; a “Monitor”, “Reference” and “Sample” RF outputs. These two last outputs feed directly to the dual-channel block converter and then feed the 2612 VHF/UHF receivers;
- Frequency span: 20 - 8000 MHz;
- Coverage range: until 30 km;
- Sensitivity: System sensitivity is the field strength (dBµV/m) required to provide specified DF accuracy including antenna noise, coax cable losses, and receiver noise; referenced to 1 Hz bandwidth and with 1-second DF averaging [82]. System sensitivity is like illustrated in Figure 3.5. For more technical characteristics see the reference [82].

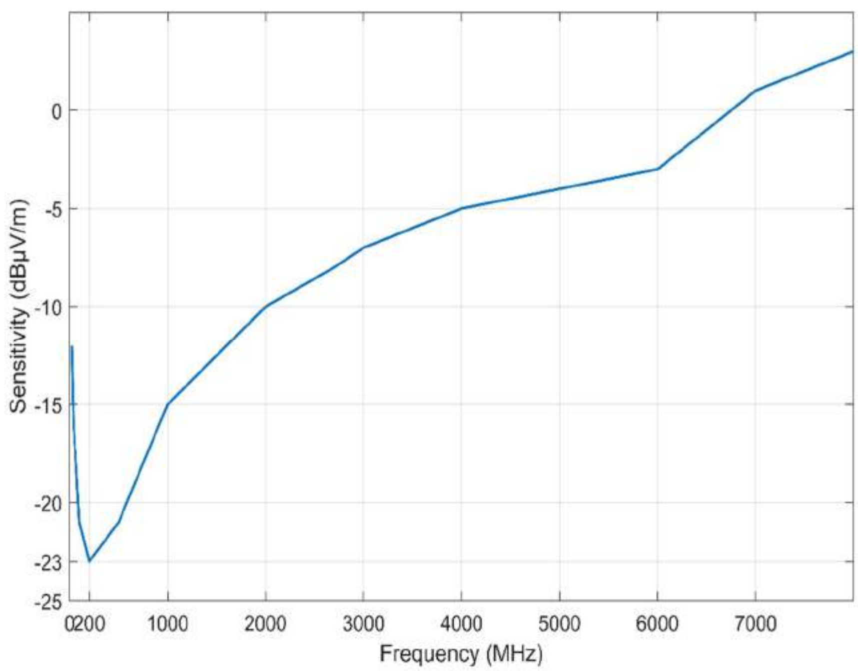


Figure 3.5. Antenna sensitivity (dBµV/m) Vs Frequency in (MHz) [82].

Table 3.1. Spectrum data collection settings.

Measurement parameters	Parameters values
Collection instrument	TCI 5093 Spectrum Processor
Collection locations	Two different areas in Algeria: ▪ Urban in the university Salah Boubnider – Constantine ▪ Rural in Bour Al-Aîcha –Ouargla
Location coordinates	▪ Constantine : N 36 16'52,3" / E 6 35' 15,4" ▪ Ouargla : N 32 0' 46,1" / E 5 20' 11,9"
Sampling time (scan) interval	5 min

3.3. Methodology for Data Collection and Analyses

3.3.1. Measurement Locations

In order to study the probability of the integration of a CRN in various environments in Algeria, two different nature locations (urban and rural) areas have been selected.

For this reason, spectrum occupancy patterns and possible spectrum opportunities were extracted and classified. A comparison of the spectrum occupancy between these two locations is presented in section 3.4. The first location was on the outdoor, upper roof of the department of political sciences at the campus of Salah Boubenider, University of Constantine 3 – Constantine, whereas the second location was outdoor in the rural area – Bour Al-Aîcha – in Ouargla. The coordinates and measurement settings are summarized in Table 3.1, and google maps locations are presented in Figure 3.6.

(a) (b)

Figure 3.6. Spectrum survey locations, (a) Constantine, (b) Ouargla.

3.3.2. Measurement Procedure and Strategy

In wide-band spectrum surveys, it is so important to compromise between the measured band and the time duration. Where any measurement hardware has some limits in terms of the recording capacity, i.e., the number of received/memorized samples. Short sampling time and short sampling frequency scan require a brief analyzing band because it produces an enormous number of received samples, and thus a very big storage space.

Therefore, the measured data has been gathered continuously by “five minutes” sampling time, for 24 hours, during 7 and 15 days across multiple frequency channels in these two different areas. Sampling frequency for each band was carried out according to their regulatory bandwidth restrictions. It was set to be taken in the middle of channels (center carrier frequency) to ensure the right detection of the signal power.

The used equipment surveys the required frequency bands by detecting the field strength of active users in this band during the selected period. This was achieved according to the measurement tasks coming from the Scorpio spectrum monitoring software interface, which allows the definition of all measurement parameters. The TCI 5093 Spectrum Processor and Receiver acquires the field strength samples for every slot time and calculates the usage occupancy in time, which is known by the term (duty cycle). Real-time Spectrum Occupancy (SO) or duty cycle (%) can be expressed as follows:

$$\boldsymbol{Spectrum\ Occupancy}\ (\%) = \frac{\boldsymbol{occupied\ period}}{\boldsymbol{Total\ observation\ period}} \times \mathbf{100} \qquad \textbf{(3.1)}$$

Where the occupied period is how much time this channel was occupied during the total observation period. This last is the sampling slot time, and it is equal to (5 minutes).

Channel field strength in (dBμV/m) is related to signal power by the following equation:

$$\boldsymbol{P_{rx}(dBm) = E(dB\mu V/m) - 20 * \log\big(f(MHz)\big) - 77.21 + G_i(dBi) - L_f} \qquad \textbf{(3.2)}$$

Where P_{rx} is the received signal power at the receiver antenna, and E is the Electrical field strength radiated at the source given by:

$$\boldsymbol{E^2 = P_r * 120\pi} \qquad \textbf{(3.3)}$$

where P_r is the radiated signal power. f is the frequency in (MHz), $G_i(dBi)$ is the isotropic antenna gain, and L_f is the path loss.

In our measurements, a dynamic threshold was used to detect the occupancy states of each frequency channel during the time. As recommended by the ITU, the threshold value should be between 5 and 10 dB above the noise level. This mode of dynamic thresholding is

known in practice (by the ITU) as the "Noise Riding threshold method". In our case, the adopted decision threshold for each frequency sampling point is set to 10 dB above the noise level. This value was employed to free the received signal from any possible adjacent transmitters' noisy signals, and it is the value set for the equipment of ANF Algeria.
The measurement bands and details are clarified in Table 3.2.

Table 3.2. List of scanned bands with exhaustive details.

	Band	Band number	Start-Stop Frequencies (MHz)	Sampling frequency (kHz)	Number of channels per band	Campaign period by days
	GSM900 (Up-Link)	1	890 - 915	200	125	15
	GSM900 (Dn-Link)	1	935 - 960	200	125	
Constantine	GSM1800 (Up-Link)	1	1730.1 – 1732.5	200	13	7
		2	1747.6 – 1752.8		27	
		3	1763 – 1770.8		30	
	GSM1800 (Dn-Link)	1	1825.1 – 1827.5	200	13	7
		2	1842.6 – 1847.8		27	
		3	1858 – 1865.8		30	
	4G (Up-Link)	1	1710.01 – 1729.99	15	1332	7
		2	1732.61 – 1747.49		993	
		3	1752.9125 –1762.8875		666	
		4	1770.9125 – 1780.8875		666	
	3G (Dn-Link)	1	2110 – 2170	200	300	7
	DVB-T	1	470 – 862	/	/	/
Ouargla	GSM1800 (Up-Link)	1	1730.1 – 1732.5	200	13	7
		2	1747.6 – 1752.8		27	
		3	1763 – 1768.8		30	
	GSM1800 (Dn-Link)	1	1825.1 – 1827.5	200	13	7
		2	1842.6 – 1847.8		27	
		3	1858 – 1863.8		30	
	4G (Up-Link)	1	1710.01– 1729.99	15	1332	7
		2	1732.61 – 1747.49		993	
		3	1752.9125 – 1762.8875		666	
		4	1768.895 – 1783.295		961	
	3G (Dn-Link)	1	2110 – 2170	200	300	7
	DVB-T	1	470 – 862	/	/	/

A. Remarks and details about Table 3.2

The presented (Start-Stop Frequencies) of the GSM1800 and the 4G are the effective frequency limits of these bands for the indicated measurement period between January and

February 2020. Recently, these bands are modified by the extension of the 4G operating bandwidth from 10 MHz to 15 MHz by 2021. In addition, mobile operators, in 2021, extended the 4G band to the 3G band, where every operator has been attributed one more 5MHz bandwidth additionally to the three previously attributed for each of them to 3G. In this way, 10 to 15MHz would be allocated to the LTE, for data transmission, and the rest of the bandwidth to the 3G, for real-time voice service.

For GSM1800, the band numbers 1, 2, and 3 are respectively the frequency bands of the operators, Djezzy/ Optimum Télécom Algérie (OTA), Mobilis/ Algérie Télécom mobile (ATM), Ooredoo/ Wataniya Télécom Algérie (WTA). Whereas, the numbers 1, 2, 3, and 4 for 4G band are Algérie Telecom (AT), Djezzy (OTA), Mobilis (ATM), Ooredoo (WTA), correspondingly. Figure 3.7. shows the GSM1800 bandwidth partitions between 2G and 4G norms for all mobile operators in Constantine.

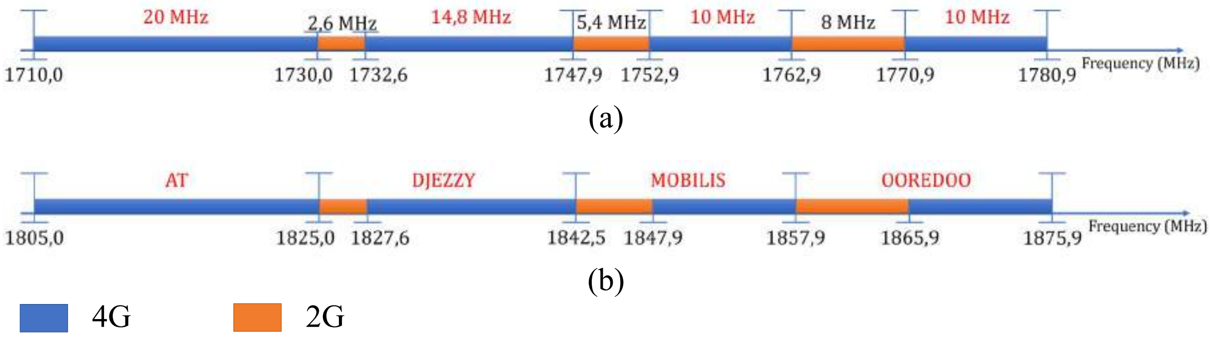


Figure 3.7. GSM1800 bandwidth partitions between 2G and 4G norms for all mobile operators in Constantine, between January and February 2020. (a) Up-Link, and (b) Down Link.

Besides, we did not analyze the DVB-T band continuously since the resource utilization in this band is static. Where in each city in Algeria, one to three channels only are used for TV TNT (Télévision Numérique Terrestre). In the first site in Constantine, two DVB-T channels of 8MHz are active all the time in the frequency bands of (510 – 518MHz) and (526 – 534). Otherwise, the rural area in Ouargla covers only one channel between (486 and 494MHz). This is since the allocation of TV channels depends on the geographical location. The only operator responsible for DVB-T diffusion is the TDA (Télédiffusion d'Algerie). Thus, the total occupancy of this band returns to the TDA.

In another hand, for the third generation (3G) too, we have, only, observed the down-link span in (2110 – 2170MHz). This band is almost full; every operator has been attributed three consecutive channels of (5MHz), and a guard interval of 10.55MHz appears the only spectrum opportunity in this frequency range in addition to 5.15MHz at the end of the band. Up-link signals in the 3rd generation are considered undetectable looking to the spread spectrum technique that hides transmitted signals under the noise floor. Knowing that only FDD (Frequency-division duplexing) is functioning in Algeria.

3.4. Spectrum Occupancy Results, Statistics, and Discussion

3.4.1. Graphical Results

Using the MATLAB toolbox, all collected data were plotted in 3D and 2D graphs to visualize the general evolution of Primary Users (PUs) spectrum occupancy. This visualization can give us a good overview of PUs activity and the potential underused frequency sub-bands. Thereby, the evaluation of available radio resources and the estimation of the possible investigation and management strategies of this precious resource. Table 3.3 shows the spectrum Occupancy graphical results of all analyzed bands for the urban and rural areas.

By observing the spectrum occupancy behavior in Table 3.3, it is remarkable that the occupancy variation during a day is quite similar throughout 15 days of the measurement campaign.

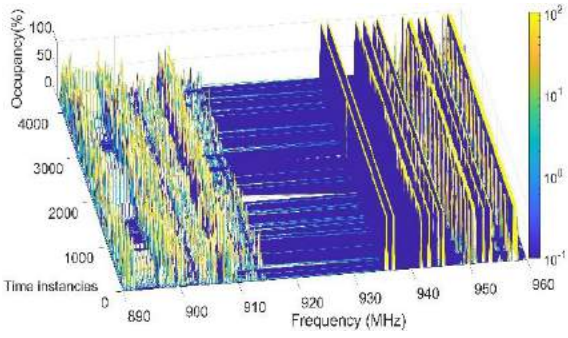
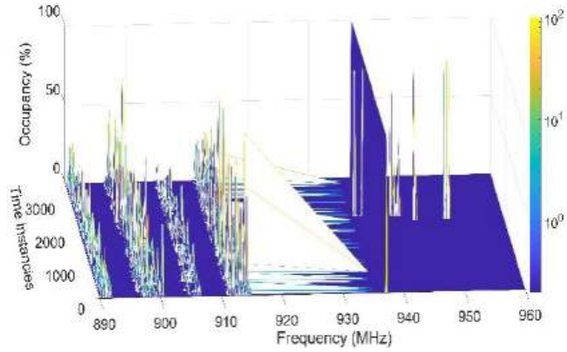
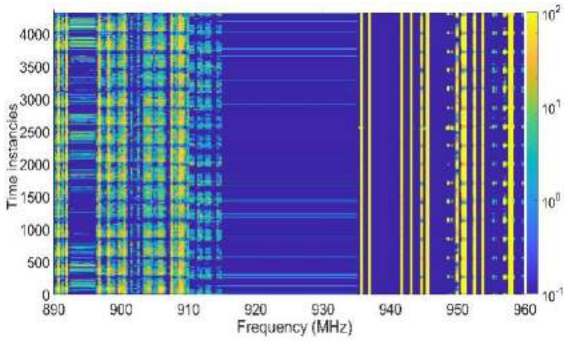
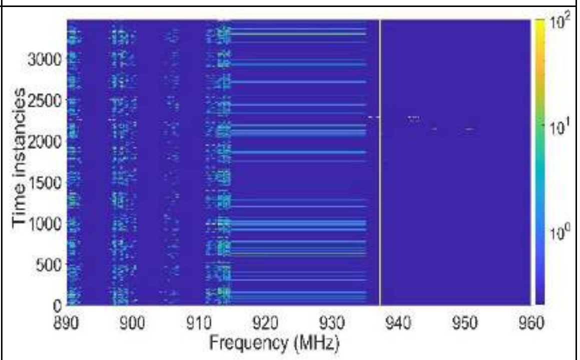
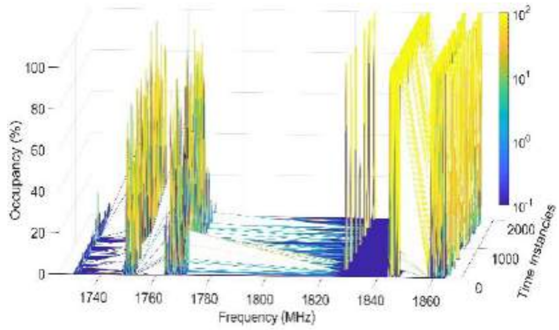
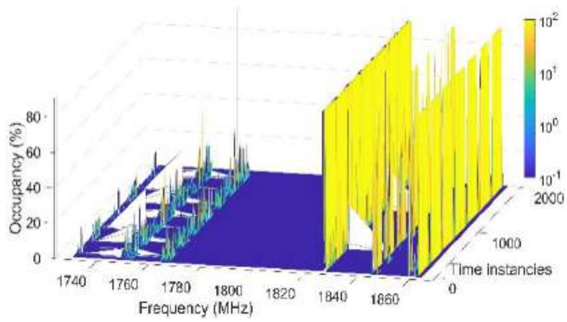
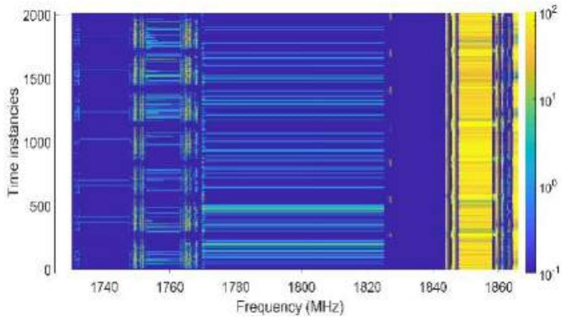
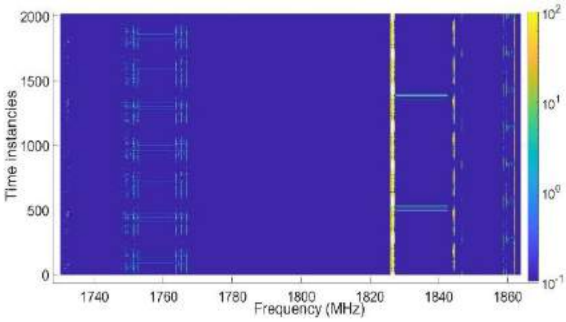
3.4.2. Statistical Results

The occupancy percentages of the collected data samples were averaged band-by-band, operator-by-operator for both regions. Besides, the average occupancy values for every operator and the total occupancy per band have been calculated in terms of the total number of samples of the considered band. Equation (3.4) was used to impute the statistical results:

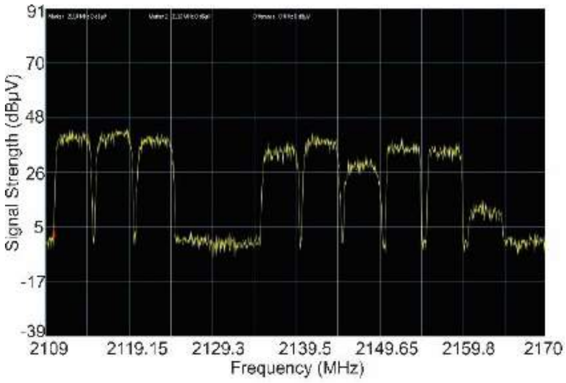
$$\boldsymbol{Average\ occupancy\ per\ band} = \frac{\boldsymbol{number\ of\ occupied\ samples}}{\boldsymbol{total\ number\ of\ samples\ of\ the\ band}} \qquad \textbf{(3.4)}$$

The statistics are collected in Table 3.4, and the occupancy values are presented using bar charts in Figures 3.7, 3.8, and 3.9.

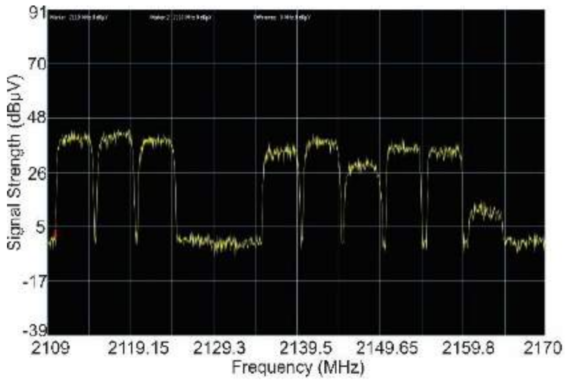
Table 3.3. Spectrum occupancy graphical results of surveyed bands, (a) 3D and (b) 2D graphs.

	Constantine	Ouargla
GSM 900	 **(a) 3D**	 **(a) 3D**
	 **(b) 2D**	 **(b) 2D**
GSM 1800	 **(a) 3D**	 **(a) 3D**
	 **(b) 2D**	 **(b) 2D**

3G (Down-Link)

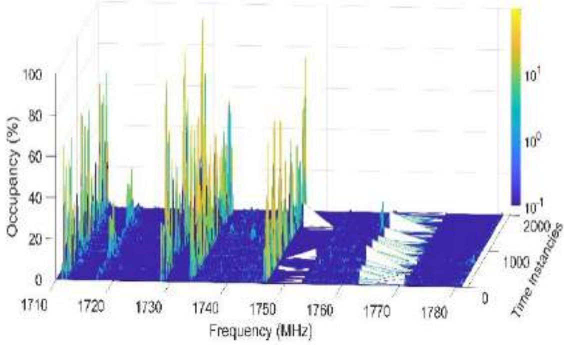


(b) 2D

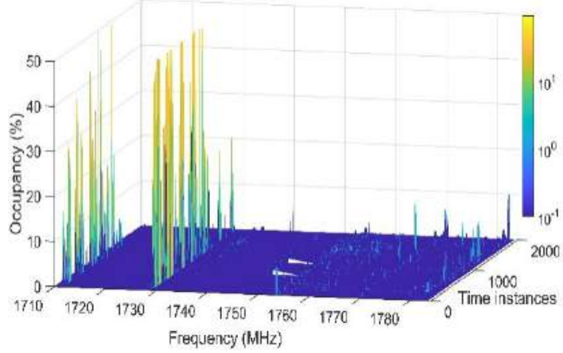


(b) 2D

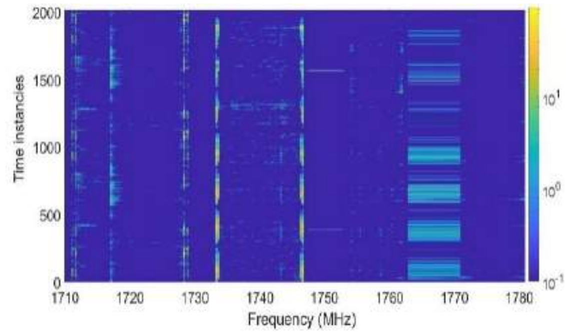
4G (Up-Link)



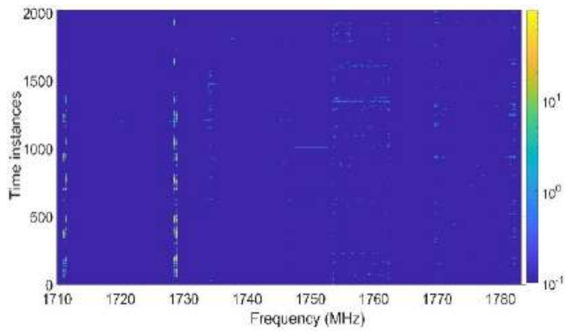
(a) 3D



(a) 3D

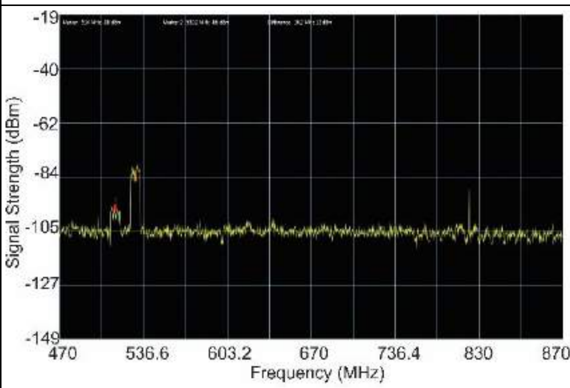


(b) 2D

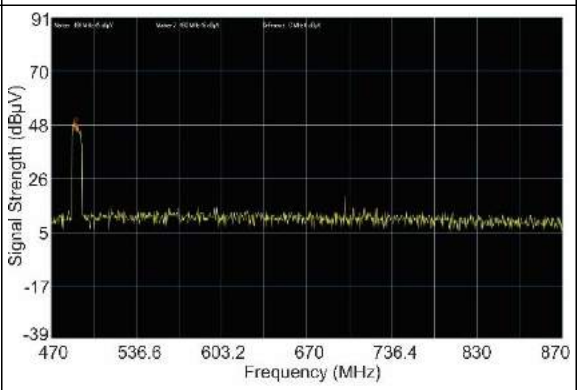


(b) 2D

DVB-T



(b) 2D



(b) 2D

Table 3.4. Average spectrum occupancies of analyzed bands in terms of mobile operators and measurement areas.

Areas	Constantine Occupancies (%)					Ouargla Occupancies (%)				
Bands / Operators	GSM900	GSM1800	3G	4G	DVB-T	GSM900	GSM1800	3G	4G	DVB-T
Algérie Télécom	/	/	/	1.1116	/	/	/	/	0.2831	/
OTA	11.4537	0.5525	24.6133	1.4105	/	0.2771	4.0462	24.6133	0.0218	/
ATM	9.0137	8.4629	24.6133	0.1273	/	1.0624	2.1510	24.6133	0.0883	/
WTA	9.7938	15.9927	24.6133	0.0522	/	0.8116	2.2311	24.6133	0.0670	/
Total occupancy per band (%)	30.2612	25.0512	73.84	2.7016	4.0816	2.1511	8.4283	73.84	0.4602	2.0408

It can be observed that GSM attributed bands are more occupied than the 4G attributed bands because for GSM the two links, Up and Downlink occupancies, are considered, which raised the occupancy in that bands. Note that the 4G Downlink band is busy all the time for information transmission, thus it is not an interesting band for the CR.

Whereas WTA mobile operator possesses the highest occupancy percentage in Constantine for GSM bands with 15.99% in GSM1800, and OTA in the second place with 11.45% for GSM900. However, OTA marks the highest occupancy value for GSM in Ouargla with 4.05%. In another hand, the 3G Dn-Link band presents the maximum levels of occupancy with an average occupancy of 73.84% of the total 3G Downlink bandwidth in both areas.

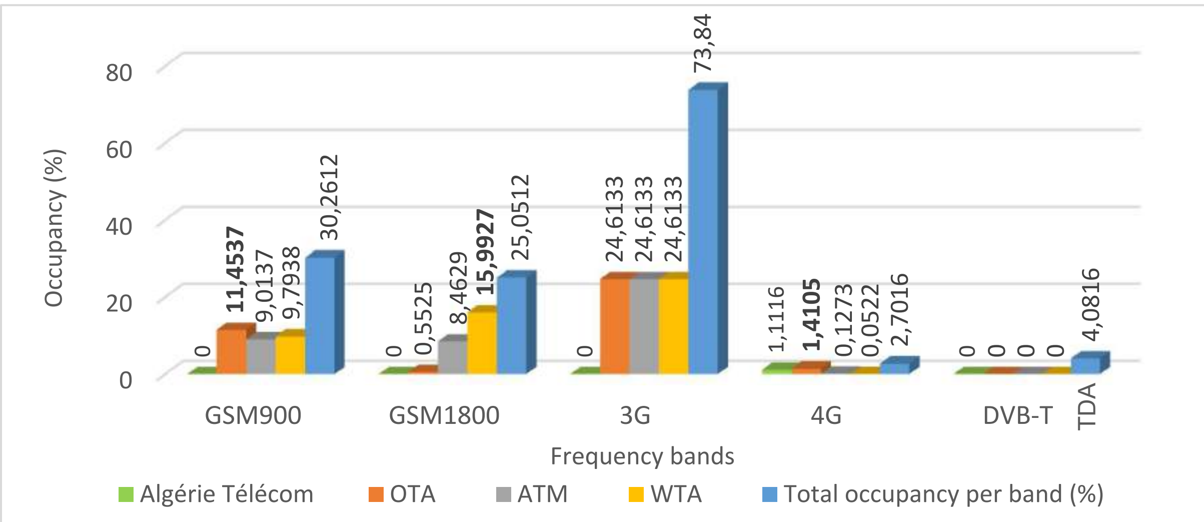


Figure 3.8. Spectral Occupancy for all bands in terms of mobile operators in Constantine.

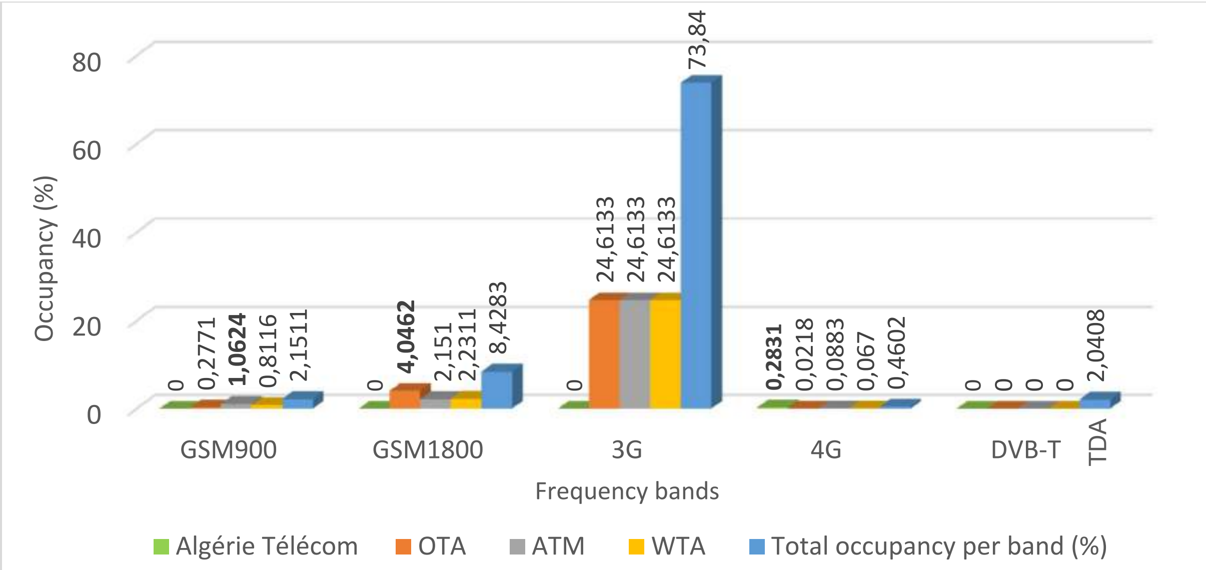


Figure 3.9. Spectral Occupancy for all bands in terms of mobile operators in Ouargla.

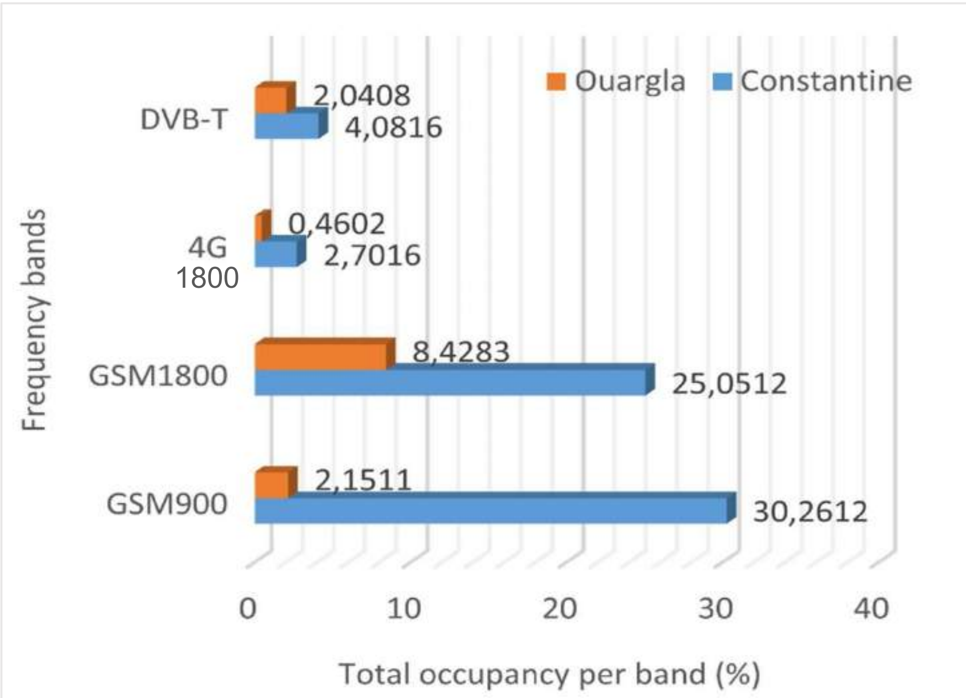


Figure 3.10. Overall spectral occupancy comparison between Constantine and Ouargla.

To investigate the amount of fully idle channels versus the other occupied channels in all the measured bands, and to distinguish the occupancy levels of radio resources the following classification was performed. As an example, the GSM900 band dataset has been used in this first investigation. The number of channels with zero utilization, out of the total number of channels in this specific band (250 channels), was summed for every time slot to get the "Free Channels" number for 15 weekdays, instant by instant. Similarly, the number of "Under-used" and "Highly-used" channels was determined. Whereas occupancy samples belong to]0, 50%[were classified as "Under-used" channels. However, "Highly-used" channels were considered as channels of more than 50% occupancy values, view Figure 3.11. In this way too, the total number of samples by each class of channels was summed and divided by the total number of samples in a specific band. The results are presented in Figures 3.12 and 3.13.

As it can be observed in Figure 3.11, it is remarkable that the number of free channels is the highest compared to under-used and highly-used channels, during the whole measurement period for both areas. It can be observed that in the rural area, the channel opportunities are away bigger than the number of used channels. Moreover, the under-used and highly-used number of channels are quite similar and curves are clearly distinguishable between free and used classes in this area.

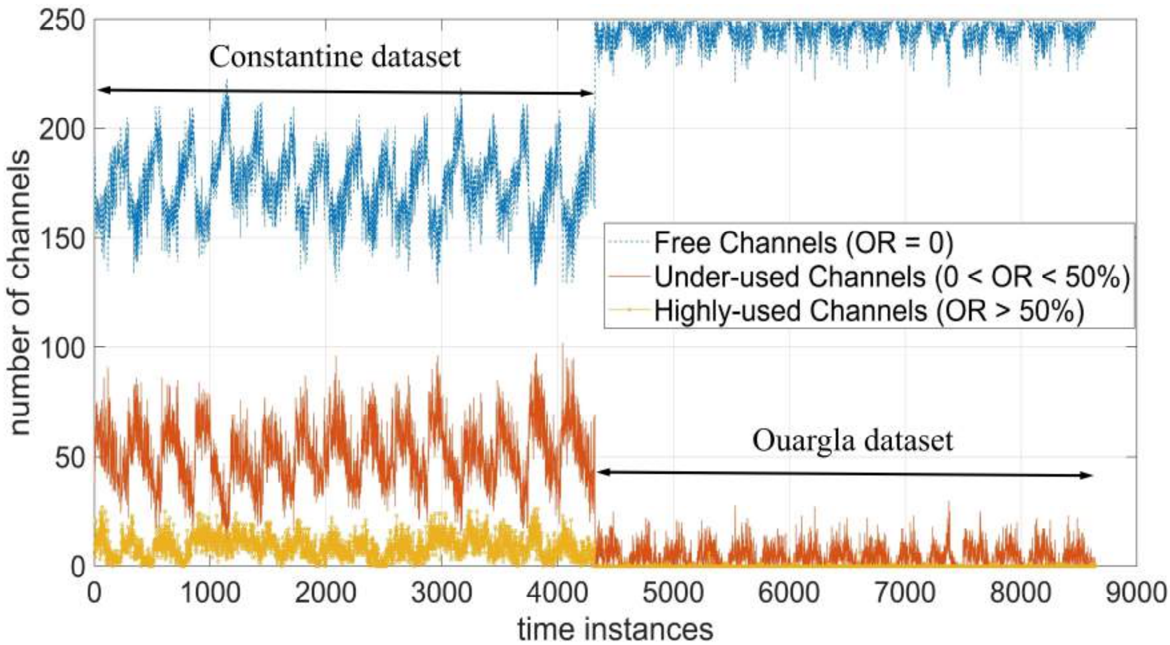


Figure 3.11. Channels classification of Constantine and Ouargla for the GSM900 band.

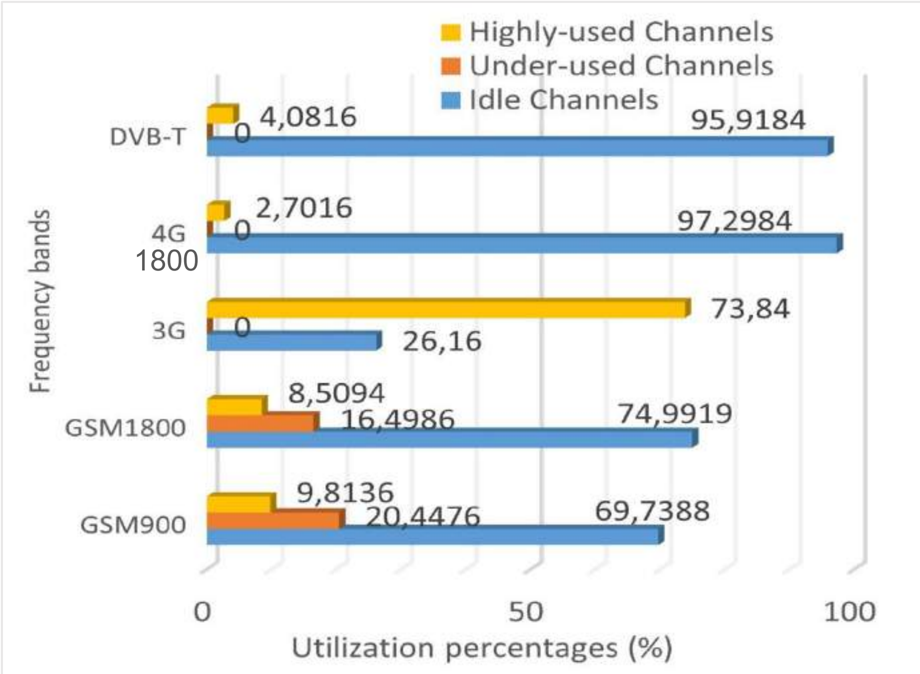


Figure 3.12. Overall utilization percentages of classified channels for Constantine.

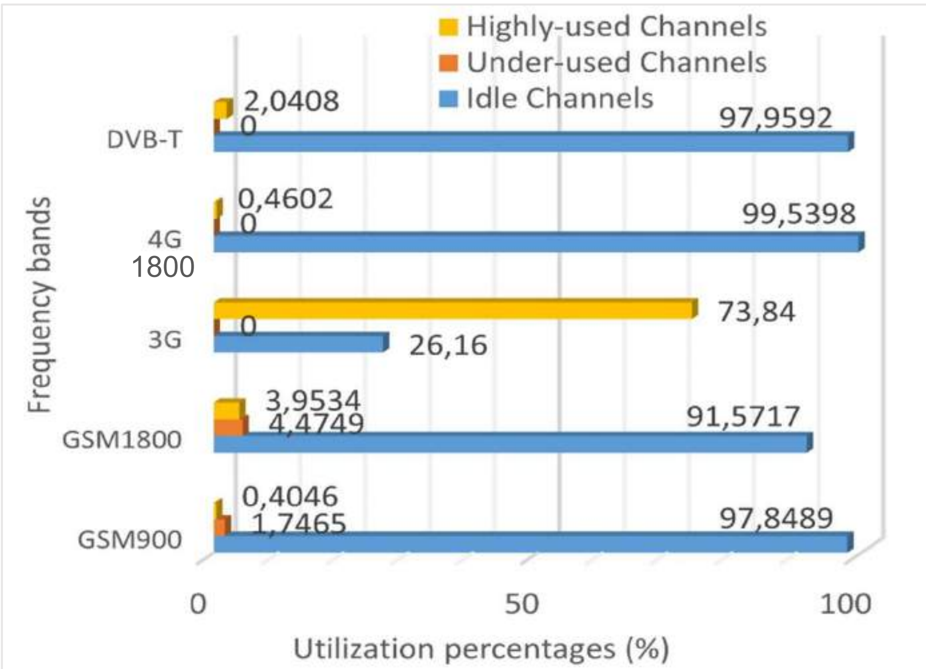


Figure 3.13. Overall utilization percentages of classified channels for Ouargla.

A. Spectrum Observatory Impact on a Management Strategy

To inspect the effect of specific spectrum observatory features upon some management strategy parameters, the occupancy in percent and the field strength of the first five minutes, thirty seconds, and three seconds of three GSM900 channels were tested and selected management choices were deduced in Table 3.5.

Figure 3.14 shows the spectrum occupancy of a sample channel for different sampling times (5min, 30s, and 3s).

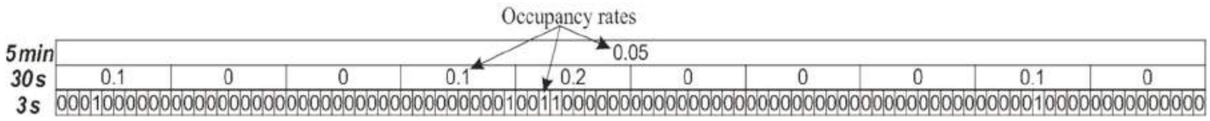


Figure 3.14. Spectrum occupancy of a sample channel for different sampling times for five minutes duration.

In CRNs, the selection of the management strategy depends on different parameters, one of the most important parameters is the probability of interference between secondary and primary users. This parameter is directly related to the sampling time. Whereas, big sensing steps would miss the detailed detection of PUs in time, which increases the probability of collision with PUs. However, reducing sampling time by rising the sensing frequency or the number of samples per time element inflates the processing requirements. Especially, during frequency resources' handoff, the SDR device performs multiple numbers of channels switching for SUs because of short transitions in time. This can also engender spectrum access delays and interferences caused by the switching delays.

Otherwise, reducing sensing time is beneficial in terms of the decreased probability of interference and the increased availability rates, and thus high spectrum opportunities detection. Short sensing time enables SUs to use even underutilized channels in time and frequency domains but it consumes higher energy and memorization capacity for high sensing frequency.

The example in Table 3.5 proves the impact of specific spectrum observatory features upon some management strategy parameters.

Table 3.5. Spectrum observatory impact upon the management strategy.

Spectrum Observatory Features				Management Strategy Parameters				
Sampling Time	Channels	Channel Occupancy (%)	Field Strength (dBµV/m)	Channel Selection	Probability of interference	Availability rate	Number of channels switching per 5min	Sensing frequency
5 min	Channel 1	5	53	✓	0.05	0	1	$\frac{1}{100} = 0.01$
	Channel 2	7.49	58	X	0.0749	0	1	
	Channel 3	5	57	X	0.051	0	1	
30 s	Channel 1	10	49	X	0.001	0.6	4	$\frac{1}{10} = 0.1$
	Channel 2	0	0	✓	0	0.5	5	
	Channel 3	6.6	46	X	0.0066	0.5	5	
3 s	Channel 1	0	0	✓	0	0.95	5	1
	Channel 2	0	0	✓	0	0.86	14	
	Channel 3	33	46	X	0.0033	0.95	11	

Through the above results the sampling time, channel occupancy, and field strength effect on the management strategy was investigated. Thereby, the CR spectrum management system in this case selects the least-occupied channel with lower field strength and probability of interference to be allocated for SUs whatever the selected sensing time.

B. Summary

Throughout the statistical results, the DVB-T spectrum band presents a substantial opportunity for spectrum reuse, especially concerning the typical propagation characteristics of electromagnetic waves in this particular band. As well, other mobile operating frequency resources are partially available during the time of the day, which offers access for dynamic opportunistic secondary users. Moreover, the spectrum analysis used in this study can assist in the regularization of dynamic spectrum access policies for unlicensed users in the future. Therefore, the implementation of a CRN is beneficial in Algeria, since the electromagnetic spectrum is not fully used even if it is already fully allocated. From our point of view, this conclusion can be generalized to any rural or urban area in Algeria, and to confirm this statistical tendency, more spectrum surveys can be investigated in other areas.

A CR spectrum management strategy should consider many parameters before performing the necessary spectrum measurements. Whereas, a good strategy is which achieves the best results with the minimum costs and risks.

3.5. Conclusion

The spectrum occupancy observatory has uncovered the real status of spectrum usage around the world, and thus it opened the horizons to new strategies of spectrum management and the new applications of cognitive radio. According to the results of this study, Algeria has a big opportunity to implement any new cognitive radio network that is based on opportunistic and dynamic access techniques. Looking at the high number of idle and under-used channels in time presented in a large part of under-used frequency bands, it can be deduced that the traditional method of fixed radio resources allocation would induce a serious spectrum scarcity problem. Therefore, a spectrum observatory management system is necessary to reduce the scarcity problem using dynamic spectrum allocation. The relative occupancy percentage of mobile communication and DVB-T bands for both locations of Algeria do not exceed 30.26%, which means that the reuse of these resources in new technologies like IoT, 5G, … is highly recommended.

Our proposed CR spectrum management approach is an efficient strategy that combines sensing, prediction, and allocation functions to ensure minimum interferences and processing requirements.

CHAPTER 4

Proposed Spectrum Predictor architecture for CR-IoT

Sections

1. ***INTRODUCTION***
2. ***METHODOLOGY***
3. ***RESULTS***
4. ***DISCUSSION***
5. ***CONCLUSION***

Abstract— *Cognitive Radio has been nominated as a key technology for the internet of things (IoT), due to its intelligent functionalities ensuring continuous connectivity for IoT objects. Spectrum prediction, as one of the core CR functions, has emerged as a leading tool to alleviate the spectrum scarcity problem. Spectrum prediction minimizes sensing and decision-making delays, and thereby it reduces collisions with Primary Users and guarantees safe access for Secondary Users (SUs). Thus, it became an inseparable part of many new spectrum allocation and mobility methods. In this work, the proposed Cognitive Radio Internet of Things model consists of Local Sensors (LS) that perform sensing instead of SUs, and a Cognitive Base Station that receives sensing results from different LSs to predict the next occupancy information and allocate frequencies for SUs. The predictor is followed by a channel extraction block for efficient spectrum allocation. Then, a low complexity spectrum prediction and preallocation system based on optimized neural network architecture is presented. Two nonlinear neural network models, Time Delay Neural Network and Nonlinear Autoregressive with Exogenous input, that are trained on a real spectral occupancy dataset, are optimized using the Bayesian Optimization algorithm and then compared. The best predictor forecasts the next occupancy rate of multiple channels simultaneously based on three dimensions, area, time, and frequency. Performance evaluation was conducted through accuracy, Mean Squared Error (MSE), and regression fit. The highest prediction accuracy was 93.5%, the regression coefficient was 0.98, and a reduced MSE of 0.0013 was obtained. Results show that the considered scheme is efficient in forecasting the spectrum availability of different bands within the IoT spectrum resources.*

Keywords— *Bayesian Optimization; Cognitive Radio Internet of Things; multichannel forecasting; real occupancy database; soft prediction; spectrum prediction; TDNN & NARX.*

4.1. Introduction

4.1.1. Background and Motivation

CR is a relevant solution to the spectrum scarcity problem that arises amid the deployment of new wireless communication systems such as CR smart grid communication networks [84], and the Internet of Things. IoT aims to connect everything and everybody in one big network, where data can be exchanged between all the elements composing it. Achieving this connectivity requires continuously observed and available radio resources. For this reason, CR has been proposed as a key technology, considering its capabilities in managing and allocating frequency resources intelligently. IoT objects with cognitive capabilities named (CR-IoT devices) are the future, allowing intelligent decisions to be made anytime, anywhere, interference-free, and to provide on-demand services [85].

Spectrum prediction has been taking a lot of attention these decades, regarding its ability to forecast the next channel states, thus alleviating spectrum sensing and decision-making delays. It has turned out to be the most efficient method for safe and opportunistic spectrum access and interference avoidance with PUs. Currently, spectrum prediction comes as a big partner to any CR function [86]. It accompanies the sensing process to minimize its considerable decision delays and energy consumption like in [87], and to guide SUs to sense only frequency bands that are predicted to be free. It also indicates the access map for SUs, *i.e.,* cognitive resource allocation, and proactive spectrum mobility [88], in addition to its major role in managing unlicensed users' frequency resources and sharing protocols.

4.1.2. Contributions

In this chapter, two popular time series forecasting algorithms, which represent a class of flexible nonlinear models, are presented and compared. TDNN and Nonlinear Autoregressive with Exogenous input (NARX) models are trained and optimized using BO, to solve the problems of coexistence and collisions between licensed and unlicensed users (PUs and SUs) by predicting the availability and activity of Radio Frequency (RF) resources. The proposed algorithms are soft, multichannel, multi-space, and multistep-ahead predictors based upon a realistic spectrum scenarios database. The Occupancy Rate (OR) parameter used in this work as input data provides enough information about the considered channel. It indicates how much this latter is occupied between two successive sampling times.

This chapter presents the following contributions:

- ✓ Development of a multichannel, multistep-ahead prediction model with a minimized number of neurons, so hardware complexity and processing time reduction using one predictor, compared to relevant works which allocate a predictor for each channel;
- ✓ Introduction of a new concept to quantify, accurately, the frequency channel's occupancy in time, which is the ”Occupancy rate”. By predicting soft occupancy rates, the spectral efficiency (utilization) is enhanced;
- ✓ Study and evaluation of NN predictors trained on real traffic scenarios and offering two areas prediction results through 3D data learning (time, frequency, space);
- ✓ Improving three NN performance metrics, accuracy, regression coefficient, and RMSE utilizing one optimization objective called the BOM metric for NN hyperparameters tuning.

4.1.3. Chapter Organization

The rest of this chapter is organized as follows. In Section 2, the used real spectrum occupancy dataset collection is described, and the proposed approach and predictive models are illustrated in addition to the simulation process. Section 3, addresses the BO NN hyperparameters tuning, and the prediction results, then a comparison with relevant works. Last but not least, section 4 provides a discussion of the obtained results, followed by a summary of our contribution as a conclusion in the last section.

4.2. Methodology

4.2.1. Dataset Collection and Preprocessing

The spectrum survey was performed in cooperation with the “Agence Nationale des Fréquences” (ANF) – Algeria, using high accuracy control station, “TCI 5093 spectrum processor” connected to “Scorpio^{TM} signal analysis software.” It can measure more than 2000 frequency channels in parallel with no sensing delay between the first and the last sensed channel. The measurements were carried out, in two areas in Algeria; one urban, in the north (University of Salah Boubnider - Constantine), and the other, rural, in the south (Bour Al-Aîcha - Ouargla), between January and February 2020.

In the areas under investigation, the GSM900 band is one of the most suitable bands in terms of wave propagation and energy efficiency for embedded systems like IoT. According to our statistics, its total 15 days occupancy is around 30.26% and 2.15% in Constantine and Ouargla respectively. Hence, exploiting this band enhances CR-IoT access and transfer opportunities.

The surveyed frequency bands [890 – 915 MHz] and [935 – 960 MHz], were divided into 250 frequency subbands (channels) of 200 kHz bandwidth. The Occupancy percentage of each channel was memorized every 5 minutes for 15 days. This corresponds to 288 samples per day and 4320 samples per 15 days. Multiplying this number by the number of channels, yields a dataset of (250×4320) samples per area, and a total size of the two areas of (250×8640) samples, presenting our input data. A dynamic threshold was used to detect the power values of each channel.

Recall that five-minute channel occupancy is given by:

$$Channel\ Occupancy\ (\%) = \frac{Occupied\ Duration}{Total\ Duration} \times 100 \qquad (4.1)$$

Where the Occupied Duration is in minutes and the Total Duration is 5 minutes that is the sampling time. Besides, the Channels' Occupancies (%) were normalized as occupancy rates, whose values lie in the interval [0, 1] to be more suitable as neural network inputs.

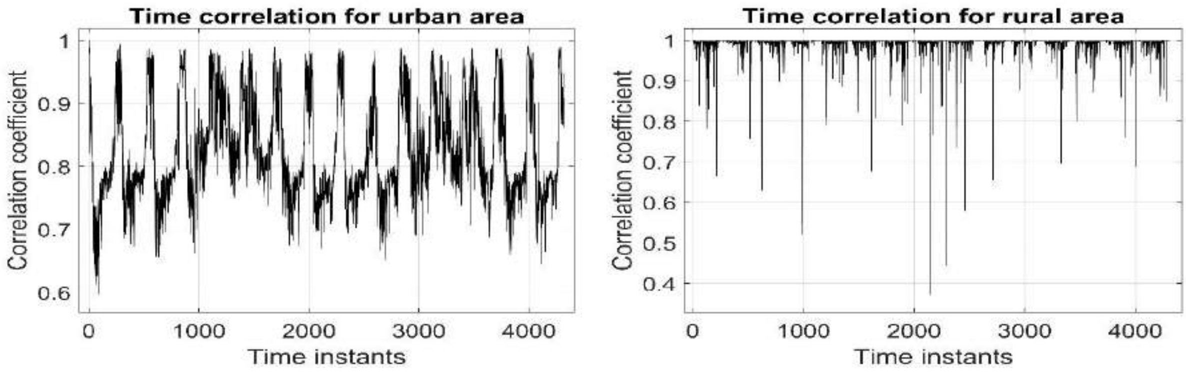
In this way, the input dataset can be represented as follows:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1K} \\ \vdots & x_{nk} & \vdots \\ x_{N1} & \cdots & x_{NK} \end{bmatrix}$$

Whereas N is the number of channels to be predicted, it is equal to 250 channels; K is the number of samples, it is equivalent to 8640 time slots, and x_{nk} is the occupancy rate of the channel "n" during the time slot "k."

In order to highlight the columns' correlation of the utilized dataset, the correlation matrix has been calculated and plotted. Figure 4.1 shows the correlation coefficient in terms of time instants (between columns), of the first time instant OR values of 250 channels (first column) with other OR values for all time instants.

The correlation coefficient presents high values and shows a kind of frequentist (pattern) in its evolution in terms of time instants in both areas. These high values and frequentist facilitate the model fitting for the NN predictors.



(a) **(b)**

Figure 4.1. Correlation coefficient in terms of time instants, of the first time instant OR values of 250 channels (1st column) with other OR values for all time instants; (a) urban area and (b) rural area.

4.2.2. Proposed Approach

The considered scenario and the prediction and pre-allocation system are illustrated in Figures 4.2 and 4.3, respectively. The proposed CR-IoT network is consisting of two overlapped areas, urban and rural. Whereas the primary and Cognitive Users (CUs) are distributed disparately from high to low densities in the urban and rural areas, respectively.

Each area is continuously surveyed through a static low-cost Local Sensor, which analyzes the spectrum bands every five minutes. The first LS sends sensing results at $(\tau t + \tau)$ to the Cognitive Base Station (CBS), and the second sends at $(\tau t + \tau + \Delta t)$. These results will be then switched, after being memorized in a matrix, to the predictor to forecast the next ORs of all frequency channels for both areas, where τ = 5min and Δt is the delay between the first received signal and the second.

After that, prediction results will be sorted in ascending order from the idle channels (OR = 0) to the completely occupied channels (OR = 1). Finally, the channels with a high probability to be free will be extracted and stacked to be attributed by priority for SUs (from free to Partially free (P. free) channels) using an allocation algorithm that will be presented in our next work, which exploits soft predictions (5 minutes ORs) for an intelligent channel allocation for CR-IoT devices.

Method 4.1 illustrates the channels' prediction and preallocation steps.

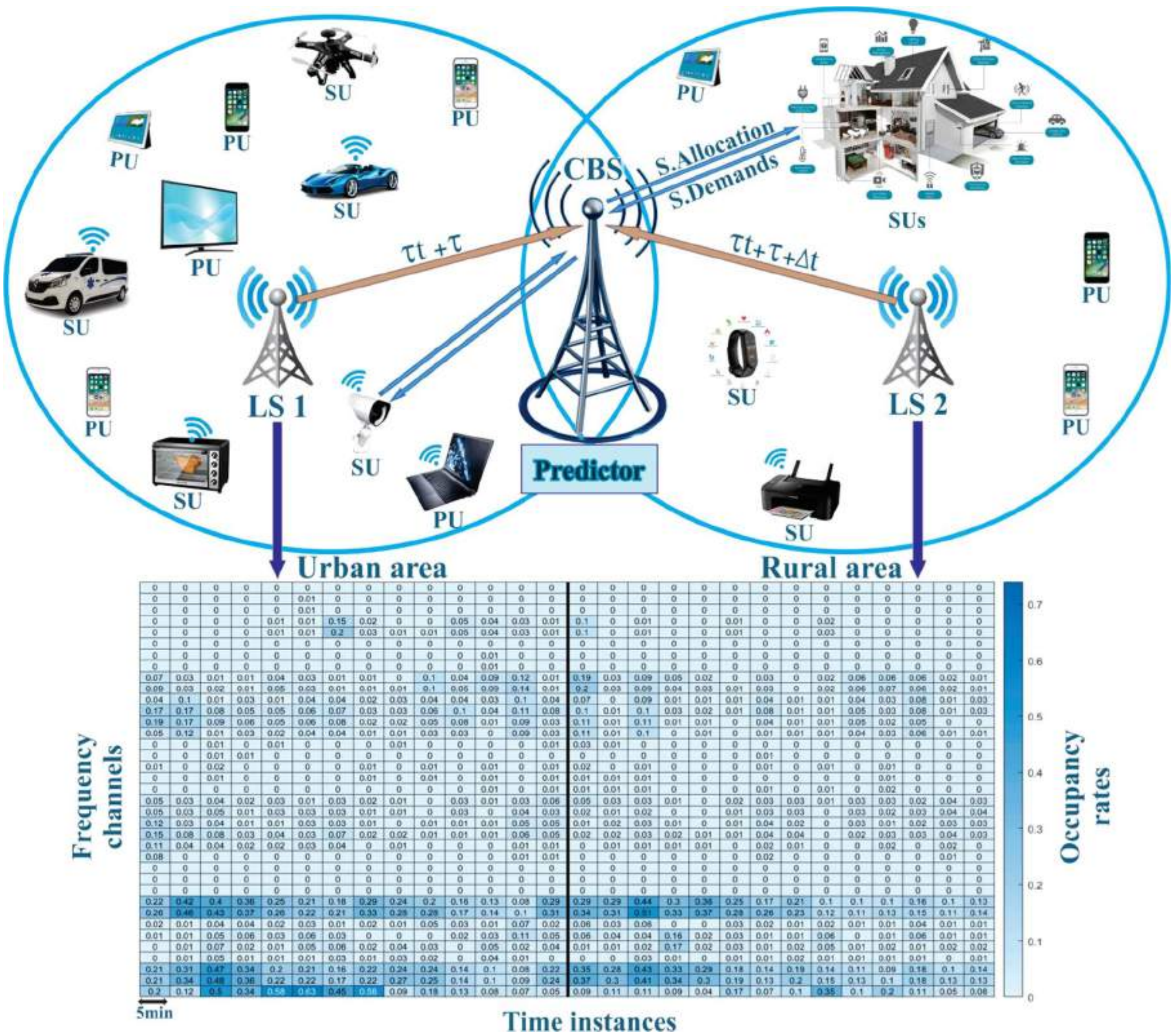


Figure 4.2. Proposed model of CR-IoT Network.

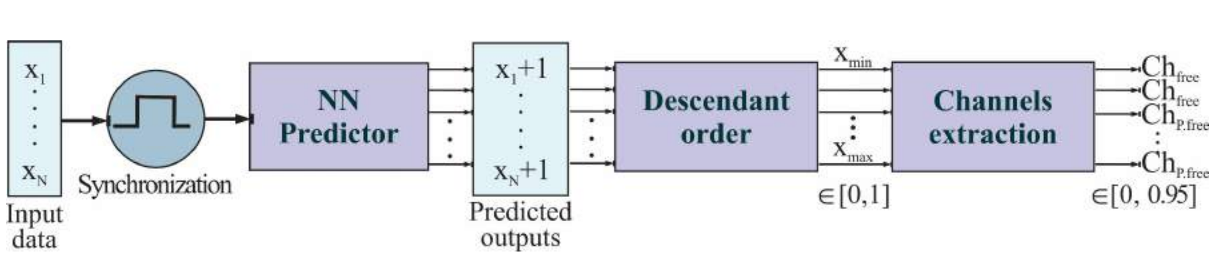


Figure 4.3. The proposed CBS prediction and pre-allocation block diagram.

Method 4.1. Channels prediction and preallocation steps.

Steps	Legend
1. *Initialization*: i = actual slot ; X_i = actual ORs input column ; $t = [(\tau t_i + \tau), (\tau t_i + \tau + \Delta t)]$; $t_{syn} = \tau$;	▪ $X_i = [X_{1k}, \dots, X_{Nk}]'$ ▪ t : time, t_i : time for actual slot (sampling time) ▪ t_{syn} : Synchronizer time.

2. *Synchronization*:
for t ***do***
if $X_i(t)$ *exists*; *if* $t = \tau t_i + \tau$ ***then***
$t_{syn} \leftarrow t$
else
$t_{syn} \leftarrow t_{syn} + \Delta t$
$X_i(t) = X_i(t_{syn})$;
end if
	▪ Synchronize coming signals X_i to maintain the delay Δt between the signal of area 1 and the signal of area 2
	▪ Update t_{syn} to t
	▪ Add delay Δt to the previous t_{syn} value

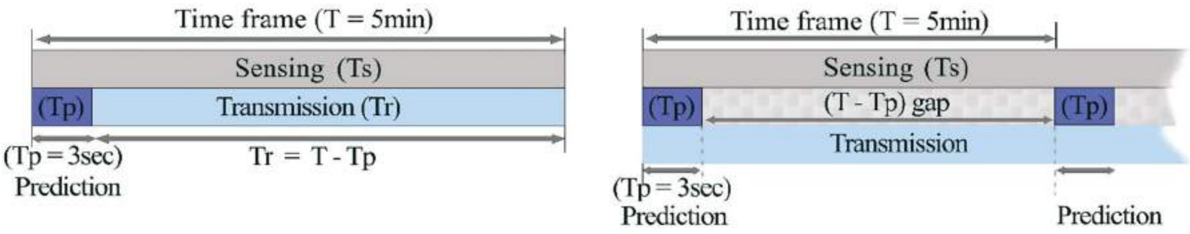
3. *Prediction*: $X_i(t+1) = predict(X_i(t))$;	▪ $predict(x)$: is the algorithm that takes the vector $x(t)$ as input and predicts the next state $x(t+1)$ of this vector.
4. *Sorting in descendent order*: $\hat{X}_i = sort(X_i(t+1))$;	▪ Arrange $X_i(t+1)$ from X_{imin} to X_{imax}

5. *Channel extraction*:
for $0 \le \hat{X}_i \le 0.95$ ***do***
extract Y_i *from* $\hat{X}_i$
end for
end for
	▪ Extract Y_i the vector containing only free to partially free channels from sorted vector $\hat{X}_i$
	▪ Y_i is the frequency channels to be allocated by priority to SUs.

6. *Allocate* Y_i	

4.2.3. Proposed time-frame structure of the CR-IoT network

In this work, two frame structures are proposed to describe sensing, prediction, and transmission durations, as illustrated in Figure 4.4. Time frame division depends on the number of prediction steps ahead, but the general repartition is as follows. Spectrum sensing operation should be continuous during the time to detect short-scale occupancy variations. Simultaneously, the predictor takes only 3 seconds, every 5 minutes, to forecast the next state, then CR-IoT devices commence transmitting for the rest of the 5 minutes. This is for a one-step-ahead prediction. Nevertheless, for one-day steps ahead, the same frame for sensing and prediction tasks, but CR-IoT devices will be transmitting continuously due to the preliminary knowledge of spectrum occupancy map of the whole day.



a) Structure for one step ahead **b) Structure for one day ahead**

**Figure 4.4. Proposed Frame Structures of the CR-IoT Network.
a) Structure for one step ahead, and b) Structure for one day ahead.**

4.2.4. Neural Network Predictor

The hard decision is an unwise approach dealing with time occupancies as input data. It is a waste of resources to assess a channel as busy based on a "0.5 threshold" while it is not fully occupied in time. Or to decide it free while it is currently partially occupied in time. Interferences with PUs are, absolutely, unavoidable. Thus, to address this issue, an "interference avoidance model" based soft prediction was proposed.

In this work, we address supervised learning NNs-based time series forecasting models, TDNN, and its recurrent copy NARX. These networks are designed to solve the regression problem related to spectrum prediction. However, the prediction algorithm should provide predictions fit, as close as possible, the target data, while minimizing the error function.

The proposed NN predictors are very useful real-time spectrum predictors, where all sensed channel occupancies (250 channels), at an instant "t", are acquired in parallel along with their delayed values, then being predicted all for the next step. Hence, compared to other works as [46], [45], and [42], where the input vector represents the M-considered previous values of only one channel thus the predictor gives forecasts for one channel, unlike our models, only one predictor is assigned to all channels in parallel, see Figures 4.5 and 4.6.

4.2.5. Activation Functions and predictor Architectures

In the proposed NN architectures, a combination of two activation functions was utilized. This compound aims to optimize the performance of the NN by limiting the error interval so that it converges towards its minimum goal. These activation functions were selected after multiple trial and error experiences on NNs.

The rectifier activation function $ReLu(s) = \max(0, s)$, was used in the first hidden layer only. Whereas, hyperbolic tangent sigmoid activation $tansig(s) = 2/(1 + \exp(-2 * s)) - 1$, was employed in the remaining hidden layers.

In Figures 4.5 and 4.6, n is the number of channels, k represents the input delays, it is the number of considered past values to predict the next value x (t + 1), z is the recurrent input delays for NARX, and TDL is a Time Delay Layer, else Y(t) is the recurrent input.

The problem definition for both networks can be resumed in equations (4.2) and (4.3). Where the next state is a function of the k previous observations, otherwise, the z previous observations of the recurrent output should be included in this function for the case of the NARX network.

- For TDNN:

$$\boldsymbol{x_a(t+1) = f(x_a(t-k) + \cdots + x_a(t-1) + x_a(t))} \quad \textbf{(4.2)}$$

- For NARX:

$$\boldsymbol{x_a(t+1) = f(x_a(t-k) + \cdots + x_a(t-1) + x_a(t) + y_a(t-z) + \cdots + y_a(t-1) + y_a(t))} \quad \textbf{(4.3)}$$

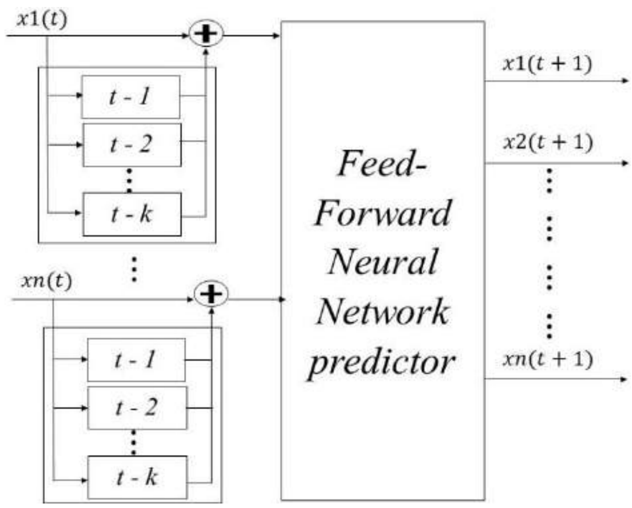


Figure 4.5. The architecture of the TDNN model.

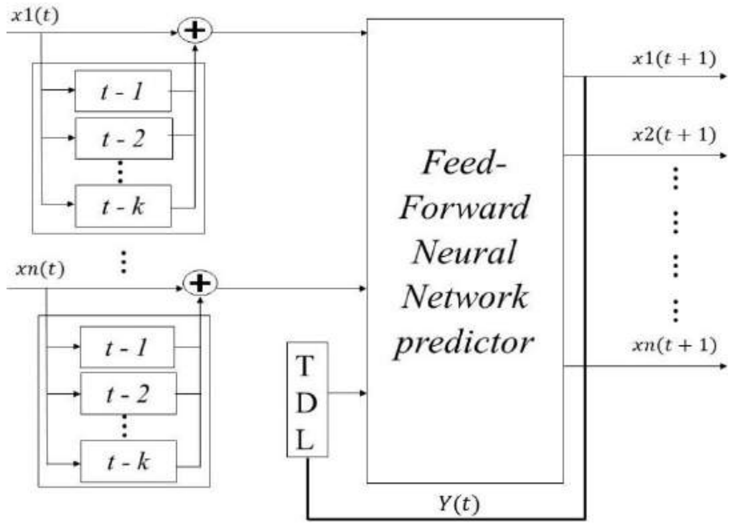


Figure 4.6. The architecture of the NARX model.

Recall $I_a = \sum_{j=1}^{k} x_a(t-j)$, denotes $x_a(t)$ is the spectrum occupancy of each channel, and $a\epsilon[1, A]$. $y_i^{(l)}$ is the output 'y' of the i^{th} neuron from the l^{th} layer.

The Feedforward Neural Network structure is presented in Figure 4.7.

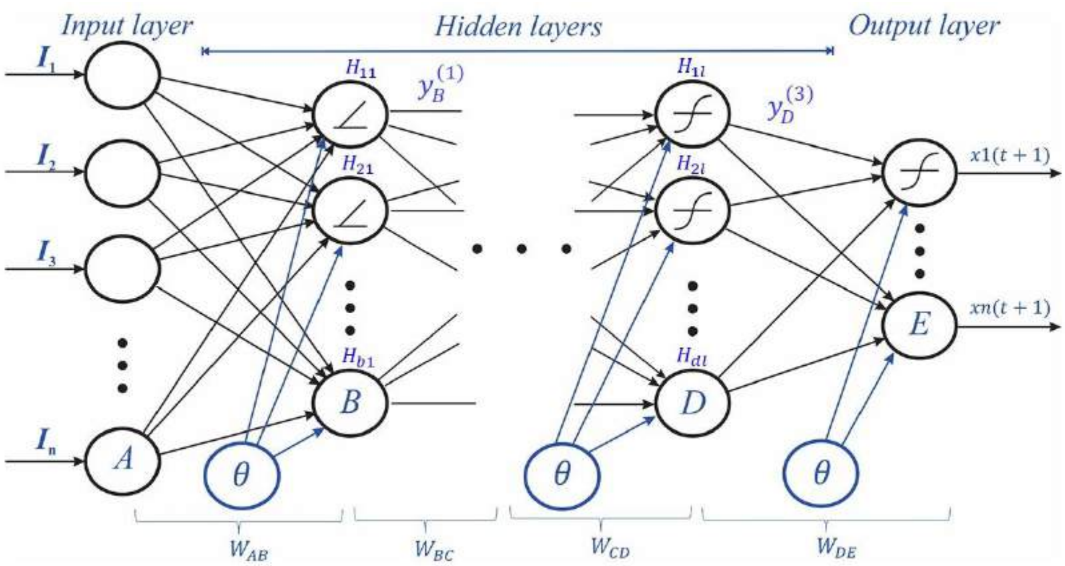


Figure 4.7. Feedforward Neural Network structure.

The following equations system mathematically expresses detailed outputs of a NN with four layers using the mentioned activation functions:

$$\left.\begin{aligned}
&\textbf{Layer 1:}\quad \boldsymbol{y_b^{(1)}} = \boldsymbol{ReLu}(\boldsymbol{\theta} + \textstyle\sum_{a=1}^{n} \boldsymbol{W_{AB}} * \boldsymbol{I_a})\\
&\textbf{Layer 2:}\ \boldsymbol{y_c^{(2)}} = \boldsymbol{tansig}(\boldsymbol{\theta} + \textstyle\sum_{a=1}^{n} \boldsymbol{W_{BC}} * \boldsymbol{y_B})\\
&\textbf{Layer 3:}\ \boldsymbol{y_d^{(3)}} = \boldsymbol{tansig}(\boldsymbol{\theta} + \textstyle\sum_{a=1}^{n} \boldsymbol{W_{CD}} * \boldsymbol{y_C})\\
&\textbf{Layer 4:}\ \boldsymbol{y_e^{(4)}} = \boldsymbol{tansig}(\boldsymbol{\theta} + \textstyle\sum_{a=1}^{n} \boldsymbol{W_{DE}} * \boldsymbol{y_D})\\
&\textbf{Output:}\quad \boldsymbol{y_e^{(4)}} = \boldsymbol{x_a}(\boldsymbol{t} + \boldsymbol{1})
\end{aligned}\right\} \qquad \textbf{(4.4)}$$

Where A, B, C, D, and E, are the number of neurons in each layer. $b\epsilon[1, B], c\epsilon[1, C], d\epsilon[1, D], e\epsilon[1, E]$, W_{ij} are the weights' vectors of the links from a layer *i* to *j*, θ is the additive bias, and H_{dl} is the hidden neuron *d* in the l^{th} layer.

4.2.6. Simulations

In this first part, various TDNN and NARX structures were trained and evaluated by exploiting BO algorithm capabilities, to reach the best network structure offering the optimal prediction performances. BO is a very useful algorithm for hyperparameters tuning, due to its way of predicting the region with the best performance. The reason that makes BO one of the best choices for hyperparameters tuning is that it explores the parameters space based on prior hypotheses about their behavior (performance). Then, this prior belief is reinforced and updated based on ongoing evaluation results (prediction performances), by calculating the probability of getting the best performance "$\boldsymbol{P(\beta|X)}$" (the behavior of the selected parameters) with considering all parameters values and trying to find the region (values zone) of parameters' values that increases this probability and minimizes the loss function. Then, it trains and evaluates the models based on a trial-and-error process to extract the best combination of parameters with the best performance. Therefore, it can converge to the optimal point fastly and efficiently. BO has the ability to combine different values (unexpected) that cannot be selected manually or in a systematic way. One systematic method is Grid search (exhaustive search), which makes a grid of the search space and then evaluates the model settings for each point, which takes infinite time to get the best results. Another method is the random search that selects combinations of values randomly from the given ranges, it is also a time-consuming process, and possibly it cannot locate the optimal point if the number of trials is limited.

Otherwise, BO is typically used in settings where the Objective Function (OF) is expensive to evaluate like in hyperparameters tuning.

The BO algorithm attempts to minimize a scalar OF (loss function) $f(x)$, for x in a bounded domain, and uses its evaluations to train a Gaussian process model. This process enables the algorithm to locate a point that minimizes the OF [89].

The optimizable NN-hyperparameters in our model which are, the number of hidden neurons and the number of layers, the input and feedback delays, were selected and combined in every iteration using the BO to cover the selected values zone and to converge to the best combination. The simulated hyperparameters values ranges are presented in Table 4.1.

The aim of exploiting this optimization is to enhance the prediction accuracy, the regression coefficient, and to decrease the error rate of the proposed predictor, in addition to set the values of the optimal hyperparameters. This can be achieved using multi-objective optimization.

Regarding the present optimization task, Multi-objective methods fit the model by improving the three predictor performances in parallel, which is done by adding three additional dimensions to the optimization problem. This would complicate the OF and consume huge processing time and hardware costs. Instead in this work, the single-objective BO was utilized in an intelligent way to reduce these costs. Thereby, a new metric was proposed that combines the maximization of both accuracy and regression coefficient, on one hand, and error minimization, in another hand using one objective metric.

The optimization was performed via the minimization of this negative metric (objective) defined as the "Bayesian Optimization Metric", which is indicated in equation 4.5:

$$\boldsymbol{BOM = -Accuracy \times R} \qquad \textbf{(4.5)}$$

The prediction accuracy is in terms of error, which makes the maximization of the accuracy minimizes automatically the prediction error. The accuracy percentage is calculated according to the following expression

$$\boldsymbol{Accuracy}(\%) = \frac{\boldsymbol{M_{Correct}}}{\boldsymbol{M}} \times \boldsymbol{100} \qquad \textbf{(4.6)}$$

Where, $M_{Correct}$ is the number of points that are correctly predicted or the number of points where the error is null, and M is the total number of output samples. "R" denotes the correlation coefficient between the outputs and targets; it measures how much the outputs are close to the target values, its value ranges in [-1, 1], and it should be positive and too close to 1 to fit the ($y = x$) line.

A. Objective function

The underlying probabilistic model for the objective function f is a Gaussian process (GP) prior with added Gaussian noise in the observations. So the prior distribution on $f(x)$ is a GP with mean $\mu(x;\theta)$ and covariance kernel function $k(x,x';\theta)$. Here, θ is a vector of kernel parameters.

In a bit more detail, denote a set of points $X = xi$ (the input hyparameters of a NN) with associated objective function values $F = fi$ (BOM values). The prior's joint distribution of the function values F is multivariate normal, with mean $\mu(X)$ and covariance matrix $K(X,X)$, where $Kij = k(x_i, x_j)$ [90].

B. ARD Matern 5/2 Kernel Function

In supervised learning, it is expected that the points with similar predictor values x_i, naturally have close response (target) values y_i. In Gaussian processes, the covariance function expresses this similarity. It specifies the covariance between the two latent variables $f(x_i)$ and $f(x_j)$, where both x_i and x_j are d-by-1 vectors. In other words, it determines how the response at one point x_i is affected by responses at other points x_j, $i \neq j$, $i = 1, 2, ..., n$. The covariance function $k(x_i, x_j)$ can be defined by various kernel functions. It can be parameterized in terms of the kernel parameters in vector θ. Hence, it is possible to express the covariance function as $k(x_i, x_j|\theta)$.

The kernel function $k(x,x';\theta)$ can significantly affect the quality of a Gaussian process regression. BO uses the ARD Matérn 5/2 kernel function. It is a Matern 5/2 covariance function with a different length scale for each predictor. It is defined as [91]:

$$\boldsymbol{k(x_i, x_j|\theta) = \sigma_f^2\left(1 + \sqrt{5}\,r + \frac{5}{3}\,r^2\right) exp(-\sqrt{5}\,r)}, \tag{4.7}$$

Where

$$\boldsymbol{r = \sqrt{\sum_{m=1}^{d} \frac{(x_{im} - x_{jm})^2}{\sigma_m^2}}} \tag{4.8}$$

The conditional probability of getting the best performance is given by:

$$\boldsymbol{P(\beta|X) = \frac{P(X|\beta).P(\beta)}{P(X)}} \tag{4.9}$$

Where β is the minimum objective value "min(BOM)", and X is the the input hyparameters of a NN to be tuned.

Three days of collected data were utilized from each area, in the BO hyperparameters tunning process to train the networks faster. Thereby, an input matrix of 250 channels by 1728 time samples (250 x 1728) was acquired, the first half of the data is from the urban area and the second half from the rural area. Data division was 85% for models training, and 15% for testing.

The Levenberg-Marquardt (LM) training function was applied to train the networks. It updates the weight and bias values according to LM optimization, which is a combination of the gradient descendent rule and the Gauss-Newton method. “trainlm” is often the fastest supervised backpropagation algorithm for NN training.

In the second part, the best network extracted from the BO process, which is a TDNN with one hidden layer of 30 neurons and an output layer of 192, (30, 192), was trained on the total length dataset of (250x8640) to enhance the prediction performances. The training and testing accuracies, as well as the MSE results, of this last network, were compared to the performance of other networks with the same number of hidden neurons but distributed in three layers, namely (10, 10, 10, 192), which were trained on the same dataset, to highlight the outperformance of intensive structures over distributed NN structures.

4.2.7. Throughput enhancement

In a hard decision model, the “0.5 thresholding rule” considers the channel occupancies less than 0.5, in the range [0, 0.5[, as idle channels which involve collisions with PUs, and decides those higher than this threshold, in the range [0.5, 1], to be busy, and thus losing a lot of spectrum opportunities. To evaluate the network throughput using soft predictions (ORs), two key indicators have taken place “improving channels utilization, and enhancing the interference avoidance”. In this way, the number of samples that present relative opportunities per channel was divided by the total number of samples for each channel to estimate the usage improvement. Whereas the mean value of samples having ORs under 0.5 was calculated for each channel to assess the amount of interference avoidance as shown in Figure 4.12.

4.3. Results

The results of the previously described simulation process, namely BO best NN structure, best performances (BOM, Accuracy, MSE, and regression coefficient), the predictors' performance comparison in terms of delays and steps ahead, and the comparison to related works, are illustrated in this section through the Tables 4.1 and 4.2, and Figures 4.8 - 4.11.

Table 4.1 shows the NN hyperparameters to be tuned using the BO algorithm (optimizable variables), and the tuning range of each variable. In addition to the best NN optimized values obtained by the BO process, and the best performances of both TDNN and NARX models using a three-days training dataset.

Table 4.1. BO tunning variables, best NN hyperparameters, and best performances using a three-days training dataset.

Optimizable variables	*Range*	*Best Optimized Values*		*Best performances*		
		TDNN	*NARX*		*TDNN*	*NARX*
Input Delays	[1, 288]	5	4	Training Accuracy (%)	**85.86**	78.82
Number of Layers	[1, 4]	1	1	Regression coefficient (R)	**0.92**	0.85
Number of Units per layer	[10, 300]	30	35	BOM	**- 79**	- 67
/	/	/	/	MSE	0.0012	0.0011

BO algorithm selects a combination of hyperparameters every iteration, then it trains the newly defined network and estimates its corresponding BOM value (Estimated min objective). For every function evaluation, the algorithm marks the estimated value of BOM and saves the actual minimum observed value until the next minimum appears. Meanwhile, it decreases the value of the Min observed objective only if the new estimated BOM value is less than the last minimum value, otherwise, it keeps the previous min value.

Figures 4.8 and 4.9 present the minimum objective (minimum of BOM metric) values versus the number of function evaluations for TDNN and NARX networks.

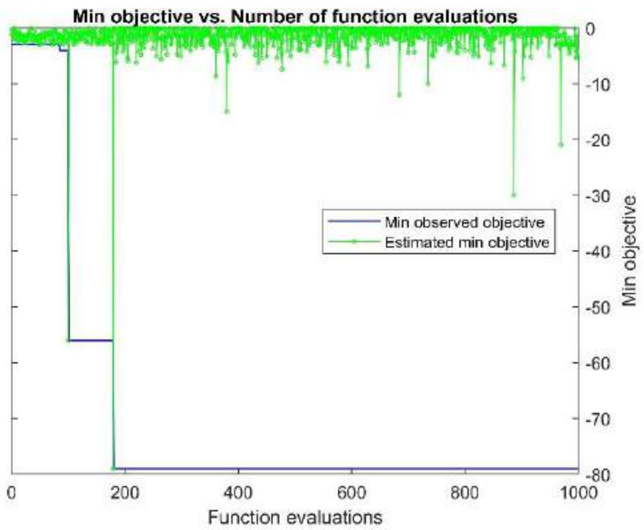


Figure 4.8. Minimum objective vs. the number of function evaluations for the TDNN model.

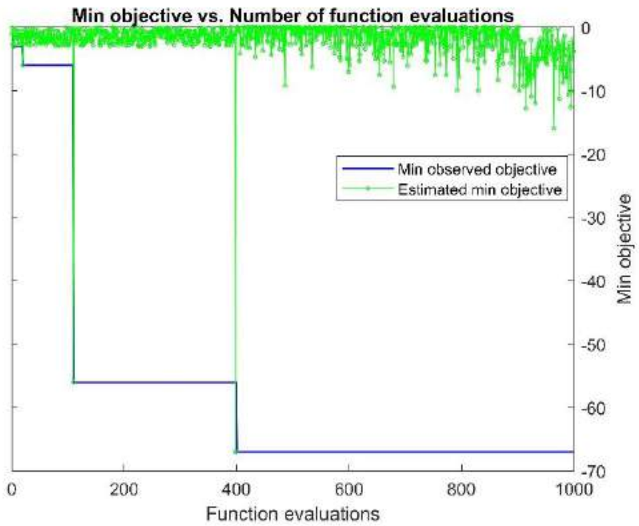


Figure 4.9. Minimum objective vs. the number of function evaluations for the NARX model.

According to the "BOM" evaluation in Figures 4.8 and 4.9, the best predictor is the TDNN compared to the NARX model, where the BOM value reached a minimum of **-79**, which corresponds to **85.86%** prediction accuracy, **0.92** R-value, and **0.0012** MSE. The results were summarized in Table 4.1.

The prediction performances of this network (TDNN) in addition to the three intensive and distributed NN structures were compared and plotted in Figure 4.10.

Table 4.2 displays the best training and testing performances of the best BO acquired TDNN and NARX networks trained on the total dataset.

Table 4.2. Best training and testing performances of the best BO acquired TDNN and NARX networks trained on the total dataset.

NN model	*number of neurons*	*steps ahead*	*Training regression "R"*	*MSE*	*Train Accuracy (%)*	*Test Accuracy (%)*
NARX	35	1 step ahead	0.92	0.0012	82	81.7
TDNN	30	1 step ahead	0.96	0.00123	89.4	88.78
	30	288 steps ahead	**0.98**	**0.0013**	**93.5**	**92.83**

Figure 4.11 illustrates the prediction performances of the best TDNN model for forecasting multi-steps-ahead. Whereas, each step represents the next 5 minutes, knowing that we tested the intensive TDNN in predicting 24 hours ahead, which is equivalent to 288 steps per day.

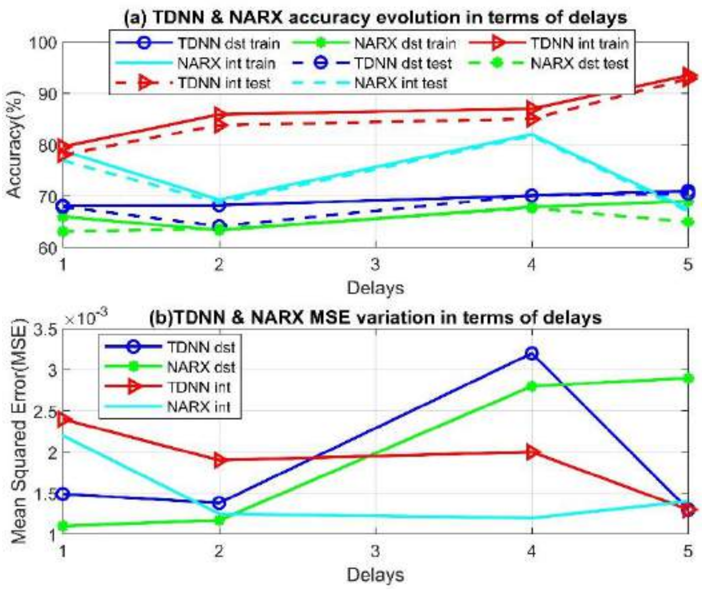


Figure 4.10. Prediction performance comparison of the best network with the three NN models, dst (distributed) and int (intensive) models versus input delays.

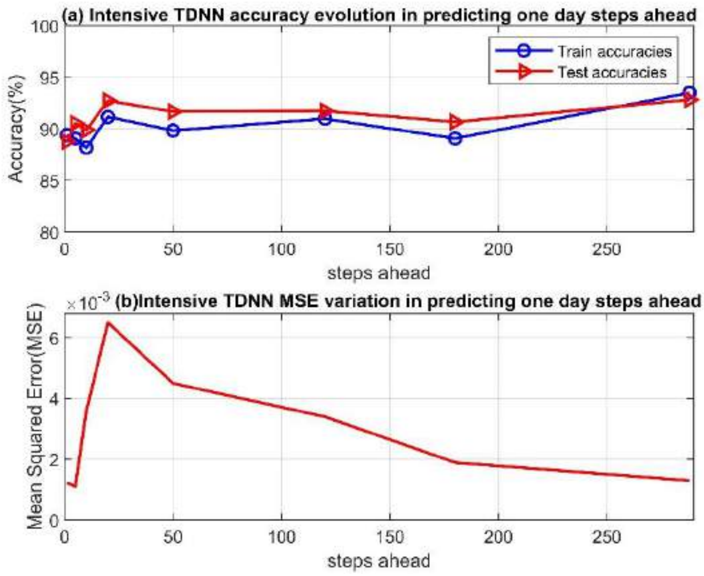


Figure 4.11. Prediction performance of the best TDNN model for forecasting multi-steps ahead.

These results endorse the fact that TDNN is a very useful algorithm for multichannel spectrum prediction, and that its intensive structure is more efficient than the distributed one with a minimized number of hidden neurons and input delays. Besides, considering the appropriate number of steps ahead during the network design and training could improve the forecasting performance.

Table 4.3 compares the structure and performance parameters of our proposed models with other neural network approaches. The comparison was in terms of the kind of utilized data, the nature of the (Input-output) resources, the Average number of neurons to predict one channel state, the Required number of neurons to predict 250 channels states, the RMSE, and the Best Accuracy (%).

Table 4.3. Structure and performance comparison with other NN approaches.

Parameters / *Approaches*	*Kind of used data*	*(Input → output) resources*	*Average number of neurons to predict one channel state*	*Required number of neurons to predict 250 channels states*	*RMSE*	*Best Accuracy (%)*
Our approach *TDNN*	Real	3D Occupancy rates → 3D Occupancy rates	0.888 ≈ 1 neuron for one channel	222 neurons	0.036	**93.5**
TDNN Mohammadjafari et al, 2019 [46]	Real and simulated	Spectrum Occupancies → Occupancies	849 neurons for one channel	212 250 neurons	0.0387	/
ERNN Taj & Akil, 2011 [45]	Generated (3 RF signal features)	cyclic prefix length 'CPL', symbol period, preambles → CPL	15 neurons for one channel	6500 neurons	0.0416	/
LSTM Shawel et al, 2018 [51]	Real	Power → power	1 LSTM predictor for one channel	250 LSTM predictors	0.01	70
DNN Ahmed et al, 2019 [52]	Generated	channel quality indicator (CQI), location indicator → sub-band, power	156 neurons for one channel	39 000	/	85
LSTM P. Chauhan et al, 2021 [87]	Real	binary time series → binary status	10 neurons for one channel	2500 neurons	0.04	≈ 91

Recall that the average number of neurons to predict one channel state is the sum of the entire number of neurons in all layers, divided by the number of outputs. In our case, it is equal to $(30 + 192)/250 \approx 0.888$. Then, on average, only one neuron is required to predict the next state of one channel. On the other hand, the required number of neurons to predict 250 channels states is 250 times the number used to predict one channel state.

Therefore, the present work provides optimization in terms of the maximization in the number of forecasted channels along with minimization in the number of Hidden Neurons (HNs), so a reduced hardware complexity compared with relevant works that employ a big number of HNs to forecast the next state of only one channel.

The employment of ORs instead of (0/1) channel status for resource allocation improves the spectrum usage while enhancing interference avoidance. Around 10% to 55% usage improvement was achieved, and an additional 5% to 40% interference avoidance enhancement was reached per channel using the proposed prediction and preallocation algorithm.

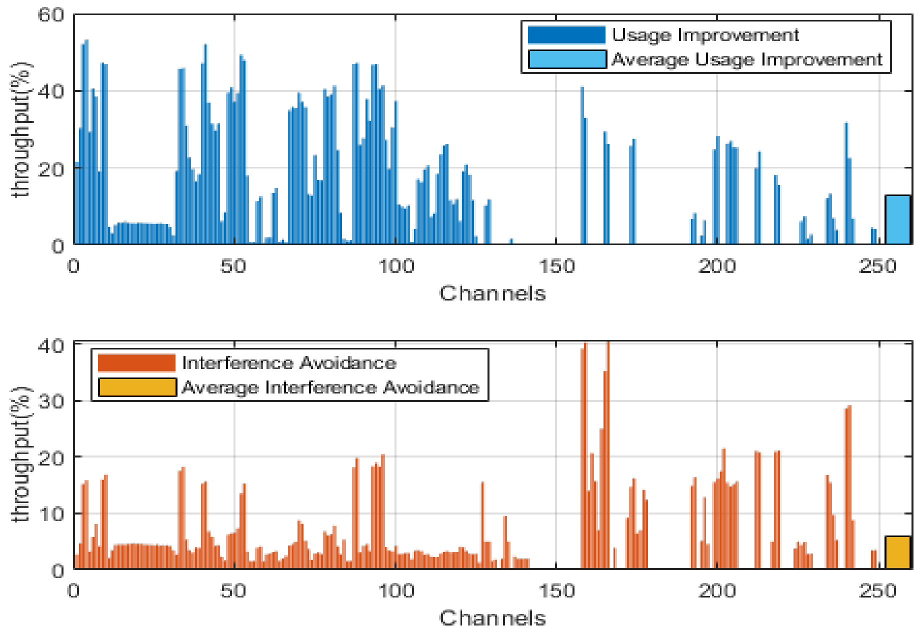


Figure 4.12. Throughput optimization per channel using the proposed method.

4.4. Discussion

The proposed NN models can predict 250 channel occupancies simultaneously. Moreover, their capability to learn, then forecast different spectrum occupancy scenarios of diverse areas (rural and urban), promotes their possibility to be applied anywhere even between two different areas within the coverage limits. However, from the prediction and regression results, the TDNN model is more appropriate to deal with different scenarios, and more applicable for real-time and large-scale spectrum forecasting than the NARX model. One other reason for TDNN outperformance is the presence of an additional feedback input in the NARX structure, which makes it quite expensive in terms of complexity and processing time, in addition to the error backpropagation that degrades its accuracy.

BO is the best single-objective optimization algorithm for NN hyperparameters tuning. The probabilistic process of variables' selection and combination makes it a powerful tool. This process can sweep the overall parameters space by evaluating the performance of the networks for multiple combinations extracted from each variable range, it can efficiently select the best structure in a reduced time.

The MSE regression was opted in this work as an evaluation parameter according to our output's nature. Predicted values in our approach are soft (ORs), therefore in supervised learning we need to measure how close the regression line is to the output samples, and how much they are divergent from the target data. Moreover, the prediction accuracy evaluation was to assess the quality of the resulting model in predicting the OR values accurately in the long term. The employment of ORs instead of (0/1) channel status for resource allocation, by the proposed prediction and preallocation algorithm, improves the spectrum usage while enhancing interference avoidance.

The proposed network architecture is composed of an input layer, one hidden layer of 30 neurons, and an output layer of 192 neurons. Via the BO process, we could get the best network hyperparameters (number of hidden layers, number of neurons of each layer, and number of adequate delays). A neural network with only one hidden layer was sufficient to fit the model due to the high linear correlation between frequency channels' ORs in the time domain. Noting that every column of 250 channels' ORs in an instant (*t*) is highly correlated to its values in all other time instances, as referred to in Figure 4.1. In addition, the temporal evolution of all frequency channels is very correlated in each area.

4.5. Conclusion

In this chapter, we have proposed two multichannel NN spectrum predictors for CR-IoT networks based on realistic spectrum occupancy scenarios. The predictors are 3D-learning-based models with a minimized number of neurons and hidden layers. Whereas we developed a TDNN model via the BO hyperparameters tuning, that can learn data extracted from multiple locations and different scenarios. Additionally, it forecasts multichannel ORs simultaneously for multi-step-ahead with efficient prediction performances.

The application of Machine Learning (ML) in CR-IoT enables its devices with restricted spectrum resources to accurately identify the spectrum holes and temporarily exploit the licensed spectrum for its communications. This is due to ML effective applications that provide the best reading, analyzing, and learning from the environment's examples which, in turn, allow extracting the most relevant parameters, making it produces very good classification, fitting, and prediction decisions.

The obtained results substantiate that TDNN is a very useful algorithm for multichannel spectrum prediction by considering only five delays and that its intensive structure is more efficient than its distributed structure. The training data results show a good fit, a high R-value of **0.98**, and a reduced MSE of **0.0013**. Moreover, high accuracy was obtained of **93.5%**. We proposed a centralized system, where sensing and prediction tasks are performed at the level of LSs and CBS respectively, so IoT devices will just access the available spectrum without losing energy in these operations. This model produces soft predictions then extracts channels by priority from the lowest occupancy probability to the highest.

CONCLUSION

General Conclusions and Perspectives

We can consider that Cognitive radio (CR) is the key technology for a new generation of wireless communication systems characterized by high QoS, high-speed data transmission, and large channel bandwidth. Indeed, it is the most promising paradigm to address the actual spectrum scarcity or spectrum efficiency problem. Through this work, we have confirmed that CR will improve effectively spectrum utilization in wireless communication systems while accommodating the increasing amount of wireless services and applications.

In this thesis, we have addressed the optimization of spectrum utilization in wireless communication systems using CR techniques, and we have discussed the capability for the implementation of a CRN in Algeria. Moreover, the CR concept with its intelligent functions and applications has been highlighted.

In order to study and simulate some CR techniques based on real spectrum occupancy scenarios from Algeria, it was necessary, for us, to perform two fundamental tasks: first, the analysis of the radio environment spectrum occupancy in the target locations using the "spectrum sensing function". Second, training a spectrum prediction model to ensure interferences avoidance with PUs during SUs access and transmission.

Spectrum measurement is the first necessary process performed for the implementation of a CRN. Our strategy states to survey continuously short-term and long-term temporal dependencies and spectrum variations in time, frequency, and space dimensions, and categorize frequency bands according to their occupancy rates, with the aim of tracking the spectral activity of PUs. Effectively, this last task provides us with a detailed comprehension of the spectrum evolution via the statistical results and offers important occupancy databases, which are very useful in the optimization of spectrum usage for wireless communication systems.

Accordingly, we have performed two measurement campaigns over two different-nature and specific locations in Algeria, one was an urban area in the north, in Constantine, and another situated in a rural area in the south, in Ouargla.

The obtained overall occupancy percentage of the considered bands (mobile communication and DVB-T) for both sites is less than 30.26%, which means that the reuse of these available resources in new technologies like IoT, and 5G, using CR techniques, can be exploited in Algeria. This confirms our first hypothesis about the overall occupancy of the spectrum, and that it is similar around the world and as well in Algeria, concerning the underutilization of radio resources. The results of these measurement campaigns were submitted for publication as a research paper.

To determine the spectrum utilization and the potential for exploitation by CR technology, several important criteria must be considered including; spectrum band characteristics, measurement system capacities, sensing and detection tasks, and measurement area specifications. The careful selection of these characteristics enhances the performance of a management strategy and vis-versa, which approves our second hypothesis.

It should be noticed that spectrum measurement is a sensitive and secret domain. Where to perform similar campaigns, it is necessary to request an authorization from the regulation bodies even if all required equipment and materials were available.

Spectrum Prediction is a promising approach for the realization of an effective CRN that provides a good QoS, optimized spectrum utilization, and better spectrum sharing with avoidance of any malicious interferences.

Via the second state of the art, an overview of the most prominent prediction techniques in CRNs was presented. Among these techniques, we worked on a spectrum prediction model based on ANNs, which showed better prediction performance. In this study, we performed spectral occupancy prediction on the GSM900 band (uplink and downlink), using real data. We obtained very promising results that clearly demonstrate the outperformance of the TDNN model compared to the NARX model in further reducing prediction errors.

The obtained results substantiate that TDNN is a very useful algorithm for multichannel multilocation and multistep ahead spectrum prediction for CRNs. The predictor has achieved efficient prediction performances not only in terms of accuracy (93.5%), R-value of (0.98), and MSE of (0.0013) but also in terms of reduced hardware complexity (30 hidden neurons), compared to the literature (NN-based predictors). Nonetheless, these predictors were used to predict the next state of only one channel, unlike our predictor that forecasts multistep-ahead ORs of 250 channels simultaneously. Therefore, our third hypothesis was proved.

In our point of view, these techniques can be applied in the next-generation wireless communication networks (5G and 6G), they can be conducted to predict the spectrum for the different radio channels and not only for the GSM band, in order to use the spectrum more efficiently.

Perspectives

Some challenges and perspectives can be explored in the future :

- To optimize the performances of the classical forecasting methods and overcome some of their limitations, hybrid prediction mechanisms, ML, and deep learning algorithms can be considered;
- The prediction concept has been studied in CRNs, right now, for two issues; occupancy prediction and mobility prediction, but the third issue which has not been studied yet, is spectrum sharing prediction. It is still waiting to be studied and modeled, because of its extreme importance in cooperative spectrum sharing, in giving access to all CUs, and consequently ensuring efficient spectrum management;
- Two states-based spectrum sensing and prediction techniques, which limit the channel state information only to (busy and idle) may lose some good opportunities to be captured. Therefore, the exploitation of multistate spectrum prediction would enhance the probability of better utilization of spectrum opportunities. Whereas, the spectrum occupancy can be classified at least into three levels, busy, idle, and underutilized. And it may exceed to predict PU's direction, modulation, or slot times to investigate even small opportunities;
- we propose the introduction of new features to the input data like geo-localization, time, channel classification, …, which would bring an added value to the spectrum prediction in CR-IoT;
- Extending our research by studying the application of CR techniques in some specific fields like IoT and 5G;
- The proposition and evaluation of an integral spectrum management system;
- For spectrum measurements:

1) we aim to expand our study to cover the whole Algerian region, thus building an efficient and effective map of the current spectrum occupancy in Algeria. In addition, we have collected data concerning the geo-localization, which will be invested in future research works;
2) Extending the measurement campaign to explore other spectrum bands.

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