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Metrology in wireless mobile networks for enhanced radio resource management

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ECOLE DOCTORALE
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DE PARIS

Thèse

Présentée pour obtenir le grade de docteur
de l'École Nationale Supérieure des Télécommunications

Spécialité : **Signal et Images**

Afef Ben Hadj Alaya-Feki

Sujet :

MÉTROLOGIE DANS LES RÉSEAUX D'ACCÈS RADIO POUR LA GESTION DES
RESSOURCES POUR LE DÉVELOPPEMENT DU CONCEPT ALWAYS BEST
CONNECTED

SOUTENUE DEVANT LE JURY COMPOSÉ DE:

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*A mes parents et mes soeurs,
A mon mari et ma fille*

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- à mes parents pour leur soutien et encouragements,
- à ma petite fille *Nour* pour tout le bonheur et la joie qu'elle m'a offert,
- et surtout à mon cher mari *Abdelmoughith*, qui a toujours été à mes cotés dans les moments difficiles et n'a jamais cessé de m'encourager et de m'aider tout au long de ces trois années.

Résumé

Introduction

Depuis l'invention de la radio communication par Marconi en 1896, les télécommunications ont subi des évolutions importantes en termes de débit et des services offerts aux utilisateurs ainsi que l'apparition de plusieurs technologies d'accès telles que GSM, UMTS, EDGE et WIFI qui peuvent coopérer pour offrir une meilleure qualité de service aux usagers. Aujourd'hui, les réseaux sans fil sont devenus un moyen de communication indispensable pour la vie personnelle et professionnelle des usagers.

En 1996, les premières discussions sur la radio reconfigurable ont commencé au sein du forum SDR [1]. Son but était de proposer des approches innovantes afin de rajouter plus de flexibilité et d'intelligence dans les réseaux sans fil grâce à l'utilisation de la radio logicielle. Ceci fut le point de départ pour la définition d'un nouveau concept appelé *la radio cognitive*. En effet, Une radio est "cognitive" si elle est capable d'observer et d'explorer son environnement extérieur (bande de fréquence, puissance du signal émis..), d'analyser et d'exploiter les résultats de son exploration pour prendre des décisions intelligentes (par exemple avec une utilisation secondaire des portions de spectre non utilisées) et d'apprendre de son expérience passée pour améliorer ses décisions au cours du temps: la radio cognitive est une radio qui reproduit le comportement cognitif humain. Cette notion est d'autant plus importante aujourd'hui, puisque les besoins en ressources radio sont en perpétuelle augmentation et que le spectre est une ressource rare et mal exploitée. En effet, une multitude de campagnes de mesures dans des localisations et des conditions différentes prouvent que les ressources spectrales sont sous utilisées (par exemple une campagne de mesure à New York a révélé que seulement 13% des ressources spectrales sont effectivement utilisées [2]).

On présente dans la Figure 1 les importantes étapes d'évolution de la radio cognitive.

Définie en 1999 par Joseph Mitola, la radio cognitive est une radio qui "peut connaître, percevoir et apprendre de son environnement puis agir pour simplifier la vie de l'utilisateur" [3]. Généralement, la notion de radio cognitive est associée avec la notion d'*accès dynamique au spectre* qui consiste à introduire plus de flexibilité dans les schémas conventionnels d'attribution et d'accès au spectre pour améliorer l'exploitation globale des ressources spectrales. Dans cette approche, *l'accès opportuniste au spectre* [4] constitue une méthode qui suscite l'intérêt de beaucoup de chercheurs. Son idée principale est d'ouvrir les ressources spectrales licenciées aux utilisateurs secondaires pour qu'ils puissent exploiter les portions du spectre non utilisées par les utilisateurs primaires à un temps et une localisation donnés. Une condition indispensable pour la réussite de cette approche est que les utilisateurs secondaires utilisent les "trous de

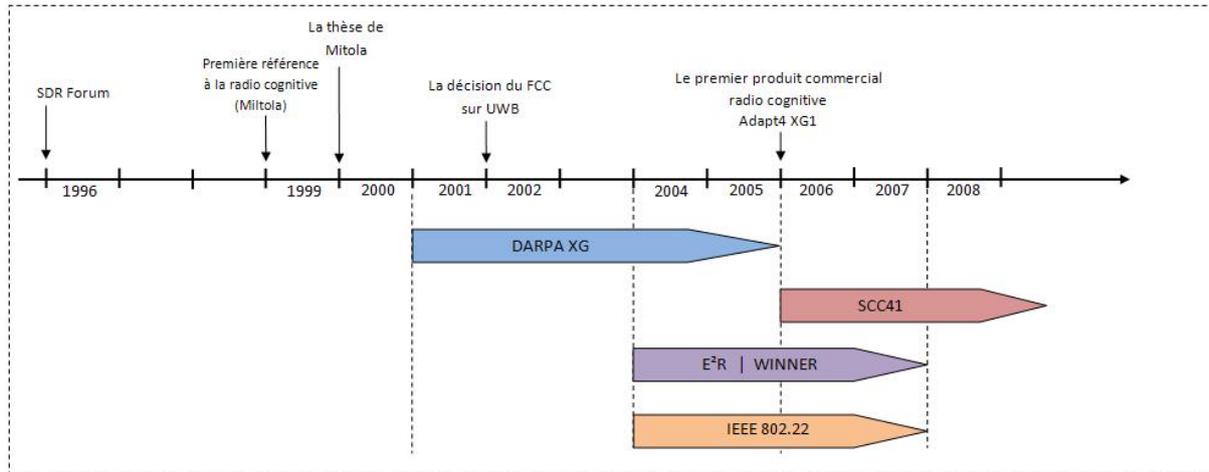


Figure 1: L'évolution de la radio cognitive.

spectre" sans générer d'interférences indésirables aux utilisateurs primaires.

Depuis les travaux de thèse pionniers de Mitola [5], la radio cognitive ne cesse de faire l'objet de recherches et d'investigation de la part des industriels, des opérateurs, des régulateurs télécoms et des institutions académiques. Ainsi, on peut citer des projets européens tels qu' E^2R (End to End Reconfirmability) [6] et *WINNER* [7] ou aussi le projet américain DARPA XG [8]. Aussi, les premiers standards implémentant des fonctionnalités cognitives ont vu le jour:

- IEEE802.22 [9]: C'est le premier standard qui implémente des fonctions de la radio cognitive dans les réseaux sans fils WRAN. En effet, il permet un accès dynamique au spectre dans les bandes de télédiffusion, sans générer des dégradations pour les utilisateurs primaires tels que les récepteurs télé. Ceci est réalisé grâce à l'exploration (sensing) des bandes de fréquence cibles et la détermination de la manière optimale d'allocation des canaux
- IEEE SCC41 [10]: C'est une famille de standards qui vise à développer des architectures et des moyens efficaces pour optimiser la gestion des ressources radio dans les réseaux d'accès hétérogènes. Elle s'intéresse à plusieurs sujets tels que la radio cognitive, l'accès dynamique au spectre, la gestion d'interférence et la coordination des systèmes mobiles.

Il est important de mentionner également que le premier produit commercial radio cognitif, Adapt4 XG1, a été développé en 2006 [11]. Il s'agit d'un dispositif qui assure la détection des utilisateurs primaires. De cette manière, il peut transmettre ses données d'une manière opportuniste dans les trous de spectre sans générer d'interférences nuisibles aux utilisateurs primaires.

Dans ce contexte de recherches actives sur les différentes problématiques de la radio cognitive, cette thèse est dédiée à "la métrologie dans les réseaux d'accès radio pour la gestion des ressources radio pour le développement du concept Always Best Connected". Le terme "métrologie" désigne l'étude scientifique des mesures.

Un des aspects importants qui devrait être davantage traité dans le contexte de la radio cognitive est celui du traitement et de la collection d'informations. En effet, cet aspect est nécessaire pour assurer une perception complète de l'environnement extérieur et permettre ainsi au réseau cognitif de prendre des décisions efficaces pour une meilleure gestion des ressources radio. A

ce jour, les recherches relatives à la collection et au traitement d'informations dans la radio cognitive se limite généralement au *sensing* du spectre pour détecter la localisation des utilisateurs primaires [12] et les trous de spectre [5] dans le but d'effectuer un accès opportuniste au spectre. Cette thèse se focalise sur la collection et le traitement d'information dans les réseaux cognitifs. Elle vise à étudier et à proposer des solutions innovantes en relation avec les mesures radio dans les réseaux sans fils, pour réaliser des fonctions de la radio cognitive. Ceci inclut le traitement des mesures radio, l'implémentation des solutions proposées dans le réseau, l'évaluation de l'efficacité des méthodes développées ainsi que les applications possibles dans un contexte de radio cognitive.

Cette thèse se compose de trois principales parties (Figure 2) qui traite chacune un aspect

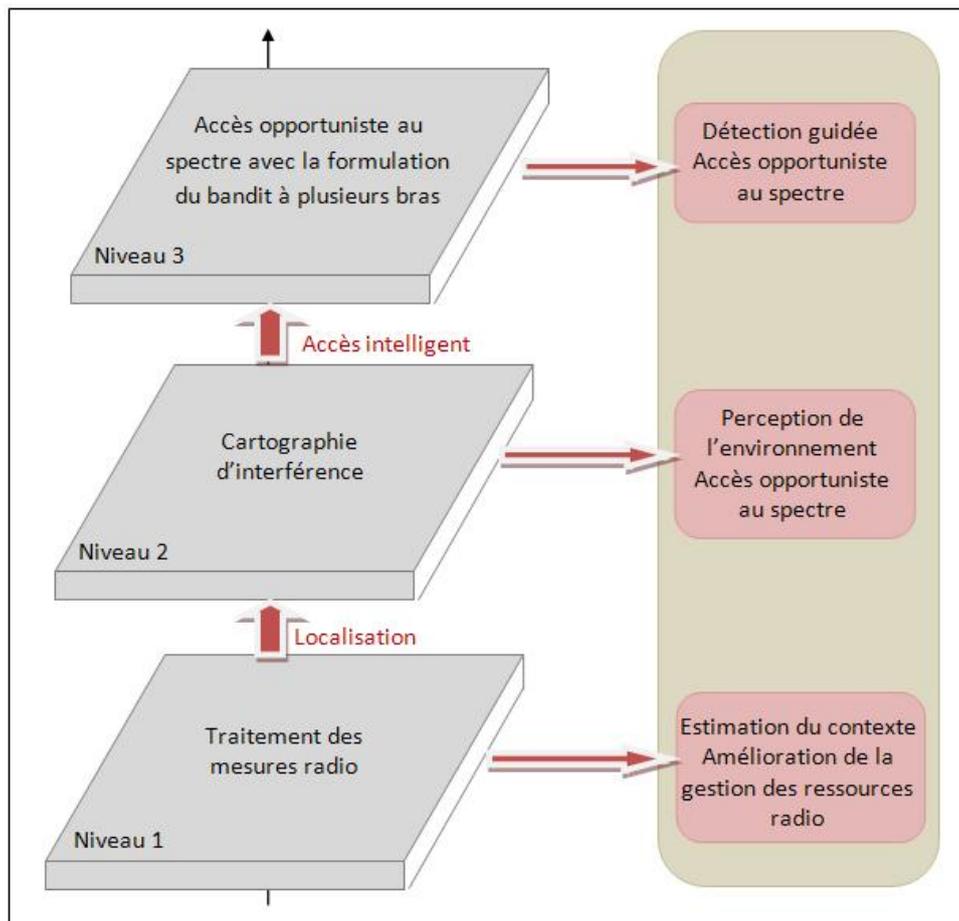


Figure 2: Présentation générale de la thèse.

différent en relation avec la métrologie dans le contexte de la radio cognitive. Notre but est de fournir une étude complète qui traite les différents problèmes liés aux mesures dans les réseaux cognitifs. Notre approche peut être décrite sous forme de trois couches (Figure 2) qui représentent un niveau de complexité croissant en termes de données et d'application/implémentation cible.

1. Couche 1: C'est la couche la plus basse qui consiste à traiter les mesures radio standards, qui circulent dans les réseaux mobiles et qui interviennent généralement dans les procédures internes de gestion des ressources radio (par exemple le mécanisme de handover).

Dans cette partie, on met au point des méthodes de traitement efficaces qui permettent d'extraire des informations supplémentaires et utiles des mesures radio. Cet aspect est traité dans le Chapitre 1 de la thèse et vise à fournir au réseau cognitif des moyens efficaces pour lui assurer une perception plus complète de son environnement extérieur, en se basant sur les mesures radio déjà existantes dans le réseau et sans pour autant générer plus de complexité (avec une implémentation hardware). Dans cette partie, on présente des méthodes de traitement (basés sur des méthodes de régression et de lissage non paramétriques) qui seront testées sur des mesures réelles, collectées sur des réseaux GSM et UMTS. Cette approche a permis de mettre au point un procédé innovant pour estimer d'une manière dynamique les composantes d'atténuations du signal propagé (cette étude a donné lieu à un dépôt de brevet). Par la suite, on propose des applications des résultats pour une implémentation effective dans le réseau en vue d'estimer le contexte radio de l'utilisateur ou aussi d'améliorer la procédure conventionnelle du handover.

2. Couche 2: On remonte à un niveau plus haut en se focalisant ici sur des mesures radio, plus riches grâce à leur agrégation avec l'information de localisation correspondante. Cette approche a pour but de fournir une vue d'ensemble complet au réseau, lui permettant ainsi de prendre les décisions adéquates pour une meilleure utilisation de ses ressources radio. Dans le chapitre 2 de la thèse, on définit un nouveau concept qui représente l'agrégation de la mesure radio avec la localisation: *la cartographie d'interférence*. On procède alors à une étude complète de cette nouvelle notion qui comporte 1- la proposition d'une implémentation réseau pour permettre une utilisation effective de la cartographie d'interférence, 2- des méthodes performantes pour permettre de construire une carte complète à partir d'un nombre limité de mesures disponibles (on détaillera notamment des procédés fixes et récursifs de construction de la carte) et 3- finalement, on testera l'utilisation de la cartographie d'interférence dans un scénario d'accès opportuniste au spectre.
 3. Couche 3: La troisième couche s'intéresse aux aspects accès et choix de canal dans le cadre d'un accès opportuniste au spectre. Ainsi, dans le chapitre 3 de la thèse, on propose de fournir aux utilisateurs cognitifs des outils statistiques pour l'aider à choisir astucieusement les canaux sur lesquels il fera du sensing et de l'accès opportuniste. Cette approche est inspirée de la problématique du *bandit à plusieurs bras* (en anglais *Multi Armed Bandit*). L'analogie de ce problème avec la volonté pour un utilisateur secondaire de réaliser un accès opportuniste au spectre réside dans la nécessité de faire un compromis entre deux objectifs différents: 1- Explorer l'environnement extérieur pour apprendre ses propriétés statistiques et détecter ainsi les trous de spectre, 2- Exploiter les informations cumulées pour décider sur quel canal envoyer ses données d'une façon opportuniste. Dans le chapitre 3 de la thèse, on expérimente cette approche théorique sur un modèle de canal du standard IEEE802.11. Etant donné que l'environnement est non-stationnaire et que l'occupation des canaux change d'une façon imprévisible et dynamique, on propose d'adapter les algorithmes "Multi Armed Bandit" aux conditions extérieures par le biais d'un paramétrage dynamique des algorithmes utilisés. Ainsi, on propose des approches temps réel et semi dynamique pour pallier le problème de non stationnarité des canaux. On présente également un exemple d'utilisation de cette approche dans le cadre du standard IEEE P1900.4.
-

Chapitre1: Optimisation de l'exploitation des mesures radio avec des méthodes de régression et de lissage non paramétriques

On assiste aujourd'hui à une évolution importante des réseaux d'accès mobile en termes de débit et de diversité des services et des architectures. Cependant, on constate une stagnation au niveau des mesures radio collectées dans les réseaux d'accès mobiles actuels qui sont nécessaires dans les mécanismes de gestion de ressource radio. En effet, on remarque que les mesures actuelles sont restreintes (généralement puissance du signal et qualité du signal). Aussi, les traitements sur ces mesures sont basiques (mesures moyennées ou filtrées) alors que les statistiques offrent des outils performants pour mieux gérer et exploiter ces mesures.

Ainsi, l'objectif de notre étude est:

- Fournir des informations supplémentaires aux réseaux pour améliorer la gestion de leurs ressources radio et répondre ainsi aux besoins croissants des utilisateurs,
- Eviter la surcharge du réseau avec une remontée fréquente de mesures et de signalisation trop importante, qui aura pour conséquence d'épuiser inutilement les ressources du réseau.

L'objectif de ce chapitre est de présenter une approche innovante pour l'exploitation des mesures radio réelles, par le biais de méthodes de régression et de lissage non paramétriques (tel que *Smoothing Spline*, *Kernel regression smoother* et *Friedman's Super Smoother*).

Méthodes de régression et de lissage non paramétriques

Les méthodes de régression et de lissage sont couramment utilisées dans la modélisation statistique et l'analyse exploratoire. Elles permettent d'exploiter les données, extraire les particularités du signal, prédire son évolution et faciliter son interprétation. On choisit une approche non-paramétrique pour l'analyse statistique des mesures radio. En effet, cette démarche générale se caractérise par une flexibilité dans le choix du modèle, se basant essentiellement sur des hypothèses de continuité et de dérivabilité des fonctions de régression.

Par définition, une fonction de régression m décrit une relation générale entre une variable explicative X et une variable de réponse Y . Ainsi, étant donnée $\{(x_i, y_i)\}_{i=1}^n$, on a:

$$y_i = m(x_i) + \varepsilon_i \quad (1)$$

where $i = 1, \dots, n$, $m(\cdot)$ est la fonction de régression inconnue et $\{\varepsilon_i\}$ sont les erreurs de régression.

Le lissage de la base $\{(x_i, y_i)\}_{i=1}^n$ implique l'approximation de la courbe m dans la relation de régression 1.9 par \hat{m} . Il peut être exprimé sous la forme d'une moyenne locale des observations Y_i dans un voisinage restreint de x .

$$\hat{m}(x_i) = \sum_{i=1}^n W_{n,i}(x_i) y_i \quad (2)$$

Avec $\{W_{n,i}(x_i)\}$ la séquence de fonctions de poids qui dépend de $\{x_i\}_{i=1}^n$.

On choisit pour cette étude deux méthodes spécifiques de régression et de lissage non paramétriques: les "splines" de lissage et Friedman's supersmoother. Ces méthodes permettent en effet de réaliser des ajustements précis sur les données et offrent la possibilité de mettre en évidence leurs particularités (telle que les changements rapides).

- Les "splines" de lissage est une classe de fonctions non-paramétriques définie par Whitaker (1923) [13]. Un "spline" $S : [a,b] \rightarrow R$ est une fonction polynomiale par morceaux, définie par:

$$S(x) = P_i(x), \quad x_{i-1} \leq x \leq x_i \quad (3)$$

Avec $i = 1, \dots, k$ and $a = x_0 < x_1 < \dots < x_{k-2} < x_{k-1} = b$ et $P_i(x)$ est un polynôme. La fonction S minimise la somme des carrés pénalisés J avec:

$$J(g) = \sum_{i=1}^n \{y_i - g(x_i)\}^2 + \alpha \int_a^b \{g''(x)\}^2 dx \quad (4)$$

g est une fonction deux fois différentiable définie sur $[a,b]$ et α un paramètre de lissage positif.

Le paramètre α permet de réaliser un compromis entre le suivie des données (exprimé par $\sum_{i=1}^n \{y_i - g(x_i)\}^2$ et les fluctuations locales (exprimé par $\int_a^b \{g''(x)\}^2 dx$).

- Friedman's super smoother est un lisseur non paramétrique, mis au point par Friedman (1984) [14]. Il est basé sur les ajustements locaux des k plus proches voisins, dans un voisinage variable du point x . Il est défini comme suit:

$$\hat{m}_k(x) = n^{-1} \sum_{i=1}^n W_{k,i}(x) Y_i \quad (5)$$

$\{W_{k,i}(x)\}_{i=1}^n$ is a weight sequence defined through the set of indexes $J_{k,x} = \{i: X_i$ est une des k observations les plus proches de $x\}$.

$W_{k,i}(x)$ est la séquence de poids tel que :

$$W_{k,i}(x) = \begin{cases} 1/k, & \text{si } i \in J_{k,x}; \\ 0, & \text{sinon.} \end{cases} \quad (6)$$

Traitement avancé des mesures de niveau dans les réseaux radio mobiles

Les données traitées sont les mesures réelles collectées sur les réseaux radio mobiles et remontées par le mobile vers le réseau. On se focalise sur les mesures de puissance telles que:

- *RXLEV*: la puissance du signal reçu définie pour le GSM,
- *UE_Tx_Power*: la puissance émise du terminal définie pour l'UMTS.

Notre étude se focalise sur les mesures de puissance car cette catégorie de mesures est caractérisée par une propriété de base : le signal mesuré a subit des atténuations dues à la propagation de l'émetteur jusqu'au récepteur (le signal subit donc les phénomènes de réflexion, de diffraction et de diffusion). Trois paramètres sont principalement identifiés pour donner une précision accrue sur la description du signal propagé : l'affaiblissement de parcours (*pathloss*), l'effet de masque (*shadowing*) et l'évanouissement rapide (*fast fading*).

Pour extraire et séparer les différentes contributions des atténuations, on emploie une analyse statistique basée sur deux méthodes spécifiques : les "spline" de lissage et Friedman super-smoother. On remarque dans la Figure 3 qu'une valeur faible de α dans l'équation 1.13 ($\alpha=0.2$) laisse des fluctuations rapides dans la courbe obtenu. Alors qu'une valeur plus grande de α (0.8) permet de diminuer considérablement ces variations mais avec une atténuation accrue des principales caractéristiques du signal initial. Le lisseur Friedman supersmoother permet alors de résoudre ce problème en éliminant seulement les variations rapides et gardant les lentes.

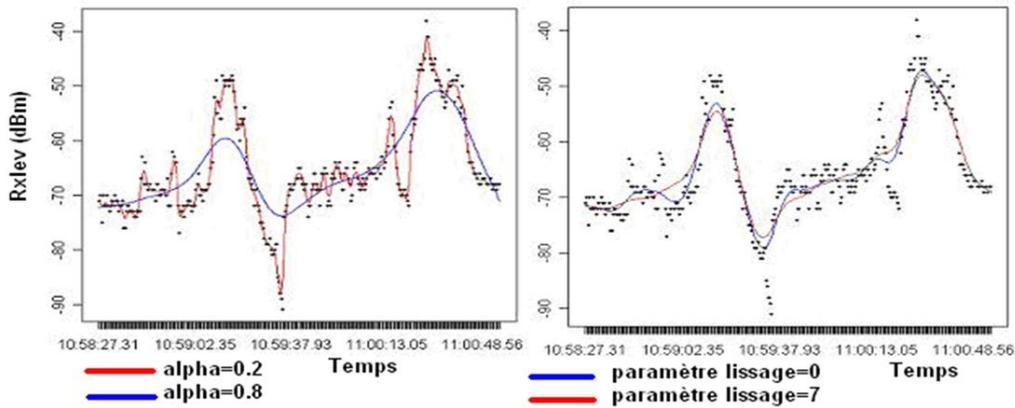


Figure 3: Application du "spline" de lissage (gauche) et Friedman's super smoother (droite) sur un vecteur de mesures de puissance RXLEV pour un utilisateur en voiture.

Estimateur proposé

L'état de l'art antérieur montre qu'il n'y a pas à ce jour une méthode directe, dynamique et intégrable permettant d'estimer les composantes d'atténuation à partir des mesures radio, en temps réel. En effet, il existe des modèles mathématiques pour décrire ces atténuations. Ces modèles correspondent à un environnement donné et ils sont validés et calibrés avec des mesures radio terrain. Donc, ils ne correspondent pas à toutes les situations possibles. Il existe également des dispositifs mesurant la propagation et l'atténuation subie par le signal radio mais ils sont complexes et difficiles à intégrer dans les réseaux radio mobiles.

On propose alors un estimateur dynamique et intégrable des composantes d'atténuation du signal radio (Figure 4) en se basant sur les équations suivantes. On désigne par SS le "spline" de lissage et FSS Friedman's super smoother.

- Affaiblissement de parcours: c'est la courbe médiane du signal radio:

$$P_k = SS(Y_k) \quad (7)$$

- Effet de masque: c'est les variations lentes du signal radio:

$$Z_k = FSS(Y_k) = Y_k + S_k \Leftrightarrow S_k = Z_k - P_k \quad (8)$$

- Evanouissement rapide: c'est les variations rapides du signal radio:

$$F_k = Y_k - (P_k + S_k) = Y_k - FSS(Y_k) \quad (9)$$

Applications

Une des alternatives d'application de notre étude est la déduction de l'état du terminal mobile selon sa vitesse, parmi trois principaux états: immobile, piéton et en voiture (Figure 5). En effet, les atténuations subies par le signal radio sont fortement liées à la vitesse du mobile. A grande vitesse, le terminal rencontre plus d'obstacles et parcourt une distance plus grande qu'à

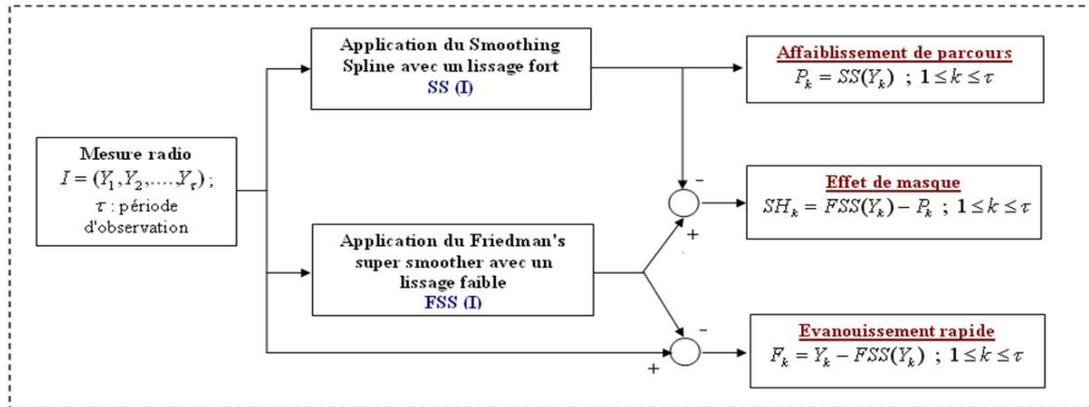


Figure 4: Estimateur dynamique des composantes d'atténuation du signal radio.

une faible vitesse. Dans ce cas, les composantes "effets de masque" (lié aux obstacles) et "affaiblissement de parcours" (lié à la distance entre l'émetteur et le récepteur) ont une plus grande dispersion de leurs valeurs. La Figure 5 illustre cette différence avec les écarts types (liés à la représentation en histogramme) de ces deux composantes d'atténuation. Ainsi, un utilisateur en voiture se caractérise avec une valeur d'écart type de ses composantes d'atténuation plus grande que les utilisateurs à plus faible vitesse.

Aussi, on propose d'appliquer les méthodes de régression et de lissage pour améliorer la

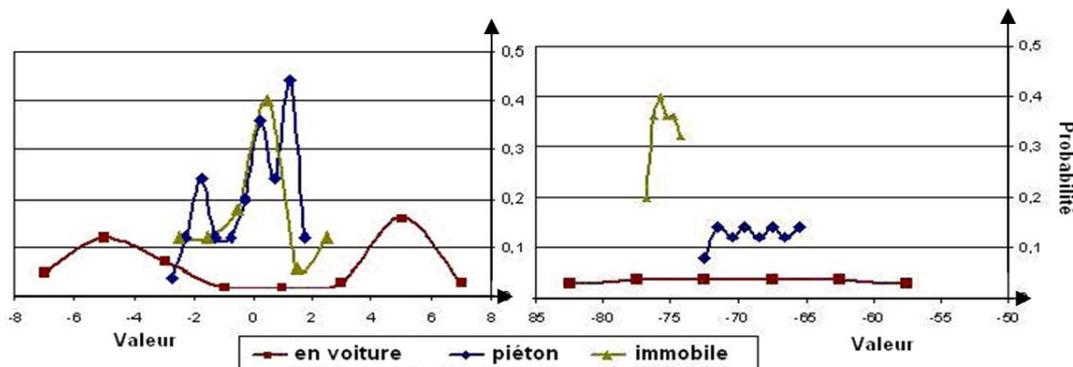


Figure 5: Différentiation de l'état de mobile avec l'effet de masque (gauche) et l'affaiblissement de parcours (droite).

procédure de handover en déterminant la liste des cellules cibles en se basant sur les variations de leurs valeur de puissance (en utilisant la pente des courbes de puissance lissées).

On a testé les méthodes de régression et de lissage sur les mesures RXLEV pour la cellule serveuse ainsi que les cellules voisines. Le but est de conclure sur une méthode qui permet une amélioration de la procédure de handover. Dans le GSM, une cellule est identifié par les paramètres ARFCN (Absolute Radio Frequency Channel Number) et BSIC (Base Station Identity Code).

Figure 1.19 illustre un exemple d'un vecteur de mesures RXLEV au cours d'un handover ayant lieu entre la cellule serveuse et la cellule voisine destinée (559,31). Cette figure montre

l'évolution du niveau du signal reçu pour toutes les cellules présentes. Figure 1.20 représente

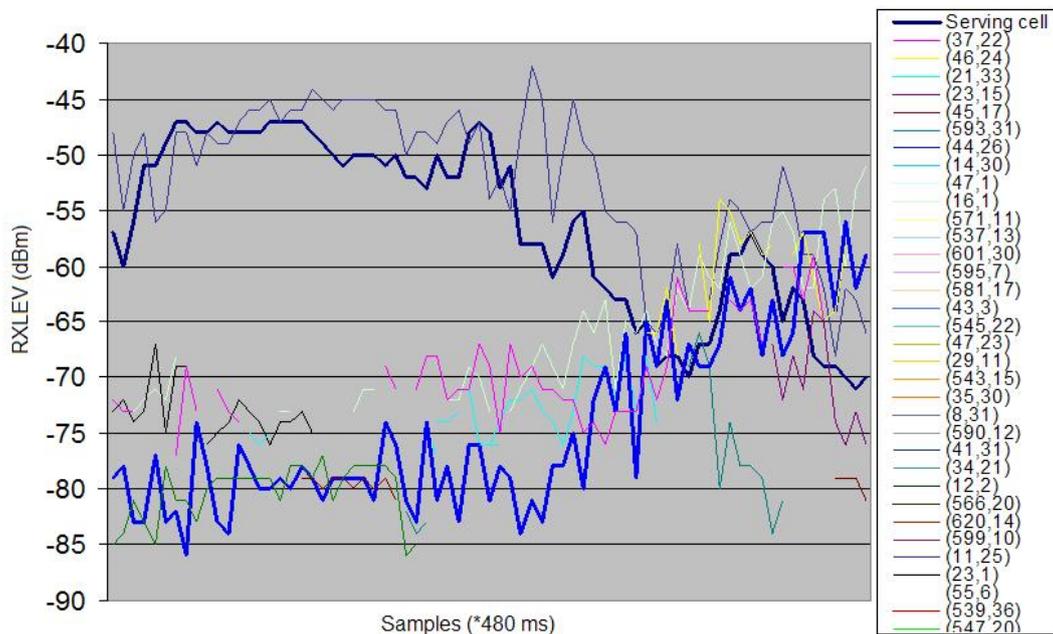


Figure 6: RXLEV pour les cellules serveuse et voisines durant un handover pour un utilisateur en voiture.

le niveau *RXLEV* pour seulement la cellule serveuse actuelle et la cellule voisine destinée. On note qu'au début le niveau *RXLEV* de la cellule serveuse est en train de décroître alors que le niveau de la cellule voisine destinée (559,31) est en train d'augmenter au cours de la même période. Après, le handover a lieu et la cellule voisine destinée devient la cellule serveuse (quand la courbe rouge disparaît).

A partir de cette observation, on a conclu sur la possibilité d'appliquer les méthodes de régression sur les niveaux de puissance des cellules pour améliorer la procédure de handover, en déterminant les cellules cibles qui pourront devenir des cellules serveuses.

En effet, l'application de la méthode "smoothing spline" avec un lissage fort (par exemple $\alpha = 1$) sur les mesures *RXLEV* de toutes les cellules (serveuse et voisines) permet d'étudier séparément l'évolution des niveaux de puissance reçu des différentes cellules (figure 1.21). Plus précisément, on s'intéresse à la pente des courbes lissées (table 1.5). Le niveau de la cellule serveuse décroît avant l'occurrence du handover. Ainsi, la pente de sa courbe lissée est négative (-0.38). La cellule cible devrait être la cellule avec le meilleur niveau de puissance. Cependant, la cellule (11,25) ne peut pas devenir la cellule serveuse même si son niveau de puissance est le plus important. En effet, le niveau de la cellule (11,25) est en train de décroître et le handover ne pourrait pas avoir lieu avec cette cellule.

Pour conclure, la cellule cible se caractérise par une pente positive (un niveau de puissance en croissance) et pourra être différencié des autres cellules voisines par la valeur de pente (de sa courbe de puissance lissée) la plus importante. Dans la figure 1.20, la cellule cible est la cellule (559,31) and sa valeur de pente est 0.53.

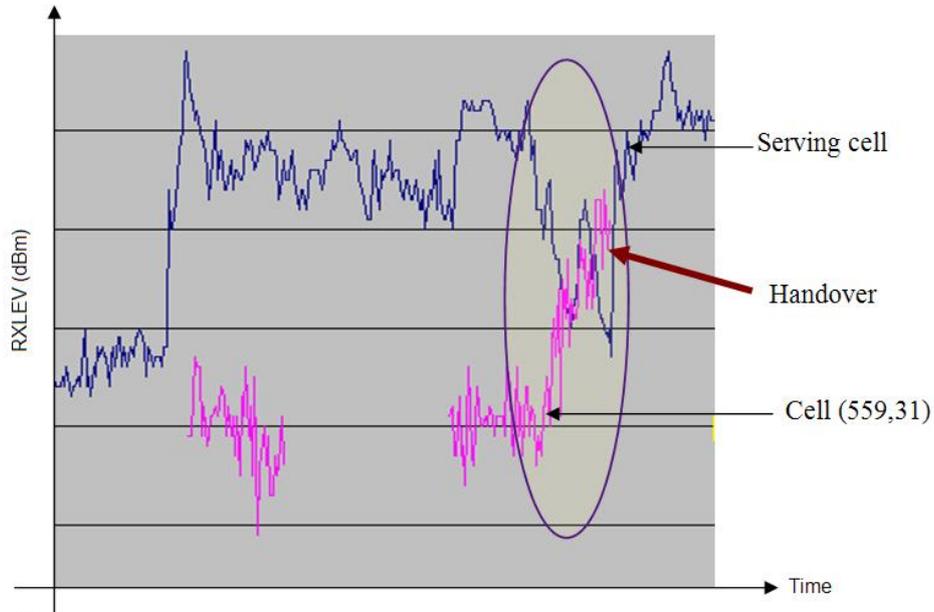


Figure 7: Exemple d'une procédure de handover.

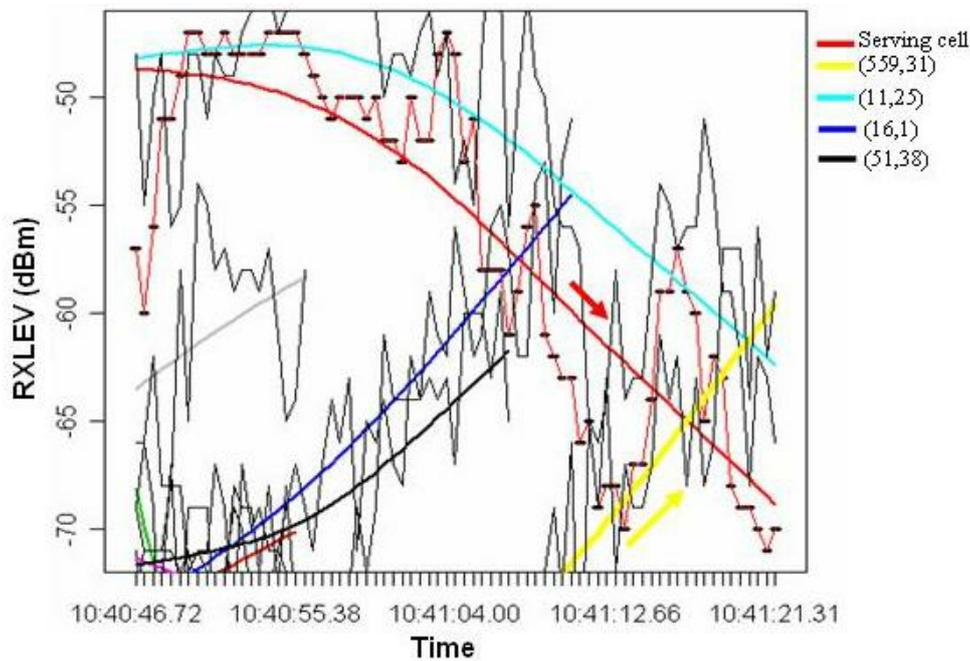


Figure 8: Application des "Smoothing spline" sur les cellules serveuses et voisines en GSM.

En se basant sur les observations précédentes, on peut conclure que les méthodes de régression et de lissage permettent d'améliorer la procédure de handover par le biais d'un algorithme amélioré de détermination de cellule cible. En effet, on propose une nouvelle approche qui consiste à améliorer le choix des cellules cibles pour la procédure de handover, en se basant sur

Table 1: Valeur des pentes après l'application du "smoothing spline" sur les mesures *RXLEV* des cellules cibles et voisines.

Case	Serving cell	(21,33)	(529,31)	(16,1)
Slope	-0,38	0,21	-1,7	0,48
Case	(559,31)	(58,35)	(51,12)	(15,26)
Slope	0,53	0,25	0,38	-0,11
Case	(11,25)	(23,1)	(616,33)	
Slope	-0,35	-0,16	0,03	

les variations de leurs signaux (exprimés sous la forme de valeurs de pentes des courbes lissées). Ceci est une approche anticipé dans le handover, dont le but est d'améliorer globalement la gestion des ressources radio. Pour conclure, on a fourni dans ce premier chapitre de thèse des méthodes et des approches innovantes qui permettent d'améliorer l'utilisation des mesures radio dans le cadre de la radio cognitive. Ces méthodes peuvent ainsi être implémentées dans les réseaux futurs et permettre ainsi une meilleur gestion des ressources radio.

Chapitre 2: La cartographie d'interférence

Dans ce chapitre, on présente *la cartographie d'interférence*: c'est un nouveau concept qui consiste à combiner les mesures radio avec l'information de localisation correspondante pour fournir une vue d'ensemble de l'environnement extérieur et permettre ainsi au réseau de prendre des décisions autonomes afin d'optimiser sa gestion des ressources radio.

La cartographie d'interférence cible particulièrement l'utilisation secondaire du spectre qui consiste à exploiter les portions de spectre non utilisées à un temps et à une localisation donnés pour envoyer des données d'une façon opportuniste. La cartographie d'interférence permettra ainsi aux utilisateurs secondaires de connaître les niveaux d'interférence sur une zone cible et de déterminer les opportunités éventuelles pour transmettre.

Dans ce chapitre de la thèse, on se focalise sur les différents aspects liés à la mise en place et le bon fonctionnement de la cartographie d'interférence au sein d'un réseau mobile. On présente un exemple d'architecture radio qui prend en compte la cartographie d'interférence par les biais d'entités responsables sur la gestion et l'exploitation de la cartographie. On propose également des procédés statistiques permettant la construction de cartographies complètes à partir d'un ensemble fini de mesures radio localisés. A la fin, on étudie un exemple d'utilisation de la cartographie d'interférence dans le contexte d'utilisation secondaire du spectre.

Présentation de la cartographie d'interférence

Le concept de cartographie dans les réseaux radio sans fils est principalement utilisé pour l'élaboration et la prédiction des cartes de couverture, de capacité et de qualité de service des réseaux radio. Le but de ces cartes est de garantir le bon fonctionnement des réseaux radio, leur maintenance ainsi que l'optimisation de leurs performances. La mise en place de cette cartographie nécessite des informations de géo-localisation sur des attributs tels que le signal d'atténuation, le niveau reçu du rapport signal sur bruit, la puissance totale reçu ou aussi des indicateurs de qualité sur la zone d'intérêt.

L'idée principale de la cartographie d'interférence est de collecter les mesures d'interférence de plusieurs éléments du réseau (terminal mobile, station de base, points d'accès, ...) avec les informations de géo-localisation correspondantes. Par la suite, on combine ces mesures localisés pour déduire une cartographie d'interférence complète sur la zone d'intérêt, en utilisant des techniques appropriées de traitement de signal tel que l'interpolation spatiale (Figure 9). La cartographie d'interférence finale correspond à une situation réelle à un instant donné t et sera valide pendant une période ΔT . Aussi, la cartographie d'interférence pourrait être construite pour plusieurs fréquences et stockés dans une base de données. Ainsi, le réseau pourrait utiliser cette base de données pour la gestion de ses ressources radio (Figure 10).

L'application du concept **Cartographie d'interférence** dans les réseaux cognitifs implique la nécessité de résoudre plusieurs problématiques. Les questions principales qui se posent pour une utilisation efficace de la cartographie d'interférence sont:

- Comment la cartographie d'interférence sera utilisée par le réseau? Quels entités seront responsables par la manipulation et l'exploitation de la cartographie?
 - Quelle est la méthode fiable qui permet de construire une cartographie d'interférence complète à partir d'un ensemble finie de mesures localisées?
-

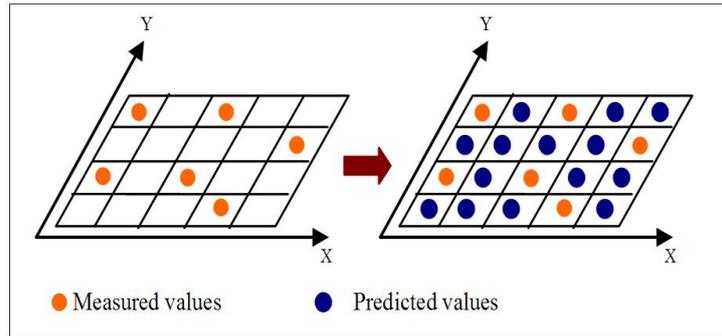


Figure 9: Le processus d'élaboration de la cartographie d'interférence.

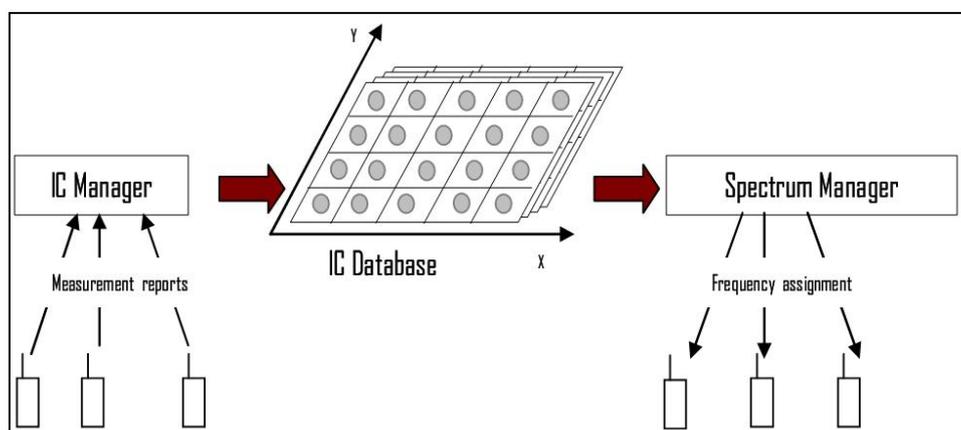


Figure 10: La cartographie d'interférence pour l'utilisation secondaire du spectre: scénario considéré.

- Quelles sont les applications possibles de la cartographie d'interférence et quelles sont les avantages par rapport aux approches conventionnelles?

La cartographie d'interférence dans la radio cognitive

On propose une implémentation possible dans le réseau (Figure 11) dans un contexte d'accès hiérarchique au spectre (avec des utilisateurs primaires et secondaires). Cette implémentation est sous forme d'une architecture centralisée qui comporte des entités centrales différentes pour la gestion du spectre, coté réseau primaire et réseau secondaire. Ces entités ont pour rôle de regrouper les demandes d'accès au spectre des utilisateurs, de connaître l'état actuel d'occupation spectrale et de distribuer d'une manière optimale les ressources entre les différents utilisateurs. Cette entité s'appuie dans ces décisions sur la cartographie d'interférence qui lui permettra d'avoir une vue d'ensemble complète sur l'état de l'environnement dans la zone cible.

Pour assurer le bon fonctionnement et la mise à jour de la cartographie d'interférence, on définit des entités responsables d'assurer ces fonctions. On propose alors:

1. Un module qui collecte les mesures radio (Measurement Collection Module),

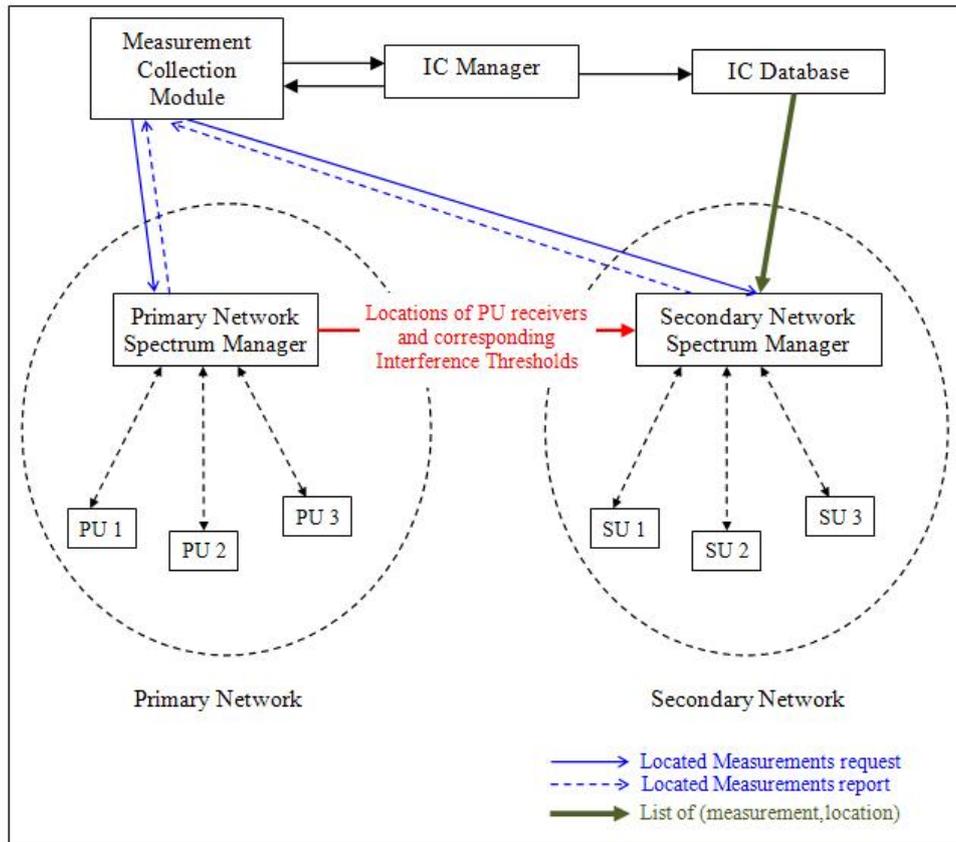


Figure 11: Implémentation réseau de la cartographie d'interférence dans un contexte utilisation secondaire du spectre.

2. Un gestionnaire de la cartographie d'interférence (IC Manager) qui a pour rôle d'analyser les mesures radio disponibles, d'évaluer la qualité de la cartographie et de la comparer à une valeur cible prédéfinie. Ce gestionnaire est responsable également de la construction d'une cartographie complète à partir d'un nombre limité de mesures et de déterminer si besoin les localisations des mesures nécessaires à demander aux terminaux (Figure 12).
3. Une base de données est nécessaire pour stocker la cartographie d'interférence d'une zone cible.

Construction de la cartographie d'interférence

La construction de la cartographie est un aspect important pour assurer une utilisation efficace de ce concept. On propose alors dans cette thèse deux approches complémentaires avec un schéma de construction fixe qui fait appel à une méthode d'interpolation spatiale (le krigeage) et un schéma de construction récursif qui rajoute au schéma fixe une boucle pour déterminer et demander des mesures supplémentaires au réseau et améliorer ainsi la qualité de la cartographie d'interférence finale.

Dans cette partie, on utilise des mesures réelles qu'on a collecté au cours d'une campagne mesure sur le réseau UMTS et avec l'aide d'un GPS pour avoir de mesures localisées d'interférence. On a aussi utilisé des mesures issues d'un simulateur radio mobile multi système pour obtenir des

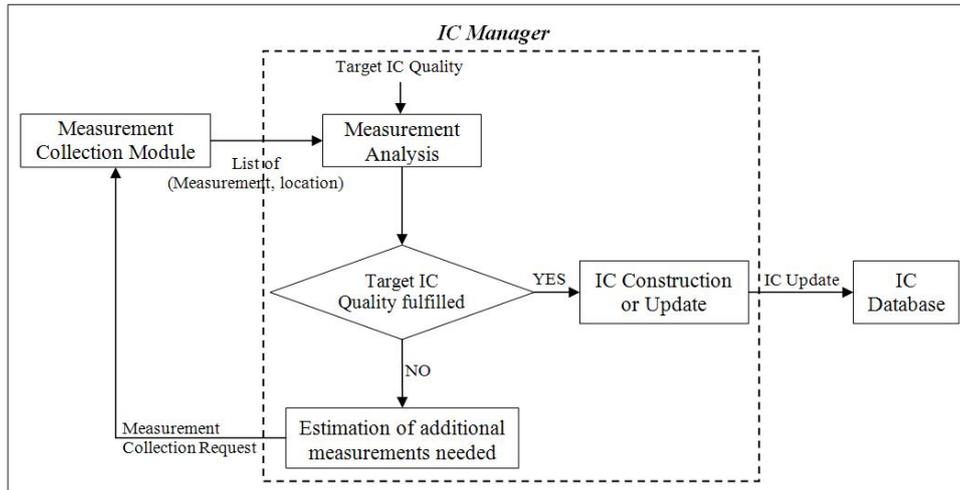


Figure 12: Manageur de la cartographie d'interférence.

cartographies d'interférence complètes sur une zone d'évaluation prédéfinie.

La méthode d'interpolation spatiale (krigeage) a été testée sur les mesures simulateur et a permis d'obtenir de bons résultats qui prouvent que cette méthode est plausible pour la construction d'une cartographie à partir d'un nombre limité de mesures (Figure 13 et Figure 14).

On a aussi testé la boucle récursive sur des données réelles en faisant appel à méthodes statistiques pour étudier la dispersion des mesures disponibles (*Complete spatial randomness test*) et aussi pour faire des opération de regroupement (*k-means clustering*) (Figure 15).

Exemple d'utilisation de la cartographie d'interférence

Pour conclure ce chapitre, on propose un exemple qui prouve l'utilité de la cartographie d'interférence dans le contexte d'un usage secondaire du spectre. Figure 16 présente un exemple d'interférence de cartographie avec les positions des utilisateurs primaires $\{PR_i\}_{i=1}^5$ ainsi que la localisation du transmetteur secondaire ST et son récepteur secondaire SR correspondant.

Le but est de déterminer si c'est possible ou non d'établir une communication entre ST et SR d'une manière opportuniste, étant donné la cartographie d'interférence actuelle et la position des utilisateurs primaires dans la Figure 16. Deux conditions doivent être vérifiées pour permettre une communication entre le transmetteur secondaire ST et son récepteur SR . La première condition est relative au récepteur secondaire, alors que la deuxième condition concerne les récepteurs primaires.

1. Au niveau du récepteur secondaire, on doit garantir un niveau de puissance reçu suffisant pour que SR ait une bonne qualité du signal reçu. Analytiquement, cette condition est équivalente à un rapport signal sur bruit supérieur à une valeur seuil prédéfinie, à la localisation du récepteur SR .

$$\left(\frac{C}{I}\right)_{SR} \geq \left(\frac{C}{I}\right)_{threshold} \quad (10)$$

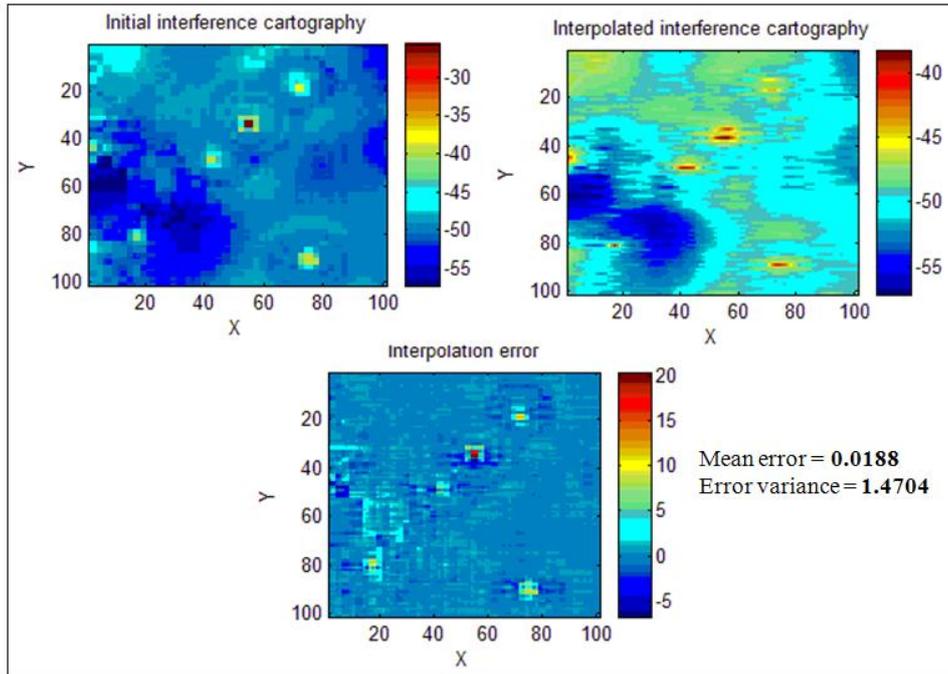


Figure 13: Exemple d'application du krigeage pour la construction de la cartographie d'interférence.

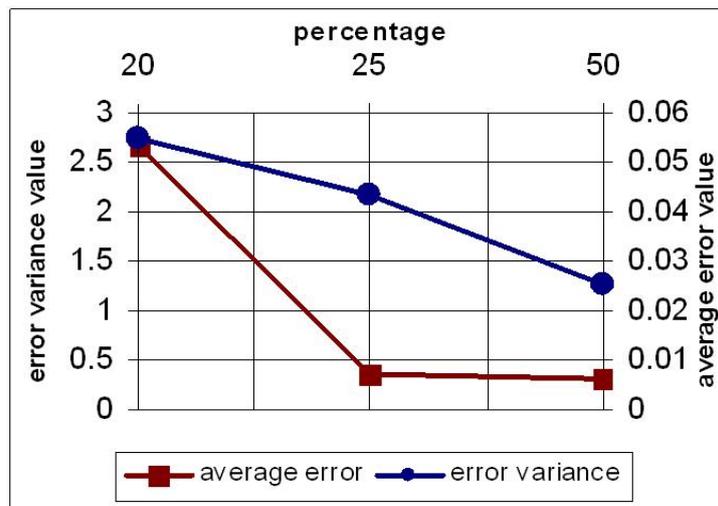


Figure 14: Evaluation des performances de l'interpolation spatiale.

with

$$\left(\frac{C}{I}\right)_{SR} = \frac{P_{SR}}{I_{(i,j)}} \tag{11}$$

Avec (i,j) les coordonnées de SR , P_{SR} est la puissance reçue par SR et $I_{i,j}$ est la valeur d'interférence totale perçue à la localisation (i,j) .

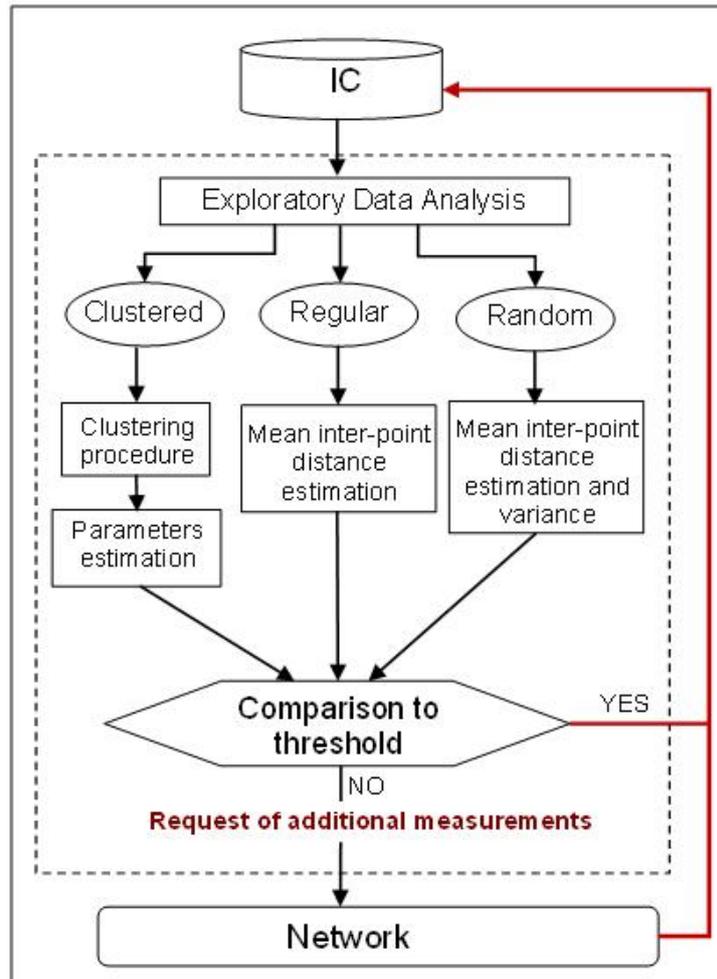


Figure 15: Procédure récursive de la construction de la cartographie d'interférence.

2. La seconde condition pour une utilisation secondaire du spectre est que la communication entre ST et SR ne provoque pas une interférence indésirable pour les récepteurs primaires dans la zone d'intérêt. Ceci veut dire que la somme d'interférence générée par la communication de l'utilisateur secondaire avec la valeur l'interférence actuelle dans la cartographie au niveau de la localisation des utilisateurs primaires ne dépassent pas une valeur maximum seuil I_{max} .

Figure 17 montre une mise à jour de la cartographie d'interférence après l'établissement de la communication entre ST et SR .

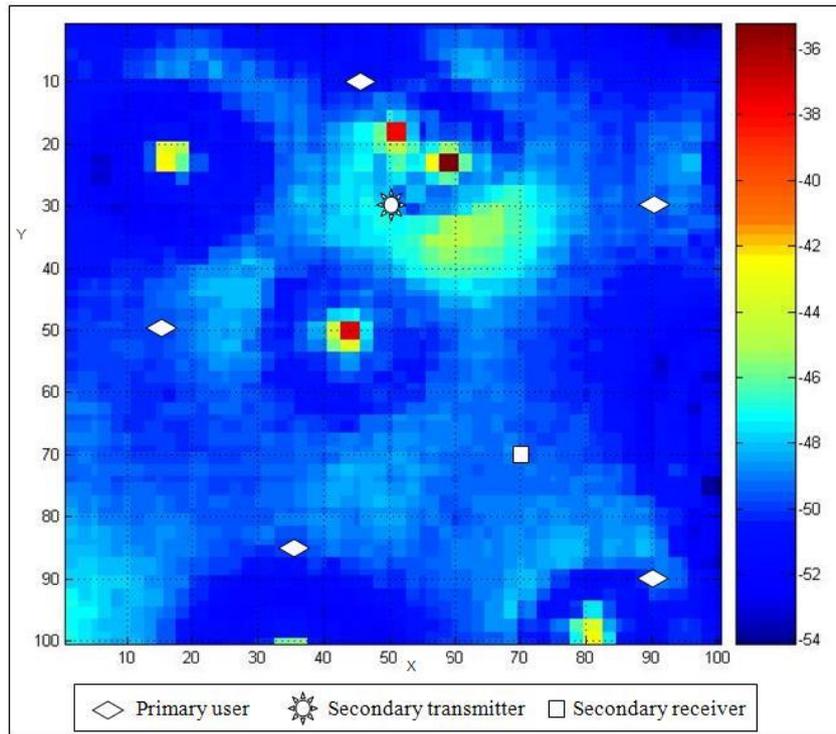


Figure 16: Exemple: Cartographie d'interférence avec les positions des utilisateurs primaires et secondaires.

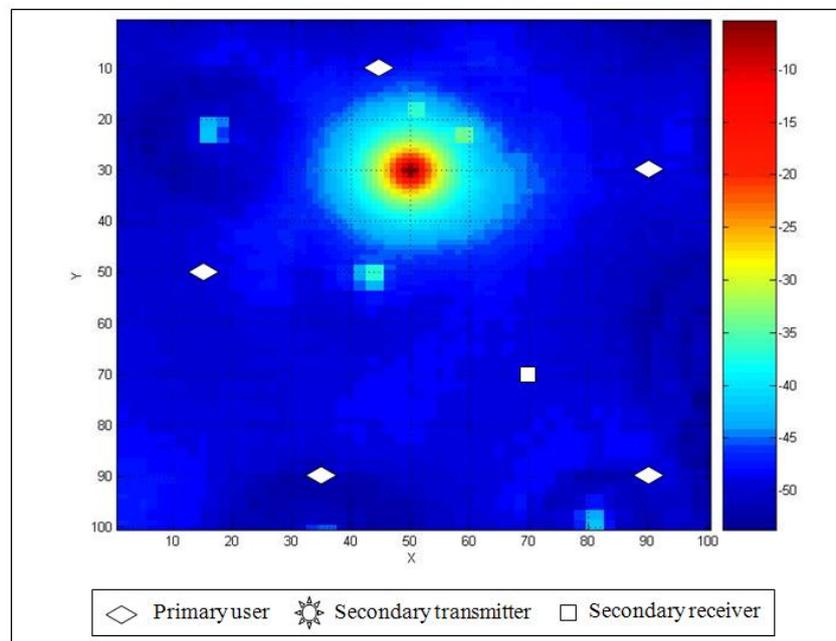


Figure 17: Mise à jour de la cartographie d'interférence.

Chapitre 3: L'accès opportuniste au spectre avec le problème du "bandit à plusieurs bras"

Utilisation du Multi Armed Bandit pour l'accès opportuniste au spectre

Le dernier chapitre de la thèse traite un aspect important de l'accès opportuniste au spectre qui est l'accès et l'exploration des canaux (sensing) pour déterminer les trous de spectre dans lesquelles un utilisateur secondaire peut envoyer ses données d'une manière opportuniste. Généralement, la méthode conventionnelle pour effectuer cette tâche est d'utiliser des moyens physiques assez complexes tels que la détection bande large (UWB). C'est la raison pour laquelle on propose une approche statistique, facile à implémenter et à utiliser par le réseau. Cette méthode s'inspire d'un problème connue appelé *bandit à plusieurs bras* (en anglais Multi Armed Bandit MAB). Cette analogie est justifié par la nécessité pour un utilisateur secondaire de réaliser un compromis entre:

1. Explorer son environnement extérieur pour mieux le connaître et appréhender ses variations et surtout détecter les portions de spectre non utilisées,
2. Exploiter les informations cumulées pour décider la manière optimale pour envoyer ses données.

L'accomplissement d'un accès opportuniste au spectre nécessite trois étapes majeures (Figure 18):

1. La première étape consiste à découvrir son environnement (Généralement, cette étape comprend le choix d'un canal cible).
2. la deuxième étape est d'explorer le canal choisi pour détecter les trous de spectre et enfin la dernière étape qui est d'envoyer ses données dans les trous déterminés. Dans ce schéma général, le MAB intervient dans la première étape en fournissant à l'utilisateur secondaire un ensemble de règles (sous forme d'algorithme) pour l'aider à choisir judicieusement à quel canal accéder (le canal avec la plus grande probabilité de présenter des trous de spectre). Ce choix est réalisé en se basant sur les décisions précédentes de l'utilisateur, ses gains relatifs (la quantité de données qu'il a réussi à transmettre) et l'algorithme MAB choisi.
3. L'étape finale consiste à transmettre dans les trous de spectre identifiés précédemment.

Application des méthodes Multi Armed Bandit

Cette nouvelle approche est testée sur un modèle d'occupation des canaux IEEE802.11. Plusieurs algorithmes MAB sont alors testés sur un exemple de scénario prédéfini (Figure 19).

A chaque instant t , l'algorithme MAB détermine le prochain canal fréquentiel à accéder, en se basant l'historique des choix précédents ainsi que l'ensemble des gains (de l'instant 1 à $(t - 1)$). Ainsi, pour chaque algorithme "bandit", on s'intéresse à la liste des canaux fréquentiels choisies à chaque instant t durant la durée totale de test (50 000 itérations). Les performances de ces algorithmes sont estimées avec une fonction de regret, qui correspond aux pertes subies par l'utilisateur secondaire pour une durée prédéfinie. Ces pertes sont engendrées par le fait que l'utilisateur secondaire ne choisit pas toujours le meilleur canal quand il fait de l'exploitation.

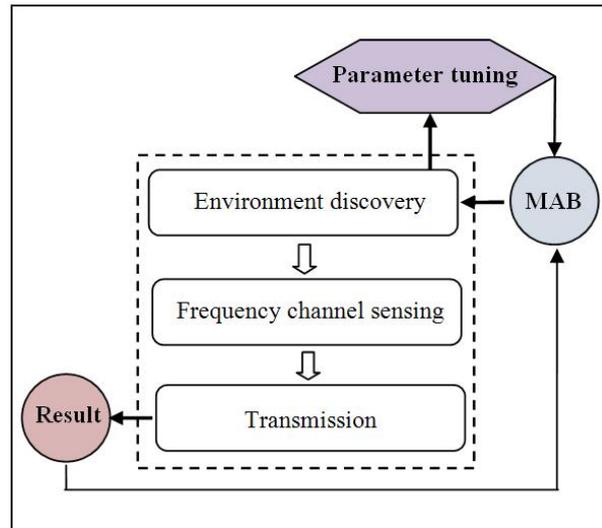


Figure 18: Rôle du Multi Armed Bandit dans l'accès opportuniste au spectre.

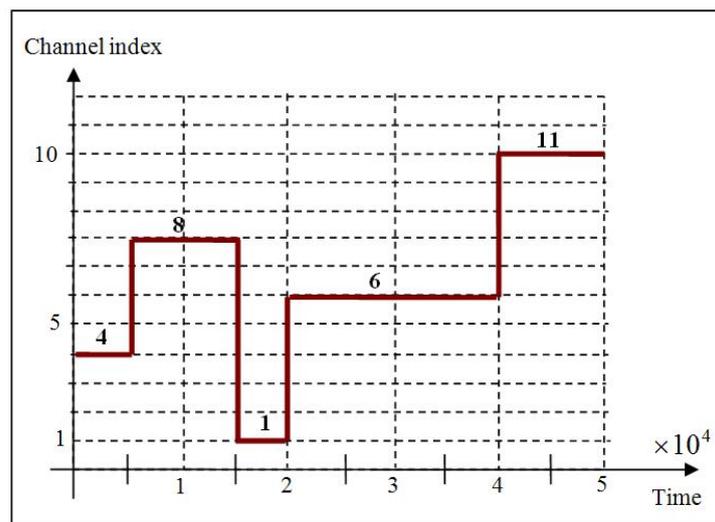


Figure 19: Le scénario test: un modèle d'occupation des canaux IEEE802.11.

La figure 20 montre les résultats avec trois variantes des stratégies UCBT: l'algorithme initial, l'algorithme périodique et la version atténuée.

La figure 21 présente les résultats obtenus avec différentes stratégies MAB (déterministes et aléatoires) et elle montre une différence claire entre les performances des algorithmes MAB testés.

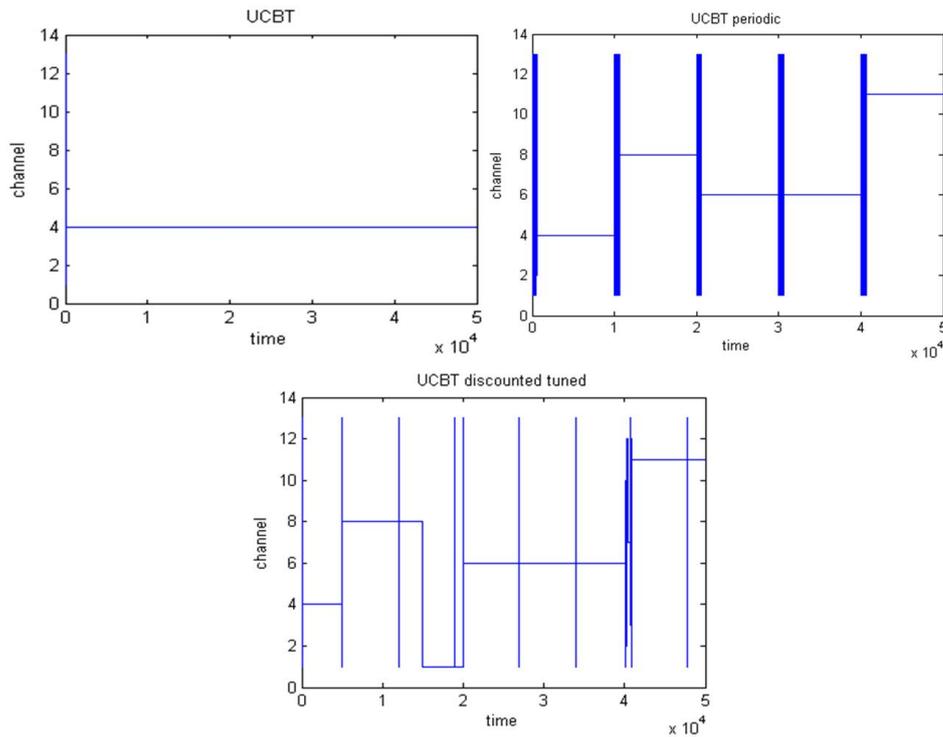


Figure 20: Performances des stratégies UCB appliqués sur le scénario test.

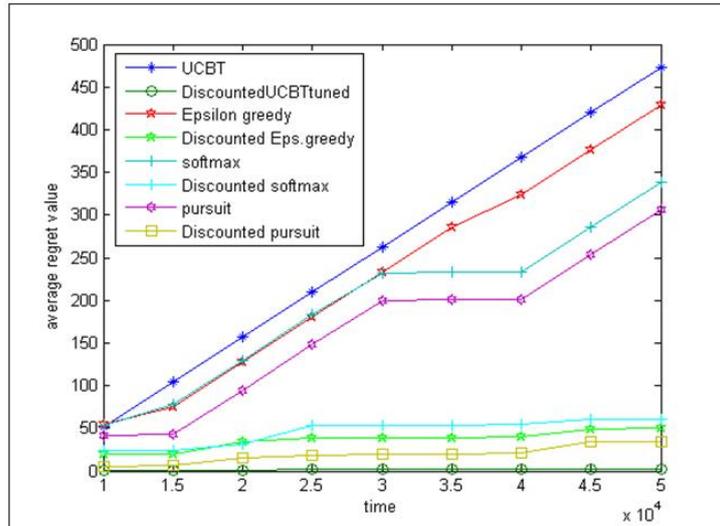


Figure 21: Performances des différents algorithmes MAB.

Réglage des paramètres du Multi Armed Bandit

On a remarqué lors de cette étude que les performances des algorithmes MAB sont fortement liées aux choix des valeurs de leurs paramètres. Etant donné que l'environnement dans lesquels évolue l'utilisateur secondaire est non-stationnaire et que l'occupation des canaux varie

d'une façon imprévisible et aléatoire, il est nécessaire d'adapter les valeurs des paramètres des algorithmes MAB utilisées aux conditions extérieures. Ainsi, un réglage automatique des paramètres des algorithmes MAB est une solution plausible pour assurer un fonctionnement optimal des stratégies MAB même dans des environnements non-stationnaires. On propose pour cela d'intégrer une option de réglage automatique des paramètres des algorithmes MAB, décrite par la Figure 22.

Dans cette approche, on propose deux méthodes différentes pour effectuer cette adaptation

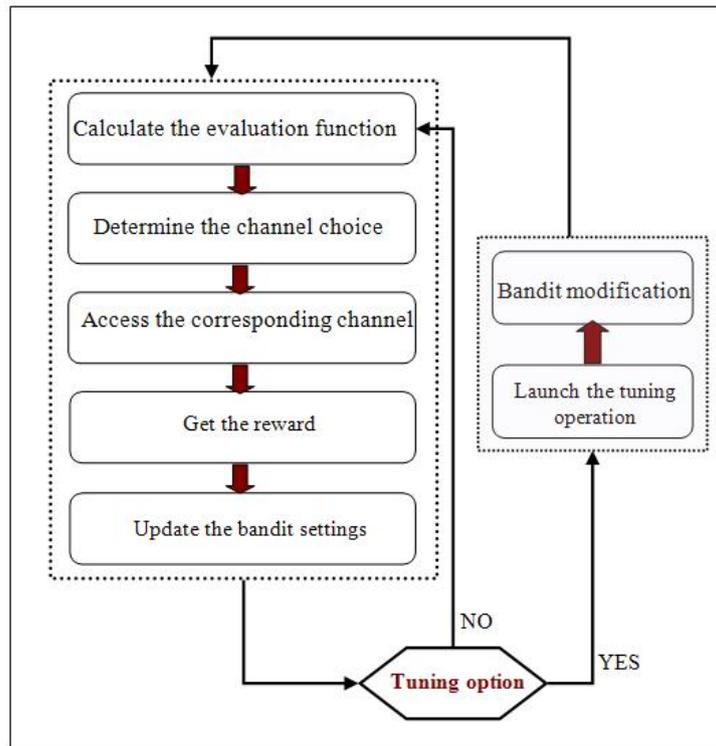


Figure 22: Organigramme de l'algorithme de bandits avec option de réglage.

des paramètres:

1. La première consiste à faire une adaptation semi-dynamique qui nécessite au préalable une étude de sensibilité des paramètres dans différentes conditions (plusieurs valeurs de stationnarité).

Pour prendre avantage de l'étude de sensibilité, on propose un schéma de réglage des paramètres semi-dynamique. Une première étape consiste à estimer régulièrement la période de stationnarité chaque T . Pour cela, on propose d'utiliser la méthode de *détection des points de changements* décrite en [15]. Cet algorithme permet en effet de détecter les changements majeurs dans le signal et de déduire par la suite les périodes de stationnarité comme différente de deux instants de changements consécutifs. Ensuite, en se basant sur l'étude de sensibilité précédente, on identifie la valeur de paramètre qui permet d'obtenir la plus faible valeur de la fonction de regret. Pour finir, une mise à jour de la stratégie MAB est réalisée pour être mieux adaptée à l'environnement actuel.

La figure 23 montre les performances des différentes stratégies d'allocation MAB en suivant la méthode semi-dynamique.

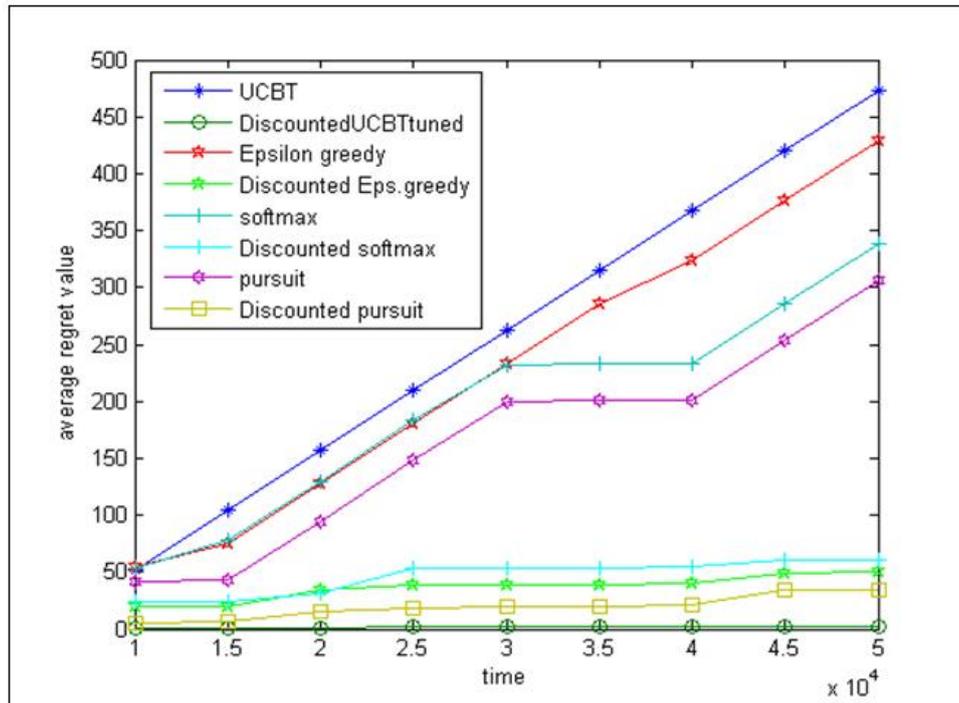


Figure 23: Performances des différentes stratégies d'allocation.

2. La deuxième méthode fonctionne d'une manière dynamique et réelle et adapte les paramètres au fur et à mesure, en s'appuyant sur des méthodes de méta-apprentissage (Meta Learning). Ceci correspond à l'utilisation d'une seconde couche d'apprentissage pour améliorer les performances de l'apprentissage de base avec un réglage dynamique des paramètres. Ainsi, les paramètres des algorithmes MAB sont mise à jour régulièrement grâce au méta apprentissage.

Dans cette étude, on applique le méta apprentissage pour choisir dynamiquement les paramètres du processus bandit dans le contexte d'un accès opportuniste au spectre. En plus de la proposition de déclenchement périodique proposé dans [16], nous avons également testé l'approche d'un déclenchement sur évènement, basée sur l'algorithme de détection de changement point [17]. La figure 24 décrit le schéma général du méta apprentissage proposé qui permet d'ajuster les paramètres des algorithmes MAB. Ainsi, on identifie deux processus bandit implémentés dans le schéma proposé:

- a) Le processus du bandit de base (BB) qui permet de choisir quel canal fréquentiel accéder,
- b) Le processus méta bandit (MB) qui détermine la valeur du paramètre de l'algorithme du processus BB.

La figure 25 mets en évidence les résultats obtenus avec les différentes approches de réglage dynamique des paramètres MAB.

Pour finir cette partie de la thèse, on propose un exemple d'implémentation de notre méthode basé sur la formulation "bandit à plusieurs bras" dans une architecture IEEE P1900.4. Dans ce scénario, un utilisateur secondaire peut recevoir des instructions d'une entité spécifique dans le

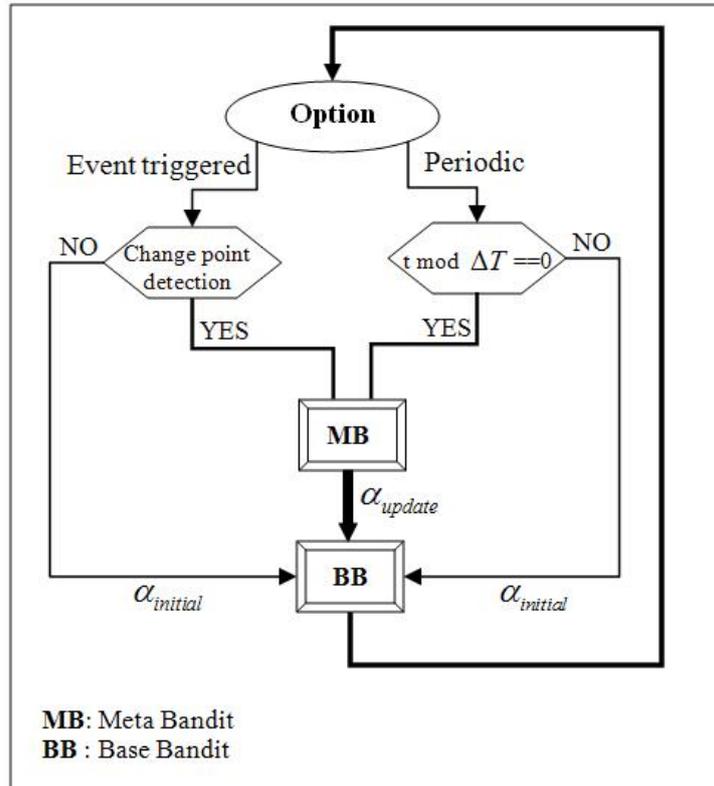


Figure 24: Architecture proposée du méta bandit.

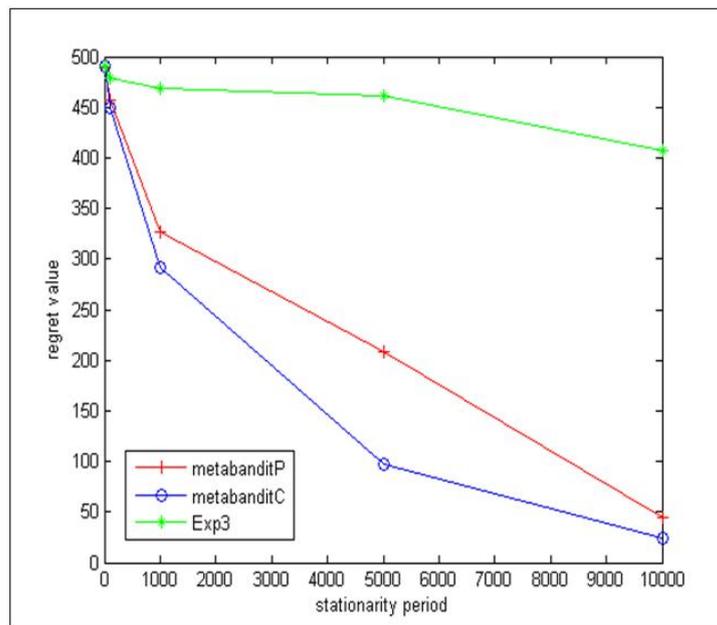


Figure 25: Comparaison entre les différentes approches online.

système P1900.4 pour effectuer un accès opportuniste sur les bandes de fréquences du système IEEE 802.11 en utilisant les algorithmes MAB.

Pour conclure, nous avons prouvé dans ce chapitre l'utilité de notre méthode pour faciliter l'accès opportuniste aux utilisateurs secondaires. Cette approche a été testée aux bandes de fréquence du système IEEE 802.11 mais notre approche est générale et constitue une solution plausible et efficace pour les autres systèmes radio.

Conclusion

Pour conclure, cette thèse vise à proposer des solutions efficaces et des approches innovantes dans le but d'améliorer la collection et la gestion d'informations dans les réseaux radio mobiles. Ainsi, on a traité trois aspects complémentaires relatifs à la métrologie dans le contexte de la radio cognitive.

Le première partie de cette thèse présente une étude sur le traitement des mesures radio standards, circulant dans les réseaux mobiles (tels que GSM et UMTS), se basant sur des méthodes de régression et de lissage non paramétriques. Cette étude montre que les mesures radio standards sont une source d'information inexploitable et que le réseau peut en profiter par le biais de méthodes de traitements adéquates pour extraire des informations utiles sur l'environnement extérieur. En effet, on a mis au point un estimateur dynamique qui permet d'estimer les composants d'atténuation subies par le signal radio en temps réel et une méthode pour déterminer le contexte de l'utilisateur selon vitesse. Ces méthodes sont testés sur des mesures terrains collectés sur le réseau GSM et UMTS. Ainsi, les résultats peuvent être améliorés avec une base de mesures radio plus importantes couvrant plus de conditions et technologies d'accès différentes.

La deuxième partie de la thèse présente un nouveau concept dans la radio cognitive, qu'on a appelé *la cartographie d'interférence*. Elle représente en effet l'agrégation des mesures radio avec l'information de localisation correspondante, qui vise à fournir un réseau une vue d'ensemble sur l'état de l'environnement dans une zone géographique cible. Dans ce chapitre de la thèse, on présente une implémentation possible dans le réseau en vue d'exploiter la cartographie d'interférence pour un accès opportuniste au spectre. On propose également des schémas de construction fixe et récursive pour permettre de construire une cartographie complète à partir d'un ensemble fini de points. Et finalement, on décrit un exemple d'utilisation de ce concept dans un scénario d'usage secondaire de spectre. Dans cette étude, on s'est focalisé sur les différents problèmes liés à la mise en oeuvre, la construction et l'exploitation de la cartographie d'interférence en se basant sur des données issues de simulateurs radio et de campagnes de mesures terrain. Un travail futur consiste à implémenter cette solution dans des simulateurs ou des réseaux réels pour adapter cette solution à chaque technologie radio et estimer les avantages de ce concept.

Enfin, la dernière partie de cette thèse s'oriente sur la problématique d'exploration et d'accès lors de la réalisation d'un accès opportuniste au spectre. On propose alors une approche statistique qui se base sur une méthode d'apprentissage par renforcement et qui s'inspire du *problème du bandit à plusieurs bras (Multi Armed Bandit)*. Cette approche est testé sur des modèles d'occupation des canaux IEEE 802.11 et les résultats prouvent l'efficacité des algorithmes pour guider l'utilisateur secondaire dans ces décisions quand au choix du meilleur canal sur lequel effectuer l'exploration (*sensing*). Les performances des algorithmes sont améliorées grâce à une adaptation astucieuse de leurs paramètres pour mieux suivre la non-stationnarité de l'environnement extérieur. Cette approche a été testée sur les bandes IEEE 802.11 mais l'approche qu'on propose ici est générale et peut être appliqué à tout autre système. Un travail futur consistera alors à implémenter cette solution sur d'autres bandes de fréquences et d'autres systèmes radios.

Thesis abstract

This thesis report describes my research work on "Metrology in wireless mobile networks for enhanced radio resource management". The main goal of the thesis is to propose effective approaches dealing with information collection, processing and utilization in cognitive radio context. These works are motivated by the necessity for wireless networks to cope with the increasing demand of throughput and services in one hand, and the inefficient use of spectral resources on the other hand.

In chapter 1, we propose to integrate advanced radio signal processing in Radio Resource Management (RRM) mechanisms in order to realize an effective and easy-to-implement exploitation of radio measurements, leading to an overall RRM improvement. Thus, we propose a complete framework that performs a signal processing analysis, based on non-parametric regression and smoothing methods, on real radio measurements (GSM and UMTS).

In chapter 2, we propose a novel concept in cognitive networks that provides awareness on the radio environment through geo-localized interference measurements: *the Interference Cartography*. The purpose of this innovative concept is to combine location information with radio measurements carried out over heterogeneous radio networks, and to provide a complete view of the environment to be used in autonomous decision making in a cognitive context. This is achieved by aggregating the already existing radio measurements that circulate in wireless networks forming the heterogeneous network panorama, combining this aggregated information with geo-localization information, performing advanced signal processing techniques to render the information complete and reliable, and updating the information to provide a viable picture of the environment for efficient detection, analysis and decision.

In chapter 3, our interest turns to the access issues in cognitive networks. Thus, we propose to provide secondary users, wishing to send data in an opportunistic manner, with appropriate tools to achieve this complicated operation. The proposed approach is inspired from the Multi Armed Bandit (MAB) problem: a reinforcement learning technique that guides the secondary user thanks to appropriate rules and policies, in order to realize simultaneously 1- The exploration of its external environment to detect unused spectrum portions and 2- The exploitation of the acquired knowledge to decide on the best channel to access.

Contents

Remerciements	iii
Résumé	v
Chapitre1: Optimisation de l'exploitation des mesures radio avec des méthodes de régression et de lissage non paramétriques	ix
Méthodes de régression et de lissage non paramétriques	ix
Traitement avancé des mesures de niveau dans les réseaux radio mobiles	x
Estimateur proposé	xi
Applications	xi
Chapitre 2: La cartographie d'interférence	xvi
Présentation de la cartographie d'interférence	xvi
La cartographie d'interférence dans la radio cognitive	xvii
Construction de la cartographie d'interférence	xviii
Exemple d'utilisation de la cartographie d'interférence	xix
Chapitre 3: L'accès opportuniste au spectre avec le problème du "bandit à plusieurs bras"	xxiii
Utilisation du Multi Armed Bandit pour l'accès opportuniste au spectre	xxiii
Application des méthodes Multi Armed Bandit	xxiii
Réglage des paramètres du Multi Armed Bandit	xxv
Conclusion	xxx
Thesis abstract	xxxi
Contents	xxxiii
List of Figures	xxxvii
List of Tables	xl
List of acronyms	xli
Introduction	1
1 Optimisation of radio measurements exploitation	7
1.1 Introduction	7
1.2 Enhancement of radio measurement exploitation	8
1.2.1 Radio Resource Management in wireless networks	8

1.2.2	Study approach	9
1.3	Radio measurement rules in wireless mobile networks	11
1.3.1	General radio propagation scheme	11
1.3.2	Radio measurements in mobile wireless networks	13
1.3.2.1	Radio measurements in GSM	14
1.3.2.2	Radio measurements in UMTS	15
1.3.2.3	Radio measurement model	17
1.4	Experimental setup	17
1.5	Theoretical presentation of regression and smoothing methods	19
1.5.1	General notions	19
1.5.2	Estimation and validation methods	21
1.5.3	Main regression and smoothing methods	23
1.6	Results in wireless networks	26
1.7	Proposed applications in wireless networks	31
1.7.1	Estimation of attenuation components	31
1.7.2	Mobile user classification	35
1.7.3	Handover procedure improvement	37
1.8	Conclusion	41
2	Interference Cartography	43
2.1	Introduction	43
2.2	Interference cartography concept presentation	45
2.3	Background and related previous works	47
2.4	Experimental setup	50
2.4.1	Simulation data	50
2.4.2	Real network data	51
2.5	Interference cartography in cognitive radio	53
2.6	Fixed IC construction scheme	56
2.6.1	Spatial interpolation	57
2.6.1.1	Theoretical presentation	57
2.6.1.2	Simulation results	59
2.7	Recursive IC construction scheme	60
2.7.1	Exploratory measurement analysis	60
2.7.2	Estimation of additional measurement requests	64
2.7.3	Example of application	64
2.8	Case study	68
2.9	Conclusion	71
3	Multi Armed Bandit for Opportunistic Spectrum Access	73
3.1	Introduction	73
3.2	Theoretical presentation of the Multi-Armed Bandit Problem	74
3.2.1	Deterministic MAB strategies	76
3.2.2	Randomized MAB strategies	77
3.3	Steered sensing with the Multi Armed Bandit	79
3.4	The network model	83
3.5	Preliminary simulation results on IEEE802.11 channel	84
3.6	MAB parameter tuning	89
3.6.1	Semi dynamic parameter tuning scheme	90
3.6.1.1	Offline sensitivity study	91

3.6.1.2	Proposed semi dynamic tuning scheme	92
3.6.2	Online parameter tuning scheme	94
3.6.2.1	Meta learning approach	95
3.6.2.2	EXP3 algorithm	98
3.6.2.3	Results	99
3.7	Use case with IEEE 802.11 in IEEE P1900.4 framework	100
3.7.0.4	Presentation of IEEE P1900.4	100
3.7.0.5	Use case description	101
3.8	Conclusion	104
Conclusion and perspectives		107
Bibliography		111
Publications and patents		117

List of Figures

1	L'évolution de la radio cognitive.	vi
2	Présentation générale de la thèse.	vii
3	Application du "spline" de lissage (gauche) et Friedman's super smoother (droite) sur un vecteur de mesures de puissance RXLEV pour un utilisateur en voiture.	xi
4	Estimateur dynamique des composantes d'atténuation du signal radio.	xii
5	Différentiation de l'état de mobile avec l'effet de masque (gauche) et l'affaiblissement de parcours (droite).	xii
6	RXLEV pour les cellules serveuse et voisines durant un handover pour un utilisateur en voiture.	xiii
7	Exemple d'une procédure de handover.	xiv
8	Application des "Smoothing spline" sur les cellules serveuses et voisines en GSM.	xiv
9	Le processus d'élaboration de la cartographie d'interférence.	xvii
10	La cartographie d'interférence pour l'utilisation secondaire du spectre: scénario considéré.	xvii
11	Implémentation réseau de la cartographie d'interférence dans un contexte utilisation secondaire du spectre.	xviii
12	Manager de la cartographie d'interférence.	xix
13	Exemple d'application du krigeage pour la construction de la cartographie d'interférence.	xx
14	Evaluation des performances de l'interpolation spatiale.	xx
15	Procédure récursive de la construction de la cartographie d'interférence.	xxi
16	Exemple: Cartographie d'interférence avec les positions des utilisateurs primaires et secondaires.	xxii
17	Mise à jour de la cartographie d'interférence.	xxii
18	Rôle du Multi Armed Bandit dans l'accès opportuniste au spectre.	xxiv
19	Le scénario test: un modèle d'occupation des canaux IEEE802.11.	xxiv
20	Performances des stratégies UCB appliqués sur le scénario test.	xxv
21	Performances des différents algorithmes MAB.	xxv
22	Organigramme de l'algorithme de bandits avec option de réglage.	xxvi
23	Performances des différentes stratégies d'allocation.	xxvii
24	Architecture proposée du méta bandit.	xxviii
25	Comparison entre les différentes approches online.	xxviii
0.26	Cognitive radio evolution.	2
0.27	Metrology overview in wireless networks.	3
1.1	Radio propagation.	11

1.2	GSM system architecture.	15
1.3	UMTS system architecture.	16
1.4	Measurement filtering in UMTS system.	16
1.5	Experimental setup.	17
1.6	Examples of RXLEV measurements for pedestrian (top) and unmoving (bottom) situations.	18
1.7	Example of UE_Tx_Power measurement.	19
1.8	Smoothing spline for unmoving (up left), pedestrian (up right) and incar (down) case.	27
1.9	Result of the smoothing spline (spar=0.8) on RXLEV dataset for incar situation.	28
1.10	Normal kernel representation.	29
1.11	Kernel regression smoother (normal) for unmoving (up left), pedestrian (up right) and incar (down) case.	30
1.12	Friedman's Super Smoother for unmoving (up left), pedestrian (up right) and incar (down) case.	31
1.13	Comparison between Kernel and Super Smoother methods.	32
1.14	Smoothing and regression methods application on RXLEV measurement.	34
1.15	Smoothing and regression methods application on UE_Tx_Power measurement.	34
1.16	Dynamic estimator of attenuation components of radio signal.	35
1.17	Estimated attenuation components.	36
1.18	Shadowing and pathloss histogram representations for unmoving, pedestrian and incar situations.	37
1.19	RXLEV for serving and neighborhood cells during handover for incar user.	39
1.20	Example of handover procedure.	39
1.21	Smoothing spline application for serving and neighborhood cells in GSM system.	40
2.1	Interference Cartography for secondary spectrum usage: considered scenario.	46
2.2	Interference Cartography elaboration process.	46
2.3	Taxonomy of dynamic spectrum access according to [18].	48
2.4	Example of Odyssee simulation.	52
2.5	Description of the measurement campaign.	52
2.6	Real measurement campaign.	53
2.7	Map of the measurement campaign.	54
2.8	Interference Cartography for secondary spectrum usage: general framework.	55
2.9	Interference Cartography Manager.	56
2.10	Fixed IC construction scheme.	57
2.11	Kriging interpolation of interference cartography.	61
2.12	Spatial interpolation evaluation.	61
2.13	Example of a real point pattern.	62
2.14	Recursive interference cartography construction.	65
2.15	Measurement locations of the case study.	66
2.16	Ripley's K function test.	66
2.17	Clustering operation.	67
2.18	Test and validation samples.	67
2.19	Kriging interpolation error.	68
2.20	Case study: interference cartography with positions of primary and secondary users.	69
2.21	Updated interference cartography.	71
3.1	Representation of the gambler dilemma in a casino.	75
3.2	The three steps of Opportunistic Spectrum Access (OSA).	80

3.3	Rule of Multi Armed Bandit in OSA functioning.	82
3.4	The IEEE 802.11 channel occupation model used as the test scenario.	85
3.5	Performances of UCB strategies on the test scenario.	86
3.6	Tuning ρ in discounted UCBT.	86
3.7	Performances of ϵ -greedy strategy.	87
3.8	Tuning the temperature parameter T in Softmax strategy with $\epsilon = 0.01$	87
3.9	Tuning the parameter α in Pursuit method with $P_{min} = 0.001$	88
3.10	Average regret for the bandit strategies on the test scenario.	88
3.11	Proposed OSA scheme including MAB.	89
3.12	Flowchart of bandit algorithm with tuning option.	90
3.13	Example of test scenarios with different stationarity periods.	91
3.14	Performances of different allocation strategies.	92
3.15	Regret value vs strategy parameter for Adaptive Pursuit method.	93
3.16	Regret value vs strategy parameter for ϵ -greedy.	93
3.17	Regret value vs strategy parameter for Softmax method.	94
3.18	Semi dynamic parameter tuning scheme.	95
3.19	Proposed meta bandit architecture.	96
3.20	Comparison between online approaches.	100
3.21	IEEE P1900.4 model [10].	101
3.22	IEEE P1900.4 use case.	102
3.23	Scenario description.	103
3.24	Thesis overview.	108

List of Tables

- 1 Valeur des pentes après l’application du "smoothing spline" sur les mesures *RXLEV* des cellules cibles et voisines. xv
- 1.1 Summary of regression and smoothing methods. 26
- 1.2 Smoothing parameters values for different mobile holder situation. 27
- 1.3 Summary of the main characteristics of tested regression methods. 30
- 1.4 Standard deviation of the attenuations components. 35
- 1.5 Curve slopes after smoothing spline application on *RXLEV* of serving and neighborhood cells. 40
- 2.1 Propagation model parameters. 51
- 2.2 Mobile terminal configuration. 51
- 2.3 Primary and secondary users’ locations. 68
- 2.4 Interference values for primary and secondary users before and after the communication between *SR* and *ST*. 70
- 3.1 Generalized Pareto distribution parameters. 84

List of acronyms

RAT	Radio Access Technology
2G	Second Generation
3G	Third Generation
B3G	Beyond Third Generation
UMTS	Universal Mobile Telecommunications System
EDGE	Enhanced Data Rates for GSM Evolution
GPRS	General Packet Radio Service
GSM	Global System for Mobile Communications
RRM	Radio Resource Management
SDR	Software Defined Radio
FCC	Federal Communications Commission
UWB	Ultra Wide Band
OSA	Opportunistic Spectrum Access
MAB	Multi Armed Bandit
RNC	Radio Network Controller
WLAN	Wireless Local Area Network
IC	Interference Cartography
AP	Access Point
BSC	Base Station Controller
CDMA	Code Division Multiple Access
CR	Cognitive Radio
MT	Mobile Terminal
UBCT	Upper Confidence Bound Tuned
PL	Path Loss
NLOS	Non Line Of Sight
LOS	Line Of Sight
QoS	Quality of Service
IEEE	Institute of Electrical and Electronics Engineers
OMC	Operation and Maintenance Center
WRAN	Wireless Rural Area Network
HSDPA	High Speed Downlink Packet Access
GPS	Global Positioning System
RXLEV	Received Signal Level
RXQUAL	Received Quality level
BSIC	Base Station Identity Code

ARFCN	Absolute Radio Frequency Channel Number
RSSI	Received Signal Strength Indicator
NBAP	Node B Application Part
RRC	Radio Resource Control
UE	User Equipment
SACCH	Slow Associated Control Channel
3GPP	Third Generation Partnership Project
CDMA	Code Division Multiple Access
SIR	Signal to Interference Ratio
RSCP	Received Signal Code Power
CPICH	Common Pilot Channel
CV	Cross Validation
GCV	Generalized Cross Validation
HO	Handover
DSA	Dynamic Spectrum Access
PU	Primary User
SU	Secondary User
WGS	World Geodetic System
TDOA	Time Difference of Arrival
ARM	Available Resource Map
REM	Radio Environment Map
IMSI	International Mobile Subscriber Identity
NSM	Network Spectrum Manager
GIS	Geographic Information System
IDW	Inverse Distance Weighting
CSR	Complete Spatial Randomness
HP	Homogeneous Poisson
ML	Meta Learning
EXP3	Exponential weight algorithm for Exploration and Exploitation
NRM	Network Reconfiguration Manager
TRM	Terminal Reconfiguration Manager
CSMA	Carrier Sense Multiple Access
CA	collision Avoidance
SIFS	Short Interframe Space
DIFS	DCF Interframe Space

Introduction

Since the invention of radio communication by Marconi in 1896, telecommunications have been subject to important evolutions and advances, aimed to provide higher data throughputs and more sophisticated services with heterogeneous Radio Access Technologies (RATs) (i.e. GSM, EDGE, GPRS, UMTS). Nowadays, wireless networks have become a crucial means of communication and an essential tool for personal and professional tasks.

First discussions on reconfigurable radio began within the SDR forum in 1996 [1]. Its goal is to propose novel approaches for the addition of further flexibility and intelligence in wireless networks by means of reconfigurable and software defined radio. This was the starting point for the cognitive radio, that was first coined by Mitola in [3]. From his point of view, a cognitive network is perceived as a network having "a cognitive process that can perceive current network conditions, and then plan, decide and act on those conditions. The network can learn from those adaptations and use them to make future decisions, all while taking into account end-to-end goals".

Since the PhD work of Mitola [5], a considerable amount of research and development effort has been spent on cognitive radio. This remarkable evolution is the natural response to an increasing demand from the users in terms of services and data throughput, combined with the current under-utilization of the spectral resources. In fact, the existing spectrum usage shows important inefficiencies due to the fixed spectral resources assignment between RATs and operators. The poor utilization of the spectrum has been demonstrated by various measurement campaigns (for example, a measurement campaign made in New York reveals that about 13% of the spectral resources are used [2]).

Therefore, an important part of the research work on cognitive radio focuses on finding solutions that target more effective use of spectral resources thanks to the addition of further intelligence and environment-aware functionalities to wireless networks. In most cases, cognitive radio is associated with *Dynamic Spectrum Management* where flexibilities are added to conventional spectrum usage schemes to improve the overall exploitation of the spectral resources. *Opportunistic spectrum access* [4] is one of such flexible schemes where the main idea is to open the licensed spectrum to secondary utilization, allowing secondary users to exploit the unused portions of the spectrum at given time and location and to transmit on these detected opportunities, as long as they do not degrade the communication quality of the primary users.

Currently, cognitive radio has gone beyond the pure research phase to arrive at the first development and standardization initiatives. These initiatives constitute an evolution for future implementation and use in wireless networks. Figure 0.26 shows the main evolution steps in cognitive radio works.

The Federal Communications Commission (FCC), the regulatory organism in USA, was among

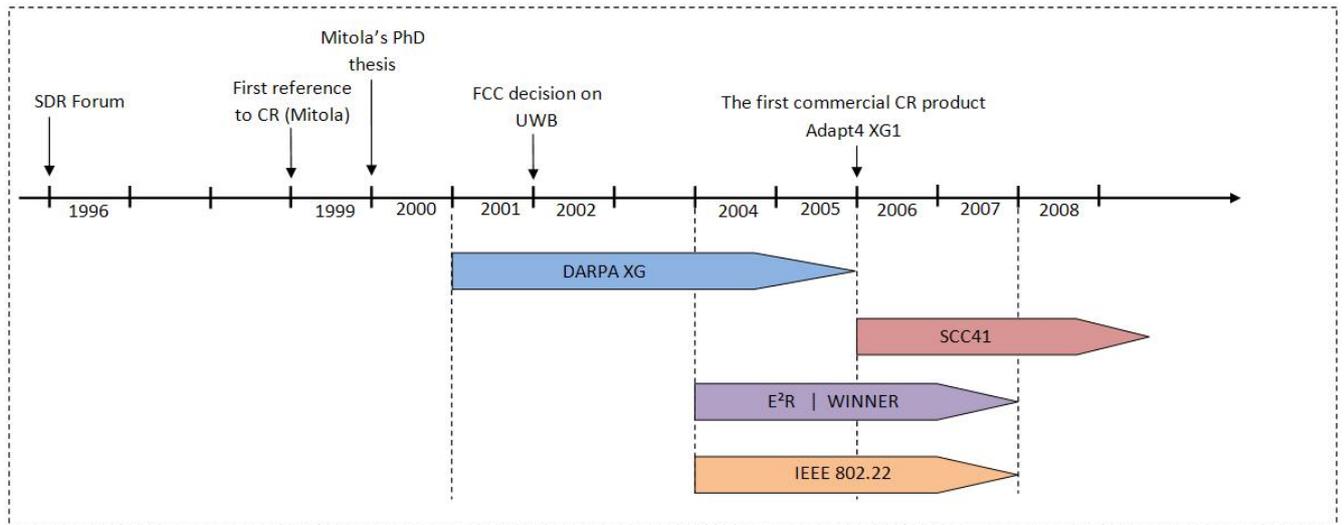


Figure 0.26: Cognitive radio evolution.

the first institutions to be interested in cognitive radio. Its first action within this context is to render the Ultra Wide Band (UWB) technology unlicensed in 2002.

Cognitive radio is an extremely challenging task due to important issues like selecting efficient architectures (with or without infrastructure, centralized or distributed), protocol structures and co-existence strategies (collaborative or competitive), finding efficient methods for information collection and processing (widely known as spectrum sensing), detecting primary users, analyzing the processed information to make 'informed decisions' on how and when to perform hierarchical access, managing mobility, etc [19]. All these issues are handled by a multitude of important projects in USA (DARPA Next Generation XG [8]) and Europe (E2R: End to End Reconfigurability [6], WINNER [7]) as well as standardization organisms:

- IEEE SCC41 [10]: It is a standard project family that aims to standardize architecture and enablers for optimization of radio resource usage in heterogeneous wireless access networks. Its interest encompasses a multitude of issues such as cognitive radio, dynamic spectrum access, the management of interference in wireless networks and the coordination between heterogeneous networks.
- IEEE802.22 [9]: It is the first standard to implement cognitive functions in Wireless Rural Area Networks (WRANs). In fact, it allows dynamic spectrum access in the TV bands, without degrading incumbent services (TV receivers, wireless microphones). This is achieved through sensing the target frequency bands and determining the most appropriate ways for channel allocation.

Also, it is important to mention that the first commercial cognitive radio product called as "Adapt4 XG1" was developed in 2006 [11]. It is a device that ensures the detection and the avoidance of primary users. Thus, it can transmit in opportunistic manner without interfering with licensed users.

In this innovative context and among the increasing research work on cognitive radio, this

this thesis is dedicated to **Metrology in wireless mobile networks for enhanced radio resource management**, where the term "metrology" stands for the scientific study of measurements. One of the most important issues that should be addressed in the cognitive radio context is information collection and processing that provides awareness on the environment and that helps cognitive networks to arrive at efficient 'informed decisions'. Research work on information collection and processing in the context of cognitive radio have so far been mostly concentrated on spectrum sensing in order to detect the localization of primary users [12] and the unused portions of the spectrum [5] for opportunistic access purposes.

To this goal, we propose to examine information collection and processing in cognitive networks through effective radio measurement processing and the set up of appropriate tools that help realization of cognitive functions (for example opportunistic spectrum access).

This thesis is composed of three main parts, each of them treating an independent aspect

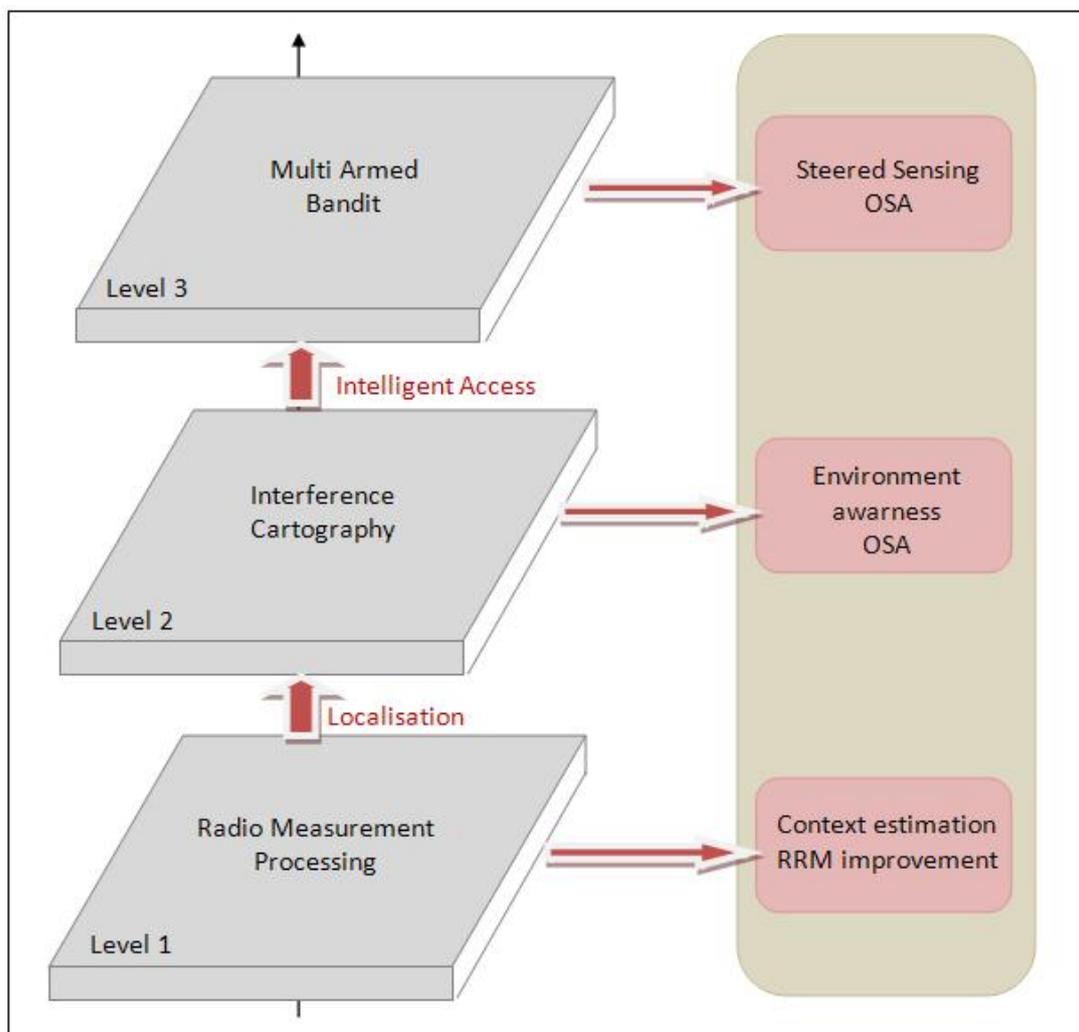


Figure 0.27: Metrology overview in wireless networks.

related to metrology in the context of cognitive radio (Figure 0.27). Our goal is to cover the different issues related to radio measurements in cognitive networks, namely:

1. The processing tools to extract useful information from reported radio measurements. The role of this information is to provide awareness on the external environment,
2. The aggregation of radio measurements with location information to provide a complete view on the state of the radio environment, aiming at an improved radio resource management,
3. Steering cognitive network decisions with appropriate rules and policies, to achieve improved spectral resource utilization.

In chapter 1, we propose to integrate advanced radio signal processing in Radio Resource Management (RRM) mechanisms in order to realize an effective and easy-to-implement exploitation of radio measurements, leading to an overall RRM improvement. Thus, we propose a complete framework that performs a signal processing analysis, based on non-parametric regression and smoothing methods, on real radio measurements (GSM and UMTS). Consequently, we make use of this analysis to propose practical applications within wireless networks. Thus, three main applications are identified. First, we propose a novel procedure that estimates the attenuation components (pathloss, shadowing and fast fading) from reported power measurements, in a dynamic and almost real-time manner (filed as a patent). Second, this estimator is used to classify the context of the mobile user based on the velocity criterion (namely *incar*, *pedestrian* or *unmoving*). Finally, we propose to improve the handover process with an enhanced target cell determination algorithm.

This chapter demonstrates that reported radio measurements are a rich and yet unexploited source of valuable information in wireless networks. The main originality of our work is that it makes use of the already existing radio measurements in the network and brings out, from the available data, additional information that are used in effective applications that bring RRM improvement, with low computational effort.

In chapter 2, we propose a novel concept in cognitive networks that provides awareness on the radio environment through geo-localized interference measurements: *the Interference Cartography*. The purpose of this innovative concept is to combine location information with radio measurements carried out over heterogeneous radio networks, and to provide a complete view of the environment to be used in autonomous decision making in a cognitive context. This is achieved by aggregating the already existing radio measurements that circulate in wireless networks forming the heterogeneous network panorama, combining this aggregated information with geo-localization information, performing advanced signal processing techniques to render the information complete and reliable, and updating the information to provide a viable picture of the environment for efficient detection, analysis and decision.

Our focus is on hierarchical access models (or opportunistic spectrum access) where licensed spectrum can be accessed by secondary users without creating harmful interference on the primary users. A complete description of a possible network implementation in a hierarchical access scheme is given, with a centralized architecture, a protocol structure that complies with the utilization of interference cartography, and a signal processing technique that constructs a complete and reliable cartography with limited number of located measurements. A case study of the proposed scheme is also given, demonstrating the utility of the notion of interference cartography for effective opportunistic spectrum access.

In chapter 3, our interest turns to the access issues in cognitive networks. Thus, we propose to provide secondary users, wishing to send data in an opportunistic manner, with appropriate tools to achieve this complicated operation. The proposed approach is inspired from the Multi

Armed Bandit (MAB) problem: a reinforcement learning technique that guides the secondary user thanks to appropriate rules and policies, in order to realize simultaneously 1- The exploration of its external environment to detect unused spectrum portions and 2- The exploitation of the acquired knowledge to decide on the best channel to access. We investigate different issues related to the application of MAB schemes for the realization of opportunistic spectrum access in cognitive networks. The main originality of this work is the experimentation of the MAB strategies on an IEEE802.11 channel model and the proposal of MAB parameter tuning schemes (semi dynamic and online approaches) to enhance the performance of the used allocation strategies in non-stationary environments. As a result, we obtain intelligent solutions that provide the secondary users with the set of rules and policies to perform efficient opportunistic spectrum access and to cope with the dynamic nature of the channels' occupation. Finally, we present a use case scenario that demonstrates the functioning of opportunistic spectrum access on IEEE802.11 bands, within the IEEE P1900.4 standard framework, using the Multi Armed Bandit strategies.

Chapter 1

Optimisation of radio measurements exploitation with Regression and smoothing methods

1.1 Introduction

The optimization of Radio Resource Management (RRM) is an important concern to telecom operators and mobile constructors, especially with the growth of data rates and user concentration in 3G mobiles. The transition from 2G to 3G technology, the growing demand for services and data rates and the appearance of new architectures and network cooperation schemes have considerably complicated the role of the RRM. In fact, the RRM encompasses the strategies and procedures responsible for the control and the management of the scarce radio frequency resources considering the users of the mobile network and the requested data rates.

The performance of RRM algorithms depends to a great extent on the way radio measurements are analyzed. In fact, in any radio access technology (RAT), radio measurements are crucial to assess the network functioning and to detect the anomalies. These measurements are standardized in each RAT within three main categories (power, quality and traffic) and can be handled either by the base station or the mobile terminal.

In spite of the considerable importance of the radio measurements in RRM procedures, the processing of this available data and the enhancement of its utilization in the network have attracted limited interest from the research community. Generally, in current radio access technologies, radio measurements undergo a basic processing before their integration in the RRM procedures. The applied processing is commonly limited to averaging or filtering operations. Lately, new types of radio measurements have been defined to carry out opportunistic spectrum access. The main example is the standardization group IEEE802.11k [20] where novel measurements are defined to improve spectrum opportunity identification with more diverse and advanced measurements (such as "the noise histogram report" and "the medium sensing time histogram report").

In this first part of the thesis, we focus on the improvement of radio measurement analysis in current radio access technologies for the purpose of enhancing the performance of RRM mechanisms. For this goal, we propose new processing approaches on standardized radio

measurements that aim at extracting additional information from existing measurements and improving internal RRM procedures. The proposed processing techniques makes use of statistical tools for non-parametric regression and smoothing on discrete data [21]. These methods have been recently introduced in non parametric statistics and are extremely helpful to exploit data, extract interesting special features, predict its evolution and facilitate its interpretation.

The main originality of this work is that it makes use of the already existing radio measurements in the network and brings out, from the available data, additional information that are extremely useful for the improvement of RRM procedures, with low computational efforts. Thus, interesting results are inferred from this analysis, based on real measurement traces collected in different environments and situations.

First, we define a dynamic estimator of the attenuation components (namely pathloss, shadowing and fast fading) given a set of consecutive reported radio measurements. This estimator has the advantage of functioning almost in real time and providing results from existing measurements with no further hardware implementation. This approach is innovative and differs from the conventional ones: requiring considerable hardware material and thus are difficult to implement in radio networks. It is important to mention here that this estimator was filed as a patent.

Adding to that, this work also leads to the definition of a method for the determination of the mobile user situation (incar, pedestrian and unmoving) as well as to the proposal of improvements in the handover procedure (with an enhanced target cell determination algorithm). Finally, we can conclude that integrating advanced radio signal processing in RRM mechanisms is an efficient and easy-to-implement way for a better use of radio measurements and thus the overall improvement of RRM procedures.

1.2 Enhancement of radio measurement exploitation

1.2.1 Radio Resource Management in wireless networks

The Radio Resource Management (RRM) is a global notion that covers different procedures and algorithms implemented in the network and dedicated to the control of the well-functioning of overall entities and functions in the radio network, so as to guarantee the required Quality of Service (QoS)[22]. The RRM is complementary to static functions mainly devoted to radio network planning that correspond to all the preliminary preparations and actions made before putting into service the network, such as:

- The Frequency assignment planning,
- The deployment of base stations,
- The determination of sector antenna direction in the base stations.

The RRM ensures optimal management of the radio resources given the fixed frequency assignment and the network planning. Roughly speaking, the role of the RRM is to adapt and control the radio network parameters so as to meet the required QoS. In the network, the RRM can function in a centric manner with a central entity responsible for the control of a sub-part of the network, for example the Radio Network Controller (RNC) in the UMTS system. Otherwise, the RRM can work in distributed manner between different entities of the network (for example

mobile terminals and base stations).

The main RRM functions are:

- **Power control:** It corresponds to the control of transmitted and received power at both the mobile terminal and the base station sides, in order to ensure that the generated interference doesn't exceed a predefined threshold and thus affects the required QoS,
- **Handover control:** This function ensures the continuity of a communication with acceptable QoS when the mobile terminal is moving. Formally, the handover allows the crossing of cell boundaries without being perceived by the terminal user,
- **Load control:** It corresponds to the control of the overall load in the network so that it doesn't exceed the allowed limit (determined at the radio network planning stage). The load control is achieved through actions that target the reduction of load on the network when necessary, for example, with a vertical handover to a foreign system (UMTS to GSM) or also the drop of low priority calls,
- **Admission control:** This function decides if a new mobile terminal can be admitted or not in the network without deteriorating the current quality of service.

The common point between all the functions of the RRM is that they are based on radio measurements that translates the state of the network at a given time and location. The available standardized radio measurements are various and depend on the target application in the RRM entity.

This is the starting point of this work, which aims at studying the main existing radio measurements in the current radio access technologies and thereafter proposing appropriate processing on these measurements while keeping in mind the network implementation constraints and the possible applications in a real radio network.

1.2.2 Study approach

Today, wireless networks are in constant evolution, providing many different and complex services for an increasing number of users. We assist to the emergence of new concepts and services involving the cooperation of different radio access technologies, seamless mobility and also cognitive radio: the intersection of wireless technology and computational intelligence [5]. Regarding this evolution, the need to reconsider the standardized radio measurements becomes a real challenge. In fact, it is necessary to follow the wireless radio network innovations and to ensure a better and more efficient RRM.

Indeed, radio measurements are the only effective way for the network to be aware of the state of the network at different locations and on several levels (traffic, quality and power). The measurements provide formal criteria for:

- **Control purpose:** That is to ensure that all the functionalities of the network does not exceed the authorized limits (for example power control, admission control and load control),
 - **Management purpose:** It stands for the well accomplishment of all actions and functions that allow the network to administer itself (for example mobility management and quality management),
 - **Monitor and optimization purpose:** The operators can request measurements to monitor the overall state of the network and to propose optimizations on it.
-

Given this reasoning, it is necessary to have frequent measurements at maximum amount of locations to guarantee the overall good functioning of the network. Nevertheless, this requires the utilization of the network resources when handling the requested measurements and reporting them. The first drawback is that the measurement is energy consuming. Second, the measurement reporting increases the amount of signaling in wireless networks, which decreases considerably the network capacity and can generate overloading.

For these reasons, each wireless technology standard specifies the periodicity of its radio measurements so as to make a trade off between assuring the required quality of service (QoS) and limiting the generated signaling due to measurement reporting.

In spite of considerable advances in radio access technologies and the significant importance of radio measurements in the radio network, we remark that the standardized measurements undergo limited processing, generally restricted to an averaging or filtering operations. The utilization of the reported measurements is only intended to perform the target test (predefined in the radio network standard) and generally these measurements remain useless thereafter. Also, we notice that the measurements are overall simple (for example direct power measure or quality measure). First investigations on more complex and advanced measurements are noted in the standardization group IEEE802.11k [20], where the measurements are defined for spectrum opportunity identification in an opportunistic spectrum access context. In IEEE802.11k, we note that the most significant change is the introduction of the histogram representation for better exploitation of the measurements by the network (for example " the medium sensing time histogram report" and "Noise histogram report").

Our idea is then to focus on the existing radio measurements in the network and to define efficient processing on these available data so as to enhance the RRM procedures. Our approach is motivated by the observation that the current standardized radio measurements are used in their crude state, without much processing (other than averaging or filtering operations) whereas they are a rich and unexploited source of information for the radio network.

Our preliminary studies on this issue show encouraging results: using statistical tools, useful information is extracted from standardized radio measurements in GSM and UMTS systems. The tested methods are:

- The wavelet transforms with the multiresolution representation: This method combined with a statistical classifier leads to the discrimination of the class of the mobile user velocity, within three categories: immobile, pedestrian and incar [23],
- The likelihood ratio function associated with the Neyman-Pearson test: This method allows to estimate whether the mobile user is indoor, outdoor or incar [24].

These results incited us to deal with more sophisticated statistical tools to extract additional information from existing radio measurements. To reach this objective, we first choose to characterize standardized radio measurements using nonparametric regression and smoothing analysis methods (namely smoothing splines, kernel regression smoother and Friedman's super smoother). The second step is the exploitation of the obtained results and a study of the possibilities of application in radio wireless networks.

The nonparametric regression and smoothing methods have been recently introduced in non parametric statistics and are extremely helpful to exploit data, extract interesting special features, predict its evolution and facilitate its interpretation. The analysis we carry out aims mainly at fulfilling two goals:

- Avoid supplementary signaling brought by more frequent reporting or definition of new measurements,
- Provide new inputs for RRM mechanisms and with the existing measurements, to meet the new demands and evolutions of wireless networks in terms of capacity and rate.

1.3 Radio measurement rules in wireless mobile networks

1.3.1 General radio propagation scheme

Wireless networks are characterized by the propagation of the signal on the air from the transmitter antenna to the receiver antenna. Thus, the propagated signal is disturbed and undergoes several attenuations and modifications such as reflexion, diffraction, diffusion and refraction. In radio propagation, three influencing parameters are mainly identified to give increased precision on the description of the propagated signal:

- Pathloss,
- Shadowing,
- Fast Fading.

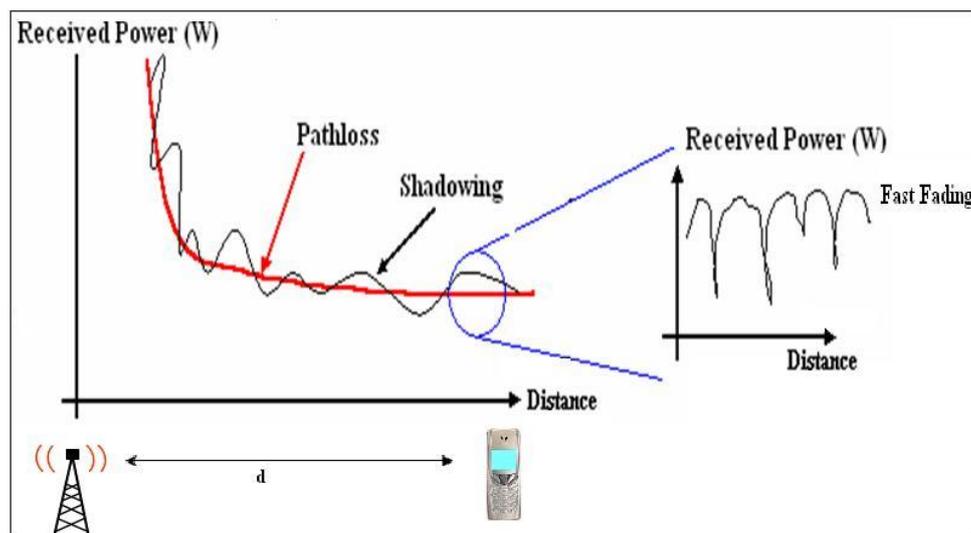


Figure 1.1: Radio propagation.

These attenuations fluctuate in time as they depend on random factors that can not be controlled (linked to the external environment). In the literature, several mathematical models are set to describe these attenuations in different environments and situations (for example urban and rural).

The pathloss is the median variations of the radio signal (Figure 1.1). In fact, the transmitted signal power decreases proportionally with the distance between the transmitter and the receiver in a wireless telecommunication system. This is due to free space wavefront spreading.

The received power depends on radiated power $EIRP$ (Equivalent Isotropic Radiated Power), gain of the receiver antenna Gr , distance d and frequency f .

$$Pr[dBm] = EIRP[dBm] + 10\log(Gr) - \underbrace{[-10\log(K) + 10\alpha\log(d) + 10\beta\log(f)]}_{PL} \quad (1.1)$$

where Pr is the received power, K , α and β are constants depending on the environment of propagation and the term PL denotes the pathloss.

Several models are set to express the pathloss depending on the surrounding environment. The most well known model is Okumura-Hata, that constitutes the base for a variety of more precise models. Y. Okumura has estimated the pathloss given the distance between the transmitter and the receiver, based on a database of measurements carried out in Tokyo, on several frequencies. Then, he has deduced graphics that translates the prevision of the pathloss given a multitude of parameters [25]. Thereafter, Hata established an empirical formula from Okumura's curves [26]. This formula permits to evaluate and model the constants related to the environment of propagation and the frequency.

For example, the COST 231-Hata model [27] is widely used in wireless mobile networks for the prediction of the pathloss attenuation, mainly in the radio network planning stage. This model is valid for frequencies between 1500 and 2000 MHz. According to the COST 231-Hata model, the pathloss PL in an urban environment is expressed in dB by the following formula:

$$PL = 46.33 + 33.9\log_{10}(f) - 13.82\log_{10}(h_b) - a(h_m) + [44.9 - 6.55\log_{10}(h_b)]\log_{10}(d) + C_m \quad (1.2)$$

With:

- $a(h_m) = [1.1\log_{10}(f) - 0.7]h_m - [1.56\log_{10}(f) - 0.8]$ for suburban environments (a city of medium size) and $a(h_m) = 3.20(\log_{10}(11.75h_m))^2 - 4.97$ for urban environments when $f > 400\text{MHz}$,
- h_m is the antenna height of the mobile terminal (in meters) comprised between 1 and 10 meters,
- $C_m = 0\text{dB}$ for a city of medium size,
- $C_m = 3\text{dB}$ for great metropolitan cities,
- h_b is the antenna height of the base station (in meters) comprised between 30 and 200 meters.

The pathloss model gives a first overview of the propagated signal. When zooming on the signal, we can notice low variations around the average curve. In fact, the pathloss model supposes that the environment of propagation is homogeneous, whereas, in reality, the radio signal undergoes additional attenuation caused by local obstacles (or masks) between the transmitter and the receiver (Figure 1.1). This type of attenuation is called shadowing.

To model the shadowing effect (called also slow fading), a random variable is added to the pathloss model (defined previously).

$$Pr[dBm] = EIRP[dBm] + 10\log(Gr) - PL[dB] + \underbrace{M[dB]}_{Shadowing} \quad (1.3)$$

M is a random variable, generally modeled as a Gaussian distribution with zero mean and standard deviation σ . A typical standard deviation for rural environment is 6 dB [28]. The shadowing is also characterized with a stationarity of a few tens of meters. The corresponding distribution function (expressed in dB) is:

$$P(M > x) = \frac{1}{\sigma \sqrt{2\pi}} \int_x^{\infty} e^{-u^2/2\sigma^2} du \quad (1.4)$$

Finally, the transmitted signal undergoes the fast fading attenuations. It is the short-term fading and it is present in the signal in form of rapid variations (Figure 1.1). It is due to multipath propagation: The presence of numerous obstacles and reflectors in the wireless propagation channel implies that the transmitted signal arrives at the receiver from various directions over a multiplicity of paths. This is called multipath and affects the transmitted signal with attenuation and delay. Fast fading results from the superposition of transmitted signals which have experienced differences in attenuation, delay and phase shift while traveling from the source to the receiver.

Two major cases are identified:

- Non Line Of Sight (NLOS): This corresponds to the case when there is no direct sight between the transmitter and the receiver. When the NLOS propagation is predominant, the fast fading rather follows the Rayleigh distribution. The Rayleigh probability density function is :

$$f(x|\sigma) = \frac{x e^{-x^2/2\sigma^2}}{\sigma^2} \quad (1.5)$$

- Line Of Sight (LOS): This corresponds to the case when there is a direct sight between the transmitter and the receiver. When the LOS propagation is predominant, the fast fading is rather modeled with the Rice distribution. The Rician probability density function is:

$$f(x|v,\sigma) = \frac{x}{\sigma^2} e^{-\frac{(x^2+v^2)}{2\sigma^2}} I_0\left(\frac{xv}{\sigma^2}\right) \quad (1.6)$$

With I_0 is the zero-order modified Bessel function of the first kind, $v > 0$ is the non centrality parameter and $\sigma > 0$ is the scale parameter. When, $v = 0$, then we retrieve the Rayleigh distribution.

Generally, the fast fading is not considered in the network deployment or design phase as it is taken into account in the power threshold defined in the receiver side (sensitivity of the receiver).

1.3.2 Radio measurements in mobile wireless networks

Radio measurements, realized by the mobile terminal or the base station, are crucial to assess mobile network reliability as they are needed to guarantee quality of service and to supervise the planned coverage area. These measurements are standardized for each wireless radio technology (GSM, UMTS, EDGE, HSDPA...) and are essentially used as input for Radio Resource Management (RRM) algorithms (for example handover and power control).

According to current radio network standards (such as 3GPP), the available metrics in the network can be divided in several categories, depending on their target use:

- Intra frequency measurements: Measurements on the same frequency as the active set. An active set corresponds to the set of base stations (for example Node B in UMTS) to which the mobile terminal is connected,

- Inter frequency measurements: Measurements on frequencies different than the active set,
- Inter RAT measurements: Measurements on channels belonging to other radio access technologies,
- Quality measurements: Measurements of quality of service and of comparison to requested QoS,
- Internal measurements: Measurements in the mobile terminal, on the transmitted and received signal level,
- Positioning measurements: Measurements of the mobile terminal position. These metrics are related to the chosen positioning technology. The widely used technique is the Global Positioning System (GPS),
- Synchronization measurements: Mainly mobile terminal synchronization measurements,
- Traffic volume measurements.

In this study, we focus on power measurements. In fact, this type of measurements is characterized with interesting properties linked to the propagation phenomenon. The idea is then to explore the hidden properties in the reported radio measurements so as to extract further informations and improve some radio resource management procedures.

For this aim, we have chosen to work on 2G and 3G technologies, namely GSM and UMTS systems. Two standardized radio measurement are specifically studied:

- RXLEV available in the GSM system,
- UE_Tx_Power available in the UMTS system.

1.3.2.1 Radio measurements in GSM

The Global System for Mobile communications (GSM) is the first and the most used technology in the second generation (2G) mobile phone systems, reaching about 80% of the global mobile market.

In GSM system, when a call is established, the mobile terminal periodically reports the signal quality to the network via *the Measurement Report Message* (uplink channel). This message is sent to the base station in every SACCH frame (every 480ms) (Figure 1.2). This report contains measurement values for serving and neighboring cells (such as Received signal level RXLEV, Received quality level RXQUAL, Base Station Identity Code BSIC, Absolute Radio Frequency Channel Number ARFCN). The *RXLEV* is the Received Signal level. It is the measure *RSSI* (Received Signal Strength Indicator) which is the wideband received power within the channel bandwidth. This parameter is coded on 64 levels (6 bits). The levels 0 to 63 correspond respectively to powers values from -110dBm to -48dBm, with a step of 1dBm. This measure is obtained after an average on instantaneous measures over a period of 480 ms and on logarithmic scale [28].

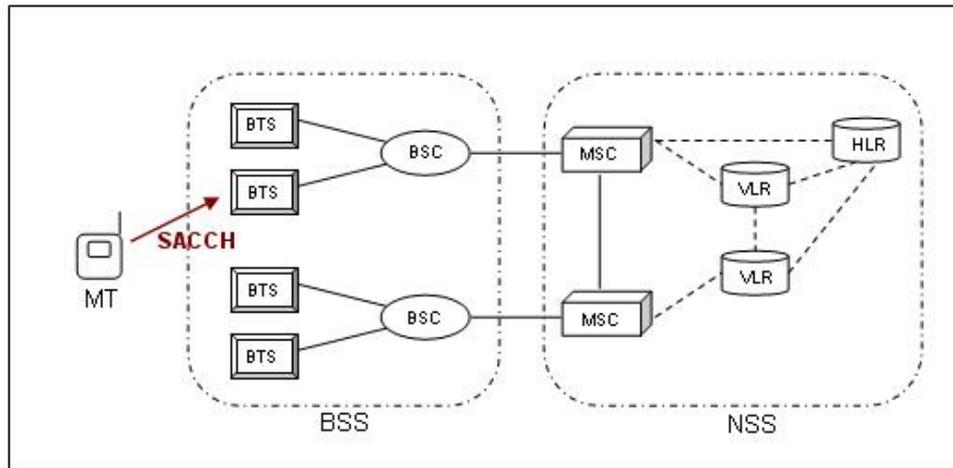


Figure 1.2: GSM system architecture.

1.3.2.2 Radio measurements in UMTS

The Universal Mobile Telecommunications System (UMTS) is a third generation (3G) mobile phone system.

In UMTS system, the radio measurements are mainly performed by the physical layer in the User equipment UE or in the Node B. Only the traffic measurements are made by the MAC layer at the RNC level (Figure 1.3). Generally, the measurements are input to algorithms and procedures located either in the UE (such as the cell selection algorithm) or in UTRAN (such as the handover algorithm). Here, we note that algorithms in RNC require measurements from UE and NodeB, whereas algorithms in UE require only measurements in UE (except for some localization procedures). The reported measurements circulate inside the network through two specific protocols (NBAP and RRC) and can be monitored in different points of the network, namely: UE, NodeB, Iub Interface, RNC and OMC (Figure 1.3). The reporting protocols are:

- Node B Application Part (NBAP) which is the signaling protocol between NodeB and RNC,
- Radio Resource Control (RRC) which is the signaling protocol between UE and RNC.

The measurements in UMTS system undergo two filtering operations before their report to the target destination in the network (the entity that requested the measurement). Figure 1.4 represents the preliminary treatments applied to the instantaneous measurement samples, before their transmission to their target destination. First, the sampled measurement M_1 goes through a Layer 1 filtering that generally consists of a simple averaging operation. Its period and precision are defined for each measurement in the standard specifications. The output of this block is denoted as M_2 . Subsequently, M_2 undergoes a layer 3 filtering. The parameters of this filtering is set by the RNC and is performed as follows.

$$F_N = (1 - a)F_{N-1} + aM_N \quad (1.7)$$

where F_N is the filtered measurement M_3 , F_{N-1} is the old filtered measurement result, M_N is the last measurement M_2 available from layer 1 and $a = \frac{1}{2}^{k/2}$ with k as the filter coefficient. Finally, the block "Evaluation of reporting criteria" decides if the obtained measurement M_3

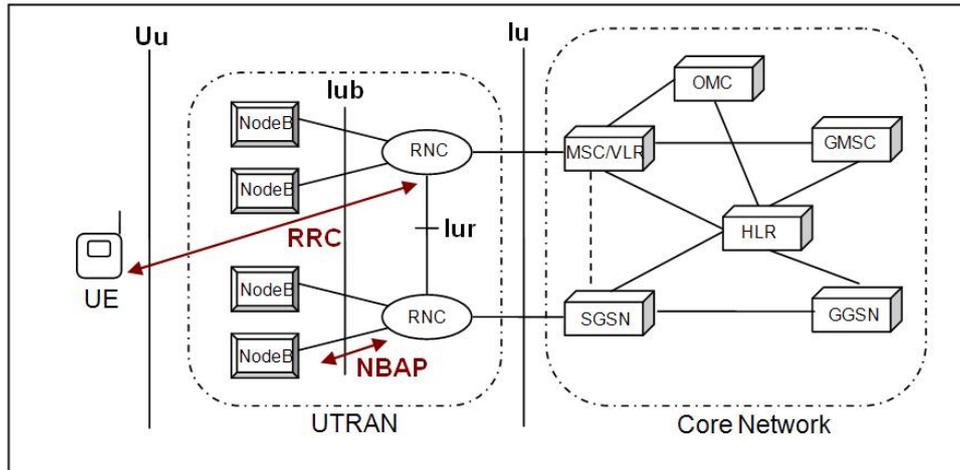


Figure 1.3: UMTS system architecture.

will be transmitted or not to the RNC. This decision depends on the criterion set previously by the RNC. This criterion can be event triggered, periodic or on demand.

The *UE_Tx_Power* is defined in the 3GPP standard and stands for the total User Equipment

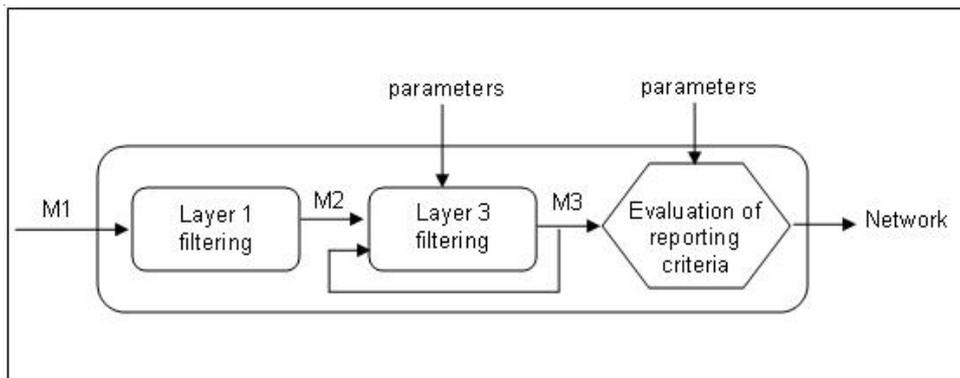


Figure 1.4: Measurement filtering in UMTS system.

(UE) transmitted power on one carrier. This metric is strongly linked to the Power Control mechanism. In fact, in mobile communications and especially in CDMA systems (such as UMTS), it is essential to control the power of the signal transmitted in the two directions, especially on the uplink (from the mobile terminal to the base station). Indeed, a mobile terminal located close to the base station and transmitting with excessive power can easily over shout mobiles that are at the cell edge (the near-far effect) or even block the whole cell.

To avoid the near-far problem, the network can use closed loop power control. This loop commands the mobile station to use a transmit power proportional to the inverse of the received power (or Signal to interference ratio SIR). This means that the transmitted power takes into account the attenuations undergone by the radio signal within the current environment. Thus, we can conclude that *UE_Tx_Power* metric includes the attenuations undergone by the propa-

gated radio signal [22] and can be relevant for this study.

Adding to that, other measurements can also be used such as:

- *CPICHRSCP*: Received Signal Code Power, which is the received power on one code after despreading, defined on the pilot symbols,
- *CPICHEc/N0*: It represents the received signal code power divided by the total received power in the channel bandwidth, which is defined as $CPICHRSCP/RSSI$.

1.3.2.3 Radio measurement model

Basing on the radio propagation model mentioned in the previous section, the standardized radio measurement signal (defined in radio access technology) is discrete and could be modeled as following:

$$Y_k = F_k + P_k + S_k + I_k \quad (1.8)$$

where F_k is the fast fading component, P_k is the pathloss component, S_k is the shadowing component and I_k is the measurement imprecision error.

As the reported measurements are generally averaged or filtered (for example *RXLEV* or *UE_Tx_Power*), it results in a decreasing of the effects of fast fading compared to the real propagated signal. Thus, in a real radio network, the component F_k corresponds to a part of the real fast fading attenuation undergone by the radio signal.

1.4 Experimental setup

This study is based on real radio measurements, extracted from the deployed radio networks (UMTS and GSM). Our measurement database results from the collection of the standardized measurements in different situations, corresponding to low, medium and high velocity of the mobile user (namely unmoving, pedestrian and incar situations). This database is constructed

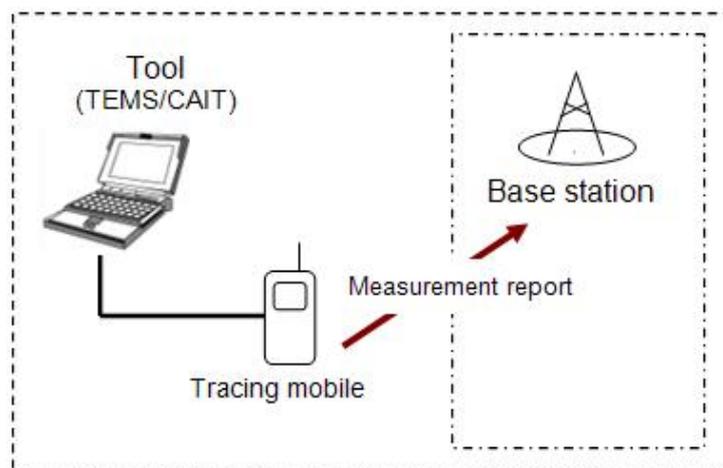


Figure 1.5: Experimental setup.

with both metrics *RXLEV* (GSM system) and *UE_Tx_Power* (UMTS system). The experimental setup (Figure 1.5) consists of:

- A tracing mobile used to collect the measurement reports (send by the mobile terminal to the access network),
- A specific software tool to decrypt the collected measurement reports. The software tool depends on the considered radio access technology. In this study, we use:
 - For the GSM system, the tool TEMS (Ericsson) with a GSM tracing mobile,
 - For the UMTS, the tool CAIT (Qualcomm) with an UMTS tracing mobile.

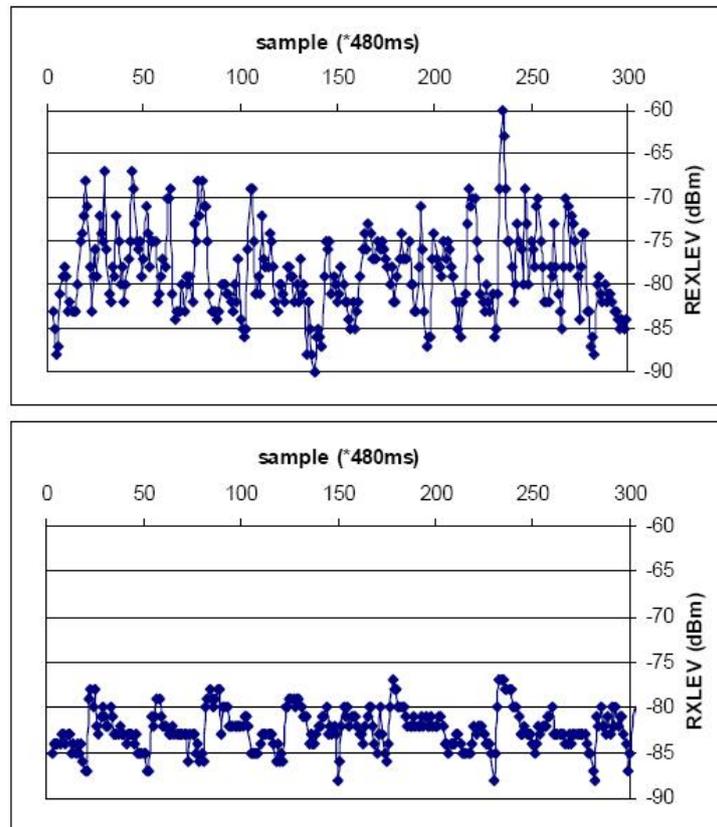


Figure 1.6: Examples of RXLEV measurements for pedestrian (top) and unmoving (bottom) situations.

Figure 1.6 shows examples of RXLEV measurements corresponding to unmoving and pedestrian situations, over a duration of about 144 seconds. The received power values varies from -90 to -60 dBm for the pedestrian case, whereas this variation is less important for the unmoving case (ranging from -90 to -75 dBm). The value (-60 dBm) corresponds to a good received signal level, which probably means that the mobile terminal is near the base station. On the contrary, the level (-90 dBm) is a bad received signal level.

We can also notice that the measurement vectors for the two cases present different types of fluctuations. In fact, fast fading is preponderant for unmoving users (short-term variation of the signal), while the effect of path loss and shadowing clearly appears for moving users (long-term variation).

Figure 1.7 represents the reported UE_Tx_Power over a duration of approximately 33 min. The measurement values range from (-35) to 20 dBm.

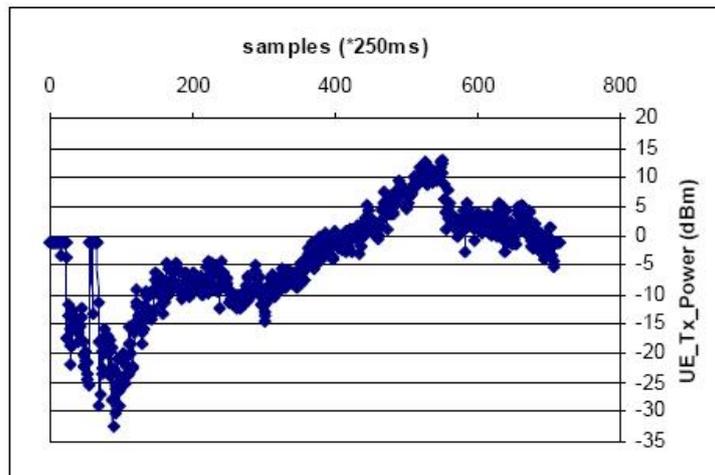


Figure 1.7: Example of UE_Tx_Power measurement.

1.5 Theoretical presentation of regression and smoothing methods

1.5.1 General notions

A regression curve describes a general relationship between an explanatory variable $X = \{x_i\}_{i=1}^n$ and a response variable $Y = \{y_i\}_{i=1}^n$. In other words, it is the technique of fitting a simple equation to discrete data points. Given $\{(x_i, y_i)\}_{i=1}^n$, the regression relationship can be expressed as:

$$y_i = m(x_i) + \varepsilon_i \quad (1.9)$$

where $i = 1, \dots, n$, $m(\cdot)$ is the unknown regression function and $\{\varepsilon_i\}$ are the regression errors. The main purposes of regression are:

- Provide a way of exploring and presenting the relationship between the design variable X and the response variable Y ,
- Give predictions of observations yet to be made,
- Give estimates of interesting properties and features of $m(\cdot)$ (for example the location of zeros or the size of extrema),
- Often the regression curve itself is not the target of interest but rather a feature, for example the derivatives.

The aim of regression analysis is to produce a reasonable analysis of the unknown response function m . By reducing the observation errors, it allows the interpretation to concentrate on important details of the mean dependence of Y on X . This curve approximation procedure is commonly called "smoothing". Depending on the regression function m , we can define two types of regression: linear and polynomial.

The linear regression approach is one of the oldest and most used statistical techniques. Given data pairs $\{(x_i, y_i)\}_{i=1}^n$, the obvious way to represent linear regression is as a method fitting a model to the observed data of the following form:

$$Y = a + bX + \text{error} \quad (1.10)$$

The linear regression is generally employed to provide a summary or an overview of the observed data in order to explore and present the relationship between the design variable X and the response variable Y . This simple modeling of the data can be used for prediction purposes.

Nevertheless, the linear regression is inappropriate for several data sets, that need more complex modeling. Hence, the polynomial regression can fit better the data with a model of the form:

$$Y = g(X) + \text{error} \quad (1.11)$$

with g a polynomial function. The classical approach is to use for g a low order polynomial. Its coefficients can be estimated by the least squares method.

The main categories of regression identified in the literature are parametric and nonparametric [29]. Parametric approach assumes that the curve g has a prespecified functional form, for example, a polynomial regression equation where the parameters are the coefficients of the independent variables. By contrast, the nonparametric approach does not project the observed data into a fixed parametrization; it rather refers to the flexible functional form of the regression curve.

In practice, a preselected parametric model might be too restricted or too low-dimensional to fit unexpected features, whereas nonparametric smoothing approach offers a flexible tool in analyzing unknown regression relationships.

In this work, we choose to employ the nonparametric approach as it offers a flexibility, and it is extremely helpful in a preliminary and exploratory statistical analysis of radio measurements. Adding to that, nonparametric modeling allows the prediction of new observations whereas classical parametric models are too restrictive to give a reasonable explanation of observed phenomena. Finally, nonparametric approach deals with the problem of missing data, often occurring in practice with real measurement tools. Nonparametric smoothing bridges the gap of missing data by interpolating between adjacent data points whereas parametric models will involve all the observations in the interpolation.

To sum up, the nonparametric approach for the estimation of a regression curve has four main purposes:

- It provides a flexible method for the exploration and the estimation of a general relationship between two variables,
 - It gives predictions of observations yet to be made without reference to a fixed parametric model,
 - It offers a tool for finding spurious observations by studying the influence of isolated points,
 - It constitutes a flexible method of substituting for missing values or interpolating between adjacent X -values.
-

The smoothing of a dataset $\{(x_i, y_i)\}_{i=1}^n$ involves the approximation of the mean response curve m in the regression relationship. This "local average" is defined from observations in a small neighborhood around x_i . This procedure can be viewed as the basic idea of smoothing:

$$\hat{m}(x_i) = \sum_{i=1}^n W_{n,i}(x_i) y_i \quad (1.12)$$

where the weight function $\{W_{n,i}(x_i)\}$ is a sequence of weights which may depend on the whole vector $\{x_i\}_{i=1}^n$. The amount of averaging is controlled by this sequence which is tuned by a smoothing parameter. Every smoothing method has generally the previous form and often the regression estimator $\hat{m}(x)$ is just called smoother.

1.5.2 Estimation and validation methods

The regression and the smoothing of a dataset $\{(x_i, y_i)\}_{i=1}^n$ can be performed in a controlled manner so as to respond to a final objective (for example a final curve without rapid fluctuations). This can be achieved through different tools and methods that quantifies specific properties of the final regression curve (i.e. the rapid fluctuations, the fit to the discrete data).

The roughness penalty criterion is a tool commonly used for the realization of regression and smoothing operations on discrete data. It is one such technique that consists at first in quantifying the rapid fluctuations in the final curve. Then, it aims at making a trade off between two objectives in the curve estimation:

- a good fit to the data that translates its main properties,
- the suppression of the rapid fluctuation in the signal.

Roughly speaking, the roughness penalty is based on a measure of the rapid local variation of a curve. Formally, given a curve g defined on an interval $[a, b]$, there are many different ways of measuring how rough the curve g is. An intuitive way of measuring the roughness of a twice differentiable curve g is to calculate its integrated squared second derivative $\int_a^b \{g''(x)\}^2 dx$. Other parameters could be considered for the roughness quantification (the maximum of $|g''|$ or the number of inflection points in g), but the integrated squared second derivative is a global measure of roughness that has considerable computational advantages.

The most widely used approach to curve fitting is least squares. If we place no restrictions at all on the curve g then we can reduce the residual sum of squares $\sum_{i=1}^n \{y_i - g(x_i)\}^2$ to zero by choosing g to be any curve which interpolates the data. Nevertheless, the interpolation is rejected in several applications as it preserves useless rapid fluctuations (which corresponds in most cases to the noise). Hence, the solution is a penalized least squares which introduces a competition between two conflicting aims in curve estimation, which are to produce a good fit to the data and to avoid too much rapid local variation.

Given any twice differentiable function g defined on $[a, b]$ and a smoothing parameter $\alpha > 0$, the penalized sum of squares is defined as:

$$J(g) = \sum_{i=1}^n \{y_i - g(x_i)\}^2 + \alpha \int_a^b \{g''(x)\}^2 dx \quad (1.13)$$

The penalized least squares estimator \hat{g} is defined as the minimizer of $J(g)$ over the class of all twice differentiable functions g . The different terms of $J(g)$ are:

- The residual sum of squares $\sum_{i=1}^n \{Y_i - g(x_i)\}^2$ measures the fit of observations by the model,
- The smoothing parameter α controls the trade-off between residual errors and local variation. If α is large then the main component in $J(g)$ is the roughness penalty term and then the rapid variations are eliminated from the minimizer \hat{g} . On the contrary, if α is small then the main contribution to $J(g)$ will be the residual sum of squares,
- The roughness penalty $\int_a^b \{g''(x)\}^2 dx$ quantifies the roughness of the obtained regression function.

Based on [29], the penalized least squares estimator \hat{g} is proved to be a natural cubic spline, characterized with the following properties:

1. It is a cubic polynomial in each interval (x_i, x_{i-1}) ,
2. At the design points x_i , the curve and its first two derivatives are continuous, but there may be a discontinuity in the third derivative,
3. In each of the ranges $(-\infty, x_1)$ and $(x_n, +\infty)$ the second derivative is zero, so that \hat{g} is linear outside the range of the data.

Computationally, we need to find the four coefficients which give the polynomial form of \hat{g} in each interval. In [29], the existence and the uniqueness of the minimizing spline curve have been proven. A natural cubic spline is completely specified given its value and second derivative at each of the knots x_i . Adding to that, given any values z_1, \dots, z_n , there is a unique natural cubic spline g with knots at the points x_i satisfying : $g(x_i) = z_i$ for $i = 1, \dots, n$.

For a given value of the smoothing parameter α in equation 1.13, minimizing $J(g)$ will give the best compromise between smoothness and goodness-of-fit. The choice of this parameter is done by two methods:

- Subjectively by plotting few curves and choosing the one that corresponds better to our objective. From exploratory point of view, this exercise is beneficial in that sense that it will draw attention to interesting features that only show up at certain values of the smoothing parameter,
- Using an automatic method of choice. The most known automatic procedure is the cross validation. The automatic procedures can be used as a starting point for fine tuning. They are almost essential if the estimated curve is to be used as a component part of a more complicated procedure or if the method is being used routinely on a large number of data sets.

The cross validation is a well known statistical method that aims at enhancing the learning from a training dataset. Formally, it consists in the partition of an initial dataset into subsamples. Consequently, the analysis is initially performed on a single subsample, while further subsamples are retained "blind" in order to be used subsequently for the confirmation and the

validation of the initial analysis.

The basic idea of cross-validation is to choose the value of α that minimizes $CV(\alpha)$ defined as:

$$CV(\alpha) = n^{-1} \sum_{i=1}^n (y_i - \hat{g}^{(-i)}(x_i; \alpha))^2 = n^{-1} \sum_{i=1}^n \left(\frac{y_i - \hat{g}^{(-i)}}{1 - A_{ii}(\alpha)} \right)^2 \quad (1.14)$$

with

$$A(\alpha) = (I + \alpha QR^{-1}Q^T)^{-1} \quad (1.15)$$

The matrix $A(\alpha)$ is called the hat matrix because it maps the vector of observed values y_i to their 'predicted values' $\hat{g}(x_i)$. $\hat{g}^{(-i)}(x_i; \alpha)$ denotes the curve estimated from the observations y_j with $j \neq i$, with the value α for the smoothing parameter, so that it is the minimizer of x_j . The quality of $\hat{g}^{(-i)}$ as a predictor on a new observation can be judged by how well the value $\hat{g}^{(-i)}(x_i)$ predicts y_i . Since the choice of which observation to omit is arbitrary, the overall efficiency of the procedure with the smoothing parameter α can be quantified by the cross validation score function $CV(\alpha)$.

The generalized cross validation (GCV) is a modified form of cross validation. It is a popular method for choosing the smoothing parameter [30].

The general form of GCV is defined as follows:

$$GCV(\alpha) = n^{-1} \times \frac{\text{residual_sum_of_squares}}{(\text{equivalent_degrees_of_freedom})^2} \quad (1.16)$$

where the parameter "Equivalent Degrees of Freedom" gives an indication of the effective number of parameters that are fitted for any particular value of the smoothing parameter. The GCV can be formulated as:

$$GCV(\alpha) = n^{-1} \frac{\sum_{i=1}^n (Y_i - \hat{g}(t_i))^2}{(1 - n^{-1} \text{tr}A(\alpha))^2} \quad (1.17)$$

The model degrees of freedom k are equal to the trace of the matrix A , while the degrees of freedom for the noise, $(n - k)$, are equal to $\text{tr}(I - A)$.

1.5.3 Main regression and smoothing methods

In this section, we present the major regression smoothing methods that we will use for the processing of radio measurements. These methods differ mainly by their specific weight functions $\{W_{n,i}(x)\}_{i=1}^n$ in the smoothing expression of a dataset $\{(x_i, y_i)\}_{i=1}^n$:

$$\hat{m}(x) = n^{-1} \sum_{i=1}^n W_{n,i}(x) y_i \quad (1.18)$$

We propose to focus on three regression smoothing techniques: the Smoothing splines, Kernel regression smoother and Friedman's super smoother.

The Smoothing spline is a class of non parametric functions defined in [13] and used for data interpolation and/or smoothing. The term "spline" is used to refer to a wide class of functions that are used in applications requiring data interpolation and/or smoothing. Splines may be used for interpolation and/or smoothing of either one-dimensional or multi-dimensional data.

Also, spline functions for interpolation are usually determined as the minimizers of appropriate measures of roughness (for example integral squared curvature) subject to the interpolation constraints. Smoothing splines are generalization of interpolation splines where the functions are set so as to minimize a weighted combination of the average squared approximation error over observed data and the roughness measure. Adding to that, the spline functions are generally of finite dimension, which is extremely useful in computations and representation. A spline $S : [a,b] \rightarrow R$ is a function defined piecewise by polynomials:

$$S(x) = P_i(x), \quad x_{i-1} \leq x \leq x_i \quad (1.19)$$

with $i = 1, \dots, k$ and $a = x_0 < x_1 < \dots < x_{k-2} < x_{k-1} = b$. Points x_i are called knots.

For a given dataset, the applied smoothing spline is deduced as the minimizer of the penalized sum of squares (Equation 1.13). Here, the obtained smoothing spline tends to make a compromise between two objectives:

- the "fidelity to the initial data" expressed through the residual sum of squares $\sum_{i=1}^n \{Y_i - g(x_i)\}^2$,
- the measure of roughness penalty $\int_a^b \{g''(x)\}^2 dx$ that quantifies the local variations in the final curve.

The degree of smoothing in the smoothing splines technique is controlled by the smoothing parameter α in Equation 1.13. It corresponds to the degree of balance between the residual error and the roughness penalty.

While the Smoothing Splines method is deduced from the penalized sum of squares, the kernel regression method offers a solution from a different point of view and defines the estimate at each point x_i as being an explicit function, usually a weighted average, of 'local' observations y_i .

A conceptually simple approach to represent the weight functions $W_{n,i}(x)$ in the smoothing expression is to describe the shape of these functions by a density function with a scale parameter that adjusts the size and the form of the weights near x_i . This shape function is referred the kernel K .

Thus, the weight sequence [21] for kernel regression smoother (for one dimensional X) is defined as:

$$W_{n,i}(x) = K_{h_n}(x - x_i) / \hat{f}_{h_n}(x) \quad (1.20)$$

Where

$$\hat{f}_{h_n}(x) = n^{-1} \sum_{i=1}^n K_{h_n}(x - x_i) \quad (1.21)$$

And

$$K_{h_n} = h_n^{-1} K(x/h_n) \quad (1.22)$$

The kernel K is a symmetric probability density function and the bandwidth parameter h_n controls the smoothness degree. A variable bandwidth selection can ameliorate the performance of the kernel regression smoother: $h_n = b(x)$.

The Nadaraya-Watson Kernel regression estimator is the most studied kernel estimator [31] and its properties are well established in the literature. The fixed design regression model for data $\{x_i, y_i\}_{i=1}^n$ on $[0,1]$ is:

$$y_i = m(x_i) + \epsilon_i \quad (1.23)$$

with x_i the design points, m the regression function and $(\epsilon_1, \dots, \epsilon_n)$ random variables which are independent and identically distributed and satisfy $E(\epsilon_i) = 0$, $var(\epsilon_i) = \sigma^2$.

The Nadaraya-Watson estimator is defined by:

$$\hat{m}_h(x) = \frac{n^{-1} \sum_{i=1}^n K_h(x - x_i) y_i}{n^{-1} \sum_{i=1}^n K_h(x - x_i)} \quad (1.24)$$

with K the kernel and h the bandwidth: the parameter that controls the smoothness of the resulting signal. The kernel regression smoother with variable bandwidth selector [29] [32] [33] is an approach to highlight the interesting features of the signal. In fact, adaptive estimation of the bandwidth is sensitive to discontinuities or change points of the signal. Thus, the calculation of the local bandwidths is based on pilot estimation of local smoothness characteristics.

Finally, the variable span smoother (Super Smoother) is proposed by Friedman in [14] and is based on local linear k-Nearest Neighbor (k-NN) fits in a variable neighborhood of the estimation point x . The construction of nearest neighbor estimates differs from the kernel estimate. The kernel estimate $\hat{m}_h(x)$ was defined as a weighted average of the response variables in a fixed neighborhood around x , determined in shape by the kernel K and the bandwidth h . Whereas, the k-NN estimate is a weighted average in a varying neighborhood:

$$\hat{m}_k(x) = n^{-1} \sum_{i=1}^n W_{k,i}(x) Y_i \quad (1.25)$$

$\{W_{k,i}(x)\}_{i=1}^n$ is a weight sequence defined through the set of indexes $J_{k,x} = \{i: X_i \text{ is one of the } k \text{ nearest observations to } x\}$.

The (k-NN)weight sequence is constructed as:

$$W_{k,i}(x) = \begin{cases} 1/k, & \text{if } i \in J_{k,x}; \\ 0, & \text{otherwise.} \end{cases} \quad (1.26)$$

The smoothing parameter k regulates the degree of smoothness of the estimated curve. It plays a role similar to the bandwidth for kernel smoothers. Thus, the choice of k is primordial in the smoothing operation. The Super Smoother makes use of optimized resampling techniques performed with the minimum computational effort. The Super Smoother is constructed using three initial smooths: the tweeter, midrange and woofer. In fact, these functions allow the reproduction of the three main parts of the frequency spectrum of $m(x)$ and are defined by (k-NN) smooths with $k = 0.05n$, $0.2n$ and $0.5n$, respectively. At each point, the Super Smoother technique chooses between the three spans using the cross-validation method. The chosen span is referred $\hat{k}(x)$. Adding to that, Friedman proposes an enhanced span formulation that produces better results. This span is noted $\tilde{h}(x)$ and is defined as follows:

$$\tilde{h}(x) = \hat{k}(x) + (0.5n - \hat{k}(x)) \times R^{10-\eta} \quad (1.27)$$

with

$$R = \left[\frac{e(x, \hat{k}(x))}{e(x, 0.5n)} \right] \quad (1.28)$$

Here, $e(x, k)$ stands for the estimated residual at the point x with the smoothing parameter k . The parameter $0 \leq \eta \leq 10$ is commonly called tone control parameter and controls the smoothing of the final curve.

To conclude, table 1.1 summarizes the main characteristics of above mentioned smoothing and regression methods.

Table 1.1: Summary of regression and smoothing methods.

Smoothing splines	Estimated based on penalized least squares regression: $J(g) = \sum_{i=1}^n \{Y_i - g(t_i)\}^2 + \alpha \int_a^b \{g''(x)\}^2 dx.$
Kernel regression smoother	Estimator defined as a weighted average of the response variables in a fixed neighborhood around x , determined in shape by the kernel K and the bandwidth h : $\hat{m}(x) = n^{-1} \sum_{i=1}^n W_{n,i}(x) Y_i.$
Friedman's super smoother	Estimator based on local linear k-nearest neighbor (K-NN) fits: a weighted average in a varying neighborhood: $\hat{m}_k(x) = n^{-1} \sum_{i=1}^n W_{k,i}(x) Y_i.$

1.6 Results in wireless networks

The first step of this work consists of applying the nonparametric regression and smoothing methods on the available radio measurements (mainly RXLEV for the GSM). The goal of this first stage is to get accustomed with these methods and to observe the results of their application on the standardized radio signals. In the following, we will present successively the obtained results with each regression method separately and then conclude.

At first, the smoothing spline techniques are tested on a database of the *RXLEV* measurements for three user situations (unmoving, pedestrian and incar). This processing is made with the splines toolbox available with the software R: a free environment for statistical computing and graphics. Two typical values are chosen for the smoothing parameter α in the penalized least squares regression (equation 1.13). The choice is (0.2;0.8) to show the effects of low and high values of the smoothing parameter α . Examples of the result of application of smoothing splines on a vector of reported measurements are depicted in figure 1.8. We notice that:

- A small value of the smoothing parameter α (0.2) leads to rapid fluctuations remaining in the resulting curve. This is due to the minimization of the effects of the roughness penalty in equation 1.13 with low smoothing parameter α . In this case, the smoothing spline behaves as a regression function that tries to link almost all the points in the considered measurement dataset,
- At the contrary, a high value of the smoothing parameter α (0.8) removes the rapid fluctuations of the initial signal and leaves only the slow variations in the resulting curve. This relatively strong smoothing with a high roughness constraint provide a good fit to the mean function of the initial data set.

As the performance of the smoothing splines is strongly dependent on the choice of the smoothing parameter α , an automatic selection method can be used for the selection of the α value. Thus, we test the cross-validation method on our measurement dataset so as to automatically deduce the appropriate smoothing parameter. Here, α is deduced as the minimizer of the function $CV(\alpha)$ defined as:

$$CV(\alpha) = n^{-1} \sum_{i=1}^n (y_i - \hat{g}^{(-i)}(x_i; \alpha))^2 \quad (1.29)$$

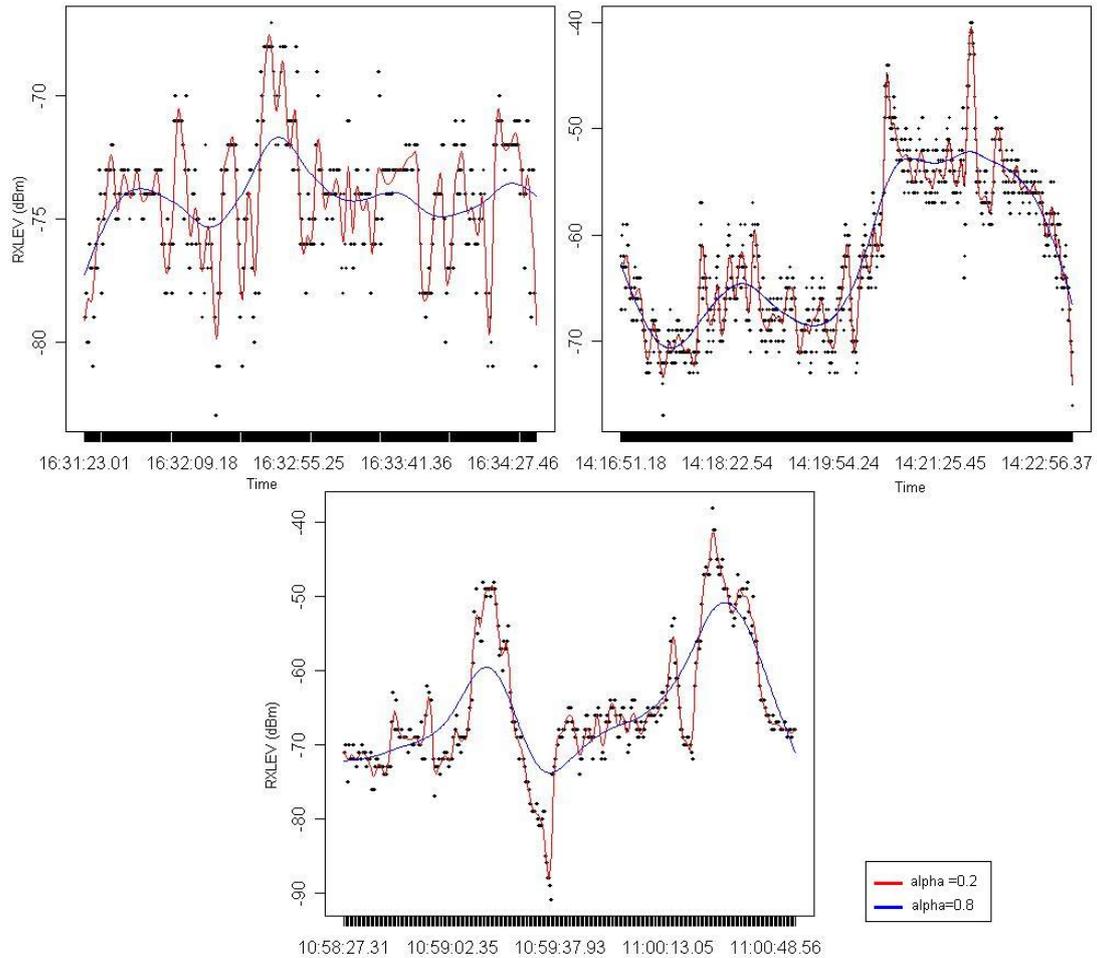


Figure 1.8: Smoothing spline for unmoving (up left), pedestrian (up right) and incar (down) case.

with g referring to the interpolated function and $Y = \{y_i\}_{i=1}^n$ the initial data set. We can conclude that the cross-validation tends to fit as much as possible the fluctuations of the initial signal by minimizing the square error between the initial data and the interpolated curve. Table 1.2 shows the obtained smoothing parameter values, for the three users situation and with the cross validation method. We notice that the smoothing parameter has a small value in all cases.

Table 1.2: Smoothing parameters values for different mobile holder situation.

Case	Smoothing parameter with Cross validation process
Pedestrian outdoor	0.1771933
Incar	0.1093802
Unmoving indoor	0.1738539

Thus, the roughness penalty effects are reduced leading to rapid fluctuations in the final curve. Thus, we can conclude that the cross validation method is appropriate to interpolate perfectly the discrete data. But, this automatic method is unable to eliminate the rapid fluctuations from

the initial signal. Thus, a possible use of this smoothing method is to fix manually the smoothing parameter (for example 0.5 in our dataset) so that a compromise between smoothness and "good to fit" is reached.

Adding to that, it is important to note that a high value of the smoothing parameter influence

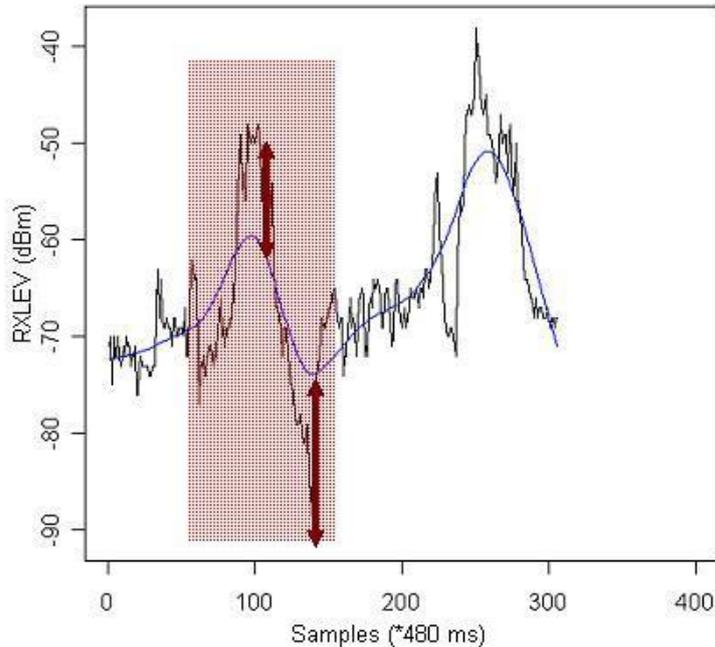


Figure 1.9: Result of the smoothing spline (spar=0.8) on RXLEV dataset for incar situation.

the singularities of the signal. In the Figure 1.9, in the red region, the smoothing signal (blue) attenuates considerably the singularities of the signal and it can't always follow the slow variations of the signal. This is inconvenient since we aim to eliminate only the rapid variations and to conserve the slow ones.

At the second stage, we test the Nadaraya-Watson Kernel regression on the same dataset to study the effects of this regression on the variations of the obtained curve. Contrary to the smoothing spline estimated by the penalized least square method, the kernel regression is rather defined as a weighted local average of the response variables Y . The weight function is commonly called kernel and it is set for each explanatory variable X . Here, the parameter bandwidth h determines the smoothness level of the result curve.

For this study, we test the Nadaraya-Watson Kernel regression estimate with fixed bandwidth. Two typical values of bandwidth are chosen: 10 and 20. Also, the kernel chosen for this estimator is the normal kernel (Figure 1.10) and is defined as:

$$K(u) = \frac{1}{\sqrt{2}} \exp\left(-\frac{u^2}{2}\right) \quad (1.30)$$

The support of the kernel function is compact. In fact, the smaller the bandwidth is, the more concentrated are weights around the local explanatory variable x .

Figure 1.11 depicts the results of application of the normal kernel regression on a dataset of

RXLEV measurement for three user situations (unmoving, incar and pedestrian). We notice that Kernel regression smoother eliminates considerably the rapid fluctuations from the initial signal without high attenuation of the slow variations. Comparing to the smoothing splines (figure 1.8), the kernel regression follows more closely the slow variations of the initial data. The rapid and important changes remain in the case of the kernel regression, whereas they are removed with the Smoothing Splines (with high smoothing parameter). These changes in the received power level corresponds generally to an abrupt change in the mobile situation (for example the effect of a street corner with the change from non line of sight to a line of sight situation).

Finally, we test the Friedman's super smoother on the same database. Thus, we apply

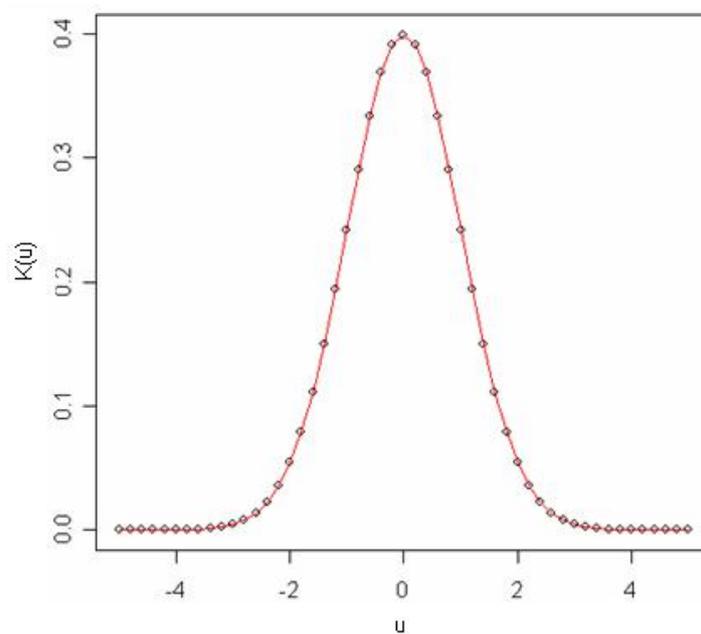


Figure 1.10: Normal kernel representation.

the Friedman's smoother with two typical parameters $bass=0$ and $bass=7$. The corresponding results are depicted in Figure 1.12. Here, the parameter "bass" corresponds to the parameter η in Equation 1.27. It controls the smoothness of the fitted curve (values of 0 up to 10 indicate increasing smoothness).

We obtain results almost similar to the kernel regression. Nevertheless, the super smoother allows a better elimination of the rapid fluctuations from the initial signal (as shown in red region of figure 1.13). A plausible explanation is that the super smoother is constructed as a weighted average in a varying neighborhood, contrary to the kernel regression which is a weighted average in a fixed neighborhood.

To conclude, Table 1.3 sums up the main properties of the three regression methods observed on the radio measurement *RXLEV*.

Based on the previous deductions, we propose possible applications of the considered smoothing and regression methods:

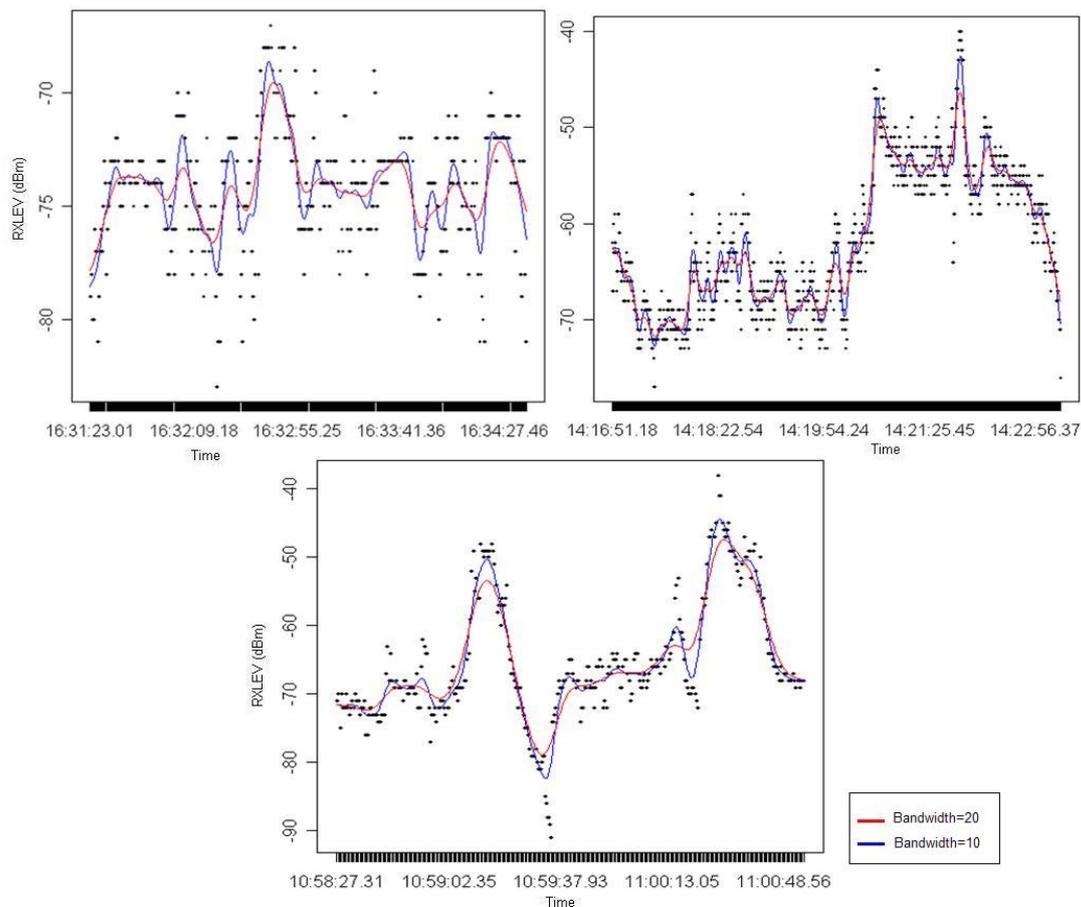


Figure 1.11: Kernel regression smoother (normal) for unmoving (up left), pedestrian (up right) and incar (down) case.

Table 1.3: Summary of the main characteristics of tested regression methods.

Smoothing Spline	A high value of the smoothing parameter influences the singularities of the signal (with high attenuation). It can't always follow the slow variations of the signal.
Kernel regression smoother	A compromise is possible between the elimination of fast and low fading.
Friedman's Super smoother	It provides a good elimination of rapid variations from the initial signal.

- Attenuation component estimation (namely shadowing, pathloss and fast fading) using available radio measurements in wireless networks,
- Mobile user classification: Estimation of mobile terminal situation as unmoving, pedestrian or incar,
- Handover process improvement with an enhanced target cell determination algorithm.

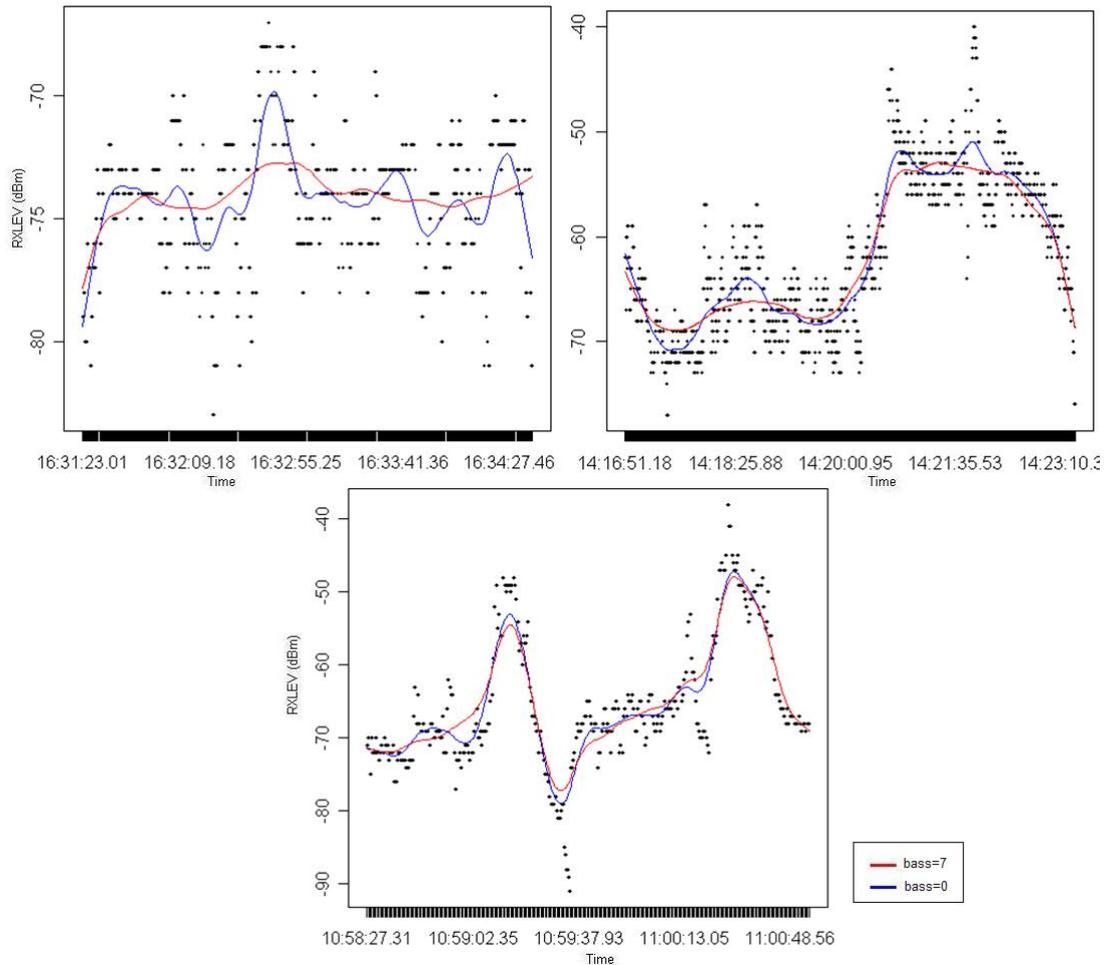


Figure 1.12: Friedman's Super Smoother for unmoving (up left), pedestrian (up right) and incar (down) case.

1.7 Proposed applications in wireless networks

1.7.1 Estimation of attenuation components

The first application we propose using non-parametric regression and smoothing methods is a dynamic and real-time estimator of the attenuation components (namely pathloss, shadowing and fast fading) from a set of standardized radio measurements (reported from real radio networks). The main originality is that it is a flexible and adaptive estimation procedure, that takes as input the reported radio measurements (already available in the network) and provides, after an observation delay, the three attenuations components.

This estimation is important for the network as it allows to extract the attenuations due to external environment propagation in almost real-time. Thus, this dynamic estimator can be used for the construction of enhanced RRM procedures that takes into account real propagation conditions instead of empirical propagation models.

Regarding the state of the art, we find out that the attenuation components are usually deduced

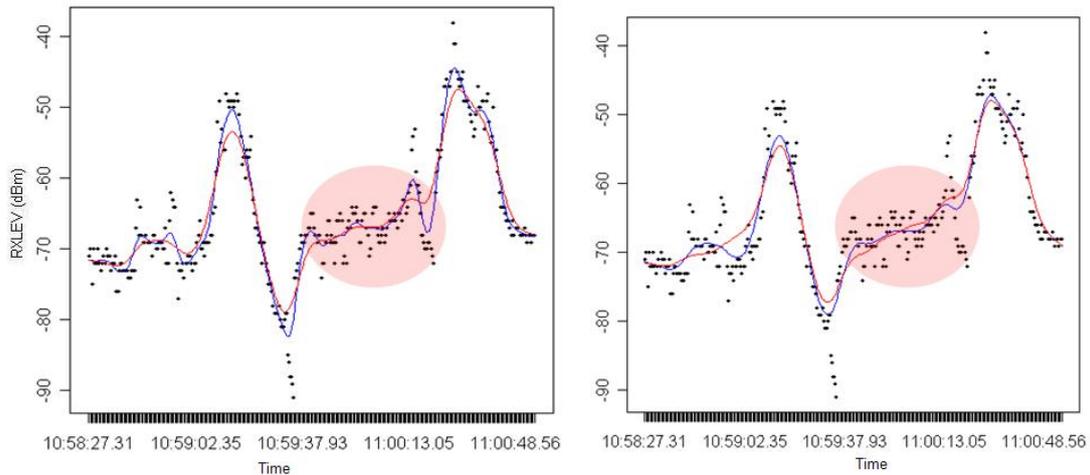


Figure 1.13: Comparison between Kernel and Super Smoother methods.

from empirical models obtained from measurement campaigns. The attenuation components can be extracted from power measurements with specific hardware equipments, such as:

- A radio receptor: It measures the envelope of the received signal. Then, it estimates the attenuation undergone by the radio signal during its propagation, given the power of the transmitted radio signal. These kind of receptors are commercialized by firms specialized in radio measurements (for example Rohde & Schwarz ESVD Test Receiver). In several radio networks, predefined power metrics are normalized (their transmission power is fixed). This method allows to calculate the total attenuation undergone by the signal during its propagation. For example, the UMTS system uses this technique to estimate the attenuation factor. Thereafter, this information intervenes in the power control mechanism,
- A channel sound: It is a device that measures continuously the impulse response of the propagation channel (transfer function amplitude and phase). This tool is developed by companies specializing in radio measurements (for example Propound of Elektrobit) or developed by research organizations.

The main weakness of these methods is that they estimate the total attenuation undergone by the signal and is unable to differentiate the three components which are the pathloss, the shadowing and the fast fading. Adding to that, the channel sound is characterized with its high complexity and cost, which makes it difficult to integrate into real wireless networks.

Thus, we can conclude that, to the best of our knowledge, there no direct, dynamic and low-complexity procedure that allows to estimate the three attenuation components of the signal from a set of consecutive measurements, in real time conditions.

Consequently, we propose a flexible and dynamic estimator that processes real radio measurement and can be implemented in the network as a software, thus avoiding addition of specific hardware.

Our method is based on non-parametric regression and smoothing methods. In fact, we noticed in the preliminary study that these statistical tools with appropriate parameters allow the estimation of the attenuation components of the radio signal. In other terms, these methods behave

as adaptive filters to extract different scales of variations from the input data (rapid, medium and slow variations). By exploiting the properties of each regression method, we are able to estimate the attenuation components of the radio signal: the pathloss (the median curve), the shadowing (slow variations) and the fast fading (rapid variations).

First, the smoothing spline (SS) with a high smoothing parameter is appropriate to estimate the median variations of radio signal, which corresponds to the pathloss component P_k (typically $\alpha = 2$ in equation 1.13). Figures 1.14 and 1.15 depict examples of the application of the smoothing spline method on power measurements, respectively *RXLEV* (incar situation with 300 samples) and *UE_Tx_Power*. The smoothing parameter α is set to 2 so as to have a maximum smoothness of the signal, resulting in the median variations of the signal due to pathloss.

$$P_k = SS(Y_k) \quad (1.31)$$

Second, The shadowing S_k is the slow fading component and translates the attenuation of the radio wave due to obstacles. To extract this component, we choose the Friedman's super smoother (FSS) with the lowest smoothing parameter (typically $bass = 0$). In fact, we have observed that this method allows a good match to eliminate the rapid variations of the signal and only keeps the slow variations (the pathloss and the shadowing components). This result is obtained since the super smoother is based on linear k nearest neighbor method, in other terms; it is constructed as a weighted average in a varying neighborhood. Thus, it offers more flexibility and ability to follow the slow variations of the signal, in all cases (for example a sudden discontinuity/change in the initial signal). To compare, the kernel smoother regression method also gives good results but it is limited by a fixed interval of treatment: it is constructed as a weighted average of the response variables in a fixed neighborhood.

Figure 1.14 and Figure 1.15 are examples of the application of the super smoother method, with a null smoothing parameter, on *RXLEV* (incar situation with 300 samples) and *UE_Tx_Power*, respectively.

As we evaluated previously the pathloss with the smoothing spline method, the shadowing component S_k is thus obtained by subtraction:

$$Z_k = FSS(Y_k) = Y_k + S_k \Leftrightarrow S_k = Z_k - P_k \quad (1.32)$$

The fast fading component F_k is then estimated directly by the following formula:

$$F_k = Y_k - (P_k + S_k) = Y_k - FSS(Y_k) \quad (1.33)$$

To study the efficiency of the above described approach, we have tested it on different user cases (indoor, outdoor, incar, pedestrian and unmoving). The obtained results show the validity of our method to extract the signal components.

Based on the previous results, we have constructed a dynamic estimator (Figure 1.16) that estimates the attenuation components of the radio signal (pathloss, shadowing and fast fading) after a period of observation τ of the reported power measurement. For example, figure 1.17 illustrates the estimated attenuation components from a vector of 300 samples of *RXLEV* measurement (figure 1.17), which corresponds to an observation window of length $\tau = 144s$.

So far, the attenuation components (pathloss, shadowing and fast fading) have been estimated from predefined empirical models, elaborated in given conditions and environments. No direct method is available in the literature to estimate these components from radio measurements in real time.

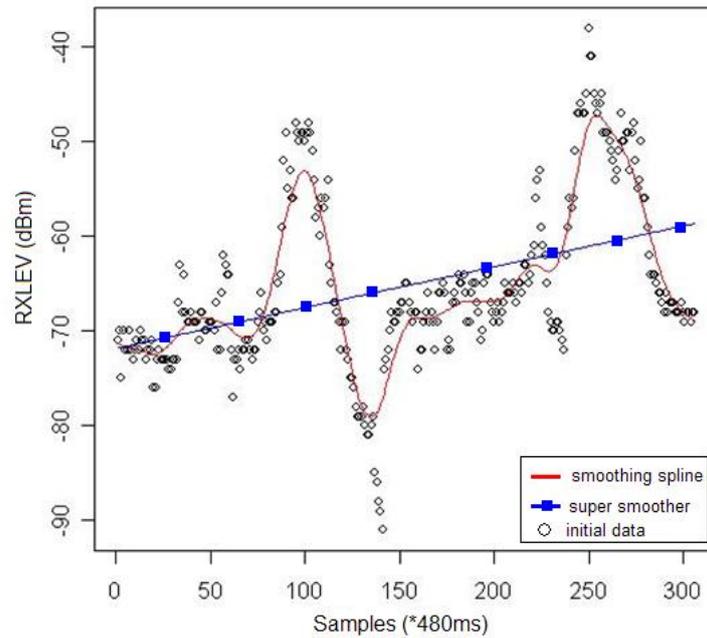


Figure 1.14: Smoothing and regression methods application on *RXLEV* measurement.

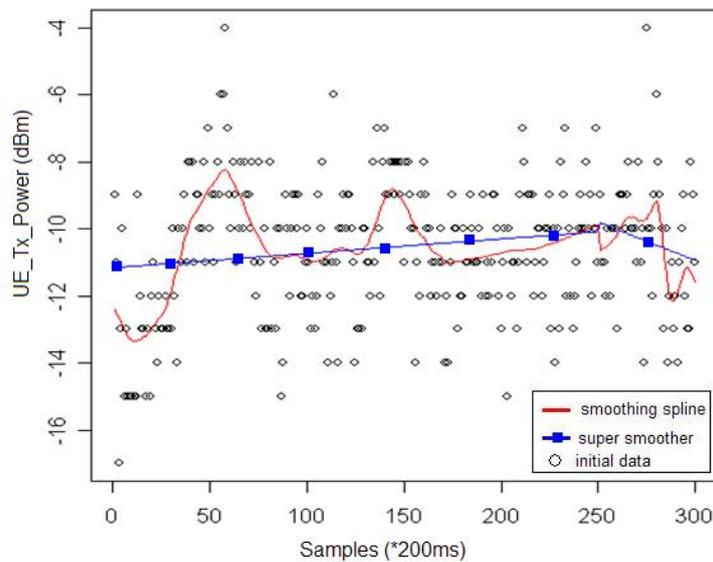


Figure 1.15: Smoothing and regression methods application on *UE_Tx_Power* measurement.

The main originality of our estimator is its validity in all environments and for all mobile user situations, with results obtained in real time (about $5 \cdot 10^{-3}$ seconds for the processing of 400 samples with Intel Pentium 4 CPU 3.40 GHz). The dynamic and flexibility properties allow the exploitation of this estimator in RRM mechanisms or any other real time application in wireless networks.

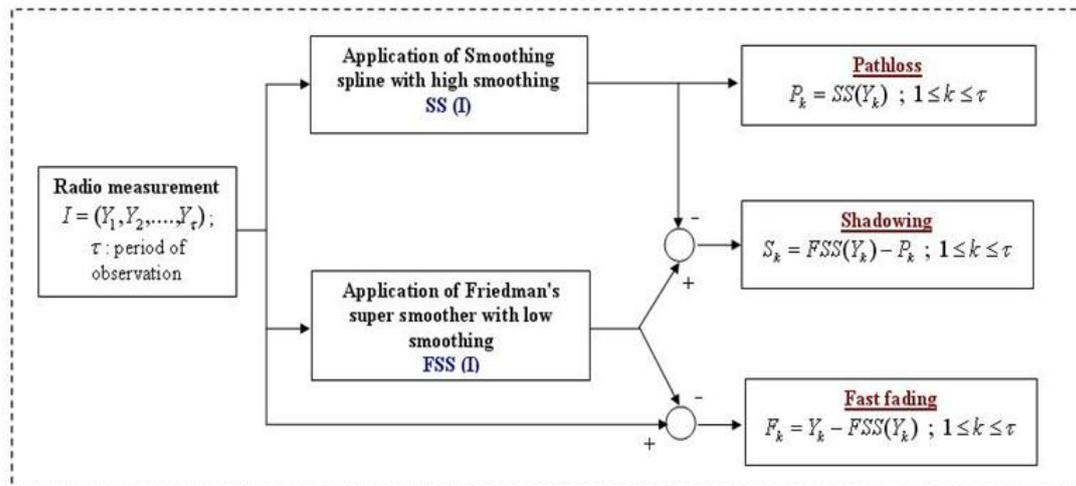


Figure 1.16: Dynamic estimator of attenuation components of radio signal.

Thereafter, we propose to make use of the attenuation component estimator to deduce a classification of the mobile terminal among three main classes related to the velocity criterion, namely unmoving, pedestrian and incar.

1.7.2 Mobile user classification

The attenuations undergone by the radio signal are strongly related to the mobile user velocity. If the mobile user is unmoving then the measured power signal doesn't present too much variation contrary to the incar or pedestrian cases. Hence, the attenuations undergone by the propagated signal are more important in the mobile case than the unmoving one. This suggests proportionality between the velocity of the mobile user and the attenuations undergone by the radio signal. For example, in the unmoving case, the pathloss is almost constant; the user doesn't move and so he doesn't meet new obstacles. On the other hand, in the incar case, the pathloss is varying.

To illustrate this difference, we use the histogram representation of each attenuation component estimated using the above mentioned dynamic estimator for three cases: unmoving, pedestrian and incar users. Figure 1.18 presents the results of this representation, with connecting points in the middle of the bars (for clarity reasons). To formulate the difference between the three cases, we calculate the standard deviation σ (Table 1.4) to measure the spread of the data.

We can verify that the incar case is characterized with the highest value of σ for the three

Table 1.4: Standard deviation of the attenuations components.

Case	Pathloss	shadowing	Fast fading
Incar	5.56	4.98	3.67
Pedestrian	1.71	1.85	2.75
Unmoving	0.93	1.34	2.07

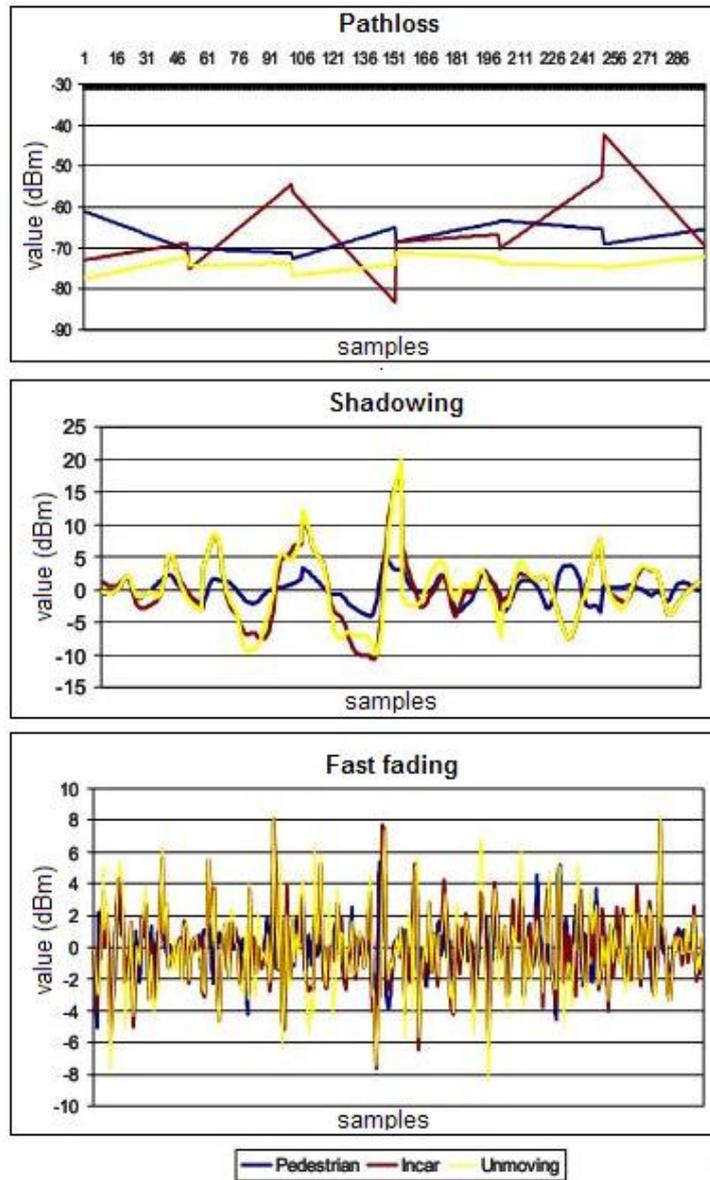


Figure 1.17: Estimated attenuation components.

attenuations components. More generally, we verify for the three attenuation components that:

$$\sigma_{unmoving} < \sigma_{pedestrian} < \sigma_{incar} \quad (1.34)$$

Hence, we can use this method to deduce thresholds on the standard deviations in order to identify the mobile user situation. These results can be more deeply exploited with an advanced statistical classifier for more efficient mobile user identification.

As our classification method is based on a dynamic and real-time estimator (Figure 1.16), we can include our dynamic classification of the mobile user context in RRM decisions, for example, choosing macro cells instead of micro cells for incar users, in order to avoid frequent and useless handover.

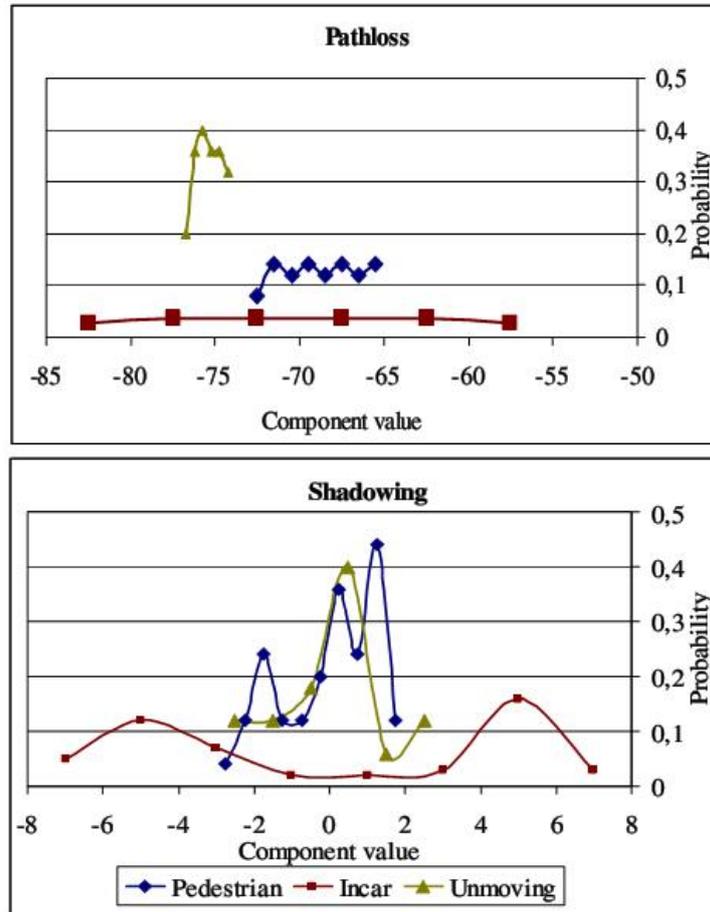


Figure 1.18: Shadowing and pathloss histogram representations for unmoving, pedestrian and incar situations.

1.7.3 Handover procedure improvement

Finally, we propose a final application of the non-parametric regression and smoothing that aims at improving the handover procedure with enhanced target cell determination algorithm.

Handover process is the RRM function responsible for the insurance of seamless mobility of the mobile terminal from a cell to another, without deteriorating the ongoing communication. This procedure is based on radio indicators translating the level of received signal and quality of service (for example in GSM, RXLEV and RXQUAL for serving and neighborhood cells). The handover algorithm implemented in current wireless networks consists mainly of two phases [34]:

1. Phase 1: is the radio measurement collection and evaluation process, in parallel to target cell determination algorithm,
2. Phase 2: is the handover triggering and execution process.

A standardized algorithm allows the determination of target cells: It is the list of neighborhood cells who are candidates for the next handover. The choice of the target cells is first made on

the criterion of the received power and then on power budget criterion [28]. This is expressed by the following equations:

$$RXLEV_NCELL(n) > RXLEV_MIN(n) + Max(0, Pa) \quad (1.35)$$

$$PGBT(n) - HO_MARGIN(n) > 0 \quad (1.36)$$

with:

- *RXLEV_NCELL*: the received signal level for the adjacent cell "n" (generally available for 16 cells),
- *RXLEV_MIN*: the trigger threshold parameter,
- $Pa = MS_TXPWR_MAX(n) - P$,
- *MS_TXPWR_MAX(n)*: the maximum transmitted power a mobile terminal is authorized to use in the adjacent cell "n",
- *P*: the maximum transmitted power of a mobile terminal, item *PGBT*: the power budget,
- *HO_MARGIN*: a parameter used in order to prevent repetitive handover between adjacent cells.

Based on the decreasing value of $PGBT - HO_MARGIN$ of each adjacent cell, the network constructs an ordered list of target cells. The handover then occurs with the first cell in this list.

In this study, we focus on the first phase of the handover process and more specifically on the target cell determination algorithm. In fact, we propose an ameliorated handover algorithm thanks to a pre-treatment on involved radio measurements for more efficient determination of target cells list.

We tested our smoothing and regression methods on *RXLEV* parameter for both serving and neighborhood cells. The goal is to conclude on a possible improvement in the handover algorithm. In GSM, a cell is identified by the parameters *ARFCN* (Absolute Radio Frequency Channel Number) and *BSIC* (Base Station Identity Code).

Figure 1.19 shows an example of *RXLEV* during a handover occurring between the serving cell and the neighborhood destination cell (559,31). This figure shows the evolution of the signal level for all present cells. Figure 1.20 represents the *RXLEV* for only the serving cell and the destination cell. We can notice that, in the beginning, the *RXLEV* of the serving cell is decreasing whereas the *RXLEV* of the destination cell (559,31) is increasing during the same time interval. After sometime, the handover occurs and the destination cell becomes the serving cell (when the red curve disappears).

From this observation, we have concluded that we can use the smoothing method on the cell levels to improve the handover algorithm, by deciding the target cells to become the next serving cell.

In fact, the application of the smoothing spline method with a high smoothing parameter (for example $\alpha = 1$) on *RXLEV* of all present cells (serving and neighborhood) allows to study the evolution of each cell separately (figure 1.21). In other terms, the smoothed curve obtained for each cell is examined to decide if the cell can become the serving cell or not. For this aim, the slope of smoothed curve is calculated (table 1.5).

The serving cell is decreasing before the handover. Thus, the slope of its curve is negative

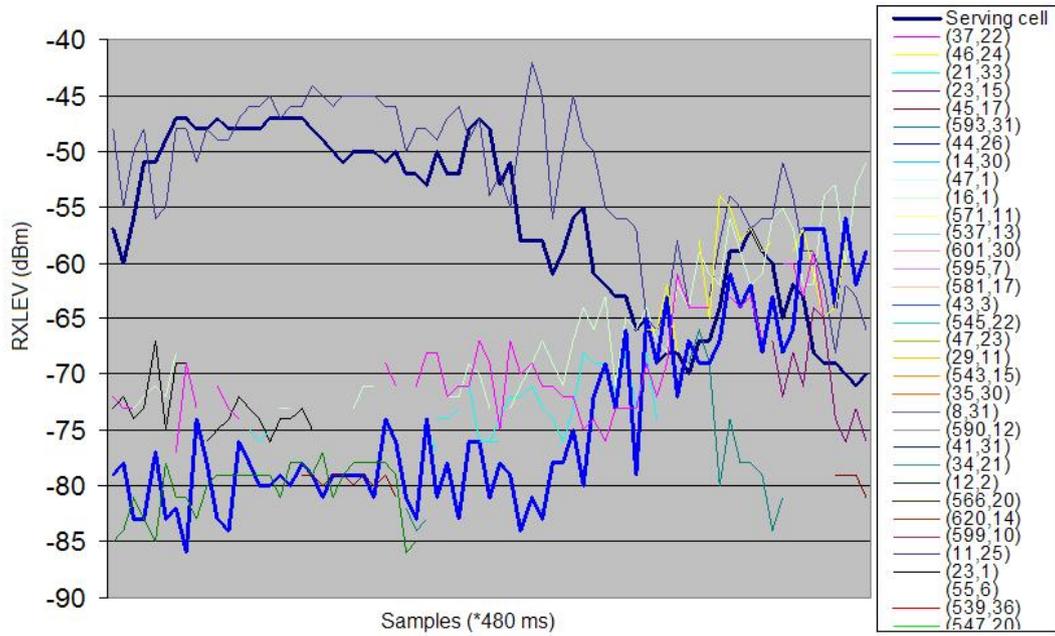


Figure 1.19: RXLEV for serving and neighborhood cells during handover for incar user.

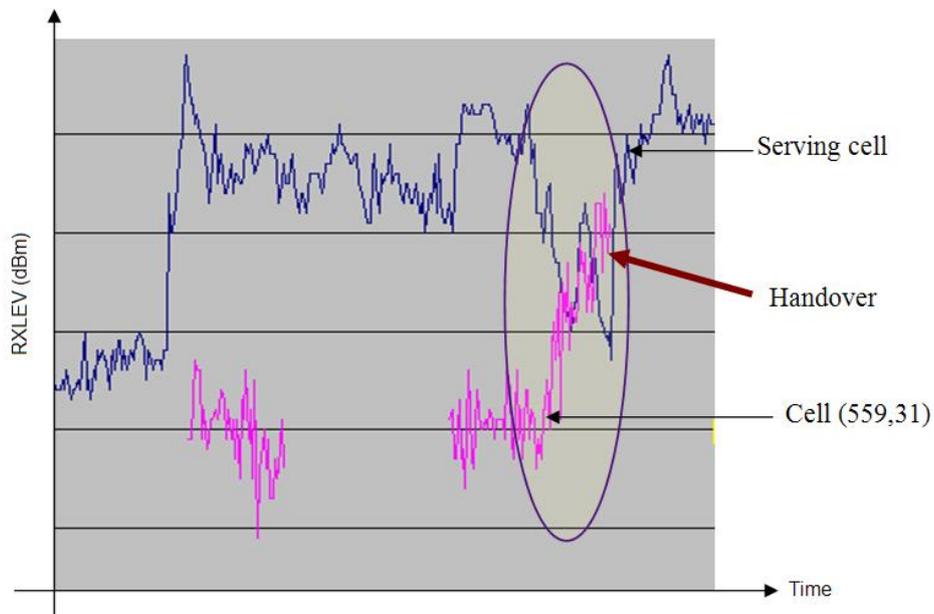


Figure 1.20: Example of handover procedure.

(-0.38). The target cell will be a cell with a higher level. Nevertheless, the cell (11,25) can not become the serving cell even if its level is higher. In fact, the level of cell (11,25) is decreasing and the handover will not occur with this cell.

Thus, the target cell is characterized with a positive slope (an increasing level) and could be differentiated from other neighborhood cells by the higher slope. In figure 1.20, the target cell

Table 1.5: Curve slopes after smoothing spline application on RXLEV of serving and neighborhood cells.

Case	Serving cell	(21,33)	(529,31)	(16,1)
Slope	-0,38	0,21	-1,7	0,48
Case	(559,31)	(58,35)	(51,12)	(15,26)
Slope	0,53	0,25	0,38	-0,11
Case	(11,25)	(23,1)	(616,33)	
Slope	-0,35	-0,16	0,03	

is cell (559,31) and its slope is 0.53.

Based on the previous observations, we can conclude that the smoothing and regression methods can ameliorate the handover process with an enhanced target cell determination algorithm. In fact, adding to the power budget parameter, we propose a novel approach that consists of determining the list of target cells more precisely, based on their variations (slope of the smoothed curve). This can be considered as an anticipated action in the handover process, which aims to improve the radio resource management algorithms.

The other advantage of such a method is that it conserves in memory previous measurements and includes them when calculating the smoothed curve.

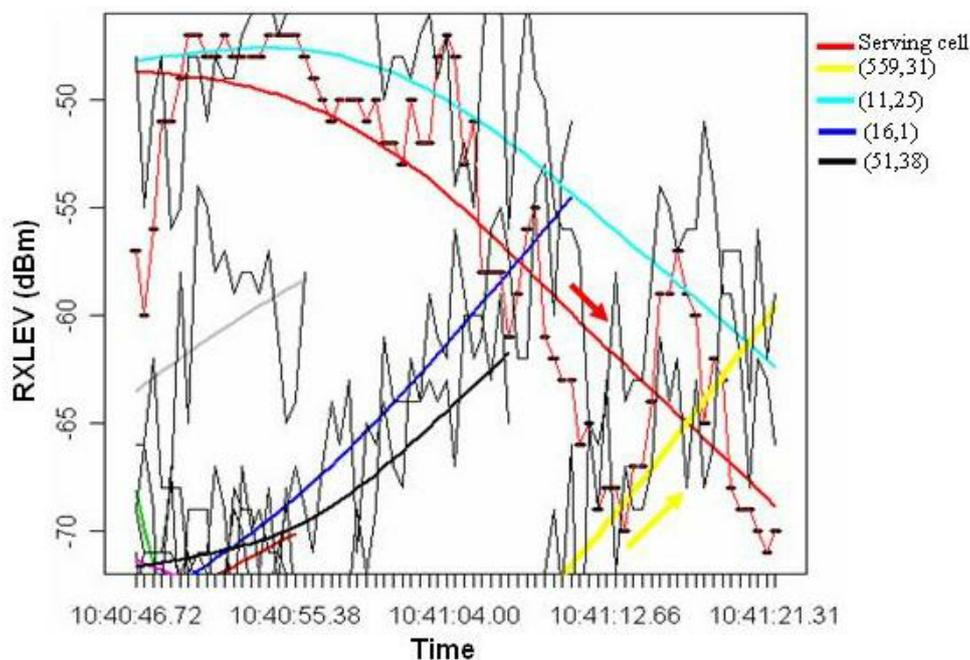


Figure 1.21: Smoothing spline application for serving and neighborhood cells in GSM system.

1.8 Conclusion

The overriding problems are the choice of what method to use in any given practical context and, given that a particular method is being used, how to choose the various parameters needed by the method.
Silverman (1981)

In this first part of the thesis, we focus on the existing radio measurements in wireless networks such as GSM and UMTS. We note that these measurement, made by the mobile terminal or the base station, are used in several RRM procedures to assess the network functioning and ensure the target quality of service. Nevertheless, we remark that these measurements are used in their crude state (generally after an averaging or filtering operations) and are commonly intended for simple tests in RRM algorithms.

This observation constitutes the starting point of this study as we believe that these reported measurements are a rich and not sufficiently exploited source of information. Adding to that, the growing demand for more services and data rates result in the development of more complex and advanced radio network architectures and the definition of more sophisticated and intelligent networks (such as cognitive radio). Here, it is important to note that the research efforts have mainly been oriented to network architectures, cooperation schemes and radio resource management procedures. Whereas, the radio measurements in radio networks have attracted little interest and no real advances are noted on this issue.

Upon these assumptions, we propose in this thesis a novel approach that consists of enhancing the exploitation of standardized radio measurements defined by heterogeneous radio access technologies. For this goal, we suggest to employ non-parametric regression and smoothing methods. These statistical tools are extremely helpful to exploit data, extract interesting special features, predict their evolution and facilitate their interpretation.

As a result, we propose three main applications in real radio networks. First, we propose a novel procedure for the estimation of the attenuation components (namely pathloss, shadowing and fast fading) based on reported radio measurements (received signal power). The main originality of this method (filed as a patent) is that it produces results in real time conditions (about $5 \cdot 10^{-3}$ seconds for the processing of 400 samples with Intel Pentium 4 CPU 3.40 GHz). Contrary to conventional high-complexity hardware solutions, our dynamic and flexible estimator allows the exploration of this innovative procedure in RRM mechanisms or any other real time application in wireless networks.

Thereafter, we use this dynamic estimator to develop a method to classify the context of the mobile user based on the velocity criterion (incar, pedestrian and unmoving). This discrimination of the user context can be used, for example, to guide the mobile terminal in high velocity situation (incar) on choosing macro cells instead of micro cells. This way the mobile terminal avoids frequent and useless handover.

Another possible application of our dynamic estimator is the improvement of radio network simulator functioning. In fact, the extracted attenuation components from real network conditions can be used in radio network simulators instead of theoretic propagation models. The goal is to have more accurate and more realistic results with the simulators, using a basis of shadowing, pathloss and fast fading components collected in different situations and environment.

Finally, the non-parametric regression and smoothing methods can improve the handover process with enhanced target cell determination algorithm. We propose to determine the list of the target cells based on their variations (slope of the smoothed curve). This can be considered as an anticipated action in the handover process, which aims at improving the radio resource management.

To conclude, we provide in this first part of the thesis flexible and dynamic methods that explore more efficiently existing radio measurements and provide real time results. These methods can be implemented in future wireless networks for an efficient use of radio measurements and for the improvement of radio resource management.

Chapter 2

Interference Cartography

2.1 Introduction

The challenges facing today's wireless networks are numerous and those facing future wireless networks will be much more. Factors like the ever-growing demand for higher capacity, substantial variety of wireless data/multimedia services and scarcity of wireless resources pushes the wireless communication actors to find effective solutions that increase the spectral efficiency. Cognitive radio is one of such solutions that target a more efficient use of the wireless resources by introducing intelligence and environment-awareness into wireless networks. The innovation in the concept of cognitive radio is the autonomy of the wireless network in resource management, which is gained through collecting information on the environment, processing this information to learn/deduce from the environment and adapt its resource allocation strategy in an effective manner to reach certain goals. Therefore, since its introduction in 2000 [19], cognitive radio has aroused a lot of excitement and interest in the wireless communications community and many interesting research work on various aspects like architecture, radio resource management, information collection and processing have emerged.

Among these aspects, spectrum management has received a special attention due to remarkable studies that show a clear under-utilization of the radio spectrum and to interesting propositions that demonstrate the possibility of much more effective spectrum utilization through more flexible spectrum management policies. These flexible spectrum management policies can extend from schemes that maintain the basic structure of the current spectrum regulation policy and introduce minor flexibilities (like Dynamic Spectrum Allocation), to more revolutionary schemes that allows more than one system to co-exist in the same band of frequency as long as the quality of communication is not degraded [35].

The later scheme is widely known as the hierarchical access model where the main idea is to open the licensed spectrum to secondary utilization, allowing secondary users to share the same frequency band with the primary users as long as they do not degrade the communication quality of the primary users.

This is an extremely challenging task due to important issues like selecting efficient architectures (with or without infrastructure, centralized or distributed), protocol structures and co-existence strategies (collaborative or competitive), finding efficient methods for information collection and processing (widely known as spectrum sensing), detecting primary users, analyzing the processed information to make 'informed decisions' on how and when to perform hierarchical

access, managing mobility, etc [19].

One of the most important issues that should be addressed in this context is information collection and processing that provides awareness on the environment and that helps to arrive at efficient 'informed decisions'. Research work on information collection and processing in the context of hierarchical access models have so far been mostly concentrated on spectrum sensing for the purpose of detecting the localization of primary users [12] and the unused portions of the spectrum (spectrum holes or white spaces) [5].

Collection and utilization of measurement data in mobile radio networks is becoming more and more efficient, thanks to recent improvements in mobile terminal, network and measurement technologies. Besides, with the recent advances in the field of Data Mining, effective and efficient exploitation techniques are being developed. Such techniques make it possible to extract useful information from the measurement data and use it effectively to enhance network performance [36][23].

With all these driving forces behind, there is a considerable amount of increase in efforts to ameliorate the performance of radio measurement utilization and collection in mobile networks. For that purpose, the definition of more complex measurements (such as the medium sensing time histogram report in 802.11k standard [20][37]), and the use of radio measurements to define models [38] have been introduced in the wireless communications community. The latter case mainly aims to detect spectrum opportunities and to realize dynamic spectrum access in the context of secondary spectrum usage.

Secondary spectrum usage allows unlicensed users (secondary users) to operate in frequency bands allocated to licensed systems (primary users) by detecting the unused spectrum portions (spectrum holes) without causing any deterioration to primary users [38]. In order to detect, identify and use the spectrum opportunities, the secondary users need spatial information of the 'state' of the spectrum. This 'state' mainly involves interference information. Specifically, the secondary transmitter has to know whether there are primary/other secondary receivers (transmitters) in the vicinity of the secondary transmitter (receiver) and how much interference can these receivers (transmitters) tolerate. Dissemination of this interference information in the secondary network needs special signalization with the primary network/other secondary networks as well as special signalization within the secondary network, which may not always be practical to implement.

In this part of the thesis, we propose a novel approach in information collection and processing and introduce the concept of Interference Cartography (IC) that combines location information with radio measurement data, providing a complete view of the environment to be used in autonomous decision making. The main idea behind the concept of IC is the aggregation of radio measurement information that normally circulates in wireless networks and the utilization of this aggregated information to be aware of the external environment for cognitive purposes.

Since interference is the major actor in any wireless network operation, almost every network management scheme uses interference information to guarantee a satisfactory level of performance. Thus, interference information already exists in wireless networks through periodic and/or event-triggered measurement reports provided by different network entities. The concept of interference cartography aggregates the pieces of interference information measured by entities of several different wireless networks at a central unit, combines this aggregated information with geo-localization information, performs advanced signal processing techniques

to render the information complete and reliable and finally updates the information to provide a viable picture of the environment for efficient detection, analysis and decision.

This part of the thesis describes a complete view of the notion of interference cartography in a hierarchical access context. A possible implementation is given with an architecture and a protocol structure that enables the use of IC, as well as a fixed and recursive method that construct a complete and reliable cartography from a limited number of located measurements. Finally, a case study of the proposed scheme is presented where an IC is constructed with partial measurement data and it is used to carry out efficient hierarchical access by secondary users.

2.2 Interference cartography concept presentation

The concept of cartography in wireless networks is mainly used in radio network prediction where maps of coverage, capacity and quality are used for network layout, maintenance, evolution and optimization. It requires geo-localized information on attributes like signal attenuation, received level of signal-to-noise ratio, received total power, best server and received level of quality indicators (throughput etc.) over the area of interest. To the best of our knowledge, the idea of combining location information with radio measurements has appeared quite recently in the research community. In [39] and [40], first investigations dealt with general databases combining environmental information with location. These databases are called Available Resource Map (ARM) in [39] and Radio Environment Map in [40]. We remark that these databases contain only available located measurements without further additional processing (more details in the Section 2.3).

The basic idea in constructing the interference cartography is to collect interference measurements from different network elements (mobile terminals, base stations, access points etc.) together with their corresponding geo-location information, and to combine them to form a complete cartography using appropriate signal processing techniques such as spatial interpolation. The final Interference Cartography corresponds to a map of the measured total interference, perceived at each location of the whole area of interest. This cartography corresponds to the real situation at a given time t and is valid during a period ΔT . Adding to that, the interference cartography can be constructed for different frequencies and stored in a database. Consequently, the network can make use of this database for the management of its radio resources.

The application of the interference cartography concept in real cognitive networks involves solutions of several challenging issues. The main questions that arise for effective utilization of the interference cartography are:

1. *How the interference cartography will be handled in the network ? Which entity is responsible for the manipulation of the cartography and its exploitation ?*

To this goal, we define a functional entity, the IC Manager, in the network that collects terminal measurements and builds a complete IC. For each frequency band of interest, the corresponding IC is stored in a database in the network, as shown in Figure 2.1. Based on the IC information, the Spectrum Manager assigns the appropriate frequencies to the terminals: The Spectrum Manager can evaluate the additional interference generated by a secondary user terminal on the surrounding receivers, and also the maximum power that the terminal can transmit without causing any harmful interference on primary users. Further details on proposed network implementation are depicted in Section 2.5.

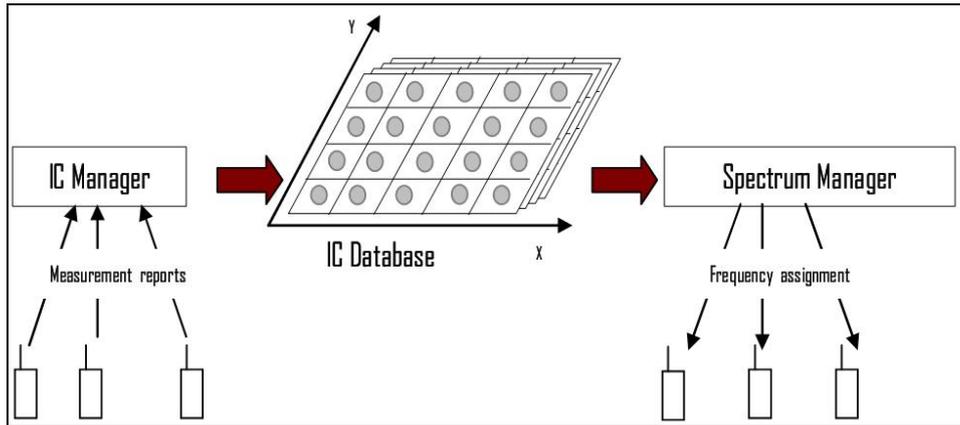


Figure 2.1: Interference Cartography for secondary spectrum usage: considered scenario.

2. *What is the reliable process to construct the complete interference cartography given a limited set of available localized measurements ?*

This stands for the construction process of the interference cartography given the reported measurements, combined with their corresponding geo-localization (Figure 2.2). This construction process can be handled in a fixed manner by only processing the current available measurements (i.e. through spatial interpolation, see Section 2.6) or in recursive manner with the estimation and the request of additional measurements in order to meet the target cartography quality (see Section 2.7).

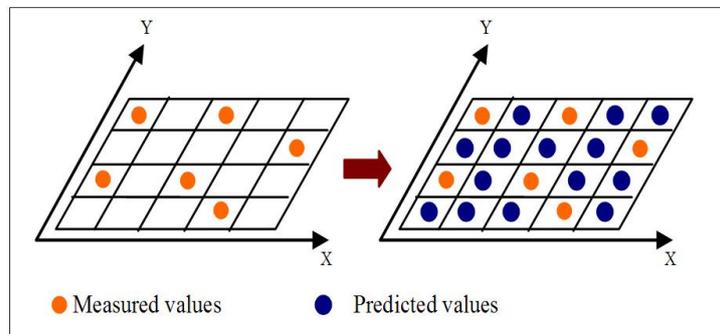


Figure 2.2: Interference Cartography elaboration process.

3. *How the complete interference cartography will be used by the network ? and what are the advantages ?*

The interference cartography is intended for efficient interference management in cognitive networks. It provides important informations on the state of the external environment (mainly in terms of interference) so as to perform efficient opportunistic spectrum access. In Section 2.8, we present a case study that demonstrates the utility of the interference cartography in hierarchical access scheme.

It is important to mention here that the interference cartography concept supposes that the location information is available with the reported radio measurements. This assumption

is realistic and we believe that future radio networks will provide this kind of aggregated measurements, by means of localization techniques. In the literature, the main proposed location techniques for wireless networks are:

- **Geographic Positioning System (GPS):** The mobile terminals are equipped with GPS receivers that determine their exact positions. These positions are identified by *longitudes* and *latitudes*, which are angular measurements, generally expressed in degrees. The latitude is measured according to the equator, whereas the longitude is determined compared to the meridian. Generally, cellular phones use a modified GPS version, referred as the Assisted GPS. It stands for an improved GPS system that provides accurate localization in poor radio conditions.
- **Hyperbolic positioning:** It corresponds to a localization method based on Time Difference Of Arrival (TDOA) technique. In fact, the location is calculated upon the time difference of arrival of a transmitted signal from a transmitter to three receivers, or from three synchronous transmitters to the same receiver.

Adding to that, the manipulation of the interference cartography requires the choice of a coordinate system. Commonly, we use the same coordinate system as the GPS, which is the World Geodetic System revised in 1984 (called WGS84). Thus, a location is identified by its unique coordinates (*Longitude, Latitude*).

Nevertheless, it is more easy and practical to manipulate a planar coordinate system. A common method is to use a kind of projection of the geographic coordinate in a given large area. For example, the projection "Lambert II extended" is a reference coordinate system valid for the whole France. The French national geographic Institute (IGN) sets a tool called *Circé* that performs the conversion from WGS84 to extended Lambert II coordinate systems [41].

2.3 Background and related previous works

This section outlines the Dynamic Spectrum Access (DSA) concept and presents the state of the art on location awareness in cognitive radio networks, with a focus on works related to the Interference Cartography concept.

Dynamic spectrum access is an emerging idea that attracts research efforts as a response to the rising demand and the scarcity of spectral resources. Generally, dynamic spectrum access is associated with cognitive radio as a form of intelligent and efficient usage of spectrum. Several works have dealt with DSA. In [18] and [42], Zhao et al. made a complete survey on dynamic spectrum access including technical and regulatory topics. Regarding the DSA classification proposed in [18] (Figure 2.3), we focus on the Hierarchical Access Model, where secondary users (SU), belonging to a secondary network can use the licensed spectrum resources of the primary network, provided they avoid any harmful interference to primary users (PU). This access model includes two cases: frequency underlay and frequency overlay. In the underlay approach, SUs can transmit simultaneously with PUs, if the resulting interference does not exceed the noise floor of PUs. This approach is compatible with Ultra Wide Band (UWB) technology. The overlay frequency approach is commonly known as Spectrum Pooling or also Opportunistic Spectrum Access. This method consists in detecting spectrum opportunities at both spatial and temporal dimensions. Consequently, the SUs can transmit in the detected white spaces without causing harmful interference to the PUs.

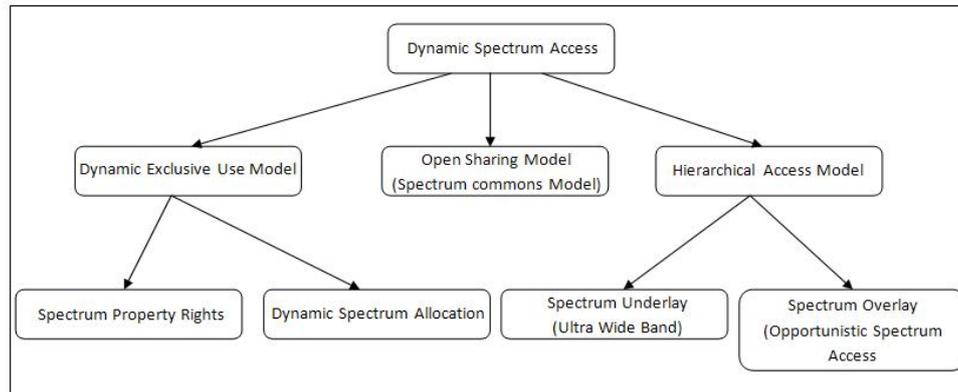


Figure 2.3: Taxonomy of dynamic spectrum access according to [18].

In [43], authors define spectrum opportunity and interference constraint in opportunistic spectrum access context. According to [43], a portion of the spectrum is identified as an opportunity if it is not used by the PU at both the secondary transmitter and its intended secondary receiver sides. This means that the secondary transmitter does not interfere with primary receivers and its intended secondary receiver is not interfered by primary transmitters.

Furthermore, the interference constraint can be described with a couple of parameters: the maximum interference power level and the maximum allowed collision probability. The first parameter refers to the interference threshold and illustrates the effect of secondary spectrum usage on active primary receivers. A generated interference exceeding this threshold value causes undesirable collision for PUs. The maximum allowed collision probability is the maximum allowed probability that the interference perceived by an active primary receiver is greater than the threshold value.

After defining Dynamic Spectrum Access and the constraints to achieve efficient opportunistic access, we focus on another aspect related to the Interference cartography concept, which is the localization. In fact, location is a new information that is being integrated progressively into future radio access technology standards. Localization can be achieved with different techniques such as Global Positioning System (GPS), Assisted GPS (A-GPS) and Time Difference of Arrival (TDOA). In the literature, several studies have focused on new architectures and mechanisms that take advantage of the location information in cognitive radio context. In [44], the authors address an overview on location awareness in cognitive radio networks. Thus, a location awareness engine architecture is proposed. It includes different tasks related to the localization such as location estimation methods, privacy issues and location-based applications. Adding to that, four main application categories are defined: location-based services, location-assisted network optimization, location-assisted transceiver algorithm optimization and location-assisted environment sensing.

In [45], authors present an example of utilization of location information in order to improve propagation models. They define a new entity called cognitive engine, which has the role of control, coordination and interpretation of different tasks of a cognitive radio network. Also, the cognitive engine exploits the location information so as to enhance its environmental knowledge and therefore optimize the system performance with an improved and reliable propagation model.

Works dealing with radio measurements combined with location information exist in the literature. In [46] and [47], the authors propose to apply spatial statistics techniques [48] for the characterization of primary and secondary users' locations. The goal is to estimate the spatial distribution of primary and secondary users as well as the cross-correlation between them, in order to define improved spectrum sharing algorithms. Different spatial statistical tools are tested on a real database of locations of television station transmitters. Consequently, modeling the primary or secondary users' locations can be employed for several applications such as characterizing client locations or service areas.

As a continuity on the previous work, the authors focus on spectrum characterization and modeling problem by processing real localized spectrum measurements, with spatial statistics and random fields [49]. Thus, this study presents results on the correlation between samples in different locations expressed with specific metrics (Geary's and Moran's indexes). Thereafter, the authors propose to perform stochastic modeling of the spectrum with Gaussian random fields.

Finally, the works that are the close to the proposed interference cartography are those involving the Available Resource Map (ARM) and the Radio Environment Map (REM) notions. The Available Resource Map (ARM) is introduced in [39]. It is defined as a real time map that includes reports of radio network activity. More precisely, this map contains the location of the transmitters, the power levels and information on the modulation, transmission band and SNR conditions. Thus, the base station (BTS) can check this map to control its corresponding terminals and to manage more efficiently the spectrum usage.

The Radio Environment Map (REM) is a generalization of the ARM. It refers to a database describing the radio environment in cognitive radio networks [40][50]. It is realized in a distributed manner based on different cognitive entities (nodes or network infrastructure). The REM is a general model that includes "multi domain environmental information, such as geographical features, available services, spectral regulations, locations and activities of radios, relevant policies and past experiences" [40]. In practice, the REM is integrated to cognitive radio networks as a database containing environmental information, history of past features and a priori radio knowledge. The main role of the REM is to enhance the performance of the cognitive radio network with faster adaptation and processing, by means of situation-aware behaviors. Also, in [40], different applications of the REM are presented for Wireless Regional Area Networks (WRAN) such as efficient spectrum sensing, optimal channel assignment, radio resource management and optimization. For more details on the functioning of REM and the obtained performances, the reader can refer to [50]. In [51], authors present simulation results of integrating REM in an IEEE802.22 network. The REM database is mainly used to improve path loss prediction and to regulate the transmission power. This way spectrum holes are more efficiently detected and overall network utility is improved.

Considering this literature work, we can state that location awareness in cognitive radio networks is an emerging topic and the preliminary results on this issue [43][44] show the potential of combining the location information with measurements in radio resource management/optimization as well as enabling cognitive functions in the radio network.

The idea of constructing a geo-localized information database presented in the Radio Environment Map (REM) [40][50] is similar to the idea behind interference cartography proposed in this thesis. However, the REM relies only on reported measurements in database construction whereas the proposed concept constructs the cartography from partial measurement data using advanced signal processing techniques, offering quality/reliability criteria and additional measurement request mechanisms to satisfy these quality/reliability criteria. To achieve a cer-

tain level of precision and reliability, large amounts of measurement data may be needed in constructing a cartography that relies only on reported measurements. It is clear that such large amounts of data are bound to create storage and dissemination problems in the network, as well as signaling overheads. The approach proposed in this work alleviates the burden of constructing, keeping and updating large measurement databases to reach the desired level of quality/reliability. Furthermore, with the rapidly increasing level of technological advances in digital signal processing, it is possible to implement efficient signal processing techniques that achieve high levels of precision and reliability with a small proportion of measurement data. Different from the existing work, the concept of Interference Cartography presented in this thesis is placed in a network implementation framework with an exploratory data analysis function that render the IC more reliable and functional.

2.4 Experimental setup

To conduct our study on the Interference Cartography, we need a database of radio measurements with their corresponding location information. This can be obtained in two ways:

- Real wireless networks: Measurements can be collected using specific tools such as scanner or tracing mobile. The corresponding location information can be provided by a GPS system. This method allows to handle realistic and correct data. Nevertheless, this approach has several disadvantages: limitations in test scenarios and collection of radio measurements, synchronization issues, practical difficulties linked to making simultaneous measurements in different locations and the availability of base station measurements (which depends on the manufacturer implementation).
- Radio simulator: This method has the advantage of providing direct access to radio measurements, depending on the simulator implementation. Also, it offers great flexibility in scenario choices. However, the simulator functioning is closely related to predefined propagation models, so the results doesn't always reflect the reality.

For this thesis, we choose to collect data with the two methods, in order to perform a complete study on Interference Cartography. On one hand, simulator data are used to study the construction issues of the Interference cartography (mainly with spatial interpolation, see Section 2.6). On the other hand, real data intervene in the recursive construction scheme of the interference cartography (see Section 2.7).

2.4.1 Simulation data

We choose a radio network simulator, developed in Orange Labs and called as *Odyssée*. This latter is a mobile network simulator that allows the evaluation of quality of service indicators on several Radio Access Technologies (RAT): UMTS, GSM and WLAN. The main advantage of this simulator is that it uses real morphology with real streets, buildings, parcs etc. and with real base station locations from the deployed Orange network. It also uses advanced propagation models (calculated from real environments). With this simulator, we can define accurately the target test area (with the help of the NetAct radio engineering tool).

To obtain localized measurements, it is however necessary to modify the functioning of the simulator so as to as to render the location information available. After the addition of this modification, we set the different attributes of the simulator as follows:

- Propagation model: A suitable propagation model is chosen depending on frequency of the target RAT (UMTS, GSM, etc.). The calculation of fading values depends on the parameters *Radius* (which determines the area of influence of a base station) and *Resolution* (the step-size with which the calculation is performed). The target area is split into square meshes of homogeneous size. For each mesh, a list of fading parameters is calculated. In this study, the used parameters are depicted in Table 2.1.

Table 2.1: Propagation model parameters.

Propagation model	Starwave (2200 MHz)
Mesh size	25 m
Radius	2 Km
Resolution	25 m

- Evaluation area: This stands for the area on which the simulation is made and the output statistics and metrics are computed. This target area is specified in the simulator through the parameter *User polygon*. It allows defining the target area size, form and location (specified with French Lambert II extended coordinate system). An example of evaluation area located in Paris and set for this study is depicted in Figure 2.4.
- The applied filter: The filter has the role of selecting the equipment components for a specific RAT in the evaluation area. Thus, it permits to choose the network elements (base stations, sectors, RNCs/BSCs etc.) that will be operational in the evaluation area. An example of a filter for a 3G network can be formulated with the following logical relation:

$$(Property + NodeB + Cell(UMTS)) \cap Polygon \quad (2.1)$$

This means that all the sites (property), base stations (NodeB) and sectors (Cell(UMTS)) are chosen within the evaluation area.

- Mobile terminal configuration: This corresponds to the configuration of the services handled by the mobile terminals and the traffic distribution among the different clutter types of the evaluation area (Table 2.2).

Table 2.2: Mobile terminal configuration.

Definition of service	3G voice service
Traffic distribution	uniform in all clutter types

2.4.2 Real network data

A measurement campaign is realized following the plan depicted in Figure 2.5 (real conditions in Figure 2.6). Five simultaneous measurement points are identified:

- A tracing mobile: The software CAIT is chosen to extract the measurements in the UMTS network,
- Scanner: The Agilent Viper test tool is run in the UMTS frequency bands,

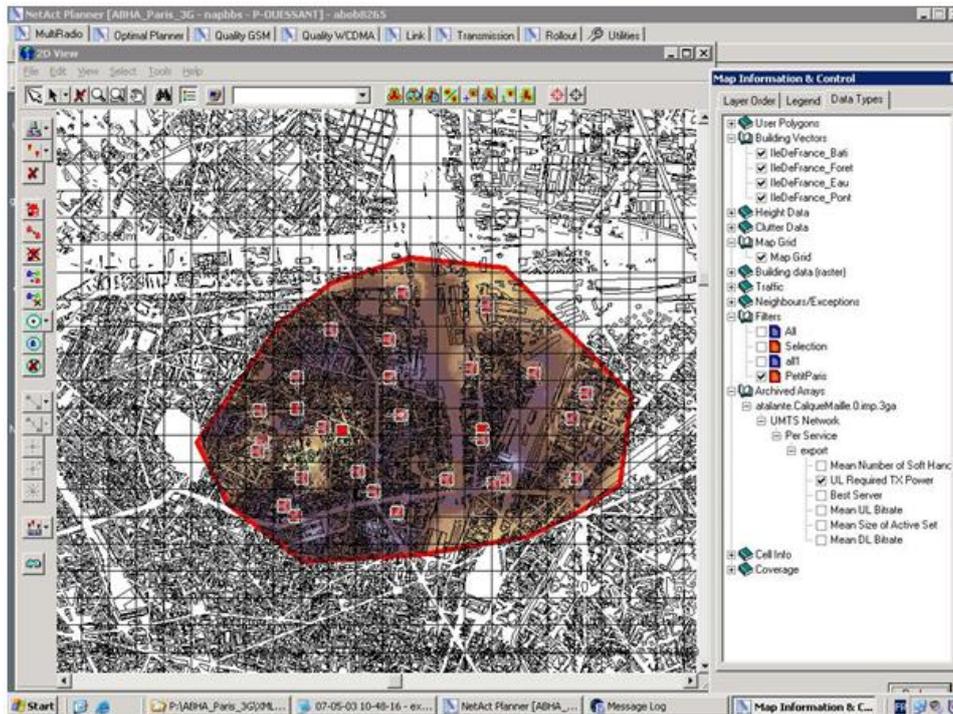


Figure 2.4: Example of Odyssee simulation.

- Global Positioning System (GPS): It determines the location of the tracing mobile,
- Radio Network Center (RNC): Measurements at this level are reported by the tool Cigale Iub,
- Operation and Maintenance Center (OMC): This entity allows to follow our tracing mobile (uniquely identified in the network by its IMSI attribute).

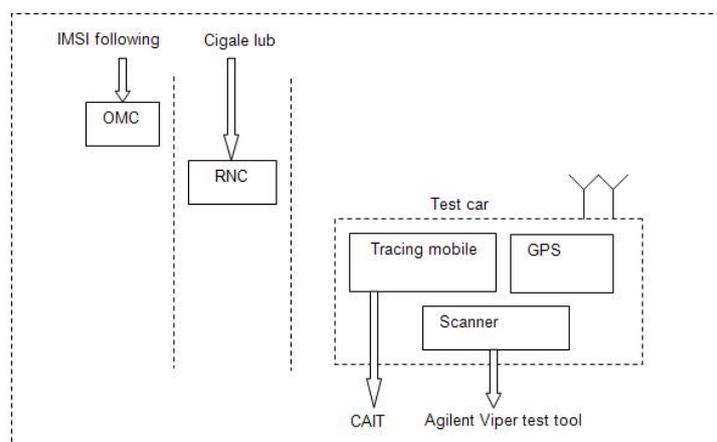


Figure 2.5: Description of the measurement campaign.

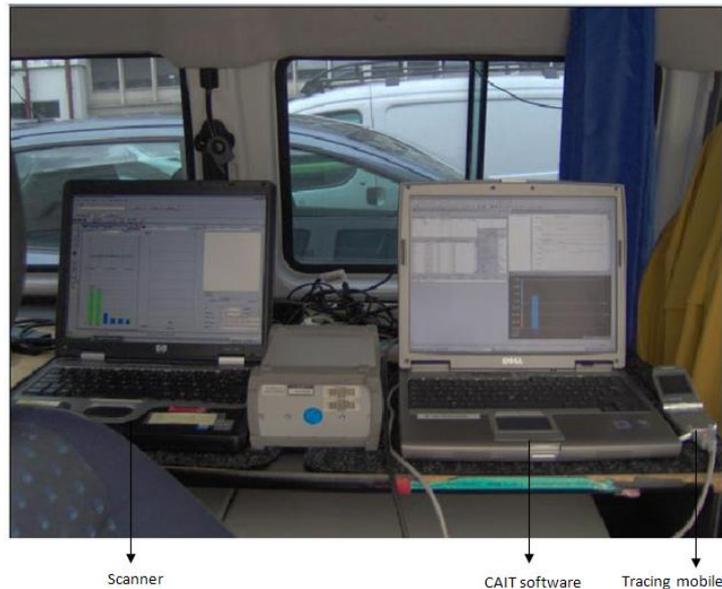


Figure 2.6: Real measurement campaign.

Our measurement plan allows collecting the radio measurements on different points of the network. In fact, in each measurement equipment (the tracing mobile, scanner, RNC and OMC), we can get different lists of radio measurements with different time periodicities. Also, in a real measurement campaign, we are always confronted with measurement/hardware problems. Thus, the definition of five measurement points provides more accurate and complete information.

Tests are made in Paris ("XVI^{ème} arrondissement") following a predefined itinerary (Figure 2.7). On this itinerary, we went along all the streets of the test area so that we obtained the radio measurements in all the possible locations of the test area. This corresponds to about 2 hours of duration.

The IMSI follow-up function was activated in the corresponding OMCs (by the operator Orange) so that we can get the radio measurements corresponding to our tracing mobile. Also, measurements at RNC level are collected thanks to the Cigale Iub application.

We chose to do the tests at different times in the same day and to follow the same itinerary, so that we get radio measurements corresponding to a different traffic value. The traffic information corresponding to our test area is supplied by the tool OSIRIS, specific to Orange Network.

2.5 Interference cartography in cognitive radio

This section presents the general framework of Interference Cartography (IC) exploitation for secondary spectrum usage. The proposed framework is described in Figure 2.8. We introduce two functional entities in the network: measurement collection module and IC manager, as well as a database that stores Interference cartographies for each frequency band of interest. The Network Spectrum Manager (NSM) denotes any entity of the network that is in charge of spectrum assignment for users, this entity can be for instance a part of a base station or an

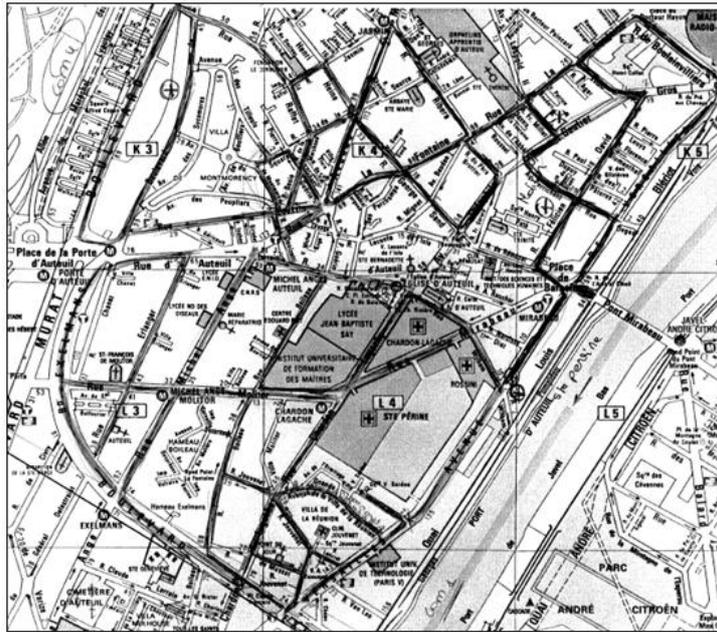


Figure 2.7: Map of the measurement campaign.

access point.

The IC manager is responsible of IC construction, based on measurements collected by the measurement collection module. The resulting IC is stored in the IC database and is used by the secondary NSM for spectrum allocation to SUs. Moreover, we suppose that the primary NSM sends to the secondary NSM the locations of primary receivers as well as the corresponding interference thresholds. The interference threshold of a given receiver is the maximum interference level acceptable by the receiver (i.e. maximum level of interference that does not cause any quality of service degradation). Based on this information, and knowing the location of the SU, the Secondary NSM evaluates the impact of a frequency allocation to this SU on primary receivers. If the resulting interference on each PU is lower than the corresponding interference threshold, then the frequency allocation is performed. A detailed case study will be explained in Section 2.8.

We suppose that the Secondary NSM is aware of the locations of all the SUs before any spectrum allocation. This means that the SUs report their locations on the Random Access Channel with the call request in case of mobile initiated calls. If the call is mobile terminated, then, the secondary NSM sends a paging message to search for the SU, on a pilot channel, and when the SU answers to the paging on the random access channel it sends also its location information.

Measurement Collection Module receives measurement requests from the IC manager, and then it determines the list of terminals that should perform these measurements among primary and secondary users. The resulting measurement requests are then sent to the corresponding NSMs. Once the measurements are performed by the terminals and reported to their NSMs, the NSMs report these measurements to the Measurement Collection Module which relays them

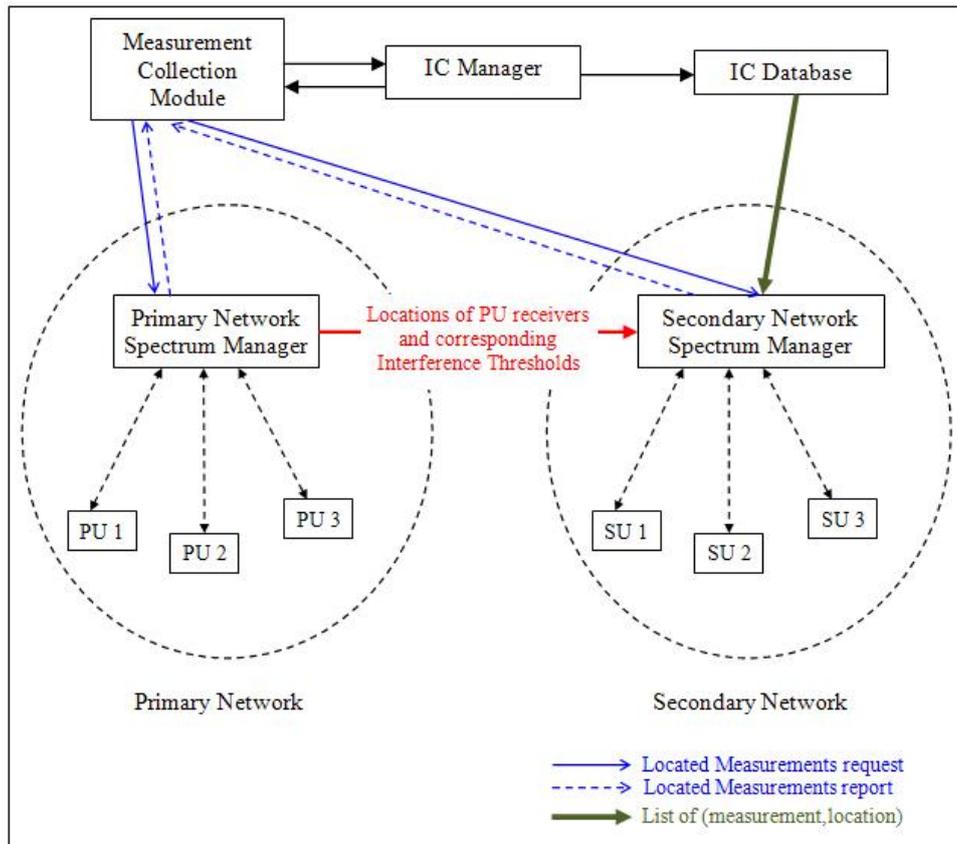


Figure 2.8: Interference Cartography for secondary spectrum usage: general framework.

to the IC manager with corresponding location information.

A detailed description of the IC manager is depicted in Figure 2.9. The IC manager analyses the measurements received from the measurement collection module and evaluates their quality. Indeed, the objective of the task "Measurement Analysis" is to evaluate some quality criteria on the obtained measurements and compare them to a given target quality. The quality criterion is deeply linked to the cartography construction method. An example of measurement quality is a metric that evaluates the distribution of the measurements over the area of interest and depicts if this distribution permits a reliable construction. For example, this metric shows a poor quality in the case of a cartography where the available measurements are not located homogeneously: the interference measurements are concentrated only in some regions of the area of interest. This metric can be generated from a *complete spatial randomness test* [52], which has the role of verifying if the observed point pattern is regular, clustered or randomly distributed (more details in Section 2.7).

If the results of the measurement quality analysis are satisfying, then the IC construction is performed using spatial interpolation techniques such as Kriging, and the resulting IC is stored in the IC database. Otherwise, the IC manager estimates that additional measurements are needed to reach the required quality indicator. For instance, the IC manager can detect an area where the spatial density of the available measurements is not sufficient. Then it asks the

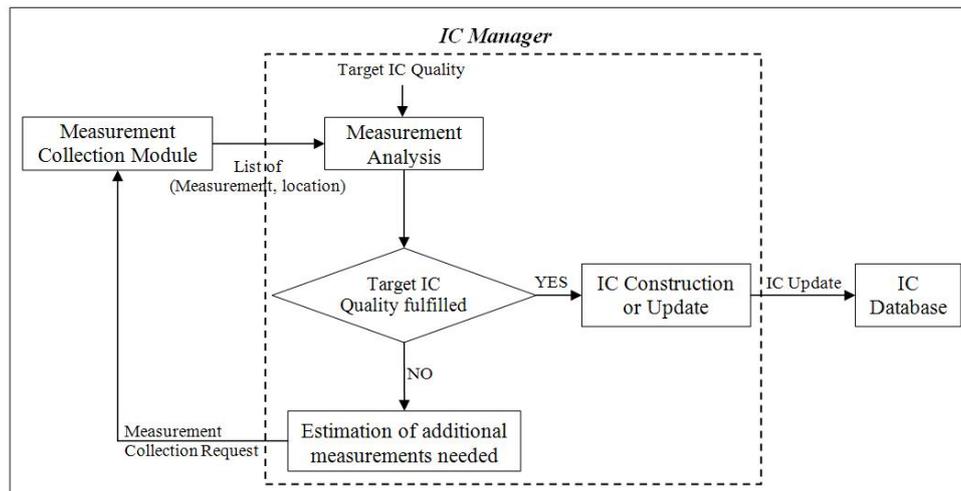


Figure 2.9: Interference Cartography Manager.

measurement collecting module to perform measurements on that area.

Section 2.6 details the fixed IC construction scheme, which stands for the procedure that can be applied to obtain an Interference Cartography from a set of available localized measurements. In Section 2.7, we add a loop to the fixed scheme in order to enhance the IC construction with the possibility of determining and requesting additional measurements to reach the target IC quality.

2.6 Fixed IC construction scheme

The fixed IC construction scheme is an important function of the IC manager. A reliable and efficient construction method is necessary to ensure effective utilization of the interference cartography. The fixed scheme corresponds to the procedure of IC construction from the available measurements only. A general framework is depicted in Figure 2.10.

Two blocks are identified. The first (IC Database) refers to the available measurements database, relative to a given frequency band. Each measurement is identified with its location within the interest area. Thus, this database includes data in the form (m, x, y) with m the interference measurement value at the location (x, y) . The temporal dimension can also be added to this database to obtain a spatio-temporal sampling of the measurements. In this case, the data stored in this database is identified by the quadruplet (m, x, y, t) with t referring to the time. The measurement database is updated every time a new measurement is reported within the area of interest.

The second block (IC Construction Procedure) is dedicated to the construction procedure. At time t , the complete interference cartography is processed from available measurements in the IC database. The construction procedure can be a spatial interpolation technique (for example Kriging) or a spatio-temporal technique derived from statistical models with spatial and temporal dimensions. Stochastic models (such as Random Fields) can also be useful for the IC construction. Apart from inputs from the measurement database, this block has several other inputs related to configuration parameters of the target interference cartography, such as the

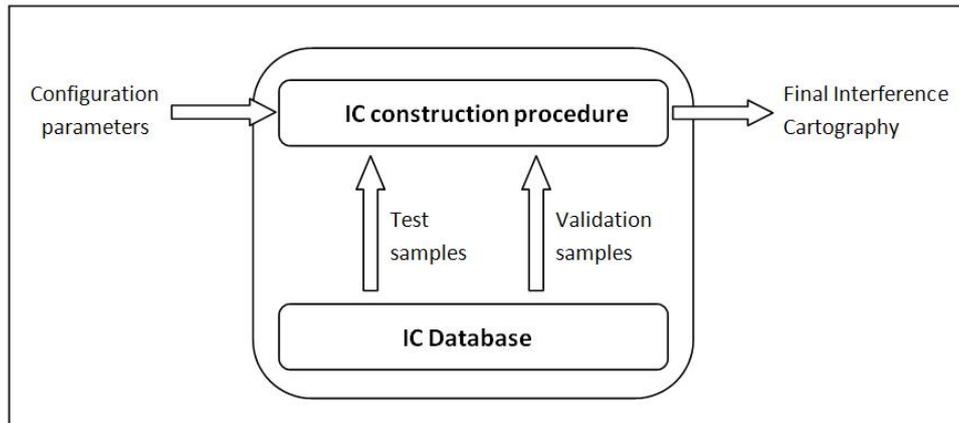


Figure 2.10: Fixed IC construction scheme.

required reliability degree and the mesh size. After the construction procedure, the complete interference cartography is obtained with the following attributes:

- **Attained precision:** This parameter depends on the chosen construction procedure. It describes how much the construction process has succeeded in calculating the missing interference values,
- **Validity duration:** It denotes the period during which the obtained interference cartography is valid and reflects the reality,
- **Satisfaction degree:** This parameter is set to illustrate how much the result of the cartography construction procedure responds to the target configuration parameters (reliability degree and precision).

To enhance the performance of this block, an additional procedure can be added to correct the construction procedure and to improve the final results. This additional procedure involves cross validation methods and/or correction models.

2.6.1 Spatial interpolation

2.6.1.1 Theoretical presentation

Spatial interpolation [53] is a well known procedure, commonly used in Geographic Information Systems (GIS). GIS refers to any system manipulating geographical referenced data for capture, storage, analysis and management purposes. Formally, spatial interpolation is a statistical procedure that estimates missing values at unobserved locations within a given area, based on a set of available observations of a random field. This interpolation is mainly based on an important principle in geography called the spatial autocorrelation. This stands for the first law of geography established by Tobler, assuming that "everything is related to everything else, but near things are more related than distant things" [54]. The main spatial interpolation techniques are the Inverse Distance Weighting (IDW), the Nearest Neighbor Interpolation, Splines and Kriging. This description shows similarities with the notion of interference cartography and specifically with its construction process providing a given set of interference measurements. Thus, we propose to test the Kriging method for the interference cartography, which is

a reliable and simple spatial interpolation technique, widely used in various domains [55].

Kriging is a well-known spatial interpolation technique, often used in geostatistics - the statistics dedicated to geographical domains such as environmental science, meteorology and mining exploration.

Kriging was first used by a mining engineer Krige [55] for the establishment of mining maps based on scattered measurements. This technique is a linear spatial interpolation method, generally referred with the acronym B.L.U.E: Best Linear Unbiased Estimator. In fact, Kriging assumes that the missing values can be estimated with weighted linear combinations of the available neighboring values. Computation of the Kriging weights are based on the relation between the observed values, expressed through the spatial autocovariance function. Besides, this interpolation technique yields a zero mean residual error (unbiased property) and minimizes the error variance. The only condition for the applicability of this technique is the first and second order stationarity of the considered data. This means that the mean and the variance functions of the observations depend only on the distances between them but not on their specific localizations.

Mathematically, Kriging calculates the estimation \hat{f} of the unknown value of a function f at the location u_p based on the available values of this function in the neighboring locations $\{f(u_i)\}_{i=1}^K$ [56]. This is expressed through a weighted linear combination. The vector u_i denotes the localization of the data. In case of two dimensional data $u_i = (x_i, y_i)$.

$$\hat{f}(u_p) = \sum_{i=1}^K w_i \times f(u_i) \quad (2.2)$$

w_i corresponds to the Kriging weights and depend on the spatial correlation between the considered data samples. Thus, the calculation of the weights involves an entity called as the semi variogram. A variogram quantifies the relationship between the average field value differences at different locations and the distance separating them. The semi variogram is defined as:

$$\gamma(h) = \frac{1}{2} \text{var} [f(u_1) - f(u_2)] \quad (2.3)$$

where $u_2 - u_1 = h$, $\{u_2, u_1\}$ refer to two different locations and h is the distance separating them. The main advantage of using the variogram is that it is independent of the mean value of the data contrary to the covariance function. Three main types of Kriging are identified as follows:

1. Simple Kriging where the random variables are stationary with known mean,
2. Ordinary Kriging where the random variables are stationary with unknown mean,
3. Universal Kriging where the random variables are not stationary.

Ordinary Kriging is probably the most appropriate spatial interpolation technique for the interference cartography. Here, the considered cartography has the form of a two dimensional grid. We assume that there are N located interference measurements available $\{m_i\}_{i=1}^N$. The aim of Kriging is to estimate the interference values in the unobserved locations within the target map $\{m_i\}_{i=1}^{N_{total}}$.

Due to practical considerations, we propose to apply an ordinary Kriging version developed by Sidler [56]. In [56], the Kriging interpolation is proposed with Von Karman covariance model [57] instead of the usual semi variogram function. The corresponding auto covariance function is:

$$C(h) = \frac{\sigma^2}{2^{v-1}\Gamma(v)} (h/a)^v K_v(h/a) \quad (2.4)$$

where h is the distance separating two locations, Γ is the gamma function, K_ν is a modified Bessel function of order $0 \leq \nu \leq 1$, σ is the variance and a is the correlation length (which stands for the distance beyond which the points are no more correlated).

The semi variogram function can be obtained from the auto covariance function with the following relation:

$$\gamma(h) = C(0) - C(h) \quad (2.5)$$

The Kriging interpolation includes the number of available neighboring observations K in the calculation of the missing values at the unobserved locations (Equation 2.2). This parameter K influences considerably the performance of the spatial interpolation. Thus, a trade off has to be made for the number of neighborhood points involved in Kriging weight calculation. A high number leads to an increased computational cost whereas a low number will probably deteriorate the performance of the interpolation. The parameter K is highly related to the nature of the data and is generally set between 12 and 32.

The performance evaluation of the Kriging interpolation can be realized through the calculation of the average error m_p and its variance δ_p , expressed as follows:

$$m_p = \frac{1}{p} \sum_{i=1}^p (\hat{f}(u_i) - f(u_i)) \quad (2.6)$$

$$\delta_p = \frac{1}{p} \sum_{i=1}^p (\hat{f}(u_i) - f(u_i) - m_p)^2 \quad (2.7)$$

The parameter p refers to the number of estimated interference values using the Kriging method.

2.6.1.2 Simulation results

In this section, we present the results of applying the Kriging interpolation technique on an example of interference cartography, obtained through a wireless network simulator. The simulator yields the interference value that a mobile terminal is subject to, at a given location of the area of interest. In this way, we can obtain a map whose mesh points contain the experienced interference levels over a predefined region. Towards this end, we have worked with a mobile network simulator developed in Orange labs (described in Section 2.4.1), which is dedicated to the evaluation of quality of service indicators on several radio access technologies (such as UMTS, GSM and WLAN).

Here, we focus on the interference cartography of a simulated UMTS network in static mode (i.e. Monte Carlo snapshots), providing 3G voice service. The considered cartography is divided into meshes of size $25m$ and the total interference is calculated for each mesh. The interference value stands for the total interference I_{tot} perceived by a probe mobile at a given location. I_{tot} is calculated as:

$$I_{tot}(i) = I_{intra}(i) + I_{inter}(i) + P_N \quad (2.8)$$

where:

- $I_{intra}(i)$ is the intra cellular interference, originating from communications of the same cell i , and caused by the non-ideal orthogonality of the intra-cell multiple access,
- $I_{inter}(i)$ is the inter cellular interference, caused by the adjacent cells ($j \neq i$),
- P_N is the thermal noise.

Figure 2.11 presents an example of interference cartography of dimensions $2500 \times 2500m$. The unit of the interference is dBm . Generally, high interference values correspond to the cell edges.

To test the Kriging interpolation method, we extract a sub-cartography with a limited proportion of the initial cartography data. For reasons of simplicity, we have extracted the sub-cartography through regular sampling. For example, the proportion 25% is obtained by taking one out of every four samples in both x - and y -axes. In this example, the initial grid has the dimensions $100 \times 100m$ samples (Figure 2.11). With a reduction to 6.25%, we have a sub-cartography of dimensions 25×25 samples. The goal of the Kriging is to perform efficient spatial interpolation on the sub-cartography so as to obtain a high similarity between the interpolated and original cartographies.

Applying the Kriging interpolation method with $K = 16$ and $\nu = 0.98$ (see Equations 2.2 and 2.4) yields the interpolated and the error cartographies of Figure 2.11.

The corresponding mean error is 0.0188 and the error variance is 1.4704. This shows the efficiency of the Kriging interpolation technique for the construction of complete interference cartography from a limited set of located interference measurements.

Figure 2.12 presents the error mean and variance for different reduction percentages. It shows that the error is inversely proportional to the amount of reduction. This is an expected result as a high reduction requires more interpolation and induces more errors. These preliminary results demonstrate that the Kriging interpolation method is a valid solution for the construction of the interference cartography given a partial database of localized measurements.

2.7 Recursive IC construction scheme

Compared to the fixed construction procedure described in Section 2.6, the recursive scheme includes a loop that permits to determine and request additional measurements from the network in order to reach the target IC quality.

2.7.1 Exploratory measurement analysis

In this section, we focus on the measurement analysis procedure, handled by the network on the set of available located measurements at time t , within a given spatial area A . The analysis of this data is done through a spatial point pattern representation $\{s_i\}_{1 \leq i \leq N}$ where each s_i denotes the location of each measurement and N is the total number of available measurements within the area of interest A . In case of two dimensional space, the locations are identified according to a pre-defined coordinate system with a couple of parameters $\{x_i, y_i\}_{1 \leq i \leq N}$.

We suppose that the confidence on the measurement operation is similar for all the locations, thus leading to measurements with the same error approximation. Upon this hypothesis, we consider an unmarked spatial point pattern. In other terms, we are only interested in the locations of the measurements. The main role of the module "Measurement Analysis" of Figure 2.9 is to analyze the available data set and to evaluate their spatial distribution and its impact on the quality of the IC construction. Additionally, this procedure is necessary for the determination of the locations of missing measurements for the production of a complete IC with the target quality. The identified measurement needs are demanded through the Measurement Collection Requests, sent to the Measurement Collection Module.

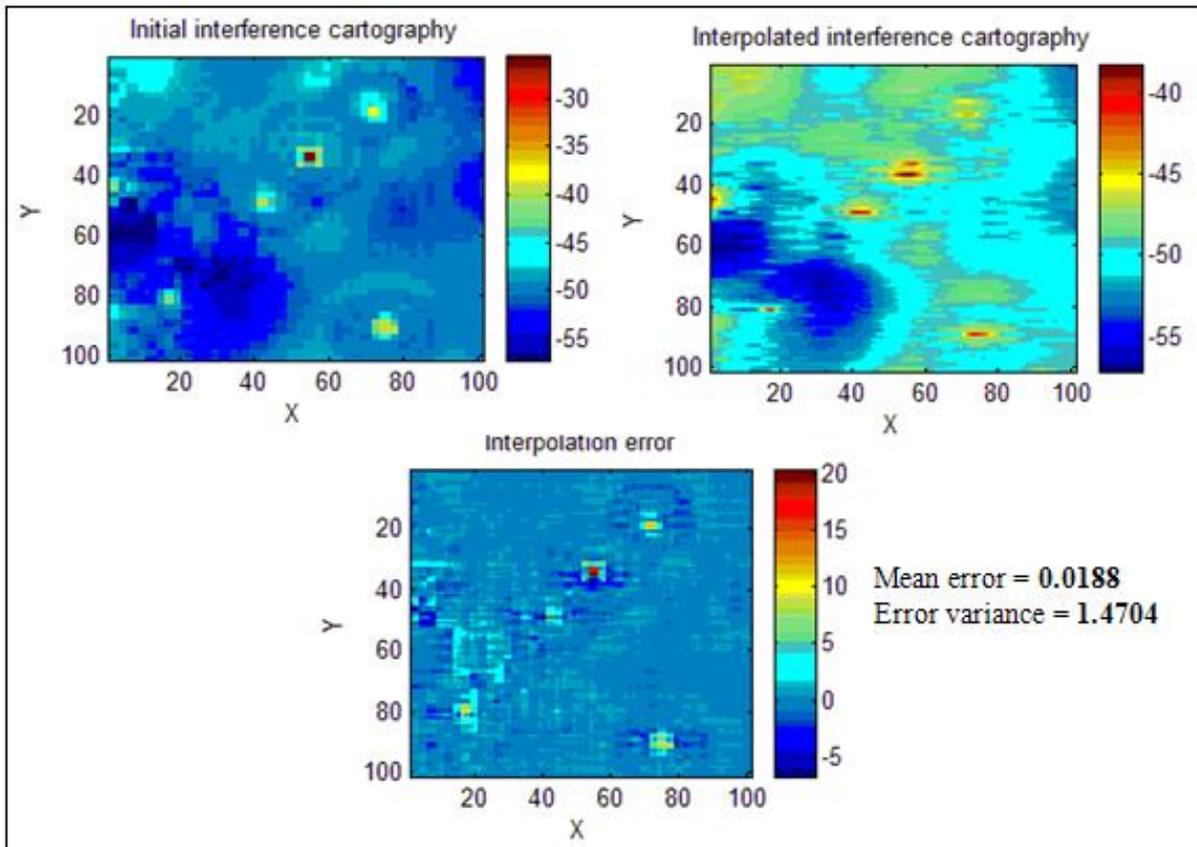


Figure 2.11: Kriging interpolation of interference cartography.

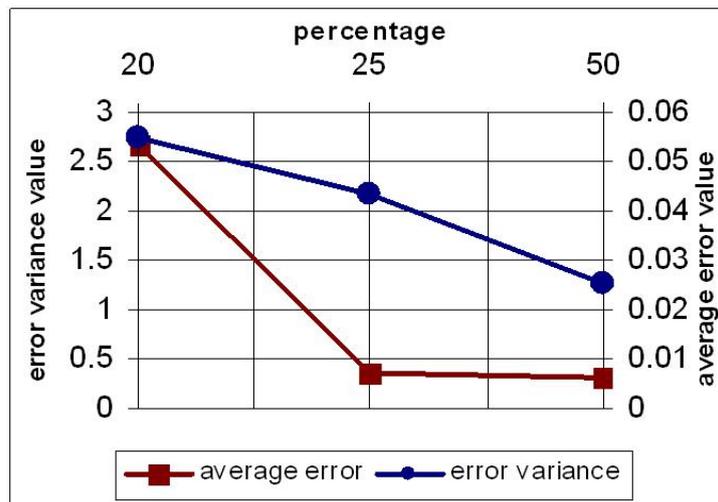


Figure 2.12: Spatial interpolation evaluation.

The combination of radio measurements with their corresponding location information induces the necessity for the network to manipulate spatially referenced data. This is relatively

novel and challenging as it requires: 1-the definition of new Radio Resource Management (RRM) algorithms that handle localization, and 2-the development of appropriate processing methods on the spatial patterns. The latter requirement evokes the use of spatial statistics because spatial statistics provides a large set of tools for exploring and manipulating spatially referenced data.

Thus, to carry out the preliminary analysis of the measurement data, we propose to use exploratory methods coming from spatial statistics on located interference measurements. The spatial exploratory methods detailed in this section can also be applied for other radio measurements than the interference, as they process only the location information.

An example of an unmarked point pattern based on real measurements is depicted in Figure 2.13. It represents the locations of received power measurements ($CPICH_Ec[dBm]$) on the map of Paris (16th arrondissement). This point pattern corresponds to a real measurement campaign made in Paris for the IC study, with a single trace mobile. It can be seen that the measurements are located across the streets of the considered test area. In realistic scenarios, the measurements are made by numerous mobile terminals (or other network entities) spread across the area of interest and will not necessarily lie only along the streets. They can be indoor, in-street, in-parks etc.

The exploratory data analysis methods that are tested on measurement locations are gen-

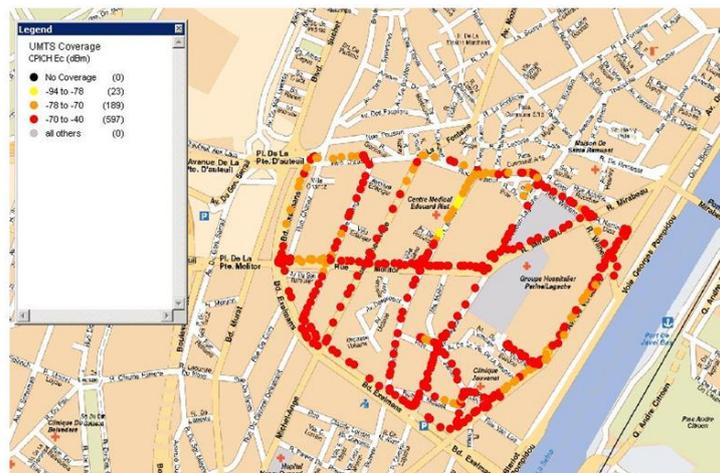


Figure 2.13: Example of a real point pattern.

erally called *functional summary statistics*. These statistics extract the main characteristics and properties of the observed spatial point patterns. Therefore, the results obtained from these statistics can guide us to determine the appropriate model and the corresponding parameters that fit the observed data set.

Usually, the first step in the exploratory analysis of spatial point patterns is to test whether it corresponds to a *Complete Spatial Random* (CSR) process. The CSR process is defined as a realization of a *Homogeneous Poisson* (HP) process. The HP process that is considered here as a reference model, is defined as a point process satisfying two conditions:

1. The number of points within a spatial area A follows a Poisson distribution characterized

by the rate parameter $\lambda|A|$ (with $|A|$ referring to the area of A and λ is the mean number of points per unit area, generally called as the intensity),

2. The point is spread out independently within the considered spatial area A . This is equivalent to saying that the numbers of points in separate regions are independent.

Based on this definition, the CSR process characterizes the spatial point pattern where the points are scattered independently over the spatial area, implying a random spatial dispersion. Thus, we can make use of the CSR tests to deduce if the observed points are randomly located or not. Generally, the CSR tests also allow us to verify some additional properties of the observed point patterns, namely *clustered* and *regular* patterns.

The functional summary statistics that test the CSR hypothesis are divided into two main categories:

1. First order analysis methods (such as the empty space function and the nearest neighbor distance distribution function),
2. Second order analysis methods (such as the Ripley's K -function and the pair correlation function).

These methods are based on the inter-point distance r between different points. The functional summary statistics evaluate the dispersion and the interaction between the points within the area of interest.

In this work, we apply the *Ripley's K-function* which is a static tool frequently used for spatial analysis and particularly for inter-point dependence [58]. Its method is summarized by the K -function expressed as:

$$K(r) = \frac{|A|}{n^2} \sum_i \sum_{j \neq i} \Pi(d_{ij} \leq r). \quad (2.9)$$

where A stands for the study area, n is the total number of points in A and $\Pi(\cdot)$ is an indicator that equals to 1 if its argument is true and 0 otherwise. Thus, this method estimates the number of surrounding points of each point of A within a circle of radius r .

A Homogenous Poisson (HP) process corresponds to a complete spatial randomness and its corresponding K -function is:

$$K(r) = \pi r^2. \quad (2.10)$$

With this in mind, we use the indicator $L(r)$ to analyze a point process pattern and test its 'randomness' with respect to the complete spatial randomness of the HM process [58].

$$L(r) = \sqrt{K(r)/\pi} - r. \quad (2.11)$$

If $L(r) = 0$, then the point pattern is assumed to be completely random. If $L(r) > 0$, this suggests aggregations between the points and then the point pattern is assumed to be clustered. On the contrary, $L(r) < 0$ implies repulsion between the points and thus the point pattern is assumed to have a regular scheme.

2.7.2 Estimation of additional measurement requests

The exploratory data analysis phase provides a first insight on the dispersion of the available measurements over the study area. The obtained characteristics (intensity, regular/random/clustered etc.) are then used to decide on the appropriate processing of the measurement dataset. The proposed processing scheme has a recursive functioning with the ability to determine and request additional measurements in order to obtain a complete cartography with the target quality.

After the exploratory measurement data analysis, we propose different treatments depending on the exploration result (Figure 2.14):

1. If the observed point pattern is evaluated as *regular*, then we propose to calculate the periodicity of the spatial pattern. It corresponds to the mean estimate of the separating distance between the located measurements. This distance is called d_r . The calculated parameter d_r is then compared to a threshold value $d_{threshold}$. This threshold value refers to the target IC average mesh size. If $d_r \leq d_{threshold}$ then the target cartography periodicity is guaranteed and there is no need for additional measurements. On the contrary, when $d_r > d_{threshold}$, then we need additional located measurements to reach the target IC quality. The additional measurements are requested in-between the currently existing data points so that the target IC periodicity is guaranteed.
2. If the observed point pattern is evaluated as *aggregated/clustered*, it means that the available measurements tend to be located close to each other and to form groups. In this case, we propose to proceed with a clustering procedure to delimit the different aggregated located measurements. Consequently, we evaluate the attributes of each cluster within the interest area, namely the centroid and the radius. Thereafter, we estimate the mean distance d_c separating the centroid of each cluster, as well as the mean inter-point distance d_i within each cluster. As in the regular pattern case, we perform a comparison of d_c and d_i with the threshold value $d_{threshold}$ to estimate whether the network will request additional located measurements or not.
3. If the observed point pattern is evaluated as *approximately random*, then it is not very easy to determine where to request additional measurements to reach the target IC quality. Nevertheless, we estimate the mean and the variance of the inter-point distance d_i and compare it to the threshold value $d_{threshold}$. If the variance value is low and $d_i \leq d_{threshold}$, then we assume that the target IC quality is reached. Otherwise, we recommend that the network requests located measurements all over the area of interest A .

It is important to mention here that the flowchart depicted in Figure 2.14 can be applied in contexts other than the IC. For example, the exploratory data analysis can be applied to resource management mechanisms in any radio access technology. In current wireless networks, the measurements are generally requested periodically or in an event-triggered manner, with no consideration of their locations. However, by using the exploratory procedure on located measurements, the network can make more efficient measurement requests. The main advantage of this action is the decrease of signaling overhead on the network side and battery saving on the terminal side.

2.7.3 Example of application

In this section, we propose a case study that demonstrates the recursive interference cartography construction, based on real interference measurements collected during a measurement

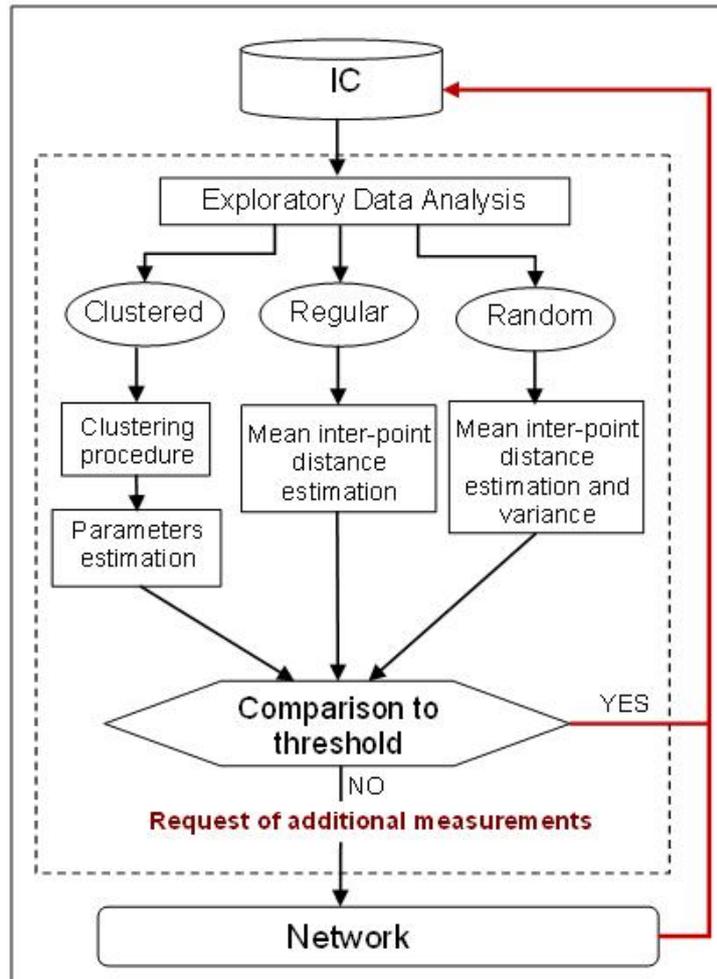


Figure 2.14: Recursive interference cartography construction.

campaign in Paris, described in Section 2.4.2. These measurements are picked with a scanner on UMTS bands. It provides the total perceived interference at each location and on a given frequency band (corresponding to a scrambling code).

The location information is provided by a Global Positioning System (GPS). For practical reasons, we convert the angular coordinates (*latitude, longitude*) to rectangular coordinates (x, y) to facilitate the processing of the measurements. We choose the projection "Lambert II extended" which is a reference coordinate system valid for whole France.

Figure 2.15 presents our case study. It depicts the positions of the available measurements over the area of interest. As a first step, we carry out the exploratory data analysis (Ripley's K-function) that processes the locations of the available measurements.

Figure 2.16 shows the calculated $L(r)$ function defined in Equation 2.11. The positive values ($L(r) > 0$) prove that the considered point pattern is aggregated/ clustered as it is expected.

Following the recursive scheme depicted in Figure 2.14, we perform a clustering operation on the data in order to delimit the different aggregated regions. For this purpose, we use the k-means clustering method. It first determines the centroid of each cluster. Then, each point in the dataset is associated with the nearest centroid based on the minimum distance method.

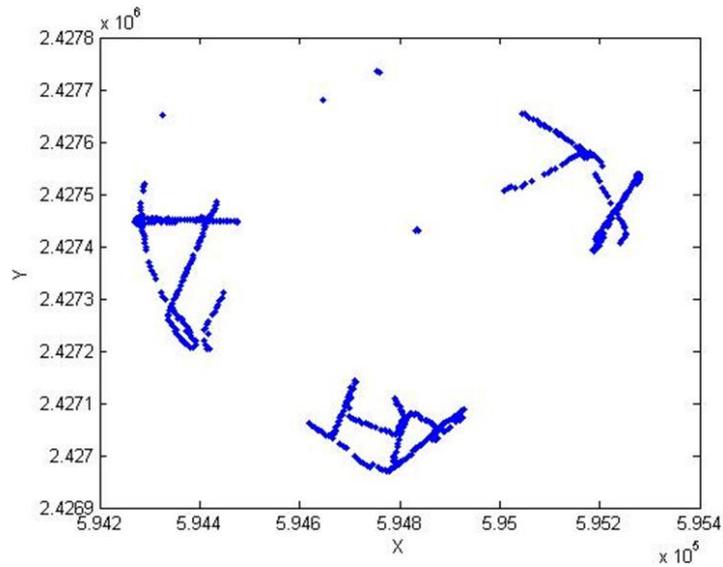


Figure 2.15: Measurement locations of the case study.

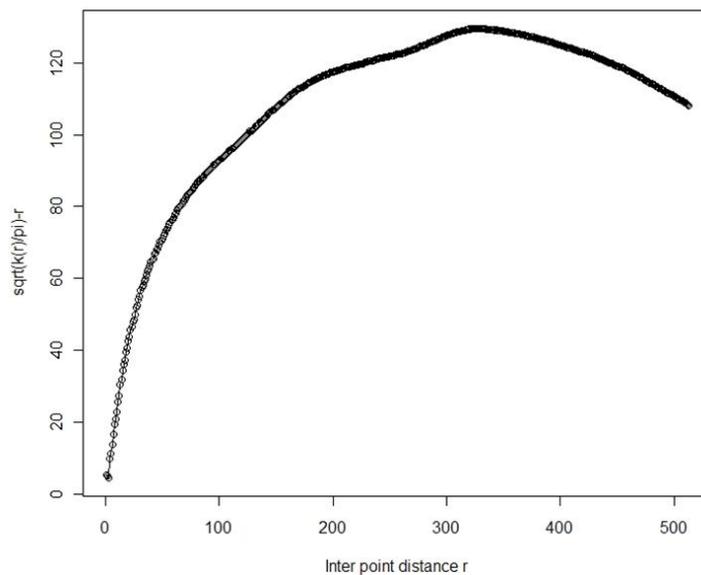


Figure 2.16: Ripley's K function test.

This leads to the final clusters depicted in Figure 2.17.

Once the clusters have been determined, we can proceed with performing intra-cluster interpolation for each cluster. Kriging can be one of the interpolation techniques used for this purpose, as proposed in Section 2.6.1. For inter-cluster data, new measurement data is requested from the network.

To test the efficiency of the kriging interpolation, we extract from each cluster a set of measurements, referred as validation data in Figure 2.18. Thereafter, the spatial interpolation is performed on the rest of data. Finally, the validation data are compared to the interpolated val-

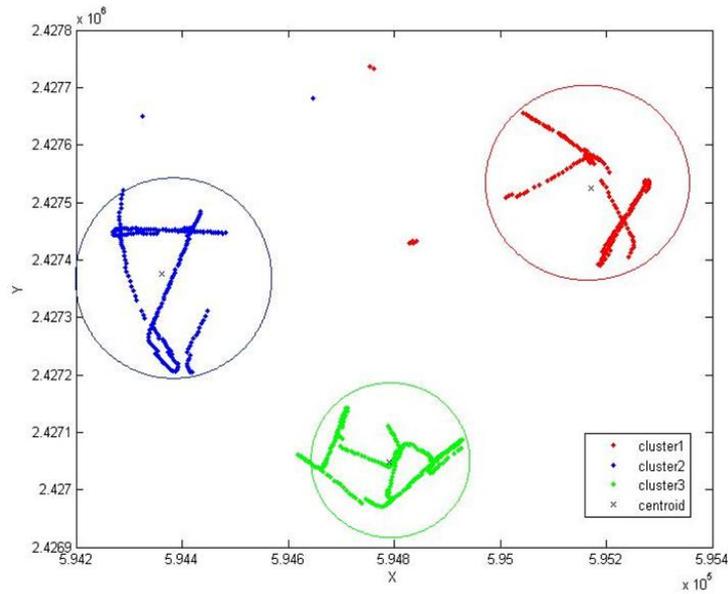


Figure 2.17: Clustering operation.

ues. The corresponding interpolation errors (mean values) are depicted in Figure 2.19 for each cluster. It shows that the kriging yields promising results for the construction of an Interference Cartography from a limited set of available measurements.

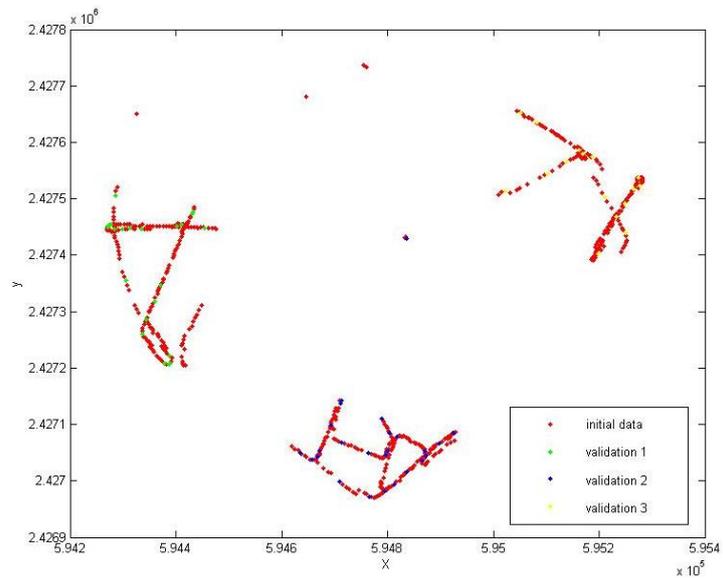


Figure 2.18: Test and validation samples.

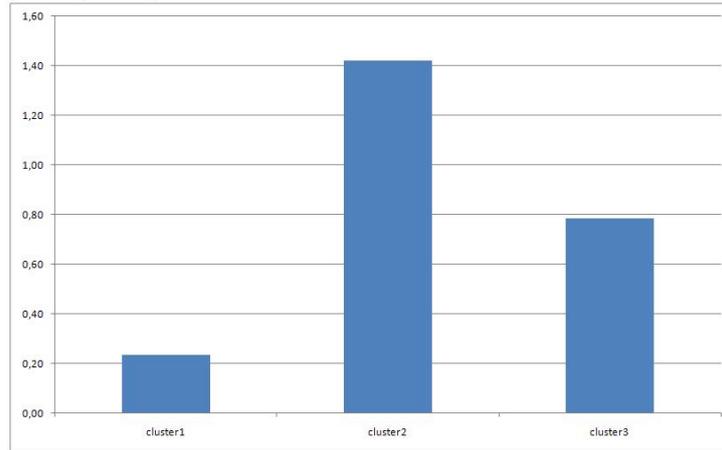


Figure 2.19: Kriging interpolation error.

2.8 Case study

We consider a case study that demonstrates the use of interference cartography in a dynamic spectrum access context. Figure 2.20 indicates the positions of primary receivers $\{PR_i\}_{i=1}^5$ as well as the locations of the secondary transmitter ST and its intended secondary receiver SR . The goal is to determine if it is possible to establish a communication between ST and SR in an opportunistic manner, given the interference cartography and the locations of the primary receivers in Figure 2.20. The mesh size of this interference cartography is $25m$. Table 2.3 indicates the locations of the secondary and primary users in mesh indices, over the area of interest.

We assume that the transmit power of ST is $21dBm$, which corresponds to the maximum

Table 2.3: Primary and secondary users' locations.

	ST	SR	PR_1	PR_2	PR_3	PR_4	PR_5
Location	(30,50)	(70,70)	(10,45)	(30,90)	(50,15)	(85,35)	(90,90)

allowed transmitted power in UMTS. At the receiver side, the received power (in dBm) is calculated as the attenuated transmitted power:

$$P_{received} = P_{transmitted} - L \quad (2.12)$$

The attenuation factor L is due to the propagation of the radio signal. It is the sum of three factors: the pathloss, the shadowing and the fast fading. In wireless networks, this attenuation is generally calculated using sophisticated propagation models, depending on the external environment. In this case study, we use the attenuation expression (in dB) that corresponds to the COST231 Hata model used for the urban environments:

$$L = 82 + 35 \times \log_{10}(d) \quad (2.13)$$

where d refers to the distance between the transmitter and the receiver expressed in km .

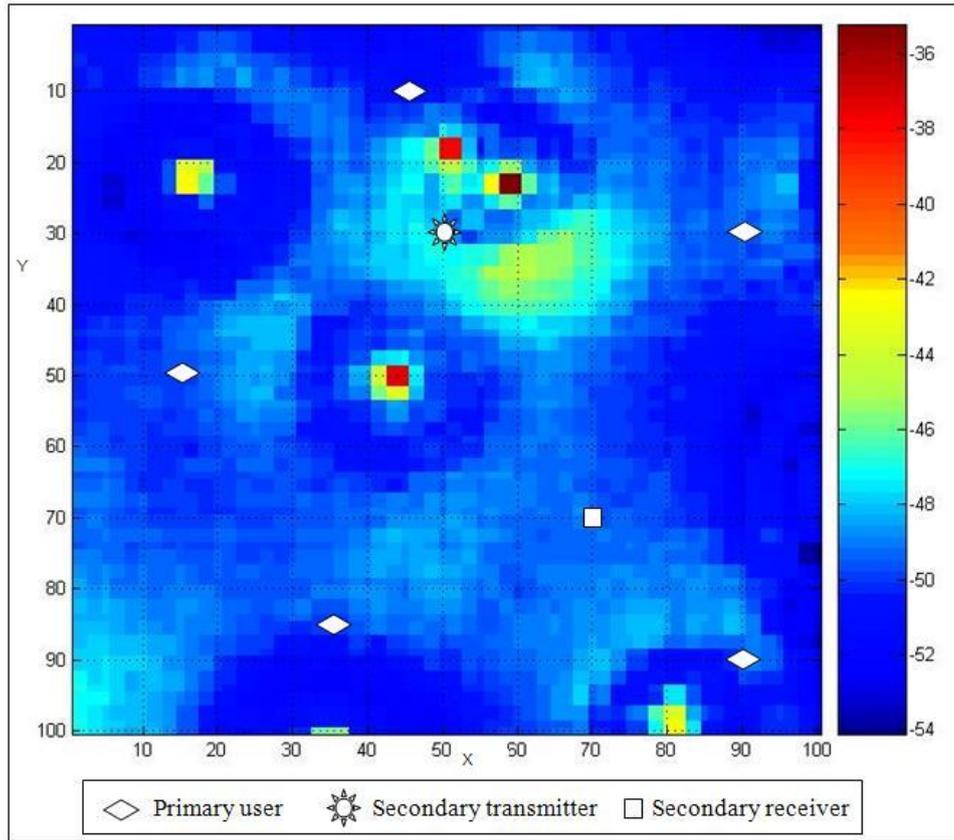


Figure 2.20: Case study: interference cartography with positions of primary and secondary users.

Two conditions must be verified to allow communication between the secondary transmitter ST and receiver SR . The first condition is relative to the secondary receiver, whereas the second condition concerns the primary receivers.

1. At the secondary receiver side, we need to guarantee a sufficient received power level so that SR has a good quality of received signal. Formally, this condition is equivalent to the signal-to-interference ratio being superior to a threshold value at the location of SR :

$$\left(\frac{C}{I}\right)_{SR} \geq \left(\frac{C}{I}\right)_{threshold} \quad (2.14)$$

with

$$\left(\frac{C}{I}\right)_{SR} = \frac{P_{SR}}{I_{(i,j)}} \quad (2.15)$$

where (i,j) refers to the coordinates of SR , P_{SR} is the received power at SR and $I_{i,j}$ is the total interference value at location (i,j) .

The attenuation factor L is calculated based on the distances on Figure 2.20: $L = 83.69dB$. As $P_{SR} = P_{ST_1} - L$, then $P_{SR} = -62.69dBm$. The corresponding interference value available from the interference cartography is $I_{(i,j)} = -49.07dBm$. Consequently, the signal to interference ratio of SR is $-13.62dB$.

2. The second condition for the secondary spectrum usage is that the communication between ST and SR does not provoke harmful interference to the primary receivers within the area of interest. In other terms, the sum of the interference generated by the SU and the interference value in the cartography at primary receiver's location does not exceed the maximum allowed value I_{max} .

Thus, the supplementary interference generated by the communication between ST and SR is calculated, and a new cartography that integrates this communication is built. In each mesh (x,y) of the cartography, the new interference value is calculated as:

$$I_{(x,y)}^{new} = I_{(x,y)}^{old} + P_{transmitted} - L \quad (2.16)$$

$$L = 142 + 35 \times \log_{10}(r) \quad (2.17)$$

$$r = \sqrt{(x_r - x_t)^2 + (y_r - y_t)^2} \quad (2.18)$$

r denotes the distance separating the secondary transmitter ST and the considered mesh location (where a primary receiver can be located).

Figure 2.21 shows the updated interference cartography after the communication is established between ST and SR . Table 2.4 indicates the interference values perceived by the primary and secondary users, before and after the communication establishment between ST and SR .

If the maximum allowed interference value for the primary user is $I_{max} = -45dBm$, then the communication between ST and SR will generate an interference inferior to the tolerable limit for all the primary receivers. Consequently, the secondary spectrum usage is allowed between ST and SR , given the transmitted power of ST and the locations of the surrounding primary receivers.

Table 2.4: Interference values for primary and secondary users before and after the communication between SR and ST .

	ST	SR	PR_1	PR_2	PR_3	PR_4	PR_5
Before	-47.22	-49.07	-51	-49.42	-49.87	-49.90	-49.39
After	∞	-48,89	-47,95	-49,13	-49,56	-49,80	-49,35

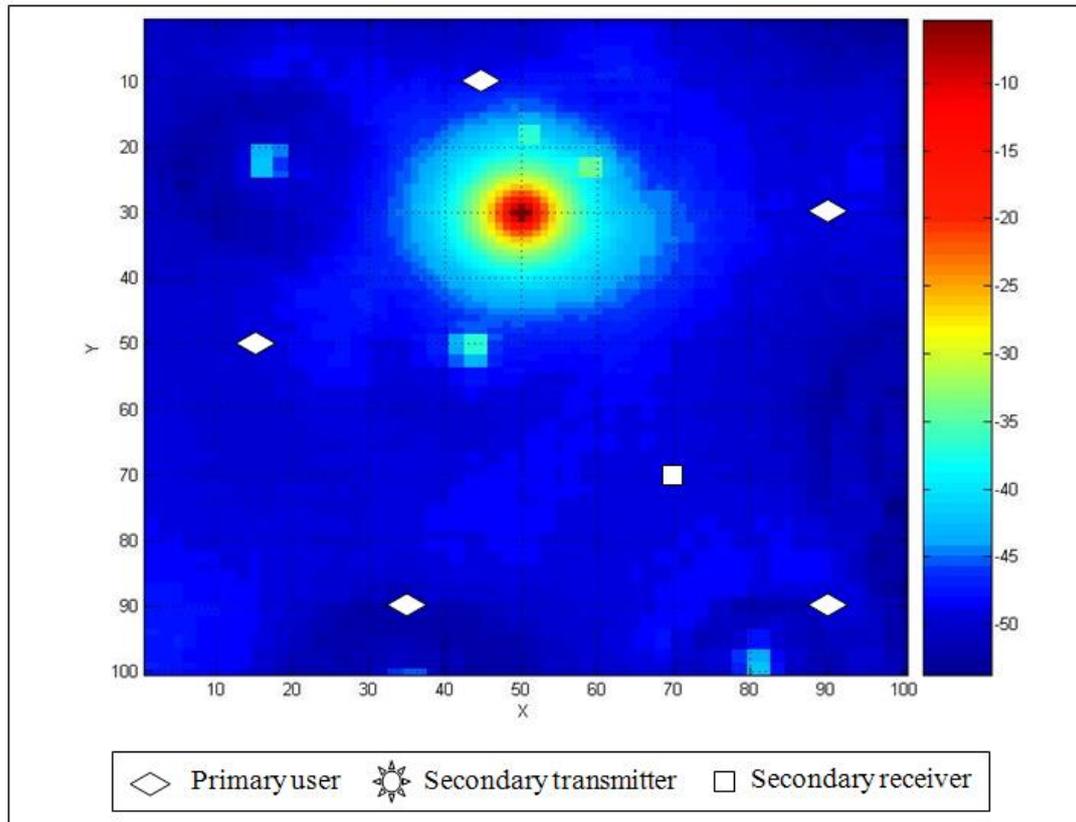


Figure 2.21: Updated interference cartography.

2.9 Conclusion

In this chapter, we introduced the notion of interference cartography. It is a novel concept that involves combining measurements coming from different radio network entities together with their corresponding geo-location information, and applying effective spatial interpolation techniques to obtain a complete map that indicates interference levels at each mesh point over the area of interest.

The Interference Cartography constitutes a valuable tool that provides awareness on the overall status of the radio environment leading to effective autonomous decisions in a cognitive context. Its utilization in a secondary spectrum usage permits the secondary network to be aware of local interference tolerance levels so that it becomes possible to detect, identify and use spectrum opportunities without disturbing the primary or other secondary users.

In this work, we propose a complete framework that investigates the different topics related to the IC implementation, as well as the elaboration of efficient construction procedures given a limited set of available measurements.

Thus, a possible network implementation of interference cartography is thoroughly described, including architectural and protocol structures in Section 2.5, where we define two additional network entities responsible for the management and the exploitation of the interference cartography: the IC manager and the Network Spectrum Manager (NSM).

The effective construction procedure of the interference cartography is an important issue for a reliable utilization in an opportunistic spectrum access context. To this goal, we investigate the fixed and the recursive IC construction schemes. The fixed procedure stands for the static method that can be applied to obtain an IC from a set of available localized measurements (Section 2.6). As an example, we propose to perform a spatial interpolation to compute the missing values. Consequently, we test the kriging interpolation method on spatial interference data obtained from a radio network simulator. The results show that the kriging is a valid solution for the construction of the IC given a partial database of localized measurements.

To enhance the final IC quality, we propose to perform a recursive construction scheme (Section 2.7). It corresponds to the addition of a loop to the fixed scheme that allows the IC manager to determine and request additional measurements from the network in order to reach the target IC quality. Application of the proposed scheme on real UMTS measurements reported by a scanner on a Parisian district has yielded promising results. This shows that the concept of IC with the proposed recursive exploratory data analysis procedure constitutes a viable solution to interference management in cognitive networks.

Based on these results, a case study that uses the IC to analyze the status of the radio environment and to decide on how to carry out the hierarchical access is also presented. The case study results reveal the utility and effectiveness of the IC in a cognitive context. This case study investigates a static scenario where temporal variations have not been taken into account. Further research should look into a dynamic scenario where temporal considerations are accounted for. Such a study will include spatio-temporal signal processing techniques to construct and to update the cartography as well as propositions for triggering and iterative update algorithms in the protocol structure.

Chapter 3

Multi Armed Bandit for Opportunistic Spectrum Access

3.1 Introduction

The way spectrum is being used in wireless communications has recently become a hot topic of debate and an emerging research topic in the wireless community. With the growing demand for broadband services and the increasing variety of wireless devices and applications, it becomes crucial to find more sophisticated and intelligent solutions that increase spectral efficiency in wireless networks. In this context, the scarcity of radio spectrum is an important issue that necessitates considerable research efforts.

Since the early days of wireless mobile networks, the frequency bands have been assigned to different technologies and operators in a static and fixed manner, excluding an adaptation to changing conditions and needs. Several measurement campaigns [59], conducted in different times and places, have proved that spectrum resources are not efficiently exploited. In other words, the traffic load is not evenly distributed between different parts of the spectrum: some frequency bands are underutilized whereas others are congested. Therefore, research has focused on new concepts and models to improve spectrum utilization. Opportunistic Spectrum Access (OSA) is one of such novelties [4] that allows secondary users to take advantage from the unused portions (i.e. white spaces or spectrum holes) of the radio spectrum, in order to increase the overall spectral efficiency.

The main issue in opportunistic spectrum access is the detection of the unused portions (white spaces) of the radio spectrum on a temporal-spatial plane and the utilization of such portions without deteriorating the quality of the primary users. Detection of white spaces involves the challenge of finding a good compromise between:

1. Exploration of the wireless environment to get information on the utilization of the radio spectrum,
2. Exploitation of the cumulated information to detect white spaces for data transmission.

This tradeoff is widely known as the exploration-exploitation tradeoff that already exists in problems of other domains. Multi-armed bandit (MAB) (first proposed by Robbins in [60])

is one of such problems encountered in computer science. The similarity between the MAB problem and the detection of white spaces in opportunistic spectrum access is discerned recently [61] and the ad-hoc reinforcement learning methods proposed for the former prove to be efficient solutions for the latter. These 'bandit' methods consist of deterministic strategies (i.e. Upper Confidence Bound algorithms) as well as randomized strategies (i.e. ϵ -greedy, Softmax, Adaptive Pursuit etc.) [62]. They provide the opportunistic user with a policy (or allocation strategy) that defines the rules as to how the user should decide on his choices and actions so as to reach a predefined objective.

In the first two parts of the thesis, we focus on the processing of radio measurements in wireless mobile networks, so as to optimize the radio resource management procedures. This includes 1- the processing of the existing radio measurements with non-parametric regression and smoothing methods and 2- the proposal of an interference cartography that combines the radio measurements with the corresponding location information.

In this final part of the thesis, we consider the channel access mechanism for the achievement of opportunistic spectrum access. Thus, we develop a complete framework that deals with the application of the Multi Armed Bandit formulation for the achievement of efficient opportunistic spectrum access. The study includes the tests of different MAB strategies on an IEEE802.11 channel model, the automatic tuning of the MAB algorithms to cope with dynamic channel occupation and finally presents a use case scenario within the IEEE P1900.4 standard.

3.2 Theoretical presentation of the Multi-Armed Bandit Problem

The Multi Armed Bandit (MAB) problem, first described in [60], is a well-known problem in machine learning that translates *the gambler dilemma* in a casino [63]. The gambler is faced with K slot machines (also called as *the bandit arms*) and he has to choose which arm to pull at each time step so as to maximize his overall gain at the end of N plays (Figure 3.1). Here, the main challenge is that the casino machines are all different, each one having a different gain distribution unknown to the gambler. Consequently, the gambler plays with the casino machines and tries to find the best arm (which is the arm generating the highest gain) at each time step t . In other terms, the gambler has to make a tradeoff between:

1. Exploring different arms so as to learn their gain distributions,
2. Exploiting the gathered information so far to play with the best arm as much as possible, in order to maximize his overall gain at the end of N plays.

In this context, one can imagine an alternative solution where the gambler finds, after a few number of trials, the arm that offers an acceptable gain and then keeps on playing with this arm during the rest of the time. However, it is clear that this solution does not lead to the maximum gain at the end as the gambler can clearly miss other arms offering more important gains. Offering solutions that target overall gain maximization, the MAB formulation provides the gambler with strategies and rules to reach his final goal of gaining the maximum amount of money at the end of the plays.

Formally, the MAB problem is equivalent to a one-state Markov decision problem where at each time step t , a decision maker selects a random variable k (i.e. the bandit arm) and gets a reward in return that corresponds to the gain obtained by performing the action of selecting the random variable at this time step. In the gambler example, the reward is the amount of money

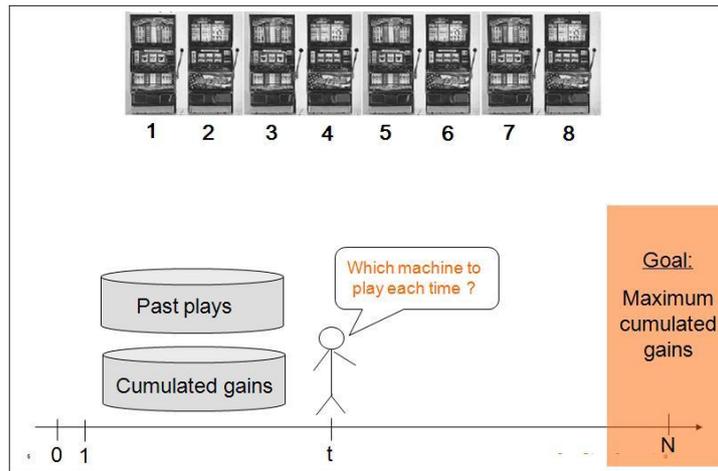


Figure 3.1: Representation of the gambler dilemma in a casino.

gained after playing a given arm, at a given time step.

The solution of the Markov decision problem is to establish a policy A which is defined as the set of rules that the decision maker must follow in order to maximize an objective function (generally the maximization of his overall gain). A policy is in the form of an algorithm (called as a *bandit algorithm* or a *bandit strategy*) that determines the next bandit arm to choose at time step t , based on past plays and the corresponding past rewards. The decision maker may not choose the best bandit arm at each time step. This is motivated by the wish to explore other arms, not necessarily the best, so as to increase its knowledge on the reward distribution of the arms and maximize the cumulated reward at the end of the plays.

Denoting the K reward distributions by (r_1, r_2, \dots, r_K) and their mean values by $(\mu_1, \mu_2, \dots, \mu_K)$, the *cumulative reward* obtained by the bandit strategy A at time step n , S_n^A , is expressed as:

$$S_n^A = \sum_{t=1}^n r_A(t) \quad (3.1)$$

where $r_A(t)$ is the reward obtained at time step t by following the bandit strategy A . Generally, the performance of a bandit strategy is evaluated through *the regret function*. The regret associated with a given bandit strategy A after n rounds of plays, R_n^A , is the expected loss induced by following the bandit strategy A compared to the optimal strategy (it is due to the fact that the decision maker doesn't play the best arm at each iteration):

$$R_n^A = \sup_B \{E[S_n^B]\} - E[S_n^A] \quad (3.2)$$

where $E[\cdot]$ stands for the expectation operation and $\sup_B \{E[S_n^B]\}$ is the maximum cumulative reward associated with the optimal strategy.

Different bandit strategies exist that provide approximate solutions to the MAB problem. These strategies can be classified in two main groups: Deterministic strategies and Randomized strategies.

3.2.1 Deterministic MAB strategies

The deterministic MAB strategies identify the best bandit arm to choose (referred as the greedy arm) in a deterministic manner based on a predefined metric, generally including the mean values of the rewards.

In [64], Agrawal defines a family of policies based on the mean value of the reward (calculated as the total sum of rewards gathered so far). More recently, Auer et al. introduced simpler and computationally efficient policies, achieving logarithmic regret uniformly over time rather than asymptotically [65]. These policies are referred as Upper Confidence Bound (UCB) algorithms. The main idea of the UCB is to set an Upper Confidence Bound (UCB) on the expected value of the rewards (referred as $\mu_{j,t}$ for arm j at time step t , thus $\mu_{j,t} \leq UCB$) so that the best arm is promoted with a high UCB. This is achieved through the addition of a bias factor $c_{t,n_{j,t}}$ to the mean value of the reward \bar{x}_j .

Let $x_{j,s}$ be the obtained reward for the bandit arm j at time step s and $n_{j,t}$ denotes the number of times bandit arm j is chosen until time step t respectively. Then, we can write the MAB metric for the bandit arm j at time step t as:

$$\bar{x}_j + c_{t,n_{j,t}} \quad (3.3)$$

Where

$$\bar{x}_j = \frac{1}{t} \sum_{s=1}^t x_{j,s} \quad (3.4)$$

and

$$c_{t,n_{j,t}} = \sqrt{\frac{2b^2 \log(t)}{n_{j,t} \times (t-1)}} \quad (3.5)$$

$c_{t,n_{j,t}}$ is the bias factor for rewards in the interval $[0,b]$.

At each time step t , the MAB algorithm chooses the bandit arm with the highest index value. This corresponds to two different situations:

- the bandit arm has the highest estimated mean reward value \bar{x}_j ,
- the bandit arm has a big uncertainty and thus needs to be chosen to enhance our knowledge about its reward distribution. In fact, a low value of $n_{j,t}$ translates the fact that the channel j has not been explored often until time t .

The UCBT algorithm (Upper Confidence Bound Tuned) was established by Auer et al. in [65] to resolve the MAB problem in stationary environments. The main characteristic of the UCBT is the use of the empirical variance in the bias factor. Thus, the bias factor in the UCBT algorithm is expressed as:

$$c_{t,n_{j,t}} = \sqrt{\frac{2 \times \text{var}(\mu_{j,t}) \times \log(\sum_{j=1}^K n_{j,t})}{n_{j,t}}} \quad (3.6)$$

with $\mu_{j,t}$ the average estimated reward for bandit arm j at time t , K the total number of bandit arms and $n_{j,t}$ the number of times the bandit arm j is chosen until t .

Here, the variance term is introduced to better tune the degree of exploration according to the stationarity of the reward distributions for the bandit arms. Consequently, the exploration is reduced for the arms with small reward variance and, on the contrary, it is increased for arms showing high variations. This calibrated exploration results in the achievement of better

performances for the MAB strategies.

The UCBT strategy is described in details by the Algorithm 1. At the beginning, an initialization stage is necessary to initialize the different parameters of the algorithm. During this stage, each bandit arm is chosen once. Thereafter, the algorithm is run normally: at first, the algorithm chooses which bandit arm to play and then the MAB parameters are updated accordingly. In

Require: Initialization: Choose each bandit arm once

for $t = 1 : N$ **do**

1- Identification of greedy arm g:

$$g = \underset{j=1}{\operatorname{argmax}}^K \left[\hat{\mu}_{j,t} + \sqrt{\frac{2 \times \operatorname{var}(\mu_{j,t}) \times \log(\sum_{j=1}^K n_{j,t})}{n_{j,t}}} \right]$$

2-Parameters update: $\forall 1 \leq i \leq K$

$$s_{i,t+1} = s_{i,t} + \Pi(I_t = i) \times r_{i,t}$$

$$n_{i,t+1} = n_{i,t} + \Pi(I_t = i)$$

$$e_{i,t+1} = e_{i,t} + \Pi(I_t = i) \times r_{i,t}^2$$

$$\operatorname{var}_{i,t+1} = e_{i,t+1} - (s_{i,t+1})^2$$

$$\mu_{i,t+1} = \frac{s_{i,t+1}}{n_{i,t+1}}$$

end for

Algorithm 1: UCBT algorithm.

this algorithm, $r_{i,t}$ denotes the obtained reward after choosing the bandit arm i at time t , I_t is the index of the bandit arm chosen at time t , $n_{i,t}$ is the number of times the bandit arm i is chosen until time t , $\operatorname{var}_{i,t}$ and $e_{i,t}$ are respectively the variance and the standard deviation of the estimated reward for the bandit arm i at time t , $\Pi(\cdot)$ equals 1 if its argument is true and equals 0 if it is false.

The periodic UCBT is a variant of the previous UCBT algorithm where the algorithm parameters used to select the bandit arms are reinitialized every ΔT iterations. Concretely, the reward estimate $\mu_{i,t}$ and the parameter $n_{i,t}$ are set to zero every ΔT time steps so as to force the algorithm to explore the environment periodically.

The discounted UCBT [66] adds a discount factor $\rho < 1$ to the original UCBT algorithm. Formally, after choosing the best channel to access, the parameters are updated according to a discount factor ρ . This factor decreases the effect of past reward estimations, leading to an increase in the exploration of the environment. Nevertheless, it is required to adjust this parameter to achieve a good performance.

3.2.2 Randomized MAB strategies

Contrary to the deterministic strategies, the randomized MAB strategies involve probabilities for choosing the bandit arm at each time step. Examples of randomized strategies are Adaptive Pursuit method, ϵ -greedy method and Softmax method [62].

The ϵ -greedy method is widely used for solving bandit problems in a non-stationary setting [65]. After identifying the greedy channel g with the highest current average reward $\mu_{j,t}$, we choose this channel g with a probability $(1 - \epsilon)$. Otherwise, we choose a random channel with a probability ϵ . A high value of ϵ permits more frequent exploration and leads to often choosing suboptimal bandit arms instead of remaining all the time with the best arm. Thus, ϵ is referred

Require: Initialization: Choose each bandit arm once

for $t = 1 : N$ **do**

1- Identification of greedy arm g

$$g = \underset{j=1}{\operatorname{argmax}}^K \left[\hat{\mu}_{j,t} + \sqrt{\frac{2 \times \operatorname{var}(\mu_{j,t}) \times \log(\sum_{j=1}^K n_{j,t})}{n_{j,t}}} \right]$$

2-Parameters update: $\forall 1 \leq i \leq K$

$$s_{i,t+1} = \rho \times s_{i,t} + \Pi(I_t = i) \times r_{i,t}$$

$$n_{i,t+1} = \rho \times n_{i,t} + \Pi(I_t = i)$$

$$e_{i,t+1} = \rho \times e_{i,t} + \Pi(I_t = i) \times r_{i,t}^2$$

$$\operatorname{var}_{i,t+1} = e_{i,t+1} - (s_{i,t+1})^2$$

$$\mu_{i,t+1} = \frac{s_{i,t+1}}{n_{i,t+1}}$$

end for

Algorithm 2: Discounted UCBT algorithm.

as the exploration parameter. The performance of this algorithm is highly related to the choice of the parameter ϵ .

The Softmax algorithm [62] differs from the ϵ -greedy algorithm in the way it assigns probabil-

Require: Initialization: Choose each bandit arm once

for $t = 1 : N$ **do**

1- Identification of greedy bandit arm g and final arm choice

$$g = \underset{i}{\operatorname{argmax}}(\mu_{i,t})$$

Choose the arm g with probability $(1 - \epsilon)$. Otherwise, choose a random arm with a probability ϵ

2-Parameters update: $\forall 1 \leq i \leq K$

$$s_{i,t+1} = s_{i,t} + \Pi(I_t = i) \times r_{i,t}$$

$$n_{i,t+1} = n_{i,t} + \Pi(I_t = i)$$

$$e_{i,t+1} = e_{i,t} + \Pi(I_t = i) \times r_{i,t}^2$$

$$\operatorname{var}_{i,t+1} = e_{i,t+1} - (s_{i,t+1})^2$$

$$\mu_{i,t+1} = \frac{s_{i,t+1}}{n_{i,t+1}}$$

end for

Algorithm 3: ϵ -greedy algorithm.

ities to different suboptimal arms. In the ϵ -greedy algorithm, the exploration is accomplished with equal probabilities among suboptimal arms whereas the Softmax algorithm differentiates the choice of the suboptimal arm by defining the probability access as function of the current reward estimate for each arm. Thus, the greedy arm has the highest selection probability and the suboptimal arms are chosen with probabilities weighted according to their reward estimates:

$$P_{i,t} = \frac{e^{\mu_{i,t}/T_e}}{\sum_{j=1}^K e^{\mu_{j,t}/T_e}} \quad (3.7)$$

where the parameter T_e is called the "temperature". High values of T_e lead to equal probabilities between suboptimal channels. On the other hand, low values of T_e increase the difference between the selection probabilities.

The adaptive pursuit strategy [62] is a class of learning methods that could be used to solve

Require: Initialization: Choose each bandit arm once

for $t = 1 : N$ **do**

1- Identification of greedy bandit arm g

$$g = \operatorname{argmax}_i(\mu_{i,t})$$

2- Probabilities update and final arm choice

$$P_{i,t} = \frac{e^{\mu_{i,t}/T\epsilon}}{\sum_{j=1}^K e^{\mu_{j,t}/T\epsilon}}, \forall i \neq g$$

Choose the arm g with probability $(1 - \epsilon)$. Otherwise, choose a random suboptimal arm with a probability $P_{i,t}$

3-Parameters update: $\forall 1 \leq i \leq K$

$$s_{i,t+1} = s_{i,t} + \Pi(I_t = i) \times r_{i,t}$$

$$n_{i,t+1} = n_{i,t} + \Pi(I_t = i)$$

$$e_{i,t+1} = e_{i,t} + \Pi(I_t = i) \times r_{i,t}^2$$

$$\operatorname{var}_{i,t+1} = e_{i,t+1} - (s_{i,t+1})^2$$

$$\mu_{i,t+1} = \frac{s_{i,t+1}}{n_{i,t+1}}$$

end for

Algorithm 4: Softmax algorithm.

the MAB problem. The corresponding algorithm choses a bandit arm at each iteration based on calculated probabilities. These probabilities are set differently for the greedy and the other suboptimal arms. We denote g the greedy bandit arm (with the highest average reward) and $\{i\}_{i \neq g}$ the suboptimal channels. The probabilities are then computed recursively, involving the parameter $P_{max} = 1 - (n - 1)P_{min}$. At each time step t , the probabilities are updated so that they "pursuit" the greedy action.

$$P_t(g) = P_{t-1}(g) + \alpha(P_{max} - P_{t-1}(g)) \quad (3.8)$$

$$P_t(i) = P_{t-1}(i) + \alpha(P_{min} - P_{t-1}(i)) \quad (3.9)$$

In fact, the probability for g is increased whereas the probability for the other suboptimal channels $\{i\}_{i \neq g}$ is decreased. The parameter α controls the rate of change of increase/decrease of the greedy probabilities and is required to be tuned (for enhanced performance).

3.3 Steered sensing with the Multi Armed Bandit

Opportunistic Spectrum Access (OSA) is one of the emerging paradigms of dynamic spectrum access that allows secondary users to share the radio spectrum with the primary (licensed) users for the purpose of increasing the overall spectral efficiency. Nevertheless, the realization of OSA involves a lot of difficulties to overcome [4]: primary user detection, detection and identification of spectrum holes (also called as white spaces), sharing of spectrum opportunities among secondary users, design of the overall system architecture (centralized or distributed), choice of OSA strategies between secondary networks (cooperative or competitive), coming up with efficient OSA spectrum policies etc.

In this part of the thesis, we focus on one of these challenges: white space detection and identification. More specifically, our perspective is built around finding frequency opportunities that can be used by secondary users to perform OSA. From this perspective, a secondary

Require: Initialization: Choose each bandit arm once

for $t = 1 : N$ **do**

1- Identification of greedy bandit arm g

$$g = \operatorname{argmax}_i(\mu_{i,t})$$

2- Probabilities update and final arm choice

$$P_t(a_g) = P_{t-1}(a_g) + \alpha(P_{\max} - P_{t-1}(a_g))$$

$$P_t(a_i) = P_{t-1}(a_i) + \alpha(P_{\min} - P_{t-1}(a_i)), \forall i \neq g$$

3-Parameters update: $\forall 1 \leq i \leq K$

$$s_{i,t+1} = s_{i,t} + \Pi(I_t = i) \times r_{i,t}$$

$$n_{i,t+1} = n_{i,t} + \Pi(I_t = i)$$

$$e_{i,t+1} = e_{i,t} + \Pi(I_t = i) \times r_{i,t}^2$$

$$\operatorname{var}_{i,t+1} = e_{i,t+1} - (s_{i,t+1})^2$$

$$\mu_{i,t+1} = \frac{s_{i,t+1}}{n_{i,t+1}}$$

end for

Algorithm 5: Adaptive pursuit algorithm.

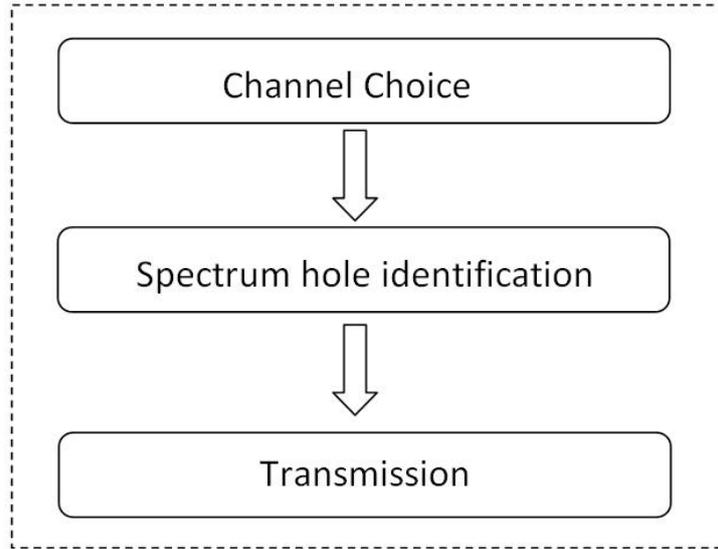


Figure 3.2: The three steps of Opportunistic Spectrum Access (OSA).

user (SU) aiming to perform OSA must follow the following three basic steps depicted in Figure 3.2: First, it chooses a frequency channel to access. Ideally, the channel that has the highest occurrence of white spaces is chosen. Unless the SU possesses the a priori knowledge on the statistical characteristics of the channels to access (which is most often the case), it has to collect information on the statistical characteristics of the channels to give an accurate decision on which channel to access. In general, wideband sensing methods that require specific hardware (including digital signal processing devices and tunable filters) are used to collect statistical information on channels. Once the first step is completed, the SU proceeds with the second step and determines the white spaces in the chosen channel. The methods proposed to carry out this frequency hole identification task can be classified in two categories:

1. Energy and cyclostationarity based methods where the detection is based on the physical

properties of the transmitted signals [67],

2. Feature based methods where the detection takes into account the large-scale a priori information, specifically the frame properties of the primary system [19].

After identifying the spectrum holes in the chosen channel, the SU finally transmits its data on the identified spectrum holes. The quality of transmission (both primary and secondary) depends on the channel choice and on the hole identification steps.

It is obvious that the SU can not perform the first and the third steps at the same time: it can not simultaneously collect information on channels through wideband sensing and actually perform the access. This creates a trade off to make between two actions:

1. Exploiting the sensing information by accessing the channel with the estimated highest level of spectrum holes,
2. Exploring the wireless medium by learning the statistical characteristics of the channels to be accessed.

This trade off is analogous to a phenomenon widely known as the exploitation-exploration dilemma in reinforcement learning [62] where the agent must make a compromise between maximizing its rewards by using the acquired knowledge and increasing its knowledge by trying new actions. Similarly, the SU must find a compromise between realizing the profit gained through the acquired information by accessing the best channel found, and getting information on the statistical characteristics of the channels in order to find the best channel to access.

In view of the fact that good channel choices lead to improved OSA performance, a considerable amount of research effort has focused on channel selection and frequency hole identification tasks [68]. To the best of our knowledge, the main research work in the literature has dealt with issues like detection and identification of white spaces through wideband sensing methods [35], construction of models (generally Markovian models) that statistically characterize the idle periods (the white spaces) [69], and definition of decision processes that derive actions for OSA [70]. Generally, these issues are studied for a given radio access technology and are valid only for predefined conditions.

This work adopts a different approach to channel selection and spectrum hole identification problem, and concentrates on the exploitation-exploration dilemma in OSA mentioned above by proposing a simple and efficient scheme that guarantees a good compromise between the two actions. The proposed scheme makes use of the similarity between a well-known problem in machine learning, the Multi-Armed Bandit (MAB) problem, and the exploitation-exploration dilemma in OSA [61]. Due to this analogy between the two concepts, the ad-hoc solutions proposed for the former within the reinforcement learning framework prove to be viable solutions for the latter [71]. Thus, the MAB approach constitutes a very interesting framework that can be applied to OSA to propose efficient channel access strategies relevant for different radio access technologies with different statistical properties.

Concretely, MAB solutions (bandit strategies) intervene in the OSA scheme during the first step of Figure 3.3 where the Secondary User (SU) tries to find the channel with the highest occurrence rate of spectrum holes. Keeping a balance between exploitation and exploration, the bandit strategy proposes a policy (a set of rules) that allows the SU to decide its actions in a way that maximizes the cumulative reward (the overall amount of transmitted data). In the literature, several authors have proposed to apply the multi-armed bandit in the cognitive

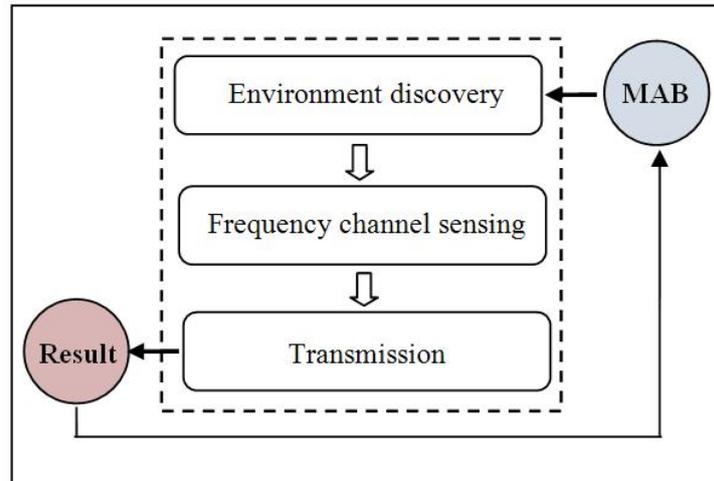


Figure 3.3: Rule of Multi Armed Bandit in OSA functioning.

radio context. In [61], the authors propose a unified framework that establishes the design of cognitive medium access using the multi armed bandit formulation. Different scenarios are considered (single user-single channel, multi user-single channel and multi channel-cognitive users). The formulation of optimal medium access strategy was first developed (in a bayesian framework), and an efficient computation of the optimal policy was introduced, using dynamic programming [72]. This approach is however rather complex, and assumes the knowledge of the state-action transition probability. Later, a low complexity index based strategy was proposed [65]. This strategy is known to have a logarithmic regret in the stationary case. Roughly speaking, if the distribution of the reward of the arms does not change over time, then the suboptimal arms will be played, on the average, only $O(\log(n))$ times in n plays.

[73] presents a practical example with the proposition of a distributed agile MAC protocol: a CSMA based protocol combined with a dynamic channel selection algorithm with a multi armed bandit formulation.

In previous studies, the distribution of the rewards (which corresponds to the gains gathered by applying the MAB procedure) for each arm of the MAB are assumed to be constant, at least for a predefined amount of time (the distribution is fixed for a block of n time slots and then change at the beginning of the next block). This does not match the dynamic channel occupation.

In this work, the analogy between the MAB problem and the OSA formulation is exploited to arrive at intelligent solutions that provide the SU with the set of rules and policies to perform efficient OSA and to cope with dynamic nature the channels' occupation.

Due to the well-known sensitivity of the reinforcement learning techniques to the statistical variations of the environment characteristics, MAB solutions are expected to have degraded performances in non-stationary environments. Since real-life wireless environments are almost always non-stationary, a realistic MAB solution to OSA has to include a mechanism that overcomes this drawback. With this perspective in mind, we propose to set automatically the parameters of the MAB strategies with two different approaches: a semi dynamic and an online parameter tuning scheme.

3.4 The network model

We consider a primary network consisting of K independent channels. The integer i refers to the channel index, $i \in \{1, \dots, K\}$. The cognitive user is allowed to scan a frequency band for a duration T , referred to as the scanning period. We use the integer t to refer to the time index. At time t and for a period of T , the amount of data that the SU can send, $r_{i,t}$, is equal to:

$$r_{i,t} = I_{i,t} \times D_{i,t} \quad (3.10)$$

where $I_{i,t}$ is the total idle duration in T and $D_{i,t}$ is the data rate. Note that $r_{i,t}$ represents the reward associated to the channel i at time step t .

Thus, the total amount of data that the SU can send over a duration of N time steps is given by:

$$W = \sum_{t=1}^N \sum_{i=1}^K r_{i,t} \quad (3.11)$$

The goal of the SU is then to maximize the expectation of this reward:

$$E[W] = E\left[\sum_{t=1}^N \sum_{i=1}^K r_{i,t}\right] \quad (3.12)$$

If the value of $r_{i,t}$ is known, then the SU will access the channel with the maximum value of $r_{i,t}$ at each iteration. Nevertheless, the secondary user ignores the values of $r_{i,t}$ for all the channels. Hence, it must achieve a trade off between exploration (sensing all the channels in order to identify the ones with greater opportunities) and exploitation (accessing the best channel identified so far). The main difficulty for the SU is to "learn" channel occupation statistics continuously, while not losing too much time on suboptimal channels. This requires suitable strategies balancing exploration versus exploitation to accommodate the dynamic channel changes. Hence, the bandit strategies that propose near-optimum solutions for the MAB problem can be used to yield effective policies for the channel choices.

The parameter T must be judiciously set: it must be large enough to permit the transmission of data but also not too large to allow the SU to explore the other channels and to search for more interesting opportunities elsewhere. In this study, we use a scan period T of 250 ms. The considered primary system is IEEE802.11. In fact, this standard uses unlicensed frequency bands (2.4 GHz or 5 GHz), which facilitates testing new mechanisms and scenarios. We test the MAB approach on simulated data that represents realistic traffic on the IEEE802.11 band. The idle durations in the test data are modeled by a generalized Pareto distribution, since it is shown to exhibit a good fit to real traffic according to [38]. The corresponding probability density function is:

$$f(t|k,\sigma) = \frac{1}{\sigma} \left(1 + k \frac{t}{\sigma}\right)^{-1-1/k} \quad (3.13)$$

where $k \neq 0$ is the shape parameter and σ is the scale parameter. These parameters are estimated from real measurements using the maximum likelihood method. A high traffic in the network corresponds to a high value of the parameter λ , which is the rate parameter of the Poisson distribution describing the traffic, defined as the number of packets per second and per channel. Based on the study realized in [38], we identify the values of k and σ corresponding to high and low traffic values (respectively $\lambda = 500$ and $\lambda = 25$) in Table 3.1).

The detected idle durations corresponds to the reward function in the MAB formulation,

Table 3.1: Generalized Pareto distribution parameters.

λ [pkts/s]	25	500
k	-0.31018	-0.0455
σ	0.0139	$1.59 \cdot 10^{-4}$

as the SU will transmit in these frequency opportunities. Rigorously, the reward function of the SU is the total amount of data he succeeds to transmit in an opportunistic manner. This corresponds to the product of the detected idle duration and the used data rate, during the total period of interest.

To study the performances of MAB strategies, we produce a test scenario using the empirical results of [38]. In this scenario, we consider 13 channels (from the IEEE802.11 band), divided into two categories:

- Channels with high traffic and few idle periods,
- Channels with low traffic and frequent idle periods.

The parameter values k and σ corresponding to high and low traffic channels are identified according to Table 3.1.

At each time step t , a channel is defined randomly as the best channel (with low traffic load) and the other channels as worse (with high traffic load). A finite time horizon of $N = 50000$ time steps is chosen, where the best channel changes 5 times randomly. Here, a time step lasts 250 ms. Thus, the test scenario corresponds to a duration of about 3.5 hours. Figure 3.4 depicts the best channel choice at each iteration during the test duration. Here, the channel 4 remains the best channel (with highest idle durations) during the first 5000 time steps. Then, channel 8 becomes the best for the following 10^4 time steps and channel 4 becomes highly loaded. Thereafter, the situation evolve and the best channel become successively 1, 6 and 11.

The test scenario depicted in Figure 3.4 is intended to test different non-stationary variants of the MAB method to evaluate the opportunistic spectrum access within an IEEE802.11 model, in a dynamic environment. Optimally, a MAB allocation strategy is able to determine the best channel with highest idle durations at each time step, so that it follows the scheme of our test scenario.

3.5 Preliminary simulation results on IEEE802.11 channel

In this section, we present the preliminary results of experimenting different MAB strategies on our test scenario described in Figure 3.4. It is important to remind that at each time step t , the bandit algorithms determine the next channel to access based on the history of past accessed channels and the corresponding received rewards (from 1 to $(t - 1)$). Thus, for each bandit strategy, we will be interested in the list of chosen channels at each time step t during the total test duration (50 000 time steps). The performance of each MAB strategy is evaluated through the regret function, which is calculated as the sum of missed idle durations.

Figure 3.5 shows the results with three variants of the UCBT strategies: the original UCBT algorithm, the periodic UCBT and the discounted UCBT.

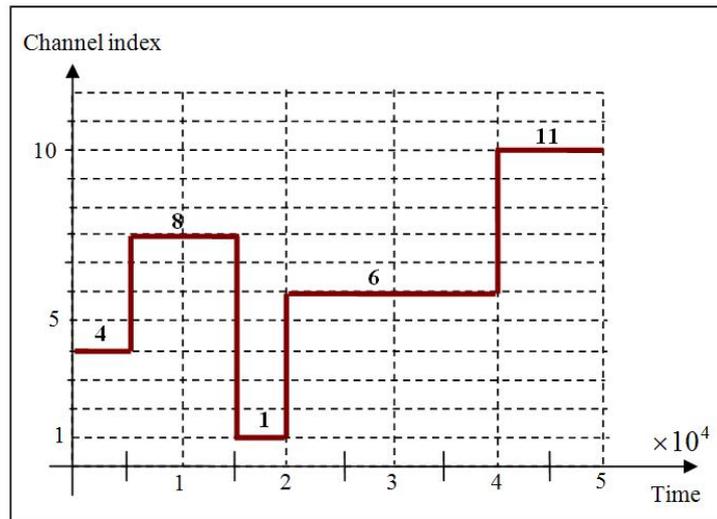


Figure 3.4: The IEEE 802.11 channel occupation model used as the test scenario.

The UCBT algorithm identifies the best channel (channel 4) in the beginning but is unable to follow the changes and remains on this same channel during the rest of the test duration.

The Performance of the periodic UCBT (with a period of 10^4) is better since this algorithm finds out the best channel periodically, each time its parameters are reinitialized. Nevertheless, we remark that there is a considerable delay between our test scenario and the result of the periodic UCBT. The performance of this algorithm highly depends on the period choice.

Finally, the discounted UCBT (with a discount factor $\rho = 0.9$) is observed to achieve a good performance on the test scenario. It is almost able to find out the best channel at each time iteration. We remark that it explores from time to time on the other channels to verify whether there is a better channel or not. Here, it is important to note that this algorithm achieves low delay values for detecting the main changes in the test scenario, which is important when performing opportunistic spectrum access. Also, we notice that it is required to adjust the parameter ρ as the performance of this algorithm highly depend on the value of the discount factor ρ . Figure 3.6 shows the result of a manual tuning of the discount factor. The best performance of the MAB strategy corresponds to the lowest regret values, which are realized with $0.6 \leq \rho \leq 0.9$. For $\rho = 1$, we obtain the original UCBT case and the corresponding regret value is about 400, which proves the bad performance of this algorithm.

The randomized strategies that perform channel choices with probabilities are also experienced on the test scenario. Since they all exhibit almost similar performances, only the performance of the ϵ -greedy algorithm is given in Figure 3.7 with $\epsilon = 0.1$. Generally, the randomized algorithms perform excessive exploration on the channels and do not leave enough time for the exploitation task. Nevertheless, their performances depend very much on the chosen MAB parameters.

Figure 3.7 shows the relationship between the regret value and the parameter ϵ for the ϵ -greedy method. For our test scenario, we notice that the minimum regret value (≈ 280) is achieved with $\epsilon = 0.04$.

Figure 3.8 depicts the relationship between the temperature parameter T_ϵ and the obtained

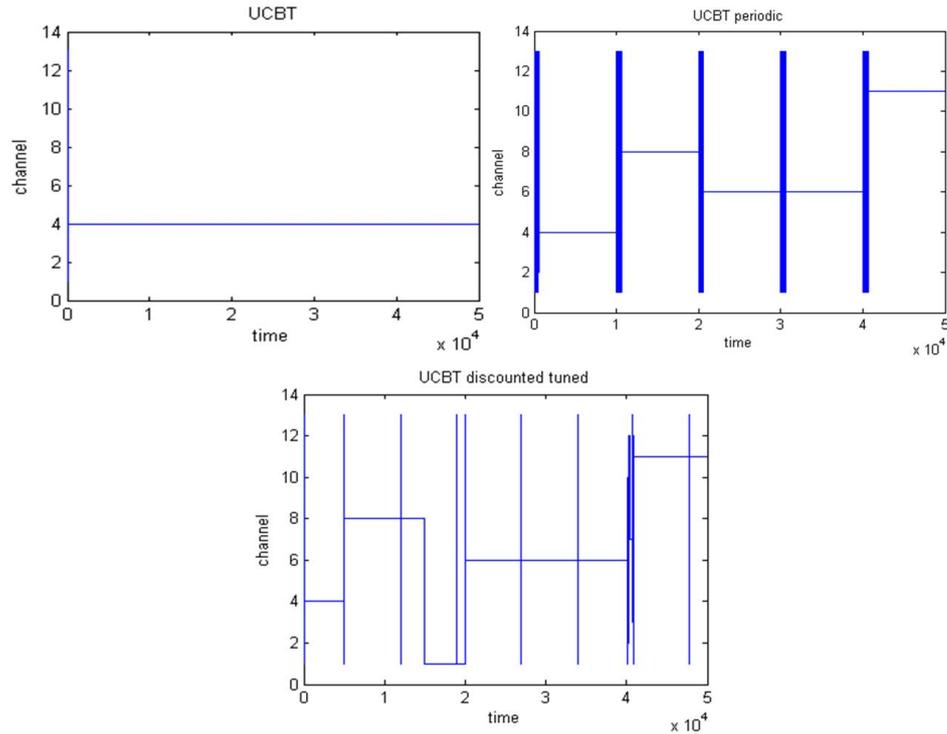


Figure 3.5: Performances of UCB strategies on the test scenario.

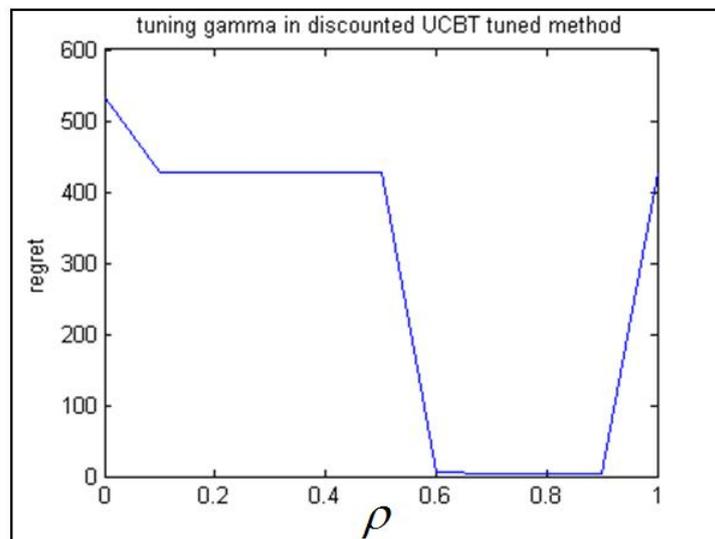
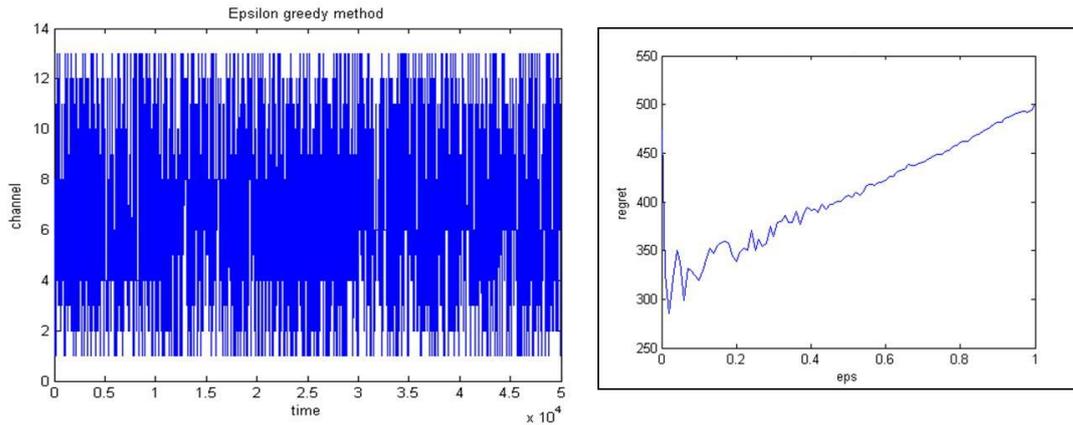
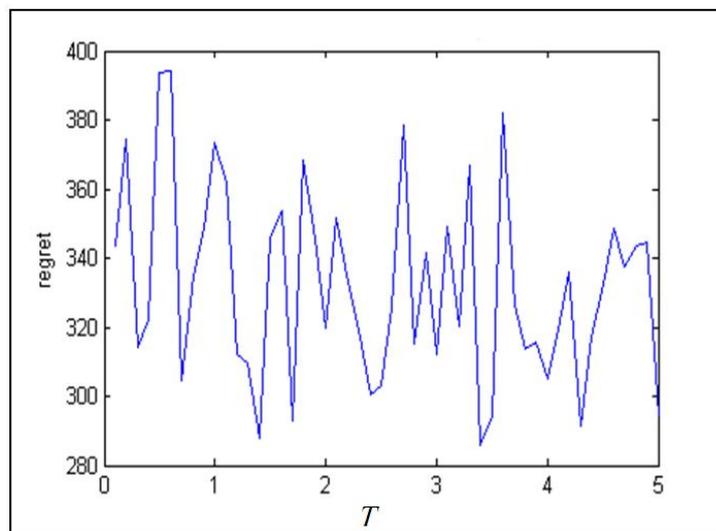


Figure 3.6: Tuning ρ in discounted UCB.

regret value (for $\epsilon = 0.01$) for the Softmax strategy. It reveals that T_e has uncontrolled effect on the regret.

Finally, Figure 3.9 shows the impact of the parameter α on the obtained regret (with $P_{min} = 0.001$) for the Adaptive Pursuit strategy. The best performance is reached with $\alpha = 0.5$ for a

Figure 3.7: Performances of ϵ -greedy strategy.Figure 3.8: Tuning the temperature parameter T in Softmax strategy with $\epsilon = 0.01$.

regret of 270.

To conclude, Figure 3.10 illustrates the average regret value obtained with the bandit strategies applied to our test scenario. The discounted UCBT outperforms the other strategies with an average regret of 20. It is followed by the periodic UCBT (with period $\Delta T = 10000$) that leads to a good performance with an average regret value of about 100. The other strategies (UCBT, Adaptive Pursuit, ϵ -greedy and Softmax) have similar poor performances with regret values reaching several hundreds at the end of the test period. It is important to note that these results are obtained with manual tuning of the bandit parameters over the entire test period. Since the test scenario reflects a non-stationary channel occupation model, parameter values that are adjusted according to the overall channel behavior clearly yield sub-optimum performances. Thus, the discounted UCBT displays a better performance than the randomized bandit strategies for the test scenario.

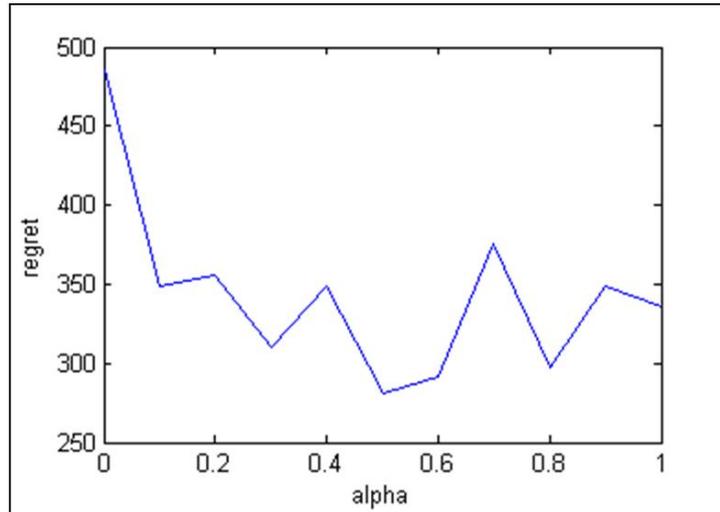


Figure 3.9: Tuning the parameter α in Pursuit method with $P_{min} = 0.001$.

The results of Figures 3.7, 3.8 and 3.9 reveal that the performances of the randomized ban-

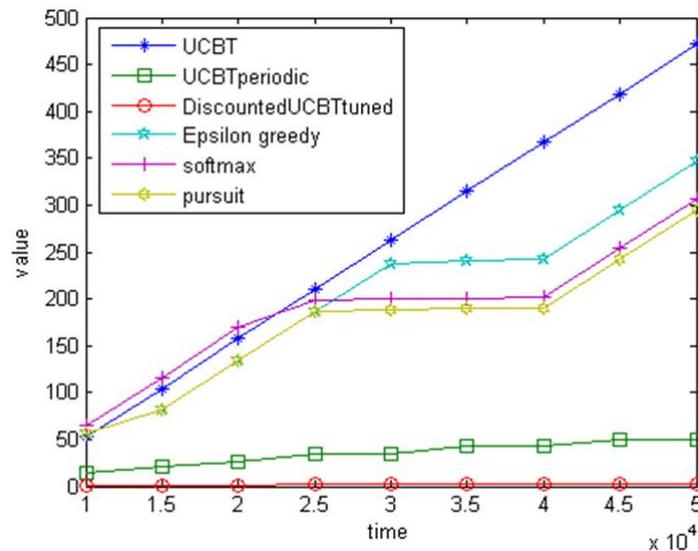


Figure 3.10: Average regret for the bandit strategies on the test scenario.

dit strategies degrade strongly if their parameters are not carefully tuned in non-stationary environments. The reinforcement learning MAB solutions are known to be sensitive to the statistical properties of the bandit arms and therefore needs careful tuning according to the dynamic variations of the environment. Therefore, an automatic tuning of the algorithm parameters is a plausible solution for enhancing the efficiency of the randomized bandit strategies in non-stationary environments. In the next section, an automatic tuning and optimization of the randomized bandit strategies in non-stationary environments is proposed and evaluated.

3.6 MAB parameter tuning

Automatic tuning of the bandit algorithms aims at improving the performance of the bandit strategies in non-stationary environments. Therefore, we propose an automatic tuning approach that ensures the adaptation of the bandit strategies to the varying statistical characteristics of the reward distributions. Thus, we can follow two approaches to establish an automatic tuning of the bandit parameters:

- A semi dynamic tuning scheme that necessitates an offline sensitivity study,
- An online tuning scheme that could be run in real time conditions.

The tuning approach (Figure 3.11) increases the adaptability and the efficiency of the MAB solution in different environments and radio access technologies. This flexibility constitutes an important feature in OSA.

Figure 3.12 represents a flowchart of the proposed MAB algorithm with an automatic tun-

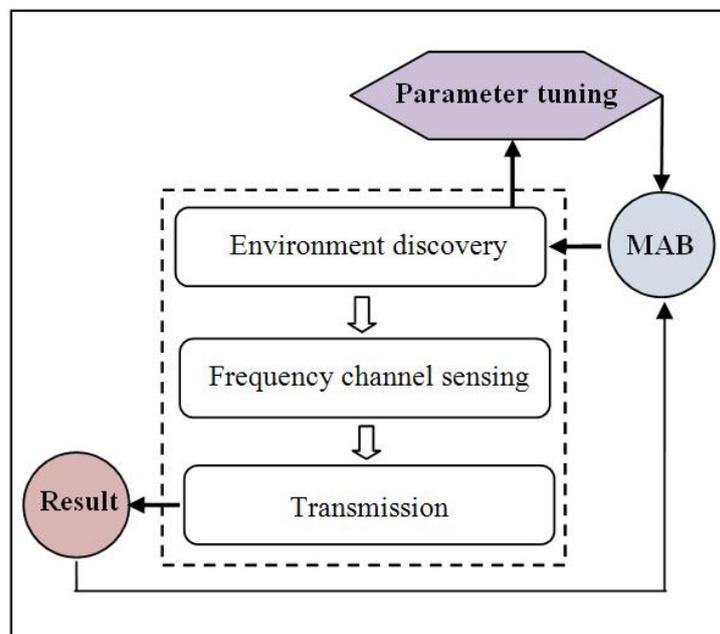


Figure 3.11: Proposed OSA scheme including MAB.

ing option. It is a generalized scheme that explains the common implementation of a bandit algorithm and the proposed intervention of the tuning option. This scheme is valid for all MAB methods (deterministic and randomized). The set of blocks on the left of Figure 3.12 corresponds to the usual functioning of a typical bandit algorithm, whereas the blocks on the right represent the tuning action.

At a given time t , a bandit algorithm can be described through five main actions. In the beginning, the evaluation function specified by the bandit algorithm is computed for each channel. It can be in the form of probabilities for randomized strategies or fixed values for deterministic strategies. Based on this calculation, the algorithm determines the next channel to choose/access. After accessing the chosen channel, the obtained reward that is the amount

of data transmitted successfully on the white spaces of the chosen channel is calculated. This reward is then used to update the bandit algorithm settings, namely:

- the associated expected mean reward of each channel k at time t : $\mu_{k,t}$,
- the number of channel access times for each channel k at time t : $n_{k,t}$.

If the tuning option is not activated, then the algorithm loops back to the beginning and re-evaluates each channel with the updated bandit settings. Otherwise, after the update operation, the tuning operation is launched automatically and the bandit algorithm is modified accordingly. At $(t + 1)$, the tuned version of the bandit algorithm is launched.

In the following, we propose to study both the semi dynamic and the online parameter

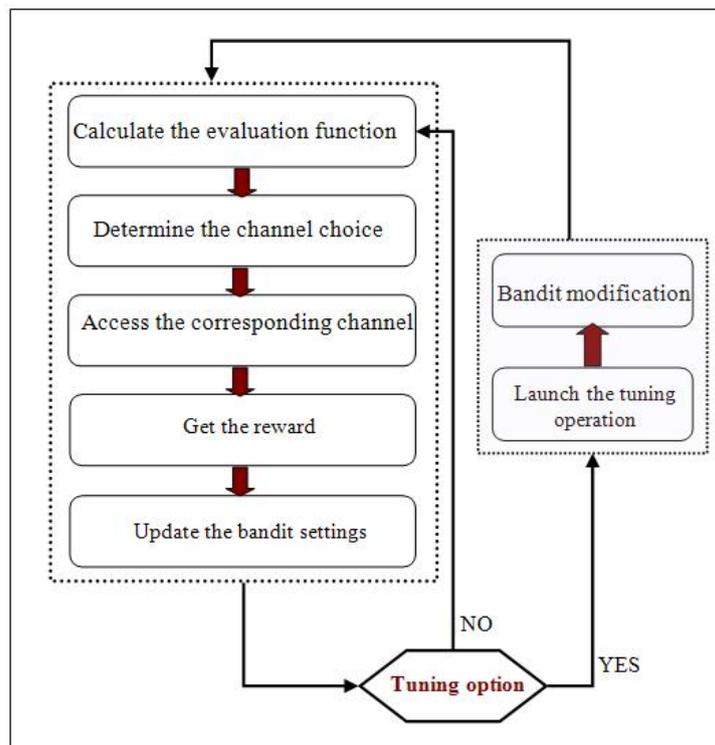


Figure 3.12: Flowchart of bandit algorithm with tuning option.

tuning schemes.

3.6.1 Semi dynamic parameter tuning scheme

At first, we propose the semi dynamic parameter tuning scheme. This approach requires the results of an offline sensitivity study that evaluates the performance of each MAB strategy in different environment conditions. More precisely, the offline study addresses the relationship between:

- the performance of the MAB strategy, evaluated through the regret function,
- the value of the used MAB parameter, namely the parameter that influences the performance of the MAB algorithm.

This relationship is studied under different values of stationarity periods. In fact, the stationarity period corresponds to the duration in which the properties of the environment remains unchanging.

In this study, the stationarity period stands for the mean period in which a channel remains the best (with the highest/most frequent idle durations). Figure 3.13 shows examples of scenarios with stationarity periods of respectively 5000 and 10000 time steps.

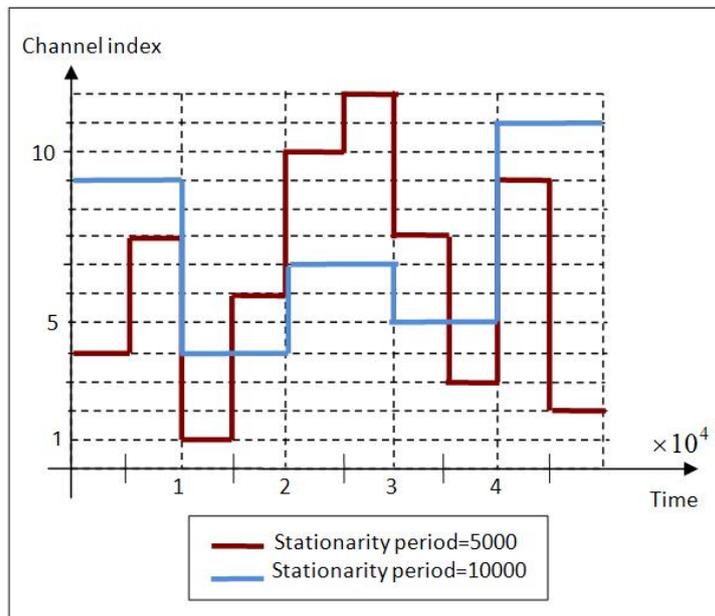


Figure 3.13: Example of test scenarios with different stationarity periods.

3.6.1.1 Offline sensitivity study

In this section, we address an offline sensitivity study of several MAB algorithms (deterministic and randomized) on an example of test scenario from the IEEE802.11 standard. This study is motivated by the great impact of the choice of the algorithm parameters choice on the MAB performance. This impact is particularly observed in dynamic environments.

To this goal, we first propose to test the performances of the original MAB algorithms compared to modified versions. Here, the proposed modification is the addition of a discount factor in the update stage of the MAB, carried out at each time iteration. Thus, we test the effect of adding a discount factor ρ in the randomized allocation strategies (ϵ -greedy, softmax and adaptive pursuit method). This factor influences the behavior of the policy by decreasing the influence of past decisions. This impacts the behaviour of the original MAB strategy by promoting the exploration task. The update of the parameters of MAB algorithms is made as follows:

$$s_{i,t+1} = \rho \times s_{i,t} + \Pi(I_t = i) \times r_{i,t} \quad (3.14)$$

$$n_{i,t+1} = \rho \times n_{i,t} + \Pi(I_t = i) \quad (3.15)$$

with $s_{i,t}$ being the sum of expected rewards, $r_{i,t}$ the reward value for channel i at time t , $n_{i,t}$ the number of iterations the channel i is accessed until time t and $\Pi(\cdot)$ equals 1 if its argument is

true and equals 0 if it is false.

Figure 3.14 shows that adding the discount factor ameliorates considerably the performances of these allocation algorithms. The main amelioration is noted for ϵ -greedy and softmax strategies. A saving of about 300 is noticed in the final regret function for these policies. Nevertheless, the deterministic discounted UCBT strategy is still better as the other randomized strategies are affected by the probability that favors the exploration task over suboptimal channels.

A second stage in this offline sensitivity study is concerned with the estimation of the ef-

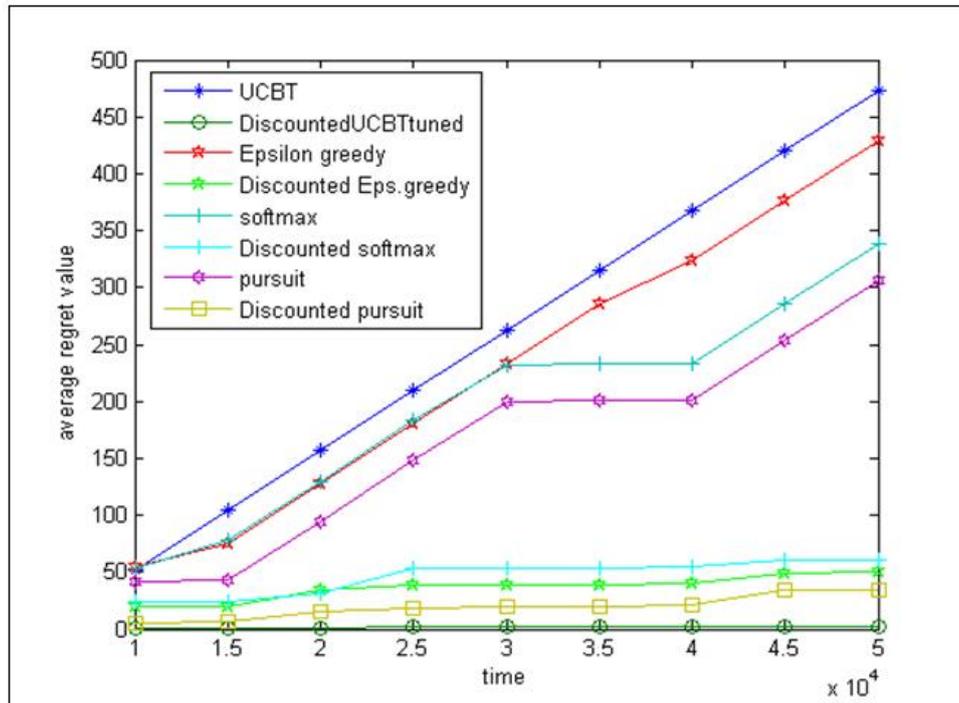


Figure 3.14: Performances of different allocation strategies.

fects of the stationarity period of the data on the allocation strategies' performances (evaluated through the regret function). Figure 3.15, Figure 3.16 and Figure 3.17 give an overview of the variation of the regret function versus the parameter value (set manually for respectively Adaptive Pursuit, ϵ -greedy and Softmax strategies), for different values of the stationarity period (10, 100, 1000, 5000 and 10000). The figures are obtained for discounted allocation strategies (Adaptive Pursuit, ϵ -greedy and Softmax) with a discount factor $\rho = 0.99$. We remark that the performances are generally degraded with low values of the stationarity values. The more rapid the environment changes, the more difficult for the allocation strategies to follow the changes in the channels.

3.6.1.2 Proposed semi dynamic tuning scheme

To take advantage of the offline sensitivity study, we propose a semi dynamic parameter tuning scheme (Figure 3.18).

A first step consists of periodically estimating the stationarity period of the considered environment every T time steps. For this, we propose to use the *change point detection* method

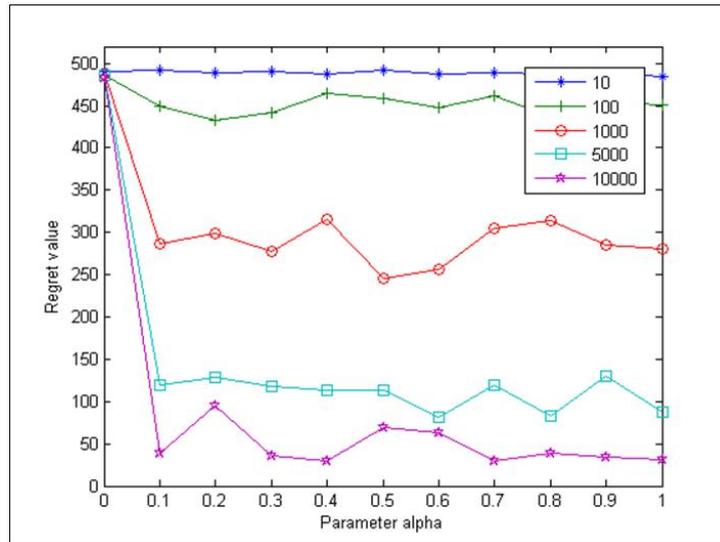


Figure 3.15: Regret value vs strategy parameter for Adaptive Pursuit method.

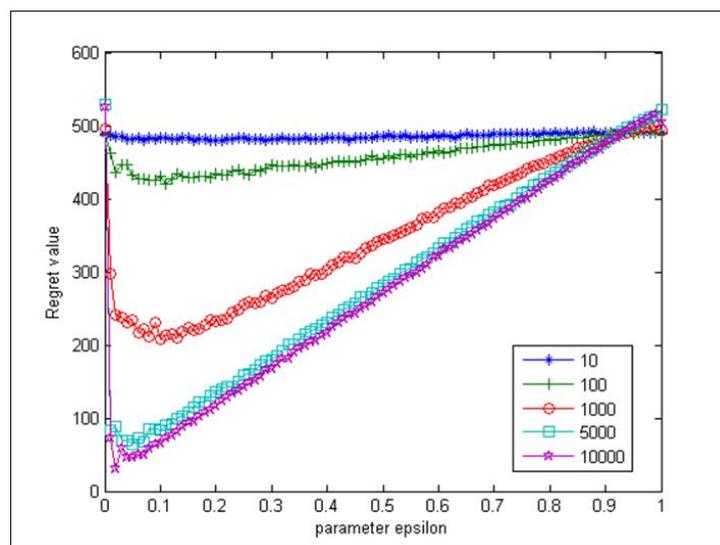


Figure 3.16: Regret value vs strategy parameter for ϵ -greedy.

described in [15]. This algorithm allows to detect the significant changes in the signals and then to deduce the stationarity period as the difference between the time occurrence of two consecutive changes.

Then, based on the offline sensitivity study described above, we identify the corresponding parameter value that achieves the minimum regret. Finally, an update of MAB strategy can be accomplished so that it fits better to the current environment.

The change point detection algorithm is based on the Page Hinkley (PH) test which is an extension of the Cumulative Sum charts (CUSUM) test introduced by Page [74]. Following the work in [17] and considering a sequence of rewards, the PH test is formulated by the Algorithm

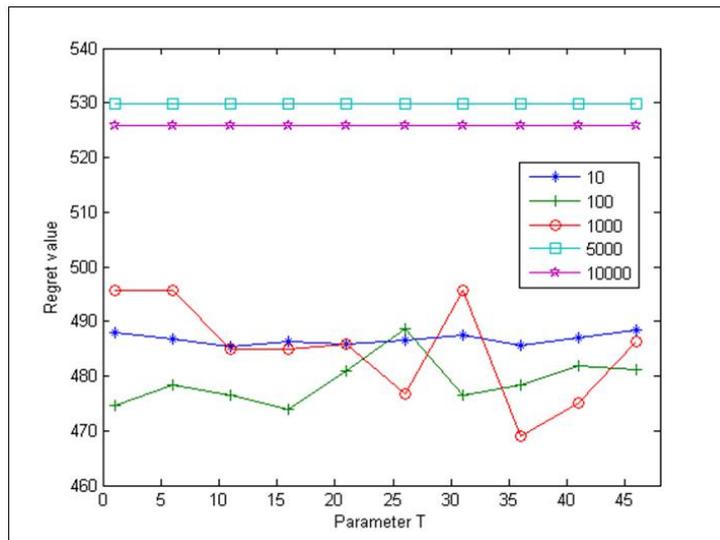


Figure 3.17: Regret value vs strategy parameter for Softmax method.

6.

This test aims to detect an abrupt change in the average curve of the reward function. Here,

$$\begin{aligned} \bar{r}_{i,x} &= \frac{1}{x} \sum_{u=1}^x r_{i,u} \\ m_{i,t} &= \sum_{x=1}^t (r_{i,x} - \bar{r}_{i,x} + \delta) \\ M_{i,T} &= \max_{t=1, \dots, T} \{m_{i,t}\} \\ PH_{i,T} &= M_{i,T} - m_{T,i} \\ \text{A change is detected at time step } T \text{ for channel } i \text{ if } PH_{i,T} &> \lambda \end{aligned}$$

Algorithm 6: Page Hinkley Test.

the average value is estimated in recursive manner from past reward values for each channel i . This mean value is noted $\bar{r}_{i,x}$. Consequently, we calculate the parameters $m_{i,t}$, $M_{i,T}$ and the final test function $PH_{i,T}$, using two parameters: δ corresponds to the jump magnitude bound (above which an alarm is raised) and λ stands for the desired false alarm detection rate.

Thus, a change is detected for channel i at time step T if the PH value is above λ . The main advantages of this test are its robustness and its minimum mean detection delay for a predefined false alarm rate.

3.6.2 Online parameter tuning scheme

In this section, we investigate the online tuning and optimization of the bandit algorithms for opportunistic access in dynamic environments. For this purpose, we propose and evaluate two different approaches:

- **Meta learning:** It stands for adding more flexibility in base learning techniques by means of appropriate adaptation of the base learning method to the target task or environment [75]. In our context, we are interested in adjusting the parameters of the base learning method according to the external environment, so that it enhances the overall performance

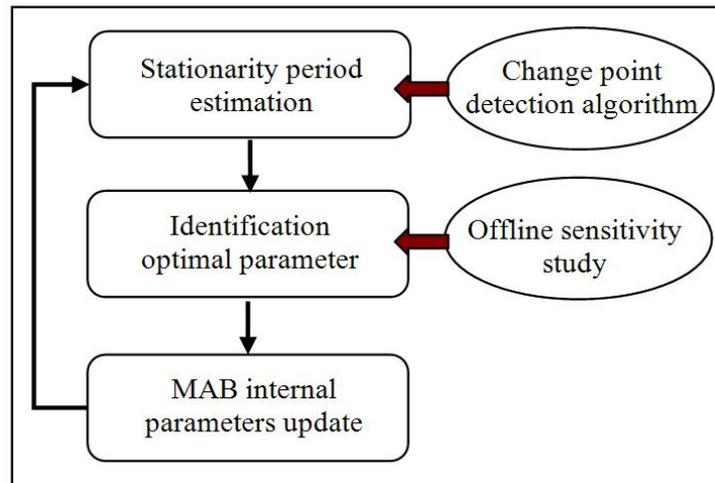


Figure 3.18: Semi dynamic parameter tuning scheme.

of the learning strategy in non-stationary conditions. For this goal, a second layer of reinforcement learning (a meta-learner) that learns the parameters of the basis reinforcement learning (the bandit procedure) is used. In addition to the periodic triggering, an event triggered approach that is based on the change point detection algorithm is proposed and evaluated.

- Exponential weight algorithm for Exploration and Exploitation (EXP3): It is an algorithm proposed by Auer in [63]. It has the advantage of not requiring statistical assumptions about the reward generation. Therefore it is worth evaluating its performance on the opportunistic spectrum access problem.

3.6.2.1 Meta learning approach

Meta learning (ML) corresponds to the utilization of a second layer of learning to enhance the performance of the base learning with dynamic tuning of the base learning parameters [76]. In this study, one of the approaches that we propose for dynamic tuning of the MAB parameters is meta learning, where the parameters of the MAB are updated continuously through a meta learning procedure.

Meta learning for non-stationary MAB problems has already been treated in the literature. In [17] and [77], an algorithm based on meta bandit (called Adapt Eve) is proposed to ensure an online learning in dynamic environments. When a change is detected in the initial data, two bandit procedures run simultaneously for a predefined duration and the best bandit is then chosen. In [16], Sikora proposes another approach of meta learning that consists in adding a second layer of reinforcement learning to the current bandit procedure. In this layer, a second bandit process is used to choose which parameter value is to be used in the base bandit process. The update rate of this meta learner is fixed, i.e. the meta learning is triggered periodically. Note that in none of the abovementioned studies, an opportunistic spectrum access context is considered.

In this work, we apply the second approach of meta learning to dynamically set the parameters

of the bandit process in an opportunistic spectrum access setup. In addition to the periodic triggering proposed in [16], we also test an event triggered approach based on the change point detection algorithm [17]. Figure 3.19 depicts the general scheme of the proposed meta bandit that provides an online adjustment of the MAB parameters. The two bandit processes implemented in the proposed scheme are:

1. The base bandit (BB) process which chooses the channel to access,
2. The meta bandit (MB) process which chooses the parameter value of the BB process.

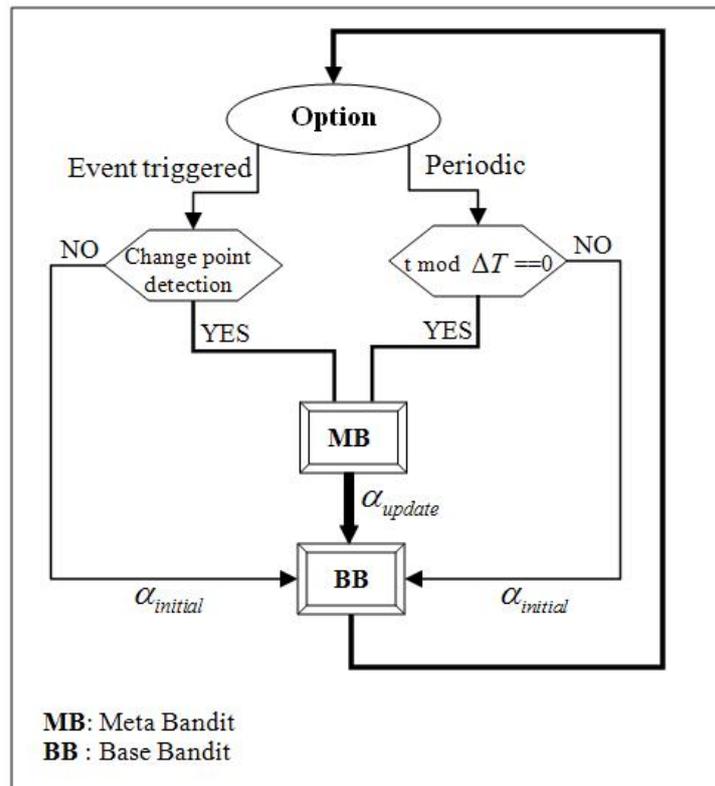


Figure 3.19: Proposed meta bandit architecture.

The algorithm operates with two possible options: periodic or event triggered. This option determines the triggering of the MB. For the periodic case, when the time index is a multiple of the period ΔT , the MB is launched and a parameter value is chosen from a set of predefined values. For the event triggered case, we test if a significant change is detected in the environment using an efficient detection algorithm: the change point detection. If a change is detected then the MB is launched and the current BB parameter is updated. Otherwise, it is kept unchanged. Obviously, the efficiency of the proposed algorithm is enhanced when the parameter update is performed only on significant change detection. Therefore, we expect the event-triggered approach to surpass the periodic one. However, we also have to keep in mind that the periodic approach is less costly than the event-triggered one and it can be a good compromise by enhancing the performance of the bandit algorithm without increasing the computational cost.

In the remaining of this section, we describe a case study of the meta bandit approach where

we use the discounted Upper Confidence Bound Tuned (UCBT) [66] algorithm as the MB, to update the parameter of the Adaptive Pursuit algorithm [62] that we use as the BB.

In the proposed scenario, the BB follows the adaptive pursuit algorithm which comes from a family of well-known ad-hoc methods in learning automata [62](see Algorithm 7). The channel allocation rule is based on greedy selection, that is, the algorithm chooses the channel i that currently has the maximum estimated reward. Once the greedy channel is determined, the pursuit method increases the selection probability of the greedy channel $P_t^{BB}(g)$, and decreases all other probabilities $P_t^{BB}(i)$ for the other suboptimal channels $i \neq g$.

The BB parameter that we aim to tune using the MB is α . After the choice is made on the channel to access based on the probabilities shown in Algorithm 7, the associated expected reward and the number of channel access times are updated.

In this algorithm, $\mu_{i,t}^{BB}$ refers to the average reward for channel i until time t , $s_{i,t}^{BB}$ denotes the

```

for t=1:N do
  1- Identification of the greedy channel  $g$ 
   $g = \text{argmax}_i(\mu_{i,t}^{BB})$ 
  2- Probabilities update and channel choice made
   $P_t^{BB}(g) = P_{t-1}^{BB}(g) + \alpha(P_{max} - P_{t-1}^{BB}(g))$ 
   $P_t^{BB}(i) = P_{t-1}^{BB}(i) + \alpha(P_{min} - P_{t-1}^{BB}(i)), \forall i \neq g$ 
  3- Parameters update
   $s_{i,t+1}^{BB} = \rho^{BB} \times s_{i,t}^{BB} + \Pi(I_t^{BB} = i) \times r_{i,t}^{BB}$ 
   $n_{i,t+1}^{BB} = \rho^{BB} \times n_{i,t}^{BB} + \Pi(I_t^{BB} = i)$ 
   $\mu_{i,t+1}^{BB} = s_{i,t+1}^{BB} / n_{i,t+1}^{BB}$ 
end for

```

Algorithm 7: The Base Bandit policy.

cumulative reward, $n_{i,t}^{BB}$ is the number of times channel i is accessed until time t , $P_{min} = 0.001$, $P_{max} = 1 - (n - 1)P_{min}$, ρ^{BB} is the discount factor set to 0.99, I_t^{BB} is the index of the channel chosen at time t , $r_{i,t}^{BB}$ is the obtained reward after accessing channel i with parameter α and $\Pi(\cdot)$ equals 1 if its argument is true and equals 0 if it is false. Note that the superscript BB stands for the base bandit.

The performance of this method is highly dependent on the choice of the parameter α ($0 \leq \alpha \leq 1$). To have an online optimization of α that tracks the environment changes, we introduce the meta bandit (MB) that chooses the optimal value of the parameter α from a set of predefined values, for example: high ($\alpha = 0.9$), middle ($\alpha = 0.5$) and low ($\alpha = 0.1$).

A deterministic MAB strategy has been chosen for the MB: the discounted UCBT [66], a well-known MAB method that achieves a good performance for opportunistic spectrum access (see Algorithm 8). As in the BB procedure, the allocation strategy of the MB depends on the greedy choice (the greedy choice being one of the α values this time). However, different from the adaptive pursuit method which is a randomized strategy, the allocation in this deterministic MB is given directly by the deterministic greedy choice denoted by h .

In the MB policy, K is the total number of alternatives for α (in this scenario, $K = 3$), $\mu_{i,t}^{MB}$ is the average reward at time t for the channel i , $n_{i,t}^{MB}$ is the number of times the value α_i is chosen until time t , ρ^{MB} is the discount factor set to 0.9 in this scenario, $s_{i,t}^{MB}$ is the cumulative reward for the parameter value α_i at time t , I_t^{MB} is the index of the parameter value chosen at

Require: Initialization: choose each parameter once
for $t=1:N$ **do**
 1- Identification of the greedy parameter indexed h

$$h = \underset{j=1}{\operatorname{argmax}}^K \left[\mu_{j,t}^{MB} + \sqrt{\frac{2 \times \operatorname{var}(\mu_{j,t}^{MB}) \times \log(\sum_{j=1}^K n_{j,t}^{MB})}{n_{j,t}^{MB}}} \right]$$

 2- Parameters update

$$s_{i,t+1}^{MB} = \rho^{MB} \times s_{i,t}^{MB} + \Pi(I_t^{MB} = i) \times r_{i,t}^{\alpha_h}$$

$$n_{i,t+1}^{MB} = \rho^{MB} \times n_{i,t}^{MB} + \Pi(I_t^{MB} = i)$$

$$\mu_{i,t+1}^{MB} = s_{i,t+1}^{MB} / n_{i,t+1}^{MB}$$

$$e_{i,t+1}^{MB} = \rho^{MB} \times e_{i,t}^{MB} + \Pi(I_t^{MB} = i) \times r_{i,t}^{\alpha_h}$$

$$\operatorname{var}(\mu_{i,t+1}^{MB}) = e_{i,t+1}^{MB} - (s_{i,t+1}^{MB})^2$$

end for

Algorithm 8: The Meta Bandit policy.

time t , $\operatorname{var}(\mu_{i,t}^{MB})$ is the standard deviation of the reward at time t for the value α_i and $r_{i,t}^{\alpha_h}$ is the obtained reward after accessing a channel chosen by the BB process using the parameter value α_h .

In practice, the two bandits operate almost simultaneously. When a channel i is chosen by the BB using the parameter α_h set by the MB, we obtain the reward $r_{i,t}^{\alpha_h}$. This reward value is then used to update the parameters of both bandits.

The meta-learner is evaluated both with a periodic triggering approach and an event triggered approach that is based on the change point detection algorithm (detailed in the Semi dynamic tuning scheme).

3.6.2.2 Exponential weight algorithm for Exploration and Exploitation (EXP3)

The online optimization of the multi armed bandit procedure can also be accomplished through the Exponential weight algorithm for exploration and exploitation, called Exp3 [63]. It corresponds to the circumstance where an adversary has complete knowledge about the game and controls the reward distribution. The main advantage of this algorithm is that it doesn't need statistical assumptions about the reward generation. In this study, we use a variant of the above mentioned algorithm, referred as Exp3.1 algorithm [63].

Exp3.1 allows to tune its parameters α and γ in an adaptive manner. In Exp3.1, whose detailed algorithm is given below, the parameter f refers to the upper bound of the total cumulated reward of the best channel, after a period T .

$$f \geq F_{max} \quad (3.16)$$

$$F_{max}(T) = \sum_{t=1}^T r_{i,t} \quad (3.17)$$

EXP3, detailed in Algorithm 9, is built in the form of rounds indexed by n and initialized to 1. Three main steps are identified. The first step consists in the calculation of the parameters α and γ using the current value of the round n .

```

Require: Initialization:  $n = 1, \tilde{s}_i = 0$  for  $1 \leq i \leq K$  and  $t = 1$ 
for  $t = 1 : N$  do
  1- Step1:
   $f(n) = 2^n$ 
   $\alpha = \sqrt[3]{(4K \ln K) / 2f(n)}$ 
   $\gamma = \min\{1, \sqrt[3]{(4K \ln K) / 2f(n)}\}$ 
  2- Step2:
   $p_i(t) = \frac{(1+\alpha)^{\tilde{s}_i(t)}}{\sum_{j=1}^K (1+\alpha)^{\tilde{s}_j(t)}}$ 
   $\hat{p}_i(t) = (1 - \gamma)p_i(t) + \frac{\gamma}{K}$  for  $1 \leq i \leq K$ 
  Choose the channel  $f(t)$  and receive  $r_{f,t}$ 
   $\tilde{s}_{f(t)}(t) = \tilde{s}_{f(t)}(t) + \frac{r_{f,t}}{\hat{p}_{f(t)}(t)}$ 
  3- Step3:
  if  $(\max_i \tilde{s}_i \geq f(n) - \frac{\gamma}{K})$  then ( $n=n+1$  and go to step1) else (go to step2)
end for

```

Algorithm 9: Exp3.1 Algorithm.

Thereafter, the probabilities $\hat{p}_i(t)$ of choosing a channel i at time t are evaluated for all the channels. These probabilities involve the parameters α and γ set in step1 of the algorithm. Based on these calculated probabilities, the algorithm choses a channel referred $f(t)$ and updates accordingly the parameter $\tilde{s}_{f(t)}(t)$.

Finally, the round n is updated in step3 when the actual best cumulative sum of reward $\max_i \tilde{s}_i$ is superior to the bound $f(n) - \frac{\gamma}{K}$. In this case, the algorithm is restarted (step1) with a higher round and with updated values of the parameters α and γ . Otherwise, the algorithm goes directly to the step2 and chooses a channel using the old values of α and γ .

3.6.2.3 Results

This section presents the results of applying the meta learning methods and the Exp3 algorithm on an IEEE802.11 channel occupation model. In the considered IEEE802.11 scenario, the bandit procedure has to choose the optimal channel from a total of 13 channels. The idle periods (white spaces) of the test data are generated by a Generalized Pareto distribution.

Based on the empirical results in [38], we extract the parameter values k and σ corresponding to high and low traffic. Thereafter, we generate random data vectors corresponding to different stationarity periods (10, 100, 5000, 10000 time steps respectively).

First, the periodic meta learning approach is tested, with the period $\Delta T = 100$. Then, the event triggered meta learning approach is tested with $\delta = 5 \times 10^{-3}$ and $\lambda = 100$. Finally, we apply the Exp3 algorithm on the same set of data.

Figure 3.20 shows the results of each method. It reveals that the meta bandit with event triggered approach (noted metabanditC) outperforms the other methods (Exp3 and periodic meta bandit) by achieving the minimum regret values. Since the event triggered approach launches the meta bandit only when necessary, it is expected to follow the environment variations better and therefore outperform the periodic approach.

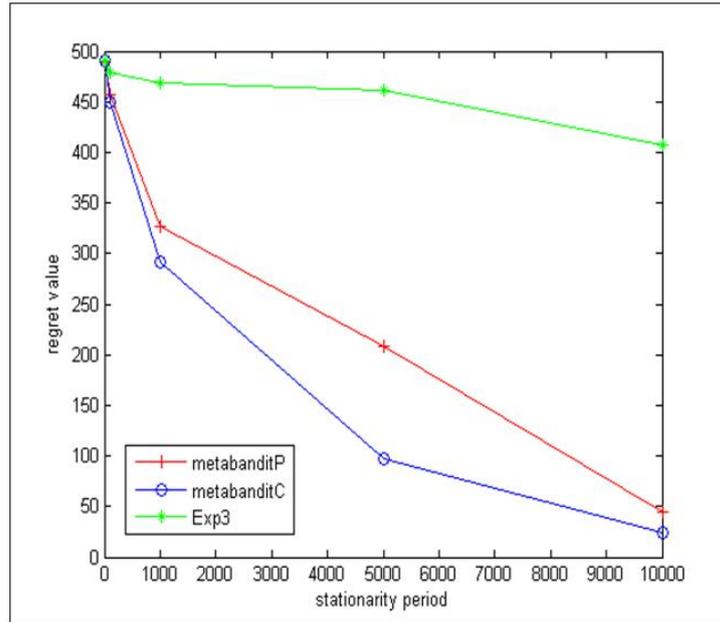


Figure 3.20: Comparison between online approaches.

3.7 Use case with IEEE 802.11 in IEEE P1900.4 framework

In this section, we present a use case scenario of IEEE802.11 temporal opportunistic access within the framework of the IEEE P1900.4 standard. In fact, IEEE P1900.4 offers a flexible framework that allows better utilization of radio resources and thus increases spectral efficiency. This represent an appropriate setting to perform opportunistic spectrum access, which means using idle frequency bands at a given time and location by the secondary users without interfering with the primary users.

In this issue, we propose a use case with the system IEEE802.11 as it provides a good scene for experimental scenarios due to its unlicensed band and the temporal characteristics of its access technology.

3.7.0.4 Presentation of IEEE P1900.4

IEEE P1900.4 [10][78][79], a part of IEEE SCC41 standard project family, aims to standardize architecture and enablers for the optimization of radio resource usage in heterogeneous wireless access networks. The standard will support distribution of the decision-process between network and terminal. Indeed, as the complexity of radio environment increases, the implementation of cognitive functions within terminals and networks is necessary to reach two goals: the improvement of user-perceived quality of service, and overall optimization of the radio resource management at the network level [80].

This standard describes the interfaces between reconfigurable elements with two P1900.4 entities: Network Reconfiguration Manager (NRM) and Terminal Reconfiguration Manager (TRM). TRMs take decisions autonomously, respecting some constraints imposed by the network. The NRM manages the overall resource optimization, but is not in charge of full management of

individual radio resource allocation. The constraints set by the NRM are called policies and are sent to terminals via the Radio Enabler (RE) (Figure 3.21). These policies are established in the policy derivation module and are based on different factors such as the external environment context and the operator's objectives.

The standard is built for three main use cases. The first use case is Dynamic Spectrum Assignment: some spectrum bands are dynamically assigned to base stations or access points. The second use case describes how IEEE P1900.4 can enable Dynamic Spectrum Access: the policies are intended to set the rules to dynamically access a given spectrum band, for instance to restrict the secondary use of the band, or to specify how the opportunistic spectrum access should be operated. The third use case emphasizes the decision distribution between network and terminal. The terminal takes decision autonomously with the range of possibilities that has been set by the network policies.

The measurement collection is an important function in IEEE P1900.4. Indeed, it is critical for the network to be able to collect measurements from the Radio Access Networks and the terminals. Measurements are used by the NRM to evaluate the efficiency of current radio resource selection policies. More precisely, the TRM module sends to NRM the terminal related context information that includes the radio measurements. This allows the NRM to update its policies for an optimized radio resource usage.

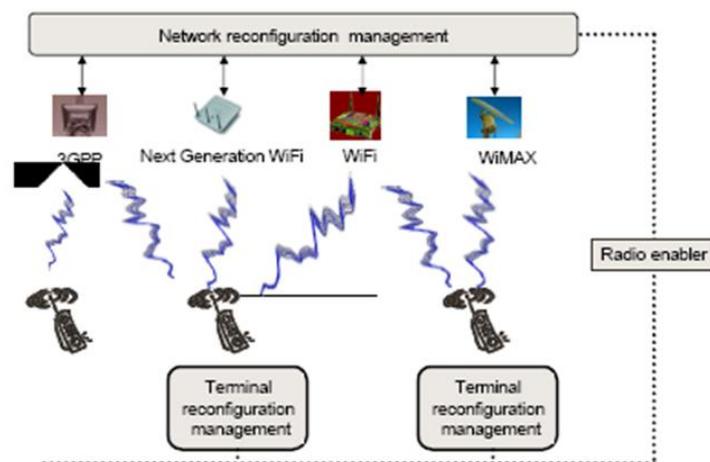


Figure 3.21: IEEE P1900.4 model [10].

3.7.0.5 Use case description

In this section, we propose a typical illustration of IEEE P1900.4 dynamic spectrum access use case. The main idea consists of allowing a mobile terminal (MT) to access in an opportunistic way to IEEE802.11 bands, using multi armed bandit strategies. The goal is to take advantage of the unused portions of the unlicensed bands intended to 802.11. The main motivation of this scenario is to improve the spectrum usage in IEEE802.11 bands by avoiding the CSMA/CA protocol as it leads to spectrum resources loss with its wait times (SIFS, DIFS, and contention window).

We propose an opportunistic spectrum access scheme based on reinforcement learning techniques. The mobile terminal has then the ability to choose in a dynamic manner which channel to access and when. The IEEE P1900.4 offers a suitable framework to apply the above-mentioned scheme in an efficient way in order to improve the overall spectrum usage. In fact, this standard allows the MT to take its decision autonomously provided it respects the directives of the network (in form of policies).

In this use case, we consider a "cognitive" MT with multi homing capabilities. In other terms, the terminal is able to use more than one protocol so that it can switch from a Radio Access Network (RAN) to another. This offers more flexibility for the achievement of better performances. In IEEE P1900.4 framework, the mobile terminal is equipped with the block TRM. The role of this module is to collect context information from the cognitive MT and informing the MT about the policies. The TRM sends the context information of the cognitive terminal to the Network Reconfiguration Manager entity. This measurement report informs the NRM entity about the environment characteristics at a given location and time (for example interference level for a given frequency band). Thereafter, the NRM combines the collected context information with other factors (such as operators objectives) to derive new policies addressed to cognitive terminals.

In our scenario, in case of high spectrum usage in RAN1 and low traffic on the IEEE802.11 bands (2.4 GHz or 5 GHz); the NRM can specify a policy that recommends the cognitive terminal to perform opportunistic spectrum access on the IEEE802.11 bands (Figure 3.22). This permits to reduce the traffic charge on the network RAN1 (for example UMTS network). Here,

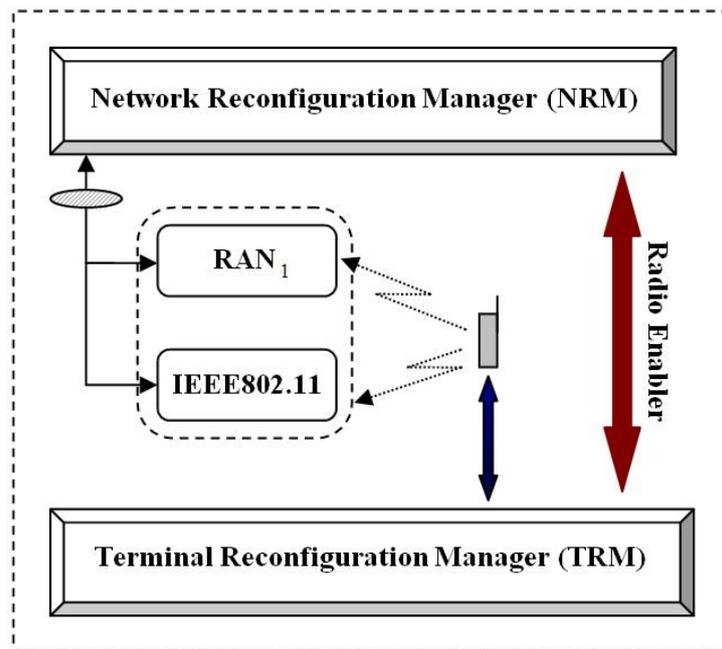


Figure 3.22: IEEE P1900.4 use case.

the cognitive MT is equipped with an intelligent algorithm, based on multi armed bandit formulation, which allows him to decide efficiently which channel to access in the IEEE802.11 band at a given time and location. This way, MT can detect the white spaces and sends its data

without causing interferences to primary users (generally the terminal has the choice between 13 channels). Thus, the cognitive MT is simultaneously connected on RAN1 and sends when possible data on IEEE802.11 bands.

We assume in this scenario that Access Points (AP) in the considered IEEE802.11 network include new functionalities that enable them to identify the intelligent terminals and handle the data they send. Thereafter, the usual legacy terminals keep using CSMA/CA to transmit to the AP. Meanwhile, the intelligent terminals detect the spectrum holes left by the legacy terminals and transmit on the idle frequency resource.

In this scenario (Figure 3.23), the MT receives a policy (Policy1) that allows him to perform an opportunistic spectrum access on the IEEE802.11 bands. After a period, the MT sends a report to the NRM through the radio enabler including radio measurements. The RE could be mapped on the RAN1. The report (sent by the TRM) describes the state of the link (such as quality of service and the cumulative reward corresponding to the total amount of data sent.). This is aimed to the module policy efficiency evaluation in the NRM (Figure 3.23). The NRM can update the policy and derive a more suitable one to meet the new changes in the environment context (Policy2 in Figure 3.23).

This way we take into account the case where several terminals use the opportunistic spectrum access at the same time, leading to congestion over the 802.11 bands. The measurement report will lead the NRM to update its policies and to limit the opportunistic spectrum access to the considered spectrum band.

Here, it is important to mention that it is necessary to achieve such opportunistic spectrum

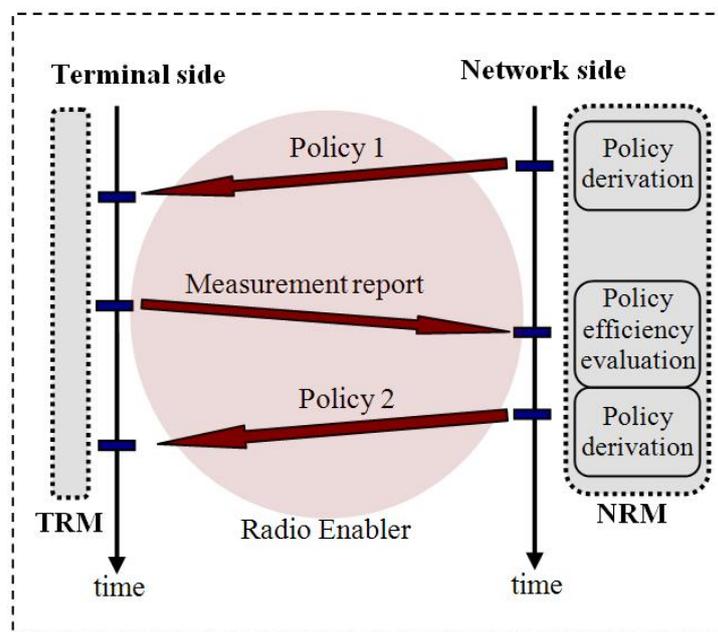


Figure 3.23: Scenario description.

access in the IEEE 802.11 band within the standard IEEE P1900.4. In fact, the cognitive terminal is unable to detect alone intelligent APs that ensure secondary usage function. This information needs to be transmitted to the terminal, for example via the standard IEEE P1900.4.

3.8 Conclusion

Opportunistic Spectrum Access (OSA) is an emerging research topic aiming at improving spectrum usage schemes in heterogeneous wireless environments. The main idea behind OSA is to take advantage of unused spectral resources at a given time and location so as to transmit data without interfering with the licensed users of the considered frequency band.

Nevertheless, the realization of OSA involves several constraints and difficulties: primary user detection, white space detection and identification, sharing of spectrum opportunities among secondary users, design of the overall system architecture (centralized or distributed), choice of OSA strategies between secondary networks (cooperative or competitive), coming up with efficient OSA spectrum policies etc.

Regarding this topic, we focus on the access problematic of the OSA. More precisely, we are interested at solving the exploitation-exploration dilemma of a secondary user. In fact, the performance of OSA is conditioned by the challenge of finding a compromise between two objectives:

- Exploring the external environment so as to acquire knowledge about the radio spectrum utilization,
- Exploitation of the cumulated knowledge to evaluate the spectrum holes and transmit data in an opportunistic manner.

This tradeoff shows similarities with a well known problem in machine learning: the Multi Armed Bandit (MAB) problem. Thus, the reinforcement learning algorithms (the bandit strategies) proposed to solve the MAB problem constitute efficient solutions for OSA.

In this last part of the thesis, we propose a complete framework that deals with effective application of the Multi Armed Bandit formulation for the achievement of opportunistic spectrum access. The main originality of this work is the experimentation of the MAB strategies on an IEEE802.11 channel model and the proposal of MAB parameter tuning schemes to enhance the performance of the used allocation strategies. As a result, we obtain intelligent solutions that provide the secondary users with the set of rules and policies to perform efficient OSA and to cope with the dynamic nature of the channels' occupation.

When external environment conditions are time-varying, automatic parameter tuning approaches enhance the efficiency of the bandit algorithms. Thus, two approaches are proposed: Semi dynamic and online parameter tuning scheme. The Semi dynamic method requires an offline sensitivity study that evaluates the performances of each MAB strategy with different parameter values and in different conditions. The online tuning approach makes use of meta learning scheme. Here, a second learner (meta learner) is added to learn the parameters of the base learner. This method is evaluated with a periodic triggering approach and an event triggered approach based on the change point detection algorithm.

Finally, we present a use case scenario of IEEE802.11 temporal opportunistic access within the framework of the IEEE P1900.4 standard. In this scenario, a cognitive terminal can receive instructions from a specific entity in IEEE P1900.4 system, so as to perform opportunistic access on IEEE802.11 bands following the multi armed bandit strategies.

To conclude, the MAB strategies, with and without tuning approaches are tested on a non-

stationary IEEE 802.11 channel occupation model and the obtained results show that the MAB strategies are viable solutions for opportunistic access in the IEEE802.11 bands. More specifically, the event-triggered approach with the change point detection method achieves much better performance compared to the other methods.

In this work, the proposed scheme is tested on an IEEE 802.11 system but the approach is general and can be applied to other systems with different statistical properties without loss of generalization. The bandit strategies have been demonstrated to achieve good performances in an OSA scenario on IEEE 802.11 bands. We believe that they constitute viable solutions for OSA regardless of the target radio access network.

Conclusion and perspectives

This thesis report describes my research work on "Metrology in wireless mobile networks for enhanced radio resource management". The main goal of the thesis is to propose effective approaches dealing with information collection, processing and utilization in cognitive radio context. These works are motivated by the necessity for wireless networks to cope with the increasing demand of throughput and services in one hand, and the inefficient use of spectral resources on the other hand.

To this purpose, we investigate three main issues related to the of measurements in wireless networks (Figure 3.24):

1. Processing of the existing radio measurements to extract further information that provides environment awareness for the cognitive network (Chapter 1),
2. Aggregation of radio measurements with the corresponding location information and the application of this concept in cognitive networks (Chapter 2),
3. Radio measurement exploitation through statistical processing, aimed at steered sensing of cognitive entities in an opportunistic spectrum access context (Chapter 3).

In Chapter 1, we focus on current standardized radio measurements in radio access technologies and we propose an innovative approach that aims at processing the reported measurements so as to extract additional information on the external environment. We experiment this idea on reported power measurements in GSM and UMTS networks using non-parametric regression and smoothing methods. As a result, we develop a dynamic estimator of the attenuation components of the received radio signal (namely pathloss, shadowing and fast fading), given a set of consecutive reported radio measurements. The main originality of this estimator (filed as a patent) is its almost real-time functioning and the production of results from existing measurements with no further hardware implementation. Adding to that, we propose a method for the determination of the mobile user situation (incar, pedestrian and unmoving) as well as a proposal of handover procedure improvement through enhanced target cell determination. To conclude, in this first part of the thesis, we begin with a "low level" analysis by proposing appropriate processing methods on existing radio measurements, employed by the network in RRM mechanisms. Our goal is to demonstrate that our approach can be implemented in future wireless networks for an efficient use of radio measurements and for the improvement of radio resource management in cognitive networks. During this work, the main challenging issue is the set up of a database of real radio measurements in different contexts and situations so as to validate the proposed processing methods and applications in wireless networks. Thus, our approach can be improved by testing it on various different measurements databases

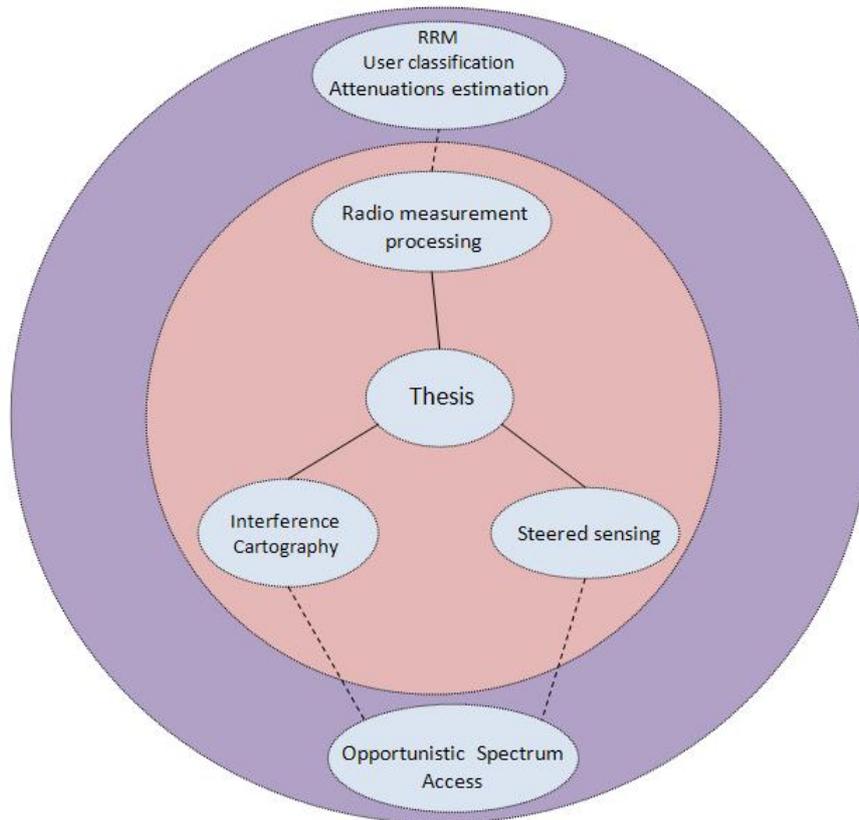


Figure 3.24: Thesis overview.

constructed from different radio access technologies (such as UMTS, EDGE, GPRS, HSDPA etc.).

In Chapter 2, we move one level "higher" and perform data analysis through the aggregation of radio measurements with the corresponding location information. Thus, we propose an original idea, called as "Interference Cartography", together with a complete framework that details its application in cognitive networks. The purpose of this novel concept is to combine location information with radio measurements carried out over the heterogeneous radio environment, and to provide a complete view of the environment to be used in autonomous decision making in a cognitive context. This is achieved by aggregating the already existing radio measurements that circulate in wireless networks forming the heterogeneous network panorama, combining this aggregated information with geo-localization information, performing advanced signal processing techniques to render the information complete and reliable, and updating the information to provide a viable picture of the environment for efficient detection, analysis and decision. Our focus is on hierarchical access models where licensed spectrum can be accessed by secondary users without creating harmful interference on the primaries.

In this chapter, a complete description of a possible network implementation in a hierarchical access scheme is given, with a centralized architecture, a protocol structure that complies with the utilization of interference cartography, and a signal processing technique (*Kriging interpolation*) that constructs a complete and reliable cartography with limited number of located measurements. Adding to that, a case study of the proposed scheme is given, demonstrating the utility of the notion of interference cartography.

Further research should look into a dynamic scenario where temporal considerations are accounted for. Such a study will include spatio-temporal signal processing techniques to construct and to update the cartography as well as propositions for triggering the iterative update algorithms in the protocol structure.

Finally in Chapter 3, we move to a "one more higher level", where we focus on the utilization of radio measurements to steer cognitive network decisions when performing Opportunistic Spectrum Access (OSA). The performance of OSA is conditioned by the challenge of finding a compromise between two objectives: 1 Exploring the external environment so as to acquire knowledge about the radio spectrum utilization, and 2- Exploiting the cumulated knowledge to determine the spectrum holes and transmit data in an opportunistic manner. Thus, we propose the utilization of the Multi Armed Bandit (MAB) formulation to provide secondary users with appropriate rules and policies for effective achievement of OSA. Besides, we also propose different tuning approaches (semi dynamic and online schemes) to better cope with the dynamic variations of channels occupation, because the reinforcement learning solutions of the MAB problem are very sensitive to the statistical properties of the environment. The proposed scheme is tested on an IEEE 802.11 system with promising results, but the approach is general and can be applied to other systems with different statistical properties without loss of generalization. The bandit strategies have been demonstrated to achieve good performances in an OSA scenario on IEEE 802.11 bands. We believe that they constitute viable solutions for OSA regardless of the target radio access network. An interesting future work is to test the implementation of MAB algorithms in real cognitive networks.

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Publications and patents

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- [1] Exploiting radio measurements in wireless mobile networks with advanced signal processing, by Afef Ben Hadj Alaya-Feki, Eric Moulines, Emmanuelle Villebrun, The Third International Conference on Wireless and Mobile Communications ICWMC 2007, Guadeloupe.
- [2] Optimization of Radio Measurements Exploitation in Wireless Mobile Networks, by Afef Ben Hadj Alaya-Feki, Alain LeCornec, Eric Moulines, Journal of Communications (JCM) - ISSN : 1796-2021 - Volume : 2 - Issue : 7, Finland, 2005.
- [3] Dynamic spectrum access with non stationary multi armed bandit, by Afef Ben Hadj Alaya-Feki, Eric Moulines and Alain LeCornec, IEEE International Workshop on Signal Processing Advances in Wireless Communications SPAWC 2008.
- [4] Informed spectrum usage in cognitive radio networks: Interference Cartography, by Afef Ben Hadj Alaya-Feki, Sana Ben Jemaa, Berna Sayrac, Eric Moulines and Paul Houze, Invited Paper to IEEE Cognitive Radio Workshop CRNETS, IEEE PIMRC 2008.
- [5] Semi dynamic parameter tuning for optimized opportunistic spectrum access, by Afef Ben Hadj Alaya-Feki, Berna Sayrac, Eric Moulines and Alain LeCornec, IEEE Vehicular Technology Conference VTC fall 2008.
- [6] Opportunistic spectrum access: Online search of optimality, by Afef Ben Hadj Alaya-Feki, Berna Sayrac, Eric Moulines and Alain LeCornec, IEEE Global Communications Conference GLOBECOM 2008.
- [7] Opportunistic spectrum access with IEEE802.11 in IEEE P1900.4 framework, by Afef Ben Hadj Alaya-Feki, Berna Sayrac, Paul Houzé and Eric Moulines, IEEE International Conference on Wireless and Mobile Computing, Networking and Communications WIMOB 2008.
- [8] Interference Cartography for Hierarchical Dynamic Spectrum Access, by Afef Ben Hadj Alaya-Feki, Berna Sayrac, Sana Ben Jemaa and Eric Moulines, IEEE International

Dynamic Spectrum Access Networks DySPAN symposium 2008.

[9] Opportunistic Spectrum Access: Exploration-Exploitation dilemma, by Afef Ben Hadj Alaya-Feki, Berna Sayrac, Eric Moulines and Alain LeCornec, submitted to the Annales of Telecommunications, special issue on Cognitive Radio 2008.

Patents

[11] Procédé d'estimation des composantes d'atténuation du signal radio propagé, by Afef Ben Hadj Alaya, Emmanuelle Vignault - N° invention: 3224.

[12] Optimisation des mesures des terminaux dans un réseau radio communication, by Afef Ben Hadj Alaya, Paul Houze, Sana Ben Jamaa - N° invention: 3675
