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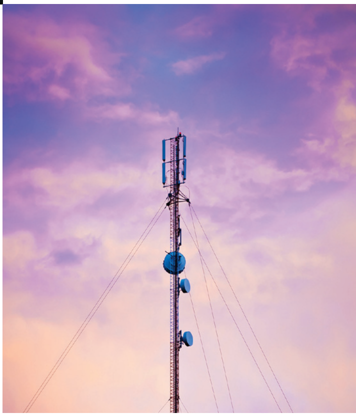
Spectrum sharing using cognitive radio system capabilities

Methods to obtain and exploit knowledge of spectrum availability

Marja Matinmikko



VTT SCIENCE 20

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Taajuuksien yhteiskäyttö kognitiivisten radiotekniikoiden avulla
Menetelmiä taajuuksien saatavuuden selvittämiseen ja hyödyntämiseen

Spectrum sharing using cognitive radio system capabilities. Methods to obtain and exploit knowledge of spectrum availability. **Marja Matinmikko.** Espoo 2012. VTT Science 20. 77 p. + app. 113 p.

Abstract

This thesis presents methods to obtain and exploit knowledge of spectrum availability for cognitive radio systems (CRSs). CRSs can change the way to access the radio spectrum in response to the growing data rate and spectrum demand of the future mobile telecommunication market. A CRS includes capabilities to obtain knowledge of system internal and external state, dynamically and autonomously adjust its operations accordingly, and learn from the results. Future CRSs can enhance spectrum sharing by exploiting temporarily and locally available spectrum while guaranteeing that primary systems remain free from harmful interference.

This thesis presents novel directional and distributed spectrum occupancy measurements for the 2.4 GHz industrial, scientific and medical (ISM) band to characterise the current spectrum use and the potential availability of spectrum for CRSs, taking into account the spatial dimension. This is the first study to show that the spectrum occupancy can vary significantly depending on the measurement location even in the same office area at the same time.

Knowledge of spectrum availability for CRSs can be accomplished by several methods, including control channels, databases, and spectrum sensing techniques, which all have different capabilities, requirements and performances. In order to use proper methods in different situations, this thesis proposes a novel band-specific approach, where the selection of the method to obtain knowledge of spectrum availability is determined separately for each frequency band based on the deployment characteristics and regulatory requirements of the specific band.

Spectrum sensing is studied in more detail by presenting analytical performance evaluation for a selected algorithm, Welch's periodogram, in a Rayleigh fading channel. Fuzzy combining is proposed for cooperative spectrum sensing, where the sensing results from several nodes are combined to improve the sensing reliability in a fading environment. In addition, a novel rule-based decision-making system with a learning mechanism is developed for the selection between different spectrum sensing techniques.This is the first work in the research literature to consider this problem. Finally, in order to exploit the spectrum and assign the available frequency channels to the different users, this thesis presents centralised and distributed channel assignment methods based on a heuristic harmony search algorithm. The presented results can be used in the development of future mobile communication systems enhanced with CRS capabilities to respond to the growing data rate and spectrum demand.

Keywords Channel assignment, cognitive radio system, cooperative spectrum sensing, frequency management, mobile communication, spectrum occupancy

Taajuuksien yhteiskäyttö kognitiivisten radiotekniikoiden avulla
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Spectrum sharing using cognitive radio system capabilities: Methods to obtain and exploit knowledge of spectrum availability. **Marja Matinmikko.** Espoo 2012. VTT Science 20. 77 s. + liitt. 113 s.

Tiivistelmä

Tämä työ esittelee menetelmiä, joilla voidaan selvittää ja hyödyntää tietoa taajuuksien saatavuudesta kognitiivisille radiojärjestelmille. Kognitiiviset radiojärjestelmät voivat muuttaa merkittävästi taajuuksien käyttötapaa vastauksena tulevaisuuden matkaviestintämarkkinan kasvavaan datanopeuksien ja taajuuksien tarpeeseen. Kognitiiviset radiojärjestelmät kykenevät saamaan tietoa järjestelmän sisäisestä ja ulkoisesta tilasta, mukauttamaan dynaamisesti ja autonomisesti toimintaansa kerätyn tiedon perusteella sekä oppimaan saavutetuista tuloksista. Tulevaisuuden kognitiiviset radiojärjestelmät tehostavat taajuuksien yhteiskäyttöä hyödyntämällä hetkellisesti ja paikallisesti vapaina olevia taajuuksia aiheuttamatta alkuperäisille käyttäjille haitallista häiriötä.

Tutkimus esittelee uusia suuntaavia ja hajautettuja taajuuksien käyttöasteen mittauksia 2.4 GHz:n ISM-taajuudella huomioiden tilasuunnan vaikutuksen. Tämä on ensimmäinen tutkimus, joka osoittaa, että taajuuksien käyttöaste voi vaihdella huomattavasti eri paikoissa samalla hetkellä jopa saman toimistotilan sisällä.

Tietoa taajuuksien saatavuudesta kognitivisille radiojärjestelmille voidaan saada usealla tavalla, esimerkiksi kontrollikanavien, tietokantojen ja taajuuksien sensorointitekniikoiden avulla. Menetelmillä on erilaiset ominaisuudet, vaatimukset ja suorituskyvyt. Jotta käytettäisiin sopivia menetelmiä eri tilanteissa, tutkimus ehdottaa uutta taajuuskaistakohtaista lähestymistapaa, jossa menetelmä valitaan kullekin taajuusalueelle riippuen sen käyttötavasta sekä reguloinnin vaatimuksista.

Taajuuksien sensorointia tutkitaan tarkemmin ja esitetään suorituskykyanalyysiä yhdelle algoritmille (Welchin periodogrammi) Rayleigh-häipyvässä kanavassa. Sumeaa yhdistelyä ehdotetaan yhteistyössä tapahtuvaan taajuuksien sensorointiin, jossa usean tahon mittaustulokset yhdistetään, jolloin saadaan parempi suorituskyky häipyvässä ympäristössä. Lisäksi työssä esitetään uusi sääntöpohjainen päätöksentekomenetelmä taajuuksien sensorointitekniikoiden valintaan sisältäen oppimismekanismin. Ehdotettu menetelmä on ensimmäinen kirjallisuudessa esitetty menetelmä sensorointitekniikoiden valintaan. Työssä esitetään lisäksi keskitetty ja hajautettu kanavien jakomenetelmä vapaiden taajuuksien hyödyntämiseen ja jakamiseen eri käyttäjien kesken perustuen harmony search -algoritmiin. Esitettyjä tuloksia voidaan hyödyntää tulevaisuuden matkaviestintäjärjestelmien kehityksessä tuomalla niihin mukaan kogniivisia radiotekniikoita vastauksena kasvaviin datanopeus- ja taajuusvaatimuksiin.

Avainsanat Channel assignment, cognitive radio system, cooperative spectrum sensing, frequency management, mobile communication, spectrum occupancy

Preface

The research for this thesis has been conducted at the Communication Platforms knowledge center of the VTT Technical Research Centre of Finland in Oulu, Finland, in the years 2008–2012. The supervisor of this thesis is Prof. Jari Iinatti from the University of Oulu. The advisors of this thesis are Docent Aarne Mämmelä and Dr Tapio Rauma from VTT.

First, I would like to express my gratitude to Mr Kyösti Rautiola and Dr Jussi Paakkari for providing me the opportunity to do the research and be the project manager in a number of cognitive radio system related projects at VTT over the years. They have given me a lot of freedom to pursue the research directions that I have found appealing. Research work for this thesis was mostly done in the Spectrum Management for Future Wireless Systems (SMAS) project funded by the Academy of Finland (decision number 134624) in 2010–2012 and the Cognitive and Opportunistic Wireless Communication Networks (COGNAC) project funded by the Finnish Funding Agency for Technology and Innovation, Tekes, in 2008–2011. I am grateful to Mrs Jaana Aarnikare from VTT for handling the financial administration of these projects, saving me a lot of time to do the actual research work. Research for this thesis was also conducted in the Opportunistic Networks and Cognitive Management Systems for Efficient Application Provision in the Future Internet (OneFIT) project in 2010–2012, funded by the European Commission, and the Cognitive Radio System Demonstration (CRAS-DE) project in 2009, funded by VTT.

I would like to thank Prof. Jari Iinatti, my thesis supervisor at the University of Oulu, for the guidance and encouragement all the way from my Licentiate thesis and the start of the publication work for the Doctoral thesis to the finalisation of the Doctoral thesis. I am deeply grateful to Docent Aarne Mämmelä from VTT, who has taught me the essence of telecommunications research right from the start in 2001 when I joined VTT to prepare my Master’s thesis. Dr Tapio Rauma had an important role by bringing his knowledge of heuristics and particularly fuzzy logic to our cognitive radio research, and his contribution is gratefully acknowledged.

I am deeply grateful to my colleagues at VTT who have helped me during the years and are co-authors of the papers in this thesis: Mr Ilkka Harjula, Mr Marko Höyhtyä, Mrs Miia Mustonen, and Mrs Heli Sarvanko. In particular, I am grateful to my officemate, Mr Ilkka Harjula, who has always had the time to listen, and to Mrs

Miia Mustonen whose help has been indispensable. I am grateful to Dr Javier Del Ser from TECNALIA Research & Innovation, Spain, for the fruitful cooperation that was started with his research visit to VTT in the COGNAC project in 2010 and turned out to be very productive. His exemplary passion for research has motivated me to find the time to do the real research work in the flurry of other activities.

This thesis work would not have been possible without the academic freedom of the SMAS project. For that opportunity, I am deeply grateful to Prof. Olav Tirkkonen and Prof. Jyri Hämäläinen from the Aalto University, who were the main drivers in the preparation of this project back in 2008–2009 when I only had a vague idea about the possible thesis topic. I would also like to thank colleagues from the Aalto University and University of Turku in the SMAS project.

Over the years, I have had the privilege to participate in a number activities related to spectrum matters of mobile communications and cognitive radio systems ranging from regulatory and techno-economical side to the technical and trialing activities. I have got to know a lot of people from the industry, research, and regulation, and received a lot of comments, support, and important input. I am deeply grateful to Pekka Ojanen, who taught me a lot about spectrum regulation and supported me in many assignments. I am grateful to Jan Engelberg and Margit Huhtala from the Finnish Communications Regulatory Authority (FICORA), Kari Horneman, Jari Hulkkonen, and Eiman Mohyeldin from Nokia Siemens Networks, and Timo Bräysy, Marcos Katz, Zaheer Khan, and Janne Lehtomäki from the University of Oulu, and Tao Chen from VTT. The support of my colleagues at the COST Action IC0905 “Techno-Economic Regulatory Framework for Radio Spectrum Access for Cognitive Radio/Software Defined Radio (TERRA)” and COST Action IC0902 “Cognitive Radio and Networking for Cooperative Coexistence of Heterogeneous Wireless Networks” is also gratefully acknowledged. Most recently, participation in the Trial programme of Tekes, and particularly the Cognitive Radio Trial Environment (CORE) project, has given me a lot of new insights into the future, and the support from all involved people is acknowledged.

I am grateful to Prof. Riku Jäntti from the Aalto University and Assist. Prof. Kenta Umebayashi from the Tokyo University of Agriculture and Technology for reviewing the manuscript and providing helpful comments. I am also grateful to Outi Hiltunen from TransMate Kielipalvelut for revising the language.

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Oulu, 25.9.2012 Marja Matinmikko

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List of original papers

This thesis is based on the following original publications, which are referred to in the text as I–X. The publications are reproduced as appendices with kind permission from the publishers.

I Matinmikko, M., Sarvanko, H., Mustonen, M. & Mämmelä, A. 2009. Performance of spectrum sensing using Welch's periodogram in Rayleigh fading channel. Proceedings of 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom). Hannover, Germany, 22–24 June 2009. Pp. 1–5. ISBN: 978-1-4244-3423-7.

II Matinmikko, M., Mustonen, M., Höyhtyä, M., Rauma, T., Sarvanko, H. & Mämmelä, A. 2010. Distributed and directional spectrum occupancy measurements in the 2.4 GHz ISM band. Proceedings of 2010 7th International Symposium on Wireless Communication Systems (ISWCS). York, U.K., 19–22 September 2010. Pp. 976–980. ISBN: 978-1-4244-6315-2.

III Matinmikko, M., Mustonen, M., Höyhtyä, M., Rauma, T., Sarvanko, H. & Mämmelä, A. 2010. Cooperative spectrum occupancy measurements in the 2.4 GHz ISM band. Proceedings of 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL). Rome, Italy, 7–10 November 2010. Pp. 1–5. ISBN: 978-1-4244-8131-6.

IV Matinmikko, M., Mustonen, M., Höyhtyä, M., Rauma, T., Sarvanko, H. & Mämmelä, A. Directional and cooperative spectrum occupancy measurements in the 2.4 GHz ISM band. Journal paper to appear in International Journal of Autonomous and Adaptive Communications Systems. ISSN: 1754-8632.

V Matinmikko, M., Rauma, T., Mustonen, M., Harjula, I, Sarvanko, H. & Mämmelä, A. 2009. Application of fuzzy logic to cognitive radio systems. IEICE Transactions on Communications, Vol. E92-B, No. 12, pp. 3572–3580. ISSN: 1745-1345.

VI Matinmikko, M., Mustonen, M., Rauma, T., & Del Ser, J. 2011. Architecture and approach for obtaining spectrum availability information. Proceedings of IEEE 73rd Vehicular Technology Conference (VTC Spring). Budapest, Hungary, 15–18 May 2011. Pp. 1–5. ISBN: 978-1-4244-8332-7.

VII Matinmikko, M., Rauma, T., Mustonen, M. & Del Ser, J. 2011. Decision-making system for obtaining spectrum availability information in opportunistic networks. Proceedings of 4th International Conference on Cognitive Radio and Advanced Spectrum Management (CogART). Barcelona, Spain, 26–29 October 2011. Pp. 1–6. ISBN: 978-1-4503-0912-7.

VIII Matinmikko, M., Del Ser, J., Rauma, T. & Mustonen, M. Fuzzy-logic based framework for spectrum availability assessment in cognitive radio systems. Submitted journal paper manuscript.

IX Del Ser, J., Matinmikko, M., Gil-López, S. & Mustonen, M. 2010. A novel harmony search based spectrum allocation technique for cognitive radio networks. Proceedings of 2010 7th International Symposium on Wireless Communication Systems (ISWCS). York, U.K., 19–22 September 2010. Pp. 233–237. ISBN: 978-1-4244-6315-2.

X Del Ser, J., Matinmikko, M., Gil-López, S. & Mustonen, M. 2012. Centralized and distributed spectrum channel assignment in cognitive wireless networks: A Harmony Search approach. Applied Soft Computing, Vol. 12, No 2, pp. 921–930.

Author's contributions

The author has had the main responsibility of writing Papers I, II, III, IV, V, VI, VII, and VIII. The author has developed the original ideas of Papers II, III, IV, V, VI, VII, and VIII. In Paper I, the author has continued the work done in our research group and extended the performance evaluation of the selected spectrum sensing method to a Rayleigh fading channel. In Papers IX and X, the author has introduced the concept of cognitive radio systems and formulated the research problem together with J. Del Ser. The simulations were done by J. Del Ser.

Contents

Appendices

Papers I–X

List of abbreviations

AWGN	Additive white Gaussian noise
BER	Bit error rate
CCC	Cognitive control channel
COGNAC	Cognitive and Opportunistic Wireless Communication Networks project
CORE	Cognitive Radio Trial Environment project
COST	European Cooperation in Science and Technology
CPC	Cognitive pilot channel
CR	Cognitive radio
CRAS-DE	Cognitive Radio System Demonstration project
CRS	Cognitive radio system
EGC	Equal gain combining
FCC	Federal Communications Commission
FICORA	Finnish Communications Regulatory Authority
GSM	Global system for mobile communications
IETF	Internet Engineering Task Force
IMT	International mobile telecommunications
ISM	Industrial, scientific, and medical
ITU-R	International Telecommunicaion Union Radiocommunication Sector
KAUTE	Kaupallisten ja teknillisten tieteiden tukisäätiö
LTE-Advanced	Long Term Evolution Advanced
MRC	Maximal ratio combining

OneFIT	Opportunistic Networks and Cognitive Management Systems for Efficient Application Provision in the Future Internet project
OODA	Observe, orient, decide, and act
PAWS	Protocol to access white space database
RAT	Radio access technology
REM	Radio environment map
RF	Radio frequency
ROC	Receiver operating characteristics
SMAS	Spectrum Management for Future Wireless Systems project
SNR	Signal-to-noise ratio
Tekes	Finnish Funding Agency for Technology and Innovation
TERRA	Techno-Economic Regulatory Framework for Radio Spectrum Access for Cognitive Radio/Software Defined Radio
TV	Television
UMTS	Universal mobile telecommunications system
VHF	Very high frequency
WLAN	Wireless local area network
WRC	World Radiocommunication Conference

1. Introduction

Wireless communications has experienced strong growth during the past decades. The role of mobile communications has become significant in people's everyday life. The demand for mobile services keeps increasing towards the year 2020, as predicted earlier by the International Telecommunication Union Radiocommunication Sector (ITU-R) in (ITU-R 2005) and more recently in (ITU-R 2011d). The predicted growth in the data rates will inevitably result in increasing spectrum demand. New spectrum was made available for the mobile service at the World Radiocommunication Conference in 2007 (WRC-07) by the ITU-R on the basis of the spectrum requirement calculations presented in (Takagi & Walke 2008, Matinmikko et al. 2009, and ITU-R 2006). These spectrum allocations were an important step in the direction of meeting the growing user demand, but yet the spectrum that was made available remained lower than the predicted demand by the year 2020.

The success of mobile communications has stemmed to a large extent from the fact that new generations of mobile communication systems were continuously developed with improved capabilities to offer and support new services. The real-life deployment of the new generations of systems was made possible by the timely spectrum allocations that guaranteed that the suitable carrier frequencies and bandwidths were made available for several operators to deploy the networks and make business. This success of deploying new generations of mobile communication systems is now challenged by the difficulty of finding suitable spectrum for mobile communications. The studies presented in (Takagi & Walke 2008, Matinmikko et al. 2009, and ITU-R 2006) have quantised the spectrum demand, and the recent studies on the predicted data rates by several sources (ITU-R 2011d, UMTS Forum 2011) support the previous findings of the ITU-R in (ITU-R 2005) of the growing mobile telecommunication market and predict even stronger growth for the next decade 2012–2022. According to (ITU-R 2011d), the data rate demand in 2015 is predicted to be four times higher than in 2012. The ITU-R will consider additional spectrum allocations for the mobile service at the next WRC in 2015 (WRC-15). The true challenge to meet the growing data rate and spectrum demand is to find suitable frequency bands where the systems could be deployed. The desirable bands for mobile communications are bounded by the natural limits due to the radio wave propagation, and making these bands available solely to mobile communications is challenging due to the unavailability of unallocated spectrum.

In the past, spectrum availability was not as restricted as today and it was enough to develop individual techniques to improve the system spectral efficiency that characterises the achievable throughput of the system over the system bandwidth. The peak spectral efficiency requirements of the next generation mobile communication systems, the International Mobile Telecommunication – Advanced (IMT-Advanced), are already very high corresponding to 15 b/s/Hz in the downlink direction and 6.75 b/s/Hz in the uplink direction, as presented in (ITU-R 2008). While improvements in the system spectral efficiencies in the development of future mobile communication systems are now more difficult to achieve, spectrum sharing among different systems could be needed in the future to accommodate all the versatile wireless systems with differing spectrum usage patterns and requirements in the available spectrum resources. This spectrum sharing could allow the operation of several systems in the same frequency bands, which could help to meet the predicted growth in the demand of wireless services.

In fact, several spectrum occupancy measurement studies have indicated that there is room for spectrum sharing, see e.g. (McHenry et al. 2006, Wellens et al. 2007, Chiang et al. 2007, Islam et al. 2008, Lopez-Benitez et al. 2009, and references therein). The spectrum occupancy measurements have estimated the utilisation rates of the frequency channels and shown that they remain quite low in many instances, except for the bands used for mobile communictions or television (TV) broadcasting. Opportunistic use of these temporarily and locally available spectrum resources could significantly improve the overall spectrum occupancy by balancing the different usage patterns of the different systems. In the attempt of developing the spectrum sharing techniques, the concept of cognitive radio systems (CRS) has emerged, and it has been recently introduced to the international spectrum regulatory framework in (RSPG 2010, ITU-R 2009a, ITU-R 2011b, ITU-R 2011c).

1.1 Overview of cognitive radio systems

There are many definitions for CRSs, and we follow the globally accepted definition from the ITU-R which states that:

"CRS is a radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives; and to learn from the results obtained." (ITU-R 2009a)

Cognitive radio (CR) has been originally coined in (Mitola 1999), where CR employs model-based reasoning about its environment, location, radio propagation, networks, protocols, user, and its own internal structure. CRS is a general definition covering a set of capabilities to obtain knowledge, make decisions and adjustments, and learn from the results. Different systems, such as mobile communication systems, could deploy CRS capabilities in their operations. CRS capabilities form the cognitive cycle which is shown in Figure 1 following (ITU-R 2011b). As an example in terms of the spectrum use, a CRS can obtain knowledge of the current spectrum availability, make decisions on which channels to access, and further learn from past actions and their results by, for example, focusing on the most promising channels. CRSs are expected to offer several benefits compared to traditional systems, such as improved efficiency of spectrum use, increased flexibility, and potential for new mobile communication applications (ITU-R 2011b).

An important point related to the use of CRS capabilities for spectrum access is that their introduction and deployment is a spectrum regulatory matter which is governed by the spectrum regulators. In order to promote spectrum sharing among different systems, the concept of CRSs has been recently introduced to the international spectrum regulatory framework, but a lot of effort is required for their successful introduction to real-world systems with practical application.

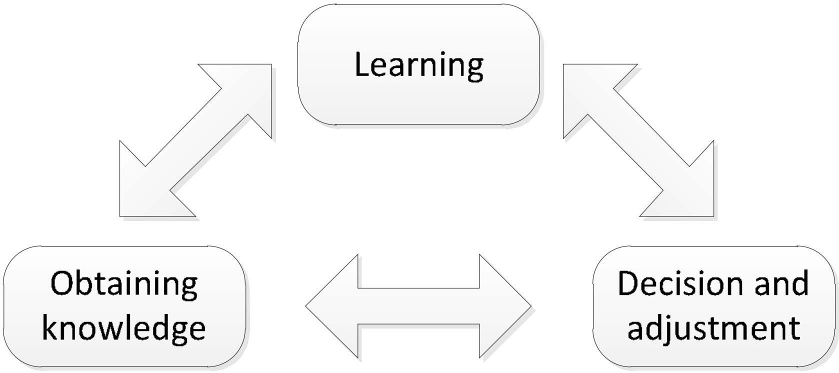

Figure 1. Cognitive cycle of the CRS capabilities following (ITU-R 2011b).

1.2 Motivation and contributions of the thesis

The development of techniques to allow sharing of the spectrum resource is of great importance in the future wireless systems to meet the growing data rate demand, and the present thesis aims at contributing to this purpose. This thesis aims at developing techniques to obtain knowledge of the spectrum availability and to use this knowledge for CRSs covering all three phases of the cognitive cycle. The research methods include analysis, simulations, and measurements.

The major motivation comes from our previous findings of the growing data rate demand resulting in growing spectrum demand for the mobile service presented in (Takagi & Walke 2008, Matinmikko et al. 2009, ITU-R 2006). This imminent need for new spectrum beyond that identified at WRC-07 to accommodate the growing user demand motivates the search for new and improved spectrum sharing techniques. This thesis is further motivated by various spectrum occupancy measurement studies (e.g. McHenry et al. 2005a, Shared Spectrum Company 2010) that have indicated that there is room for vast improvements in the current spectrum occupancy by using spectrum sharing techniques on certain bands. Finally, the newly developed CRS capabilities, already recognised by the ITU-R in (ITU-R 2011b, ITU-R 2011c), can become major building blocks in the future mobile communication systems in the quest for new spectrum opportunities allowing the mobile communication systems to fulfil the growing data rate and spectrum demand using CRS capabilities.

The CRS related research literature has become vast during the recent years. However, the deployment of CRS capabilities is still at its infancy and the practical approaches for CRS operations are still unclear. An important step in the assessment of the feasibility of the introduction of CRSs into the spectrum regulatory framework has been to assess the spectrum availability for cognitive radio type of operations. Spectrum occupancy measurement studies have been conducted to characterise the current status of spectrum use in different spectrum bands, see e.g. (Islam et al. 2008, McHenry et al. 2006, Naganawa et al. 2011, Shared Spectrum Company 2010, Wellens et al. 2007). Many of the previous spectrum occupancy measurement studies have been conducted from a single measurement location at a time and they have not characterised the spectrum use of certain bands accurately, as there has been a mismatch between the measurement location and the actual use of the band. For example, outdoor measurements (Islam et al. 2008, Shared Spectrum Company 2010, Valenta et al. 2009) were done covering the 2.4 GHz industrial, scientific, and medical (ISM) band, while most usage is in indoor locations by wireless local area network (WLAN) devices. To more efficiently capture the influence of the measurement location and direction on the spectrum use and thus the spectrum availability for CRS, this thesis has conducted spectrum occupancy measurement studies where the measurements have been conducted from two closely spaced locations simultaneously and shown that the spectrum occupancy, and thus the spectrum availability for CRSs, can vary significantly depending on the measurement location and direction.

A key requirement for a CRS is that it has to operate according to the Radio Regulations of the ITU-R that govern the use of radio spectrum as stated in (ITU-R 2011b). Therefore, if a CRS is deployed in frequency bands that have higher priority or primary systems, the CRS has to guarantee that it does not cause harmful interference to the primary systems. In essence, this requires that the CRS has techniques to obtain accurate knowledge of the current status of the spectrum use indicating whether a given frequency channel is free or occupied. There are several methods to obtain knowledge of spectrum availability, including control channels, databases, and spectrum sensing techniques (ITU-R 2011b, RSPG 2010). Different methods are more suitable in different situations depending on the requirements set for the use of the band and the capabilities of the individual methods. While much research has been conducted on the individual methods, the selection of methods between databases, control channels, and spectrum sensing, or the individual techniques inside these general classes has received very little attention. This thesis proposes a band-specific approach where the method to obtain the spectrum availability information is determined based on the characteristics of the systems and the regulatory requirements of the band in question.

For one of the methods to obtain knowledge of spectrum availability, namely spectrum sensing, this thesis presents performance evaluation of a specific spectrum sensing algorithm, Welch periodogram, and introduces a performance metric, the time between failures in detection. This thesis also introduces fuzzy logic for the first time for cooperative spectrum sensing, where the observations from several CRS nodes are combined to improve the performance in particularly in a fading environment. There are several different spectrum sensing techniques available in the research literature, and the different techniques have different capabilities, performances and requirements. The selection among the spectrum sensing techniques has not been studied before. This thesis presents a simple fuzzy rule-based decision-making system for the selection of spectrum sensing methods. This work is the first one in the research literature to accomplish this, thus opening a new research topic of selection of spectrum sensing methods for a specific situation.

After the spectrum availability for the CRS is known, there emerges a need to have methods to access the spectrum. When there are several users wishing to access the available frequency channels, there is a need to assign the free channels among the users. This thesis presents a channel assignment technique based on harmony search algorithm covering both centralised and distributed approaches.

This thesis is based on ten original papers, which are summarised in Chapter 3 and enclosed as appendices. Other supplementary publications of the author related to CRS and spectrum for mobile communication systems include (Chen et al. 2008, Chen et al. 2011, Chen et al. 2012, Harjula et al. 2011, Höyhtyä et al. 2011b, Höyhtyä et al. 2011c, Irnich et al. 2008, Khan et al. 2011, Matinmikko & Azuma 2008, Matinmikko et al. 2008a, Matinmikko et al. 2008b, Matinmikko et al. 2008c, Matinmikko et al. 2008d, Matinmikko et al. 2009, Matinmikko & Bräysy 2011, Mustonen et al. 2009, Mustonen & Matinmikko 2011, Rauma & Matinmikko 2011a, Rauma & Matinmikko 2011b, Sarvanko et al. 2008, Sarvanko et al. 2011a, and Sarvanko et al. 2011b).

1.3 Outline of the thesis

This thesis is organised as follows. Chapter 2 reviews the relevant literature on CRSs with a focus on spectrum occupancy measurements and the CRS capabilities, including techniques to obtain knowledge of spectrum availability, assign channels among users, and learn from the results. Chapter 3 presents a summary of the original papers. Chapter 4 presents conclusions from the studies of this thesis, including the main findings, limitations and future work. Finally, Chapter 5 provides a summary.

2. Cognitive radio system concept and capabilities

This chapter reviews the general CRS concept and the relevant CRS capabilities for the purpose of this thesis. First, a general overview of CRS is given together with a review of spectrum occupancy measurements. Then, the three key capabilities of CRS, including capabilities to obtain knowledge, adjust, and learn, as defined by the ITU-R, are reviewed from the spectrum viewpoint, summarising methods to obtain knowledge of spectrum availability, channel assignment techniques, and finally learning techniques.

2.1 General overview

There are various definitions for CRS concepts. According to (Mitola 1999), the coiner of the term 'cognitive radio', a CR employs model-based reasoning about its environment, location, radio propagation, networks, protocols, user, and its own internal structure. Moreover, a CR should be aware of the communications needs of its user, overall context of anticipated communications events, and degree of success towards communications goals offered by alternative courses of action (Mitola 1999). A CR continually observes, orients itself, creates a plan, decides and then acts, and in addition, learning may be pursued in the background (Mitola & Maguire 1999).

According to (Haykin 2005), a CR "is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming radio frequency (RF) stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind: highly reliable communications whenever and wherever needed and efficient utilisation of the radio system." The two key functions of a CR according to (Haykin 2012) are 1) a radio scene analyser at the receiver to identify spectrum holes and 2) dynamic spectrum manager and transmit-power controller at the transmitter to allocate the spectrum holes among multiple CR users.

We have adopted the internationally agreed general definition of CRS by the ITU-R presented in (ITU-R 2009a) and summarised in Chapter 1. The CRS operations form the cognitive cycle of Figure 1. In general, a CRS can be considered as a set of techniques for obtaining knowledge, decision making and adjustment, and learning that are applicable to a wide variety of wireless systems for improving the efficiency of spectrum use. The cognitive cycle is an application of the “observe, orient, decide, and act” (OODA) loop to radio systems. The OODA loop, originally created by John Boyd for military use in the early 1970s, includes a feedback loop in which past interactions with the environment guide current and future interactions (Thomas et al. 2005). The CRS cycle of the ITU-R can be considered as a modified version of the OODA loop where the “orient, decide and act” phases are combined into one phase, i.e. decision making and adjustment, and the learning phase is included specifically.

Research on CRS has been extensive since its discovery in (Mitola 1999), and a number of studies have appeared since then. Moreover, there is a large number of overview papers covering various aspects of CRSs, see e.g. (Akyildiz et al. 2008, Ben Letaief & Zhang 2009, Cabric et al. 2006, He et al. 2010, Jondral 2007, Liang et al. 2011, Marshall 2009, Pawelczak et al. 2011, Wang & Liu 2011).

An overview of the architectural evolution of CRS is summarised in (Mitola 2009). Recent standardisation and regulation activities on CRS in different forums are summarised in (Filin et al. 2011, Yoshino 2012). An overview of performance evaluation and performance metrics for CRS is presented in (Zhao et al. 2009a). Cooperation in CRS has been reviewed in (Ben Letaief & Zhang 2009). Signal processing in CRS has been reviewed in (Ma et al. 2009), including signal processing techniques to obtain knowledge of spectrum availability and interference control. An overview of spectrum management approaches for CRS is given in (Akyildiz et al. 2008). Use of artificial intelligence in CRS has been reviewed in (He et al. 2010). CRS implementation and testbed activities are summarised in (Pawelczak et al. 2011).

Information theory has been applied to the CRS in order to assess the fundamental capacity limits in different settings, see e.g. (Goldsmith et al. 2009, Devroye et al. 2006, Devroye et al. 2008, and Jovicic & Viswanath 2009). Information theoretic approaches for CRS operations include underlay, overlay and interweave models, see (Goldsmith et al. 2009) for a detailed review. The underlay model corresponds to the situation where the CRS can transmit only if the interference generated to non-CRS receivers is below some acceptable threshold. In the overlay approach, the CRS can transmit simultaneously with the non-CRS node but uses part of its transmission capabilities to relay the data from the non-CRS node. This approach assumes that the CRS has knowledge of, for example, channel conditions and messages of non-CRS nodes. In the interweave model, the CRS transmits only when the non-CRS nodes are not transmitting. This requires that the CRS node has accurate knowledge of the current status of the spectrum availability. Furthermore, from the information theoretic viewpoint, the concept of interference alignment has been developed for efficient sharing of the channel between multiple users (Cadambe & Jafar 2008). The information theoretic studies in general assume a lot of knowledge, such as the interference of the CRS caused to other nodes, channel conditions, and messages of other nodes, which in practical CRS operations are impossible to obtain. However, the studies can provide some insight to the theoretical limits of CRS in the different spectrum sharing situations. An example of applying information theoretic approaches to resource management in real-life mobile communication systems is the concept of coordinated multipoint transmission and reception, which is a coordination technique among multiple cell sites and has recently been incorporated Long Term Evolution Advanced (LTE-Advanced) development at Third Generation Partnership Project (3GPP) (Sawahashi et al. 2010).

The increasing demand for wireless products and services is resulting in a greater density of wireless devices, which requires new technology and spectrum regulatory approaches to accommodate the increasing amounts of wireless transmissions, see (Peha 2009). In practice, this could call for spectrum sharing, which can be cost-efficient means to access the spectrum. Peha (2009) has defined different models for spectrum sharing based on whether the devices are coexisting or cooperating and whether sharing among devices is among equal status or between primary and secondary devices. In the different sharing models, the sharing conditions and motivations for sharing can be different.

2.2 Efficiency of spectrum use

2.2.1 Metrics

There are several metrics to characterise how efficiently wireless systems use the radio spectrum. For mobile communication systems, *spectral efficiency* has been an important metric already for decades, see (Hatfield 1977). Old measures for the spectral efficiency in the circuit-switched systems included mobiles per channel, Erlangs per channel, Erlangs per megahertz, and Erlangs per megahertz per square mile (Hatfield 1977). In today's packet-based mobile communication networks, a common metric is the link spectral efficiency, which measures the achievable data rate per bandwidth over a single link in bits/s/Hz. To take into account the effect of multiple links, the system-level spectral efficiency metrics are used. As an example, the spectral efficiency of a mobile communication system is defined in (Werner & Jesus 2009) as "the sum of user throughputs for all user terminals served by a certain radio cell, divided by the overall system bandwidth per link direction, calculated for the maximum load that still allows fulfilling the satisfied-user criterion of a selected service in terms of data rate and delay". The development of advanced techniques for mobile communication systems including antenna, modulation, coding, multiple access, interference mitigation, and radio resource management techniques has resulted in significant improvements in the spectral efficiencies, and the natural limits are getting close. Thus, significant improvements in the spectrum use of the future mobile communication systems need to be searched from other sources than the spectral efficiency dimension.

Another important metric to characterise the efficiency of spectrum use is *spectrum occupancy*, which describes the utilisation rate of the frequency channel. Spaulding and Hagn (1977) have defined spectrum occupancy as *channel transmission occupancy*, which is the fraction of the measurement time that the detected power in the channel exceeds a threshold. The average spectrum occupancy is typically presented as a percentage value which describes the utilisation rate of the frequency channel. The spectrum occupancy of a frequency channel is often denoted also as duty cycle. The spectrum occupancy metric has recently received a considerable amount of interest as a potential dimension to improve the efficiency of spectrum use.

2.2.2 Spectrum occupancy measurement studies

Spectrum occupancy measurement studies aim at quantifying the proportion of time that a certain frequency channel is occupied in a given area. Spectrum occupancy measurements can be used to assess the current status of spectrum use and the availability of spectrum for CRS type of operations. For regulators, it is a tool to monitor how efficiently the current spectrum allocations are being used in reality. The ITU-R guidelines for spectrum occupancy measurements are presented in (ITU-R 2011a), and the measurement of the spectrum occupancy of short-range devices is discussed in (ITU-R 2009b).

In general, spectrum occupancy measurements collect measurement data, process the data to assess the spectrum occupancy, and develop models to characterise the spectrum occupancy (Datla et al. 2009). Spectrum occupancy measurements are typically performed using energy detection such as those reviewed here. In energy detection, the received signal energy is compared to a threshold, and the observations below the threshold are declared to denote a free channel. In fact, the general definition of spectrum occupancy (Spaulding & Hagn 1977) implies the use of the received signal energy.

The key factors that influence spectrum occupancy measurements are measurement channel bandwidth, number of channels, observation time per channel, revisit time (i.e. time to visit all channels to be measured and return to the first channel), and duration of monitoring, see (ITU-R 2011a). The measurement parameters are interrelated and compromises are needed. Channel bandwidth and revisit time of the spectrum occupancy measurements need to be adjusted according to the systems operating in the spectrum band. To capture all transmission in a band, the maximum revisit time needs to be half of the minimum of the “on” or “off” times of any transmission in the band, whichever is shorter. This is impractical for bursty transmissions of digital systems, and therefore a statistical approach is usually taken where the revisit time can be made larger if the total duration of monitoring is long enough to provide enough samples. The lower the spectrum occupancy, the more samples are needed for the same confidence level.

Spectrum occupancy measurement studies can give indications on the potential availability of spectrum bands for CRS operations, but a careful analysis is needed in the interpretation of the measurement results. In particular, there are limitations related to spectrum occupancy measurements that are based on energy detection which does not detect signals that are below the noise level. Therefore, some signals such as spread spectrum signals may remain unseen by spectrum occupancy measurements. For this reason, spectrum occupancy measurement studies can give too low spectrum occupancy values compared to the actual occupancy. This can give an overly optimistic view of the availability of spectrum for CRS operarations. In addition, the studies are sensitive to the threshold setting. For more details about the limits of energy detection, see (Tandra & Sahai 2008). In addition, some spectrum bands are used to receive only purposes, and therefore their occupancy cannot be captured using the spectrum occupancy measurements with energy detection. For the detection of receive-only stations, other techniques, such as the measurement of the local oscillator power leakage (Wild & Ramchandran 2005), will be needed. Furthermore, the occupancy of adjacent channels is of interest in assessing the availability of spectrum for CRS since the practical wireless systems deploy receivers that do not fully filter out signals appearing in adjacent channels, which limits the potential availability of spectrum for CRS.

Spectrum occupancy measurement studies are here classified into two categories: general studies and focused studies. General spectrum occupancy measurement studies cover a wide range of frequencies that are used by different services, while focused spectrum occupancy measurement studies concentrate on a selected frequency band and characterise its use in more detail.

General spectrum occupancy measurement studies have been conducted in several different countries, see e.g. China in (Han et al. 2010), the Czech Republic in (Valenta et al. 2009), Germany in (Wellens et al. 2007), Ireland in (Erpek et al. 2007b), Japan in (Naganawa et al. 2011), the Netherlands in (Schiphorst & Slump 2010), New Zealand in (Chiang et al. 2007), Singapore in (Islam et al. 2008), Spain in (Lopez-Benitez et al. 2009), and the US in (Erpek et al. 2007a, McHenry & Chunduri 2005, McHenry & Steadman 2005a, McHenry & Steadman 2005b, McHenry & Steadman 2005c, McHenry et al. 2005a, McHenry et al. 2005b, McHenry et al. 2006, Roberson et al. 2006, Pagadarai & Wyglinski 2009, Shared Spectrum Company 2010). General spectrum occupancy measurement studies have shared a common observation that the measured spectrum occupancies have remained rather low in certain locations and frequency bands. In fact, these studies have been a major source of motivation for the development of CRS techniques to gain access to bands whose current spectrum occupancy is low.

A large set of spectrum occupancy measurements have been conducted in the US in the 30 MHz–3 GHz frequency band. McHenry et al. (2005b), McHenry et al. (2006) and Roberson et al. (2006) have measured spectrum occupancies in an urban environment in Chicago, where the average occupancy was found to be 17.4%. McHenry et al. (2005a) have measured spectrum occupancy in a very dense urban environment in New York, where the average occupancy was found to be 13.1%. McHenry & Chunduri (2005) have measured spectrum occupancy from a roof top in Virginia, where the average occupancy was 11.4%. McHenry and Steadman (2006a) have measured spectrum occupancy in a rural environment in Virginia, where the average occupancy was only 3.4%. McHenry and Steadman (2006b) have measured spectrum occupancy in an urban environment in Virginia, where the average occupancy was 6.9%. McHenry and Steadman (2005c) have measured spectrum occupancy in a radio-quiet zone in West Virginia, where the average occupancy was less than 1%. Erpek et al. (2007a) have measured spectrum occupancy in a rural area in Maine, where the average occupancy was as low as 1.7%. Spectrum occupancy measurements have also been conduceted in a dense urban environment in Virginia in (Shared Spectrum Company 2010) in an attempt to find new bands for mobile communications, and TV bands were found to be the least promising for sharing. In general, in all of the studies, the bands with TV transmission and mobile communications showed the highest spectrum occupancies.

Erpek et al. (2007b) have measured spectrum occupancy in Dublin, Ireland, and found that the average occupancy was 13.6% with most usage in bands with TV transmission and mobile communications. Chiang et al. (2007) have measured spectrum occupancy in New Zealand over the frequency range 806–2750 MHz. The overall spectrum occupancy averaged over this band was found to be in the order of 6.2%, indicating that there is potential for CRS operations. Wellens et al. (2007) have performed indoor and outdoor measurements in Germany in the 20 MHz–6 GHz band. The outdoor measurements below 3 GHz showed very high noise due to man-made noise, which resulted in high spectrum occupancies as energy detection was used in the measurements. The spectrum occupancy was found to be very low in the 3–6 GHz band.

Islam et al. (2008) have measured spectrum occupancies in Singapore over the frequency range 80–5850 MHz and found out that a significant amount of the spectrum has very low occupancy offering thus a lot of potential for CRS operations. The average occupancy over the whole measured frequency range was only 4.54%. Lopez-Benitez et al. (2009) have performed spectrum occupancy measurements in outdoors in Spain over the frequency range from 75 MHz to 3 GHz. Lopez-Benitez and Casadevall (2010) have conducted spectrum occupancy measurements in indoor and outdoor locations in Spain covering the 75–7075 MHz band. The measured spectrum occupancies varied depending on the measurement location. The overall measured spectrum occupancies were rather low, while certain bands, such as bands used for TV transmission and mobile communications, exhibited higher spectrum occupancies. The measured spectrum occupancies were typically lower in indoor locations compared to outdoor locations.

Valenta et al. (2009) have measured spectrum occupancy in the 100 MHz–3 GHz band in a suburban environment in the Czech Republic and found the total occupancy to be less than 6.96%. Most usage was found in bands used for mobile communications, and very low occupancy was seen at the 2.4 GHz ISM band, as the actual usage there is indoors. Schiphorst and Slump (2010) have measured spectrum occupancy of the band 100–500 MHz in the Netherlands and proposed the use of moving measurement devices in addition to fixed measurement sites. Naganawa et al. (2011) have measured the frequency range 100 MHz–2 GHz in four different locations and the 2.4 GHz ISM band using a mobile measurement node. Most usage was seen in bands with TV transmission and mobile communications. Moreover, the 2.4 GHz ISM band spectrum occupancy was found to be as high as 73.6%.

The influence of the measurement location and direction has received very little attention in the research literature and only few papers have considered it. Pagadarai and Wyglinski (2009) have performed spectrum occupancy measurements in the US taking into account the measurement direction using 6 sectors and showed that the spectrum occupancy varies depending on the measurement sector. Shah et al. (2006) have proposed a distributed spectrum occupancy measurement approach, where several measurement devices are used simultaneously to measure the spectrum occupancy. The measurements were proposed to be combined from several measurement devices, but no results were presented for the distributed approach.

Focused spectrum occupancy measurement studies have mainly concentrated in the 2.4 GHz ISM band, see e.g. (Biggs et al. 2004, Denkovski et al. 2010, Geirhofer et al. 2006, Hanna & Sydor 2011, Lehtomäki et al. 2012). Some studies, such as (Blaschke et al. 2007, Ellingson 2005, De Fransisco & Pandharipande 2010, Holland et al. 2007), have also considered other bands. Blaschke et al. (2007) have conducted spectrum occupancy measurements in the band used by Global System for Mobile Communications (GSM). The measurements showed that the spectrum occupancy varied depending on the situation (e.g. big event or normal day) and the overall spectrum occupancy was around 43%, which in fact is rather high compared to the findings of general spectrum occupancy measurement studies. Holland et al. (2007) have measured power levels in the 900 MHz and 1800 MHz bands used by mobile communication systems during a big sports event in Germany. The power levels during the event were observed to be higher than during a normal day. Ellingson (2005) has measured spectrum occupancy in the 0–270 MHz band and identified that there is room for CRS operations in this band. De Fransisco and Pandharipande (2010) have measured the 2.36–2.4 GHz band in the Netherlands currently used for land mobile radio and amateur radio services. The measured spectrum occupancies were very low in the order of 0.1–2.2% with a maximum of 16.7% on one sub-band.

An early spectrum occupancy measurement study in the 2.4 GHz ISM band is presented in (Biggs et al. 2004). Measurements were conducted in several different locations and the occupancies were seen to vary over the locations and the measurement time with higher occupancy in the day time. The results indicated that there is room for more activity in the band.

Denkovski et al. (2010) have measured the 2.4 GHz band and studied the influence of the measurement parameter settings on the measurements and indicated that the resolution bandwidth and sweep time should be selected based on the signals to be detected. Hanna & Sydor (2011) have used several measurement devices to measure the spectrum occupancy of the 2.4 GHz ISM band. The measurements showed that the location has a big influence on spectrum occupancy, which can vary even in short distances. Lehtomäki et al. (2012) have measured spectrum occupancy of the 2.4 GHz ISM band with energy detection using adaptive thresholding. Noise power estimation was used to set the threshold.

Statistical modelling of spectrum occupancy has been carried out in (Fleurke et al. 2004, Geirhofer et al. 2006, Geirhofer et al. 2007, Guerin 1987, Ghosh et al. 2010, Gibson & Arnett 1993, Lopez-Benitez & Casadevall 2011, Pagadarai & Wyglinski 2009, Spaulding & Hagn 1977, Stabellini 2010, Wang & Salous 2011, Wellens et al. 2009). Spaulding and Hagn (1977) have modelled spectrum occupancy using a first-order Markov chain. Guerin (1987) has modelled spectrum occupancy in a mobile communication band by modelling the channel occupation time with an exponential model. Gibson & Arnett (1993) have used a two-state Markov chain. Geirhofer et al. (2006) have developed a continuous time semi-Markov model to characterise spectrum occupancy in the 2.4 GHz ISM band based on measurements. Pagadarai and Wyglinski (2009) have modelled spectrum occupancy with a four-state Markov model. Ghosh et al. (2010) have developed a spectrum occupancy model where the appearance of a primary user is modelled with a Poisson process and the time between two consecutive primary user arrivals is exponentially distributed. Lopez-Benitez and Casadevall (2011) have modelled spectrum occupancy with a two-state discrete-time Markov model.

Stabellini (2010) has modelled the mean idle times in the 2.4 GHz ISM band and shown that generalised Pareto distributions match with the measurement data. Fleurke et al. (2004) have studied the statistical modelling of spectrum occupancy and suggest using random sampling where the time between taking the samples from the same channel is made random instead of using a fixed channel revisit time. This is used to get independent samples to reduce the number of samples needed.

In addition to spectrum occupancy measurements discussed above there is also other radio environment related information available that could be combined with the spectrum occupancy information to help the CRS in its operations. *Radio environment maps* (REM) have been proposed in (Zhao et al. 2007a and Zhao et al. 2007b) to describe the real world by collecting radio environment related data, such as geographical information, activity profiles and locations of the radio equipment, available networks, spectrum regulations, and past experiences, into a database. The REM can be updated based on new observations from the CRS nodes and it can be used in the decision making in the CRS. The spectrum occupancy measurement data could be one type of radio environment data fed into the REM database. Thus, the REM can be interpreted as an extension of the spectrum occupancy measurements, as they can capture the spectrum occupancy information and combine this with other radio related data.

2.3 Methods to obtain knowledge of spectrum availability

Spectrum occupancy measurement studies have indicated that there are spectrum opportunities for CRS operations, but measurement studies alone are not sufficient to allow the CRS to access the bands with low spectrum occupancy; more accurate and timely knowledge of spectrum availability is needed. In fact, there are several different methods to obtain knowledge of spectrum availability for the CRS. Following (ITU-R 2011b) and (RSPG 2010), the methods can be classified into three general categories: control channels, databases, and spectrum sensing. These three general methods have different capabilities and requirements, and all of the methods include several different individual techniques with different characteristics, requirements, and capabilities. Figure 2 illustrates the considered methods. Methods to obtain knowledge of spectrum availability have been classified in (Höyhtyä et al. 2007) into active awareness and passive awareness. Active awareness refers to spectrum sensing, while passive awareness denotes the case where the CRS obtains the knowledge from outside via, e.g., control channels and databases. Next, the methods and their variants are discussed in more detail.

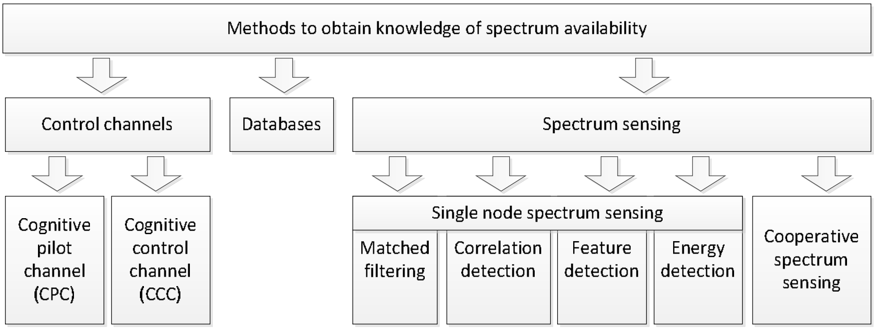

Figure 2. Methods to obtain knowledge of spectrum availability for CRS.

2.3.1 Control channels

The CRS can listen to wireless control channels to retrieve information about spectrum availability. In the control channel approach, the CRS receives information from sources internal or external to the CRS node, such as base stations or other CRS nodes, via a predefined channel (ITU-R 2011b). The two most common control channel approaches for CRS are cognitive pilot channel (CPC) and cognitive control channel (CCC) (ETSI 2010, ITU-R 2011b). A feasibility study on the implementation options for CRS control channels is presented in (ETSI 2012).

The CPC approach originates from (E^2R 2007) and has received a lot of attention in the early studies of CRS in, e.g., standardisation (ETSI 2009). The CPC is a channel that is used to regularly push information to the CRS node (ITU-R 2011b).

The CPC is a centralised approach that can help a mobile terminal to identify operators and access technologies and their assigned frequencies in a given area. In the CPC operational procedure, a CRS node first switches on and detects and synchronises with the CPC. The CRS node obtains information from the CPC about, for example, available operators, radio access technologies (RAT), frequencies, policies, and load situation, and can start operations using this information (ETSI 2009, ITU-R 2011b).

The CCC approach is a distributed control channel approach, which can be used to deliver information in real time between different CRS nodes in a given area. The CCC can be used to exchange different types of information spectrum availability, including locally available frequency bands, spectrum sensing results, policies, spectrum usage rules, and spectrum needs of a system (ITU-R 2011b).

There are challenges related to the use of control channels to obtain knowledge of spectrum availability for CRS. A general challenge related to control channels is to find the right amount of control information to be shared as the control data exchange consumes system resources. The timing requirements for the control data exchange need to be satisfied to guarantee that the information remains usable. In the CPC approach, the data to be delivered to the CRS nodes needs to be updated regularly. In the CCC approach, the CRS nodes need to be synchronised. In general, the reliability of the data transmitted over the control channels needs to be ensured.

2.3.2 Databases

The CRS can access databases to obtain knowledge of spectrum availability. The use of databases has received rather limited amount of interest in the CRS research literature in the past but is now attracting more interest. In fact, in the CRS standardisation and regulation, databases have been identified as a major building block to retrieve information about spectrum availability. The Federal Communications Commission (FCC) in the US has finalised rules to make the unused spectrum in the TV bands available for unlicensed broadband wireless devices in (FCC 2010). The use of these so-called TV white spaces in the US requires that the unlicensed devices have a geolocation capability and a capability to access a database to protect the incumbent users from interference. The database will include information about the incumbent systems and tell the device which channels can be used at its location.

Similar to the TV white space situation in the US, the upcoming use of TV white spaces in the UK is likely to require database access, see (Ofcom 2010). In general, in the database approach in (Ofcom 2010), a master CRS device will first consult a list of databases on a website hosted by the regulator, select its preferred database from the list, and send its parameters describing its location and information about the device to the database. The database will then return details of the frequencies and power levels the master CRS is allowed to use. It is also possible that the master CRS device signals to a slave CRS device the frequencies and power levels it may use when communicating with the master device. In this case, the slave device does not need to contact the database.

Internet Engineering Task Force (IETF) is currently standardising a protocol to access white space database (PAWS) for the TV white spaces in (IETF 2012). Local TV white space databases are currently under development in different countries. In the US, the FCC has conditionally designated nine entities as TV white space database administrators in (FCC 2011). Other efforts to build TV white space databases are currently on-going, for example, in Finland (see Fairspectrum 2012) and in some cities in Germany and Slovakia (see COGEU 2012).

The most important benefit of the database approach is that it can be guaranteed that the incumbent systems remain free from harmful interference, as this feature is built in the database system by registering them in the database and defining adequate safemargins. The CRS nodes can only access the bands that have been guaranteed to be safe. When the CRS nodes use the database access to obtain knowledge of the spectrum availability, they will need to know their exact locations in order to retrieve the correct information in their operational area (ITU-R 2011b). Thus the CRS nodes will need to equiped with location capability. An important requirement for the database access is that the communications between devices and databases is secure (FCC 2010). There are also challenges related to management responsibility and update rate (ITU-R 2011b). The time scales involved in the use of databases do not enable real-time operations of obtaining knowledge and updating knowledge of spectrum availability because there are access delays and update delays.

2.3.3 Spectrum sensing

Spectrum sensing is a method for the CRS nodes to obtain knowledge of spectrum availability without requiring any intervention with the other spectrum users. While control channels and databases can be considered as a means to distribute the spectrum availability information that is first obtained somehow, the spectrum sensing techniques can directly provide this information for the CRS node. Spectrum sensing techniques aim at distinguishing signals from noise by processing the received samples of the radio spectrum and making a decision of the presence/absence of the signal based on this. A lot of research effort has been put on the development of different spectrum sensing techniques. For overviews, see e.g. (Ben Letaief & Zhang 2009, Ghasemi & Sousa 2008, Liang et al. 2011, Quan et al. 2008, Wang & Liu 2011, Yücek & Arslan 2009, Cabric 2008).

Classification of spectrum sensing techniques

The development of individual spectrum sensing techniques for CRS operations has been massive during the recent years. There are several different spectrum sensing techniques that have very distinct capabilities, performances, requirements, and complexities. The performance of a spectrum sensing technique is typically characterised with the probability of detection and the probability of false alarm. The probability of detection denotes the probability that the given spectrum sensing technique makes a correct decision about the signal being present when in fact there is signal. The probability of detection is a measure to assess how well a CRS node can detect the presence of the signal using the specific spectrum sensing technique, and thus, how efficiently it can protect other higher priority systems. The probability of false alarm denotes the probability that the spectrum sensing technique indicates that there is signal when in fact there is no signal present. The probability of false alarm is a measure to assess how efficiently the CRS node can perceive spectrum opportunities. It is desirable that the spectrum sensing technique provides high probability of detection and low probability of false alarm, but these two requirements are conflicting, as the measures are interrelated for a given spectrum sensing algorithm, and thus compromises are needed. The interrelations of these two probabilities are characterised by the receiver operating characteristics (ROC), see (Urkowitz 1967).

The spectrum sensing techniques can be classified in several ways, see e.g. (Ghasemi & Sousa 2008, Liang et al. 2011, Quan et al. 2008, Wang & Liu 2011, Yücek & Arslan 2009) for overviews. In the following, we first consider different spectrum sensing algorithms for a single-node spectrum sensing case, where one CRS node performs the sensing functionality.

Matched filtering is a coherent detection technique that correlates the unknown received signal with a known signal and compares the result to a threshold. It can offer very good detection performance and fast operation, but requires a lot of *a priori* information about the signal types, including the precise waveform of the signal to be sensed, which in a practical CRS situation may not be realistic. In practical scenarios, the phase of the received signal may not be known, which leads to noncoherent matched filtering that uses an envelope detector after performing the correlation. Moreover, the implementation of matched filtering is very complex since a separate receiver is needed for each signal waveform.

Correlation detection or the waveform-based sensing in (Yücek & Arslan 2009) uses a stored version of the signal type and correlates the received signal with such stored version. As wireless communication systems use a predetermined standardised formats, there can be known pilot patterns that can be used for correlation detection. Correlation detection has good detection performance and can operate fast, but requires *a priori* information about the signals to be sensed and synchronisation. Correlation detection is closely related to matched filtering. Matched filtering computes the correlation in a sliding way, while correlation detection calculates the correlation for a single delay at a time. For a given delay in matched filtering, correlation detection gives the same outcome as matched filtering.

Energy detection is a noncoherent detection technique that estimates the received signal energy by summing up the energy from the received signal and by comparing the result to a threshold, see e.g. (Urkowitz 1967). Energy detection is simple and does not require any *a priori* information; however, it is sensitive to threshold setting, requires many samples to provide satisfactory performance, and cannot operate at low signal-to-noise ratios (SNR), see (Tandra & Sahai 2008).

Analytical performance evaluation for energy detection in additive white Gaussian noise (AWGN) and Rayleigh fading channels has been presented in (Digham et al 2007). Due to the analytical tractability of the performance of the energy detection and its simplicity, it has become the single most popular spectrum sensing technique in the research literature.

Feature detection uses a property where modulated signals contain cyclostationary features as opposed to pure noise in the channel. Typically, feature detection algorithms calculate the spectral correlation function from the autocorrelation of the received signal and determine the presence or absence of the signal based on this. Moreover, feature detection can calculate the covariance matrix of the received signal vector, and based on the characteristics of this matrix, a decision on the presence or absence of the signal can be made. As such, feature detection does not require *a priori* information and has better detection performance than energy detection, but at the cost of a higher computational complexity. The performance of feature detection can be approved when *a priori* information is available and used in the algorithm. For example, if the channel covariance matrix is known, the estimator-correlator receiver structure can be used, see e.g. (Lim et al. 2008).

Inclusion of the spatial dimension and the recent developments in advanced antenna technologies into spectrum sensing can offer potential for performance improvements in the CRS operations. It is possible to improve the performance of spectrum sensing by using multiple antennas for reception, such as in (Pandharipande & Linnartz 2007). Moreover, the inclusion of the direction of arrival estimation into spectrum sensing has the potential to identify new spectrum opportunities in the angular dimension, see e.g. (Yücek & Arslan 2009, Tsakalaki et al. 2010, and Xie et al. 2010). Sarvanko et al. (2011a) have quantified the achievable gains in terms of the number of links in a given area by using directional antennas in transmission and reception compared to omni-directional antennas with promising results.

Cooperative spectrum sensing uses several CRS nodes to perform spectrum sensing and makes a global decision about the presence or absence of the signal based on the measurements from several nodes (Cabric et al. 2004, Ghasemi & Sousa 2005). Two common forms for making the global decision are data fusion and decision fusion (Ben Letaief & Zhang 2009). Data fusion is often called soft decision making, while decision fusion is called hard decision making, see (Yücek & Arslan 2009). In data fusion, the individual CRS nodes send the spectrum sensing results before making any decision about the presence or absence of the signal. In terms of energy detection, this means that the CRS nodes send the measured energy to a centralised decision making that combines the measured energies from the different nodes using some rule. Ma et al. (2008) have derived an optimal data fusion technique for cooperative energy detection that maximises the probability of detection for a given probability of false alarm where the observed energies from the CRS nodes are weighted and summed. The optimal scheme becomes equal gain combining (EGC) in the high SNR regime and maximal ratio combining (MRC) in the low SNR regime corresponding to equal weights and weights proportional to the SNR, respectively.

In decision fusion (Ben Letaief & Zhang 2009), the individual CRS nodes make local decisions about spectrum availability and communicate these decisions to a central decision-making entity that forms the global decision using some rule. The general rule is the *m*-out-of-*M* rule, where the signal is declared to be present when at least *m* CRS nodes out of all *M* nodes have declared the presence of the signal. The common decision fusion rules used in the spectrum sensing research literature are the AND, OR, and majority combining rules that correspond to the situation that all nodes, one node or most of the nodes declare the signal to be present. The AND, OR, and majority are obtained from the general *m*-out-of-*M* rule, when *m* is equal to *M*, *m* is equal to one, or *m* is equal to half of the nodes, see e.g. (Ben Letaief & Zhang 2009).

Sun et al. (2007) have proposed to use two thresholds for decision fusion in energy detection, where the decision is sent if the energy is below the lower threshold or above the higher threshold and no decision is sent if the observed energy is between the two thresholds. Mustonen et al. (2009) have proposed using two two-bit quantised decisions for cooperative spectrum sensing, which are obtained using three thresholds. This approach was shown to offer performance improvements using Welch’s periodogram (Welch 1967) in an AWGN channel compared to a single-bit quantisation.

Challenges of spectrum sensing

There are many challenges related to the use of spectrum sensing techniques to obtain knowledge of spectrum availability for the CRS. The major challenge for spectrum sensing is the hidden node problem which according to (ITU-R 2011b) occurs “when a CRS node cannot sense another node transmitting (for example, due to radio propagation conditions) or cannot sense the presence of a receive only node and therefore incorrectly assumes that the frequency channel is not in use“. This generic interpretation of the hidden node problem captures many aspects, including those related to the wireless propagation environment, which complicates the detection of the presence of signals as they may be severely attenuated and faded. The spectrum sensing techniques experience the so-called SNR wall phenomenon, which means that the performance of spectrum sensing algorithm saturates at certain SNR, below which the detector will fail to be robust no matter how long it can observe the channels (Tandra & Sahai 2008). Recent developments to circumvent the SNR wall problem are available, see (Polydoros & Dagres 2012). This problem is particularly challenging in practical deployment scenarios where multipath fading and shadow fading are inherently present and the SNR can be too low for reliable detection. Shadow fading is particularly challenging as the performance of spectrum sensing using a single CRS node is severely degraded, and thus one node alone cannot reliably detect the presence of the signals, see e.g (Ruttik et al. 2007).

To overcome the challenges of the wireless propagation environment, cooperative sensing is proposed, but it has also several challenges, see e.g (Wang & Liu 2011, Ben Letaief & Zhang 2009, and Yücek & Arslan 2009). Cooperative sensing results in large amounts of data exchange between the CRS entities, which increases complexity. In particular, the time used for spectrum sensing reduces the time available for the actual communications, as the CRS nodes need to wait the sensing duration to access the channel and cooperative sensing can further increase the waiting time (Ben Letaief & Zhang 2009, Yücek & Arslan 2009). Moreover, shadow fading is typically correlated, and thus the CRS nodes should be located outside the correlation distance to experience independent shadow fading to improve the detection performance (Ghasemi & Sousa 2008, Ruttik et al. 2007), which may be difficult in practical network deployments.

The control of aggregate interference is also a challenge when multiple CRSs simultaneously access the same channel without coordination based on their local spectrum sensing results. This can result in intolerable aggregate interference from the CRSs to the primary systems (Ghasemi & Sousa 2008). A particular challenge of spectrum sensing is that it is very difficult to detect the receive-only users (RSPG 2010), and thus other methods than spectrum sensing are needed in the spectrum bands with such use.

Moreover, different spectrum sensing techniques have their own limitations, see e.g. (Yücek & Arslan 2009, Wang & Liu 2011, and Ghasemi & Sousa 2008). For example, energy detection is particularly sensitive to noise uncertainty, while the complexity of more advanced sensing techniques is challenging. The implementation of spectrum sensing algorithms is in fact a key challenge. While some spectrum sensing techniques can offer good detection performance, their complexity becomes the bottleneck and they cannot currently be implemented.

Optimisation of spectrum sensing

The functioning of a given spectrum sensing technique is highly dependent on the selection of its parameters. The optimisation of the parameters of spectrum sensing algorithms has recently received growing interest in the research literature. The main focus has been in the optimisation of various parameters of the energy detection, including threshold, sensing time, number and order of channels to be sensed, number of cooperative nodes, etc. Energy detection has been used mainly due to the fact that the performance of energy detection can be presented in an analytical form, see (Digham et al. 2007), and offers thus analytical expressions for the optimisation problem formulations.

Threshold setting is critical for energy detection as it directly influences the performance, and many papers have addressed the optimisation of threshold setting. The threshold is typically set according to the estimated noise level and the desired probability of false alarm (Lehtomäki et al. 2005). Quan et al. (2008) have considered a multi-band spectrum sensing situation where the CRS senses multiple sub-bands simultaneously using energy detection. Optimal thresholds for energy detection in the different sub-bands are derived in order to maximise the achievable throughput for the CRS network with constraints on the interference to incumbent systems. Zhang et al. (2009) have optimised cooperative spectrum sensing with energy detection by optimising the threshold for energy detection and the number of nodes to be used as a threshold in the cooperative spectrum sensing.

The optimisation of the sensing time for energy detection has also been studied in several works. Ghasemi and Sousa (2007) have optimised the sensing time for energy detection in order to maximise the average throughput of the CRS. Liang et al. (2009) have optimised the sensing duration for energy detection in order to maximise the achievable throughput for the secondary users with the constraint of sufficient protection for the primary user.

The joint optimisation of sensing time and some other parameter has been considered in several papers. Sensing time and power allocation for energy detection have been optimised in (Pei et al. 2009) in order to maximise the average achievable throughput for the CRS network subject to constraints on the probability of detection and the total transmission power. Stotas and Nallanathan (2011) have optimised the sensing time and transmission powers for energy detection in order to maximise the throughput of the CRS. Peh et al. (2009) have optimised the sensing time and the number of users to be set as threshold in cooperative spectrum sensing decision fusion rule in order to maximise the achievable throughput of the secondary network with sufficient protection to incumbent users based on (Liang et al. 2009). Noh et al. (2010) have optimised the sensing time and the period between two consecutive sensing slots for energy detection in order to maximise the CRS throughput with constraint on interference to the incumbent user. Xiong et al. (2009) have optimised the sensing time for energy detection and the weights used for cooperative combining in order to maximise a global probability of detection. Lee and Akyildiz (2008) have optimised the sensing time and the transmission time in order to maximise the sensing efficiency subject to interference constraints on the incumbent users. The sensing efficiency is defined as the ratio of the transmission time over the whole sensing cycle that consists of sensing time and transmission time in the periodic sensing.

Other parameters have also been optimised as summarised in the following. Hoang et al. (2010) have optimised the scheduling of spectrum sensing and data transmission to maximise the CRS network throughput assuming that the instantaneous channel state information is available. Hamdaoui (2009) has developed an approach to select when a CRS node should seek for a new subchannel to be sensed to discover spectrum opportunities. In addition, the number of frequency bands for spectrum sensing has been optimised while balancing the requirements for minimising the sensing overhead and increasing the likelihood of finding spectrum opportunities. Datla et al. (2009) have optimised the times for sensing, transmission and being idle based on spectrum occupancy history information and proposed to allocate more sensing time to channels with high probability of channel availability. Choi (2010) has developed an adaptive sensing approach for the CRS node to decide whether to sense, transmit, or switch channel in order to maximise spectrum use while restricting interference to incumbent users. Nguyen et al. (2011) have optimised the number of subchannels to be sensed in order to maximise the achievable throughput with contraints on the energy used for sensing. The optimisation of the order in which channels should be sensed has been studied in (Jiang et al. 2009) based on the channel quality and the probability of channel availability. Khan et al. (2011) have considered a distributed scenario where CRS nodes determine the order of channels to be sensed autonomously without communicating with each other, resulting in a collision-free situation.

The selection of the spectrum sensing technique itself for a specific situation has received very little attention in the research literature. Yücek and Arslan (2009) have compared the properties of different spectrum sensing techniques and put the techniques on a scale based on their assumed complexities and accuracies. Bagayoko et al. (2012) have considered the selection of spectrum sensing techniques and proposed an approach where the sensing technique that can offer the required performance at the lowest SNR, while satisfying regulatory requirements is selected as the technique to be used.

2.4 Channel assignment techniques

After the CRS nodes have knowledge about the spectrum availability in their operational area, the next step is to select the frequency channel to be used for communications. Where there are several CRS nodes wishing to access the same set of channels, there is a need to develop methods to assign the channels among the users. In general, the channel assignment problem is typically formulated as an optimisation problem where the goal is to find the best channel assignment that optimises a certain performance metric. For channel assignment in CRS, the typical optimisation problem has been to maximise the overall throughput of the CRS network. After formulating the optimisation problem, several different techniques can be used to solve the problem, such as graph theory algorithms, stochastic algorithms, game theoretic algorithms, genetic algorithms, and swarm intelligence (De Domenico et al. 2012). The decisions on the channel assignments can be made in a centralised or distributed way. Figure 3 shows a classification of the channel assignment techniques. A comparison of centralised and distributed approaches is presented in (Salami et al. 2011). For an overview of channel assignment for CRS, see (De Domenico et al. 2012).

Centralised decision making can be used to coordinate the use of resources between CRS nodes in scenarios where global configuration and optimisation are required and a central decision-making entity is deployed (ITU-R 2011b). Centralised decision making can help the CRS to avoid local sub-optimisation and to use network and radio resources in the most effective manner possible (ITU-R 2011b). The centralised architecture is simple and easy to control from a network operator point of view, but when the number of CRS nodes increases, challenges could arise, such as scalability, information exchange, processing capability, and delay (ITU-R 2011b). A single centralised entity would not be able to control a very large CRS network due to scalability problems. In addition, there will be delays from the data collection and resource management in a large network.

Distributed decision making is based on localised decisions of distributed network entities (ITU-R 2011b, Akyildiz et al. 2008). Distributed decision making can be non-cooperative or cooperative, depending on whether the CRS nodes cooperate in the information collection and decision making (Akyildiz et al. 2008). Cooperative decision making can lead to better performance for the whole CRS network but requires information exchange between the nodes, which results in control burden. The delays in distributed approach can be smaller compared to the centralised approach but stability can be a challenge, as there is no guarantee that the proposed outcome behaves in a predictable manner. Cooperative decision making can be considered as an intermediate form between centralized decision making and non-cooperative distributed decision making.

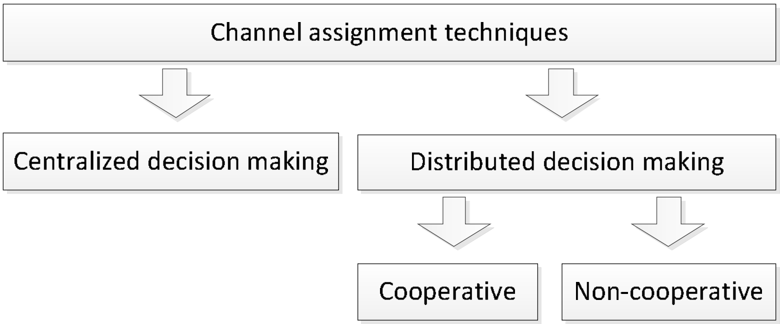

Figure 3. Classification of channel assignment techniques.

Nie and Comaniciu (2006) have modelled the channel assignment problem among a set of links between CRS nodes using game theory. The goal is to assign channels among the links in order to obtain a target bit error rate (BER) over the links assuming perfect knowledge of the interference conditions on the frequency channels. The approach is distributed considering both non-cooperative and cooperative cases. Ji and Liu (2007) have also used game theory to model channel assignment.

Zhao et al. (2009b) have used genetic algorithm, quantum genetic algorithm and particle swarm optimisation in channel assignment using three optimisation criteria that reflect the CRS network throughput. Yu et al. (2010) have considered distributed channel assignment in order to maximise the sum of throughputs of the links while taking into account fairness among the links. Di Lorenzo and Barbarossa (2011) have used a swarm intelligence algorithm in a distributed cooperative approach for the channel assignment problem.

2.5 Learning techniques

Finally according to its definition, a CRS is capable of learning from the results obtained. This is where the CRS goes beyond an adaptive system, as it includes a learning mechanism. According to (Claasen & Mecklenbräuker 1985), an adaptive system can adapt itself to the changing environment, which can lead to a better performance. The key features of an adaptive system include *a priori* knowledge, quality criterion, algorithm, and a signal processing device. Learning systems are higher order adaptive systems where not only the parameters but also the algorithm or the criterion can be adapted to the specific conditions (Claasen & Mecklenbräuker 1985). According to a general definition from (Mitchell 1997) "a computer program is said to learn from experience with respect to some class of tasks and performance measure, if its performance at tasks as measured by the performance measure improves with experience".

Learning in the CRS context aims at enabling performance improvements for the CRS by using stored information of its past actions and their results (ITU-R 2011b). For an overview of learning in CRS, see e.g. (He et al. 2010, Bantouna et al. 2012). An important part of the learning process is to collect, store and maintain information in the changing operational environment and potentially use this information in future transmission (ITU-R 2011b). Different learning techniques can be included in the CRS to train the existing algorithms and models and enable the CRS to learn from the results of their actions. The learning techniques can be classified into three general classes: supervised learning, unsupervised learning, and reinforcement learning (Duda et al. 2001). Supervised learning techniques, such as case-based reasoning, use pairs of input signals and known outputs as training data to generate a function that maps the inputs to desired outputs. Unsupervised learning techniques, such as clustering, aim at determining how the data are organised. Reinforcement learning techniques, such as Q-learning, observe the impact of actions in the environment and use this information in guiding the learning algorithm.

Learning can be used to change the decision-making algorithms by, for example, changing the rules of a rule-based decision-making system. When learning is incorporated to the system, two further components are needed: a process monitor and an adaptation mechanism (Driankov et al. 1993). A process monitor can be used to evaluate the performance of the decision-making system to find out potential weaknesses, misbehaviour, or potential for improvements. The adaptation mechanism processes information received from the process monitor and makes updates and adaptations to the decision-making system to operate in the changing situations.

According to (Mitola & Maguire 1999), learning applications in cognitive radio include autonomously determining the structure of the radio environment as it changes. In (Clancy et al. 2007), learning has referred to finding out when and where the CRS node should transmit. Learning has been applied to channel selection in (Höyhtyä et al. 2011a), where the channel with the longest predicted idle time was selected based on predicting the future idle times of different channels. Learning was used to identify the traffic type on the channels and to select the prediction method based on the traffic type. In (Jiang et al. 2011), reinforcement learning was applied to channel selection with an emphasis on learning efficiency. Tekin et al. (2009) have selected the channels to be sensed by finding the channels with low occupancy with a learning mechanism and focusing the sensing effort on these channels to obtain better transmission oppotunities.

3. Summary of the original papers

The literature review on CRS capabilities presented in Chapter 2 has revealed several gaps in the CRS related research literature. For example, the influence of the measurement location and direction has not been addressed thoroughly in spectrum occupancy measurement studies. Moreover, the selection of the spectrum sensing techniques has received very little attention. In the following, the contents and contributions of the ten original papers are summarised with respect to the prevailing gaps in the research literature.

3.1 Overview of the papers

The contents of the original papers of this thesis fall into the general cognitive cycle of CRSs, as depicted in Figure 4. The first capability of the CRS for obtaining knowledge captures two aspects: study on the potential availability of spectrum for CRS operations by using directional spectrum occupancy measurements (Papers II, III, and IV) and research on spectrum sensing techniques (Papers I and V). The second capability of CRSs, i.e. decision making and adjustment, covers here two aspects: the selection of the methods to obtain knowledge of spectrum availability (Papers VI, VII, and VIII) and the channel assignment among users with harmony search algorithm after the spectrum availability is known (Papers IX and X). Finally, the third capability of CRSs here includes the introduction of learning to the selection of spectrum sensing techniques (Paper VIII).

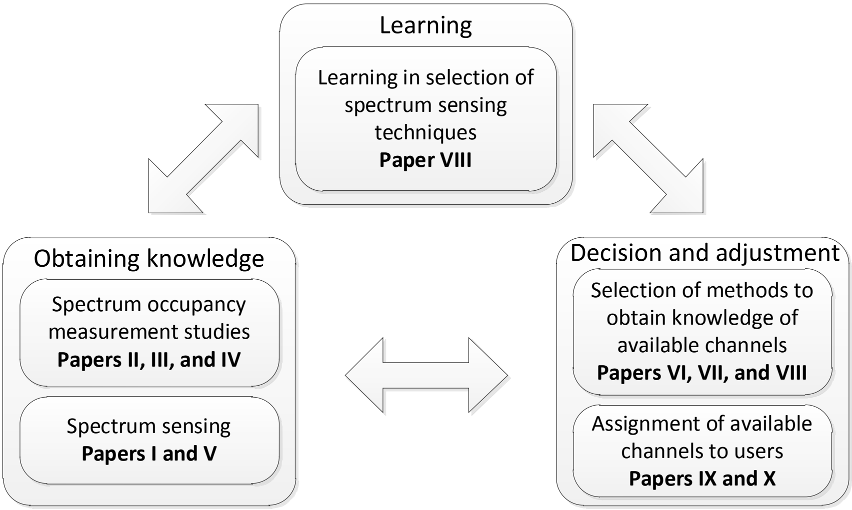

Figure 4. Relation of the original papers to the cognitive cycle.

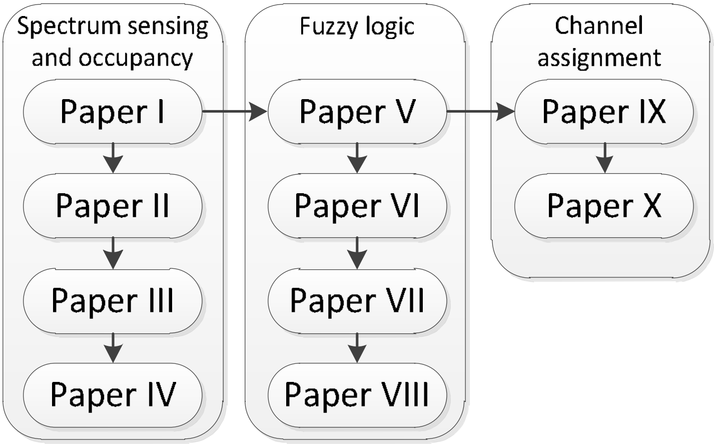

Figure 5. Flow of the relations of the original papers.

Figure 5 shows a flow of the relations of the original papers. The starting point for the thesis work has been Paper I on the analytical performance evaluation of a spectrum sensing technique, which has led to two research directions: 1) spectrum occupancy measurement studies in Papers II, III, and IV, and 2) cooperative spectrum sensing with fuzzy combining in Paper V. Paper V is an introduction to fuzzy logic in CRSs with a review of applications of fuzzy logic to telecommunications, discussion on the general problem formulations in the CRSs, and the characteristics of fuzzy logic and in general heuristics, which could find many application areas in CRS problem formulations. As a result, two research directions has arisen from Paper V: 1) selection of methods to obtain knowledge of spectrum availability and particularly the selection of spectrum sensing methods using fuzzy logic in Papers VI, VII, and VIII, and 2) channel assignment using heuristics in Papers IX and X. The original papers include analysis, simulations and measurements as shown in Table 1.

Table 1. Research methods used in the original papers.

Papers:	I	II	III	IV	V	VI	VII	VIII	IX	X
Analysis	x						x	x		
Simulations	x				x	x	x	x	x	x
Measurements		x	x	x						

3.2 Distributed, directional and cooperative spectrum occupancy measurements

Paper II presents distributed and directional spectrum occupancy measurement studies in the 2.4 GHz ISM band by using separately located measurement devices to characterise the spectrum occupancy in an indoor office environment. Paper II introduces the concept of directional spectrum occupancy and defines it as the fraction of time that received power in the frequency channel exceeds a threshold level in the measurement direction. Paper III introduces the concept of cooperative spectrum occupancy and defines it as the fraction of time that the frequency channel is occupied after the observations from several measurement entities, such as measurement devices or antennas, have been combined.

The motivation for focusing on the 2.4 GHz ISM band is that it is readily available for CRS type of operations without any regulatory changes which would be required for the deployment of CRS on other than licence-exempt frequency bands. Moreover, the transmission power levels are severly limited in this band, providing a versatile environment for the characterisation of the spectrum use over a small area.

In Paper II, two separately located measurement devices with directional antennas have been used to measure the spectrum occupancy in the same office area from two opposite directions. The aim of the study is to characterise the spectrum occupancy and the resulting spectrum availability for CRS more accurately, taking into account the spatial dimension in the form of the measurement location. This is the first time that measurements are simultaneously carried out from more than one location and direction at a time. The paper introduces the metric of directional spectrum occupancy that takes into account the measurement direction. The measurement results in the paper show that spectrum occupancy varies significantly in the same office area depending on the measurement location and direction. This is particularly the case in the 2.4 GHz ISM band, where the transmission power levels are limited by the regulatory decisions and thus the resulting spectrum use varies significantly even over short distances because there are multiple devices operating in the same band. The study shows the influence of the presence of several signal sources and the specific frequency bands that they are using in practical deployment scenarios. The influence of the spatial dimension on the actual spectrum occupancy is an important point to be taken into account in the design of CRS techniques as spectrum availability is heavily dependent on the location. This was confirmed by the measurements.

Since the measurement from a single location may not be enough to characterise the actual spectrum occupancy in a given area, Paper III introduces the concept of cooperative spectrum occupancy, which is obtained by combining measurement results from several antennas at the same measurement device or across different measurement devices using decision fusion rules. This paper was the first one to perform such combining of measurements. It was earlier proposed in (Shah et al. 2006), but no results were shown. The paper applies AND, OR, and majority decision fusion rules known from cooperative spectrum sensing in, for example, (Ben Letaief & Zhang 2009) and discusses their applicability. The selection of the decision fusion rules influences the cooperative spectrum occupancy significantly, as shown in Paper III. The AND rule, where the channel is declared occupied when all measurement entities see it occupied, results in the lowest spectrum occupancy. The OR rule, where the channel is declared occupied when at least one measurement entity sees it occupied, results in the highest spectrum occupancy. The majority rule, where the channel is declared occupied when at least half of the measurement entities see it occupied, results in an occupancy that is between the AND and OR rules.

If the CRS decides to access the frequency channels based on the cooperative spectrum occupancy measurement results, the selection of the decision fusion rules influences the potential availability of spectrum opportunities for the CRS and the potential interference experienced by the primary system. From the primary system point of view, the OR rule results in the potentially lowest interference for the primary system while offering the lowest amount of spectrum opportunities for the CRS. The AND rule results in the highest amount of spectrum opportunities for the CRS but also the highest potential interference to the primary system. The majority rule is in between the AND and OR rules.

Paper IV uses the principles of directional and cooperative spectrum occupancies from Papers II and III and applies them to a new set of measurements. The paper further introduces the concept of short-term local spectrum occupancy, which is obtained by grouping of measurement results from a set of adjacent subchannels and measurement time instants in order to assess the time variations in the spectrum occupancy in more detail over a selected subchannel of interest. This approach can be used to assess the availability of spectrum for CRS in more detail for specific radio access technologies (RATs), as the granularity of interest can be selected according to the bandwidth of the system in question. It can also be useful in the development of channel assignment techniques for future CRS.

In the measurements, the ISM band has been divided into 256 frequency subchannels, of which each subchannel has a bandwidth of 333 kHz. Approximately 1,000 samples are taken from each frequency subchannel and each channel from the same antenna is revisited approximately every 80seconds.

3.3 Spectrum sensing studies

3.3.1 Performance of spectrum sensing using Welch's periodogram in Rayleigh fading channel

Paper I presents performance evaluation for a selected spectrum sensing method, namely Welch's periodogram, in a Rayleigh fading channel. Welch's periodogram is one of the most common techniques in the spectral estimation, see e.g. (Kay 1988). It is particularly interesting as it can reduce the variance of the estimate by segmenting the original measurement data set in to smaller segments and computing the power spectral density for the segments separately and obtain the final estimate by averaging over the segments. This idea of segmenting was originally presented in (Bartlett 1948), and the Welch's prediogoram from (Welch 1967) extends it to allow the segments to overlap each other. Welch's periodogram has been applied to spectrum sensing in CRS in, for example, (Fantacci & Tani 2009), where it was used to identify spectrum opportunities in the very high frequency (VHF) band used by aeronautical communications.

Paper I is an extension of earlier work performed in our research group in (Sarvanko et al. 2009). The paper derives analytical probability of false alarm and probability of detection for Welch's periodogram in a Rayleigh fading channel. This is done based on the analytical probability of false alarm and probability of detection of the energy detection algorithm presented in (Digham et al. 2007). Simulations are presented to verify the analytical results. Cooperative spectrum sensing has also been considered to improve the performance of spectrum sensing in a fading environment. This specific spectrum sensing technique and channel model have been chosen because they allowed analytical tractability and had not been studied before in the research literature. The goal of the paper was not to compare different spectrum sensing techniques but to analytically derive the performance of one spectrum sensing technique.

The paper highlights the importance of the probability of detection as the metric when a CRS uses spectrum sensing to protect primary systems from harmful interference in the same frequency band. To characterise the protection requirements of the primary users, the paper proposes a new performance metric, the time between failures in detection, which is of practical importance to the primary user. The commonly used probability of detection metric does not show how often the failures in detection occur in practical time scales, i.e. what is the average time between the failures. The new metric presents how often a primary user could be susceptible to potential interference from a CRS due to failures in the detection of the presence of the primary systems. This metric can be easily calculated from the probability of detection and the time between the sensing decisions.

3.3.2 Fuzzy combining for cooperative spectrum sensing

Paper V discusses the design challenges in the development of CRS techniques and highlights the role of compromise centric decision making in the design of CRS where conflicting requirements are present. For spectrum sensing in particular, it is important to protect the incumbent systems from harmful interference from the CRS in the form of high probability of detection while guaranteeing that the CRS itself can attain desirable performance in the form of low probability of false alarm. Paper II shows how the traditional combining rules in cooperative spectrum sensing can be implemented using fuzzy logic. The paper further indicates that in the case of versatile operational conditions where, for example, the nodes have varying SNRs, the fuzzy combining can be better than the traditional approaches. Fuzzy decision making has the capability to give more value to the observations that are more certain and give less value to uncertain observations.

3.4 Selection of methods to obtain knowledge of spectrum availability

3.4.1 Band-specific approach for the selection of methods

From the different methods to obtain knowledge of the spectrum availability including control channels, databases, and spectrum sensing techniques discussed in Section 2.3, it is important to use proper methods in each situation. The different methods have different capabilities and requirements and thus are more suitable in different situations. In real-life deployment, there is a need for a band-specific approach where the methods to be used are determined for each frequency band depending on the deployment characteristics and regulatory requirements on the bands.

The selection of methods to obtain knowledge of spectrum availability among control channels, databases, and spectrum sensing has been discussed in Paper VI, where a three-stage decision-making flow is presented. The first step is to select the method to obtain spectrum availability information among CPC, database, and spectrum sensing. The second stage is to select the spectrum sensing technique and its parameters, provided that spectrum sensing was selected in the first stage. The third stage is to select the combining technique and its parameters for cooperative spectrum sensing, provided that cooperative spectrum sensing is used. The selection of the sensing technique is discussed more closely in Section 3.4.2.

In Paper VII, the selection of the methods to obtain knowledge of spectrum availability has been applied to opportunistic networks, which are operator-governed, local and temporary extensions of the mobile communication infrastructure network. The paper includes a discussion of suitable frequency bands for the opportunistic networks and potential methods to obtain knowledge of spectrum availability in the different frequency bands. The approach is further extended in Paper VIII with a more detailed discussion on the potential frequency bands for opportunistic networks, including bands with primary allocation to mobile service, bands with secondary allocation to mobile service, and licence-exempt bands. The band-specific approach proposed in Papers VII and VIII indicates that, for example, in bands with primary allocation to mobile service, the method to obtain knowledge of spectrum availability is likely to be based on a control channel approach. On bands with secondary allocation to mobile, the regulator can determine, for example, that a database approach is needed, such as in the use of TV white spaces in the US (FCC 2010). In the licence-exempt bands, it is likely that there is no requirement to use a specific method but the only feasible method could be spectrum sensing, as the CRS can use it independently without requiring any interventions with the other systems. Moreover, the CRS could collect spectrum sensing information in a database over time to facilitate learning to aid in decision making.

3.4.2 Rule-based decision-making system for the selection of spectrum sensing techniques with a learning mechanism

In a case where a CRS uses spectrum sensing to obtain knowledge of spectrum availability, it is important to select the proper spectrum sensing techniques from the wealth of the available techniques with different capabilities and requirements, as discussed in Section 2.3.3. Paper VI is the first paper in the research literature on the selection of spectrum sensing techniques. Thus, it could be said that it opens up a new research topic. In the three-stage decision making flow in Paper VI, the second stage concerns selecting the spectrum sensing method and its parameters and the third stage selecting the combining technique and its parameters for cooperative sensing, provided that spectrum sensing was selected in the first stage.

For the second stage of selecting the spectrum sensing technique, Paper VI presents a simple fuzzy rule-based decision-making system to select among three general classes of spectrum sensing methods, including energy detection, waveform based detection, and correlation based detection. Four input parameters are used for the decision making, including requirement for detection probability, available time, available *a priori* information, and operational SNR. Each of the four input parameters is characterised with two possible values: high and low, resulting in 16 possible combinations of inputs with 16 rules. A rule-base has been developed to map the inputs and outputs of the decision making.

Fuzzy rule-based decision-making system was chosen for the selection of spectrum sensing techniques as it allows the modelling and processing of very different types of information in a simple and human understandable way. Fuzzy decision making has been previously proposed for cross-layer optimisation for CRS in (Baldo & Zorzi 2008) and access point selection in (Baldo & Zorzi 2009) with promising results. Fuzzy decision making resembles human thinking, allows fast operations as it does not require iterations, and does not experience unexpected outcomes as they are determined beforehand when building the model. It has been considered to be suitable for compromise-centric decision making with conflicting requirements. The selection of spectrum sensing techniques consists of conflicting requirements and different types of information for the decision making, which seemed a promising application area for fuzzy logic.

Traditional fuzzy logic techniques have been used here, including triangular membership functions in order to keep the model simplest. When more complicated fuzzy logic techniques are used, the decision-making system becomes more complex and can introduce phenomena that are difficult to trace back. The developed fuzzy decision-making system for the selection of spectrum sensing techniques is very simple, and the selection of the shapes of the membership functions does not have big influence. In a more complicated decision-making system, the optimisation of the membership functions is also meaningful.

Paper VII continues the research of Paper VI and adds cooperative energy detection to be included as a possible spectrum sensing technique. A decision tree is presented to characterise the decision-making flow. Performance evaluation is presented to assess the probabilities of the outcomes from the decision making using probabilities for the input parameters. The performance of the decision-making systems is compared to the situation where a single spectrum sensing is used instead of decision making. This is done using analysis. The use of sensing technique selection is shown to improve the performance compared to using a single sensing technique instead.

Paper VIII presents a revised fuzzy rule-based decision-making system for the selection of spectrum sensing techniques, where the previous decision-making systems from Papers VI and VII have been substantially revised by refining the underlying assumptions of the spectrum sensing techniques, introducing matched filtering as an additional spectrum sensing technique, and considering a realistic spectrum sharing scenario in the licence-exempt ISM band. Moreover, two of the input parameters are extended to be characterised with three possible values: high, medium and low, resulting in 36 possible input combinations and rules in the rule-base. Performance evaluation is presented to assess the probabilities of the outcomes from the decision making and to compare the decision-making system to the situation where a single spectrum sensing is used instead of decision making. This is done using analysis. The performance evaluation shows the proportion of occasions that the system works well when the decision-making system is used and compares it to when a single technique is used instead. When only a single sensing technique is used, there may be several instances when the given technique fails due to a mismatch between the capabilities of the technique and the operational conditions. The results indicate that the use of the decision making is highly beneficial.

Learning is further introduced to the selection of spectrum sensing techniques in Paper VIII. Learning mechanism can be included into the decision-making system to adjust the rules or the input and output membership functions. The learning mechanism could identify changes in the operational environment or policies and trigger corresponding changes in the decision-making system. As an example, a change in characteristics of the spectrum sensing techniques could be implemented with a change in the corresponding rule. In particular, learning can be incorporated into the decision-making system by collecting information about the underlying signal waveforms during operations, which allows the decision-making system to select a spectrum sensing technique with better detection performance but which also requires *a priori* information.

3.5 Channel assignment using harmony search algorithm

Paper IX applies a heuristic harmony search algorithm from (Geem et al. 2001) to the channel assignment problem for CRS where a set of available frequency channels is distributed among the CRS links. The channel assignment among the links is optimised by minimising the overall BER averaged over all the links. The harmony search algorithm was selected to solve this optimisation problem because it had outperformed other meta-heuristic approaches in several optimisation problems, as shown in (Geem 2009) and references therin. The harmony search had not been applied to CRS channel allocation problem formulation before, thus offering a promising application area.

In the channel assignment problem, the nodes are assumed to be able to communicate with all other surrounding nodes within a communication distance. The influence of the spatial dimension on the spectrum availability discussed in the spectrum occupancy measurements in Papers II, III and IV has been taken into account by considering that different sets of available channels can be present at the different CRS nodes. The focus in Paper IX is on a centralised approach where a centralised entity performs the channel allocation among the links. Performance evaluation with simulations is done for the developed algorithm. In addition, a distributed approach is also sketched without performance evaluation. The algorithm was shown to offer close to optimal solution at dramatically lower computational complexity compared to exhaustive search.

Paper X extends the channel assignment work of Paper IX by elaborating further on the distributed approach. In this approach, each CRS node broadcasts its candidate channel assignment to neighbouring nodes at certain iterations with a certain probability. The distributed approach assumes a separate control network for the exchange of control data between the nearby nodes, which increases the complexity of the system. However, the amount of control data to be exchanged has been kept low.The performance of the proposed channel assignment method based on harmony search is compared to a genetic algorithm. The channel assignment algorithm is shown to outperform genetically inspired algorithms in the simulated scenarios.

The results of Papers IX and X show that the harmony search algorithm can be applied to CRS problem formulations and it can offer very good performance in the channel assignment problem compared to genetic algorithms. The harmony search algorithm can balance the trade-off between the explorative and exploitative behaviour of algorithm by storing good local solutions in the harmony memory, while the randomisation approaches in the algorithm permit to explore the global search space effectively. Paper X has also proposed that the distributed approach uses probabilistic data exchange among the nodes where the best candidates are broadcast to neighbouring nodes only with a certain probability to reduce the amount of control data exchange.

4. Discussion and conclusions

The CRS research has gained big momentum during the past decade since its discovery in 1999. In fact, it is getting more and more challenging to pick up the most relevant CRS works from the wealth of research papers, as new studies on the general CRS concept and its capabilities appear continuously in the research literature. On the other hand, CRS is still a topic that is far from being reality in everyday wireless communication systems and international spectrum regulatory framework and cannot obtain this position with only general level research. This section dicusses the main findings and limitations of the studies presented and depicts future research directions.

4.1 Main findings

Several *spectrum occupancy measurement* studies have recently been conducted around the world, and they have made a common major finding: there is room for spectrum sharing using CRS capabilities in the current framework of spectrum use as the spectrum occupancy is currently low. This thesis has made contributions to focused spectrum occupancy measurement studies by presenting the first studies to show that spectrum occupancy and thus the resulting spectrum availability for CRS can vary significantly depending on the location even in the same office area. This is an important practical point to be taken into account in the design of CRS techniques for obtaining knowledge of spectrum availability and assignment of channels among users, as spectrum availability seen by the different CRS nodes can vary significantly in the same area. This is not only due to the wireless propagation characteristics, but also due to the fact that there can be multiple users transmitting at separate locations, and the corresponding radio environment becomes more complicated than what can be observed only from a single location. One potential application area for distributed and directional spectrum occupancy measurements using several separately located measurement stations simultaneously would be to compare the measured spectrum occupancies in several locations. The measurement results and the information about the actual systems that are deployed in the measured bands in the given locations could be used to identify frequency bands that could potentially be shared with other systems in certain locations.

Spectrum sensing is a topic that is currently under a large amount of interest in the telecommunications research community. While new publications appear constantly, the potential use of the spectrum sensing techniques in practical systems to protect incumbent systems is severely challenged by its limitations to guarantee reliable detection performance in the fading environment. The spectrum sensing studies presented here have highlighted the importance of the performance evaluation of spectrum sensing techniques in fading environments and presented analytical performance evaluation for Welch's periodogram in a Rayleigh fading channel. A new performance metric has been proposed to assess the time between failures in detection, which is of interest to the primary systems whose presence is detected using spectrum sensing. Cooperation among the CRS nodes in the form of cooperative spectrum sensing is seen to be essential in the fading environment as one node alone could see severely attenuated signals that are indistinguishable from noise. Moreover, it is not enough that one node observes the spectrum availability as it can differ significantly even in short distances as shown by our spectrum occupancy measurement studies.

One potential application area for spectrum sensing is to use it to obtain information about spectrum availability in the current ISM bands. The use of the ISM band is typically uncoordinated between different types of systems, but there can be coordination within a system such as in the WLAN system, where carrier sensing is used to avoid transmissions when the channel is occupied. Spectrum sensing could be used to improve spectrum sharing between different types of systems. For example, the WLAN operations are quite static in certain locations, and other users could deploy spectrum sensing techniques to identify the channels that are currently used by the WLANs and avoid those channels leading to potentially lower interference to both systems. With the recent advances in the spectrum sensing techniques, it could be possible to enhance the sharing between the different systems in the ISM band, which in the long run could lead to relaxation of the current regulatory rules that are based on the duty cycle and the limited transmission power levels.

This thesis has presented a *band-specific approach for the selection of methods to obtain knowledge of spectrum availability* in order to use the proper methods to meet the characteristics and the regulatory requirements of the specific frequency band. The band-specific approach is a very simple idea which is common in the spectrum regulatory domain but has not received attention in the CRS research literature. It has practical importance in the real-life deployment of CRS techniques as the systems with CRS capabilities will need to follow the band specific regulatory requirements. In fact, the regulation can eventually decide which methods should be used to obtain knowledge of spectrum availability in each specific spectrum band. The proposed band-specific approach is applicable to all different frequency bands and, in particular, it could be applied to spectrum bands that have been allocated to mobile service but include also other type of use. Instead of completely clearing the bands from previous use, which is costly and time-consuming, the use of these bands could be made possible using the CRS capabilities for sharing between the different systems in the same band. This could be beneficial in the attempt to fulfil the growing data rate demand of the future wireless systems.

This thesis has further highlighted the importance of the *selection of spectrum sensing techniques* and their parameters. While the optimisation of the parameters of certain spectrum sensing techniques, namely energy detection, has been considered in the research literature, there is no prior work on the selection among different spectrum sensing techniques. This thesis has identified the gap and made the first contributions to fill it. In fact, the research on the individual spectrum sensing techniques is now mature enough to proceed to the next stage of thinking when and where the different algorithms could find practical applications. As an example, the selection of spectrum sensing tehniques could be applied to devices operating in the ISM bands where they could use the most suitable spectrum sensing technique to avoid interference from other uncoordinated users in the band. In the future, the selection of the spectrum sensing techniques could be applied in situations where multiple secondary CRSs are accessing the same frequency band and they do not exchange information about their spectrum use with each other. While e.g. databases or control channels would be used to guarantee that the incumbent systems remain free from harmful interference, spectrum sharing between the multiple equal-priority CRSs could be accomplished using spectrum sensing, and there it would be important to select the most proper sensing techniques to be used.

The *channel assignment* studies presented here have applied a heuristic harmony search algorithm to optimise the channel assignment among CRS links in order to minimise the overall BER. The channel assignment studies have discussed the both centralised and distributed approaches and taken into account the notion that different CRS nodes may experience different spectrum availabilities, which is a realistic scenario. Moreover, a distributed channel assignment algorithm is developed to keep the control data exchange among the neighbouring nodes at a reasonable level.

4.2 Limitations

There are limitations associated with the studies presented here. The *spectrum occupancy measurement* studies using energy detection are heavily dependent on the threshold setting, as only the measurements above the threshold are counted in the spectrum occupancy. The resulting spectrum occupancies using energy detection can be too low as the method does not capture signals that are below the noise. This work did not treat the threshold setting thoroughly but only set the thresholds empirically. Thus, the actual values of the spectrum occupancies presented are are only indicative. However, the aim was not to obtain exact values but rather to quantify the impact of the spatial dimension in the spectrum occupancy at a more general level. Furthermore, the time-scales are important and here only a very coarse study was shown.

The *spectrum sensing* studies of this thesis are limited to the performance evaluation of a single spectrum sensing technique, Welch's periodogram, in a simplified propagation environment. Thus the performance evaluation does not provide a comprehensive study. The selected spectrum sensing technique is commonly used in the spectral estimation, and the technique and the channel model were selected to offer analytical tractability while being distinct from the *a priori* work available in the research literature. The performance of the sensing technique was not compared to any other sensing technique as the goal was to present analytical performance of the selected algorithm. In addition, the selected spectrum sensing technique was not applied to any real-life system to assess its function because currently spectrum sensing is considered to be only applicable to a limited set of situations in the spectrum regulation.

The *band-specific approach for the selection of methods to obtain knowledge of spectrum availability* is preliminary and considers the frequency bands with primary allocation to mobile service, bands with secondary allocation to mobile service and licence-exempt bands at a general level. In practice, the situation of the spectrum use is more complicated and it can vary between different countries. Thus, the actual situation and the resulting band-specific approach are much more complex in reality than depicted here.

The work on the *selection of the spectrum sensing techniques* was preliminary with the major aim of opening up a new research direction instead of providing a comprehensive solution to the problem. The work identified critical factors that influence the selection of the spectrum sensing technique and other factors could also be taken into account. The decision-making method presented relied on a number of assumptions to characterise the general classes of spectrum sensing methods. Inside the general classes, there are several individual techniques with very distinct characteristics, performances, and requirements. The developed decision-making method considered only a limited set of spectrum sensing techniques and the classification of the spectrum sensing methods requires more detailed investigations.

The *channel assignment* work has assumed that the information exchange between the CRS nodes is ideal. In the centralised approach, all required information is assumed to be available for the centralised decision-making entity and the results of the decision making are assumed to be communicated to the nodes ideally. In the distributed approach, the control data exchange among the neighbouring nodes was assumed to be ideal and to require a separate control data network. The channel assignment approach assumes that the CRS nodes are controlled by the same entity, thus it does not cover the situation where a set of secondary users would compete for the same resources without communicating with each other.

4.3 Future work

Based on the CRS studies reviewed from the research literature and those conducted in this thesis, two general-level major future research directions can be identified. One direction is the development of advanced CRS capabilities for operation in specific frequency bands that are governed by the spectrum regulation, and the inclusion of the most promising techniques into the *international spectrum regulation*. The other direction is the demonstration of the CRS capabilities in *trials and testbeds in realistic scenarios* to showcase the functionality of the developed algorithms and approaches and their potential benefits. These two research directions are interrelated, since the inclusion of the CRS capabilities into the international spectrum regulatory framework would benefit from real-life trials of the developed CRS concepts in realistic scenarios.

When going into more details in the specific CRS research topics of this thesis, future research directions can be identified in all of the topics. Future work in *spectrum occupancy measurement studies* could be done to study the availability and suitability of the spectrum opportunities for the operations of specific systems with CRS capabilities in specific frequency bands. In fact, distributed spectrum occupancy measurement studies could be done in the future for this purpose to capture the spectrum occupancy in a given area with several measurement devices and compare the measurements with the knowledge of the specific systems in the specific area and spectrum band. This information could be used to identify spectrum bands that are potential for sharing. In addition, a more fine-grained study in the time domain could be carried out to get more insight about the short-term spectrum opportunities. Since the measurement direction is important in spectrum occupancy measurements, it would also be useful to introduce the direction of arrival estimation into the measurements for more accurate characterisation of the spectrum occupancy in the spatial domain. The direction of arrival estimation has been introduced into the context of spectrum sensing with promising results but increases the complexity, which may become challenging for spectrum occupancy measurements.

In the research on *spectrum sensing techniques*, the development of reliable spectrum sensing techniques that can guarantee satisfactory protection for the incumbent systems in realistic propagation conditions with manageable complexity is still a true challenge. While spectrum sensing research literature typically considers the scenario where the spectrum sensing techniques are used to protect primary users, in practice it is challenging to guarantee sufficient protection for the primary user in realistic settings. In fact, future work on spectrum sensing could be focused on the development of techniques to facilitate spectrum sharing between multiple CRSs with equal status. Spectrum sensing techniques could be used to control interference among multiple CRSs in the same frequency band to make better use of the shared resource. The development of an implementable spectrum sensing technique that can offer high probability of detection in realistic situations would be an important target for future research.

When it comes to the *band specific approach for the selection of methods* to obtain knowledge of spectrum availability, the major topic for future work is the more detailed study of the potential bands for CRS operations, derivation of the requirements for the protection of the primary users in the specific spectrum band, and the development of methods of obtaining accurate knowledge of spectrum availability in these bands. To a large extent, the selection of the method to obtain knowledge of spectrum availability in each band is a regulatory decision, and the actual selection is done at the time of making the regulatory decisions. Thus, in addition to writing research papers regarding this topic, it is important to take part in the actual decision-making process when it takes place in the regulation. In addition, the selection of the method takes place also when several CRSs are operating in the same frequency band. There, the method to be used to obtain knowledge of spectrum availability can be done based on different criteria and is typically not determined by the regulator. Instead, it is left for the technology to handle the spectrum sharing between equal secondary users and the regulator is not likely to decide the rules for it. The selection of the method to be used to control interference among multiple CRSs could be a potential topic for future research.

This thesis has started a new research direction about the *selection of the spectrum sensing techniques*. While the spectrum sensing research papers claim to use sensing to protect incumbent systems on licensed bands, this may not be the case in realistic spectrum bands where the licensed systems have the rights of use as determined by the time of assigning the licence. The goal in our spectrum sensing selection studies has been to highlight the importance of thinking where the spectrum sensing techniques could be used in practice, which is not thoroughly covered in the current spectrum sensing research literature. Significant amount of future research is needed to make the sensing selection practical. The input parameters for the selection were rather preliminary, and additional work is needed to find more proper input parameters for the decision-making system. In particular, a potential topic for future study is to extend the method to consider the situation where multiple CRSs are accessing the same channel and how they could benefit from the spectrum sensing. A closer look into the classification of the spectrum sensing techniques, the individual techniques inside the general classes, and the underlying assumptions of techniques is needed to develop a more realistic decision-making system. The imperfections in the spectrum sensing techniques could be taken into account and a more thorough performance evaluation for the CRS with the decision-making system in the form of achievable capacities could be done.

Future work on *channel assignment techniques* could consider the amount of control information needed for the decision making in centralised and distributed approaches. Development of methods to efficiently distribute the required control information and to reduce the amount of control information would be an important topic to consider for practical applications. Practical spectrum sharing scenarios can have multiple secondary systems wishing to access the same set of channels without communicating with each other and the development of channel assignment techniques for this is a future challenge.

Finally, the inclusion of *learning techniques* into the future wireless systems with CRS capabilities deserves further attention. In fact, there is room for new innovations in the development of learning mechanisms that could deliver improvements in the system performance. While the definition for CRS implies the inclusion of learning, this part deserves future research to make it part of the real systems in specific spectrum bands. The learning techniques developed so far in the CRS context are not very comprehensive. In fact, the learning techniques could be a major differentiator for the devices equipped with CRS capabilities compared to devices without the learning mechanisms.

5. Summary

This thesis has presented methods to obtain and exploit knowledge of spectrum availability for CRSs. A CRS has the capabilities to obtain knowledge of system internal and external state, dynamically and autonomously adjust its operations accordingly, and learn from the results. As the future mobile telecommunication market is expected to experience strong growth in the next decade, the spectrum demand of future mobile communication systems will increase as well. While it is more and more challenging to find new spectrum for any wireless system, the CRS technology can be used to facilitate spectrum sharing between wireless systems in response to the growing data rate demand. The CRS technology can offer significant improvements in the current spectrum occupancy, as future wireless systems with CRS capabilities could use temporarily and locally free spectrum resources while offering protection for primary systems from harmful interference.

This thesis has reviewed the relevant literature on the CRS concept and its capabilities as well as spectrum occupancy measurement studies. Novel distributed and directional spectrum occupancy measurements have been conducted in the 2.4 GHz ISM band to assess the current status of spectrum use and the potential availability of spectrum for CRS operations. The measurement approach has taken into account the influence of the spatial dimension and shown for the first time in the research literature that the spectrum occupancy can vary significantly depending on the measurement location even in the same office area.

There are several methods to obtain knowledge of spectrum availability for CRS, including control channels, databases, and spectrum sensing, which all have different capabilities, requirements and performances. This thesis has highlighted the importance of selecting the proper methods in each situation at hand and proposed a novel band-specific approach, where the selection of the method is determined separately for each frequency band based on the deployment characteristics and regulatory requirements of the specific band.

Spectrum sensing has been studied in more detail and an analytical performance evaluation has been presented for a selected algorithm, Welch's periodogram, in a Rayleigh fading channel. Cooperative spectrum sensing to improve the sensing reliability in a fading environment has been studied with fuzzy combining for collecting and combining of the sensing results from several CRS nodes. In addition, a novel fuzzy rule-based decision-making system with a learning mechanism has been developed for the selection between different spectrum sensing techniques. This decision-making system is the first one in the research literature to consider the problem of selecting the spectrum sensing technique. Finally, in order to exploit the spectrum and assign the available frequency channels to the different users, this thesis presents centralised and distributed channel assignment methods based on a heuristic harmony search algorithm.

The results presented here can be applied to wireless systems operating in different frequency bands. In particular, the introduction of CRS capabilities to the development of future mobile communication systems can offer potential to respond to the growing data rate and spectrum demand.

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PAPER I

Performance of spectrum sensing using Welch's periodogram in Rayleigh fading channel

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Performance of Spectrum Sensing Using Welch's Periodogram in Rayleigh Fading Channel

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***Abstract*—In this paper we present theoretical performance evaluation of spectrum sensing with energy detection using Welch's periodogram for cognitive radio systems. We generalize the theoretical expressions for the probability of detection and the probability of false alarm of energy detection in Rayleigh fading channel to the case of Welch's periodogram. We verify the theoretical results by simulations both in single node and cooperative sensing scenarios. In particular, cooperation is crucial in fading environment. Protection of primary systems from harmful interference is the key requisite for the introduction of cognitive radio systems into the future spectrum regulatory framework if the systems are deployed on the same spectrum bands. The primary user's concern is how often it could be susceptible to potential interference from the cognitive radio system, which, as we show, is dependent on the probability of detection. Therefore, performance evaluation and in particular the probability of detection is critical in assessing the potential capabilities of the future cognitive radio systems.**

I. INTRODUCTION

The radio frequency spectrum is a limited natural resource. The use of radio spectrum requires certain level of administration to protect the wireless systems from harmful interference, as has been demonstrated during the past 100 years. During the decades, spectrum bands have been allocated to different services, such as mobile, fixed, broadcast, fixed satellite and mobile satellite services, along with their appearance. Each country has an administration that manages spectrum use in its area but international cooperation, e.g. at the International Telecommunication Union (ITU), is needed since radio waves propagate over national borders. More information on the use of radio frequencies is given in [1].

The challenge in today's wireless telecommunication market is the difficulty for new services to enter the market as acquiring access to spectrum is difficult. Cognitive radio systems with the capabilities to obtain knowledge and dynamically adjust their performance to the radio operational environment and learn from the results, offer a potential technical approach for the challenge. In fact, the work towards the international introduction of cognitive radio techniques into the spectrum regulatory framework that governs the use of radio spectrum has been started. While administrator in some countries, such as the Federal Communications Commission (FCC) in the US, promote cognitive radio techniques, the introduction of cognitive radio techniques in the global scale requires still much effort. For example in Europe the spectrum regulatory framework is more scattered and currently cognitive radio discussions are in the starting point.

Important step on the global scale for the possible deployment of cognitive radio systems is the next World Radiocommunication Conference of the ITU in 2011 (WRC-11) that will consider regulatory measures and their relevance to enable the introduction of software-defined radio and cognitive radio systems. If the cognitive radio systems used the spectrum belonging to a primary user owning the rights of use for the spectrum, the primary user should be well protected from harmful interference. Therefore, finding suitable performance metrics and evaluation of the cognitive radio techniques' performance with the metrics are crucial for the potential introduction of future cognitive radio systems. The detection of primary users is thus critical and if it is done with spectrum sensing techniques, the reliability and performance evaluation of the spectrum sensing techniques are important.

Typically, the performance of spectrum sensing is evaluated with the probability of detection and probability of false alarm that constitute to the receiver operating characteristics (ROC) [2]. From the primary user's point of view, the probability of detection is critical as it determines how often primary user is susceptible to potential interference from the cognitive radio system. This is because the time between failures in detecting the presence of primary user depends on the probability of detection. Therefore, we are interested in the probability of detection as a measure for spectrum sensing performance.

The fundamental results on the theoretical ROC for spectrum sensing using energy detection in additive white Gaussian noise (AWGN) and Rayleigh and Nakagami fading channels were presented in [3]. The theoretical performance analysis of energy detection presented in [3] was generalized to Welch's periodogram [4] in AWGN channel and verified by simulations in [5]. In fading environment spectrum sensing becomes more challenging due to the uncertainty from radio wave propagation. To obtain satisfactory performance, cooperation between several cognitive radio nodes is needed as proposed in [6]. In [6] theoretical performance evaluation was presented for cooperative sensing in fading channels. The ROC for autocorrelation based spectrum sensing was evaluated in Rayleigh fading channels with different diversity techniques in [7]. The influence of Rayleigh fading on cyclostationary

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feature detection was studied in [8]. In [9] the performance of cooperative spectrum sensing in Rayleigh fading channels was derived by taking into account the errors in the feedback channel. The performance of cooperative spectrum sensing in fading channels using linear combination of local statistics from individual cognitive radios was derived in [10].

In this paper we extend the theoretical performance analysis of energy detection from [3] to Welch's periodogram [4] in Rayleigh fading channel. We present the theoretical probability of detection and probability of false alarm of Welch's periodogram in Rayleigh fading channels and verify the performance with simulations. The results are also extended to cooperative sensing. The fading is assumed to be slow compared to the observation window of Welch's periodogram, i.e. corresponding to a snap-shot method.

The rest of this paper is organized as follows. In Section II we present the theoretical expressions for the probability of detection and the probability of false alarm for energy detection in Rayleigh fading channel. In Section III we present the considered system model and extend the theoretical expressions of energy detection from Section II to Welch's periodogram. The results including analytical and simulated ROC are presented in Section IV. Finally, conclusions are drawn in Section V.

II. PERFORMANCE OF SPECTRUM SENSING

A. Performance measures

The performance of spectrum sensing is typically characterized with ROC that captures the relations of the probability of detection and the probability of false alarm that are interrelated. The probability of false alarm describes how efficiently the spectrum opportunities can be perceived. The probability of detection measures how well the cognitive radio system notices the presence of primary systems. The probability of detection is a critical performance measure because the sensing methods to be deployed in the future cognitive radio systems should protect the primary users from harmful interference if they are deployed on the same spectrum bands.

From the primary user's point of view the critical performance measure is the time between the potential appearance of sources for harmful interference that correspond to failing in detecting the presence of primary user. To fulfill the requirements set by the primary user, the time between failures in detection should be kept low. Following the radar literature [2] where the time between false alarms (i.e. time between detecting a target when there is no target) is critical, we can derive the time between failures in detection T_{fd} from the probability of detection P_{d} as

$$T_{\mathrm{fd}} = \frac{T_{\mathrm{dec}}}{1-P_{\mathrm{d}}}, \tag{1}$$

where T_{dec} denotes the time between sensing decisions in periodic spectrum sensing. T_{dec} depends on the primary user's tolerance to harmful interference.

B. Energy detection

In spectrum sensing using energy detection, the received signal is filtered, squared and integrated. In fading channel, the output from the integrator, i.e. the decision variable, follows conditional chi-square distribution that is conditioned on the channel state. The theoretical probabilities of detection and false alarm for energy detection in AWGN, Nakagami and Rayleigh fading channels were derived in [3].

The probability of false alarm P_{f} in AWGN and Rayleigh fading channels can be computed from the central chi-square distribution with N degrees of freedom as [3]

$$P_{\mathrm{f}} = \frac{\Gamma\left(N/2, \dfrac{\lambda}{2\sigma^2}\right)}{\Gamma(N/2)}, \tag{2}$$

where $\Gamma(.,.)$ and $\Gamma(.)$ are the incomplete and complete gamma functions, respectively, N is the number of degrees of freedom, σ^2 is the variance of the I component of the complex AWGN, and λ is the decision threshold.

According to [3], the probability of detection P_{d} in AWGN channel can be calculated from the noncentral chi-square distribution with N degrees of freedom as

$$P_{\mathrm{d}} = Q_{N/2}\left(\sqrt{\frac{s^2}{\sigma^2}}, \sqrt{\frac{\lambda}{\sigma^2}}\right), \tag{3}$$

where $Q_{N/2}(.,.)$ is the Marcum Q-function and s^2 is the noncentrality parameter of the distribution of the detector output.

The probability of detection in Rayleigh fading channel is obtained from (3) by averaging over the fading distribution [3]. Then, the probability of detection becomes

$$\begin{aligned} P_{\mathrm{d}} &= e^{-\frac{\lambda}{2\sigma^2}} \sum_{i=0}^{N/2-2} \frac{\left(\dfrac{\lambda}{2\sigma^2}\right)^i}{i!} + \left(\frac{2\sigma^2+s^2}{s^2}\right)^{N/2-1} \\ &\times \left[e^{-\frac{\lambda}{2\sigma^2+s^2}} - e^{-\frac{\lambda}{2\sigma^2}} \sum_{i=0}^{N/2-2} \frac{\left(\dfrac{\lambda s^2}{2\sigma^2(2\sigma^2+s^2)}\right)^i}{i!} \right]. \end{aligned} \tag{4}$$

C. Cooperative detection

Fading environment significantly influences the probability of detection as the propagation path between the primary user and the cognitive radio node might experience a deep fade during the spectrum sensing. To guarantee high enough probability of detection acceptable to the primary users, cooperation between cognitive radio nodes will be needed.

There are different approaches and rules for combining the sensing results from several cognitive radio nodes, such as AND, OR and majority rules. Here we use the OR rule where a decision on the presence of the primary user is made if one of the cognitive radio nodes detects the primary user. The theoretical joint probabilities of false alarm and detection for n cooperative nodes can be calculated from [6]

$$Q_{\mathrm{f}} = 1-\left(1-P_{\mathrm{f}}\right)^{n} \tag{5}$$

$$Q_{\mathrm{d}} = 1-\left(1-P_{\mathrm{d}}\right)^{n}, \tag{6}$$

where the probability of false alarm P_{f} and the probability of detection P_{d} are obtained from (2) and (4) for the energy detection in Rayleigh fading channel.

III. WELCH'S PERIODOGRAM

A. System model

We use the system model presented in Fig. 1 for evaluating the performance of spectrum sensing using Welch's periodogram [4] in Rayleigh fading channel. We are interested in the ROC including the probability of detection and the probability of false alarm in both single node and cooperative sensing scenarios. In the considered system model, the primary user transmits quadrature phase shift keying (QPSK) symbols over a 1 MHz bandwidth. The data is transmitted over a Rayleigh fading channel where AWGN is summed.

At the cognitive radio receiver, the received signal is first converted down to baseband. Energy detection with Welch's periodogram is used for detecting the presence of the primary user's signal. In Welch's periodogram the downconverted signal is first lowpass filtered. Then, the signal is divided into M nonoverlapping or overlapping segments and the segments are processed with fast Fourier transform (FFT). After FFT the samples are squared and averaged over the M segments. L samples are taken from the output of Welch's periodogram around the assumed frequency of the baseband signal and an average over the L samples is taken. Finally, the decision on the presence or absence of the primary user's signal is done by comparing output from the detector with a threshold. The difference of Welch's periodogram compared to the traditional energy detection comes from the segmenting of data before the FFT operation.

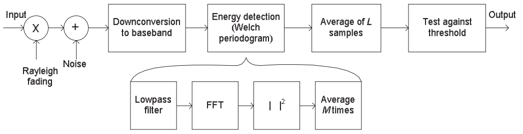

Figure 1. Block diagram of system model.

B. Receiver operating characteristics

Next we derive the analytical receiver operating characteristics for Welch's periodogram in Rayleigh fading channel. We can rewrite the probability of false alarm and the probability of detection for the energy detection presented in (2) and (4) to Welch's periodogram [4] following the analysis presented in [5] for the AWGN channel. In the case of Welch's periodogram, the number of degrees of freedom N in (2) is replaced by $2LM$, where L is the number of frequency bins used for averaging around the assumed frequency of the baseband signal and M is the number of segments over which averaging is done. The probability of false alarm for Welch periodogram can then be analytically calculated from

$$P_{\mathrm{f}} = \frac{\Gamma\left(LM, \frac{\lambda}{2\sigma^{2}}\right)}{\Gamma(LM)}. \tag{7}$$

The probability of detection for the energy detection in (4) can be rewritten in the case of Welch's periodogram by replacing N with $2LM$ and approximating the noncentraility parameter s^2 with LMA^2T, where A is the signal amplitude and T is the symbol length. Then, the probability of detection for Welch's periodogram in Rayleigh fading channel becomes

$$\begin{aligned} P_{\mathrm{d}} &= e^{-\frac{\lambda}{2\sigma^{2}}} \sum_{i=0}^{LM-2} \frac{\left(\frac{\lambda}{2\sigma^{2}}\right)^{i}}{i!} + \left(\frac{2\sigma^{2}+LMA^{2}T}{LMA^{2}T}\right)^{LM-1} \\ &\times \left[e^{-\frac{\lambda}{2\sigma^{2}+LMA^{2}T}} - e^{-\frac{\lambda}{2\sigma^{2}}} \sum_{i=0}^{LM-2} \frac{\left(\frac{\lambda LMA^{2}T}{2\sigma^{2}(2\sigma^{2}+LMA^{2}T)}\right)^{i}}{i!} \right]. \end{aligned} \tag{8}$$

For cooperative sensing using Welch's periodogram with the OR rule, the theoretical joint probabilities of false alarm and detection for n cooperative nodes can be calculated from (5) and (6) where the probability of false alarm P_{f} and the probability of detection P_{d} are obtained from (7) and (8), respectively.

IV. RESULTS

The analytical results for the performance of Welch's periodogram in Rayleigh fading channel derived in Section III are next verified with Monte Carlo simulations. We are interested in the ROC of Welch's periodogram that captures the relations of the probability of detection and the probability of false alarm and consider both single node sensing and cooperative sensing.

In the simulations complex QPSK signals are transmitted with symbol rate $R_{\mathrm{s}} = 500$ ksymbols/s over a one tap Rayleigh fading channel. The fading is assumed to be slow compared to the observation interval of the sensing method. Thus, the channel is assumed to remain constant during the transmission of the data block but it varies randomly between the transmissions of consecutive data blocks. Independent complex AWGN samples are added to the signal after fading. Welch's periodogram is used to detect the presence of the primary user signals. The number of frequency bins averaged around the assumed frequency of the baseband signals L is equal to 1 or 10. The number of segments M to which the received signal samples are divided before FFT is equal to 1 or 8. We use nonoverlapping segments. Welch's periodogram uses an FFT of size 512 or 1024 which at the same time is equivalent to the segment length and the length of the rectangular window. The block length is 410 symbols and the symbol length T is 20. Thus, 8200 samples are taken from from the primary user's signal. The product of the FFT size and M corresponds to the number of samples used for processing in Welch's periodogram, which varies from 512 to 8192 with different combinations of input parameters. Signal-to-noise ratio (SNR) is $\frac{E}{N_0} = \frac{A^2 T}{2\sigma^2}$ where the noise variance σ^2 is 0.5.

To quantify the different combinations of the probability of detection P_d and the probability of false alarm P_f, we use a sliding threshold λ. The threshold is slid between the smallest and largest values of the output of the detector with a small step size and thus all combinations of P_d and P_f can be captured.

Figs. 2-6 present the ROC of Welch's periodogram in AWGN and Rayleigh fading channels for single node and cooperative sensing with different parameter values. For single sensing node case, the theoretical ROC for Welch's periodogram in Rayleigh fading channels is calculated from (7) and (8), and in AWGN from (2) and (3) with the same parameter changes as in the Rayleigh fading (see Section III B or [5]). The theoretical ROC for cooperative spectrum sensing in Rayleigh fading channel using the OR decision rule is obtained by inserting (7) and (8) into (5) and (6).

In Fig. 2 the theoretical and simulated ROC for single sensing node are given in AWGN and Rayleigh fading channels with SNR equal to 2 dB or -3dB, M equal to 8, L equal to 1 and FFT size equal to 1024. The simulations verify the theoretical results. The performance in Rayleigh fading channel is severely degraded as compared to the AWGN case which shows that single node sensing is not reliable in fading environment due to uncertainty of radio wave propagation. Fig. 3 shows the same results for the single sensing node as Fig. 2 but now M is equal to 1 and L equal to 10. The results are close to those of Fig. 2 and follow the theoretical results. In Fig. 4 the same parameters are used as in Fig. 3 but now FFT size is changed from 1024 to 512. This change only slightly degrades the performance of Welch's periodogram.

Next we consider cooperative spectrum sensing. Figs. 5 and 6 show the theoretical and simulated results for two and three cooperative nodes, respectively, using the same parameter values as Fig. 2. The theoretical results for AWGN are shown for comparison to show how significantly Rayleigh fading degrades the performance. In fading environment, cooperation is therefore necessary to obtain reliable sensing results.

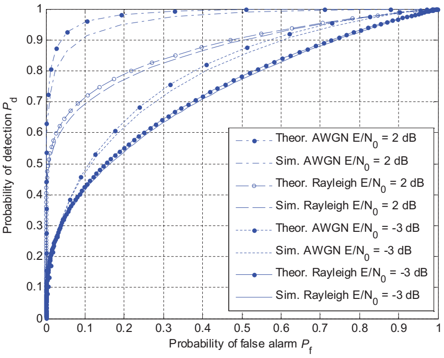

Figure 2. ROC for single sensing node in AWGN and Rayleigh fading channels with SNR = 2 dB or -3dB, M = 8, L = 1, and FFT size = 1024.

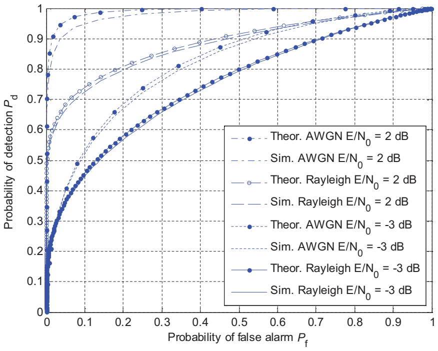

Figure 3. ROC for single sensing node in AWGN and Rayleigh fading channels with SNR = 2 dB or -3dB, M = 1, L = 10, and FFT size = 1024.

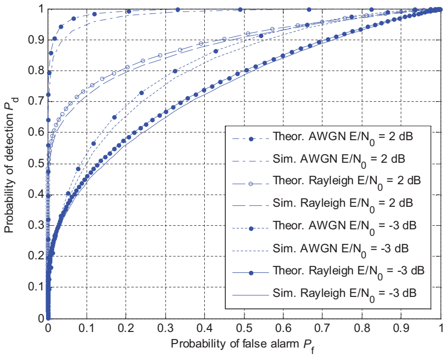

Figure 4. ROC for single sensing node in AWGN and Rayleigh fading channels with SNR = 2 dB or -3dB, M = 1, L = 10, and FFT size = 512.

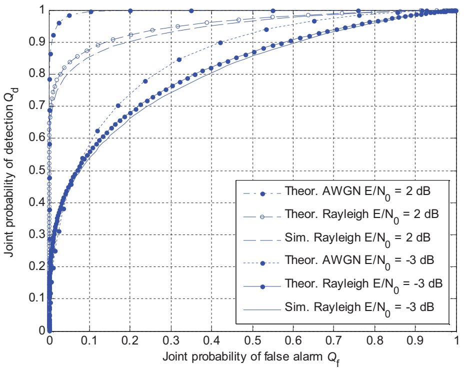

Figure 5. ROC for two cooperative sensing nodes in Rayleigh fading channel with SNR = 2 dB or -3dB, $M = 8$, $L = 1$, and FFT size = 1024.

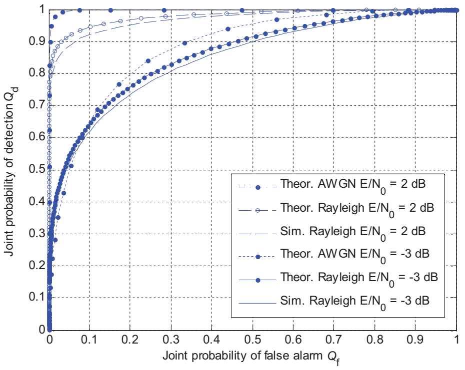

Figure 6. ROC for three cooperative sensing nodes in Rayleigh fading channel with SNR = 2 dB or -3dB, $M = 8$, $L = 1$, and FFT size = 1024.

V. CONCLUSION

In this paper, we have evaluated the performance of spectrum sensing using Welch's periodogram in Rayleigh fading channels for cognitive radio systems. The performance measures considered were the receiver operating characteristics that quantify the relations of the probability of detection and the probability of false alarm.

The probability of detection will be a critical performance measure for spectrum sensing. In particular, the introduction of cognitive radio techniques into the future spectrum regulatory framework requires taking the primary user system's view point if the systems are to be deployed on the same spectrum bands. Then it is critical how often the primary user of the spectrum tolerates failures in detection by the cognitive radio system, i.e. sources of potential interference to the primary user. For this we predict that the time between failures in detection becomes the crucial parameter. The time between failures in detection sets the requirements for the performance of spectrum sensing techniques in terms of probability of detection. This is because the time between failures in detection depends on the probability of detection that should be made very high.

We have derived theoretical expressions for the probability of detection and the probability false alarm for Welch's periodogam in Rayleigh fading channel from the general results of energy detection in Rayleigh fading. We have also verified the theoretical expressions with simulations. The sensing performance in Rayleigh fading channel is significantly lower compared to the AWGN channel. We have demonstrated the benefit from cooperation between cognitive radio nodes to improve the sensing performance. In fading environment, cooperation will be crucial to obtain sensing performance that is acceptable for the primary user.

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PAPER II

Distributed and directional spectrum occupancy measurements in the 2.4 GHz ISM band

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Distributed and Directional Spectrum Occupancy Measurements in the 2.4 GHz ISM Band

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Abstract— **This paper presents distributed and directional spectrum occupancy measurements in the 2.4 GHz ISM band. Spectrum occupancy measurements can be used to assess how efficiently the spectrum bands are used today. Future cognitive radio systems can improve the spectrum occupancy by filling the gaps in the prevailing spectrum by opportunistically using unoccupied channels. Most of the spectrum occupancy measurements in the literature have been conducted by using a single measurement device with an omnidirectional antenna. The resulting spectrum occupancy values have presented an average of the overall situation. To characterize the influence of the spatial dimension on the spectrum occupancy in a given area, we introduce the directional spectrum occupancy metric. Directional spectrum occupancy is defined as the fraction of time that the received power in a channel exceeds a threshold in a given measurement direction. We have used two separately located measurement devices with directional antennas to measure the directional spectrum occupancy in an office area with heavy traffic load. The results indicate that the spectrum occupancy is heavily dependent on the measurement location and direction. The influence of the spatial dimension is therefore very crucial in the development of future cognitive radio systems.**

I. INTRODUCTION

The growing demand of wireless services has led to ever increasing spectrum requirements for wireless systems [1]. The challenge of finding suitable spectrum to accommodate the growing user needs has given motivation to search for new advanced spectrum management approaches. Recently, several spectrum occupancy measurement campaigns have been conducted in different geographical locations and spectrum bands over various time spans to assess the current situation in spectrum use, see e.g. [2]-[7]. The common observation is that the measured overall spectrum occupancies are quite low, but there are large variations depending on the time, frequency band, and location.

Spectrum occupancy is an important metric for the spectrum administrations in the assignment of frequency bands and monitoring of their use. The seminal work of Spaulding and Hagn from 1977 [8] defines the spectrum occupancy for a channel as the fraction of time that the received power in the channel exceeds a threshold level. This definition for spectrum occupancy has been widely used in the measurement studies since then. For example, the spectrum occupancy in [2] was similarly defined as the fraction measured in time and frequency dimensions where the received signal strength exceeds a threshold. Duty cycle was defined as the fraction of time the signal is on the frequency band. Occupied spectrum in a band was calculated as the product of the average duty cycle and the bandwidth. The overall occupancy was obtained by dividing the sum of the occupied spectrum with the total amount of spectrum. According to the measurements in [2], the average occupancy over six different locations was found to be only 5.2% with the maximum occupancy 13.1% in New York City and minimum occupancy 1% in a rural area.

These low measured spectrum occupancy values have recently motivated a lot of research on cognitive radio systems (CRS). CRS is defined by the International Telecommunication Union Radiocommunication sector (ITU-R) in [9] as “a radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives; and to learn from the results obtained.” CRS can thus obtain knowledge of e.g. the current spectrum use in the surrounding environment and dynamically adjust its transmissions accordingly to operate on channels where the spectrum occupancy is low.

In the global spectrum regulatory framework the ITU-R is currently defining spectrum occupancy and its measurement in response to Question ITU-R 233/1 [10]. As for the time being, this definition is not yet ready. Since the spectrum occupancy measurements are an important tool for the administrations that govern the use of spectrum in their own country, a harmonized approach is important in the global scale. Global harmonization is important since it can be desirable to compare the spectrum occupancy measurement results from different countries. In the global regulatory framework the ITU-R has defined measurement procedures and techniques for spectrum occupancy measurements in [11]. The measurement work is currently continuing in the ITU-R Working Party 1C (WP 1C) in response to [10]. Spectrum occupancy measurement techniques for short-range systems such as wireless local area networks (WLAN) are considered in [12]. The harmonization of spectrum occupancy measurements in the research world has been discussed in [5].

Spectrum occupancy measurements can give hints on which parts of the spectrum band are inefficiently used and thus offer potential for CRS operations where the unoccupied spectrum is opportunistically used without causing harmful interference to the primary users of the spectrum. However, even the low percentage values for the spectrum occupancy

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can encompass a lot of usage that must be reliably detected by the CRS in order to be exploited. In general, CRS can significantly improve the spectrum occupancy which translates into more traffic being carried on the same spectrum.

Traditionally the spectrum occupancy measurements have been conducted using a single measurement device with an omnidirectional antenna [2]-[5]. These measurements can give an overview of the overall spectrum occupancy in the given location, but do not consider the influence of the spatial dimension thoroughly. A rotating antenna was used in [2] to measure the signals arriving from different directions, but the results were presented as an average where the antenna direction was averaged out. In [6] four directional antennas were used at one measurement device to take into account the spatial dimension in the spectrum occupancy measurements. In [7] six directional antennas were used to characterize the influence of spatial dimension. The results from both [6] and [7] showed that the spectrum occupancy varies depending on the measurement direction.

Motivated by the findings of [6] and [7], this paper proposes a new metric, the directional spectrum occupancy, to characterize the influence of the spatial dimension in the spectrum occupancy measurement studies. The directional spectrum occupancy was in essence used in [6] and [7] without giving definitions for it. Both [6] and [7] used a single measurement device with directional antennas. We extend the measurement approach by performing distributed and directional spectrum occupancy measurements using two measurement devices with directional antennas to monitor the same office area from different directions. We present an empirical study on spectrum occupancy measurements in the industrial, scientific and medical (ISM) band at 2.4 GHz in an office environment to study the influence of the spatial dimension on the spectrum occupancy over five working days in January 2010. The ISM band is shared by several short-range low-power systems such as Bluetooth, WLAN, and microwave ovens.

The rest of this paper is organized as follows. Section II presents the measurement setup for the spectrum occupancy measurements and describes how the measurements are processed to calculate the directional spectrum occupancies. Section III shows the results from the spectrum occupancy measurement studies and finally Section IV draws some concluding remarks.

II. MEASUREMENT SETUP AND APPROACH

A. Measurement System

The measurement system used for the spectrum occupancy measurements in the 2.4 GHz ISM band is 7signal Sapphire [13]. The measurement system can monitor the quality and performance of WLAN networks using seven antennas. We have used two measurement devices and selected three antennas from each device to monitor the spectrum occupancy in the same office area from opposite directions. Fig. 1 shows the measurement site and floorplan. The distance between the two measurement devices is 45 m and the office area is about 700 m^2. The devices are placed at 1 m height from the floor. The antennas are vertically polarized and directional with a beamwidth of 70°.

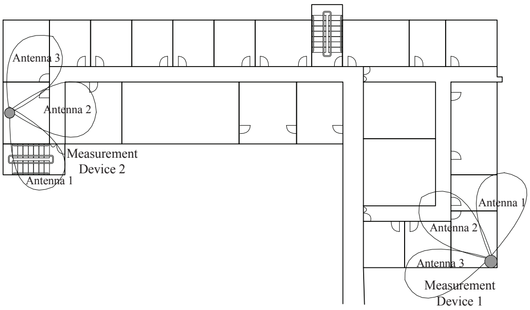

Fig. 1. Measurement site and floorplan

The measurements are taken from the ISM band 2400-2485 MHz which is divided into 256 subchannels with a channel spacing of 333 kHz. As an output, the measurements give the measured power level in dBm on different subchannels at different measurement times at different antennas. 1000 samples are taken from each subchannel in less than a second and averaged to obtain the average power level on the subchannel. The measurements are taken periodically from the subchannels from each antenna. Each subchannel from the same antenna is revisited approximately every 1 min 20 s which is imposed by the hardware. The measurements are stored into a database from where they are read for processing.

B. Processing of Measurements

We define directional spectrum occupancy as the fraction of time that the received power in the channel exceeds a threshold level in the measurement direction. This definition explicitly includes the influence of spatial domain in the form of the measurement direction. The measurements from each antenna are first quantized to one bit decision on spectrum occupancy by comparing the signal level to a threshold according to

$$D_{n,a,c,t} = \begin{cases} 1, if\ P_{n,a,c,t} > \gamma \\ 0, if\ P_{n,a,c,t} \leq \gamma \end{cases} \tag{1}$$

where n is the index for measurement device, a is the index for antenna, c is the index for subchannel, t is the index for sample times, $P_{n,a,c,t}$ is the measured power, and γ is the threshold. A subchannel is declared occupied if the measurement is above the threshold, i.e. $D_{n,a,c,t} = 1$, and otherwise unoccupied, i.e. $D_{n,a,c,t} = 0$. The threshold can be set e.g. from noise level measurement and by adding a margin. The new aspect in (1) is that the measurement direction is taken into account in the form of the antenna index a as the measurements are collected and processed per antenna.

The directional spectrum occupancy for each antenna at the measurement device is calculated from the quantized occupancy decisions from (1) by dividing the number of samples that exceed the threshold by the total number of samples. Thus the directional spectrum occupancy from measurement device *n*, antenna *a*, and subchannel *c* is obtained from

$$S_{n,a,c} = \frac{\sum_{t=1}^{T_{n,a,c}} D_{n,a,c,t}}{T_{n,a,c}} \qquad (2)$$

where $T_{n,a,c}$ is the total number of samples from measurement device *n*, antenna *a*, and subchannel *c* during the measurement period. As the time between visiting the same subchannel is large (approximately 1 min 20 s), the measurements taken from the same subchannel at different time instants are uncorrelated and we can use (2) to calculate the directional spectrum occupancy.

III. RESULTS

The distributed and directional spectrum occupancy measurements have been conducted in the third floor of an office building over one working week from Monday to Friday from 8 AM to 4 PM in January 2010. The measurements are taken from the ISM band 2400-2485 MHz. There are approximately 15 WLAN access points in the given office area. The two measurement devices are monitoring the same office area from different directions and see partially different operational environment, e.g. different WLAN access points. In addition, there is Bluetooth usage in the same band.

Fig. 2 shows an example of the measured power levels from measurement device 1 using antenna 1 during one hour. Fig. 3 shows the power levels on the different subchannels from three antennas from measurement device 1 averaged over one working day. Fig. 4 shows the same information from measurement device 2 for the same working day. The measurements show that there are differences in the measured power levels at the different antennas in each measurement device indicating the influence of the spatial dimension. The comparison of Fig. 3 and Fig. 4 shows that the separately located measurement devices have large differences in the measured power levels because the measurement devices see partially different radio environments.

Next the power levels are quantized to decisions on the spectrum occupancy according to (1) and the resulting directional spectrum occupancies are calculated from (2) for the different antennas and measurement stations. The threshold setting is done by using the noise measurements and adding a margin of 15 dB to the noise level. Fig. 5 shows the average directional spectrum occupancy from three antennas in measurement device 1 averaged over five working days. Fig. 6 shows the same information from measurement device 2 for the same measurement period. The figures show that the directional spectrum occupancies measured from the different antennas in the same measurement device are similar in shape but the power levels are different. The comparison of Fig. 5 and Fig. 6 shows that there are differences in the directional spectrum occupancies measured from the two different measurement stations indicating that the spectrum occupancy varies greatly depending on the measurement location.

In particular in the ISM band the transmission power levels need to be kept low to allow efficient frequency reuse and coexistence of different license-free devices. In short range communications such as the transmissions in the ISM bands the spectrum occupancies are heavily dependent on the measurement location. The two measurement stations see partially different WLAN access points operating on different channels and thus some channels are more occupied in one measurement device compared to the other. Finally, the directional spectrum occupancies over the five working days are collected to Fig. 7 and Fig. 8 for measurement device 1 and measurement device 2, respectively. The figures show the temporal variations in the spectrum occupancy.

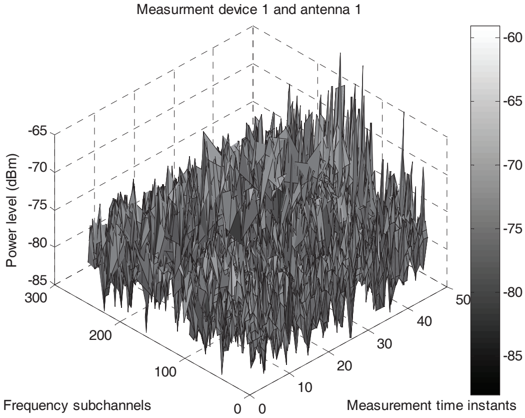

Fig. 2. Power levels from one antenna in measurement device 1 during the first hour of the first working day

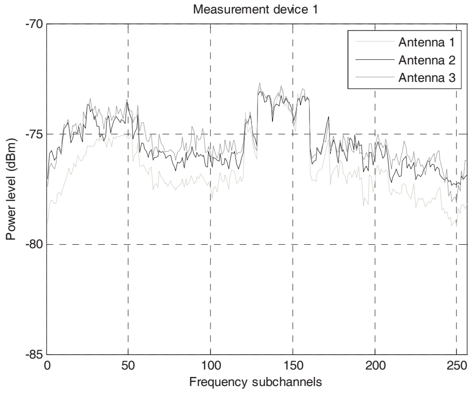

Fig. 3. Average power levels from three antennas in measurement device 1 over the first working day

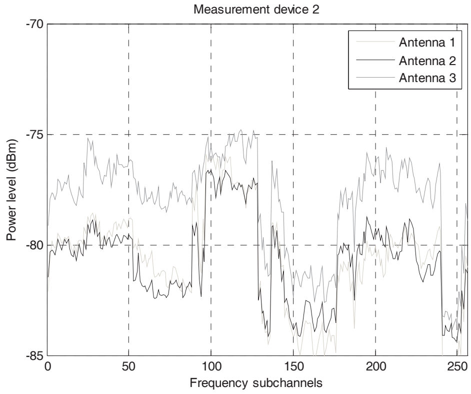

Fig. 4. Average power levels from three antennas in measurement device 2 over the first working day

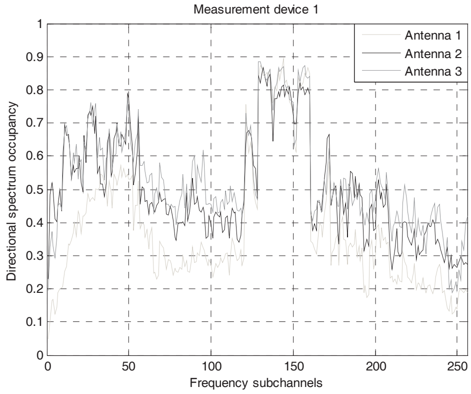

Fig. 5. Average directional spectrum occupancy from three antennas in measurement device 1 over five working days

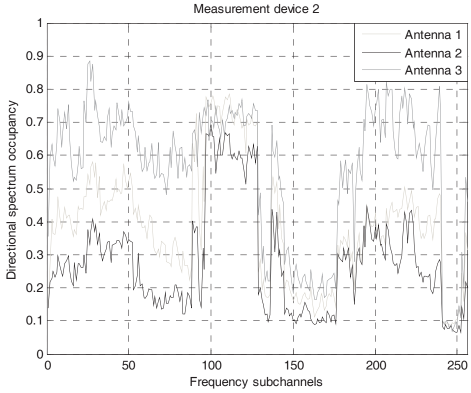

Fig. 6. Average directional spectrum occupancy from three antennas in measurement device 2 over five working days

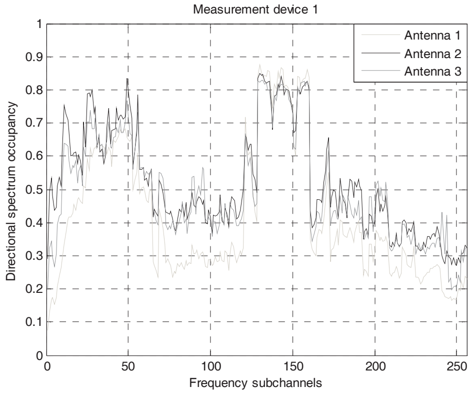

Fig. 7. Average directional spectrum occupancy from three antennas in measurement device 1 over five working days

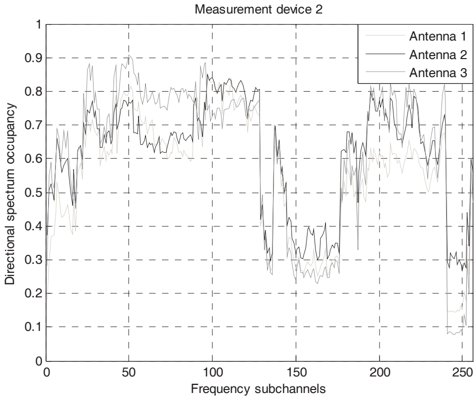

Fig. 8. Average directional spectrum occupancy from three antennas in measurement device 2 over five working days

In general, the measured spectrum occupancies are quite high. However, the aim of this study was not to evaluate the actual spectrum occupancy values because they are heavily dependent on the measurement time scale and setting of threshold. The measurement time scale considered in this study is rather coarse which does not allow the detailed study of the spectrum occupancy on the packet level in very short time scales. Thus the gaps in transmissions between the packets are not captured with the shown measurements and the measured spectrum occupancies tend to overestimate the actual occupancy as the small gaps are not detected.

Still according to the measurements there is room in the ISM bands for CRS type of operations to fill the gaps where the spectrum occupancy is low. Traditionally by network planning the operating channels of e.g. WLAN access points can be adjusted to minimize the interference by using non-adjacent WLAN channels in the different access points located in the same area. The inclusion of CRS techniques into the systems adds to the dynamical flexibility by allowing the adjustment of the operational channel to be conducted in smaller time-scales according to the current channel availability. CRS techniques can be used to dynamically avoid collisions by avoiding highly occupied channels. This at the same time leads to higher spectrum occupancy and higher system throughput. Currently CRS is still under development phase and no large scale deployments are available. Thus the recently conducted spectrum occupancy measurements do not characterize the performance of CRS as they were not operating on the measurement bands. In the future, spectrum occupancy measurement studies can be used to show the improvements in the spectrum use that are obtained when CRS are deployed to coexist on the same spectrum bands with other systems.

CRS techniques are particularly appealing for short-range communications because they should not cause harmful interference to higher priority users of the same spectrum and thus the interference distance has to be limited. The measurement studies indicate that the spatial dimension is particularly important and the spectrum occupancy should be evaluated in different locations.

IV. CONCLUSION

Spectrum occupancy measurement studies have been a major driving force for the development of cognitive radio systems that can exploit unused spectrum opportunities. Spectrum occupancy measurements have identified that there are large temporal and spatial variations in the spectrum occupancy on different spectrum bands and thus offer potential for CRS operations in the vacant bands.

Previous spectrum occupancy measurement studies have mainly used a single measurement device with an omnidirectional antenna. Recent spectrum occupancy measurement studies have shown that spectrum occupancy varies depending on the measurement direction. In this paper we have introduced the directional spectrum occupancy metric to characterize the spatial dimension in the spectrum occupancy measurements. We have conducted a spectrum occupancy measurement study in the 2.4 GHz ISM band to study the long-term spectrum occupancy in an office environment over five working days. We have taken a distributed and directional approach where the same office area is monitored from two different locations using directional antennas thus taking into account the spatial dimension.

According to the measurements, the spectrum occupancy is heavily dependent on the measurement location and direction as the measurement devices and antennas see a different environment in particular when the systems are operating in short-range as in the ISM band. The measurements from the same device with different antennas have similarities in shape but the power levels are different. The directional spectrum occupancy measured from the different directional antennas can characterize the spectrum occupancy in the given area showing the spatial variations of spectrum occupancy. Moreover, measuring the spectrum occupancy from several locations at the same time can further improve the accuracy of the overall spectrum occupancy in the given area.

The purpose of this study was not to obtain specific values for spectrum occupancy since they are heavily dependent on the threshold setting. Instead, the aim was to characterize the influence of spatial dimension by using directional measurements. Limitations of this work are that the measurements do not capture the spectrum occupancy in short time scale on the packet level, but are taken over a longer time with reduced time resolution. The long-term information of spectrum occupancy can be beneficial in the selection of most suitable channels for operation in future cognitive radio systems.

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PAPER III

Cooperative spectrum occupancy measurements in the 2.4 GHz ISM band

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Cooperative Spectrum Occupancy Measurements in the 2.4 GHz ISM Band

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Abstract—**This paper presents cooperative spectrum occupancy measurements in the 2.4 GHz ISM band. Spectrum occupancy describes the efficiency of spectrum use in terms of the proportion of time that the bands are occupied. In this paper, spectrum occupancy is measured from two measurement devices with several directional antennas. The spectrum occupancy information obtained from the different antennas and measurement devices is combined using techniques known from the cooperative spectrum sensing research for future cognitive radio systems. We introduce a new metric, the cooperative spectrum occupancy, to characterize the resulting spectrum occupancy that is obtained by combining the occupancy measurements from the antennas with different combining techniques, such as AND, OR, and majority combining rules. Since the transmission power levels at ISM band are low to allow efficient frequency reuse, the resulting spectrum occupancies are heavily dependent on the measurement location. Instead of averaging out the influence of the spatial dimension, the new metric can give more insights into the actual spectrum occupancy in a given area taking into account the spatial dimension.**

Keywords-cooperative spectrum sensing, measurement; spectrum occupancy; WLAN.

I. INTRODUCTION

Efficient use of the radio spectrum has become one of the most important design criteria in the development of future wireless systems. There are several different metrics for assessing the efficiency of spectrum use. The spectrum occupancy metric [1] describes the fraction of time that the received power in the frequency band exceeds a threshold level. Thus, the spectrum occupancy characterizes the overall rate of spectrum use on the frequency band which depends on the systems' duty cycle. The spectrum occupancy does not considering the actual useful effect for the system in terms of the achievable throughput of the system in the given band.

The spectrum efficiency metric [2] on the other hand describes how efficiently a system uses its bandwidth in terms of the traffic that the system can carry per bandwidth per area or cell. During the recent years, much effort has been spent on developing techniques that can accommodate more traffic per bandwidth and cell such as advanced antenna techniques, modulation and coding techniques, and multiple access and interference mitigation techniques. As a result the spectrum efficiency of future mobile telecommunication systems, such as IMT-Advanced, is expected to be high. The minimum peak spectral efficiency requirements for IMT-Advanced are 15 bit/s/Hz for downlink and 6.75 bit/s/Hz for uplink [3].

In the future, significant improvements in the efficiency of spectrum use can be made by developing techniques that can improve the spectrum occupancy of different bands. Promising techniques for achieving this are cognitive radio systems (CRS). International Telecommunication Union Radio-communication sector (ITU-R) has defined CRS in [4] as "radio system employing technology that allows the system to obtain knowledge of its operational and geographical environment, established policies and its internal state; to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives; and to learn from the results obtained." CRS can thus obtain knowledge of e.g. the current spectrum use in the surrounding environment and dynamically adjust its transmissions accordingly to operate on channels where the spectrum occupancy is low.

Spectrum occupancy measurements can be used to do spectrum planning and assess how well the spectrum assignments are operating. Recently several measurement campaigns have been conducted in different locations and spectrum bands, see e.g. [5]-[11]. Most of the spectrum occupancy measurements have been conducted with a single measurement device using an omnidirectional antenna, such as [5]-[7]. Measurements with directional antennas were conducted in [8], [9], and [11]. The results showed that the spectrum occupancy varies depending on the measurement direction thus highlighting the influence of the spatial dimension on the spectrum use. In [10] distributed spectrum occupancy measurements were performed using several measurement devices with omnidirectional antennas in a cellular band. The measurements from the distributed measurement devices were proposed to be combined with combining techniques known from the cooperative spectrum sensing [12]. However, no results were given on the combined measurements in [10].

Distributed spectrum occupancy measurements with directional antennas in the 2.4 GHz industrial, scientific, and medical (ISM) band were presented in [11]. Two measurement devices with three directional antennas were used to measure the directional spectrum occupancy that takes into account the influence of the spatial dimension. The results in [11] showed that in particular in the ISM band with low-power short-range

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devices the influence of the spatial dimension on the spectrum occupancy is important. The ITU-R has studied spectrum occupancy measurement for short-range communication and emphasizes the importance of the measurement location [13].

In this paper, we extend the distributed and directional spectrum occupancy measurements from [11] and introduce a new metric, the cooperative spectrum occupancy, which is obtained by combining the spectrum occupancy measurement results from several antennas and measurement devices. Instead of simply averaging out the influence of the measurement direction by calculating the average of the spectrum occupancies over the antennas and devices, we propose a new approach. Here the spectrum occupancies measured at the different antennas and measurement devices are combined with the combining techniques known from the research on cooperative spectrum sensing [12]. The new cooperative spectrum occupancy is calculated from the combined decisions. The new metric can give more insight into the influence of the spatial dimension in the spectrum occupancy. The distributed and directional spectrum occupancy measurements in the 2.4 GHz ISM band in an office over one working week in January 2010 summarized in [11] are processed to obtain the cooperative spectrum occupancies.

The rest of this paper is organized as follows. Section II introduces the new cooperative spectrum occupancy metric and shows how it is calculated. Section III presents the measurement setup. Section IV shows the measurement results from the cooperative spectrum occupancy studies. Finally, Section V draws conclusions.

II. COOPERATIVE SPECTRUM OCCUPANCY

Cognitive radio systems require accurate knowledge of the spectrum usage in the surrounding environment if they aim at exploiting the unused spectrum opportunities opportunistically on bands that have higher priority users. Spectrum awareness can be achieved e.g. via spectrum sensing techniques which try to distinguish the presence of signals from the case where only noise is present by using signal processing techniques. Spectrum sensing with hard decision making becomes a two hypothesis testing problem where each cognitive radio node makes a decision on the presence or absence of the signal (i.e., 1 or 0 denoting signal present or absent). Due to the uncertainty of noise and radiowave propagation, one measurement device cannot guarantee fully reliable signal detection as the signals can be severely attenuated due to e.g. obstacles along the propagation path.

Cooperative spectrum sensing [12] has gained a lot of interest in the study of future cognitive radio systems in order to improve the reliability of spectrum sensing. Exploiting the spatial dimension via cooperation increases the detection probability because the probability that all users experience the worst channel conditions decreases. More reliable spectrum sensing results decrease the interference caused to the primary users of the spectrum and are thus important for the potential deployment of cognitive radio systems.

The general combining rule for cooperative spectrum sensing is the “*m* out of *N* rule” where a cooperative decision on the signal presence is done using observations from *N* cognitive radio nodes. Signal is declared present if *m* or more nodes detect the signal. The “*m* out of *N* rule” combining rule can be formulated as [14]

$$D = \begin{cases} 1, if \sum_{n=1}^{N} D_n \geq m \\ 0, if \sum_{n=1}^{N} D_n < m \end{cases} \tag{1}$$

where D_n is the decision of the *n*th cooperative cognitive radio node and *m* is the number of nodes that is set as the threshold. OR, AND, and majority combining rules are obtained from (1) by setting $m = 1$, $m = N$, or $m = \lceil N/2 \rceil$ corresponding to the cases that signal is declared present if one node, all nodes, or most of the nodes detect the presence of the signal.

The principle of cooperative spectrum sensing can be extended to the spectrum occupancy measurements to improve the reliability of the spectrum occupancy measurements. In essence, the spectrum occupancy measurements are based on collecting spectrum sensing results over time and calculating the proportion of measurements where signal is declared to be present in the measurement period. Previous spectrum occupancy measurement studies have been mainly conducted using a single measurement station. In [10] cooperative spectrum sensing decision rules were proposed to be used for distributed spectrum occupancy measurements, but no results were given. Here, we extend the principle of cooperative spectrum sensing to distributed and directional spectrum occupancy measurements and define the new cooperative spectrum occupancy.

The spectrum occupancy is defined as the fraction of time that the received power in the frequency band exceeds a threshold level [1]. We define the cooperative spectrum occupancy as the fraction of time that the spectrum is occupied after the observations from several measurement entities (e.g. antennas and measurement devices) have been combined. The first step in the calculation of the cooperative spectrum occupancy is to quantize the measured power levels into decisions on spectrum occupancy. To calculate the directional spectrum occupancy the measured power levels are first quantized into one bit hard decisions by comparing to a threshold as in [11] according to

$$D_{n,a,c,t} = \begin{cases} 1, if\ P_{n,a,c,t} > \gamma \\ 0, if\ P_{n,a,c,t} \leq \gamma \end{cases} \tag{2}$$

where *n* is the index for measurement device, *a* is the index for antenna, *c* is the index for subchannel, *t* is the index for sample times, $P_{n,a,c,t}$ is the measured power, and γ is the threshold. A subchannel is declared occupied if the measurement is above the threshold, i.e. $D_{n,a,c,t} = 1$, and otherwise unoccupied, i.e. $D_{n,a,c,t} = 0$. The threshold can be set e.g. from noise level measurement and by adding a margin.

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To combine the spectrum occupancy measurements from several antennas at the measurement device we can use the general "*m* out of *N* rule" from (1) which now becomes

$$D_{n,c,t} = \begin{cases} 1, if \ \sum_{a=1}^{A} D_{n,a,c,t} \geq m \\ 0, if \ \sum_{a=1}^{A} D_{n,a,c,t} < m \end{cases} \tag{3}$$

where $D_{n,c,t}$ is the decision of the *n*th cooperative cognitive radio node on subchannel *c* at with sample time index *t*, *a* is the index for antennas, *A* is the total number of antennas, and *m* is the number of entities that is set as the threshold for the combing rule. OR, AND, and majority combining rules are obtained from (3) by setting $m = 1$, $m = A$, or $m = \lceil A/2 \rceil$.

Combining rule in (1) and (3) treats the observations from the different nodes equally. In reality, some nodes can be more reliable than others due to e.g. better propagation conditions leading to higher signal-to-noise ratios (SNR). Instead of equal gain combining, weights could be assigned to the nodes to value the observations of certain nodes over others by applying e.g. SNRs as weights. However, in practice it can be difficult to accurately know the SNRs on the bands that are being studied. Therefore, we resort to equal gain combining in (3).

Finally, the cooperative spectrum occupancy per measurement devices is calculated from

$$C_{n,c} = \frac{\sum_{t=1}^{T_{n,c}} D_{n,c,t}}{T_{n,c}} \tag{4}$$

where $T_{n,c}$ is the total number of samples from measurement device *n* and subchannel *c* during the measurement period of interest and $D_{n,c,t}$ is obtained from (3). While (3) is used to combine the measurements from several antennas at one measurement device, the approach can be extended to combine the measurements from several measurement devices with several antennas Then the cooperative spectrum occupancy for subchannel *c* from (4) becomes

$$C_c = \frac{\sum_{n=1}^{N} \sum_{t=1}^{T_{n,c}} D_{n,c,t}}{\sum_{n=1}^{N} T_{n,c}} \ . \tag{5}$$

where the summations are performed over the measurement devices.

III. MEASUREMENT SETUP

The measurement system used for the spectrum occupancy measurements in the 2.4 GHz band is 7signal Sapphire [15].

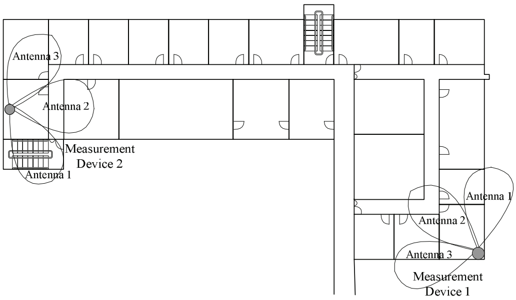

Figure 1. Measurement site and floorplan.

The measurement system can monitor the quality and performance of WLAN networks using seven antennas. We use two measurement devices and select three antennas from each device to monitor the spectrum occupancy in the same office area from opposite directions. Fig. 1 shows the measurement site and floorplan. The distance between the two measurement devices is 45 m and the office area is about 700 m^2. The antennas are vertically polarized and directional with a beamwidth of 70°.

The measurements are taken from the ISM band 2400-2485 MHz which is divided into 256 subchannels with a channel spacing of 333 kHz. As an output, the measurements give the measured power level in dBm on different subchannels at different measurement times at different antennas. 1000 samples are taken from each subchannel in less than a second and averaged to obtain the average power level on the subchannel. The measurements are taken periodically from the subchannels from each antenna. Each subchannel from the same antenna is revisited approximately every 1 min 20 s. The measurements are stored into a database and read from the database for processing.

The measurements are quantized to one bit decision on spectrum occupancy by comparing the signal level to a threshold according to (2). Subchannel is declared occupied if the measurement is above the threshold and otherwise unoccupied. The threshold is set from noise level measurement and a margin is added. The margin is set to 15 dB. The decisions from the three different antennas at each measurement device are combined using AND, OR, and majority combining rules from (3). The resulting cooperative spectrum occupancies are calculated from (4) and (5).

IV. RESULTS

The spectrum occupancy measurements have been conducted in the third floor of an office building over one working week from Monday to Friday from 8 AM to 4 PM in January 2010. The measurements are taken from the ISM band 2400-2485 MHz that is used by e.g. Bluetooth and wireless local area network (WLAN) devices. There are approximately 15 WLAN access points in the given office area. The two measurement devices are monitoring the same office are from different directions and see partially different operational environment, e.g. different WLAN access points. The threshold setting is done by using noise measurements and adding a margin of 15 dB to the noise level.

Fig. 2 presents the directional spectrum occupancy from three antennas at measurement device 1 measured over one working day using (4). Fig. 3 presents the same information from the second measurement device in the same day. The different antennas at the same measurement device are pointing at different directions and thus the resulting measured power levels are different but similar in shape. The two different measurement devices see partially different access points and thus there are differences in the spectrum occupancies on different subchannels. Fig. 4 shows the cooperative spectrum occupancies obtained by combining the measurements from three antennas at measurement device 1 using AND, majority, and OR combining rules over one working day. Fig. 5 shows the cooperative spectrum occupancies from the measurement device 2. The cooperative spectrum efficiencies are lowest for the AND combining rule because all antennas need to see the channel occupied. The cooperative spectrum efficiencies are highest for the OR combining rule because there it is enough that one of the antennas sees activity in the channel. Majority combining rule is in between the two other rules since there two out of the three antennas need to see the channel occupied.

The measurements from the measurement devices 1 and 2 have been combined using AND, majority and OR combining rule in Fig. 6 over the second working day using (5). The cooperative spectrum occupancy is highest for OR combining rule because then it is enough that some antenna at one device sees the subchannel occupied. The cooperative spectrum occupancy is lowest for AND combining rule because there all antennas and devices need to see the channel occupied. In this measurement work, we have not studied the reliability of the different combining schemes. Some combining schemes can be more accurate in certain measurement scenarios. In particular, weighted combining could be more pertinent. If for example some measurement directions are more important than others, they could be valued more.

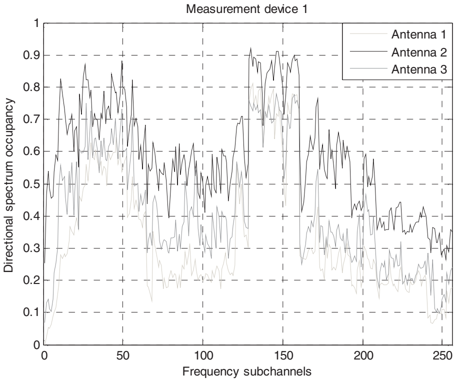

Figure 2. Directional spectrum occupancy from three antennas in measurement device 1 over the second working day.

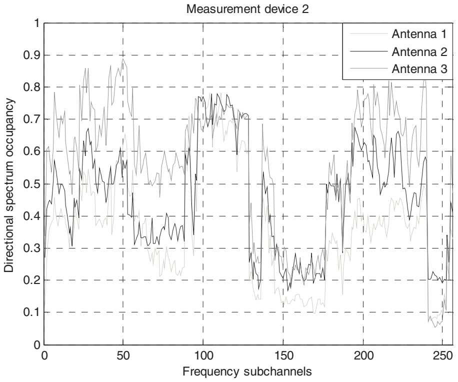

Figure 3. Directional spectrum occupancy from three antennas in measurement device 2 over the second working day.

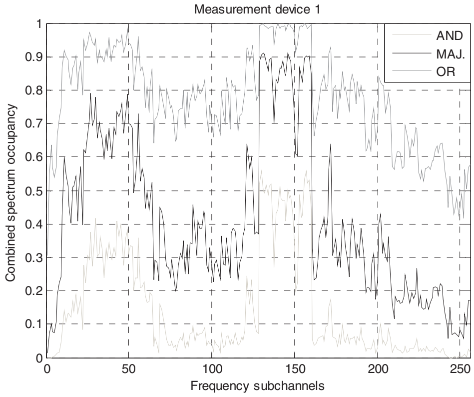

Figure 4. Cooperative spectrum occupancy using AND, majority, and OR combining rules at measurement device 1 over the second working day.

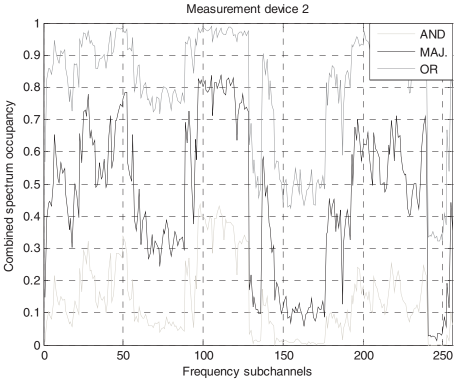

Figure 5. Cooperative spectrum occupancy using AND, majority, and OR combining rules at measurement device 2 over the second working day.

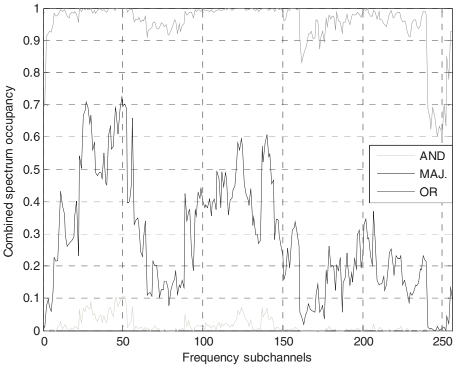

Figure 6. Cooperative spectrum occupancy using AND, majority, and OR combining rules from both devices over the second working day.

V. CONCLUSIONS

The spectrum occupancy is heavily dependent on the measurement location particularly in the ISM bands where transmission power levels are low. The spectrum occupancy values can differ even in the same office area due to the locations of the transmitters and the radio propagation environment. One measurement device can capture the spectrum occupancy only partially. If several directional antennas are used, the occupancies can become more accurate. Moreover, if several spectrum occupancy measurement devices are used, the spatial variations of the spectrum occupancy can be captured more accurately. The question then becomes how to process the measurements from several antennas and devices.

Cooperative spectrum sensing using several cognitive radio nodes for detecting the presence of primary user signals improves the reliability of spectrum sensing due to the diversity effect. Similarly, the reliability of spectrum occupancy measurements could be improved by conducting the spectrum occupancy measurements from several locations. We have extended the principle of cooperative spectrum sensing into the measurement of spectrum occupancy. We have performed spectrum occupancy measurements in the 2.4 GHz ISM band with two measurement devices with three directional antennas at each measurement device. We have proposed a new metric, the cooperative spectrum occupancy that is obtained by combining the spectrum occupancy measurements from several antennas and measurement devices using the combining techniques from cooperative spectrum sensing (e.g. “m out of N rule” combining rule). Instead of averaging out the influence of the spatial dimension, the cooperative spectrum occupancy can more accurately describe the actual spectrum use considering the spatial dimension. However, it may not be feasible to combine measurements from devices that are located too far away from each other.

In the future, the efficiency and reliability of the combining schemes could be studied. Measurements from some nodes could be more accurate and valuable and their effect on the combined spectrum occupancy could be increased by using weights that depend on e.g. SNR.

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PAPER IV

Directional and cooperative spectrum occupancy measurements in the 2.4 GHz ISM band

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of Autonomous and Adaptive Communications
Systems.

Directional and cooperative spectrum occupancy measurements in the 2.4 GHz ISM band

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Abstract: This paper presents directional and cooperative spectrum occupancy measurements in the 2.4 GHz industrial, scientific and medical band. Spectrum occupancy characterises the efficiency of spectrum use in terms of identifying the proportion of time that a given frequency channel is occupied. Directional spectrum occupancy measurements are carried out using two separately located measurement devices with directional antennas to capture the influence of the spatial dimension on the spectrum use. The measurements from the different antennas are further combined using decision fusion techniques to get cooperative spectrum occupancies that give a more accurate view of the actual spectrum use. The resulting directional and cooperative spectrum occupancies are valuable input to the development of future cognitive radio systems where unoccupied channels could be accessed opportunistically. The measurements results indicate that the spectrum occupancy can vary significantly in the same office environment depending on the measurement location and direction.

Keywords: adaptive communications; cognitive radio system; cooperative spectrum sensing; measurement; spectrum occupancy; WLAN; wireless local area network.

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1 Introduction

Wireless communication systems use the radio spectrum to provide a diverse set of services. Efficient use of the radio spectrum has become an important aspect in the design of future wireless systems as the growing data rate demand is restrained by the limited availability of spectrum (see Takagi and Walke, 2008).

Several metrics have been developed to characterise the efficiency of spectrum use. One of the metrics is the link spectral efficiency that measures the data rate per bandwidth over a single link in bits/s/Hz. The link spectral efficiency describes the achievable throughput over only a single link without considering the overall system throughput. In Werner and Jesus (2009), the spectral efficiency has been defined for a cellular system as the sum of the user throughputs for all terminals served by a given cell divided by the overall system bandwidth per link direction, calculated for the maximum load that still allows fulfilling the satisfied user criterion in terms of data rate and delay. This system level spectral efficiency is an important measure to describe how efficiently a wireless communication system uses the spectrum that has been allocated to it in terms of the achievable system throughput per system bandwidth. The link and system level spectral efficiencies have recently been improved significantly with, e.g. adaptive modulation and coding techniques, multi-antenna techniques, interference avoidance and mitigation techniques and advanced multiple access techniques. To achieve significant improvements in the spectrum use to meet the growing data rate demand in the future, drastically new approaches are needed.

Spectrum occupancy is another measure for assessing the efficiency of spectrum use in terms of describing the utilisation rate of frequency channels. Spectrum occupancy of a channel presents the proportion of the measurement time that the detected power in the channel exceeds a threshold (Spaulding and Hagn, 1977). Spectrum occupancy measurements, such as SSC (2011), Lopez-Benitez et al. (2009) and Wellens et al. (2007), have indicated that there are many spectrum bands which are only lightly occupied indicating that there is a lot of room for improvement in the spectrum use. Spectrum occupancies could be enhanced, e.g. by allowing different services to share the same spectrum bands following a given etiquette and rules for coexistence.

Today, a highly promising approach for improving the spectrum occupancy is the use of cognitive radio techniques (Haykin, 2005) to access frequency channels that are lightly occupied without causing harmful interference to higher priority systems. Cognitive radio systems defined by the International Telecommunication Union Radiocommunication sector (ITU-R) are capable to obtain knowledge of their operational and geographical environment, established policies and internal state; to dynamically and autonomously adjust their operational parameters and protocols according to obtained knowledge to achieve predefined objectives; and to learn from the results obtained (ITU-R, 2009, p.3). Wireless communication systems using cognitive radio techniques could thus obtain knowledge of the current spectrum use and select frequency channels that are temporarily and spatially unoccupied and adjust their operations such that the higher priority systems are protected from harmful interference.

One of the key requirements for cognitive radio operations is accurate knowledge of the current state of the spectrum use. A commonly used method for obtaining this information in the research domain is spectrum sensing where samples of the received signal are processed to determine whether a given frequency channel is occupied or free (see e.g. Letaief and Zhang, 2009; Yücek and Arslan, 2009 and references therein). A traditional spectrum sensing method used in the cognitive radio research is the energy detection (Urkowitz, 1967) where the received signal energy is summed up and compared to a threshold to decide whether the frequency channel is occupied. Energy detection is simple and does not require *a priori* information about the signals but has performance limitations as discussed in Tandra and Sahai (2008).

In the development of cognitive radio techniques, it is important to have real-life data to assess the potential of the new spectrum access approaches. Previous spectrum occupancy measurement studies have mainly considered the overall spectrum occupancies measured in outdoor locations over a wide spectrum range (see e.g. Lopez-Benitez et al., 2009; SSC, 2011). The actual spectrum occupancy situation in indoor locations varies significantly from the outdoor situation due to e.g. building penetration losses and different usage patterns. Thus, separate measurements are needed in outdoor and indoor locations to capture the actual usage of the band in different locations. The development of cognitive radio techniques is expected to progress stepwise. In particular, the industrial, scientific and medical (ISM) bands with low transmission power level limits are very promising for cognitive radio techniques especially, in the first phase because they can be accessed already today and they do not have higher priority users. While the measurements in SSC (2011) and Lopez-Benitez et al. (2009) have mainly considered the spectrum occupancies over several bands in outdoor locations, the corresponding ISM spectrum occupancies in indoor locations can vary significantly from the outdoor measurements. Yet, the usage of the ISM bands is very important in indoor locations due to the transmission power limitations that limit the achievable transmission ranges. For capturing the actual spectrum occupancy of ISM bands in indoor locations, separate spectrum occupancy measurements of ISM bands have been carried out in, e.g. Biggs et al. (2004), Denkovski et al. (2010), Geirhofer et al. (2006) and Ghosh et al. (2010).

The focus of this paper is on the directional and cooperative spectrum occupancy measurement studies in the 2.4 GHz ISM band to capture the influence of the measurement direction and location on the spectrum use. This paper is a revised and expanded version of a paper entitled ‘Distributed and directional spectrum occupancy measurements in the 2.4 GHz ISM band’ presented at the *Seventh International Symposium on Wireless Communication Systems (ISWCS)* in York, UK, on 19–22 September 2010 (Matinmikko et al., 2010a) and a paper entitled ‘Cooperative spectrum occupancy measurements in the 2.4 GHz ISM band’ presented at the *Third International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL)* in Rome, Italy, on 7–10 November 2010 (Matinmikko et al., 2010b). The approaches taken in the two conference papers have been extended. New measurement results are presented and frequency dependent spectrum occupancies are shown over time. Also a new metric, the short-term local spectrum occupancy, is introduced to characterise the time variance of the spectrum occupancy and grouping of adjacent subchannels. The influence of the different cooperative approaches has also been elaborated further.

The rest of this paper is organised as follows. Section 2 gives an overview of previous work on spectrum occupancy including definitions and measurement studies. Calculation of the directional and cooperative spectrum occupancies is presented in Section 3. Section 4 presents the measurement system. Results of the spectrum occupancy measurements are shown in Section 5. Finally, Section 6 concludes this paper.

2 Previous work on spectrum occupancy

2.1 Definitions for spectrum occupancy

Spaulding and Hagn (1977) have defined the spectrum occupancy of a frequency channel as the fraction of measurement time that the received power in the channel exceeds a threshold. This definition implies the use of energy detection to determine whether the channel is occupied or free since the received power is compared to a threshold. This definition for spectrum occupancy has been widely used. The term duty cycle has been commonly used to denote spectrum occupancy in many of the spectrum occupancy measurement studies where the measurement approach is based on energy detection, such as SSC (2011), Lopez-Benitez et al. (2009) and Wellens et al. (2007). In general, the spectrum occupancy denotes the fraction of the measurement time that the channel is declared occupied. The actual decision-making for determining the channel occupancy can also be based on other approaches than the energy detection.

The spectrum occupancy is an important tool for administrations to monitor the use of the radio spectrum and to assess how efficiently the spectrum allocations are working. It is important for the administrations to ensure that the spectrum resource is used efficiently as there is continuous demand for new spectrum for different services. The ITU-R has presented guidelines for frequency channel occupancy measurements in ITU-R (2007). The terminology for the measurements is also presented there. The work is currently continuing in the ITU-R on the definition and measurement of spectrum occupancy.

To study the influence of the measurement direction, Matinmikko (2010a) has defined the directional spectrum occupancy as the fraction of time that the received power in the channel exceeds a threshold in the given measurement direction. Moreover, Matinmikko (2010b) has defined the cooperative spectrum occupancy as the fraction of time that the channel is occupied after the observations from several measurement entities (e.g. antennas and measurement devices) are combined as using decision fusion rules.

2.2 Measurement and modelling studies

Several spectrum occupancy measurement studies have been recently reported in the literature (see e.g. Biggs et al., 2004; Denkovski et al., 2010; Geirhofer et al., 2006; Ghosh et al., 2010; Lopez-Benitez et al., 2009; Pagadarai and Wyglinski, 2009; Shah et al., 2006; SSC, 2011; Stabellini, 2010; Wellens et al., 2007). In general, the measurement studies have used energy detection to determine the spectrum occupancy on different frequency bands. The measurements have revealed that there are large variations in the spectrum occupancy depending on the measured frequency band and the time of the day. Many spectrum bands are only lightly occupied and there is room for spectrum sharing with e.g. cognitive radio techniques. Typically, the measurement studies have reported the measured signal strengths as a function of frequency or as a function of frequency and time in three dimensions. The average duty cycles have been shown as a function of frequency. The duty cycles have also been presented on a given frequency band over time.

Recently, there have been efforts to take into account the influence of the spatial dimension in the measurement studies. In Lopez-Benitez and Casadevall (2010), measurements were done in two locations and the resulting spectrum occupancies varied significantly depending on the location. In Pagadarai and Wyglinski (2009), spectrum occupancy measurements were done in several locations and directional antennas were used. The results indicated that the spectrum occupancies vary depending on the measurement direction.

ISM bands offer potential for cognitive radio operations because they can be accessed already now and they do not encompass higher priority users. Outdoor measurement studies, such as Lopez-Benitez et al. (2009), have not captured the spectrum occupancies of bands where there are several low power indoor transmission systems like in the case of the 2.4 GHz ISM band with wireless local area network (WLAN) traffic. Therefore, separate studies for the spectrum occupancies on ISM bands have been carried out in Biggs et al. (2004), Denkovski et al. (2010), Ghosh et al. (2010) and Stabellini (2010).

Distributed spectrum occupancy measurements using several measurement devices were performed on a cellular band with omnidirectional antennas in Shah et al. (2006). The measurements were proposed to be combined using known decision fusion techniques that are used in cooperative spectrum sensing in cognitive radios (see e.g. Letaief and Zhang, 2009; Yücek and Arslan, 2009). However, no results on the cooperative spectrum occupancy measurements were presented. Motivated by the above findings, we performed directional and distributed spectrum occupancy measurements with two measurement devices with directional antennas in Matinmikko et al. (2010a). Furthermore, the directional spectrum occupancy measurements were further combined with decision fusion techniques to present cooperative spectrum occupancies in Matinmikko et al. (2010b).

Finally, in several studies the measurement data have been further processed to develop statistical models for the spectrum occupancy. Statistical modelling of the idle and busy times of WLAN traffic has been done in Geirhofer et al. (2006) using a continuous time semi-Markov model. The primary user activity has been modelled in time domain with geometric and lognormal distributions in Wellens et al. (2009). Ghosh et al. (2010) have developed a spectrum occupancy model where the idle and busy times follow exponential distributions.

3 Calculation of spectrum occupancy

3.1 Directional and cooperative spectrum occupancy

The calculation of the spectrum occupancy using the principles of energy detection is done based on measurements of the signal power levels. The measured signal power levels are first quantised into one bit hard decisions to characterise whether a given frequency subchannel is occupied or free. In the case of directional spectrum occupancies, the quantisation is made by comparing the signal power level $P_{n,a,c,t}$ measured at device n, antenna a, suchannel c and sweep time index t against a threshold γ according to

$$D_{n,a,c,t} = \begin{cases} 1, & \text{if } P_{n,a,c,t} > \gamma \\ 0, & \text{if } P_{n,a,c,t} \le \gamma \end{cases} \tag{1}$$

The subchannel c is declared occupied if the measured signal level is above the threshold and free if it is below or equal to the threshold.

The directional spectrum occupancy is calculated from the quantised samples from Equation (1) by dividing the number of occupied channel instances with the total number of samples. Thus, the directional spectrum occupancy for device n, antenna a and subchannel c is

$$S_{n,a,c} = \frac{\sum_{t=1}^{T_{n,a,c}} D_{n,a,c,t}}{T_{n,a,c}} \tag{2}$$

where $T_{n,a,c}$ is the total number of samples taken from device n, antenna a and subchannel c during the measurement period.

The directional spectrum occupancy obtained from (2) denotes the situation from one antenna of one measurement device. Next, we present the calculation of the cooperative spectrum occupancy. The quantised measurements from Equation (1) can be combined over the antennas using known decision fusion techniques that have been applied to, e.g. cooperative spectrum sensing in cognitive radio systems (see Letaief and Zhang, 2009; Yücek and Arslan, 2009 for details). Using the m-out-of-M decision fusion rule, the combined decision metric is obtained from

$$D_{n,c,t} = \begin{cases} 1, & \text{if } \sum_{a=1}^{A} D_{n,a,c,t} \geq m \\ 0, & \text{if } \sum_{a=1}^{A} D_{n,a,c,t} < m \end{cases} \tag{3}$$

where $D_{n,a,c,t}$ is the decision on the channel occupancy (1 corresponds to occupied and 0 free) of device n and antenna a on subchannel c at sweep index t obtained from Equation (1), A is the total number of antennas and m is the threshold for the decision fusion rule. The m-out-of-M decision fusion rule in the case of cooperative spectrum occupancy measurements means that the subchannel is declared occupied if m or more antennas see the subchannel occupied.

The combining rules commonly used in cooperative spectrum sensing, namely the OR, AND and majority combining rules, are obtained when $m = 1$, $m = A$ and $m = \lceil A/2 \rceil$, where $\lceil \; \rceil$ denotes rounding up to the next largest integer (Letaief and Zhang, 2009). These cases correspond to the situations that one, all or at least half of the entities declare the channel occupied. OR rule is conservative and can protect the higher priority systems because it suffices that one entity sees the channel occupied. Using the combined metric given in Equation (3), the cooperative spectrum occupancy for device n on subchannel c is calculated from

$$C_{n,c} = \frac{\sum_{t=1}^{T_{n,c}} D_{n,c,t}}{T_{n,c}} \tag{4}$$

where $T_{n,c}$ is equal to $T_{n,c,a}$ for any a, if the same amount of samples is taken from each antenna.

3.2 *Short-term local spectrum occupancy*

The calculation of the spectrum occupancies in Equations (2) and (4) uses the measurements collected over a measurement period of $T_{n,a,c}$ samples over the measurement band. If the spectrum occupancies are calculated over the whole measurement duration such as one day, then the resulting spectrum occupancies present the average values. In practice, the spectrum occupancies vary depending on the time as indicated in, e.g. SSC (2011). When the bandwidth of the system operating on the band is wider than the measurement subchannel bandwidth, such as in the case of WLAN on

ISM bands, adjacent measurement subchannels are likely to encompass similar spectrum occupancies. This motivates us to extend the above approach to characterise the time variance and frequency dependency of the spectrum occupancy by defining short-term local spectrum occupancy.

The short-term local spectrum occupancies from device *n* are calculated by grouping a set of adjacent subchannels into a subband *s* and averaged over a time period *p* of consecutive measurement sweep indices according to

$$L_{n,s,p} = \frac{\sum_{c=c_1}^{c_2} \sum_{t=t_1}^{t_2} D_{n,c,t}}{(c_2 - c_1 + 1)(t_2 - t_1 + 1)} \tag{5}$$

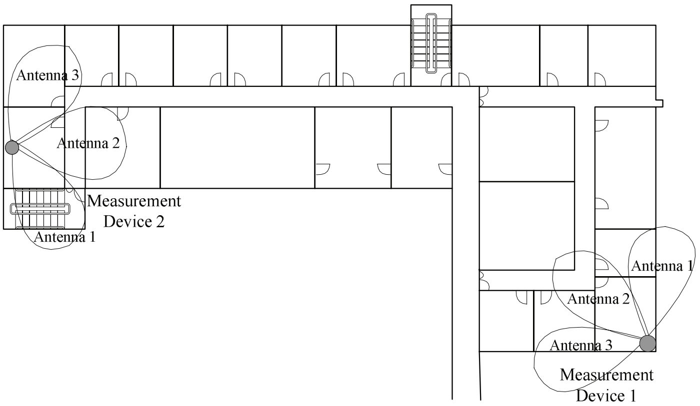
where c_1 and c_2 are the start and end subchannel indices and t_1 and t_2 are the start and end sweep indices. This measure can be useful in the development of channel selection techniques for future cognitive radio systems that can exploit the history of spectrum use in selecting the most promising channels. For example, it is possible to identify differences in the subband occupancies and select the most promising channels for operations. The width of the considered subband can be altered depending on the transmission characteristics of the cognitive radio system. Here, it should be noted that the accuracy of the spectrum occupancy is dependent on the number of samples taken (see e.g. Spaulding and Hagn, 1977). The accuracies of the resulting short-term local spectrum occupancies may not be as high as the long-term spectrum occupancies because the number of samples is smaller.

4 Measurement setup and system

The spectrum occupancy measurements have been carried out in the 2.4 GHz ISM band in an office environment in March 2011. The measurement system is 7signal Sapphire presented in 7signal (2011). The measurement system includes several measurement stations each equipped with seven antennas. We have used two separately located measurement devices and selected three adjacent antennas to monitor the spectrum occupancy in the same office area from opposite directions as shown in Figure 1. The goal is to capture the influence of the spatial dimension on the spectrum occupancies using separately located measurement devices. The distance between the devices is approximately 45 m, and the office area is in the order of 700 m^2. The devices are placed at 1 m height.

The spectrum band of interest is 2.400–2.485 GHz ISM band which is shared by several short-range systems including most notably WLAN and Bluetooth systems. The reason for choosing this band for the measurements is that, it is likely to be the first deployment scenario for cognitive radio systems because it is already available, easy to access and offers a lot of potential for improvement in spectrum use. The current systems operating in this band include some capabilities to detect other users in the band but with advanced cognitive radio techniques it could be possible to significantly improve their operations by avoiding occupied channels. The previous spectrum occupancy measurement studies in this band presented in Biggs et al. (2004), Denkovski et al. (2010), Ghosh et al. (2010) and Stabellini (2010) have not considered the influence of the measurement direction and location.

Figure 1 Measurement sites and floor plan



Source: Matinmikko (2010a,b); Reproduced by permission of IEEE (©2010 IEEE).

The measurement band is divided into 256 subchannels with a channel spacing of 333 kHz. The measurements present the measured power level in dBm from different antennas on different subchannels at different measurement times. The measurement approach is based on energy detection. The motivation for using energy detection is its simplicity and fastness as its computational complexity is low and it does not require *a priori* information about, e.g. signal waveforms. However, the performance of the energy detection is limited because it is not able to capture weak signals. About 1,000 samples are taken from each subchannel in less than a second to obtain the average power level on the subchannel. The measurements are taken periodically from the subchannels from each antenna. Each subchannel from the same antenna is revisited approximately every 1 min 20 sec. The measurements are collected into a database from where they are ready to be processed according to the approach presented in Section 3.

5 Numerical results

We have used the measurement setup described in Section 4 to obtain directional and cooperative spectrum occupancies according to approach presented in Section 3. The threshold for the quantisation of the measured signal power levels into decisions on the subchannel occupancy according to Equation (1) has been chosen by first performing noise level measurements and then adding a margin, which is a common way in the spectrum occupancy measurement studies. The noise level measurements gave –91 dBm and margin was empirically set resulting in a threshold equal to –75 dBm.

Firstly, we consider the overall spectrum occupancy situation measured over 1 hr. Quantised measurement results for 1 hr period from antenna 1 in measurement device 1 over the whole bandwidth are shown in Figure 2. The horizontal axis denotes the subchannels from 1 to 256 and the vertical axis corresponds to the measurement times in minutes. White colour indicates that the subchannel is free and grey colour corresponds to an occupied subchannel. Similarly, the directional spectrum occupancies in the same measurement device from antennas 2 and 3 are shown in Figures 3 and 4, respectively. The figures illustrate that the measurements from the three antennas are correlated but there are some differences. The antenna in the middle, i.e. Figure 3, captures more subchannels being occupied which is logical because it is pointing towards the centre of the office area as shown in Figure 1.

Figure 2 Directional spectrum occupancy from antenna 1 in measurement device 1 over 1 hr

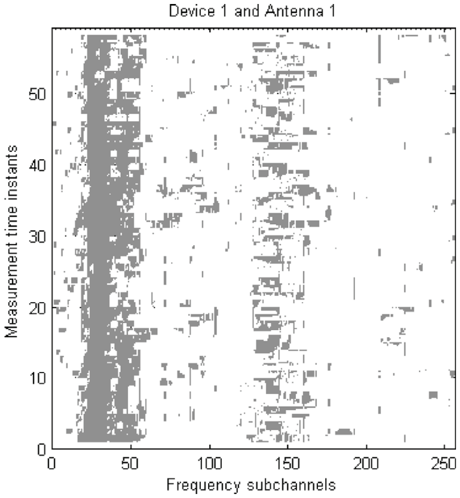


Figure 3 Directional spectrum occupancy from antenna 2 in measurement device 1 over 1 hr

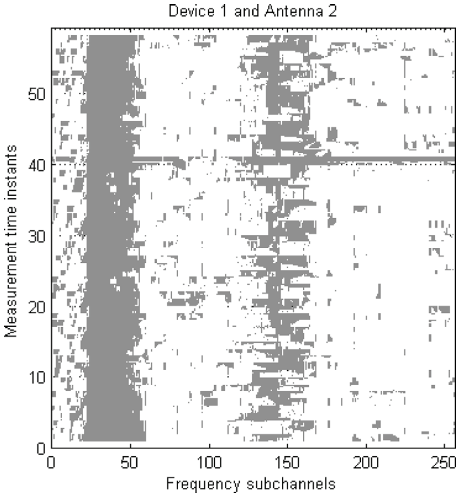


Figure 4 Directional spectrum occupancy from antenna 3 in measurement device 1 over 1 hr

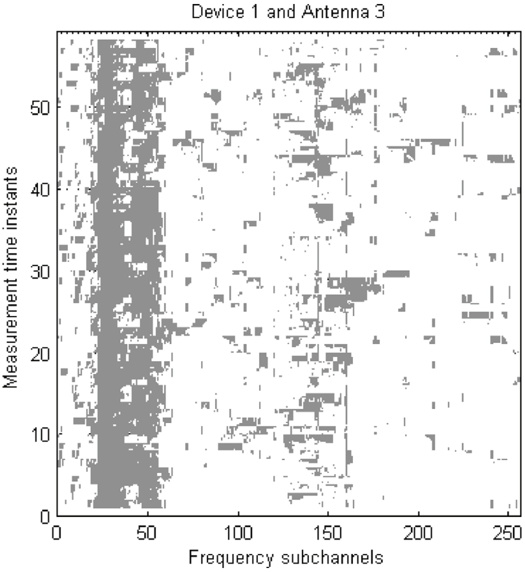


Figure 5 presents the quantised measurement results for 1 hr from antenna 2 in measurement device 2. Thus, Figures 3 and 5 present the spectrum occupancy situation in the same office area during the same hour measured from opposite directions. It is interesting to note that the two measurement devices see quite different radio environments. They see partially different access points. This is due to the so-called hidden node problem which is often mentioned as a drawback of a system that relies solely on spectrum sensing to get the knowledge on the spectrum usage (see e.g. Yücek and Arslan, 2009). Hidden node problem occurs when the secondary user cannot detect the presence of the primary user device, e.g. due to the location of the devices. For example, a secondary user located nearby device 1 would most probably detect the same access points as device 1. His transmission, however, might cause interference to all the access points in the area (also to those seen only by the device 2) depending on the location of the receiver. Cooperative spectrum sensing is often seen as a way to reduce the hidden node problem (Letaief and Zhang, 2009; Yücek and Arslan, 2009). It is important to take into account in the design of channel access techniques for future cognitive radio systems that the spectrum occupancy situation can vary significantly depending on the measurement location. The primary users' transmission powers have a significant influence on the requirements because it is easier to detect users that have higher transmission power levels.

Next, we consider the cooperative case where the decisions on the subchannel occupancy are made combining the measurements from several antennas in device 1 using Equation (3). In the case of three antennas, the OR, majority and AND combining rules correspond to $m = 1$, $m = 2$ and $m = 3$ in Equation (3), respectively. The measurements presented in Figures 2–4 are combined using the OR combining rule in

Figure 6. The cooperative decisions using the majority combining rule are shown in Figure 7. The decisions using the AND combining rule are shown in Figure 8. The figures show that using the OR rule, more subchannels are occupied compared to majority and AND rules.

Figure 5 Directional spectrum occupancy from antenna 2 in measurement device 2 over 1 hr

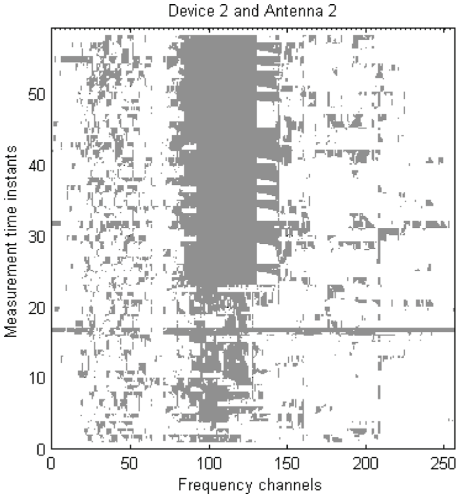


Figure 6 Cooperative spectrum occupancy from measurement device 1 over 1 hr using OR combining rule

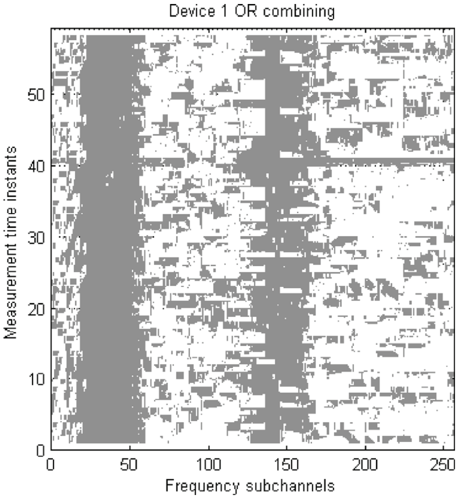


Figure 7 Cooperative spectrum occupancy from measurement device 1 over 1 hr using majority combining rule

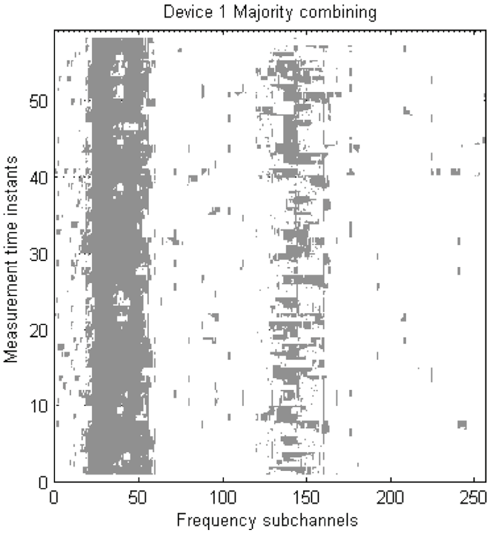
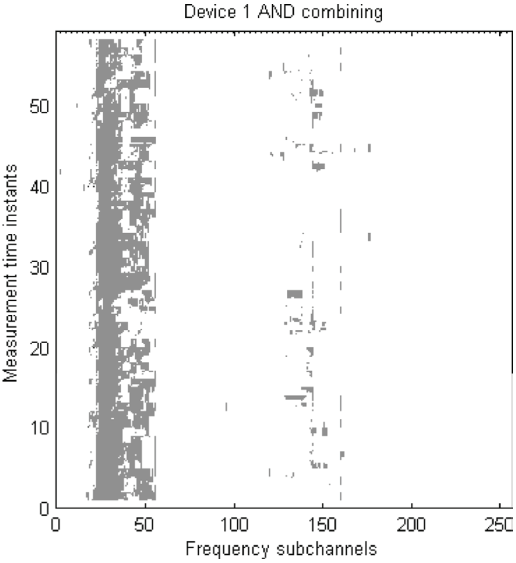


Figure 8 Cooperative spectrum occupancy from measurement device 1 over 1 hr using AND combining rule



Next, we calculate the directional spectrum occupancies over one day. Figures 9 and 10 present the directional spectrum occupancies from all three antennas in devices 1 and 2, respectively. The results indicate that the measured spectrum occupancies from the different antennas at the same device are correlated. However, there are large differences in the spectrum occupancies between the two measurement devices. Device 1 sees more spectrum use around subchannels 20–60 and 130–160, while device 2 captures more spectrum use around subchannels 80–120. Figure 11 shows the cooperative spectrum occupancies from device 1 over the one day measurement interval. OR combining scheme has highest cooperative spectrum occupancy followed by majority and AND rules.

From Figures 9 and 10, we select two 20 MHz subbands that encompass different occupancy when measured from the two separately located devices and study their time variations. The given 20 MHz subband consists of 60 adjacent subchannels. The directional spectrum occupancies have been averaged over the 20 MHz subband and 2 hr time interval according to Equation (5). Table 1 presents the directional spectrum occupancies over the subbands f_1 and f_2 that correspond to the bands 2.40–2.42 GHz (subchannels 1–60) and 2.42–2.44 GHz (subchannels 61–120), respectively. The results show that the spectrum occupancies measured at the two devices differ significantly. On the subband f_1, quite low spectrum occupancy ranging from 11% to 34% is seen by the antennas of device 2, whereas the antennas of device 1 see much higher occupancy levels up to 78%. A clear difference of at least 10% units can be seen in the spectrum occupancy measured in subband f_1 by device 1 between the office hours (08–18) and the night-time. On the subband f_2, the difference between the two devices is not as clear as in the case of subband f_1. However, even in this case the antennas of device 2 give approximately 20% units higher spectrum occupancy values than the antennas of device 1.

Figure 9 Directional spectrum occupancy from measurement device 1 over one day

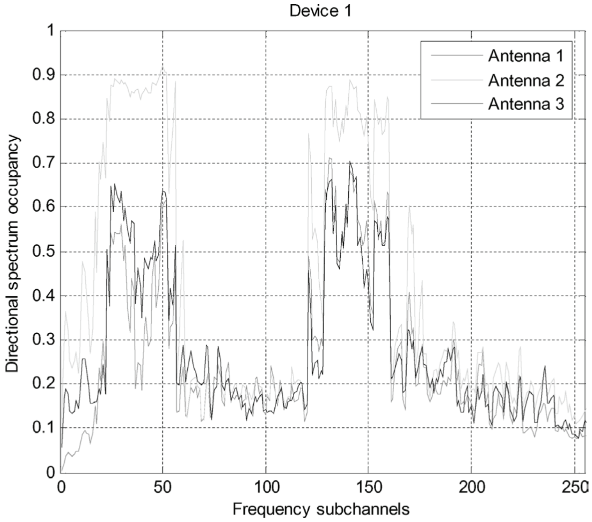


Figure 10 Directional spectrum occupancy from measurement device 2 over one day

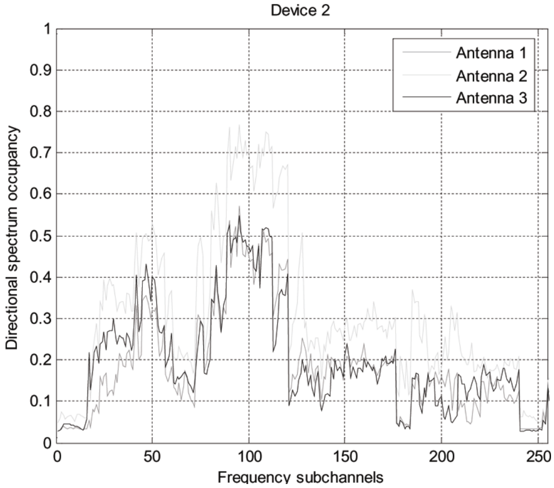
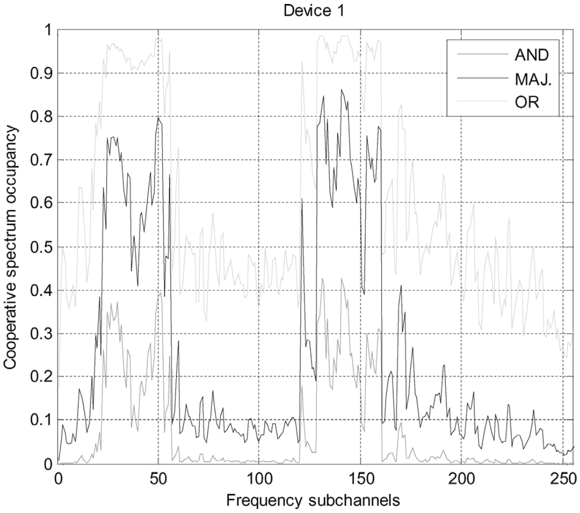


Figure 11 Cooperative spectrum occupancy from measurement device 1 over one day



The measurements from the different antennas are further combined using OR, majority and AND combining rules and the resulting cooperative spectrum occupancies are shown in Table 2. The results indicate that the cooperative spectrum occupancies depend heavily on the selected combining scheme. For example, when the measurements conducted by different antennas of the device 1 are combined using OR scheme, subband f_1 is occupied over 80% of the time during the office hours and approximately half of the time according to device 2. When the AND scheme is used for combining the measurements of different antennas, the corresponding numbers are 30% and 3% for devices 1 and 2, respectively.

Table 1 Directional spectrum occupancy measured over one day

	Device 1						*Device 2*					
	Antenna 1		*Antenna 2*		*Antenna 3*		*Antenna 1*		*Antenna 2*		*Antenna 3*	
Time	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2
00–02	0.17	0.16	0.53	0.14	0.25	0.15	0.11	0.27	0.28	0.50	0.23	0.31
02–04	0.19	0.17	0.53	0.16	0.22	0.17	0.11	0.34	0.27	0.57	0.23	0.31
04–06	0.20	0.17	0.52	0.15	0.22	0.15	0.13	0.37	0.28	0.57	0.23	0.37
06–08	0.20	0.17	0.58	0.15	0.26	0.18	0.17	0.40	0.29	0.59	0.25	0.40
08–10	0.32	0.14	0.74	0.17	0.50	0.18	0.21	0.42	0.33	0.59	0.21	0.40
10–12	0.35	0.14	0.78	0.21	0.55	0.20	0.18	0.46	0.34	0.58	0.22	0.43
12–14	0.38	0.14	0.77	0.19	0.54	0.20	0.18	0.38	0.30	0.53	0.20	0.37
14–16	0.43	0.23	0.77	0.26	0.56	0.26	0.16	0.36	0.29	0.53	0.18	0.31
16–18	0.37	0.19	0.74	0.21	0.42	0.18	0.11	0.31	0.26	0.50	0.15	0.31
18–20	0.29	0.18	0.65	0.18	0.34	0.18	0.14	0.29	0.26	0.49	0.20	0.34
20–22	0.29	0.17	0.65	0.18	0.33	0.17	0.16	0.26	0.27	0.43	0.20	0.27
22–24	0.24	0.20	0.59	0.20	0.29	0.17	0.17	0.25	0.28	0.43	0.23	0.29

Table 2 Cooperative spectrum occupancy measured over one day

	Device 1						*Device 2*					
	OR		*Majority*		*AND*		*OR*		*Majority*		*AND*	
Time	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2
00–02	0.68	0.38	0.24	0.06	0.03	0.00	0.47	0.72	0.14	0.31	0.02	0.06
02–04	0.68	0.42	0.23	0.07	0.03	0.00	0.47	0.76	0.14	0.38	0.01	0.09
04–06	0.67	0.40	0.24	0.06	0.03	0.00	0.47	0.78	0.16	0.42	0.02	0.11
06–08	0.71	0.41	0.28	0.08	0.05	0.01	0.51	0.80	0.18	0.46	0.03	0.14
08–10	0.82	0.41	0.53	0.08	0.21	0.00	0.53	0.78	0.20	0.47	0.03	0.16
10–12	0.83	0.45	0.60	0.09	0.25	0.01	0.53	0.78	0.19	0.50	0.03	0.19
12–14	0.84	0.44	0.58	0.08	0.26	0.01	0.51	0.75	0.16	0.42	0.02	0.11
14–16	0.84	0.58	0.61	0.16	0.30	0.01	0.47	0.73	0.14	0.38	0.02	0.09
16–18	0.82	0.47	0.52	0.09	0.20	0.01	0.41	0.70	0.11	0.34	0.01	0.08
18–20	0.75	0.45	0.40	0.08	0.13	0.01	0.45	0.71	0.13	0.34	0.01	0.07
20–22	0.77	0.44	0.39	0.08	0.11	0.01	0.47	0.66	0.15	0.25	0.02	0.04
22–24	0.72	0.47	0.32	0.10	0.08	0.01	0.48	0.66	0.18	0.27	0.03	0.05

6 Conclusions

This paper has presented directional and cooperative spectrum occupancy measurements in the 2.4 GHz ISM band where several systems coexist and share the same spectrum using low transmission power levels. According to the measurements, the spectrum occupancies can vary significantly depending on the measurement direction and location. There is correlation in the measurements from adjacent antennas in a device while separately located devices can see substantially different spectrum use. This is important in the design of channel selection techniques for cognitive radio systems because it may not be enough to characterise the spectrum use from a single location only. In the case of two-directional communications, the directional spectrum occupancy can be very beneficial in the selection of the transmission channels.

Moreover, we have presented cooperative spectrum occupancies that are obtained by combining the measurements from several antennas using different decision fusion rules. The cooperative spectrum occupancies vary depending on the combining scheme and the selection of the scheme depends on the requirements set for the system. In the primary–secondary user settings, the secondary users are not allowed to cause harmful interference to the primary users and thus, the interference protection is the major design criterion. In this case, the OR scheme can be a good choice because majority and AND combining rules are more loose and can miss more primary user occupancy. If the primary user system can tolerate some interference, then it is more beneficiary to use majority rule to improve the secondary users' throughput. The AND combining scheme is likely to be unrealistic since it is unlikely that all measurement entities see the channel occupied due to uncertainties of radio-wave propagation resulting in underestimations of the spectrum occupancy. By defining spectrum occupancies over time intervals and adjacent subchannels, we can assess the time variance of the spectrum occupancy over a subband. This can be beneficial in the development of channel selection schemes that can exploit the history information of the spectrum occupancy.

The spectrum occupancy values are heavily dependent on the selected threshold in energy detection. The purpose here was not to present actual values for the spectrum occupancy but rather present the approaches for directional and cooperative spectrum occupancies that try to capture the influence of the spatial dimension on the actual spectrum use. The threshold setting has not been discussed thoroughly in this paper. Moreover, the spectrum occupancy measurements using energy detection cannot capture all the spectrum use this giving an overly optimistic view of the available spectrum.

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PAPER V

Application of fuzzy logic to cognitive radio systems

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INVITED PAPER *Special Section on Dynamic Spectrum Access*

Application of Fuzzy Logic to Cognitive Radio Systems

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SUMMARY This paper reviews applications of fuzzy logic to telecommunications and proposes a novel fuzzy combining scheme for cooperative spectrum sensing in cognitive radio systems. A summary of previous applications of fuzzy logic to telecommunications is given outlining also potential applications of fuzzy logic in future cognitive radio systems. In complex and dynamic operational environments, future cognitive radio systems will need sophisticated decision making and environment awareness techniques that are capable of handling multidimensional, conflicting and usually non-predictable decision making problems where optimal solutions can not be necessarily found. The results indicate that fuzzy logic can be used in cooperative spectrum sensing to provide additional flexibility to existing combining methods.

key words: *cognitive radio, cooperative sensing, efficient spectrum use, fuzzy logic, radio resource management, spectrum sensing*

1. Introduction

Cognitive radio systems (CRS) are emerging as a new paradigm for more efficient use of radio and network resources. These systems are capable of obtaining information of the underlying radio operational environment and policies, dynamically adjusting their actions accordingly and learning from the results to further improve the performance.

The design of future CRS will face new challenges as compared to traditional cellular systems. The operational environment is heterogeneous consisting of several access technologies with diverse sets of terminals with the common goal of providing high user satisfaction [1]. Moreover, an eclectic array of services will be provided. Distributed network architectures will appear alongside with centralized structures. The conventional network design by considering only one isolated network will no longer be sufficient. Indeed, joint resource management across networks will be required for more efficient use of distributed resources, such as spectrum. The decision making problems in radio resource management of CRS will have more degrees of freedom due to the increased dimensionality and the dynamic operational environment. As a result of the conflicting requirements and restrictions an engineering compromise needs to be sought, particularly for the decision making process. In fact, in the complex environment with compressed time scales, optimal solutions cannot be found and the design challenge will be to find good enough solutions. Thus in the envisaged scenario for CRS, novel design techniques are needed.

The decision making for resource management in future CRS is heavily based on the knowledge of the operational environment. Environment awareness techniques for collecting information on the current resource use and state of nature will be important. In particular, information on the current spectrum use with e.g. spectrum sensing techniques will be critical for the successful deployment of CRS. Obtaining reliable information in the dynamic and uncertain environment is a true challenge for future CRS.

Fuzzy logic is an attractive technique particularly in cases where target problems are difficult to model with traditional mathematical methods, but are at the same time easier for human people to understand. In industrial control systems, fuzzy logic control has proven useful when linearity and time-invariance of the controlled process cannot be assumed, when the process lacks a well posed mathematical model, or when the human understanding of the process differs from its mathematical model [2]. Fuzzy logic resembles human like thinking being thus efficient for compromise centric decision making, and therefore it is well suited for multidimensional decision making problems. The rule-based decision making achievable by fuzzy logic enables efficient inclusion of incomplete information. The flexibility provided by the decision making architecture has proven to be suitable for dynamic and distributed environment [3]. In addition, it provides savings in computational complexity.

With the characteristics of future CRS in mind, the capabilities of fuzzy logic offer good potential to be applied in CRS as suggested in e.g. [1] and [4] for cross-layer design and reconfiguration, respectively. In this paper, we review applications of fuzzy logic to telecommunications and focus on CRS. While previous work on fuzzy logic for CRS has focused on radio resource management and cross-layer design, in this paper we extend the approach to radio environment recognition techniques. In particular, we propose a novel fuzzy logic-based cooperative spectrum sensing technique where the cooperative decision making process is implemented using fuzzy logic. The proposed fuzzy decision making technique includes traditional combining schemes as special cases and is therefore particularly beneficial in realistic operational environments as it can be flexibly adjusted to the changing conditions.

The remainder of this paper is organized as follows.

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Section 2 provides an overview of fuzzy logic and its applications to telecommunications and in particular to CRS. Section 3 describes cooperative spectrum sensing for CRS and proposes a new fuzzy combining for the decision making process. Section 4 presents performance evaluation of the proposed fuzzy decision scheme. Section 5 outlines future research directions for the use of fuzzy logic in CRS. Finally, Sect. 6 draws the conclusions.

2. Overview of Applications of Fuzzy Logic to Telecommunications

Modern telecommunications is more oriented to mathematical knowledge than to any kind of experience or human understanding based knowledge. However, fuzzy logic has been proposed to solve many typical telecommunications problems since the 1990's. Application areas vary greatly from radio interface algorithms to resource management. Here we provide an overview of fuzzy logic and its use in telecommunications including receiver algorithms, radio resource management and cognitive radio systems.

2.1 Introduction to Fuzzy Logic

Fuzzy logic was first introduced by L.A. Zadeh, who studied methods to extend binary logic to cover more general linguistic notation [5]. The research started first with fuzzy mathematics, and first engineering applications were developed later, see for example [6]. In generally, fuzzy logic and fuzzy decision making is divided into three consecutive phases [2]:

1. Fuzzification: The input variables (e.g. measurement results) are fuzzified using predefined membership functions (MBF). Unlike in binary logic where only 0 and 1 are accepted, also numbers between 0 and 1 are used in fuzzy logic. This is accomplished with the MBFs to which the input variables are compared. The output of the fuzzification is a set of fuzzy numbers.
2. Fuzzy reasoning: Fuzzy numbers are fed into a predefined rulebase that presents the relations of the input and output variables with IF-THEN clauses. The output of the fuzzy reasoning is a fuzzy variable that is composed of the outputs of the THEN clauses.
3. Defuzzification: The output of the fuzzy reasoning is changed into a non-fuzzy number that represents the actual output of the system, e.g. control action.

There exist many mathematical methods for the above mentioned phases, but the most used methods fit well for most cases [2]. The advantage of fuzzy logic has been the capability to exploit human knowledge into computer based decision making. Additionally, the computational simplicity of fuzzy logic has been seen as a strength in embedded systems [3].

2.2 Fuzzy Logic in Receiver Algorithms

Fuzzy logic has been applied in receiver algorithms including e.g. beamforming, decoding of error-correction codes, channel equalization, channel estimation, interference cancellation, synchronisation, and multiuser detection. For example, in [7] authors show that the implemented fuzzy logic equalizer can reach or even exceed the results of the traditional equalizer. A more recent approach is presented in [8], where fuzzy logic is applied to channel estimation in multiple input multiple output (MIMO) orthogonal frequency division multiplexing (OFDM) system.

In general, the benefit of exploiting fuzzy logic in receiver algorithms is not outperforming conventional schemes but rather achieving similar performance with less computational complexity. This clearly results in power saving, reduced costs and less development work.

2.3 Fuzzy Logic in Radio Resource Management

Fuzzy logic has found many applications in resource management including for instance handoff, call admission control, channel allocation, buffer management, congestion control, routing, scheduling, power control, and radio access technology (RAT) selection. An early review of the applications of fuzzy logic to radio resource management from 1998 is given in [9]. In the following we review some of the applications.

One of the first works using fuzzy logic in telecommunications was the handoff problem in cellular network studied in [10]. The approach to the solution is pattern-recognition type of fuzzy algorithms that are based on training vectors that represent pilot cases for tuning the MBFs. The use of fuzzy logic for vertical handoff with radio and optical wireless systems was studied in [11]. Both networks have good performance under certain conditions, but may lead to poor quality of service (QoS) when used in unclear or dynamically changing conditions. The fuzzy vertical handover algorithm is capable of adapting to network and traffic changes and incorporating the uncertain conflicting metrics to carry out a comprehensive decision with little cost.

An example of managing simultaneously several resources is found in [12], where a neural fuzzy control for radio resource management is presented for hierarchical cellular systems. The main target is to maintain a good QoS by using and controlling several influential radio and network parameters, e.g., handoff failure probabilities, resource availabilities, and data rate. This is done by two-layered decision making architecture where the first layer handles the cell selection, and the second layer performs the call-admission and rate control using a neural network with fuzzy logic control leading to improved channel utilization and reduced handoff rate.

In [13] resource management is extended to multiple networks and neural fuzzy control for joint radio resource management for balancing the traffic over several RATs is presented. In the two-phase decision making system the best cell of each radio network is first chosen, and then the selection between networks is done using criteria such as signal strength, resource availability, and estimated mobile speed.

Fuzzy logic is used for the decision making as it is good at explaining how to reach suitable decisions from inaccurate and distinct information. By means of defining reasonable rules, it is possible to simplify the large state space of solution possibilities existing in a complex problem. Neural networks were used for properly tuning MBFs of the fuzzy system since neural networks are good at recognising patterns using learning procedures. Additionally, the approach made it possible to use other existing heuristic information, such as user and operator policies, as a guideline to the fuzzy decision making. The joint radio resource management with fuzzy neural control [13] was extended to consider both intraoperator and interoperator levels and also economic aspects in [14].

The above examples show the potential of fuzzy logic techniques for resource management in communication systems. In particular, the joint radio resource management over multiple cells and RATs using fuzzy logic and learning capabilities of neural networks are promising building blocks for the future CRS.

2.4 Cognitive Radio Systems

Recently, research on fuzzy logic based CRS has emerged [1], [4], [15]–[19]. In [1] fuzzy logic is proposed for cross-layer optimisation in CRS. The challenges in cross-layer design include modularity, information interpretability, imprecision and uncertainty, complexity and scalability [1]. The goal is to optimize the parameters of different layers by taking into account the different needs of the different services. Since there is no individual solution that can achieve optimal quality for all applications, the CRS should have capabilities to understand the different service requirements and use artificial intelligence techniques to adapt the configuration of the systems in the time-variant operational environment. Fuzzy logic is proposed to be used as a generic knowledge presentation and control implementation base for the cross-layer optimisation in cognitive radios. This is achieved by describing the parameter values of the systems on the different layers as linguistic variables. Link layer information can be determined by measurements while upper layers might need to interpret cross-layer information.

The fuzzy logic cross-layer optimisation techniques [1] can achieve performance improvements and seems to be more modular and reusable than traditional cross-layer solutions. Additionally, the benefit of the technique is technology neutrality that allows independent implementations of the layers as the technology-specific information processing is kept within the layer and information required by other layers is presented using a common representation. Complexity of the approach is lower compared to other cross-layer solutions. However, it requires significant standardization efforts.

In [15] a cooperative spectrum sensing scheme is proposed. The technique takes into account the reliability of the sensing results at different cognitive radio nodes. The final decision on the presence of primary users (PU) is done based on the combined results from several cognitive radio nodes whose decisions are weighted with the credibility. The credibility of the sensing node is determined in a training stage with fuzzy evaluation. However, the training process is not described well and the actual use of fuzzy techniques remains unclear.

In [16] fuzzy decision making is used for cognitive network access where cognition refers to the detection of the users' needs and the provision of wireless services most adequate to meet the requirements. Fuzzy decision making chooses the most appropriate access opportunity by using cross-layer information, past history, and shared knowledge among different devices through a knowledge base. Fuzzy decision making is used to process cross-layer communication quality metrics and to estimate the expected transport layer performance that is compared to QoS requirements of the application. The results indicate good performance and fairness as well as flexibility.

Early attempts of using fuzzy logic to channel selection in CRS are made in [17] and [18]. In [17] mobile ad hoc networks with cognitive radio capabilities are studied. Channel selection is done using fuzzy logic by taking into account the traffic conditions on the channels. In [18] fuzzy logic is used to select the most suitable secondary user (SU) for accessing the spectrum. The rule based decision scheme takes into account spectrum efficiency, user mobility, and distance to the PU under the constraint of not interfering with the PU. In [19] a fuzzy logic power control scheme is proposed to allow SUs to transmit simultaneously with the PUs on the same band.

In [20] spectrum handoff in CRS is considered where CRS can transmit during PU operation if it does not cause harmful interference to PU. Spectrum handoff denotes the vacation of the spectrum that the SU is using due to harmful interference generated to PU or too low QoS of the SU itself. In the first stage the transmission power of the cognitive radio is determined using fuzzy control based on qualitative estimations of the distance between the SU and the PU. In the second stage the handoff decisions or adjustments to SU's transmission power are made with fuzzy control based on determined transmission power, bit rate of SU and observed transmission power of PU.

In [4] the decision making for terminal reconfigurations for adapting to user needs, system resources and RAT availability is done with fuzzy logic. Fuzzy logic is found to be useful in taking into account multiple contradictory requirements as the reconfiguration decisions are multi-objective optimizations problems.

From the previous work on applications of fuzzy logic to CRS, the benefits of fuzzy logic are its capabilities to provide good results in multidimensional optimization problems with conflicting requirements. Moreover together with other intelligent algorithms, fuzzy logic can be used to provide learning capabilities to improve the performance. However, not much work exists on using fuzzy logic for environment awareness techniques e.g. spectrum sensing.

3. Cooperative Spectrum Sensing

3.1 Spectrum Sensing

Spectrum sensing is a fundamental technique for CRS for identifying spectrum opportunities. The goal in spectrum sensing is the detection of the presence of PUs which is done by simple two-hypothesis testing: signal present or signal absent. The performance of spectrum sensing is typically characterized by the the receiver operating characteristics (ROC) that capture the relations of the probability of detection and the probability of false alarm. The probability of detection measures how well the CRS can detect the presence of primary systems. It is thus a critical design parameter as it indicates how often the primary system can be susceptible to harmful interference from the CRS if they are deployed on the same spectrum bands. The probability of false alarm describes the chances on which the spectrum sensing unit detects a primary user when none is actually present, thus indicating how efficiently the spectrum opportunities can be perceived.

A fading environment significantly influences the performance of spectrum sensing as the propagation path between the primary user and the cognitive radio node might experience the fluctuations of the channel during the sensing process. To guarantee high enough probability of detection acceptable to the primary users, cooperation between cognitive radio nodes can be exploited as indicated in [21].

3.2 Combining Rules

In cooperative spectrum sensing the decisions on the presence of the primary user are based on observation results from several cognitive radio nodes. The final decision making process can be classified into data fusion and decision fusion [22]. In data fusion the measurements from the nodes are collected by a fusion centre and the final decision is made based on the combined measurements. The observed information is combined following a given rule, e.g., equal gain, signal-to-noise ratio (SNR) based weighting, etc. Data fusion is often also called soft combining. Reporting of the measurement results from several nodes to a fusion centre requires considerable signaling as well as efficient quantization.

In decision fusion the individual nodes report their decisions to a fusion centre that combines the decisions with some rule (e.g., AND, OR or majority combining). The reporting of only the decisions instead of the individual measurements requires less signaling. The general combining rule for cooperative spectrum sensing is "m out of N rule" that can be presented as [22]

$$D = \sum_{n=1}^{N} D_n \begin{array}{ll} \geq & m: \text{ signal present} \\ < & m: \text{ signal absent} \end{array} \tag{1}$$

where D_n is the decision of the nth cooperative cognitive radio node (i.e., 1 or 0 denoting signal present or absent), N is the total number of the cooperative nodes, and m is the number of users that is set as the threshold. OR, AND and majority combining rules are obtained from (1) by setting $m = 1$, $m = N$, or $m = \lceil N/2 \rceil$ corresponding to the cases that PU is declared present if one node, all nodes, or most of the nodes detect the PU.

The above mentioned decision fusion scheme uses one bit hard decisions. To improve the overall performance, quantized soft decisions using more bits to represent the decision of each cooperative node can be used. By using more than one bit it is possible to give an indication on the reliability of the observation. In [23] two-bit quantized soft decisions are formed by using three thresholds instead of one. The decisions are combined by summing up the individual two-bit decisions obtained using Welch's periodogram and comparing them to a threshold that corresponds to majority combining. The results of the two bit quantized decisions are compared to AND, OR and majority rules as well as to a non-quantized case. The results indicate that the performance is improved by the two-bit decisions in additive white Gaussian noise (AWGN) channel and that the performance with two-bit quantized decisions is comparable to non-quantized soft decisions.

Two-bit quantized soft decisions are also investigated in [24] and the performance is compared to non-quantized soft combining and hard decision combining using OR rule. The paper investigates the performance in a Rayleigh fading channel using traditional energy detectors. The results are given both as probability of detection and SNR wall reduction. SNR wall refers to an SNR threshold below which the energy detection is impossible. The results in [24] indicate that almost all the achievable benefit from soft decision combining can be obtained by using just two bits which was also described in [23]. In [25] energy detection is used and the information between cooperative users is sent using one bit. However, the reliability of the information is indicated so that only the users that evaluate their information to be reliable report their decisions.

3.3 Cooperative Fuzzy Combining Scheme

To test the feasibility of fuzzy logic for the mathematical cooperative spectrum sensing combining schemes given in (1), we constructed a simple fuzzy decision making algorithm for decision fusion for the simple case of three cooperative cognitive radio nodes. The fuzzy combining scheme is constructed using basic methods in fuzzy reasoning and defuzzification. The proposed scheme takes as an input the decisions from the individual cooperative cognitive radio nodes and produces as an output the combined sensing result, i.e., PU present or absent.

The developed fuzzy system is simple and includes three inputs with three MBFs each and one output with five MBFs. The names of the input MBFs describing the strength of the individual sensing nodes' decisions are *low*, *med* and *high* indicating the likelihood of the presence of

PU signal. The names of the output MBFs describing the strenght of the combined sensing result are *low*, *quite low*, *med*, *quite high*, and *high* indicating the combined likelihood of the presence of PU signal.

The inference method used is the Max-Product and the defuzzification method is the center of area [26]. The input variable MBFs are triangular and the output MBFs are triangles of equal shape and size. Both input and output MBFs are normalized between 0 and 1, corresponding to the sensing decisions that 0 is *signal absent* and 1 *signal present*. Positions of output MBFs are in 0, 0.25, 0.5, 0.75, and 1.0 describing the joint decision. The MBFs are constructed such that they implement the majority combining from (1), i.e. $m = 2$. Alternatively, the MBFs could be selected to implement OR or AND rules. The output from the fuzzy inference system is compared to threshold equal to 0.5 and the PU is declared present if the output is equal to or exceeds the threshold.

The rules are of the form IF X_1 IS A_{1a} AND X_2 IS B_{2a} AND X_3 IS C_{3a} THEN Y_1 IS D_{1y}, where A_{ia}, B_{ia}, C_{ia} and D_{iy} are linguistic labels of variables X_i and Y_i used in the rules respectively. The number of rules is 27. Table 1 presents a part of the rulebase, from which all combinations can be derived due to the symmetry of the rulebase. For example, the rule in the first row in Table 1 denotes that if all three cognitive radio nodes report *low* (i.e. likelihoold of PU presence is low), the combined fuzzy decision is *low* and the signal is declared to be absent. The rule in the last row denotes that if one node reports *low* (i.e. likelihoold of PU presence is low) and two nodes report *high* (i.e. likelihoold of PU presence is high), the combined decision is *quite high* and the signal is declared to be present. The remarkable aspect of fuzzy inference is that several rules can be partially true at the same time because the input variables can partially belong to several input MBFs at the same time. The system output is then a combination of outputs from several rules which allows to take into account the uncertain observations, i.e., signal not clearly absent or present, but gives them only little weight.

Table 1 Rulebase for cooperative fuzzy combining.

Input 1	*Input 2*	*Input 3*	*Output*
low	low	low	low
low	low	med	quite low
low	low	high	quite low
low	med	low	low
low	med	med	quite low
low	med	high	med
low	high	low	quite low
low	high	med	med
low	high	high	quite high

4. Performance Evaluation

4.1 Description of System Model

The performance of the proposed cooperative fuzzy combining scheme is compared with AND, OR, and majority decision rules with simulations in terms of the ROC. In the simulations, complex quadrature phase shift keying (QPSK) signals are transmitted over a 1 MHz channel with symbol rate R_s = 500 Ksymbols/s over an AWGN channel or one-tap Rayleigh fading channel with AWGN. The fading is assumed to be slow compared to the observation interval of the sensing method. Thus, the channel is assumed to remain constant during the data block but it varies randomly between consecutive blocks. Spectrum sensing at the individual nodes is done with Welch's periodogram [27], see Fig. 1. For more details on the system model, see [28].

The received signal samples are divided into M segments (here $M = 8$) before the FFT. The segment length is equal to the FFT size (here 1024) which is also the length of the rectangular window. The number of frequency bins averaged around the assumed frequency of the baseband signals L is equal to 1. The block length is 410 symbols and the symbol length T is 20 samples. Thus, 8200 samples are taken from the PU signal. The product of the FFT size and M corresponds to the number of samples used for processing in Welch's periodogram, which is 8192. SNR is defined as $E/N_0 = (A^2T)/(2\sigma^2)$ where E is the symbol energy, N_0 is the noise spectral density, A is the signal amplitude, and the noise variance σ^2 is 0.5.

One cognitive radio node collects the sensing results from the other two cooperative cognitive radio nodes and performs the decision fusion with the fuzzy scheme presented in Sect. 3.3. To quantify all different combinations of the probability of detection and the probability of false alarm, we use several values for the sensing threshold. The performance of the fuzzy decision making scheme is evaluated in AWGN and Rayleigh fading channels with one-bit hard and two-bit quantized soft decisions. Comparisons are made to AND, OR and majority combining rules.

4.2 One-Bit Decisions

First, we study the performance of the proposed cooperative fuzzy combining scheme and the three other combining rules (AND, OR and majority) using one bit hard decisions for the three cooperative cognitive radio nodes. Each node is assumed to have the same SNR, −7 dB in AWGN channel

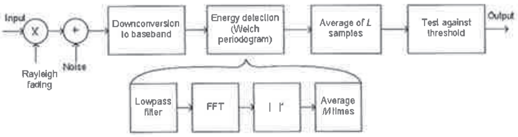

Fig. 1 Welch periodogram.

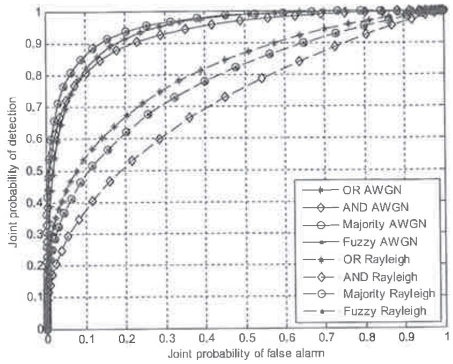

Fig. 2 Performance of one-bit decisions in AWGN and Rayleigh fading.

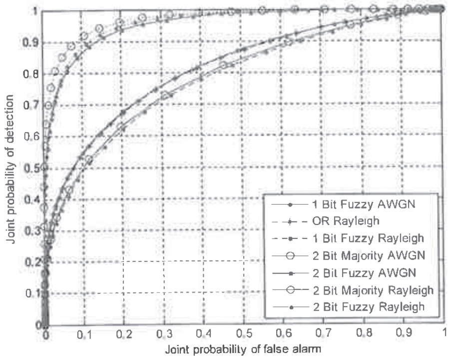

Fig. 3 Performance of two-bit decisions in AWGN and Rayleigh fading.

and −4 dB in Rayleigh fading channel. The sensing results are shown in Fig. 2. The results in AWGN channel are better than in Rayleigh fading channel even that higher SNR values are assumed for the Rayleigh fading channel. From the traditional combining rules, the majority combining is the best in AWGN channel while OR rule is the best in Rayleigh fading channel due to its conservative nature. The cooperative fuzzy combining rule takes the same decisions as the majority combining rule and thus their performances are equal. However, the decision making method is different.

The proposed fuzzy combining scheme acts similarly to the majority rule but alternatively, the fuzzy reasoning system can easily be made to resemble AND or OR rules by either changing the rule base or the positions of the output MBFs. The benefit of the fuzzy reasoning system is flexibility. It can easily be adjusted to fulfil different requirements in different operational environments.

4.3 Two-Bit Quantized Decisions

A more interesting case for fuzzy logic is the use of quantized soft decisions instead of single bit hard decisions. This situation is particularly attractive for fuzzy inference system where several rules are partially true at the same time, and the decision result is influenced by the outcomes of each rule. This takes into account the decisions that are not well described by the hard decisions.

To test the suitability of fuzzy combining with quantized decision, we use two-bit quantization with three thresholds as in [23]. The two outermost thresholds were placed equidistant from the central threshold with a distance of 0.13 in absolute terms in all cases as in [23].

The results of using two-bit quantized decisions with cooperative fuzzy combining rule and majority combining and one-bit decisions with OR and fuzzy rules are shown in Fig. 3. The results of two-bit AND and OR decisions are omitted because the ROC curve representation does not quantify the differences between one bit and two bit cases for AND and OR rules. The same SNRs are assumed as in the one-bit case. The plots from Fig. 3 show that both two-bit fuzzy and two-bit majority combining schemes improve the performance of spectrum sensing as compared to the one-bit case with the same combining rules. In AWGN channel the two-bit majority combining rule is better than the two-bit fuzzy combining scheme. In the more challenging Rayleigh fading channel the fuzzy combining scheme outperforms the two-bit majority rule. The two-bit fuzzy implementation achieves the same performance as OR rule. The results indicate that fuzzy combining scheme is applicable also in the more realistic channel conditions.

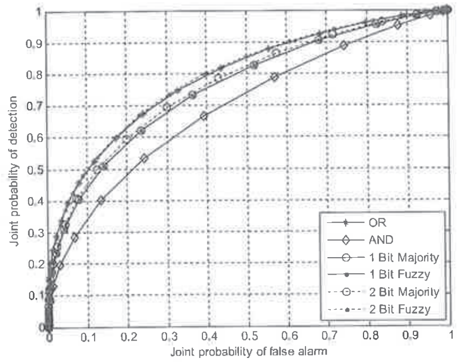

Fig. 4 Performance of two-bit decisions with unequal SNRs in and Rayleigh fading.

Next we study the performance when the three cooperative cognitive radio nodes have unequal SNR values in Rayleigh fading channel corresponding to more realistic operational environments. Two of the nodes have SNR −5 dB while one node has SNR −7 dB. The results of using unequal SNRs are shown in Fig. 4. The results indicate that cooperative fuzzy combining scheme is even better than the other techniques, including the 1 bit OR rule. It seems that when going to more complex operational environments with e.g. variable SNRs, the benefits of fuzzy logic include not only flexibility but also performance improvements.

5. Discussion and Future Directions

Fuzzy logic has been applied to solve different problems in telecommunications systems. Application areas vary greatly from radio interface algorithms to resource management, and even cross-layer optimization. It seems that telecommunications has been one application area for fuzzy logic, but it has not been any major source of new innovations in the development of fuzzy logic methods.

When analyzing different application areas, we found that in receiver algorithms there often exist an optimal mathematical solution, and there are no needs to find out more accurate or better algorithms. The main purpose has been to implement a fuzzy algorithm that approximate the mathematical solution, and in most cases satisfactory results have been achieved. Benefits of fuzzy logic are found in other aspects, such as requirements of less computational complexity, less development work required, or power saving. On the other hand, new arising requirements caused by CRS affect the requirements of radio interface related algorithms in a new way. In addition, there is not much work done on the more advanced systems exploiting OFDM and MIMO techniques, offering thus great potential for future research on fuzzy logic.

In resource management we found more similarities to knowledge based systems that have been a typical application area for fuzzy logic [3]. In resource management the decision making problems are typically multivariable, where compromises are inevitable. There appear conflicting requirements and the optimal solution does not exist or is very difficult to find. These conditions are very typical to knowledge engineering and to knowledge based fuzzy systems.

Complex operational environments and the characteristics of future CRS give rise to the need for decision making approaches that are capable of handling multifaceted, conflicting, and non-predictable resource management where no optimal solutions exist. The decision making process in future CRS will be based on obtaining knowledge of the radio operational environment which is challenging in the dynamic environment. Fuzzy logic appears to be useful for CRS as it has been applied in similar settings in other fields. One important reason to use fuzzy logic in industrial applications has been the presupposition that the exact optimal solution do not often exist for the problems to be solved due to e.g., the complex nature of the problem. In such cases knowledge-based fuzzy system can produce good enough results, but not optimal. Current trends in telecommunication emphasize more efficient use of resources and environmentally oriented solutions leading to finding computationally less consuming solutions and optimizing resources use.

Future CRS will need to take into account the underlying policies arising from the operational environment, e.g., spectrum regulation. The inclusion of the policies into the decision making process at different levels in the network could be accomplished with fuzzy logic. Learning from the past experience will be an essential part of dynamic network management in future CRS. Together with other intelligent methods, fuzzy logic can be utilized as a part of learning mechanisms to further improve the system performance.

6. Conclusion

In this paper we have presented an overview of application of fuzzy logic to telecommunications. The characteristics of future cognitive radio systems offer great potential for applying fuzzy logic based techniques. We have proposed a new combining scheme for cooperative spectrum sensing based on fuzzy logic. Fuzzy logic can be used in cooperative spectrum sensing to provide additional flexibility to existing combining methods.

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PAPER VI

Architecture and approach for obtaining spectrum availability information

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Architecture and Approach for Obtaining Spectrum Availability Information

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Abstract—**This paper presents a novel architecture and approach for obtaining spectrum availability information in future cognitive radio systems (CRS). CRS can opportunistically access spectrum by identifying unoccupied channels while keeping higher priority systems on the same channel free from harmful interference. Knowledge of the current state of the spectrum use is of utmost importance for CRS operations. There are different techniques for obtaining spectrum availability information including e.g. cognitive pilot channels, databases, spectrum sensing techniques, and combinations thereof. For spectrum sensing there are different algorithms and cooperative combining techniques with different characteristics and capabilities in terms of e.g. performance, complexity, and requirement of a priori information. This paper presents a unified architecture for selecting methods for obtaining spectrum availability information taking into account the operational environment and underlying policies. In addition, a novel low complexity heuristic decision making method is presented for selecting the spectrum sensing technique taking into account different capabilities and requirements while being adaptable to the changing environment.**

Keywords-cognitive pilot channel; cognitive radio system; database;decision making; spectrum sensing.

I. INTRODUCTION

Wireless communication systems operate on spectrum bands that are allocated to different services, such as mobile, fixed, broadcast, fixed satellite and mobile satellite. Significant growths in the data rate requirements for the future mobile telecommunication market are predicted towards the year 2020 [1]. Increasing aggregate and per user data rate requirements lead to higher spectrum demand for future mobile communication systems as notified by the International Telecommunication Radiocommunication sector (ITU-R) and indicated in [2]. A fundamental problem facing the future wireless systems is where to find suitable carrier frequencies and bandwidths. While new spectrum identifications were made for International Mobile Telecommunication (IMT) systems at World Radiocommunication Conference in 2007 (WRC-07) of the ITU-R [2], the predicted spectrum demand in 2020 will still remain higher than what is likely to be made available in the future.

Advanced spectrum sharing techniques that allow different systems to coexist on the same spectrum resource will be important mechanisms in the future. Opportunistic spectrum access without causing harmful interference to higher priority systems on the same band by cognitive radio techniques has recently become a promising approach in the research domain. As defined by the ITU-R in [3], a cognitive radio system (CRS) is able to obtain knowledge of its operational and geographical environment, established policies and its internal state, to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives, and to learn from the results obtained.

Pre-requisite for allowing opportunistic spectrum access by CRS techniques is accurate and timely spectrum availability information which requires reliable detection of the presence of higher priority systems in order to protect them from harmful interference. There are several techniques for obtaining spectrum availability information including e.g. cognitive pilot channels, databases, and spectrum sensing techniques [4]. Cognitive pilot channels are carriers where the systems broadcast spectrum availability information on given bands. In database approach, CRS can access a database that includes information of the spectrum availability and associated rules in the given area. With spectrum sensing techniques CRS can capture the status of the spectrum use without interventions with the underlying systems by processing samples of the received signal spectrum. In general, cognitive pilot channels and databases are forms of distributing information spectrum availability information. The actual information can be gathered in several ways.

Particularly in the case of spectrum sensing, there are various classes of spectrum sensing techniques, such as energy detection, correlation based detection, waveform based detection, matched filter detection, and cooperative combining techniques, see e.g. [5] and references therein. Moreover, inside these classes there are several different algorithms that have been developed to specific situations, such as for detecting certain signal types. Different spectrum sensing techniques require different amount of a priori information, vary in complexity, and their performances are different in given situations and environments. While much research has been conducted on the development of the individual sensing algorithms and combining schemes, less attention has been paid on the efficient selection of the techniques for the given situation. In particular, the work has mainly focused on optimizing certain parameters of a single sensing technique.

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Previous work on adaptive allocation of spectrum sensing resources has focused on determining values for certain parameters in response to some optimization problem with respect to some constraints, see [6]-[13]. Optimization of sensing duration was studied in [6] to maximize the achievable throughput for the secondary network under the constraint that the primary users are sufficiently protected. The objective was the minimization of the probability of false alarm under the constraint of probability of detection. In [7] the optimization of sensing time and power allocation were considered in order to maximize the average achievable throughput subject to constraints on probability of detection and total transmit power.

In [8] the achievable throughput of the secondary network was maximized for cooperative spectrum sensing by optimizing the sensing time and the number of users for cooperation sensing decision rule extending the approach taken in [6]. Scheduling of spectrum sensing and data transmission was optimized in [9] based on the channel state information to maximize the network throughput. Spectrum sensing framework for adapting the time-resolution of the spectrum sensing scheme based on channel occupancy information was proposed in [10]. In [11] the optimal number of spectrum bands to be sensed was determined balancing the requirement for minimizing sensing overhead and increasing the likelihood of finding spectrum opportunities. Adaptive sensing scheme was proposed in [12] to decide whether to sense, transmit, or switch the channel by maximizing the spectrum utilization while restricting interference to primary users. Finally, optimal sensing framework was developed in [13] consisting of sensing time optimization, spectrum selection and scheduling for cooperative sensing.

It is characteristic of [6]-[13] that they typically consider the optimization of only one parameter and already this turns out to be a complex problem. In this paper we propose a novel architecture for selection of methods for obtaining spectrum availability information based on the underlying operational environment. The architecture integrates existing approaches for obtaining spectrum availability information. For spectrum sensing, the architecture further selects the most suitable spectrum sensing technique from a set of techniques using heuristic decision making techniques by taking into account the underlying requirements and capabilities.

The rest of this paper is organized as follows. In Section II we describe the research problem. Section III presents the proposed architecture. Section IV presents the heuristic decision making method for selecting the spectrum sensing technique. Finally, conclusions are drawn in Section V.

II. RESEARCH PROBLEM

Future cognitive radio systems will need to be capable of operating in versatile operational conditions. Devices can be freely circulated in Europe and the same piece of equipment should be able to operate in other countries without causing any problems. Situations in the spectrum use can vary in different countries and thus the devices need to be highly adaptable to the prevailing conditions in terms of being capable of providing accurate spectrum availability information. This requires that methods for obtaining the spectrum availability information must be adapted to the operational environment and conditions. This becomes particularly important in Europe where despite of harmonization of spectrum use across the countries there can be some differences in the spectrum allocations that are challenging for deployment of CRS techniques because different primary user systems can exist on certain spectrum bands in different countries.

The problem to be solved in this paper is how to obtain spectrum availability information in future CRS to meet given requirements in different operational conditions. While different methods are more appropriate in certain situations, the overall approach needs to be defined for choosing the best methods. In particular in the case of spectrum sensing, the problem becomes the parameterization of the spectrum sensing, e.g. the selection of suitable spectrum sensing and cooperative combining techniques and their parameters to meet the requirements in the specific situation. The aim here is to create a system that can provide reliable decisions on the current spectrum use efficiently in different operational environments, e.g. different spectrum bands and different configurations in a simple way. The operational environment for cognitive radio systems is predicted to be versatile and dynamic, and thus the techniques need to be applicable to a wide variety of situations and conditions. The time-scales for adaptations in the dynamic and complex operational environment with conflicting requirements will be compressed and optimal solutions are difficult to be found [14]. Thus the design goal becomes to find good enough solutions with reduced complexity.

III. ARCHITECTURE FOR OBTAINING SPECTRUM AVAILABILITY INFORMATION

The general architecture for obtaining spectrum availability information is presented in Fig. 1. There are three main classes of methods for obtaining the information, i.e. cognitive pilot channels, databases, and spectrum sensing systems [4]. While cognitive pilot channels and databases are means to deliver or share the spectrum availability information, spectrum sensing techniques can actually provide this information. Even if the spectrum sensing is the only method that allows cognitive radio to access the spectrum independently without requiring effort from the primary user, detection and protection of systems present in the spectrum is a non-trivial technical problem due to e.g. hidden node problem, silent receivers and low power satellite signals. A cognitive pilot channel is a dedicated carrier providing frequency usage information for the intended band in a given area. The concept was developed with the incentive to overcome potentially time consuming scanning processes. The same motivation is also behind the database concept. The main challenge with both approaches is related to providing information which is up to date and local enough to enable efficient use of spectrum opportunities. It also needs to be ensured that the cognitive radios that rely on the information in the database or cognitive pilot channel are able access it. [4] The given three techniques for obtaining information are not mutually exclusive e.g. the database may serve as a sharing point for sensing information that has been gathered via multiple cognitive radios.

In the first stage, the spectrum awareness method is selected among cognitive pilot channels, databases and spectrum sensing. In fact, the policies can directly determine which of the spectrum availability information gathering techniques can be used in a given spectrum band and the first part of the decision making block becomes simple execution of the decisions implied in the policies. Output from the first stage can be one or several techniques because it may be likely that several techniques will be required by the regulation to guarantee the reliability of the spectrum availability information. For example database can be required for obtaining spectrum availability information in case where the spectrum use of the higher priority system changes slowly. On the other hand, spectrum sensing techniques may be required for detecting short-term local short range users whose presence cannot be efficiently captured by databases. This approach was taken e.g. by the FCC in the use of TV white spaces. The prerequisite for using the spectrum holes on the TV bands is to incorporate geo-location and access to the database containing the information of the spectrum usage. In addition to this, systems may use spectrum sensing to detect the presence of the wireless microphones but this is not mandatory anymore [15]. Moreover, a combination of several techniques can be required to allow the coexistence of several cognitive radio systems on the same spectrum. Certain techniques could be used to detect the presence of higher priority users, while other techniques would be needed to detect other cognitive radio systems with equal priorities among each other.

If spectrum sensing is selected in the first stage, the second stage is to select the most suitable spectrum sensing techniques for the given situation. CRS nodes perform spectrum sensing functions based on instructions obtained from the upper layer decision making method. CRS nodes include software blocks that are parameterized from the upper layer decision making method to use the selected spectrum sensing resources. These resources can include e.g. sensing technique and its parameters (e.g. thresholds), sensing duration, sensing start time and end time, channels (carrier frequencies and bandwidths) to be sensed, etc.

Finally, in the third stage the cooperative spectrum sensing technique is selected. In cooperative sensing, a fusion center collects the sensing data from several CRS nodes and cooperatively forms the spectrum availability information. This is done because due to the radiowave attenuation and noise, spectrum sensing measurements at a single cognitive radio node may not be reliable enough as the signals from other systems can be attenuated below the detection sensitivity. Cooperative spectrum sensing can be used to guarantee sufficient protection of higher priority systems in the more realistic fading environments. Fusion center can be a CRS node which includes software blocks that are parameterized from the upper layer in terms of e.g. number of cooperative CRS nodes, combining techniques (data fusion, decision fusion), parameters for combining technique (thresholds, weights), control schemes for collecting and distributing sensing results, etc. Spectrum availability information is used to select suitable transmission channels for adaptive transmission and the results are also stored into a database. Spectrum sensing results can be collected into a database that can be used to aid the decision making and include learning capabilities where in addition to parameter changes, also the algorithms and optimization criteria are changed according to the conditions and environment.

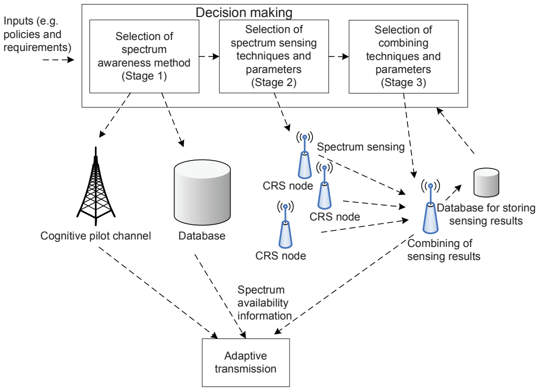

Figure 1. Architecture for selection of techniques for obtaining spectrum availability information.

The decision making block in Fig. 1 presents the upper layer of the system that makes the actual resource allocation decisions for the lower layer which consists of the individual cognitive radio nodes and their functions. The novel aspect of the proposed architecture is that the upper layer decision making block adapts the system to versatile operational conditions. It optimizes the whole spectrum availability information gathering system instead of focusing only on a subset of e.g. spectrum sensing parameters. The two-layer architecture makes it possible to keep components of different levels simple. The vital component in this is the decision maker in the upper level; it transforms existing requirements into control strategy which is then implemented by adjusting the parameters of lower level components.

IV. HEURISTIC DECISION MAKING METHOD FOR SELECTION OF SPECTRUM SENSING TECHNIQUES

The second stage in the decision making process is associated with the selection of spectrum sensing and techniques and their parameters. This part in the decision making process becomes activated if spectrum sensing is selected as spectrum awareness method in the first stage. The decision making block can be seen as an expert system that optimizes the existing telecommunication environment based on given requirements and possibilities. In cognitive radio systems several methods have been proposed for this, such as neural networks, genetic algorithms, fuzzy and other rule-based systems, and game theory. However, the focus has mainly been on the resource allocation of the transmission resources, i.e. selection of channels among a set of cognitive radio nodes. There has not much work on the allocation of the resources to be used to obtain the spectrum availability information. In particular, the decision making for selecting the most suitable spectrum sensing techniques has not been addressed before. Here we present a simple heuristic decision making method that selects the spectrum sensing technique, which corresponds to the second stage of Fig. 1.

The decision making method for the selection of spectrum sensing techniques is illustrated in Fig. 2. Typical affecting parameters are chosen from existing policies and requirements and they are used as input variables for the decision making. Here we have identified four input parameters: requirement for detection probability, available time, available a priori information, and operational signal-to-noise ratio (SNR). Particularly for spectrum sensing the probability of detection is the crucial performance metric because protection of higher priority systems on the same spectrum bands is of utmost importance. The decision making process can be done for example using fuzzy logic, as we present later in Table 1.

The output of the decision making is the chosen spectrum sensing technique. The selection of the spectrum sensing techniques is made between three classes of techniques, namely energy detection, correlation based detection, and waveform based detection, see e.g. [5]. These are general classes of spectrum sensing techniques and include several different algorithmic variants that have different characteristics and capabilities.

The heuristic decision making is done using fuzzy logic, see [14]. The developed fuzzy system is simple and consists of four input parameters and one output parameter. The process of fuzzy decision making consists three phases: fuzzification, decision making, and defuzzification. The input variables are first fuzzified using predefined membership functions (MBF). We have used two MBFs to characterize the input parameters, namely 'low' and 'high'. Fuzzy numbers are then fed into a predefined rulebase that presents the relations of the input and output variables with IF-THEN clauses. The output of the fuzzy reasoning is a fuzzy variable that is composed of the outputs of the THEN clauses. The fuzzy variable is then changed into crisp number that is the actual result of the fuzzy decision making. Here we have used four MBFs for the output, each corresponding to a different sensing technique, i.e. energy detection, correlation based detection, waveform based detection, and no available technique. There are several methods for different phases of fuzzy decision making, and results dependent heavily on them. Additionally different kinds of shapes of MBFs affect on the decision making results.

The rulebase of the fuzzy decision making system is shown in Table I. The underlying assumptions in the development of the rules for selecting the spectrum sensing technique is that energy detection can operate fast and does not need a priori information on e.g. the waveforms but requires high operational SNR and cannot fulfill high requirements for probability of detection. Correlation based detection is assumed to provide higher probability of detection than energy detection but it requires more time for processing. Operational SNR and a priori information requirements are the same for correlation based detection and energy detection. Waveform based detection is assumed to provide high probability of detection, but it requires high processing time and high a priori information but can operate at low SNRs.

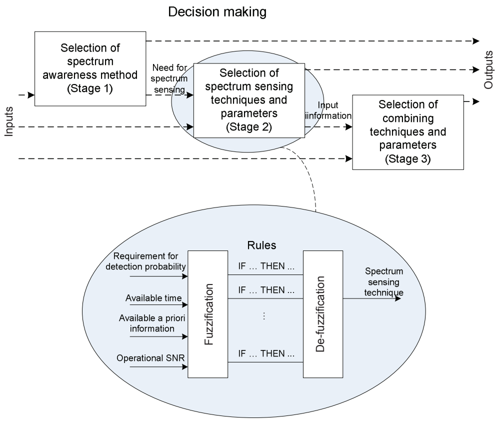

Figure 2. Decision making method for selection of spectrum sensing techniques.

TABLE I. RULES FOR SELECTION OF SENSING TECHNIQUES

Input parameters				**Output**
Requirement for detection probability	**Available time**	**Available a priori information**	**Operational SNR**	**Spectrum sensing technique**
low	low	low	low	None
low	low	low	high	Energy detection
low	low	high	low	None
low	low	high	high	Energy detection
low	high	low	low	None
low	high	low	high	Energy detection
low	high	high	low	Waveform based detection
low	high	high	high	Energy detection
high	low	low	low	None
high	low	low	high	None
high	low	high	low	None
high	low	high	high	None
high	high	low	low	None
high	high	low	high	Correlation based detection
high	high	high	low	Waveform based detection
high	high	high	high	Correlation based detection

If the requirements are not met by any of the sensing techniques, the output of the decision making block is that none of the available spectrum sensing techniques is capable of providing the required probability of detection in the given operational conditions. The decision making system selects the lowest complexity spectrum sensing technique that fulfills the requirements. The assumption for the order of complexities of the different techniques is that energy detection is the most simple, followed by covariance based detection and waveform based detection. For example, the second row in Table 1 shows that if the first three inputs are 'low' and the operational SNR is 'high', the output is energy detection.

The motivation to use fuzzy logic can be found when analyzing the characteristics of different input variables. Their numeric values can deviate considerably in different systems, but the main decision making process remains the same, which guides us to use fuzzy representation.

V. CONCLUSIONS

In this paper we have presented an architecture and approach for obtaining spectrum availability information. The developed architecture can be applied to obtain information on the current spectrum use for future cognitive radio systems that can coexist with other systems on given spectrum bands. The proposed approach consists of three stages. In the first stage the overall approach for obtaining the spectrum availability information is selected between cognitive pilot channels, databases, spectrum sensing, and combinations thereof. If CRS are deployed on spectrum bands that include higher priority systems, the selection between these techniques will be governed to a large extent by the regulator. This is because the protection criteria for protecting the higher priority spectrum users will be defined by the regulator including the means for finding out the presence of higher priority systems. Thus the policies will determine which techniques can be used on certain spectrum bands. On the other hand, CRS can also be used on other kind of bands that do not have higher priority systems such as ISM bands. There the selection of the spectrum awareness technique is not so much restricted by the policies but could be done based on other inputs to optimize the performance.

In case the spectrum availability information is obtained via spectrum sensing techniques, the selection of the most suitable spectrum sensing and cooperative combining techniques and their parameters becomes an important design goal. We have presented a novel low complexity heuristic decision making method that selects the suitable spectrum sensing technique. The selection is done based on input information on the requirements for sensing and operational conditions. The aim is that the decision making block configures the spectrum sensing blocks according to changing requirements and operational conditions. The least complex spectrum sensing technique that fulfills the requirements is selected. At the moment, the selection is made only between three major classes of spectrum sensing techniques, namely energy detection, correlation based detection and waveform based detection with simplified requirements and capabilities.

In the future, the decision making block will be extended to include more input and output parameters performing more complete configuration of the sensing and combining blocks. This approach would handle optimization of several parameters under conflicting requirements leading to good enough solutions that have practical meaning. Future studies will include the consideration of what actions should be taken when none of the spectrum sensing techniques fulfills the requirements in the given situation. In particular, the inclusion of cooperative spectrum sensing decisions is a promising topic to be studied. In addition, the actual requirements of the primary user systems on different spectrum bands to be protected could be taken into account in designing the rule-based decision making scheme.

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PAPER VII

Decision-making system for obtaining spectrum availability information in opportunistic networks

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Decision-Making System for Obtaining Spectrum Availability Information in Opportunistic Networks

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ABSTRACT

Opportunistic networks with cognitive management systems can improve the resource use in future wireless communication networks by forming local clusters that are temporary extensions of the infrastructure and governed by the operator. This paper presents a decision making system that selects the techniques for obtaining spectrum availability information in opportunistic networks. The proposed decision making system selects the most suitable technique(s) from cognitive control channels, databases, and spectrum sensing techniques. Moreover, a novel and simple rule-based expert system is developed to choose the spectrum sensing technique among energy detection, correlation-based detection, and waveform-based detection. The selection is made based on the required probability of detection, operational SNR, available time, and available a priori information. The developed rule-based decision making system is presented in the form of a decision tree to illustrate the dominating paths that influence the decisions. Situations where none of the considered spectrum sensing techniques can meet the given conditions are identified and new approaches are proposed including cooperative sensing and changing of the channel. Results are presented to verify the functioning of the proposed decision making system and to show the relative frequencies of the different selected sensing techniques. Significant improvements can be obtained when the decision making system is used compared to using a single sensing technique instead.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Wireless communication.

General Terms

Algorithms, Management, Performance, Design.

Keywords

Cognitive radio system, Cooperative spectrum sensing, Database, Heuristic decision making.

CogART '11, October 26-29, Barcelona, Spain.

1. INTRODUCTION

Today's mobile communication networks are base station centric in the sense that communication between the nodes is handled in a pre-defined network configuration via base stations. Future networks are envisaged to be capable of optimizing their resource use by establishing temporary ad hoc clusters that can operate in a more autonomous manner. Such opportunistic networks are operator governed, temporary, and coordinated extensions of the infrastructure, see e.g. [1]-[2]. Opportunistic networks are dynamically created in places and at times they are needed to serve the users in the most efficient way. Opportunistic networks can comprise network elements of the infrastructure, and terminals potentially organized in an infrastructure-less manner.

Cognitive radio systems (CRS) have recently emerged as a promising technique to improve the use of various resources in future wireless networks. According to the International Telecommunication Union Radiocommunication sector (ITU-R), CRS is able to obtain knowledge of its operational and geographical environment, established policies and its internal state, to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives, and to learn from the results obtained [3]. Extensive research efforts are currently carried out to develop various cognitive radio techniques, see e.g. [4] and references therein.

In some previous works (e.g. [5]), opportunistic networks are considered as an evolution of mobile ad hoc networks (MANETs). In such case, the nodes of opportunistic networks are enabled to communicate with each other, they do not have any knowledge about the network topology, and routes between the nodes are built dynamically. The use of cognitive radio techniques in the context of opportunistic networks has recently become a promising approach [1]-[2]. The establishment of opportunistic networks requires information on the spectrum availability. Opportunistic networks can be established on different types of spectrum bands, e.g. operator governed mobile systems bands, industrial, scientific and medical (ISM) bands as well as bands where the opportunistic network can act as a secondary user guaranteeing protection for the higher priority systems from harmful interference arising from the opportunistic network, such as TV bands.

There are different methods for obtaining spectrum availability information in cognitive radio systems. The methods currently considered in the spectrum regulatory framework include cognitive control channels, databases, and spectrum sensing techniques [6]. Different methods are more suitable in different situations depending on e.g. service requirements, node capabilities, and spectrum bands. While there has been much progress in the development of the individual techniques for obtaining spectrum availability information, such as spectrum sensing techniques, there has not been much research on how to efficiently select the techniques in a given situation.

Work on the selection of spectrum sensing methods was initiated in [7] where the properties of the different sensing methods were compared and put on a scale according to their complexities and accuracies. The focus has traditionally been in the development of the individual spectrum sensing techniques and optimizing their parameters. For example, the spectrum sensing functionality has been optimized in [8] to maximize the detection efficiency in terms of maximizing the use of the primary user spectrum. Motivated by the findings of [7], we proposed a simple framework for selecting the methods for obtaining spectrum availability information in [9]. To the best of our knowledge, there has been no other previous work on the actual decision making for the selection of the spectrum sensing techniques in addition to [9].

In [9], the selection was first done between the major classes of spectrum availability information techniques, i.e. cognitive pilot channels, databases, and spectrum sensing. Second, a simple rule-based decision making method for selecting the spectrum sensing technique was developed. The selection was made between energy detection, correlation-based detection, and waveform-based detection. The considered selection criteria were required probability of detection, operational signal-to-noise ratio (SNR), available time, and available a priori information. There were several occasions where none of these sensing techniques could be used to fulfill the requirements in the given conditions.

This work takes a step beyond [9] by extending the approach for obtaining spectrum availability information to the situation of establishing opportunistic networks. The different types of spectrum bands for opportunistic networks are discussed in detail and the suitable techniques for obtaining spectrum availability information on the different bands are outlined. The specific goal is to develop a scheme capable of handling the versatile operational radio environment existing in the real world and, in particular, in the European framework where the spectrum use varies from one country to another. While an opportunistic network can operate in a frequency band in one country, the operational conditions could be quite different in another country. The establishment of opportunistic networks requires different factors to be taken into account, resulting in the situation where different spectrum availability information techniques need to be used. Thus, the aim of this work is to develop a simple yet efficient decision making system for selection of techniques to obtain spectrum availability information in opportunistic networks that are capable of operating in diverse conditions and environments. The decision making system from [9] is developed further to handle the cases where none of the sensing techniques is applicable by introducing cooperative sensing and changing of channel. Moreover, results are presented to verify the performance of the decision making system.

The rest of this paper is organized as follows. Opportunistic networks with cognitive management systems are elaborated in Section 2, whereas the proposed decision making system is presented in Section 3. Results are given in Section 4. Finally, conclusions are drawn in Section 5.

2. OPPORTINISTIC NETWORKS WITH COGNITIVE MANAGEMENT SYSTEMS

As the modern wireless communication networks are facing new challenges such as the demand for new and diversified services, opportunistic networks can be seen as a promising approach to e.g. expand the coverage of the infrastructure or resolve cases of congested access and thus provide cost-efficient solutions [1]-[2]. In our studies, opportunistic networks are governed by the operator and they are managed and coordinated with the infrastructure by advanced cognitive systems. These cognitive management systems will facilitate close cooperation between the infrastructure and the opportunistic networks to ensure efficiency in resource use and service provisioning. They will include capabilities for decision making and learning, and provide policies, resources and other information that will govern the opportunistic network.

The cognitive management systems will be in charge of handling the lifecycle of the opportunistic networks. Four major phases in the lifecycle can be identified: suitability determination, creation, maintenance, and termination of the opportunistic network. In the first phase, the suitability of the opportunistic network approach is determined case by case based on aspects such as involved applications, candidate nodes and their capabilities, available spectrum, and the expected gains for the operator e.g. reduced cost or improved coverage. Creating the opportunistic network requires selection of e.g. spectrum, nodes, access technique, and interconnection of the nodes. There can be also different criteria for making the decisions due to different operational conditions and network internal requirements. Furthermore, maintaining the opportunistic network requires also modifications on the network due to alterations in e.g. context, profiles and policies. At a certain point, the opportunistic network will need to be terminated due to e.g. an end of application use, identification of a more efficient way of offering the application or a forced termination.

This paper is focused on the first two phases, namely, suitability determination and creation of opportunistic networks in terms of finding suitable spectrum for the opportunistic network. In particular, we consider the different techniques for obtaining spectrum availability information and how the selection between the techniques could be done in a practical and cost-efficient way.

3. PROPOSED DECISION MAKING SYSTEM

3.1 Selection of Techniques for Obtaining Spectrum Availability Information

The main components in the selection of techniques for obtaining spectrum availability information are presented in Figure 1. The input on the left is a set of information typically given in the form of policies on the use of spectrum in the given area, which are set by the national spectrum regulatory authorities. First the selection is done among the three main classes for obtaining spectrum availability information, including cognitive control channels, databases, and spectrum sensing techniques, based on the input information. The actual selection of the spectrum for the establishment of the opportunistic network and the transmissions in the opportunistic network are then done by using the spectrum availability information obtained via the selected technique(s).

Opportunistic networks can be established on different types of spectrum bands, e.g. operator governed mobile systems bands, license-free ISM bands, and bands where the opportunistic network operates as a secondary user guaranteeing protection for

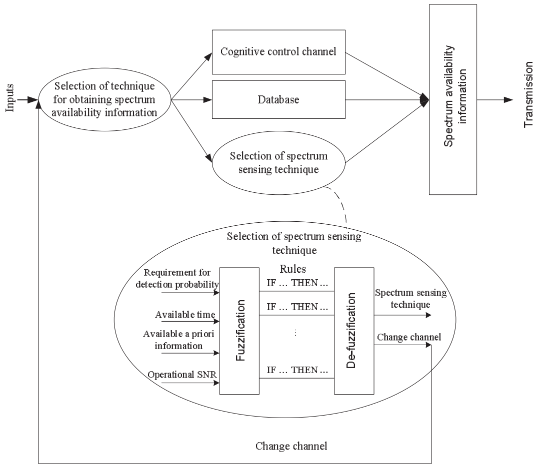

Figure 1. Decision making system for selecting the techniques to obtain spectrum availability information.

the higher priority systems from harmful interference such as TV white spaces. Operations on different spectrum bands call for different approaches in the process of obtaining spectrum availability information. The new aspect in operator-governed opportunistic networks is that the opportunistic networks can use the spectrum resource governed by the operator, which in turn can coordinate better the resource use inside its own network. This offers an extra degree of efficiency when compared to traditional approaches for opportunistic networks.

On operator governed bands, two types of situations can arise. In the first situation, the operator establishes an opportunistic network on its own licensed band where it has complete sovereignty over the spectrum. The operator can then use the resource availability information from the infrastructure network side in the establishment of the opportunistic network. In this case, the signaling using control channels inside the network allows the opportunistic network to obtain information on the available spectrum. In the second situation, the operator establishes an opportunistic network on a licensed band that belongs to another operator. In this case, the operator of the opportunistic network can obtain information about the available spectrum resources from the other operator owning the band via e.g. external cognitive control channels or accessing a shared database.

On license-free bands there are typically no high priority systems and all spectrum users have to obey a certain set of rules in terms of e.g. transmission power levels. Information about the current spectrum usage can help the opportunistic network to optimize its resource use by avoiding parts of the spectrum undergoing heavy traffic load such as heavily loaded WLAN channels in the ISM band. It is likely that the different systems operating on the license-free band do not inform each other about their spectrum use via cognitive control channels or databases because there is currently no obligation to do so. The only remaining way to obtain information about the spectrum use is to resort to spectrum sensing techniques.

On bands where the opportunistic network is created as a secondary system to coexist with higher priority systems, the predefined spectrum regulator set policies will determine which of the techniques can be used to obtain spectrum availability information. Opportunistic networks can be established on such bands if they can protect the primary users from harmful interference. The requirements for the spectrum availability information are likely to vary on a band-by-band basis, since different primary user systems will require different means and levels of protection due to their characteristics. The means for protecting the primary user are defined by the regulator and they will determine which spectrum availability information techniques, or which combination of them should be used. It is also possible that there are several different types of higher priority systems that the opportunistic networks have to protect from harmful interference, which may require several different approaches for obtaining spectrum availability information on the same band. For example, operation on TV white spaces is likely to require database approach in Europe [10] as in the U.S. On some bands, the primary systems could provide information about the spectrum availability via cognitive control channels. There may also be bands where the information on primary user spectrum use is not provided via cognitive control channels or databases, and hence the remaining solution is spectrum sensing.

3.2 Rule-based Decision Making System for Selection of Spectrum Sensing Technique

If spectrum sensing is first selected for obtaining spectrum availability information, the next step is to select the specific spectrum sensing algorithm and its parameters. In [9] we presented a fuzzy rule-based decision-making system for selecting the spectrum sensing techniques between energy detection, correlation-based detection, and waveform-based detection. The different spectrum sensing techniques are discussed in more detail in [7]. The decision-making system in [9] utilizes four input parameters: required probability of detection, operational SNR, available time, and available a priori information. The required probability of detection characterizes the level of protection for the higher priority systems. Operational SNR is considered to be a long-term characteristic of the primary user signal levels at the constituent node of the opportunistic network. Available time characterizes the capabilities and requirements of the cognitive radio node. Available a priori information characterizes how much information is known at the cognitive radio node about the other systems waveforms operating on the same spectrum band. The output of the decision-making process is energy detection (either with or without cooperation), correlation-based detection, waveform-based detection, or no available spectrum sensing technique for the situation at hand. The different spectrum sensing techniques differ in performance and complexity, therefore their suitability depends on each addressed scenario.

Each of the four input parameters is assigned two input values: low and high. This leads to 16 different possible combinations of the inputs. Each of the different input combinations is assigned one rule that leads to one output. The rules are presented in the form of IF – THEN clauses. The rules are constructed based on the following assumptions. Energy detection is assumed to be capable of operating fast and with no a priori information of e.g. the waveforms. However, it requires high operational SNR, and cannot efficiently fulfill high requirements imposed on the probability of detection. On the other hand, correlation-based detection is assumed to provide higher probability of detection than energy detection, but it requires more time for processing. Operational SNR and a priori information requirements are the same for correlation-based detection and energy detection.

Likewise, waveform-based detection is assumed to provide high probability of detection at low SNRs, but it requires high processing time and a significant amount of a priori information. With these assumptions in mind, the aim of the proposed selection scheme is to select the simplest spectrum sensing scheme. Therefore, we have sorted the different sensing techniques in ascending order of their complexities, such that energy detection results in the simplest technique, followed by correlation-based and waveform-based detection methods.

Out of the 16 combinations of input parameters in the rule-base in [9], there were eight outputs where none of the considered three spectrum sensing techniques was applicable. By elaborating on these special situations, we next determine additional steps that the decision making system should take in order to proceed further. The resulting rules are presented in Table 1 in the form of IF – THEN clauses. The rule-base is extended from [9] by introducing two new outputs to the situations where previously none of the sensing techniques was capable of operating.

It was shown in [12] that cooperative spectrum sensing where several cognitive radio nodes perform the spectrum sensing simultaneously and combine their sensing results with some combining rule can be used to improve the probability of detection. Thus in the case when the requirement for the probability of detection is high, SNR is high and available time is low, the output of the decision-making system can be cooperative energy detection. Hence, the corresponding output from the decision making system is cooperative energy detection. Here we assume that the additional time required for the signaling and combining of the sensing results is small since the opportunistic networks have control channels to exchange the information. It should be noted that cooperative sensing cannot be used if the underlying conditions for the given spectrum sensing technique are violated, i.e. even cooperation cannot change the surrounding circumstances. For example, in the case that the requirement for the probability of detection is high and both SNR and the available time are low, cooperative spectrum sensing is not feasible but the decision is to change channel. This is because energy detection does not work at low SNRs even in cooperative case, and the other sensing techniques require more time and cannot be used in cooperative mode.

Table 1. Rules for the selection of sensing technique

Rule 1: IF A is A_1 AND B is B_1 AND C is C_1 AND D is D_1 THEN E is E_5
Rule 2: IF A is A_1 AND B is B_1 AND C is C_1 AND D is D_2 THEN E is E_5
Rule 3: IF A is A_1 AND B is B_1 AND C is C_2 AND D is D_1 THEN E is E_5
Rule 4: IF A is A_1 AND B is B_1 AND C is C_2 AND D is D_2 THEN E is E_3
Rule 5: IF A is A_1 AND B is B_2 AND C is C_1 AND D is D_1 THEN E is E_1
Rule 6: IF A is A_1 AND B is B_2 AND C is C_1 AND D is D_2 THEN E is E_1
Rule 7: IF A is A_1 AND B is B_2 AND C is C_2 AND D is D_1 THEN E is E_1
Rule 8: IF A is A_1 AND B is B_2 AND C is C_2 AND D is D_2 THEN E is E_1
Rule 9: IF A is A_2 AND B is B_1 AND C is C_1 AND D is D_1 THEN E is E_5
Rule 10: IF A is A_2 AND B is B_1 AND C is C_1 AND D is D_2 THEN E is E_5
Rule 11: IF A is A_2 AND B is B_1 AND C is C_2 AND D is D_1 THEN E is E_5
Rule 12: IF A is A_2 AND B is B_1 AND C is C_2 AND D is D_2 THEN E is E_3
Rule 13: IF A is A_2 AND B is B_2 AND C is C_1 AND D is D_1 THEN E is E_4
Rule 14: IF A is A_2 AND B is B_2 AND C is C_1 AND D is D_2 THEN E is E_4
Rule 15: IF A is A_2 AND B is B_2 AND C is C_2 AND D is D_1 THEN E is E_2
Rule 16: IF A is A_2 AND B is B_2 AND C is C_2 AND D is D_2 THEN E is E_2

In the rule-base in Table 1, input parameter A refers to the requirement for the probability of detection and A_1 corresponds to low requirement and A_2 to high requirement. Parameter B refers to the operational SNR and correspondingly B_1 stands for low SNR regime and B_2 for high SNR regime. Input parameter C denotes the available time. In case of C_1 there is little time available and in C_2 much time available. Input parameter D is the available a priori information about the primary user system waveforms. D_1 means that there is little a priori information available and D_2 much a priori information. Finally, the output parameter E denotes the decision of the system. Accordingly, E_1 corresponds to energy detection, E_2 correlation-based detection, E_3 waveform based-detection, E_4 cooperative energy detection, and E_5 changing the channel.

The input and output membership functions for the fuzzy decision making system are very simple and drawn in Figure 2. The input parameters are fuzzified using input membership functions. The fuzzy decision making is done by using fuzzified inputs to produce an output function which is defuzzified into a crisp number that constitutes the outcome of the decision-making process, i.e. selected sensing technique. At first sight this decision making problem is well-posed, and might be solved by resorting to traditional rule-based expert systems. However, with fuzzy logic the decision-making process may provide additional valuable information in cases where a spectrum sensing technique cannot be chosen and cooperative methods are taken into use. In such cases the information on how the final result is achieved is useful. From a methodological viewpoint, the fuzzy reasoning is done using traditional max-dot method, whereas defuzzification is performed by using the maximum method [11].

Furthermore, to get a better understanding of the situation, the rule base in Table 1 has been modified into the form of a decision tree in Figure 3. The decision tree is a graphical representation of possible paths in the decision-making process. Ovals denote the input parameters, whereas the rectangles are used to denote a decision. When one input takes a certain value (here, either low or high), only a subset of the overall set of paths will be available.

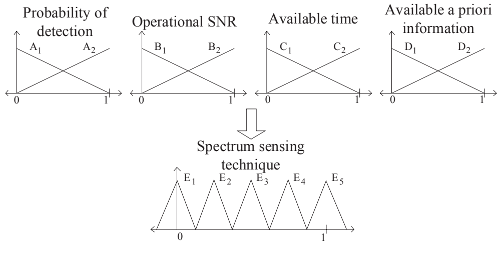

Figure 2. Decision making system for selecting the techniques to obtain spectrum availability information.

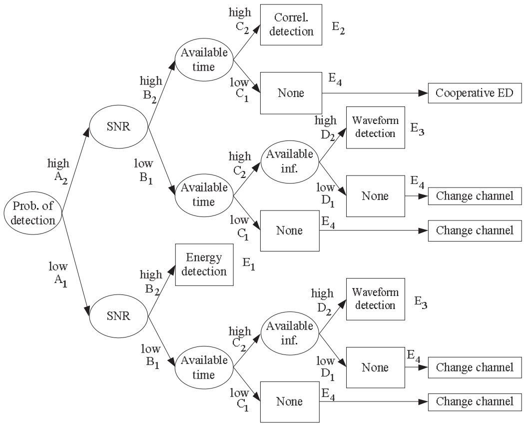

Figure 3. Decision tree describing the selection of spectrum sensing techniques and actions.

The reason is that only a subset of the combinations of the four input parameters is feasible. The decision-tree representation is not fully suitable for fuzzy decision-making systems, because typically many paths of the tree may be triggered at the same time. However, this renders a good graphical view for the possible paths.

In general, heuristic decision making systems can be suitable for situations where the process cannot be easily modeled with mathematical approaches, but is intuitively understandable. Furthermore, decisions need to be taken in situations where the input information is uncertain. Analyzing the availability of spectrum is clearly a challenging task especially when there is not enough time, resources, or additional information of potential traffic characteristics. In such cases, decisions have to be done based on vague information, and in those kinds of cases fuzzy logic and other heuristic methods have proved to be understandable, powerful, reliable, and even simple and low-complex. The benefit of the proposed approach is that there are no surprising outputs from the decision making since the outputs have been determined beforehand when developing the rules. Moreover, the decision making is fast and does not require any iterations.

4. RESULTS

We have implemented the proposed fuzzy decision making system and evaluated its performance. To the best of our knowledge, the decision making system presented in this paper and the one in [9] are the only decision making system currently available for selecting the spectrum sensing techniques. Thus there are no other decision making systems that could be used for benchmarking the performance. First we evaluate the proportions of the different outcomes from the decision making system with different input values by calculating the probability for the occurrence of a given outcome. This is done by selecting the rules that result in a given outcome from the rule-base, and summing up the probabilities of the occurrences of these rules. When all the inputs are equally probable, the probability for a given outcome is obtained simply by calculating the number of rules with the given outcome and dividing this with the total number of rules, i.e. 16.

Table 2. Results from performance evalution

	Input set 1		Input set 2		Input set 3	
	Outcome (%)	Success (%)	Outcome (%)	Success (%)	Outcome (%)	Success (%)
ED	25	25	21	21	24	24
CD	12.5	25	34,3	49	6.4	16
WD	12.5	25	14.7	49	9.6	16
CED	12.5	37,5	14.7	35.7	9.6	33.6
CC	37.5	100	15.3	100	50.4	100

When the different inputs are assigned different probabilities, the rules from the rule-base with a given output are weighted with the probability of the occurrence of this rule which is obtained from the probabilities for the different inputs. The performance of the decision making system is also evaluated by comparing it to the situation when there is no decision making but only single sensing technique is used. This evaluates the probability of success of each sensing technique.

The results from the performance evaluation are shown in Table 2. Three different sets of input parameters are used. Input set 1 corresponds to the case of all inputs being equally probable i.e. $p(A_1)=p(A_2)=p(B_1)=p(B_2)=p(C_1)=p(C_2)=p(D_1)=p(D_2)=0.5$. Input set 2 corresponds to $p(A_1)=p(B_1)=p(C_1)=p(D_1)=0.3$ and $p(A_2)=p(B_2)=p(C_2)=p(D_2)=0.7$. Input set 2 denotes $p(A_1)=p(B_1)=p(C_1)=p(D_1)=0.6$ and $p(A_2)=p(B_2)=p(C_2)=p(D_2)=0.4$. The column “Outcome” in Table 2 presents the percentages of the different outcomes from the decision making system. The different outcomes are denoted as following: energy detection (ED), correlation-based detection (CD), waveform-based detection (WD), cooperative energy detection (CED), and changing of channel (CC).

The column “Success” shows the percentage of situations that the given sensing technique is applicable but not necessarily the best choice in the given input parameter configuration when the decision making system is not used. In practice, changing of the channel, which here has 100% success, is not a good solution as it requires the process to be repeated to find another channel. When the decision making system is used, there is always an action taken. If only a single sensing technique is used instead, there are several occasions where the given sensing technique is not applicable and thus those opportunities will be lost. For example, using ED in input set 1 corresponds to losing 75% of the chances since ED is only successful in 25% of the situations. The results in Table 2 with different input parameter sets indicate that the applicability of the different sensing techniques varies heavily depending on the input parameters and their values.

5. CONCLUSIONS

In this paper, we have studied the problem of finding spectrum opportunities for opportunistic networks. Opportunistic networks can be established on different kind of spectrum bands, and thus it is likely that different types of methods will be needed to obtain knowledge of the spectrum availability. We have discussed the different spectrum types and what kind of approaches they might require including cognitive control channels, databases, and spectrum sensing. In particular, the establishment of an opportunistic network may require a combination of several different methods.

In addition, we have presented a simple rule-based decision making system based on fuzzy logic for the selection of spectrum sensing techniques between three main classes, namely, energy detection, correlation-based detection, and waveform-based detection. Four input parameters have been considered in the decision-making procedure: required probability of detection, SNR, available time, and available a priori information. The developed decision-making system has been formulated in the form of a decision tree, which helps discerning the most influential parameters and paths. As there are many combinations of the input parameters where there is no spectrum sensing technique that would match the requirements and the operational conditions, we have developed alternative steps. It is possible that in some case, cooperative sensing can help while in other cases the resulting action is to try to find another channel on which to operate. Results have been presented to quantify the benefits of the proposed decision making system. The results have shown the proportions of the different outputs from the decision making system with different combinations of the input parameters. The results show that the use of the proposed decision making system helps the opportunistic network to adjust to the changing operational conditions compared to using a single technique instead. If only a single sensing technique is used without the decision making system, many of the transmission opportunities are lost when the input parameters that define the operational conditions and requirements do not match the capabilities of the sensing technique.

In the future, the number of membership function characterizing the input parameters and the output decisions can be increased to allow a more detailed description of the problem. In this case, the input parameters can be modeled more accurately. On one hand, this increases the number of rules and increases complexity. However, it allows the system to better adapt to the existing and changing requirements. In particular, the different spectrum sensing techniques could be scaled in terms of their capabilities and characteristics. The output of the decision making could be drawn from a larger set of selected spectrum sensing techniques including new yet still impractical approaches such as compressive sensing.

6. ACKNOWLEDGMENTS

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PAPER VIII

Fuzzy-logic based framework for spectrum availability assessment in cognitive radio systems

Journal paper manuscript.

Fuzzy-logic based Framework for Spectrum Availability Assessment in Cognitive Radio Systems

Marja Matinmikko, Javier Del Ser, *Senior Member, IEEE,* Tapio Rauma, and Miia Mustonen

Abstract

This paper presents a novel decision-making system for the selection of methods to obtain knowledge of spectrum availability in future mobile communication systems equipped with cognitive radio system (CRS) capabilities. The proposed decision-making scheme selects the methods to obtain knowledge of spectrum availability between control channels, databases and spectrum sensing based on the specific requirements of the frequency band at hand. The developed decision-making system considers realistic frequency bands and spectrum sharing scenarios, including bands with primary allocation to mobile service where the operator governs the spectrum use, bands with co-primary or secondary allocation to mobile service where the primary users have to be protected from harmful interference, and finally license-exempt bands, where different systems coexist in uncontrolled interference conditions. Specifically, a novel rule-based decision-making system with a learning mechanism is developed to select among different spectrum sensing techniques including matched filtering, correlation detection, feature detection, energy detection, and cooperative sensing. The decision making system is further applied to operator-governed opportunistic networks, which are dynamically created temporary extensions of the mobile infrastructure networks. Performance evaluation is done by assuming changing operational conditions so as to elucidate the gains of the proposed decision making system with respect to the case when the sensing approach is kept fixed.

Index Terms

Control channel, cognitive radio system, database, frequency channel, spectrum sensing.

I. INTRODUCTION

Wireless telecommunications have experienced a sharp growth during the last decade. Mobile communication systems have reached worldwide deployment with constantly increasing numbers of users and ever-growing data rates. New generations of mobile communication systems have provided improved capabilities to offer a diverse set of services ranging from voice transmission and short message delivery services to highly data-intensive

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communications. In this context, advanced techniques have been developed and taken into use to satisfy the growing user demand in terms of per user and aggregate data rates. One of the key factors in the success of mobile communication systems was the fact that spectrum had been made available in time for the new generations of systems with increasing spectrum requirements (see [1] for details). Indeed, spectrum has traditionally been the key asset of an operator to offer connectivity and services, and the mobile communication systems have been planned to exploit their spectrum assignments with high spectral efficiencies and spectrum occupancies.

While the requirements of the end user for wireless traffic have been increasing in a continuous fashion, the radio spectrum has become a limited resource, as elucidated by the recent spectrum identifications for the mobile service (see [1], [2]). In fact, the availability of new spectrum for sole primary allocation to mobile service is by itself challenging, due to the lack of unallocated spectrum support. Thus, new radio spectrum made available for mobile communication systems is likely to be shared with other systems, which calls for the development of efficient spectrum sharing techniques.

In particular, research on cognitive radio systems (CRSs) has recently emerged to develop new techniques to facilitate spectrum sharing inside a given system, as well as among different systems. As defined by the International Telecommunication Union Radiocommunication sector (ITU-R [3]), a CRS is able to obtain knowledge of its operational and geographical environment, established policies and internal state, to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives, and to learn from the results obtained. CRSs are expected to provide several benefits such as an improved efficiency of the spectrum use, an increased flexibility and potential for new mobile communication applications [4]. CRS techniques are expected to be major building blocks in the future mobile communication systems, such as IMT-Advanced.

When it comes to optimizing the use of resources in mobile communications with increased users requirements, another emerging paradigm hinges on establishing opportunistic networks that are governed by an operator and created on demand [5]. These networks are temporary extensions of the infrastructure including cognitive management systems to manage the resource usage and coordinate with the infrastructure. Inherent capabilities of such cognitive management systems are, among others, self-management and learning mechanisms (e.g. [5]). An important aspect to be tackled when creating an opportunistic network is to select the participant nodes and the communications resources, particularly the spectrum to be used [6].

Since future mobile communication systems with cognitive and opportunistic characteristics - such as the aforementioned opportunistic networks - are expected to possess capabilities for intelligent decision making and learning, heuristics have emerged as an appealing research line in the related literature for their application through distinct processing stages involved in the cognitive cycle, e.g. see [7]-- [10] and references therein. For different systems to operate on the same spectrum band, it is of utmost importance that they have accurate knowledge of the current status of the spectrum utilization. The methods to obtain knowledge of spectrum availability commonly studied in the research include spectrum sensing techniques, databases and control channels [11]. It is likely that different methods will be required in different spectrum bands due to the distinct spectrum sharing conditions resulting from the different systems and regulatory conditions on the bands. Such a heterogeneity in the utilized methods to obtain knowledge of spectrum availability can be exemplified by the spectrum sharing challenges of wireless networks on the so-called TV white spaces [12], where spectrum availability detection is implemented by means of databases with geolocation. By contrast, spectrum sensing is used instead for the detection of primary networks and other coexisting secondary networks.

Despite the substantial amount of work on the individual methods to obtain knowledge of spectrum availability existing in the research literature, the selection of the methods themselves has received so far very scarce attention. This observation gets even more relevant due to the fact that the spectrum sensing related literature is particularly vast, and has originated so far a flurry of sensing methods with different capabilities and requirements (e.g. see [13], [14] and bibliography there included). Optimal spectrum sensing frameworks for optimizing certain parameters of spectrum sensing techniques have been developed in e.g. [15], [16]. However, notwithstanding its operational relevance in future CRSs, the selection of the techniques itself has been set in a lower research priority level. One of the few contributions dealing with the selection of spectrum sensing techniques is [17], where a low-complexity heuristic decision-making system for the selection of methods was proposed aimed at detecting spectrum availability. The approach in [17] was further extended and applied to opportunistic networks in [18], together with a discussion on different spectrum bands for opportunistic networks and a performance evaluation. Another approach for the selection of the spectrum technique was presented in [19], where the sensing technique that can offer the required performance at the lowest SNR while satisfying regulatory requirements was selected.

On the other hand, an inherent capability of the CRS (and, in general, of any cognitive cycle) is the ability to learn from the results obtained [3]. Learning aims at improving the system performance by using stored information of its previous actions and their results [4]. Learning techniques for cognitive systems have been discussed thoroughly in the literature, e.g. [8], [9], [20]. Early work on learning for CRSs [9] included the learning of *where* and *when* other radios will be transmitting. An overview of learning in cognitive systems is presented in [8], where learning of context information and user preferences was used to build knowledge on network capabilities. Likewise, learning in channel selection for CRSs was studied in [20], where the channel selection was done by predicting future idle times in different channels, and by choosing the channel with the longest predicted idle time. Learning was introduced to the system to identify the traffic types on the different channels, and to select the prediction method based on this information. Furthermore, the selection of the spectrum bands could take advantage of the statistical modeling of the spectrum occupancy of different bands as done in [21], where analytical spectrum occupancy models are validated with real-life measurements.

This paper deals with the selection of spectrum for opportunistic networks with cognitive management systems, with a focus on the selection of the methods to obtain knowledge about the current spectrum availability for CRS. Despite its intrinsic technical interest above argued, to the authors knowledge no previous work on the adaptive selection of different spectrum detection methods in opportunistic networks has been reported in the literature. To be concise, the paper presents a novel adaptive decision-making system with a learning mechanism for the selection of spectrum availability detection methods in opportunistic networks. The manuscript builds upon previous research of the authors in [17], [18] by:

1) considering realistic spectrum sharing scenarios for mobile communication systems and specifically, opportunistic networks on different spectrum bands;
2) substantially revising previously proposed decision-making systems for the selection of spectrum sensing methods by refining the underlying assumptions, and extending the system so as to include a new spectrum sensing method; and
3) adding learning capabilities to the decision-making engine.

Computer simulations are run to shed light on the outperforming behavior of the proposed decision-making scheme with respect to traditional fixed spectrum sensing schemes in situations where the operational conditions (i.e. signal-to-noise ratio - SNR, target quality of the detection procedure, speed, complexity and availability of a priori information of the signals to be detected) are dynamic.

The paper is organized as follows: first, opportunistic networks with cognitive management systems and spectrum sharing scenarios for mobile communication systems are described in Section II. The proposed adaptive decision making system with learning capability is introduced in Section III. Section IV shows results of the performance evaluation for the decision making system. Finally, concluding remarks are drawn in Section V.

II. OPPORTUNISTIC NETWORKS AND SPECTRUM SHARING SCENARIOS FOR MOBILE COMMUNICATION SYSTEMS

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

A. Opportunistic Networks with Cognitive Management Systems

Opportunistic networks [22] are temporary, localized network segments that are governed by the radio access network operator, which provides e.g. resources, policies, and knowledge on profiles and context. Opportunistic networks are thus local and temporary coordinated extensions of the mobile communication network infrastructure. Opportunistic networks include cognitive management systems to manage the resource usage and coordinate with the infrastructure. Due to the fact that they are operator-governed, the life cycle of opportunistic networks consists of the following phases [22]: 1) Suitability determination: the operator assesses the convenience of setting up a new opportunistic network by e.g. discovering new nodes and/or finding spectrum opportunities; 2) Creation: a feasible configuration for the opportunistic network is selected including the selection of e.g. participant nodes and spectrum; 3) Maintenance: quality of service (QoS) of the data flows in the opportunistic network are monitored and controlled, and corrective actions are performed on demand to maintain the network operations; and 4) Termination: resources are reallocated when the opportunistic network is released.

Opportunistic networks can be established in different deployment scenarios as discussed in [22]. As an example, the opportunistic network can be established in a situation where a given device cannot connect to the network operators infrastructure due to the lack of coverage or mismatch in the available radio access technologies. In this hypothesized coverage extension situation (graphically depicted in Figure 1), the opportunistic network is established to create a link between the initial device and the infrastructure by using a device that has connection to both. Another example is the opportunistic capacity extension, where a device cannot access the operator infrastructure due to the congestion of the available resources at the serving access node. In this case, the access is redirected through an opportunistic network to avoid the congested network segment. Coverage extension and capacity extension in future mobile communication networks have been considered by using relaying in a number of works, e.g. [23]. Moreover, an opportunistic network could be established in a disaster situation to recover the network operations.

B. Spectrum Bands and Sharing Scenarios for Mobile Communication Systems

Mobile communication systems with opportunistic networks can be established in different types of spectrum bands. In fact, the selection of the spectrum band for the opportunistic network is an important step in the creation of the opportunistic network [5], [6]. An initial discussion on suitable spectrum bands for opportunistic networks was given in [18] and is further elaborated here. Following the Radio Regulations of the ITU-R [24], operator governed opportunistic networks may be established in the following types of spectrum bands:

1) Bands with primary allocation to mobile service;
2) Bands with co-primary allocation to mobile service;
3) Bands with secondary allocation to mobile service; and
4) License-exempt bands.

Table 1 provides an example of different types of spectrum bands for opportunistic networks and their assumed characteristics. Based on the table, it is clear that the opportunistic network will have a different status and thus face a different spectrum sharing scenario depending on the selected spectrum band. For instance, on a band with primary allocation to mobile service (case 1) and written in capitals in Table 1, the operator governs the use of the spectrum band and can internally decide on the resource allocation between the opportunistic network and the normal infrastructure network. The spectrum sharing scenario and the resulting interference scenario are fully controlled by the operator with advanced interference mitigation techniques available in the mobile communication networks. On a band with co-primary allocation to mobile service (case 2), the operator wishing to deploy the opportunistic network has to ensure that other primary users (i.e. other radio communication services) remain free from harmful interference. This is most likely implemented with licensed shared access (LSA) rights and consulting a database. Then, the operator can establish the opportunistic network on the band similarly as in case 1 with primary allocation to mobile. The opportunistic network has a primary status in its area defined by the LSA license and can use its internal control channels to coordinate between the opportunistic network and the infra-structure network.

On a band with secondary allocation to mobile service (case 3) and written in normal characters in Table 1, the opportunistic network has lower priority compared to the primary spectrum user and has to guarantee that the primary user does not suffer from harmful interference from the opportunistic network. The secondary user cannot claim protection from harmful interference from stations of the primary service. Moreover, spectrum sharing between several secondary users, i.e. opportunistic network(s) and others that have secondary spectrum allocation, may yield another problem as they share the same spectrum. An example of this is the TV white space in the 470-790 MHz band where the opportunistic network has to protect the TV broadcasting service and other primary systems and share the spectrum also with other secondary users. In a license-free spectrum band corresponding to case 4, all spectrum users including the opportunistic network can equally access the band but are not protected from harmful interference resulting in an uncontrolled interference conditions. The users have to obey the regulatory constraints set for the use of the band, but in general the constraints only limit e.g. the transmission power levels. Thus, there is a high probability of harmful interference to the opportunistic networks resulting from the other uncoordinated spectrum users.

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

III. PROPOSED ADAPTIVE DECISION-MAKING SYSTEM FOR SELECTION OF METHODS TO OBTAIN KNOWLEDGE OF SPECTRUM AVAILABILITY

For the creation of an opportunistic network on a selected spectrum band, the availability of the spectrum needs to be examined and assessed. To this end, there is a wide range of different techniques to obtain information on the spectrum availability, such as control channels, databases and spectrum sensing techniques [4], each of which features highly different capabilities and requirements. Thus, it is of utmost importance to use a proper method for each situation. To efficiently, autonomously and intelligently implement the selection of such a method, we here present an adaptive decision-making system for the selection of the spectrum availability detection methods in opportunistic networks.

A. General Overview of the Proposed Decision-making System

A general overview of the adaptive decision-making system is presented in Figure 2. First, the spectrum band is selected for the opportunistic network. The next step is to select the proper method to obtain knowledge of spectrum availability for the given spectrum band between the three general classes of spectrum availability detection methods, namely control channels, databases, and spectrum sensing techniques. Depending on the selected spectrum band, different detection methods result to be more appropriate. On bands with primary allocation to mobile service, the operator assigns the resources to the opportunistic network using its internal control channels. There is no need to worry about primary users.

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

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

Finally, on license-exempt bands there is no requirement to use a specific method and the other spectrum users are not requested to inform about their spectrum use. Thus, the remaining way to obtain knowledge of the current spectrum use is to resort to spectrum sensing techniques. The spectrum sensing results can be stored into a database during the operations of the opportunistic network and this information can be used in the future in addition to the instantaneous spectrum sensing results. If spectrum sensing is selected as the spectrum availability detection method, the actual spectrum sensing method needs to be selected next.

B. Rule-based decision-making system for spectrum sensing technique selection

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

1) Considered spectrum sensing techniques and their characteristics: The goal of spectrum sensing is to identify whether a given frequency channel is occupied or vacant by observing the characteristics of the received radio signal. Five different spectrum sensing approaches will be addressed in this manuscript motivated by the presentations in [17]–[19]. The approach presented here does not intend to be exhaustive in terms of the considered spectrum sensing methods, their classification or assumptions, but rather acts as the starting point as these are the only earlier work on the selection of the sensing techniques in the research literature. The first spectrum sensing method considered here, the energy detection, estimates the received signal energy by summing up the energy from the received signal and by comparing the result to a threshold which is determined based on the noise level. Energy detection is simple and fast, and does not require any a priori information; however, it is sensitive to threshold setting and cannot operate at low SNRs. The second of the spectrum sensing techniques considered here, the correlation detection, uses a stored version of the signal type and correlates the received signal with such stored version. The correlation detection has good detection performance and can operate fast but requires a priori information about the signal waveforms to be sensed, though. The third sensing scheme, the feature detection, hinges on the property that modulated signals contain cyclostationary features as opposed to the noise in the channel. These properties inherent to modulated signals can thus be exploited to differentiate the signals from noise. There are various types of feature detection algorithms. Here, we have taken an example feature detection method which calculates the covariance matrix of the received signal vector and based on the characteristics of this matrix, decides on the presence or absence of signal. As such, this detection method does not require a priori information and has better detection performance than energy detection, but at the cost of a higher computational complexity. Note however, that there are also different spectrum sensing algorithms that could fall under the category of feature detection with different characteristics regarding e.g. requirements on a priori information and operational SNR.

Matched filtering, as the fourth considered spectrum sensing method, renders a very good detection performance and fast operations, but it requires a lot of a priori information about the signal types including the precise waveform of the signal to be sensed. It is a coherent detection technique that correlates the unknown received signal with a known signal and compares the result to a threshold. Matched filtering is closely related to correlation detection but is more complex. The implementation of matched filtering is very complex since a separate receiver is needed for each signal type. Thus the requirements and the complexity of the matched filtering are very high. Finally, cooperative spectrum sensing can be used to improve the sensing reliability by performing spectrum sensing at several nodes at the same time and making collaborative decisions on the availability of spectrum. Here we consider cooperative energy detection. Cooperation requires exchange of information between the nodes and thus increases the complexity. Table 2 summarizes different classes of spectrum sensing methods and their assumed characteristics. Note, however, that here the assumed characteristics of the spectrum sensing are quite rough and slightly different from those presented in [17], [18].

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

Different spectrum sensing methods have different ROC curves for a given SNR. The higher the probability of detection for a given probability of false alarm, the more reliable the detection is, which is desirable for cognitive radio operations to protect other systems. On the other hand for a fixed requirement on the probability of detection, the different spectrum sensing methods have different probabilities of false alarm and it is desirable to have lower probability of false alarm offering better system performance as the spectrum availabilities are being wasted less. For instance, there are closed form expressions for the ROC of energy detection in Additive White Gaussian Noise (AWGN) and Rayleigh fading channels (e.g. [25]). With a better sensing technique, it is possible to reduce the probability of false alarm for the same requirement in terms of the probability of detection, yielding an improved overall system performance. Thus, the selection of the proper spectrum sensing method influences the performance of the system.

2) Fuzzy rule-based decision-making system for selection of spectrum sensing techniques: Based on the assumed characteristics of the spectrum sensing methods discussed above, we have developed a simple fuzzy rule-based decision making system for the selection of the spectrum sensing method. The fuzzy decision-making method was first introduced in [17] and later extended and applied to opportunistic networks in [18]. Here, the decision making system has been substantially modified. Some of the assumptions have been changed and a new spectrum sensing method, the matched filtering, has been added. The basic principle of the use of fuzzy decision making has been presented in [17] and [18], which finds its roots on traditional methods from fuzzy logic [26]. Fuzzy logic is particularly attractive for the selection of spectrum sensing techniques as it allows the modeling and processing of very different types of information in a simple and human understandable way. Fuzzy decision making resembles human thinking, allows for fast operations as it does not require iterations, and does not experience unexpected outcomes as they are determined beforehand when building the model. It has been considered to be suitable for compromise-centric decision making with conflicting requirements. The selection of spectrum sensing techniques consists of conflicting requirements and different types of information for the decision making, which lay the basis for a promising application area for fuzzy logic.

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

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

The proposed fuzzy decision-making system has several benefits. It is a one-shot method and does not iterate, thus it operates very fast. Also note that there are no unexpected outcomes from the decision-making system, since all the possible outputs are determined beforehand when the rules are developed. It should be also noted that there are various classifications for spectrum sensing methods and several variants of spectrum sensing methods inside the different classifications with different capabilities. The scope of this manuscript focuses on presenting a very rough classification addressing a limited set of sensing methods, thus addressing the aforementioned variants for future work. However, the fuzzy decision making system is very flexible, and consequently changes in e.g. the underlying assumptions on the spectrum sensing methods are straightforward to be included in the process by simply changing the outputs of the corresponding rules. This allows the decision making system to be easily adjusted to cover different spectrum sensing methods.

3) Inclusion of a learning mechanism: Learning is an important part of the CRS to improve its performance by using stored information of its previous actions and their results [4]. When learning is incorporated to the system, two components are further needed [26]: a process monitor and an adaptation mechanism. The process monitor is a method used for evaluating the performance of the decision-making system in order to find out potential weaknesses, miss-behavior, or potential for improvements. The adaptation mechanism processes information passed by the process monitor so as to update and adapt the decision-making system to changing situations. Figure 4.a illustrates a general learning mechanism based on performance evaluation of the target system and adaptation of the decision making system accordingly. Likewise, Figure 4.b shows an example of how the learning mechanism can be applied to the adaptive decision-making system for spectrum availability detection.

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

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

IV. PERFORMANCE EVALUATION

In order to check the performance of the developed decision-making system, we consider an opportunistic coverage extension scenario where a given device is located out of the coverage of the infrastructure network and, thus, an opportunistic network is created to serve the device (see Figure 1). Here, a device does not have access to the infrastructure network while another device is in the coverage area of the infrastructure base station and provides connectivity to the other device. In this scenario, the devices are assumed to be closely located, and the QoS requirements of the considered application are assumed to be loose. Therefore, we can select a band with low guarantee of protection against interference from other users. The power limits associated with the license-exempt ISM bands can be fulfilled in the given scenario since the nodes of the opportunistic network are closely located. Thus we select the license-exempt ISM band from Table 1, which is free of charge, does not require a license for operations, and can still satisfy the requirements posed by the given application. The most potential method for spectrum availability detection on the ISM band is spectrum sensing. Thus, we will further need to select the spectrum sensing method using the fuzzy decision-making system for the spectrum sensing method selection presented in Section 3.2. At this point it should be pointed out that, to the best of our knowledge, there is no other decision-making system in the research literature to which the performance of our proposed system could be directly compared apart from the present work and our previous research in [17] and [18].

We now inspect the performance of the proposed fuzzy decision-making system for selecting among spectrum sensing methods by assessing the proportions of the different outcomes of the decision making with different input parameter distributions using a similar approach as in [18]. To evaluate the proportions of the different outcomes, we select the rules resulting in a given output from the rule-base and weight the resulting rules with the probabilities of the occurrence of the rules. In addition, we also calculate the success rate of the decision making by comparing it to a situation where the decision-making is not used but a single spectrum sensing method is always used instead. The success is evaluated by evaluating the percentage of occasions where a given sensing technique is applicable with certain input parameter distributions, but may not be the best one at hand.

We consider the four input parameter sets presented in Table 4, where the percentage values represent the proportion of inputs that fall under a given input membership category, (i.e. “low”, “medium” or “high”) depending on the input parameter. The input parameter set 1 describes the situation where all input values are equally likely.

Input parameter sets 2 and 3 describe a typical setting for ISM band where the required probability of detection is low, there is much time available but no a priori information about the other signals. The difference between the input parameter sets 2 and 3 is the assumption on the operational SNR. Input parameter set 2 assumes that in 50% of the occasions the operational SNR is high and 50% low. Input parameter set 3 assumes that in 20% of the occasions the operational SNR is low and 80% high, which means that in this situation the other users are located closer to the opportunistic network than in the input parameter set 2. Finally, input parameter set 4 is modified from input parameter set 2 to reflect a situation where the opportunistic network has operated on the ISM band for some time and stored sensing information to a database and processed this information to extract a priori knowledge of the underlying signals. This knowledge adds up to available a priori information about the signals, and thus the input parameter set for available a priori information has been changed such that in 50% of the occasions there is a "medium" level of a priori information.

Having posed the above scenarios, Table 5 presents the proportions of the outcomes from the decision making with each of such input parameter sets. Specifically, the percentages shown in the table represent how often each of the sensing methods is selected as output from the decision making. The results verify that the selected spectrum sensing methods depend heavily on the input parameter distributions; this fact can be made intuitively clear if the reader notices that the decisions between the different methods are based on a limited number of key input parameters which differ between different spectrum sensing methods.

Table 5 also presents the success rates of the individual spectrum sensing methods with the different input parameter sets. The success rates show the percentage of occasions where each of the sensing methods alone is successful with the given input parameter sets. Therefore, this corresponds to the situation where the spectrum sensing method is kept fixed and the percentage shows how often the fixed sensing method is actually applicable. In fact, the results show that the success rates of the individual spectrum sensing methods are rather low, which means that most of the time, keeping the spectrum sensing method fixed results in failure. The proposed adaptive decision-making system can select the most proper spectrum sensing method for each situation, and thus the opportunities are not wasted compared to keeping the sensing method fixed. The results indicate that the proposed fuzzy decision-making system can improve the success rate significantly. Note that the success rate of "Change channel" is always 100% which is not a desirable situation, since no action is taken but a new channel needs to be selected.

V. CONCLUSIONS AND FUTURE WORK

In this paper we have developed an adaptive decision-making system for the selection of methods to obtain knowledge of spectrum availability for mobile communication systems, which to the authors knowledge is novel in the related literature. The proposed decision-making system has been applied to operator-governed opportunistic networks that are local and temporary extensions of the infrastructure network. They can be established on different types of spectrum bands covering all valid real-life spectrum bands such as bands with primary allocation to mobile service, bands with co-primary allocation to mobile service, bands with secondary allocation to mobile service, and license-exempt bands. The opportunistic network will have a different status depending on the spectrum band resulting in different spectrum sharing scenarios. In bands with primary allocation to mobile, the spectrum decisions are an operator internal problem and interference can be controlled by the operator. In bands with co-primary allocation to mobile, the operator has to ensure that other primary services remain free from harmful interference but has also primary status itself. In bands with secondary allocation to mobile, the opportunistic network has to share the spectrum with primary users as well as other secondary users. In license-free bands, the opportunistic network has to share the spectrum with other equal-priority users and cannot claim protection from harmful interference. Different methods to obtain knowledge of spectrum availability are applicable to different spectrum bands, which is an important facilitator for spectrum sharing of different systems in the same spectrum band but has not been tackled in the research literature in the past.

The developed decision-making system first selects the proper method to obtain knowledge of spectrum availability for the given spectrum band from control channels, databases and spectrum sensing. The decision making system further includes a simple rule-based system for the selection of specific spectrum sensing techniques between matched filtering, correlation detection, feature detection, energy detection and cooperative sensing, provided that spectrum sensing has been selected as the detection method. The decision-making system is further improved by introducing a learning mechanism to the system. The obtained results from computer simulations have shown the performance gains of the proposed approach with respect to fixed spectrum sensing schemes when the operational constraints are particularly dynamic.

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

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TABLE I

EXAMPLE SPECTRUM BANDS FOR OPPORTUNISTIC NETWORKS AND THEIR ASSUMED CHARACTERISTICS.

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

TABLE II

CONSIDERED SPECTRUM SENSING METHODS AND THEIR ASSUMED CHARACTERISTICS.

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

TABLE III

RULEBASE FOR THE SELECTION OF THE SPECTRUM SENSING METHOD.

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

TABLE IV

INPUT PARAMETER SETS FOR THE FUZZY DECISION-MAKING SYSTEM.

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

TABLE V

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

		Input parameter set 1	Input parameter set 2	Input parameter set 3	Input parameter set 4
Energy detection	Proportion of outcomes	16.7%	50%	80%	50%
	Success rate	16.7%	50%	80%	50%
Correlation detection	Proportion of outcomes	44.5%	0%	0%	25%
	Success rate	55.6%	0%	0%	50%
Feature detection	Proportion of outcomes	8.3%	50%	20%	25%
	Success rate	19.5%	50%	20%	25%
Matched filtering	Proportion of outcomes	5.6%	0%	0%	0%
	Success rate	33.4%	0%	0%	0%
Cooperative energy detection	Proportion of outcomes	2.7%	0%	0%	0%
	Success rate	33.3%	50%	80%	50%
Change channel (none of sensing methods is applicable)	Proportion of outcomes	22.2%	0%	0%	0%
	Success rate	100%	100%	100%	100%

PAPER IX

A novel harmony search based spectrum allocation technique for cognitive radio networks

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A Novel Harmony Search based Spectrum Allocation Technique for Cognitive Radio Networks

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***Abstract*—This paper outlines the application of the heuristic Harmony Search (HS) algorithm for efficient spectrum allocation in cognitive radio networks under a minimum Bit Error Rate (BER) criterion. Our proposed algorithm provides a higher degree of diversity in the search process by virtue of its particular improvisation procedure, as opposed to evolutionary computation techniques used so far for this optimization problem. In our work both centralized and distributed implementations of our approach are proposed and detailed. The first set of simulation results made for one single HS instance running over a fixed network show, on one hand, that our approach achieves near-optimum spectral channel assignments at a very low computational complexity. On the other hand, satisfactory results obtained for a distributed implementation of our algorithm pave the way for future research aimed at comparing our approach with avantgarde genetically-inspired spectrum allocation techniques.**

I. INTRODUCTION

In recent years Cognitive Radio (CR) has emerged as a flexible technology to opportunistically adapt to any available spectrum availability. By properly configuring the RF frontend as a function of the prevailing spectrum occupancy, CR-enabled networks allow for an improved spectrum usage with respect to (w.r.t.) traditional non-cognitive approaches. As such, practical CR networks entail optimization problems related to the efficient management of different functionalities. For instance, genetically-inspired multi-objective optimization of throughput, Bit Error Rate (BER) and interference level in point-to-point cognitive radio communications was studied in [1], [2]. Fuzzy logic has also been applied for distributed cooperative spectrum sensing [3], dynamic bandwidth allocation [4], cross-layer design [5] and reconfiguration [6]. Further examples of heuristic resource allocation in cognitive radio systems utilize Particle Swarm Optimization [7] and Simulated Annealing [8].

Specifically, we focus on a CR network where the constituent nodes sense and detect different sets of available spectrum channels. The optimization goal is hence to find the optimum channel allocation that maximizes an overall network performance metric while simultaneously minimizing the amount of interference among nearby nodes. Due to its numerical intractability as the dimensions of the network increase, this optimization problem, usually referred to as *dynamic spectrum allocation*, has been traditionally tackled by means of genetically-inspired optimization approaches (e.g. see [9], [10] and references therein).

In this paper we propose a novel spectrum allocation technique based on the Harmony Search (HS) heuristic algorithm, which hinges on imitating the behavior of a music orchestra in the process of improvising a harmony [11]. This algorithm has been applied on a wide variety of optimization problems (e.g. multicast routing [12] or CDMA detection [13]), for which it has been proven to outperform traditional genetic approaches for high-dimensional scenarios by virtue of its explorative behavior. This manuscript poses the mathematical formulation of the analyzed CR scenario, as well as the spectrum allocation optimization problem under a minimum average Bit Error Rate (BER) approach which, as will be later explained, depends on the amount of interference among nearby nodes. Both preliminary centralized and distributed implementations of our algorithm will be detailed in depth, and extensive Monte Carlo simulation results will assess the near-optimum performance of the proposed allocation scheme for a variety of simulated networks.

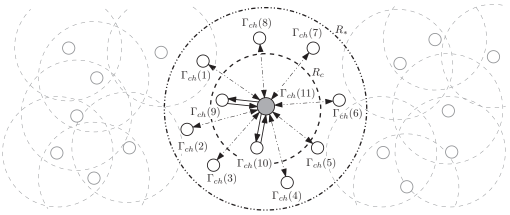

Fig. 1. Cognitive network model, where bold and dash-dotted lines correspond to communication and potentially interfering links, respectively.

The rest of the paper is structured as follows: Section II presents the CR network model adopted in this work, and introduces the underlying spectrum allocation optimization problem. Next, Section III elaborates on the centralized and distributed implementation of the proposed HS allocation

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approach, whereas Section IV discusses the obtained simulation results for several randomly-generated network instances. Finally, Section V concludes the paper by drawing some concluding remarks and future lines of research.

II. SYSTEM MODEL

As depicted in Figure 1, the considered CR network model is composed of N cognitive nodes capable of operating on multiple frequency channels simultaneously. Each node $i = 1, \ldots, N$ senses a subset of locally-available frequency channels $\Gamma_{ch}(i) \subseteq \Gamma_T$, where Γ_T denotes the overall set of channels in which the utilized spectrum band is divided. In this setup every node wants to communicate, as reliably as possible, to any other node located within a circular range R_c [m]. We assume full-duplex communications, i.e. the link from node i to node j may be assigned a different channel than that from j to i. Therefore, every pair of directional links between node i and j may use $\mathcal{H}_{ij}$ possible channels, where $\mathcal{H}_{ij} \triangleq \Gamma_{ch}(i) \cap \Gamma_{ch}(j)$. Besides, any link outgoing from node i interferes with any link incoming at node j if the following two conditions hold: 1) the distance d_{ij} from node i to node j falls within a circular range of radius $R_* \geq R_c$ [m]; and 2) both links use the same frequency channel.

Each radio link undergoes a power loss factor Δ_{ij} proportional to $1/d_{ij}^{\alpha}$, where α denotes the power attenuation exponent. Additive white Gaussian noise with variance σ^2 is also considered at every link. The transmitted power per node $P_t(i)$ is equally split over all outgoing links with different channel assignments. Furthermore, a power penalty loss per link function $0 < \Psi(i,h) \leq 1$ accounts for the number of outgoing links from node i with same channel assignment. Mathematically,

$$P_h(i) = \frac{P_t(i)\Psi(i,h)}{\text{unique}\{h_{ij} : d_{ij} \leq R_c\}}, \tag{1}$$

where $P_h(i)$ stands for the available transmit power per link at node i and channel h, and $\text{unique}\{\cdot\}$ returns the number of different elements in its argument. Finally, nodes will employ uncoded M-QAM modulation with Gray mapping, for which we will adopt the analytical approximation for the Bit Error Rate (BER) derived in [14].

Provided that we have in total ξ communication links, we are interested in finding the optimum ξ-length set of channel assignments $\mathbf{H}^\star$ (i.e. $\mathbf{H}^\star = \{h_{ij}^\star\}$ $\forall i,j$ such that a communication link from i to j exists, with $h_{ij}^\star \in \mathcal{H}_{ij}$) that minimizes the overall Bit Error Rate (BER) averaged over the ξ links. If we denote as $\mathcal{H}^\times$ the Cartesian product of all available channel assignments $\mathcal{H}_{ij}$, then we have

$$\mathbf{H}^\star = \arg\min_{\mathbf{H}\in\mathcal{H}^\times} \frac{1}{\xi} \sum_{h_{ij}\in\mathbf{H}} 0.2 \exp - \frac{1.6 P_{h_{ij}}(i)\Delta_{ij}(M\text{-}1)^{\text{-}1}}{\sigma^2 + \sum\limits_{\substack{k\neq i \\ d_{kj}\leq R_*}} P_{h_{ij}}(k)\Delta_{kj}}, \tag{2}$$

where the denominator in the exponent corresponds to the additive noise variance plus the power from other interfering nodes under the assumption of Gaussian signalling. Observe that, as opposed to previous works (e.g. [9]) where a binary interference model was adopted, we allow for the coexistence of links with same origin but different destination nodes on a given spectrum channel. Based on this rationale, this problem can be regarded as that of optimum spectrum allocation in *underlay* cognitive radio networks. Also note that an exhaustive search over the entire solution space of the optimization rule described in expression (2) would require $|\mathcal{H}^\times|$ metric evaluations.

III. PROPOSED HS SPECTRUM ALLOCATION TECHNIQUE

To efficiently obtain the sought optimum channel assignment $\mathbf{H}^\star$, we propose to apply the aforementioned HS algorithm consisting of a set (harmony memory) of iteratively refined candidate ξ-length channel assignment vectors $\{\mathbf{H}(k)\}_{k=1}^{K}$ (*harmonies*) undergoing intelligent combinations and mutations of their constituent entries $h_{ij}(k)$ (*notes*). Such HS intelligent procedures are controlled by two real-valued parameters θ (*Harmony Memory Considering Rate*, HMCR) and ϑ (*Pitch Adjustment Rate*, PAR), both $\in [0,1]$. On one hand, θ sets the probability that the new value for a certain note $h_{ij}(k)$ belonging to a given harmony $\mathbf{H}(k)$ is drawn from the values of the same note in any of the other $K-1$ harmonies in the harmony memory; otherwise, it is uniformly taken from the corresponding alphabet $\mathcal{H}_{ij}$. On the other hand, ϑ defines the probability that the new value for the note $h_{ij}(k)$ is drawn from its neighboring value in the corresponding alphabet $\mathcal{H}_{ij}$. The successive application of these two procedures produces K new potential candidates at every iteration, which are then evaluated by means of the fitness function in expression (2). Consequently, the harmony memory is updated with those K candidates with best fitness among the K newly generated harmonies via HMCR and PAR, and those K harmonies remaining from the previous iteration. This procedure is iteratively repeated until a fixed number of iterations $\mathcal{T}$ is completed.

The flow diagram describing the operational procedure of the proposed HS algorithm is shown in Figure 2, and comprises 3 sequential steps:

1. **Initialization**: at the first iteration, no *a priori* knowledge on the solution is assumed. Therefore, the entries $h_{ij}(k)$ of $\mathbf{H}(k)$ for $k \in \{1, \ldots, K\}$ are drawn uniformly from the corresponding alphabet $\mathcal{H}_{ij}$. A iteration counter is started, i.e. $t = 1$.
2. **Improvisation**: both the HMCR and PAR processes are sequentially applied to each note $h_{ij}(k)$. As a result, a new set of K improvised harmonies or candidate channel assignments is produced.
3. **Evaluation**: the value of the fitness function in the righthand expression of equation (2) is computed for each newly produced candidate $\mathbf{H}(k)$. Based on such metric values and the K remaining from the previous iteration, the K harmonies with *best* (in this case, lowest) metric value are stored in the harmony memory. If $t < \mathcal{T}$, the algorithm iterates by setting $t = t+1$ and by returning to step 2. Otherwise, the algorithm is halted

and the best channel assignment is given[1] by $\mathbf{H}(1)$.

Furthermore, a perturbation criterium is included in the above iterative procedure to prevent the algorithm from falling in local minima: at every iteration, the algorithm checks whether the best candidate channel assignment has not changed during a certain number $\mathcal{T}_p$ of consecutive iterations. If so, the algorithm randomly resets the $K-1$ harmonies with higher metric. Every time this perturbation technique is applied, $\mathcal{T}_p$ is increased to $\beta\mathcal{T}_p$, where β is a fixed value in the range $\mathbb{R}(1,\infty)$.

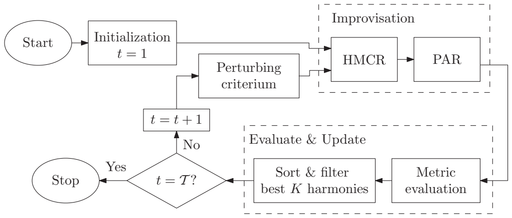

Fig. 2. Flow diagram of the proposed HS algorithm.

In order to enhance the convergence behavior of the proposed algorithm, and inspired by the results in [15], we further consider a linear progressions of the values taken by θ and ϑ along the iterations $t \in \{1,\ldots,\mathcal{T}\}$. Specifically, the value of the HS parameter (either θ or ϑ) increases (or decreases) linearly with the iteration index t. By denoting starting and ending values of the considered parameters with subindexes s and e, respectively, such linear progression is given, for $t=1,\ldots,\mathcal{T}$, by

$$\theta(t)=\theta_s+\frac{\theta_e-\theta_s}{\mathcal{T}-1}(t-1), \qquad (3)$$

where, for the PAR, θ should be replaced by ϑ.

Heretofore we have dealt with the centralized implementation of a spectrum channel allocation scheme. When shifting to its distributed counterpart, we will opt for a so-called *island* approach, where each constituent node of the network executes a separate instance of the HS algorithm (as was adopted in [1] for genetically-inspired allocation techniques). Every $\mathcal{T}_c$ iterations ($1<\mathcal{T}_c<\mathcal{T}$) each sensor sends its best candidate channel assignment to all nodes at distance less than or equal to R_c.

IV. SIMULATION RESULTS

In order to verify the performance of the proposed centralized HS allocation procedure, we have first considered a CR network with $N=25$ nodes randomly deployed over a 1170×1170 [m^2] grid. Communication and interference radius are set to $R_c=250$ and $R_*=500$ [m], respectively. We further assume $|\Gamma_T|=20$ available frequency channels, and each node senses a subset of frequency channels $\Gamma_{ch}(i)$ ($i=1,\ldots,N$) uniformly drawn from Γ_T, where $4\leq|\Gamma_{ch}(i)|\leq11$. This yields 2.8 links per node on average for a total of $\xi=70$ communication links. The modulation order is $M=4$, and the transmission power per node is set to $P_t(i)=1\ \forall i$. The power penalty function $\Psi(i,h)=1/\gamma_h^i$, where γ_h^i denotes the number of outgoing links from i to different destinations with same assigned channel h. Notice that since γ_h^i is updated for every candidate matrix $\mathbf{H}(k)$ ($k=1,\ldots,K$), so is $\Psi(i,h)$ accordingly. It is also important to observe that in this scenario, the number of metric evaluations required by an exhaustive search for the optimum $\mathbf{H}^\star$ is $|\mathcal{H}^\times|\approx4.362\cdot10^{25}$. In what relates to the power loss factor, α is set to 4, and the proportionality constant for Δ_{ij} is chosen so as to yield a mean power loss of 22 dB averaged over a R_c-radius circle. Finally, $\sigma=5\cdot10^{-4}$.

The first set of simulations aims at checking the behavior of the proposed HS algorithm as a function of 1) the value of the parameters $\{\theta,\vartheta\}$ driving the proposed HS algorithm; and 2) the application of a perturbation criteria for avoiding uniformities in the set of iteratively refined $\{\mathbf{H}(k)\}_{k=1}^{K}$. Thus, the harmony memory size is set to $K=20$ candidates, $\mathcal{I}=250$ iterations, and $\{\theta,\vartheta\}$ are either set to a fixed value $\{0.5,0.1\}$, or decreased/increased linearly as shown in expression (3) with $\{\theta_s,\theta_e,\vartheta_s,\vartheta_e\}=\{0.9,0.5,0.01,0.1\}$. As for the perturbing method, $\mathcal{T}_p=10$ and $\beta=2$.

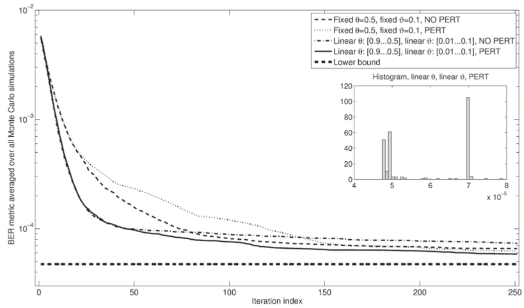

Fig. 3. BER metric versus iteration index averaged over 250 simulations.

Figure 3 depicts the metric from expression (2) versus the iteration index averaged over 250 different executions of the HS algorithm over a network with the above parameters. The bold dashed horizontal asymptote corresponds to the BER metric obtained by running the proposed algorithm over the simulated scenario for $\mathcal{I}=10^5$ iterations. First observe that for either fixed or linear $\{\theta,\vartheta\}$, the HS algorithm gets closer to the minimum metric bound by applying the aforementioned perturbation technique, at the cost of degrading the convergence rate. Also note that the best performance is achieved by imposing a linear progression of $\{\theta,\vartheta\}$ as a function of the iteration index. For this last case, not only the number of metric evaluations is dramatically decreased w.r.t. an exhaustive search ($\sim1.15\cdot10^{-20}$%), but 1 out of the 250 Monte Carlo simulations hit the lower bound with just one HS instance running on the network.

Once the good performance of our approach has been assessed through this first set of results, a similar simulation-

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[1] This implicitly assumes that the K harmonies conforming the harmony memory are always sorted in ascending order of their associated metric.

based study has been carried out over 2 additional networks comprising 20 and 50 CR-enabled nodes. The parameters of such networks – along with those of the previously simulated network – are shown in Table I. Notice that due to the high dimensionality of the solution space (row labeled as $|\mathcal{H}^{\times}|$), the *optimum*[2] metric has been obtained by averaging the best metric rendered by 10 executions of the proposed HS algorithm with linear progression of the parameters after $25 \cdot 10^5$ iterations.

TABLE I
PARAMETERS OF THE 3 SIMULATED COGNITIVE RADIO NETWORKS.

Parameter	$N = 20$	$N = 25$	$N = 50$
$\lvert\Gamma_T\rvert$	15	20	30
$\min\lvert\Gamma_{ch}(i)\rvert$	4	4	6
$\max\lvert\Gamma_{ch}(i)\rvert$	8	10	12
σ	$7.5 \cdot 10^{-4}$	$5 \cdot 10^{-4}$	$2.5 \cdot 10^{-4}$
$\lvert\mathcal{H}^{\times}\rvert$	$1.94 \cdot 10^{23}$	$4.36 \cdot 10^{25}$	$2.293 \cdot 10^{-6}$
Opt. Metric	$2.041 \cdot 10^{-8}$	$4.742 \cdot 10^{-5}$	$2.293 \cdot 10^{-6}$

Table II summarizes the simulation results obtained for these two CR networks. Observe that since HS is basically a random intelligent search method, the metric achieved through iterations in multiple executions of the algorithm over a given network will render a $\mathcal{T}$-dimensional random variable. Consequently, the simulation results must be viewed statistically. Based on this rationale, the table lists, for each simulated scenario, the mean and standard deviation of the metric after $\mathcal{T}$ iterations of the HS algorithm, along with the minimum value taken by this random variable within 100 executions of the algorithm. Having said this, observe that the statistical performance of the HS allocation procedure with linear progression of its parameters dominates the HS allocation procedure with constant value of such parameters. Furthermore, such results are close to the optimum metric in Table I, and are again achieved by means of significantly less metric evaluations than an exhaustive search procedure.

TABLE II
MONTE CARLO NUMERICAL RESULTS FOR CENTRALIZED SPECTRUM ALLOCATION ALGORITHMS.

N	$\mathcal{T}$	Value	HS, constant	HS, linear
20	1000	Mean	$8.896 \cdot 10^{-6}$	$1.154 \cdot 10^{-6}$
		Min	$3.745 \cdot 10^{-7}$	$2.578 \cdot 10^{-8}$
		Std	$7.688 \cdot 10^{-6}$	$1.445 \cdot 10^{-6}$
25	150	Mean	$7.163 \cdot 10^{-5}$	$6.851 \cdot 10^{-5}$
		Min	$4.763 \cdot 10^{-5}$	$4.742 \cdot 10^{-5}$
		Std	$2.925 \cdot 10^{-6}$	$2.755 \cdot 10^{-6}$
50	1500	Mean	$3.65 \cdot 10^{-5}$	$3.988 \cdot 10^{-6}$
		Min	$4.838 \cdot 10^{-6}$	$2.293 \cdot 10^{-6}$
		Std	$2.286 \cdot 10^{-5}$	$5.14 \cdot 10^{-6}$

Finally, a third set of simulations considers the distributed implementation of the proposed HS approach on the aforementioned 25-node CR network with $\mathcal{T} = 150$, $K = 20$ and a broadcasting period equal to $\mathcal{T}_c = 5$. The perturbing method utilized in the centralized implementation of our scheme is no longer needed here, since broadcasting the best candidate among nearby nodes suffices for preventing each distributed HS algorithm to escape from local minima. Therefore, $\mathcal{T}_p$ is set to ∞. With these parameters, the mean, minimum and standard deviation of the metric after $\mathcal{T} = 150$ iterations – averaged over the 25 nodes and 20 executions of the algorithm – result in $\{5.254 \cdot 10^{-5}, 4.96 \cdot 10^{-5}, 2.333 \cdot 10^{-6}\}$ (HS with constant parameters) and $\{5.133 \cdot 10^{-5}, 4.759 \cdot 10^{-5}, 3.215 \cdot 10^{-6}\}$ (HS with linear progression of its parameters).

V. CONCLUSIONS

In this paper we have presented a novel spectrum allocation algorithm for wireless cognitive radio networks based on the HS algorithm. By defining a cognitive radio network model, we have described both centralized and distributed implementations of the HS algorithm specifically tailored for the problem at hand. Besides, a linear progression of the HS parameters have been designed so as to balance between the explorative and exploitative behavior of our approach. Experiments carried out for networks of varying size have verified that the performance of the proposed HS scheme gets close to the optimum solution of the underlying optimization problem at a dramatically lower computational complexity than an exhaustive search procedure. Future research will be conducted towards comparing the performance of the spectrum allocation approach herein presented to that of genetically-inspired schemes.

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[2] We adopt this nomenclature even though in general, heuristics do not guarantee that the best solution will be ever achieved.

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PAPER X

Centralized and distributed spectrum channel assignment in cognitive wireless networks: A Harmony Search approach

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Centralized and distributed spectrum channel assignment in cognitive wireless networks: A Harmony Search approach

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ABSTRACT

This paper gravitates on the spectrum channel allocation problem where each compounding node of a cognitive radio network is assigned a frequency channel for transmission over a given outgoing link, based on optimizing an overall network performance metric dependant on the level of interference among nearby nodes. In this context, genetically inspired algorithms have been extensively used so far for solving this optimization problem in a computationally efficient manner. This work extends previous preliminary research carried out by the authors on the application of the heuristic Harmony Search (HS) algorithm to this scenario by presenting further results and derivations on both HS-based centralized and distributed spectrum allocation techniques. Among such advances, a novel adaptive island-like distributed allocation procedure is presented, which dramatically decreases the transmission rate required for exchanging control traffic among nodes at a quantifiable yet negligible performance penalty. Extensive simulation results executed over networks of increasing size verify, on one hand, that our proposed technique achieves near-optimum spectral channel assignments at a low computational complexity. On the other hand, the obtained results assess that HS vastly outperforms genetically inspired allocation algorithms for the set of simulated scenarios. Finally, the proposed adaptive distributed allocation approach is shown to attain a control traffic bandwidth saving of more than 90% with respect to the naive implementation of a HS-based island allocation procedure.

1. Introduction

Today the mobile telecommunication market is a major business sector and plays a big role in people's everyday life. Wireless communications operate on spectrum bands that are allocated to different services, such as mobile, fixed, broadcast, and satellite. Forecasts for the future mobile telecommunication market [1] predict sharp increases in per-user and aggregate data rates within the time span 2010–2020, resulting in an ever-growing spectrum demand in the future [2]. Thereby, a fundamental problem to be encountered by future wireless systems is where to find suitable carrier frequencies and bandwidths for operation, because most of the spectrum bands are already allocated. New spectrum identifications were made for International Mobile Telecommunication (IMT) systems at the World Radiocommunication Conference (WRC-07) of the International Telecommunication Union Radiocommunication Sector (ITU-R) [2]. However, such spectrum identification happened to be lower than the actual estimated spectrum demand.

In order to satisfy the demand of future wireless services, new advanced spectrum management approaches are urgently needed. Spectrum sharing techniques that allow different systems to coexist on the same scarcely available spectrum band will be important in the development of future wireless systems. As such, cognitive radio techniques have recently emerged by offering huge potential to optimize the spectrum usage. As defined by the ITU-R, a cognitive radio system is able to obtain knowledge of its operational and geographical environment, established policies and its internal state, to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge in order to achieve predefined objectives, and to learn from the obtained results [3]. Thus, cognitive radio systems can be aware of the spectrum use in their surrounding environment, make decisions on the transmission channels according to the channel availability information, and further improve their performance by employing intelligent learning techniques. In this context, we refer as *cognitive radio network* to a network composed of nodes with cognitive radio system capabilities.

In fact, the development of techniques for obtaining knowledge, decision making, and learning in cognitive radio systems is currently a research topic undergoing intense activity within the scientific community. As the operational environment for cognitive

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radio systems is predicted to be highly dynamic and versatile, such techniques need to be applicable to a wide variety of situations and conditions. The time-scales for adaptations in the dynamic and complex operational environment with conflicting requirements will be compressed. As a result, traditional numerical methods might not guarantee attaining optimum solutions to underlying optimization problems in a fast and scalable fashion. Consequently, the design goal becomes to find good enough solutions at a reduced computational complexity.

In order to address this performance-complexity tradeoff in cognitive radio systems, heuristic algorithms have recently attracted great attention, mainly motivated by their experience-based operation methodology and self-learning capabilities that render near-optimum solutions at a significantly reduced computational cost. A plethora of cognitive radio related optimization problems have benefited from the application of heuristic approaches. For instance, in [4,5] genetically inspired evolutionary algorithms have been applied to the simultaneous multi-objective optimization of throughput, Bit Error Rate (BER) and interference level in point-to-point cognitive radio communications. Rate and power allocation in multiuser Orthogonal Frequency Division Multiplexing (OFDM) systems was optimized via a heuristic successive user integration algorithm in [6], which follows a series of previous contributions (e.g. [7,8]) on resource allocation heuristic techniques for this particular OFDM scenario. Fuzzy logic was also proven to be an efficient approach for distributed cooperative spectrum sensing [9], dynamic bandwidth allocation [10], cross-layer design [11] and reconfiguration [12]. Synergy between heuristics and resource allocation in cognitive radio systems is also evidenced by contributions on the application of Particle Swarm Optimization [13] and Simulated Annealing [14] to this communication paradigm.

This manuscript deals with the spectrum channel allocation problem where transmission channels for the links in a cognitive radio network are allotted to each node based on optimizing an overall network performance metric, while simultaneously minimizing the amount of interference among nearby nodes. Given its numerical intractability as the network size increases, this optimization paradigm has been traditionally tackled by means of genetically inspired optimization approaches, e.g. [15,16] and references therein. In line with this specific topic, the authors in [17] sketched a novel spectrum allocation technique based on the Harmony Search (HS) heuristic algorithm, which is based on mimicking the behavior of a music orchestra in their attempt to achieve the best harmony [18]. This algorithm has been lately applied on a wide variety of communication problems (e.g. multicast routing [19], engineering design [20] or CDMA multiuser detection [21,22]), for which it has been proven to outperform traditional genetic approaches. In such a reference a cognitive radio network model was introduced, which allows for additive interference (as opposed to binary-interference models as in [15]). Our preliminary work in [17] also drafted the fundamentals of the herein proposed HS-based allocation procedure, along with computer simulation results corresponding to a reduced set of scenarios. The present manuscript builds upon this previous research by:

- Thoroughly delving into the roots of the HS resource allocation technique first described in [17], where a new single-parametric logarithmic progression of the probabilistic parameters ruling the underlying combinatorial computations of the algorithm is introduced as a novel contribution over this reference.
- Proposing a novel *adaptive* distributed spectrum allocation technique based on a *probabilistic* island approach, along with an analytic indicator quantifying the number of transmitted bits required by such an scheme. This new scheme is shown to significantly decrease the bandwidth required for exchanging information among the nodes, at the cost of a slight degradation in the overall performance of the distributed algorithm.
- Extensively analyzing the convergence behavior of the proposed HS allocation procedure over a *wider* range of simulated scenarios, and by further incorporating, beyond [17]: (1) a simulation-based optimization study on the values of the parameters driving the performance of the algorithm and (2) a statistical performance comparison with its genetically inspired counterpart. Numerical results will verify that our proposed HS-based optimization scheme outperforms genetic approaches, specially when the size of the network increases.

The rest of this manuscript is organized as follows: Section 2 presents the adopted model for our cognitive radio network and poses the spectrum allocation optimization problem, whereas Section 3 elaborates on the centralized and distributed HS heuristic optimization procedure tailored for the problem at hand. Next, Section 4 discusses intensive numerical results obtained for several network instances and finally, Section 5 ends the paper by drawing some concluding remarks and related future research lines.

2. System model

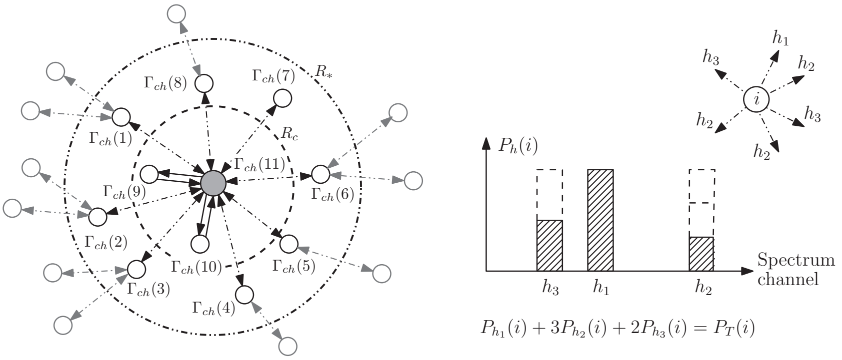
First described in [17], the cognitive radio network model under consideration is depicted in Fig. 1a, which consists of N nodes capable of operating on multiple frequency channels. Each node $i = 1, \ldots, N$ operates on a subset of locally available frequency channels $\Gamma_{ch}(i) \subseteq \Gamma_T$, where Γ_T denotes the set of channels in which the overall spectrum band is divided (with cardinality $|\Gamma_T| \geq |\Gamma_{ch}(i)| \, \forall i$). In this scenario every node wants to communicate to any other node located within a circular range R_c [m] via full-duplex links, i.e. the link from node i to node j may be assigned a different channel h_{ij} than that from j to i. Based on this rationale, every pair of directional links between node i and j may use $\mathcal{H}_{ij} \triangleq \Gamma_{ch}(i) \cap \Gamma_{ch}(j)$ possible spectrum channels, where $h_{ij} \in \mathcal{H}_{ij}$. Furthermore, any link outgoing from node i interferes on any link incoming at node j provided that the following two conditions are simultaneously met: (1) the distance d_{ij} from node i to node j is within a circular range of radius $R_* \geq R_c$ [m] and (2) both links utilize the same frequency channel.

As for the signal propagation through the wireless medium, nodes employ uncoded M-QAM modulation with Gray mapping, for which we will adopt the analytical approximation for the BER derived in [23]. Regarding the transmitted power per node $P(i)$, it is assumed to be linearly split over all different spectrum channels utilized by node i. Besides, a power penalty loss per link function $0 < \Psi(i, h) \leq 1$ accounts for the number of outgoing links from node i with same assigned channel $h \in \Gamma_{ch}(i)$, which will be hereafter denoted as $\xi(i, h)$. Mathematically,

$$P_h(i) = \frac{P(i)\Psi(i, h)}{\text{unique}\{h_{ij} : d_{ij} \leq R_c\}}, \tag{1}$$

where $P_h(i)$ denotes the available transmit power per link at node i and channel h, and unique$\{\cdot\}$ returns the number of different elements within its argument. An illustrative example of this power allocation for $\Psi(i, h) = 1/\xi(i, h)$ is plotted in Fig. 1b. We assume that each radio link is subject to a power loss factor Δ_{ij} proportional to $1/d_{ij}^{\alpha}$, where α denotes the power attenuation exponent. Additive White Gaussian Noise (AWGN) with variance σ^2 is also considered at every link.

If ξ^t stands for the number of communication links existing in the above network model, we are interested in finding the optimum ξ^t-length set of channel assignments $\mathbf{H}^{\star}$ (i.e. $\mathbf{H}^{\star} = \{h_{ij}^{\star}\} \, \forall i, j$ such that a communication link from i to j exists, with $h_{ij}^{\star} \in \mathcal{H}_{ij}$) that minimizes the overall BER averaged over the ξ^t links. By resorting to



(a) (b)

Fig. 1. (a) Signal model assumed for the considered cognitive wireless network. Here, bold and dash-dotted lines stand for communication and potentially interfering links, respectively and (b) example, for a generic node i ($i\in\{1,\ldots,N\}$), of the local power assignment per link given by expression (1).

the analytical BER approximation of [23], this optimization problem can be expressed as

$$\mathbf{H}^\star=\operatorname*{argmin}_{\mathbf{H}\in\mathcal{H}^\times}\frac{1}{\xi t}\sum_{h_{ij}\in\mathbf{H}}0.2\exp\left[-\frac{1.6P_{h_{ij}}(i)\Delta_{ij}(M-1)^{-1}}{\sigma^2+\sum_{\substack{k\neq i\\ d_{kj}\leq R_*}}P_{h_{ij}}(k)\Delta_{kj}}\right],\qquad(2)$$

where the denominator in the exponent corresponds to the additive noise variance plus the power from other interfering nodes under the assumption of Gaussian signalling. Notice that we denote as $\mathcal{H}^\times$ the Cartesian product of all available channel sets per link $\mathcal{H}_{ij}$. Also observe that, as opposed to previous related works (e.g. [15]), we do not adopt a binary interference model, but we allow for the coexistence of links with same origin but different destination nodes on a certain spectrum channel. Having said this, our posed problem can be regarded as that of optimum spectrum allocation in *underlay* cognitive radio networks.

3. Proposed HS heuristic spectrum allocation technique

To efficiently obtain the sought optimum channel assignment $\mathbf{H}^\star$, we propose – as was first done in [17] – to apply the heuristic HS algorithm, which relies on a set of candidates $\{\mathbf{H}(k)\}_{k=1}^{K}$ (harmony memory) for $\mathbf{H}^\star$, which are iteratively refined by means of intelligent combinations and mutations of the constituent channel assignments $h_{ij}(k)$. Following the notation in [18], we will hereafter refer to a possible candidate set $\mathbf{H}(k)$ as *harmony*, whereas *note* denotes any of its compounding entries $h_{ij}(k)$, with $k\in\{1,\ldots,K\}$.

The HS refining procedures are driven by two real-valued parameters, both drawn from the range [0, 1]: (1) the so-called *harmony memory considering rate* θ, which establishes the probability that the new value for a note $h_{ij}(k)$ inside a given harmony $\mathbf{H}(k)$ is taken from the values of the same note from any of the other $K-1$ harmonies in the harmony memory (otherwise it is randomly drawn from the corresponding alphabet $\mathcal{H}_{ij}$) and (2) the *pitch adjustment rate* ϑ, which acts as a fine adjusting rate of the note vocabulary by defining the probability that the new note value for a given note $h_{ij}(k)$ is picked from its neighbor value in the alphabet $\mathcal{H}_{ij}$. The successive application of these two procedures generate a new set of potential K candidates. Based on this new set, the harmony memory is updated whenever any of such K new improvised candidates or *harmonies* at a given iteration sounds *better* (under a certain fitness criterion) than any of the K harmonies remaining from the previous iteration. This procedure iterates until $\mathcal{T}$ attempts or iterations are completed.

In our study we consider three different numerical progressions of the values taken by θ and ϑ, which allow trading explorative for exploitative behavior of the algorithm through the iterations $t\in\{1,\ldots,\mathcal{T}\}$. Namely:

- **Constant**: the HS parameter at hand is kept fixed to a constant value over the iterations of the algorithm, e.g. for the harmony memory considering rate, $\theta(t)=\theta\ \forall t\in\{1,\ldots,\mathcal{T}\}$. This corresponds to the standard implementation of the algorithm.
- **Linear**: as first proposed in [24], in this case the value of the HS parameter increases (or decreases) linearly with the iteration index t. By denoting starting and ending values of the considered parameters with subindexes s and e, respectively, the linear progression of the harmony memory considering rate is given, for $t=1,\ldots,\mathcal{T}$, by

$$\theta(t)=\theta_s+\frac{\theta_e-\theta_s}{\mathcal{T}-1}(t-1),\qquad(3)$$

where, for the pitch adjustment rate, θ should be replaced by ϑ.
- **Logarithmic**: in this third case (novel with respect to [17]), the progression is set logarithmic through an arbitrary factor $\zeta\in\mathbb{R}^+$ that allows for tuning the convexity of the parameter progression in the range $t\in\{1,\ldots,\mathcal{T}\}$. Specifically for the harmony memory considering rate, we set

$$\theta(t)=\theta_s\left[1-\Omega(\theta_s,\theta_e)\left(\frac{\log(t-1)}{\lambda(\theta_s,\theta_e,\zeta)\log(\mathcal{T}-1)}\right)^{\frac{1}{\zeta}}\right]\qquad(4)$$

where

$$\Omega(\theta_s,\theta_e)\triangleq\operatorname{sgn}(\theta_s-\theta_e),\qquad(5)$$

$$\lambda(\theta_s,\theta_e,\zeta)\triangleq\left[\Omega(\theta_s,\theta_e)\left(1-\frac{\theta_e}{\theta_s}\right)\right]^{-\zeta},\qquad(6)$$

and, again, the logarithmic pitch adjustment rate is obtained by rewriting expressions (4) through (6) with ϑ. In the above definitions $\operatorname{sgn}(x)=+1$ if $x\geq 0$ and -1 otherwise. Fig. 2 depicts $\theta(t)$ versus t for $\theta_s=0.9$, $\theta_e=0.5$ and a wide range of values of ζ.

The flow diagram of the centralized version of the HS algorithm is depicted in Fig. 3a, and consists of 3 steps:

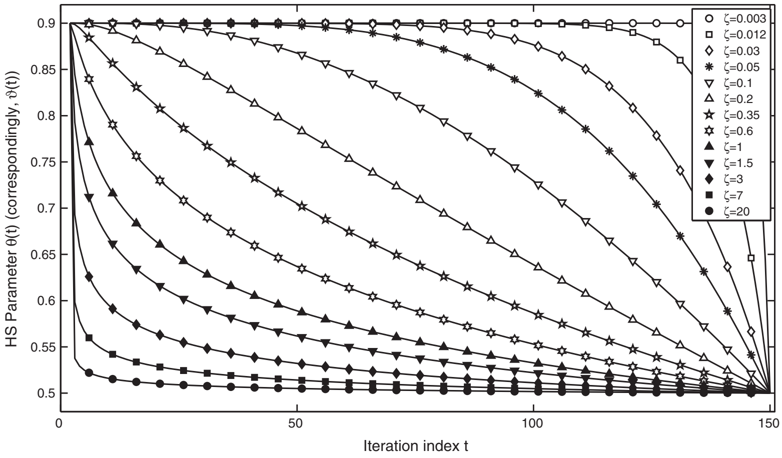
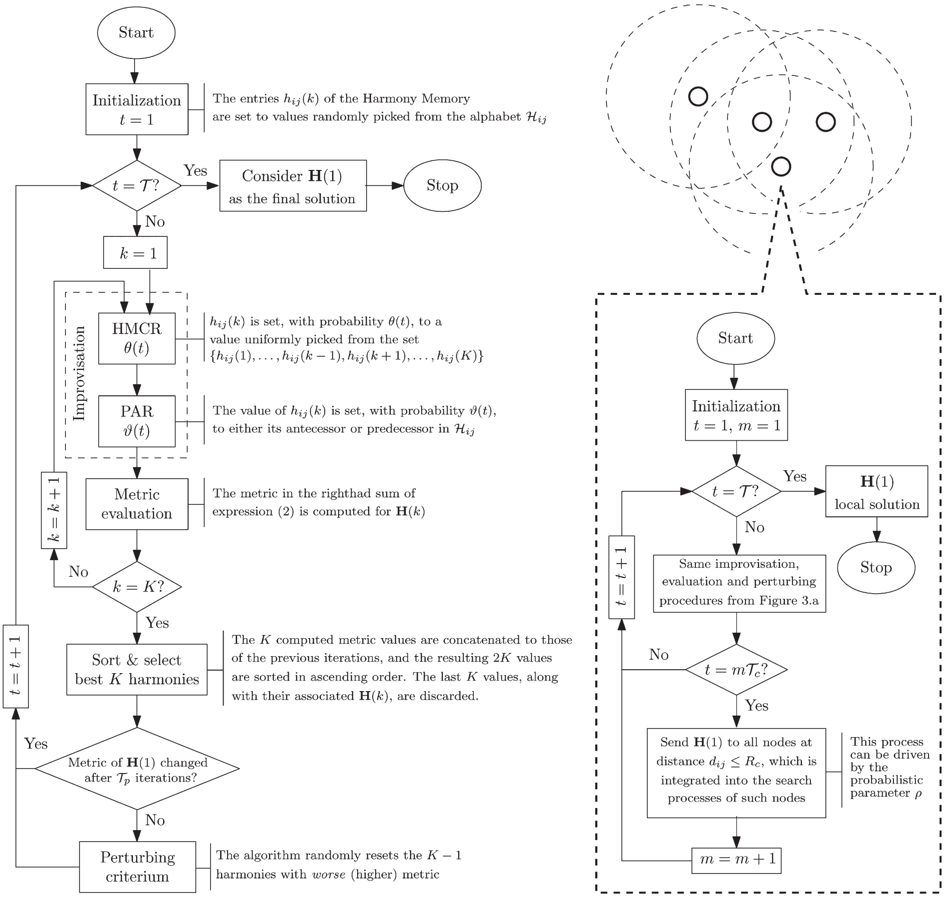


Fig. 2. Logarithmic progression of the HS parameter $\theta(t)$ versus iteration index t for several values of ζ.



(a) (b)

Fig. 3. Flow diagram of (a) the centralized HS algorithm and (b) the distributed HS algorithm. In these figures, t denotes iteration index.

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

B. In the **improvisation** procedure, both the harmony memory considering rate and the pitch adjusting rate (driven by real-valued parameters $\theta(t)$ and $\vartheta(t)$) are sequentially applied to each note $h_{ij}(k)$. As a result, a new set of K improvised harmonies or candidate channel assignments is produced.

C. At each iteration the quality **evaluation** of the improvised harmony memory is made based on the fitness function in the righthand expression of Eq. (2). Based on such metric values and the K remaining from the previous iteration, the K harmonies with *best* (lowest) metric are stored in the harmony memory. If $t < \mathcal{T}$, the algorithm iterates by setting $t = t + 1$ and by returning to step B. Otherwise, the algorithm stops and the best channel assignment is given by $\mathbf{H}(1)$, provided that the K harmonies conforming the harmony memory are arranged in ascending order of their associated metric.

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

3.1. Distributed HS channel allocation scheme

Let us now delve into the distributed implementation of the centralized HS channel allocation procedure, whose flow diagram is illustrated in Fig. 3b. By assuming perfect a priori knowledge of the network parameters (e.g., distances, available channels per link $\mathcal{H}_{ij}$ and noise variance σ^2) at all nodes, we will adopt a so-called *island* approach, where each constituent node of the network executes a separate instance of the HS algorithm (as was adopted in [4] for genetically inspired allocation techniques). Every $\mathcal{T}_c$ iterations ($1 < \mathcal{T}_c < \mathcal{T}$) each node broadcasts its best candidate channel assignment to all nodes at distance less than or equal to R_c. Observe that this approach requires communicating a total of Υ bits over an assumed separate control network, which is given by

$$\Upsilon = \left\lfloor \frac{\mathcal{T}}{\mathcal{T}_c} \right\rfloor \sum_{l=1}^{N} \mathcal{N}(l) \sum_{\substack{i,j \\ d_{ij} \leq R_c}} \log_2 |\mathcal{H}_{ij}| \quad \text{[bits]}, \tag{7}$$

where $\mathcal{N}(l)$ denotes the number of communication links outgoing from node l. In order to reduce the transmission overhead through the control underlay network, an alternate broadcasting approach – novel with respect to [17] – will be also considered by (1) allowing best candidate diffusion only when its metric has changed within the last $\mathcal{T}_c$-length period and (2) by utilizing a novel parameter $\rho \in [0, 1]$ that establishes the probability of disseminating the best candidate harmony through a given link. Section 4 will elaborate on how to optimally set the value of this new probabilistic parameter ρ.

4. Numerical results

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

As explained in Section 2, the set of available frequency bands at a certain node may differ from those at another node in the network. In order to model this diversity of available frequency bands, each node operates on a subset of frequency channels $\Gamma_{ch}(i)$ ($i = 1, \ldots, N$) uniformly drawn from Γ_T, where $\gamma_{ch}^{min} \leq |\Gamma_{ch}(i)| \leq \gamma_{ch}^{max}$. This uniform distribution of available channels at the compounding nodes of the network may reflect worst-case application scenarios where there is no relationship between the physical location of nodes and their set of available frequency channels, e.g. when dealing with spatially uncorrelated colored interferers. Also note that in already existing wireless technologies such as 802.11a, 802.11h or 802.15.4 (in the 2.4 GHz band), the overall number of spectrum channels $|\Gamma_T|$ is fixed to 12, 23 and 16, respectively. However, this work will consider $|\Gamma_T|$ as an additional factor to vary the overall complexity of the simulated scenarios, hence its value will be made arbitrary yet increasing with the size of the network.

Observe that two conditions must be necessarily met in order to enable communication between node i and j: (1) both nodes must be in range of each other, i.e. $d_{ij} \leq R_c$ and (2) they must have at least one available band in common, i.e. $\Gamma_{ch}(i) \cap \Gamma_{ch}(j) \neq$. Once both above conditions are fulfilled, effective communication between nodes will depend on the available power budget $P_h(i)$ for the transmitting node i and channel h, as well as on the number of neighboring nodes sharing band h with such a node. In this context, the transmission power per node equals $P(i) = 1$ $\forall i$. Likewise, the power penalty function $\Psi(i, h)$ is chosen to be $1/\xi(i, h)$, where $\xi(i, h)$ denotes the number of outgoing links from i to different destinations with same assigned channel h. Notice that since $\xi(i, h)$ depends on every generated candidate channel assignment $\mathbf{H}(k)$, so do $\Psi(i, h)$ and $P_h(i)$ accordingly, as expression (1) and Fig. 1b clearly show. This procedure allows for a simple local power allocation method between simultaneous communications held over the same frequency channel at a given node; more sophisticated approaches such as considering power allocation as part of the allocation algorithm are deferred for future research, as indicated in Section 5.

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

As a contribution over our preliminary work in [17], a simulation-based study has been first performed to shed light on the performance of the considered different progression schemes of the parameters ruling the proposed algorithm. Focusing on scenario

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

[2] Due to the high dimensionality of the allocation problem (column $|\mathcal{H}^{\times}|$ in Table 1), we opt to refer to the metric obtained through long simulation as *optimum* metric even though there is no guarantee that the global optimum is asymptotically attained by the proposed heuristics.

Table 1
Parameters of the 7 simulated cognitive radio networks.

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

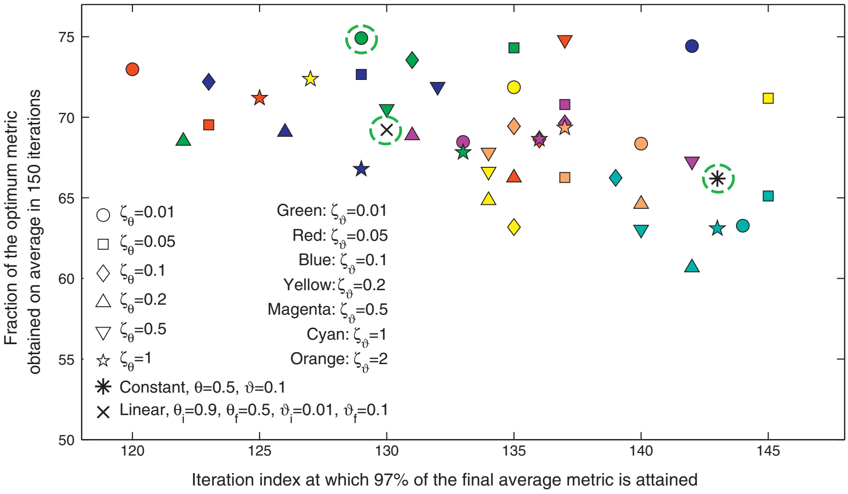

Fig. 4. Results for the simulation-based study of the performance of the *centralized* HS spectrum allocation algorithm. The horizontal axis measures the convergence *speed* of the algorithm (e.g. leftmost points correspond to fast-converging configurations), whereas the vertical axis reflects the accuracy of the utilized algorithm with respect to the optimum metric in Table 1 (bottommost points stand for configurations approaching the optimum metric after 150 iterations). Selected configurations have been circled in dashed light green. (For interpretation of the references to color in the figure caption, the reader is referred to the web version of the article.)

5, Fig. 4 summarizes the results of such study for $K = 20$, $\mathcal{T} = 150$, $\mathcal{T}_p = 10$ and $\beta = 2$. In this plot, the horizontal axis stands for the iteration index where the metric – averaged over 100 executions of the algorithm – is at 97% of the best average metric produced after 150 iterations. In other words, the horizontal axis can be understood as a quantifiable metric of the convergence rate of the allocation procedure at hand. The vertical axis, however, represents the percentage of the optimum metric (rightmost column in Table 1) obtained on average in 150 iterations, i.e. the vertical axis stands for the accuracy of the algorithm with respect to the best achievable value of the metric shown in the righthand part of expression (2). In this plot each marker corresponds to a simulated progression of the HS parameters (constant, linear or logarithmic), as can be read in the included legend. Therefore, markers located in the upper-left part of the plot would belong to *good* configurations of the HS parameter progression (fast convergence rate and produced metric value close to the optimum one), whereas those located in the lower-right area of the plot would correspond to *bad* configurations (slow convergence to metric values far from their optimum). It should also be noted that although the logarithmic case has been simulated for a range of $[\zeta_\theta, \zeta_\vartheta]$ combinations, the values selected for $[\theta, \vartheta] = [0.5, 0.1]$ (constant) and $[\theta_s, \theta_e, \vartheta_s, \vartheta_e] = [0.9, 0.5, 0.01, 0.1]$ (linear and logarithmic) have been chosen based on a separate simulation-based analysis, which is not shown for the sake of brevity.

First observe that the constant progression ($*$) is outperformed, in terms of best balancing the tradeoff between accuracy and convergence rate of the algorithm, by the linear ($\times$) and most of the simulated logarithmic progression cases. Our benchmark will hereafter consider 4 different algorithms: (1) HS with constant parameters $[\theta, \vartheta] = [0.5, 0.1]$; (2) HS with linear parameter progression using $[\theta_s, \theta_e, \vartheta_s, \vartheta_e] = [0.9, 0.5, 0.01, 0.1]$; (3) HS with logarithmic parameter progression given by $[\zeta_\theta, \zeta_\vartheta] = [0.01, 0.01]$ and identical $[\theta_s, \theta_e, \vartheta_s, \vartheta_e]$ as in the linear case; (4) a standard genetic algorithm (GA), which employs[3] a population of 20 *chromosomes* with an elite pool size of 10 individuals, a Roulette–Wheel selection process [25] with an uniform crossover rate [26] of $P_c = 0.7$, and a mutation probability of $P_m = 0.2$. It should be emphasized that to the authors' knowledge, the spectrum allocation problem considered in this paper has so far been tackled mostly by means of genetically inspired approaches [15,16]. For this reason it is fair to compare the performance of the proposed HS allocation procedure with that of the GA technique, which in addition is another contribution of this work over [17]. Furthermore, setting the population size to K ensures a fair comparison in terms of equal number of metric evaluations per iteration.

Having said this, Table 2 lists the Monte Carlo results of the aforementioned 4 algorithms for the 7 simulated scenarios. Observe that since HS hinges on a random albeit intelligent search procedure, the results of multiple executions of the algorithm over a given network must be viewed statistically. In other words, the metric achieved along iterations is a $\mathcal{T}$-dimensional random variable. Consequently, the table includes, for each simulated case and scenario,

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

Table 2
Monte Carlo numerical results for centralized spectrum allocation algorithms.

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

the mean and standard deviation of the random variable corresponding to the metric attained after $\mathcal{T}$ iterations, along with the minimum value taken by this random variable within 100 executions of the algorithm. At this point it is important to remark that a Wilcoxon two-sided rank sum test has been performed over all possible experiment pairs in the listed set of performed experiments. This non-parametric statistical hypothesis test has verified that the medians of all simulated experiments are statistically different to each other with a confidence level of 95%. Notice that as opposed to the conventionally used Student's *t*-test, the Wilcoxon rank sum test does not assume any gaussianity on the distribution of the tested experiments. Consequently, this test provides some analytical insight on the significance of the number of performed simulations without requiring any side assumption on the statistical nature of the samples themselves.

Regarding Table 2, first observe that the HS allocation procedure along with the logarithmic progression of its operational parameters outperforms any other simulated approach in all terms (mean, minimum and standard deviation), specially when the dimensions of the underlying optimization problem (given by $|\mathcal{H}^{\times}|$ in Table 1) increase. Also note that when considering the naive version of both GA and HS algorithms applied to the problem at hand (i.e. by imposing no progression on the parameters governing such heuristics), the dominance of HS over GA still holds for this first centralized scenario. Based on these observations, one can conclude that the proposed centralized HS allocation procedure with logarithmic progression of the parameters is specially suitable for large-scale applications where the number of nodes and/or available spectrum channels is notably high, which is in turn of increasing interest in the related literature [27,28].

The second set of simulations performed in this study considers the distributed implementation of the proposed HS approach with $\mathcal{T} = 150$, $K = 20$ and a broadcasting period equal to $\mathcal{T}_c = 5$. We will concentrate on scenario 5, although the conclusions extracted from this second study have been proven to be extensible to the rest of considered scenarios. Not shown for the sake of clarity, preliminary simulations revealed that the application of the perturbing criteria is no longer needed in the distributed approach of the algorithm, since sharing the best candidate among nearby nodes suffices for each instance of the HS allocation approach to escape from local minima[4]. Therefore, in what follows $\mathcal{T}_p$ will be set to ∞.

Analogously to the previous centralized allocation scheme, we first perform a simulation-based study on the convergence rate and accuracy of different progression schemes of the HS parameters $[\theta(t), \vartheta(t)]$ in this distributed allocation setup. The lower and upper limits are set as before, i.e. $[\theta, \vartheta] = [0.5, 0.1]$ (constant) and $[\theta_s, \theta_e, \vartheta_s, \vartheta_e] = [0.9, 0.5, 0.01, 0.1]$ (linear and logarithmic). The results are depicted in Fig. 5, for which the best metric attained after $\mathcal{T}$ iterations has been averaged over all nodes existing in the network and 20 different executions of the algorithm. First observe that as expected, the convergence of the distributed configurations (represented in the horizontal axis) is in general faster than its centralized counterparts. Also note that a higher percentage of the optimum metric is achieved by virtue of the collaborative operation of the island-like HS allocation algorithm. The best performance – again, in what relates to the tradeoff between accuracy and convergence speed – is obtained by imposing a logarithmic progression of the HS parameters, with $[\zeta_\theta, \zeta_\vartheta] = [1, 0.01]$.

Based on these results, finally Fig. 6 depicts the value of the metric in expression (2) along iterations, averaged over all the compounding nodes and 20 executions of the HS allocation algorithm on scenario 5. The plot includes results for (1) a genetically inspired island-like distributed spectrum allocation approach with simulation-based optimized crossover and mutation rates $[P_c, P_m] = [0.7, 0.2]$ (red); (2) HS allocation approach with constant (green), linear (blue) and logarithmic (magenta) progression of the parameters; and (3) HS with logarithmic progression of the parameters, but incorporating the aforementioned probability ρ of disseminating the best candidate harmony through any outgoing link (brown). To properly set its value, one should intuitively infer that nodes with low number of communication links should have a high probability of broadcasting their best candidate vector in order to effectively enhance the overall performance of the

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

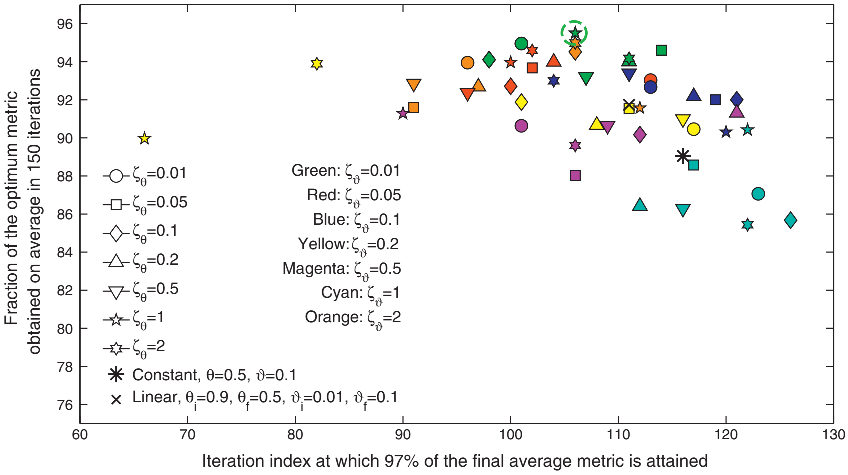

Fig. 5. Results for the simulation-based study of the performance of the *distributed* HS spectrum allocation algorithm. As in Fig. 4, the horizontal axis quantifies the convergence *speed* of the algorithm, whereas the vertical axis reflects its accuracy. The selected configuration has been circled in dashed light green. (For interpretation of the references to color in the figure caption, the reader is referred to the web version of the article.)

network. Based on this rationale, in our simulations ρ is adaptively set, for each node $l \in \{1, \ldots, N\}$ satisfying $\mathcal{N}(l) > 0$, as

$$\rho \triangleq \rho(l) = \frac{1}{1+\mathcal{N}(l)}, \tag{8}$$

where as defined before, $\mathcal{N}(l)$ denotes the number of communication links outgoing from node l. Also included are in the legend the mean, minimum average metric and standard deviation of the random variable representing the value of the metric after $\mathcal{T} = 150$ iterations. First observe that despite its faster convergence rate, the GA based distributed allocation procedure is statistically outperformed by the results corresponding to any of its HS counterparts, which may due to the more explorative behavior of the former. Also observe that by inserting the adaptive probability $\rho(l)$, the mean, minimum metric and the standard deviation after $\mathcal{T}$ iterations is still kept below those of the GA approach. On the other hand, for this simulated scenario the average number Υ of broadcasted bits defined in expression (7) is decreased from 178.863×10^3 (no adaptive probability or, equivalently, $\rho(l) = 1\ \forall l$) to 11.498×10^3 average bits per execution of the algorithm. Consequently, a control traffic saving of 93.572% is obtained at a slight performance degradation, which nevertheless keeps the statistical performance metrics below those of the GA approach used heretofore. This last result is particularly interesting for applications characterized by underlay control networks with stringently constrained communication resources, as well as for cases where it is imperative to reduce the data processing at the node to its minimum (e.g. wireless sensor networks).

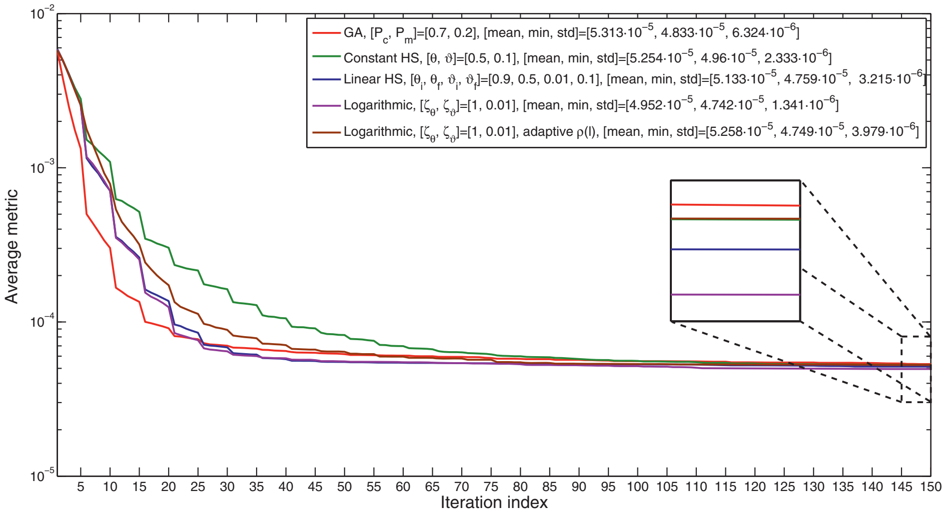

Fig. 6. Average metric versus iteration index of the *distributed* (island) spectrum allocation algorithm for GA, HS with distinct progression of its parameters, and the adaptive probability $\rho(l)$ defined in expression (8).

5. Concluding remarks and future research lines

In this paper we have presented novel technical advances and results built upon our preliminary work in [17] on a novel spectrum allocation algorithm for wireless cognitive radio networks based on the Harmony Search (HS) algorithm. Specifically, the manuscript has thoroughly described both centralized and distributed implementations of the HS algorithm specifically tailored for the problem at hand. An emphasis is placed on (1) a novel single-parametric logarithmic progression of the parameters driving the algorithm, which allows balancing the tradeoff between the explorative and exploitative behavior of the heuristic allocation procedure; and (2) a novel adaptive probabilistic distributed allocation technique that permits to alleviate the amount of exchanged control traffic required between nearby nodes. This work has also compared the performance of this HS-based algorithm with that of its genetic counterpart, the latter having been shown to be outperformed by the first when simulated over networks of increasing size. As for the proposed distributed allocation technique, further simulation results verify that huge control traffic savings are obtained by virtue of our novel adaptive probabilistic procedure, at a negligible performance degradation with respect to a conventional island-like scheme.

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

- The PAR probabilistic operator in its definition here formulated (see Section 3) essentially embodies a random perturbation technique, since there is no criteria imposed on the alphabet of the underlying set of channels so as to claim that when applied, the PAR process leads to a candidate solution with better fitness value. Although this PAR operator suffices for escaping from local minima, the overall convergence of the allocation algorithm can be boosted if the PAR process is supplied with information on the already allocated resources (e.g. locally available frequency channels and/or power distribution), and redesigned accordingly.
- In reference to the linear power penalty function $\Psi(i, h)$, we foresee to incorporate the power allocated to each outgoing link over a certain spectrum channel as another optimization parameter of the proposed allocation procedure. By jointly optimizing power and channel allocation one may further enhance the error rate performance of the setup for a given overall power budget $\sum_{i=1}^{N} P(i)$. However, this optimization problem requires specific local search procedures whose design and application to the distributed spectrum allocation problem is currently under investigation.
- The proposed distributed implementation of the algorithm assumes a dedicated underlay control network that allows for the error-free exchange of allocation information between neighboring nodes. In practice, overlay control networks are rather preferred due to the optimized sharing of communication resources. In this context, we are currently analyzing and deriving extensions of this work to the joint dynamic spectrum allocation of both control and data networks based on HS heuristics, along with techniques to address the higher priority of control traffic in such an allocation.

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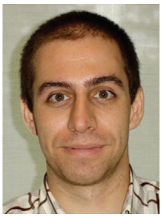

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Title	**Spectrum sharing using cognitive radio system capabilities** **Methods to obtain and exploit knowledge of spectrum availability**
Author(s)	Marja Matinmikko
Abstract	This thesis presents methods to obtain and exploit knowledge of spectrum availability for cognitive radio systems (CRSs). CRSs can change the way to access the radio spectrum in response to the growing data rate and spectrum demand of the future mobile telecommunication market. A CRS includes capabilities to obtain knowledge of system internal and external state, dynamically and autonomously adjust its operations accordingly, and learn from the results. Future CRSs can enhance spectrum sharing by exploiting temporarily and locally available spectrum while guaranteeing that primary systems remain free from harmful interference. This thesis presents novel directional and distributed spectrum occupancy measurements for the 2.4 GHz industrial, scientific and medical (ISM) band to characterise the current spectrum use and the potential availability of spectrum for CRSs, taking into account the spatial dimension. This is the first study to show that the spectrum occupancy can vary significantly depending on the measurement location even in the same office area at the same time. Knowledge of spectrum availability for CRSs can be accomplished by several methods, including control channels, databases, and spectrum sensing techniques, which all have different capabilities, requirements and performances. In order to use proper methods in different situations, this thesis proposes a novel band-specific approach, where the selection of the method to obtain knowledge of spectrum availability is determined separately for each frequency band based on the deployment characteristics and regulatory requirements of the specific band. Spectrum sensing is studied in more detail by presenting analytical performance evaluation for a selected algorithm, Welch’s periodogram, in a Rayleigh fading channel. Fuzzy combining is proposed for cooperative spectrum sensing, where the sensing results from several nodes are combined to improve the sensing reliability in a fading environment. In addition, a novel rule-based decision-making system with a learning mechanism is developed for the selection between different spectrum sensing techniques.This is the first work in the research literature to consider this problem. Finally, in order to exploit the spectrum and assign the available frequency channels to the different users, this thesis presents centralised and distributed channel assignment methods based on a heuristic harmony search algorithm. The presented results can be used in the development of future mobile communication systems enhanced with CRS capabilities to respond to the growing data rate and spectrum demand.
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Julkaisun sarja ja numero
VTT Science 20

Nimeke	**Taajuuksien yhteiskäyttö kognitiivisten radiotekniikoiden avulla** **Menetelmiä taajuuksien saatavuuden selvittämiseen ja hyödyntämiseen**
Tekijä(t)	Marja Matinmikko
Tiivistelmä	Tämä työ esittelee menetelmiä, joilla voidaan selvittää ja hyödyntää tietoa taajuuksien saatavuudesta kognitiivisille radiojärjestelmille. Kognitiiviset radiojärjestelmät voivat muuttaa merkittävästi taajuuksien käyttötapaa vastauksena tulevaisuuden matkaviestintämarkkinan kasvavaan datanopeuksien ja taajuuksien tarpeeseen. Kognitiiviset radiojärjestelmät kykenevät saamaan tietoa järjestelmän sisäisestä ja ulkoisesta tilasta, mukauttamaan dynaamisesti ja autonomisesti toimintaansa kerätyn tiedon perusteella sekä oppimaan saavutetuista tuloksista. Tulevaisuuden kognitiiviset radiojärjestelmät tehostavat taajuuksien yhteiskäyttöä hyödyntämällä hetkellisesti ja paikallisesti vapaina olevia taajuuksia aiheuttamatta alkuperäisille käyttäjille haitallista häiriötä. Tutkimus esittelee uusia suuntaavia ja hajautettuja taajuuksien käyttöasteen mittauksia 2.4 GHz:n ISM-taajuudella huomioiden tilasuunnan vaikutuksen. Tämä on ensimmäinen tutkimus, joka osoittaa, että taajuuksien käyttöaste voi vaihdella huomattavasti eri paikoissa samalla hetkellä jopa saman toimistotilan sisällä. Tietoa taajuuksien saatavuudesta kognitivisille radiojärjestelmille voidaan saada usealla tavalla, esimerkiksi kontrollikanavien, tietokantojen ja taajuuksien sensorointitekniikoiden avulla. Menetelmillä on erilaiset ominaisuudet, vaatimukset ja suorituskyvyt. Jotta käytettäisiin sopivia menetelmiä eri tilanteissa, tutkimus ehdottaa uutta taajuuskaistakohtaista lähestymistapaa, jossa menetelmä valitaan kullekin taajuusalueelle riippuen sen käyttötavasta sekä reguloinnin vaatimuksista. Taajuuksien sensorointia tutkitaan tarkemmin ja esitetään suorituskykyanalyysiä yhdelle algoritmille (Welchin periodogrammi) Rayleigh-häipyvässä kanavassa. Sumeaa yhdistelyä ehdotetaan yhteistyössä tapahtuvaan taajuuksien sensorointiin, jossa usean tahon mittaustulokset yhdistetään, jolloin saadaan parempi suorituskyky häipyvässä ympäristössä. Lisäksi työssä esitetään uusi sääntöpohjainen päätöksentekomenetelmä taajuuksien sensorointitekniikoiden valintaan sisältäen oppimismekanismin. Ehdotettu menetelmä on ensimmäinen kirjallisuudessa esitetty menetelmä sensorointitekniikoiden valintaan. Työssä esitetään lisäksi keskitetty ja hajautettu kanavien jakomenetelmä vapaiden taajuuksien hyödyntämiseen ja jakamiseen eri käyttäjien kesken perustuen harmony search -algoritmiin. Esitettyjä tuloksia voidaan hyödyntää tulevaisuuden matkaviestintäjärjestelmien kehityksessä tuomalla niihin mukaan kogniivisia radiotekniikoita vastauksena kasvaviin datanopeus- ja taajuusvaatimuksiin.
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Spectrum sharing using cognitive radio system capabilities

This thesis presents methods to obtain and exploit knowledge of spectrum availability for cognitive radio systems (CRSs). CRSs can change the way to access the radio spectrum in response to the growing data rate and spectrum demand of the future mobile telecommunication market. Future CRSs can enhance spectrum sharing by exploiting temporarily and locally available spectrum while guaranteeing that primary systems remain free from harmful interference.

This thesis presents novel directional and distributed spectrum occupancy measurements to characterise the current spectrum use and the potential availability of spectrum for CRSs, taking into account the spatial dimension. The thesis proposes a band-specific approach where the selection of the method to obtain knowledge of spectrum availability between spectrum sensing, databases and control channels is determined separately for each frequency band based on the deployment characteristics and regulatory requirements of the specific band. Spectrum sensing is studied in more detail by presenting analytical performance evaluation. In addition, a novel fuzzy rule-based decision-making system with a learning mechanism is developed for the selection between different spectrum sensing techniques. Finally, this thesis presents centralised and distributed channel assignment methods based on a heuristic harmony search algorithm to assign the available frequency channels to the different users.

The developed generic framework for obtaining knowledge of spectrum availability for CRS is applicable to different frequency bands and wireless systems. In particular, the results can be applied to future mobile communication systems by introducing CRS capabilities to respond to the growing data rate demand.

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