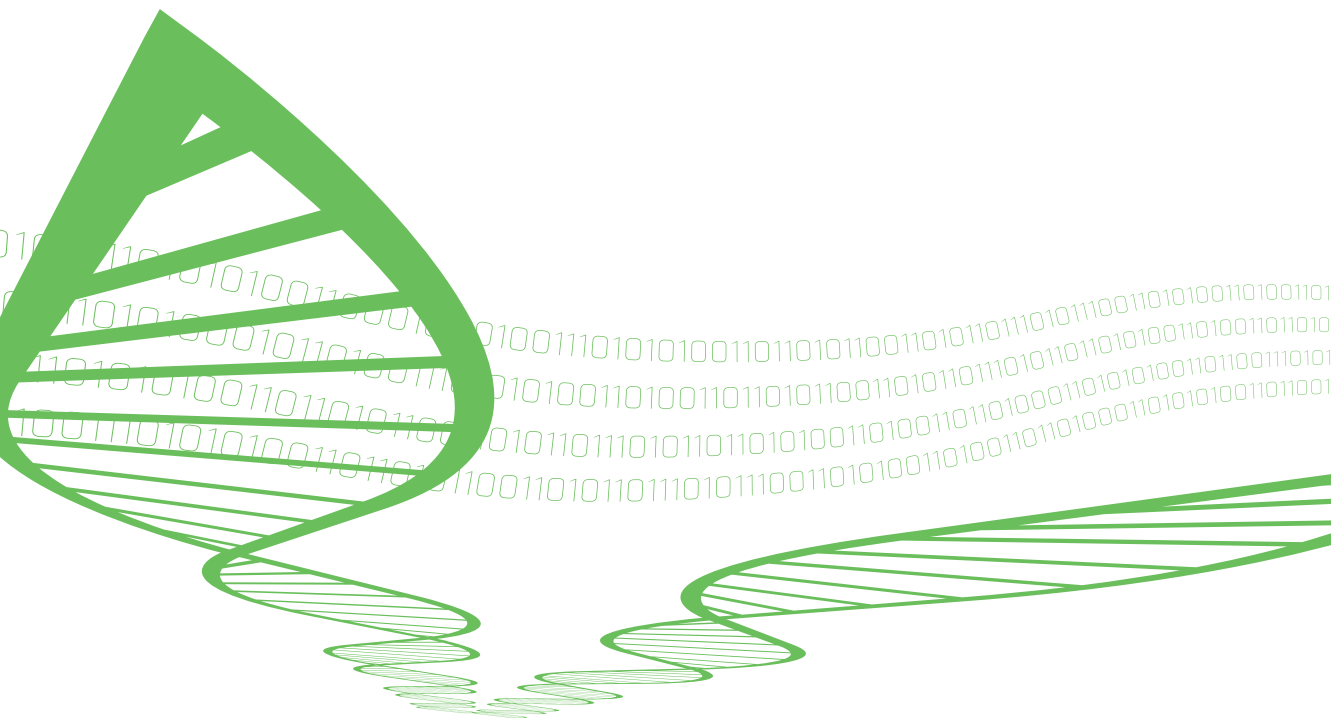# Adaptive power and frequency allocation strategies in cognitive radio systems

Marko Höyhtyä

VTT

# Adaptive power and frequency allocation strategies in cognitive radio systems

Marko Höyhtyä

*Thesis for the degree of Doctor of Science to be presented with due permission for public examination and criticism in OP-Sali (Auditorium L10) Linnanmaa, at the University of Oulu, on the 12th of September at 12 o'clock noon.*

**V̇TT**

**Adaptive power and frequency allocation strategies in cognitive radio systems**

# Abstract

This doctoral thesis comprises a summary of novel results considering (1) channel selection in a cognitive radio system (CRS) using history information and (2) power allocation in a selected frequency band assuming a fading channel. Both can be seen as methods to manage interference between in-system users as well as to the users of other systems operating in the same geographical area and frequency band. Realization of CRSs that are using various methods to obtain information about environment and making intelligent decisions based on that information requires the use of adaptive transmission. Adaptive techniques proposed in this thesis enable efficient operation of CRSs in varying radio environment.

History information and learning are essential factors to consider in the CRS design. Intelligent use of history information affects throughput, collisions and delays since it helps to guide the sensing and channel selection processes. In contrast to majority of approaches presented in the literature, this thesis proposes a classification-based prediction method that is not restricted to a certain type of traffic. Instead, it is a general method that is applicable to a variety of traffic classes. The work develops an optimal prediction rule for deterministic traffic pattern and maximum likelihood prediction rule for exponentially distributed traffic patterns for finding channels offering the longest idle periods for secondary operation. Series of simulations were conducted to show the general applicability of the rule to a variety of traffic models. In addition, the thesis develops a method for traffic pattern classification in predictive channel selection. Classification-based prediction is shown to increase the throughput and reduce the number of collisions with the primary user up to 70% compared to the predictive system operating without classification.

In terms of the power allocation work, the thesis defines the transmission power limit for secondary users as a function of the detection threshold of a spectrum sensor as well as investigates theoretical water-filling and truncated inverse power control methods. The methods have been optimized using rational decision theory concepts. The main focus has been on the development and performance comparison of practical inverse power control methods for constant data rate applications. One of the key achievements of the work is the development of the filtered-x LMS (FxLMS) algorithm based power control. It can be seen as a generalized inverse control to be used in power control research, giving a unified framework to several existing algorithms as well.

**Keywords**     dynamic spectrum access, prediction, closed-loop method

**Adaptiiviset tehon ja taajuuden allokoinnin strategiat kognitiivisissa radiojärjestelmissä**

# Tiivistelmä

Tämä väitöskirja sisältää yhteenvedon tuloksista koskien 1) historiatietoa käyttävää kanavanvalintaa kognitiiviradiojärjestelmässä ja 2) tehon allokointia valitulla taajuuskanavalla häipyvässä kanavassa. Molemmat menetelmät auttavat häiriönhallinnassa sekä järjestelmän omien käyttäjien välillä että muiden samalla alueella toimivien järjestelmien suhteen. Ympäristötietoa useilla eri menetelmillä keräävien ja tämän tiedon mukaan älykkäitä päätöksiä tekevien kognitiiviradiojärjestelmien toteuttaminen vaatii adaptiivisten lähetystekniikoiden käyttöä. Väitöskirjassa ehdotettujen adaptiivisten menetelmien käyttö mahdollistaa kognitiiviradiojärjestelmien tehokkaan toiminnan vaihtuvassa radioympäristössä.

Historiatiedot ja oppiminen ovat olennaisia kognitiiviradiojärjestelmän suunnittelussa huomioitavia asioita. Älykäs historiatietojen käyttö vaikuttaa kapasiteettiin, törmäyksiin ja viiveisiin, koska se auttaa ohjaamaan sensorointia ja kanavanvalintaprosessia. Toisin kuin valtaosa kirjallisuuden menetelmistä, väitöskirja ehdottaa luokitteluun perustuvaa menetelmää, joka ei rajoitu tiettyyn liikennemalliin. Ehdotettu menetelmä on yleinen ja toimii useiden liikenneluokkien kanssa. Työssä on kehitetty optimaalinen ennustussääntö deterministiselle liikenteelle ja suurimman uskottavuuden estimaatti eksponentiaalisesti jakautuneelle liikenteelle, kun tavoitteena on löytää lähetyskanavat, jotka tarjoavat mahdollisimman pitkät vapaat ajat sekundääristä käyttöä varten. Väitöskirja osoittaa simulointien avulla sääntöjen soveltuvan myös muille malleille. Lisäksi työssä on kehitetty luokittelumenetelmä liikennemalleille ja osoitettu luokitteluun perustuvan ennustavan kanavanvalinnan lisäävän kapasiteettia ja vähentävän törmäyksiä primäärisen käyttäjän kanssa jopa 70 % verrattuna luokittelemattomaan ennustavaan kanavanvalintaan.

Tehoallokointityössä on määritelty lähetystehorajoja sekundäärisille käyttäjille spektrin sensoroinnin ilmaisukynnyksen funktiona ja tutkittu teoreettista täyttömenetelmää ja katkaistua kanavainversiomenetelmää. Menetelmiä on optimoitu käyttäen rationaalista päätösteoriaa. Pääfokus tehonsäätötyössä on ollut käytännöllisten vakiodatanopeutta käyttävien inverssimenetelmien kehittämisessä ja suorituskykyvertailuissa. Yksi väitöskirjatyön pääsaavutuksista on ollut FxLMS-algoritmiin perustuvan tehonsäätömenetelmän kehittäminen. Sen voi katsoa olevan yleinen inverssisäätöalgoritmi, jonka erikoistapauksina saadaan määriteltyä monet käytännölliset algoritmit.

# Preface

The research for this thesis was conducted at the Communications Platform knowledge center of the VTT Technical Research Centre of Finland in Oulu, Finland in the years 2006–2013. The work was also carried out at the Berkeley Wireless Research Center (BWRC), California, USA from February 2007 to February 2008. The supervisors of this thesis are Research Professor Aarne Mämmelä from VTT and Prof. Jari Iinatti from the University of Oulu.

First, I would like to thank Mr. Kyösti Rautiola, Mr. Markku Kiviranta, Mr. Pertti Järvensivu, and Dr. Jussi Paakkari for their trust in letting me pursue the research in directions I have found promising and personally appealing. I have had freedom to balance my working time between my project management duties, project preparations and research work. The administrative support of Jaana Aarnikare is acknowledged with gratitude. I am grateful to Mr. Gary Kelson for the opportunity to work at BWRC. Cooperation with Dr. Sofie Pollin, Dr. Danijela Cabric, and Prof. Anant Sahai gave me a much wider view of the area of cognitive radio systems and helped me in focusing my research in the right direction.

When I started to do this research, cognitive radio was a rather recently found topic that started to emerge strongly only after Haykin published his seminal paper in 2005. We started the first CR project at VTT in 2006, in which I concentrated on adaptive power control problems as a natural continuation of the M.Sc. thesis work I had finished in 2005. Later, after gaining more knowledge and having fruitful discussions with Dr. Pollin during the Berkeley visit, I decided to start investigating predictive channel selection methods in parallel with power control research. I received good feedback both from academia and from industry people on this topic from the beginning, which convinced me to continue my efforts over several years.

The research work has mostly been performed during three projects funded by Tekes – the Finnish Funding Agency for Innovation (CHESS in 2006–2008, COGNAC in 2008–2011, SANTA CLOUDS in 2011–2013). The work has also been supported by the RATIONALE project, funded by the Scientific Advisory Board for Defence (Matine) in 2009–2011, the SMAS project, funded by Academy of Finland in 2011, the ACROSS project, funded by the European Space Agency in 2011–2012, and the GLOBALRF project in 2014, funded by Tekes. In addition to the above-mentioned research projects, I have been privileged to obtain financial support in the form of personal grants from the Jenny and Antti Wihuri Foundation,

# Academic dissertation

# List of publications

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

I     M. Höyhtyä and A. Mämmelä, "Adaptive inverse power control using an FxLMS algorithm," in *Proc. IEEE Vehicular Technology Conference* (*VTC Spring*), pp. 3021–3025, April 2007. ISBN: 1-4244-0266-2.

II    A. Mämmelä, A. Kotelba, M. Höyhtyä, and D. P. Taylor, "Relationship of average transmitted and received energies in adaptive transmission," *IEEE Transactions on Vehicular Technology*, vol. 59, pp. 1257–1268, March 2010. ISSN: 0018-9545.

III   M. Höyhtyä, A. Kotelba, and A. Mämmelä, "Practical adaptive transmission with respect to rational decision theory," in *Proc. IEEE Vehicular Technology Conference* (*VTC Spring*), pp. 1–5, May 2011. ISBN: 978-1-4244-8332-7.

IV   M. Höyhtyä, A. Sahai, D. Cabric, and A. Mämmelä, "Energy efficient inverse power control for a cognitive radio link," in *Proc. International Conference on Cognitive Radio Oriented Wireless Networks and Communications* (*CrownCom*), pp. 264–271, August 2007. ISBN: 978-1-4244-0814-6.

V    M. Höyhtyä, T. Chen, and A. Mämmelä, "Interference management in frequency, time, and space domains for cognitive radios," in *Proc. IEEE Wireless Telecommunications Symposium* (*WTS*), pp. 1–7, April 2009. ISBN: 978-1-4244-2588-4.

VI   M. Höyhtyä, "Secondary terrestrial use of broadcasting satellite services below 3 GHz," *International Journal of Wireless & Mobile Networks*, vol. 5, pp. 1–14, February 2013. ISSN: 0975-4679.

VII  M. Höyhtyä and A. Mämmelä, "Adaptive inverse power control using the modified filtered-x least mean square algorithm," *Journal manuscript* (submitted for review).

VIII    M. Höyhtyä, S. Pollin, and A. Mämmelä, "Performance improvement with predictive channel selection for cognitive radios," in *Proc. International Workshop on Cognitive Radio and Advanced Spectrum Management* (*CogART*), pp. 23–27, February 2008. ISBN: 978-1-4244-2139-8.

IX    M. Höyhtyä, S. Pollin, and A. Mämmelä, "Classification-based predictive channel selection for cognitive radios," in *Proc. IEEE International Conference on Communications* (*ICC*), pp. 1–6, May 2010. ISBN: 978-1-4244-6402-9.

X    M. Höyhtyä, J. Vartiainen, H. Sarvanko, and A. Mämmelä, "Combination of short term and long term database for cognitive radio resource management," *Invited paper*, in *Proc. International Symposium on Applied Sciences in Biomedical and Communication Technologies* (*ISABEL*)*,* pp. 1–5, November 2010*.* ISBN: 978-1-4244-8131-6.

XI    M. Höyhtyä, S. Pollin, and A. Mämmelä, "Improving the performance of cognitive radios through classification, learning, and predictive channel selection," *Advances in Electronics and Telecommunications*, vol. 2, pp. 28–38, December 2011. ISSN: 2081-8580.

XII    M. Höyhtyä, H. Sarvanko, M. Matinmikko, and A. Mämmelä, "Autocorrelation-based traffic pattern classification for cognitive radios," in *Proc. IEEE Vehicular Technology Conference* (*VTC Fall*), pp. 1–5, September 2011. ISBN: 978-1-4244-8328-0.

# Author's contributions

The contents of the papers can be divided into two main categories. Novel algorithms and performance measurement methods for adaptive transmission, particularly for power allocation, are considered in Papers I–VII. The novel idea of using classification of traffic patterns jointly with prediction in the channel selection process is discussed in Papers VIII–XII. Channel selection and power control are discussed jointly in Paper V.

The author has had the main responsibility of writing Papers I and III–XII. The author has developed the original ideas of Papers III–VI and VIII–XII. The contributions to other papers are as follows: In Papers I and VII, the author has formulated the research problem together with A. Mämmelä. The author made the analysis, implemented the simulation model, made the literature review, and analyzed the results together with Prof. Mämmelä. In Paper II, the author formulated the problem together with A. Mämmelä and A. Kotelba. The author carried out simulations and conducted mathematical analyses related to signal-to-noise ratio (SNR) distributions and bit-error-rate (BER) performance when power control is applied in a Rayleigh fading channel. In all the original papers, the co-authors have provided valuable comments and criticism.

# Contents

# List of symbols and abbreviations

3GPP      3$^{rd}$ Generation Partnership Project

AGC       Automatic gain control

ASA        Authorized shared access

AWGN    Additive white Gaussian noise

BER        Bit error rate

CAPC-1   Conventional 1-bit adaptive power control

CDMA    Code division multiple access

CH         Cluster head

CR         Cognitive radio

CRS        Cognitive radio system

D2D        Device-to-device

DSM       Dynamic spectrum management

DVB-SH   Digital video broadcasting – satellite services to handheld devices

EU         European Union

FCC        Federal Communications Commission

FxLMS    Filtered-x LMS

GSM       Global system for mobile communications

$I^2R$          Institute for Infocomm Research

IEEE       Institute of Electrical and Electronics Engineers

ISM        Industrial, scientific, and medical

ITU-R     International Telecommunication Union Radiocommunication Sector

LMS       Least-mean square

| LSA | Licensed shared access |
| LTE | 3GPP long term evolution |
| MAC | Medium access control |
| MMSE | Minimum mean square error |
| MQAM | M-ary quadrature amplitude modulation |
| OFDMA | Orthogonal frequency division multiple access |
| OODA | Observe, orient, decide, and act |
| P2P | Peer-to-peer |
| PU | Primary user |
| QoS | Quality of service |
| RF | Radio frequency |
| RL | Reinforcement learning |
| RSSI | Received signal strength indicator |
| SCL | Secondary users channel load |
| SINR | Signal-to-interference-and-noise ratio |
| SIR | Signal-to-interference ratio |
| SNR | Signal-to-noise ratio |
| SU | Secondary user |
| TETRA | TErrestrial Trunked RAdio |
| TV | Television |
| TVBD | TV bands device |
| UMTS | Universal Mobile Telecommunications System |
| WLAN | Wireless local area network |

| $c_k$ | Coefficient of the FxLMS algorithm |
| $\hat{h}_k$ | Estimated instantaneous channel gain |
| $k$ | Index |
| $n_k$ | Additive white Gaussian noise |
| $w_k$ | Correction term |
| $x'_k$ | Filtered input signal |

| | |
|---|---|
| $\hat{x}_k$ | Estimated input signal |
| $j$ | Integer |
| $M$ | Number of symbols in modulation constellation |
| $n$ | Integer |
| $N$ | Number of prediction methods for a predictive channel selection system |
| $T_{\text{OFF}}$ | Length of an idle time of a channel |
| $T_{\text{ON}}$ | Length of a busy time of a channel |
| | |
| $\varepsilon_k$ | Error signal |
| $\mu$ | Adaptation step of the FxLMS algorithm |

# 1. Introduction

Wireless systems rely on spectrum use to provide their services. Traditionally, different portions of the spectrum have been allocated to different wireless systems, such as mobile cellular systems and television, and licenses are required to operate within those bands. These licensed systems are called primary users (PU) of the spectrum. However, the potential for new spectrum allocations is shrinking because the expansion of wireless communications is continuing and new systems are emerging faster than the ageing systems currently in use are becoming extinct. The situation has led to the scarcity of spectrum globally.

Spectrum sharing techniques seem to provide good solutions to the ever-increasing demand of wireless services by enabling a more efficient use of the limited spectrum resource. A spectrum sharing arrangement can be basically defined by two defining features (Peha 2009). The first is whether the sharing is based on cooperation or coexistence. The second defining feature is whether the question is about sharing among equals or primary-secondary sharing. Motivations and the sharing conditions in these models can differ clearly from each other. Cognitive radio (CR) techniques can be used to enable any of these arrangements.

## 1.1 Cognitive radio system

The term cognitive radio was coined by Joseph Mitola in (Mitola & Maguire 1999, Mitola 1999). He described the cognitive radio approach as devices and networks that are "sufficiently computationally intelligent about radio resources and related computer-to-computer communications to detect user communications needs as a function of use context, and to provide radio resources and wireless services most appropriate to those needs." A CR continuously observes, orients itself, creates a plan, makes decisions based on the plan and orientation, and then acts based on those decisions.

After Haykin published his seminal paper (Haykin 2005), the term cognitive radio changed to mean mainly dynamic spectrum access oriented operation. According to (Haykin 2012) two key functions of a CR are (1) a radio scene analyzer at the receiver to identify spectrum holes, i.e., available frequency channels at certain time and at certain location, and (2) dynamic spectrum manager and transmit-power controller at the transmitter to allocate the spectrum holes among

multiple CR users. Haykin described a simpler cognitive cycle, compared to Mitola's general one, focusing on the dynamic spectrum use aspects. The cognitive cycle depicted in Figure 1 defines the operation of a CRS.
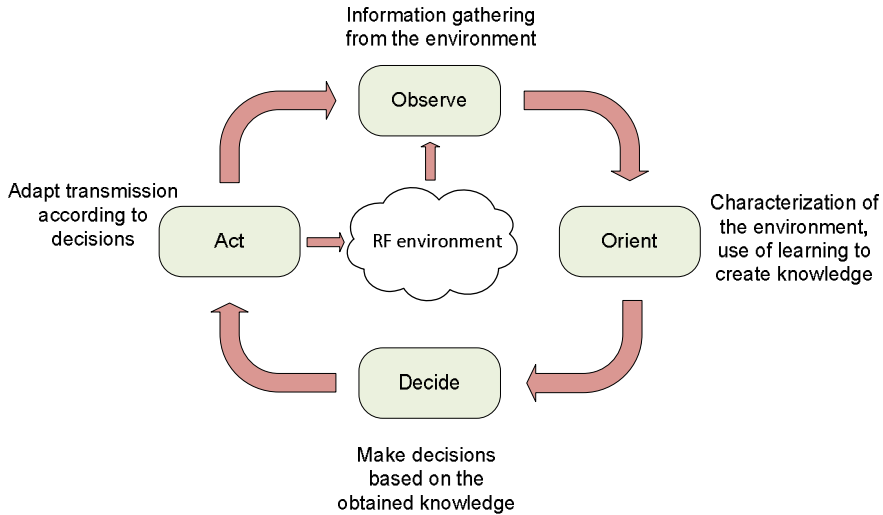


**Figure 1.** Cognitive cycle as an OODA loop.

The official recent definition developed by the International Telecommunication Union Radiocommunication Sector (ITU-R) states that the cognitive radio system is (ITU-R SM.2152, 2009): "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." This general definition broadens the scope again to other than frequency resources as well.

The cognitive cycle presented in the previous examples is based on the "observe, orient, decide, and act" (OODA) loop that was developed by John Boyd in the 1970s to analyze success of American pilots in the Korean War (Brehmer 2005). In his later work, Boyd developed the OODA loop into a more general model of winning and losing. Figure 1 shows the cognitive cycle as an OODA loop operating in the radio frequency (RF) environment.

The main aim of cognitive radios is to improve spectral efficiency by actively sensing the environment and then filling the gaps in a licensed spectrum by their own transmissions. The sensing needs to be performed rather often to obtain a reliable situational awareness picture of the RF environment. Sensing with sub-Nyquist sampling is called compressive sampling (Candes & Wakin 2008). Sensing information can be used in defining traffic patterns of the primary users, characterizing the channel use in time domain. CRSs can also obtain spectrum use

pattern passively outside from one's own communication system, e.g. from dedicated control channels or databases (Höyhtyä et al., 2007). Spectrum awareness is a basic prerequisite for a cognitive radio system to operate in a shared band with the primary users. The transmission of the primary users has to be either reliably detected or passively known, and spectrum awareness should ensure adaptive transmission in wide bandwidths without causing interference to the primary users.

## 1.2   Motivation and contribution of this thesis

The biggest challenge in CRSs is designing clever algorithms that will take all the needed information that is available – including location of the cognitive radio nodes, sensing information, traffic patterns of the different users, database information of nations and regulations, etc. – and make decisions about where in the spectrum to operate at any given moment (Rubenstein 2007) and how much power to use in that band. The task is challenging even for a single CR link where users have to connect with each other on a single frequency channel among many possible ones before starting the data transmission. The mobility of CRs makes this a very demanding task. When there is a CR network with many simultaneous communicating links, things become even more complicated. Many questions arise: How to choose which frequency bands and channels to use? What characteristics are needed to know about "spectrum holes"? How can we share the band in a non-interfering manner? How should frequency and power be allocated? In general, transmission parameters have to be adapted based on the sensed spectrum and propagation channel estimates. In this thesis, the term "channel" refers to a frequency channel. When the propagation channel between the transmitter and the receiver is considered, it is explicitly mentioned.

When the research work on channel selection for this thesis started, most of the cognitive radio literature was focusing on reactive channel selection methods, as in (Jing et al., 2005) and (Stevenson et al., 2009). These methods use instantaneous information about the environment, such as spectrum being idle or busy, as a basis for the spectrum decision. The idea to take history information into account in the channel selection based on the primary user traffic models was shortly discussed in (Haykin 2005). Later, several different prediction and channel selection models for stochastic and deterministic traffic were proposed, including (Clancy & Walker 2006, Acharya et al., 2006, Li & Zekavat 2008, Yau et al., 2009, Tercero et al., 2011).

A common problem for the proposed methods is that they are working based on the assumption that the primary traffic follows a specific distribution. In reality, different traffic patterns exist in different primary bands and channels. Thus, we started to develop a more general method for classification-based predictive channel selection. The CRS should be able to learn and classify the traffic in different channels and then apply specific prediction methods based on that knowledge. A classification method and prediction rules for both stochastic and

deterministic traffic were developed in order to find the longest idle times for the secondary operation among the channels of interest. The methods have been simulated with several different traffic patterns. In addition, we have made measurement studies in different bands to verify the practicality of the proposed approach. The classification method was further improved by reducing the errors caused by noise and incoherent spectrum sensing. The resulting method searches periodicity from the sensed binary pattern using a discrete autocorrelation function. The proposed method finds the type of the traffic with a high probability when the investigated channels include both stochastic and deterministic traffic patterns. This research direction has been attracting more attention recently. For example, the work on the primary user's traffic pattern estimation in (Zhang & Shin 2013) is a promising step towards a classification-based channel selection in the future.

Majority of the works are using short-term information as the basis for channel selection, but some authors have also proposed using long-term information, such as (Li & Zekavat 2008) or (Vartiainen et al., 2010). The latter use long-term information to guide sensing to the most promising channels and consequently reduce the sensing time. We have extended the idea by a combined use of the short-term and long-term databases. The long-term database reduces the sensing time by prioritizing the channels while the short-term database allows classification and prediction in the bands of interest. The method reduces delays experienced by the CRS users because less time is needed for sensing and finding suitable channels for secondary transmission.

When a channel is selected for secondary transmission, the CRS needs to control its transmission power during the active communication. Several researchers have been investigating transmission power control for CRSs. Transmission power limit settings have been developed based on measurements of the own signal (Kolodzy 2006, Zhang 2009) or the primary user signal (Hoven & Sahai 2005, Mishra et al., 2007, Hamdi et al., 2013). In addition to knowing the maximum limit, transmission power needs to be controlled based on a fast varying environment, such as a fading channel.

Adaptive power control methods have been studied since the 1960s, when the paper (Hayes 1968) proposing an adaptive transmission strategy over a Rayleigh fading channel was published. Numerous theoretical and practical adaptive methods have been proposed for wireless centralized systems; e.g., in (Salmasi & Gilhousen 1991, Pat. U.S. 5 056 109 1991, Goldsmith & Chua 1997, Yang & Chang 1999, Frantti 2006, 3GPP 2011). All these papers have considered inverse control approaches that are heavily applied in other areas such as channel equalization (Proakis 2001) and interference cancellation (Widrow & Walach 1996). The so-called filtered-x LMS (FxLMS) algorithm, which was independently introduced in (Morgan 1980, Burgess 1981, Widrow et al., 1981), is perhaps the most used inverse control algorithm in noise and interference cancellation applications. This thesis is the first to apply the FxLMS method to power control, providing a unified framework for the existing state-of-the-art inverse power control algorithms and linking them to the LMS literature. In addition, a novel method to calculate power

limits for CRSs based on the performance of the spectrum sensors is proposed and applied to several scenarios in the satellite band.

The selection of suitable performance criteria for adaptive communication system is not a trivial task. The adaptive transmission system should be analyzed based on the efficiency of use of resources. Two alternative ways of measuring the performance in terms of energy have been used in the literature, namely average transmitted (Hayes 1968) and average received energies per symbol (Proakis 2001), usually normalized by the receiver noise spectral density. Transmitted energy is the basic system resource in adaptive systems and should be used in performance comparisons (Mämmelä et al., 2006). In addition, normalization of the channel has to be carefully considered in performance measurements to obtain fair results between different techniques (Xiang & Pietrobon 2003, Mämmelä et al., 2006). Several different criteria are reviewed in (Biglieri et al., 1998), including optimization of link spectral efficiency in ergodic channels. A recently proposed risk-reward metric uses rational decision theory concepts in finding the best theoretical adaptive transmission method in nonergodic channels (Kotelba & Mämmelä 2008). In this thesis, we extend the work of (Mämmelä et al., 2006) by generalizing the results concerning SNRs and normalization of the channel, and by providing analytical expressions for the distribution of SNRs. In addition, we develop and apply the metric from (Kotelba & Mämmelä 2008) to rank several adaptive transmission strategies, including the FxLMS method.
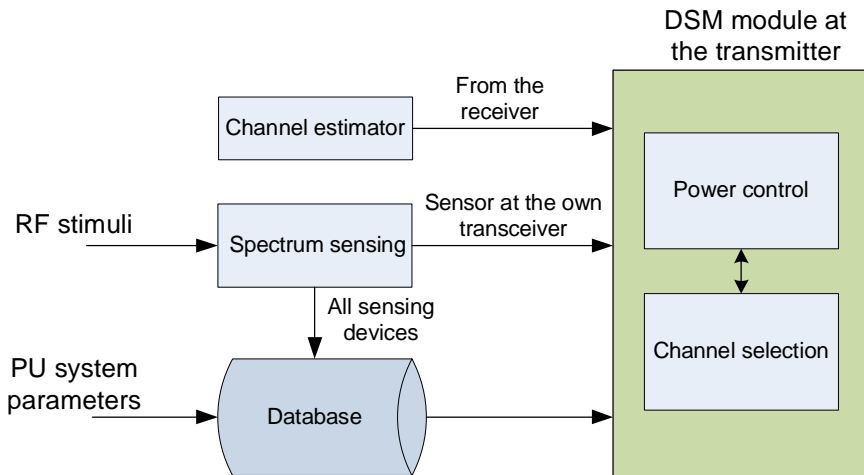


**Figure 2.** High-level system model.

The high-level system model for the developed methods is shown in Figure 2. The CR senses the spectrum periodically and stores the information into the database. The database may also include information on the primary system such as transmission power and noise figure. The dynamic spectrum management (DSM) module

uses the sensing information and database for power and frequency allocations. The channel history is used to predict future spectrum use in the channels of interest. The same channel is used as long as it is available, and when the CR needs to switch the channel, for example, due to a primary user appearance, it selects a free one with the longest predicted idle time. Power is controlled adaptively based on the propagation channel estimates and by taking the sensing data and PU parameters into account. The CR uses minimum transmission power to achieve the required quality of service. This saves energy and minimizes the interference to the primary user, leading to inverse control approaches. This thesis provides answers to the above-mentioned problems and the following research questions:

1) How to implement an efficient adaptive inverse control method for power control over fading channels? (Papers I, IV, and VII)

2) How to select suitable performance criteria for fair comparison of different adaptive transmission techniques? (Papers II and III)

3) How to adapt transmission power taking the spectrum sensing information into account? (Papers V and VI)

4) What is an efficient way of using traffic pattern learning and prediction for channel selection in spectrum sensing-based spectrum access? (Papers V, VIII, IX and XI)

5) How long-term and short-term history information could help in the channel selection process? (Paper X)

6) How to make traffic pattern classification robust against noise and spectrum sensing errors? (Paper XII)

This thesis is based on twelve original papers, which are summarized in Chapter 3 and enclosed as appendices. Other supplementary publications of the author related to CRSs and adaptive transmission include (Chen et al., 2009, Höyhtyä et al., 2007, Höyhtyä et al., 2011, Höyhtyä et al., 2012, Höyhtyä et al., 2013b, Matinmikko et al., 2008, Matinmikko et al., 2010a, Matinmikko et al., 2010b, Matinmikko et al., to be published, Mämmelä et al., 2006, Mämmelä et al., 2011, Sarvanko et al., 2010, Sarvanko et al., 2011, Sarvanko et al., 2012, and Vartiainen et al., 2010). In addition, the work has produced two patent applications on resource management for cognitive radio systems (Höyhtyä et al., 2010 and Höyhtyä et al., 2013a).

## 1.3 Outline of the thesis

The thesis is organized as follows: Chapter 2 provides incentives for spectrum sharing and reviews the relevant literature on adaptive frequency and power allocation strategies for cognitive radio systems. Chapter 3 includes a summary of the original papers, providing short answers to presented research questions. Chapter 4 presents the main results and contributions of this thesis, including limitations and hints for future work. Chapter 5 provides the summary.

# 2.  Review of the literature

This chapter reviews the relevant frequency and power allocation strategies for the purpose of this thesis. First, the chapter reviews incentives for the development of cognitive radio systems taking into account the global situation. Then, the chapter provides an overview and classification of channel selection strategies for spectrum sensing and data transmission. The chapter also classifies and reviews power allocation strategies. Finally, the chapter discusses learning techniques applicable to CRSs.

## 2.1  Incentives for spectrum sharing

The most important driver for research and development of cognitive radio systems has been the need for additional spectrum. For example, mobile communication systems are expected to run out of spectrum while attempting to accommodate the fast-growing mobile data traffic (ITU-R M.2243, Cisco 2013). The frequency bands have already been allocated to different wireless systems, giving licensed users exclusive access to blocks of spectrum. Spectrum measurement studies have shown that many frequency bands are not efficiently used. For example, measurements conducted on the below-3 GHz spectrum in Chicago (Roberson et al., 2006) and in Barcelona (López-Benitez et al., 2009) show that as much as over 80% of these bands are not used during the measurement campaign. These measurements were made using a rather small-resolution bandwidth. It was shown in (Höyhtyä et al., 2013b) that the analysis bandwidth has a significant effect on the results. Both the bandwidth of the devices already operating in the band and the bandwidth of the device aiming for opportunistic access in this particular band should be taken into account in the analysis. However, in all the above-mentioned measurement campaigns, the majority of the spectrum was not used regardless of the resolution used in the analysis. Significant capacity improvements could be achieved through a more efficient use of the underused spectrum resources.

One might think that a good way to improve the situation would be to clear and reallocate parts of the spectrum to better support the growing demands, for example, with respect to mobile communication systems. A regulator could clear the spectrum nationwide and ensure consistent rules throughout the band (Peha 2009). Unfortunately, clearing and reallocation of the spectrum is not sustainable

due to the high price in terms of cost, delays and the occasional need to switch off incumbent users. For example, clearing one 95 MHz band in the USA would take 10 years, cost USD 18 billion, and cause significant disruptions (PCAST report 2012). Thus, more dynamic spectrum sharing options are needed. Increased spectrum sharing is essential to addressing today's serious scarcity of available spectrum. Regulators will have a key role in supporting the innovations in this area. The role is described in (Peha 2009) as follows: "Regulators must ensure the rules that unleash new technologies while controlling interference are legally and technically feasible. Otherwise, new technologies are not ready for use." Without good rules for spectrum sharing, greedy devices transmitting with greater power, duration, or bandwidth than necessary will prevent other devices from operating sufficiently in the same band. In one extreme, that can lead to a tragedy of commons, where many devices consume too much of the shared resources and all devices experience inadequate performance as a result.

**Incentives described for spectrum sharing in federal bands in the USA**

Due to the above-described problems concerning clearing and reallocation of the spectrum, several incentives for more efficient federal spectrum use and sharing were described in (GAO report 2012). We will shortly review the proposals below.

- The first incentive is *assessing spectrum fees* to help to free spectrum for new users. Licensees using the spectrum inefficiently could benefit from spectrum sharing since the secondary users would pay for accessing their band.

- Secondly, *expanding the availability of unlicensed spectrum* would promote more experimentation and innovation for shared spectrum use as well as increase the shared spectrum use using Wi-Fi-type wireless transmission.

- A third important incentive is *identifying federal spectrum that can be shared and promoting sharing*. FCC granted permission to T-Mobile to perform tests to explore sharing between commercial wireless services and federal systems operating in the 1755–1780 MHz band.

- The fourth idea is *requiring agencies to give more consideration to sharing and efficiency*. The requirement forces the agencies to advance the inclusion of spectrum sharing techniques in near future to improve the efficiency of the spectrum use.

- *Improving and expediting the spectrum-sharing process* is clearly needed. The whole process should be made more flexible and transparent to users seeking for more bandwidth.

- Finally, *increasing the federal focus on research, development and testing* of technologies that can enable sharing, and improve spectral efficiency is needed. Several technologies promise to enable dynamic sharing to make spectrum use efficient. However, much more real-world experiments would be needed to be able to see the potential and applicability of the proposed techniques.

A possible way for sharing spectrum using an interesting tool called spectrum currency is described in (PCAST report 2012). Spectrum currency is a synthetic currency to "buy" spectrum rights. It provides an initial valuation and then incentives to Federal agencies to be efficient in their spectrum allocation. Nowadays the agencies do not need to be efficient in their spectrum use but this new mechanism would reward efficient users with a trade for real money. More efficient use of spectrum would include reducing agencies' own need for spectrum and sharing spectrum with other agencies and non-government users.

**Drivers defined for spectrum sharing in Europe**

The European Commission lays out the regulatory background, the drivers and enablers, and the challenges for more shared use of spectrum in order to meet the objectives of the Europe 2020 strategy in the Communication (COM(2012) 478). Three clear drivers described in the report include:

(1) wireless broadband,
(2) wireless-connected society, and
(3) research and innovative technologies.

Regarding driver 1, it is concluded in (COM report 2012) that "Shared use of licensed or licence-exempt wireless broadband frequencies enables cost savings for mobile network operators, affordable Internet connectivity and infrastructure sharing possibilities." Wireless-connected society has led to a situation where a majority of new wireless technologies are developed for license-exempt band operation. Clearly the low spectrum access barriers foster development and deployment of more resilient wireless technologies. Finally, funding for both the European Union (EU) level research activities and national activities in Europe have enabled the development of new technologies. The technologies are currently being tested in many ongoing projects and programs.

   As an example of a promising candidate, a new model called the licensed shared access (LSA) approach would provide additional users with spectrum access rights and guaranteed quality of service. In addition, the model would allow incumbents to continue to use the spectrum while also providing spectrum capacities to other users. A definition of the LSA is: "A regulatory approach aiming to facilitate the introduction of radio communication systems operated by a limited number of licensees under an individual licensing regime in a frequency band already assigned or expected to be assigned to one or more incumbent users. Under the LSA framework, the additional users are allowed to use the spectrum (or part of the spectrum) in accordance with sharing rules included in their rights of use of spectrum, thereby allowing all the authorized users, including incumbents, to provide a certain QoS" (RSPG13-529, 2013). The model is under intensive study in Europe right now. The authorized shared access (ASA) concept is a special case of the LSA, enabling mobile communication systems such as the 3rd Generation Partnership Project (3GPP) Long-Term Evolution (LTE) to access bands of other communication systems while ensuring good operational conditions

for both systems. The first demonstration of the ASA concept using real LTE network and devices was recently (April 2013) carried out in Ylivieska, Finland by VTT Technical Research Centre of Finland and its research and industrial partners (Matinmikko et al., 2013).

**Other drivers for cognitive radio systems**

As a minimum, the following benefits of CRSs have been recognized: more efficient spectrum use, better accessibility and enhanced ease of use, better adaptability, better connectivity, increased scalability and improved reliability, lower energy consumption, increased efficiency, and lower prices (Ahokangas et al., 2012). As a new and emerging area of business opportunity, the CRS context so far lacks coherent and holistic market research and market estimates. However, several drivers for the business can be identified in several domains. The drivers behind the CRS business, presented in (Ahokangas et al., 2012) and (Casey et al., 2010), can be seen in Table 1. These drivers should facilitate the emergence of business opportunities around CRSs during the coming years.

**Table 1.** Drivers behind the cognitive radio systems business.

| **Political**<br>liberalization of spectrum regulation, threat of losing control of the spectrum market, allocation of unlicensed bands | **Economic**<br>operators using the spectrum more efficiently, incumbent operators' fear of losing market control, increased number of local operators, vertical/horizontal integration |
|---|---|
| **Social**<br>demand for additional spectrum, growth of connected devices, high bandwidth consuming applications, diffusion of flat rate pricing, substitution of wired with wireless, fear of radio emissions | **Technological**<br>cognitive and reconfigurable devices, locality of spectrum markets, decentralization of intelligence in wireless networks, interference issues, bottlenecks in backhaul |

Another multidimensional model proposed to describe the business potential has been proposed recently in (Fomin et al., 2011). The domains in this work are market, technology, and policy. It has been noted by the authors that each and every driving force in any of the domains will have a certain barrier acting as a counter-force. Thus, the main idea behind the co-evolutionary analysis provided in the article is that it helps to identify the cross-related factors in other domains that may help to overcome the effect of the primary barriers in the domain under investigation. The message provided in the article is that coordinated gradual development of cross-related factors across all three domains is required in order for CR technologies to realize their full benefits.

## 2.2 Channel selection for cognitive radio systems

Intelligent selection can be seen as a multi-phase process that is described in Figure 3. In the first phase, the data are classified. The basic reason for this is the estimation process in the second phase. Estimation is done with models which creates a need for classification, i.e., the estimation model is selected based on the classification. Classification can be performed, for example, to automatically recognize attributes of incoming signal such as type of jammers, carrier frequency, or modulation type (Dostert 1983, Hamkins & Simon 2006). Finally, the third phase is decision, which is made based on the estimation, for example, to select the center frequency for the receiver.
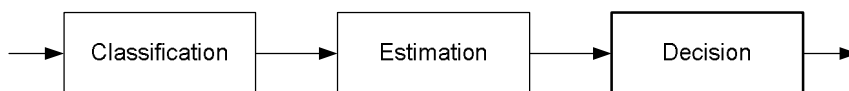


**Figure 3.** Intelligent selection process.

The frequency bands and channels the CRS is able to access over a wide frequency range may have different characteristics. Path loss, interference, available bandwidth, and availability of spectrum holes over time, among others, vary considerably. Thus, channel selection is a very important task to perform in order to fulfil the needs of CRS users. The goal of channel selection is to find the most suitable spectrum bands and channels for requesting services and applications. As discussed in (Masonta et al., 2013) and (Lee & Akyildiz 2011), the CRS system needs to characterize the bands and channels by considering the current radio conditions and the primary user activity to find the best transmission opportunities. By selecting the best channels for own transmission, the CRS is able to, for example, decrease delays of own transmission, increase throughput, and decrease collisions with the primary user.

Several methods can be used in characterization of spectrum opportunities, including geo-location services and spectrum sensing. We will mainly concentrate on sensing-based spectrum access schemes that are widely investigated in the literature. The main reason for the interest is the fact that sensing-based access does not require the primary users to alter their existing hardware or behavior. We will discuss channel selections from two different perspectives:

(1)  selecting/ordering channels for spectrum sensing and
(2)  selecting channels for data transmission among sensed channels.

The classification is shown in Figure 4. We will discuss the proposed classification in detail in the following sections.
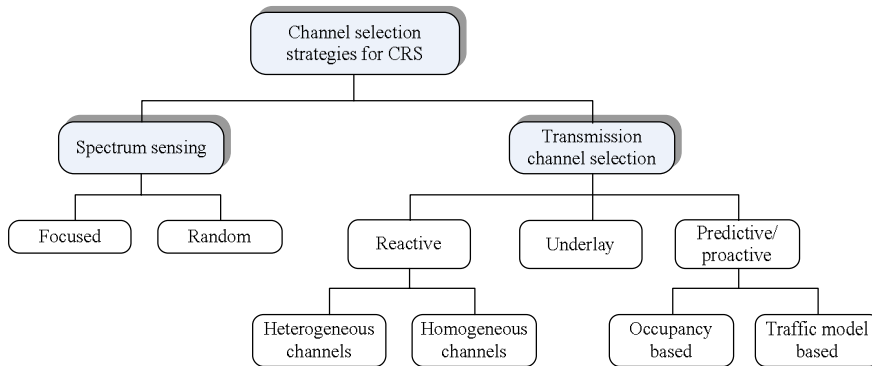
**Figure 4.** Classification of channel selection strategies.

### 2.2.1 Selecting channels for spectrum sensing

Spectrum sensing can be defined as a task of obtaining awareness about the spectrum usage and existence of primary users in a geographical area (Yűcek & Arslan 2009). While there are other possible approaches to obtaining spectrum awareness, such as databases and control channels (Höyhtyä et al., 2007), the advantage of spectrum sensing is the ability to provide the spectrum information autonomously. The CRS senses the spectrum and can use this information directly without the need to cooperate with other systems. However, cooperation with the sensing nodes of the CRS can increase the reliability of sensing considerably (Mishra et al., 2006). A lot of effort has been put on the development of spectrum sensing techniques during the recent years, see e.g., (Yűcek & Arslan 2009), (Matinmikko 2012) and references therein. Advantages and limitations of techniques such as energy detection, feature detection, and matched filter detection have been studied intensively. Instead of focusing on sensing techniques themselves, we discuss here the selection of channels for spectrum sensing.

Usually in sensing-based opportunistic spectrum access, the CRS performs periodic spectrum sensing (Zhao et al., 2008), (Zhou et al., 2008). When the primary user appears in the channel, the CRS needs to stop transmission and continue it using another available channel. The length of a sensing period is limited by the maximum tolerable interference time of the primary system. In addition, for wideband spectrum sensing, a cognitive radio is capable to sense only a limited bandwidth of spectrum during a certain time period (Jia et al., 2008), (Chang & Liu 2008). Thus, there is clearly a time constraint for spectrum sensing. The used time depends both on the sensing method as well as on the primary signals. Thus, it makes sense to use channel selection in spectrum sensing. The aim is to avoid consuming resources in channels that do not offer good transmission opportunities and to decrease delays in finding good channels. Channel selection for spectrum sensing can be classified into two main classes:

(1) focused channel selection, where only a subset of channels is sensed using certain criteria, and

(2) randomly selecting either a subset or all the channels to be sensed.

**Random channel selection for sensing**

Random channel selection refers to the case where the channels to be sensed are not selected based on any *a priori* information. This method can be used efficiently especially when the bandwidth is limited and the time constraint allows the system to sense all the channels if needed. A limited bandwidth for spectrum sensing allows computational burden to be restricted and a limited target spectrum selection enables to prevent that a single type of a CRS occupies the majority of spectrum opportunities (Sahin & Arslan 2006). It is proposed in (Sahin & Arslan 2006) that a regulator should allocate spectrum bands for different types of cognitive radios depending on the intended range and the throughput requirements.

There are several different possibilities on how to perform the sensing among the possible channels even when there are no specific criteria given how to choose the channels. A simple option is to start spectrum sensing among the channels in an ascending order. The sensing is performed until a free channel is found, and the system starts using it. Another option is to randomly sense channels among possible ones until a free one is found (Luo et al., 2009). Although both the random and the serial search exhibit similar detection time performance, the random search provides a better fairness to allocate a potential free channel, whether it is at the beginning or end of the channel sequence (Luo & Roy 2007).

The CRS can also sense all channels and then select some available ones randomly for each requesting user. However, random selection can take too much time to find a suitable channel (Luo et al., 2009). Thus, several methods have been proposed to improve the process. For example, several antennas can be used to simultaneously detect multiple channels (Neihart et al., 2007). If wide bandwidths are considered, the largest improvements can be achieved by the use of focused channel selection strategies, described in sections below. As a hybrid method between these two approaches, a two-stage sensing process is proposed to improve the detection time in several papers (Luo et al., 2009), (Youn et al., 2006), (Park et al., 2006). First, fast energy detection is performed among all channels. Second, a more sensitive fine sensing, such as the feature detection method, scrutinizes the focused set of channels found promising at the first stage. The rationale behind this approach is as follows: Energy detection is a faster but not as reliable method as feature detection. It can be used to measure the power levels among candidate channels. The channels can be ordered based on the received power levels (Youn et al., 2006). A channel with low power has a high probability to be an unoccupied channel and fine sensing is performed only on those channels.

**Focused channel selection for sensing**

Instead of randomly selecting the channels for sensing, several authors have been studying how to improve the performance of the sensing process by focusing it on better channels using *a priori* knowledge about the spectrum occupancy statistics. Spectrum occupancy, or channel transmission occupancy as referred to in (Spaulding & Hagn 1977), can be defined as the fraction of measurement time that the detected power in the channel exceeds a threshold. In addition, optimization of sensing parameters, for example, in time domain has been under intensive research. Long-term information gathered in a certain location can be used in avoiding sensing of certain channels (Kim & Shin 2008), (Harrold et al., 2011), (Vartiainen et al., 2010) and focusing the spectrum sensing on more promising channels.

The objective of (Kim & Shin 2008) is to maximize the discovery of spectrum opportunities by sensing period adaptation and to minimize delay in finding an available channel. The more frequent the sensing is, the more the CRS is able to find spectrum opportunities. However, each sensing causes overhead due to the time consumed in sensing. Thus, there is a clear trade-off between sensing-time overhead and discovery of opportunities. The authors in (Kim & Shin 2008) propose a method for optimization of a sensing period and test it with simulations using exponentially distributed ON and OFF times in the primary traffic. In addition, an optimal sensing order is proposed. The channels should be sensed in a descending order using the probability of them to be idle. The most probable idle channels should be sensed first.

Detection timing and channel selection for CRSs is studied in (Zhou et al., 2008). Detection timing helps to determine the start of the next sensing block, i.e., estimates how long the secondary user is able to transmit before sensing again. It is shown in the paper that as the channel transition rate from idle to busy state or from busy to idle state increases, the optimal inter-sensing duration becomes smaller or larger, respectively. The channel selection algorithm in (Zhou et al., 2008) uses also information on the idle state probabilities in each channel, as was presented in (Kim & Shin 2008).

It was discussed in (Jiang et al., 2009) that if the channels are identical (except for availability probabilities) and independent, the proposed strategies of sensing the channels in a descending order of the channel availability probabilities are optimal if the adaptive modulation is not used. Identical means here that the channel gains are above a certain threshold and thus acceptable for transmission. However, this does not lead to optimality when adaptive modulation is used. Dynamic programming solutions for deriving the optimal channel selection for spectrum sensing, i.e., sensing orders, are provided in the paper. The optimal order may vary from one time slot to another due to correlation between the ON and OFF states among different time slots. Since the computational complexity of the proposed method is rather high, some suboptimal strategies with lower complexity and comparable performance would be needed.

In the method discussed in (Vartiainen et al., 2010), the spectrum data are gathered over a long-term period and stored in the database. When a cognitive radio needs to find an unoccupied channel for data transmission, it sends a query to a database to receive a set of channel candidates. Channel candidates are a set of promising channels that are possibly free based on the detection history at the request time. Optimization of a sensing strategy would minimize the time to find a suitable channel as well as the energy consumed in the searching process. As described in (Harrold et al., 2011) the long-term process is used in discovering channels which are likely to be lightly used at particular times and days and prioritizing them for future channel sensing. In addition, history knowledge can be used in removing channels that have previously been noted as being constantly occupied from the pool of channels that are to be sensed.

A very recent work in (Khan et al., 2013) proposes a sensing order selection for the distributed cognitive radio network. The proposed method uses a so-called success counter in the channel selection where both the probability of a successful transmission and the probability of collision information are used in defining the sensing strategy. Random channel selection is shown to cause collisions among the autonomous CRs. In the proposed method, the CR nodes autonomously select the sensing order without coordination from a centralized entity. It is shown that the proposed strategy enables the CRs to converge to a collision-free sensing strategy. A disadvantage of the proposed method is the assumption of zero probability of missed detections.

### 2.2.2  Selecting channels for data transmission

A natural next step after spectrum sensing is to select channels for data transmission. Transmission channel selection can be classified into three main categories:

(1) underlay transmission in a channel where the primary user is operating,

(2) reactively selecting new available channel when needed; and

(3) predictive channel selection where history information is used to assist the selection.

**Underlay transmission**

Underlay transmission refers to a simultaneous transmission with the primary user as long as interference caused is below an acceptable limit (Werbach 2002, Goldsmith et al., 2009). Therefore, a cognitive user's power is limited by the interference constraint. The so-called interference temperature concept was proposed to use measured interference information in dynamic spectrum management (Kolodzy 2006), (Sharma et al., 2007). The large challenge in the concept is the fact that cognitive radios cannot be aware of the precise locations of the primary receivers and they cannot measure the effects of their transmissions on all possible receivers. It was proposed in (Kolodzy 2006) that measurements from many fixed

and mobile sites would be gathered and integrated to create an overall power flux density map across a large area. Another possibility is to use a separate sensor network over the operation area. However, the requirement for the density of the sensing devices is very high to accurately map the situation including shadowing effects. Related correlation distances have been studied, for example, in (Gudmundsson 1991). FCC actually abandoned the interference temperature concept since nobody could show effective ways to measure accurate interference information (FCC 2007).

In practice, if the primary user does not tell anything about the detected interference levels back to the secondary system, the operation has to be based on clear rules. The rules will cover the channel selections with transmission power limits. Link budget calculations as well as real measurements can be used to determine the possible signal levels for coexistence. Underlay transmission have also been proposed for device-to-device (D2D) communication underlaying cellular networks in (Yu et al., 2011). Use of low powers limits the area of coverage for underlay transmitters. Relay techniques can be used to reach remote destinations (Lee & Akyildiz 2011), (Hussain et al., 2012). The proposed technique in (Hussain et al., 2012) ensures the relay link SNR above a certain value while keeping the interference below a defined threshold.

**Reactive channel selection methods**

The methods that select the transmission channels reactively when required, such as in the case of a primary user appearance, are called reactive channel selection methods (Jing et al., 2005, Yang et al., 2008). These methods mainly use instantaneous information on the channel quality as a basis for the operation. We will review them shortly before concentrating on proactive/predictive channel selection strategies. Proactive approach means that decisions can be made based on prediction, not only reactively based on some detected changes in the environment.

*Homogeneous channels*: Even though a lot of work has been made on characterizing channels based on several different criteria, there is also a considerable amount of work found in the literature assuming homogeneous channels; see e.g., (Zheng & Cao 2005), (Cao & Zheng 2008), and (Feng & Zhao 2010). Available channels are considered to be equally good for secondary transmission. In the simplest case, the spectrum sensing makes only a binary decision on the channels (Letaief & Zhang 2009). The sensed channel is either available or not available due to a presence of primary users. Sensing results of several nodes can be combined with certain rules to obtain more reliable information on the spectrum use. Then, the available channels are allocated to requesting secondary users, assuming the channels to be equally good (Feng & Zhao 2010).

In the methods proposed in (Zheng & Cao 2005) and (Cao & Zheng 2008), devices select channels independently based on local observations. Each channel is assumed to have an identical throughput capacity, i.e., their channel quality due to fading, shadowing, and other environmental factors is assumed to be similar.

Fairness between users in a distributed network is governed by the use of spectrum rules that ensure enough bandwidth for end users. The method proposed in (Feng & Zhao 2010) modifies the Institute of Electrical and Electronics Engineers (IEEE) 802.15.4 medium access control (MAC) protocol designed for wireless sensor networks and uses it in a cluster-based cognitive network. When the current channel becomes unavailable, the cluster head (CH) waits for the start of the next sensing interval. After finding an available channel, the CH broadcasts the information to the sensors through the dedicated control channel. All sensors listen to the control channel at the beginning of each sensing interval, receive information about the available channel, and switch to the given channel. Thus, the first available channel is selected for transmission.

A reason to prefer simplicity in channel characterization and selection is to experience short delays in channel selection and to minimize the control overhead. However, a better performance might be achieved in many cases if more detailed information than pure binary data on channels is available.

***Heterogeneous channels***: Many reactive channel selection approaches consider heterogeneous channels. Channels can be ordered based on their characteristics. Interference criterion, i.e., characterizing the channels based on the interference level and selecting the channels with the lowest interference levels for transmission, is proposed, for example, in (Jing et al., 2005). The authors in that paper proposed that the channel switch should be carried out only after the interference power level of a clearer channel is at least 10% less than in the used channel to avoid unnecessary oscillations in channel switching. Interference estimation at the mesh routers was proposed in (Ramachandran et al., 2006) for channel assignment in multi-radio mesh network. It is discussed in (Stevenson et al., 2009) how interference metric is used in channel selection in the IEEE 802.22 standard-based systems designed for secondary operation in TV bands. Finally, interference-based resource allocation has been considered in orthogonal frequency-division multiple access (OFDMA)-based cognitive radio network in (Almalfouh & Stuber 2011) taking into account out-of-band emissions as well.

In addition to instantaneous interference values, several other criteria have been proposed for channel selection in the literature. Available bandwidth at the request time has been used as a selection criterion, for example, in (Clancy et al., 2007), where the cognitive radio system aims at selecting the channel with the largest bandwidth for secondary operation. A method for determining the spectrum capacity taking into account the spectrum switching delay is introduced in (Lee & Akyildiz 2011). The importance of the recovery delay from failure in the communication has been considered in (Azarfar et al., 2012) as well, providing guidelines for robust communication using cognitive radios.

A channel selection approach considering jointly spectrum sensing information and traffic load in channel selection is proposed in (Timmers et al., 2010). Secondary users estimate the opportunistic traffic load in each channel and put this value in the Secondary users Channel Load (SCL) vector. When a user wants to start a communication, it selects the channel with the lowest SCL value. Multi-

criteria selection has also been studied in (Rodriquez-Colina et al., 2011), (Sarvanko et al., 2012), and (Correia et al., 2012), where several parameters such as received signal strength indicator (RSSI), delay, bandwidth, and transmission power are jointly considered in selecting the most suitable channel for transmission. An interested reader may look at the thorough review of different spectrum characterization aspects provided in (Masonta et al., 2013).

**Predictive channel selection methods**

Due to the nature of cognitive radio operation, it would be desirable to know what is happening in the transmission channels in the near future. That would ensure better transmission possibilities to secondary systems and keep interference to the primary system at the minimum level. A CRS samples and collects multi-domain information about the environment, including information about spectrum occupancy, location, traffic, and network state. This information could be used in predicting how the spectrum will be used in the near future. A CRS should make intelligent decisions based on the observation results, e.g., identify spectrum holes, learn behavior of primary users, and find the optimal spectrum bands to use.

Use of history information in channel selection leads to predictive strategies. The strategies can use different levels of intelligence from determining long-term or short-term occupancies to sophisticated prediction algorithms matched to traffic patterns of the primary users. The following sections review the proposed methods in the area.

*Occupancy-based channel selection*: Increase of spectrum occupancy has been the main target for cognitive radio systems since the seminal paper of (Haykin 2005) was published. Channel selection based on the occupancy values of different channels is thus a convenient way for cognitive operation. A channel with low/minimum occupancy is selected for the secondary use. Measurement of spectrum occupancy requires history knowledge about the use. Both long-term and short-term information can be used in defining the spectrum occupancy for different channels.

Long-term spectrum occupancy measurements have been reported, for example, in (Harrold et al., 2011), where suitability of channels for cognitive radio use are categorized based on the occupancy values. Occupancy-based selection has been shown to provide a good performance with a measured traffic in the Universal Mobile Telecommunication System (UMTS) and the Global System for Mobile Communications (GSM) bands (Wellens et al., 2008). Also occupancy of other CRs is taken into account in (Rehmani et al., 2011). The idea is to avoid channels where primary users are operating and favor channels with a high number of other cognitive users to be able to disseminate data throughout the network. Methods to estimate the occupancy of PU traffic have been proposed, for example, in (Kim & Shin 2008), (Liang & Liu 2012), and (Gabran et al., 2013).
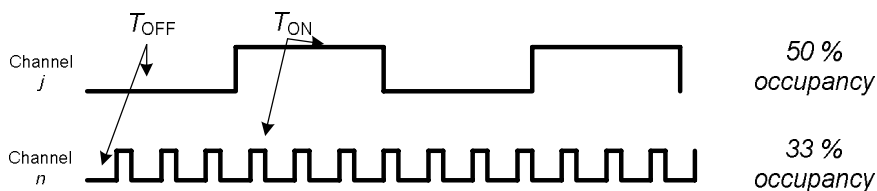
**Figure 5.** Suitability of channels based on occupancy and idle time.

Pure occupancy-based selection does not guarantee selection of good channels for cognitive radio system in all scenarios. Consider an example shown in Figure **5** where one channel has 50% occupancy with long idle and busy periods, such as 1 minute each. Another channel might have 33% occupancy with very short periods, such as 1 second idle times. Clearly the first channel would be a better choice for the secondary use when it is available. One of the most important metrics in selecting suitable channels is the length of the availability period.

***Traffic model-based channel selection*:** Data traffic transmitted in a network can be temporally characterized with the traffic pattern. In a wireless environment, two basic classes of traffic patterns exist (Haykin 2005): (1) deterministic patterns, where the PU transmission is ON, then OFF during a fixed time slot, and (2) stochastic patterns, where traffic can be described only in statistical terms. A traditionally used model assumes the arrival times of packets to be modeled as a Poisson process while the service times are modeled as exponentially distributed. This model is widely used due to the analytical tractability even though measurements have shown heavy-tail distributions such as Pareto distribution to model better the service times of bursty data traffic delivered, for example, on the Internet (Willinger et al., 1997). An example of packet traffic is shown in Figure 6.

Stochastic traffic patterns occur, for example, in cellular networks as well as in short-range wireless transmission systems such as Wi-Fi. Fully deterministic signals can be modeled as completely specified functions of time so there is no uncertainty. The frame structure makes the traffic pattern fully or partially deterministic. Partially deterministic means that the ON time starts periodically but its length can vary. One period consists of one ON time followed by one OFF time. The definition also covers the deterministic periodic case where the ON and OFF times are fixed. Examples of deterministic traffic patterns include TV broadcasting with longer periods and radar transmission with rather short periods. A deterministic long-term component can be seen in several bands such as cellular mobile communication systems due to daily rhythm of the users (López-Benitez & Casadevall 2011).

The most important thing to know from the CRS point of view is the model of the spectrum use at the location of interest. Figure 6 shows how the ON and OFF times of a transmission link can be formed from the packets that are transmitted over this channel. The upper part of the figure shows, for example, how the packets are arriving at a router faster than it can transmit. That causes waiting time to

the packet transmission. The ON time consists of service times of the packets in the queue. A channel is not occupied when there is nothing to transmit.
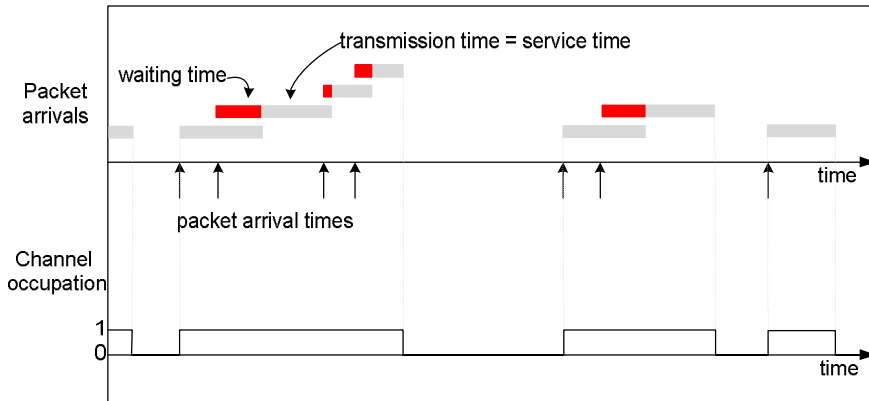


**Figure 6.** Traffic and channel occupancy model for packet transmission: packets arriving faster than they can be transmitted.

At a given time, a radio channel may be either reserved or available for secondary spectrum use. Thus, instead of traffic patterns in the traditional sense, we will concentrate more on discussing the spectrum occupancy patterns of the primary users. In this model the PU activities follow an alternating ON/OFF pattern, in which the OFF time can be exploited by the CRS. A good overview of the ON/OFF traffic patterns is provided in (López-Benitez & Casadevall 2012). A generally applied ON/OFF traffic pattern studied, for example, in (Gabran et al., 2013) assumes both the ON and the OFF times to be exponentially distributed. However, it has been noted that in real systems, other distributions provide more adequate results. The generalized Pareto distribution is appropriate for various radio technologies at long time scales, while at short time scales the most appropriate function is technology-dependent (López-Benitez & Casadevall 2012). For example, Weibull distribution can be used to characterize the length of idle periods in Terrestrial Trunked Radio (TETRA) systems while gamma distribution is better for modelling GSM traffic patterns.

Due to the problem of occupancy-based selection described at the end of the previous section, several authors have considered channel selection models that aim to select channels based on idle time statistics. (Clancy & Walker 2006) investigate the predictability when the primary traffic is assumed to be representable by a cyclostationary random process. Prediction of TV broadcast traffic is studied in (Acharya et al., 2006). Availability of a channel metric to capture both spectrum availability and frequency of interruptions from the primary user is used in performance analysis. Furthermore, usability of channel metric uses weighted average of availability to obtain short-term and long-term statistics of the channel occupancy. In addition to the primary-secondary model, prediction can be applied to recognition

of the radio resource availability generally in a heterogeneous environment (Takeuchi et al., 2008), (Kaneko et al., 2008).

Traffic prediction in (Li & Zekavat 2008) is performed using binomial-distributed arrival times and gamma-distributed service times. The goal is to estimate the probability of a channel being idle within the expected time period using this information. The justification of the binomial distribution is behind the assumption that the number of service arrivals of primary users is limited within a time period. Negative binomial distribution has been noticed to model the number of time-slots within an ON or OFF period in GSM systems (López-Benitez & Casadevall 2012). Exponential, periodic, and periodic-exponential traffic patterns are considered in (Yang et al., 2008). In the latest traffic model, the duration of the ON (or OFF) period is fixed and the duration of the OFF (or ON) period is exponentially distributed. A description of a proactive approach where the channel is changed before a PU appears is given. The exponential traffic pattern is also studied in (Yau et al., 2009), who consider packet error rates in channel selection. In addition, lognormal distribution and extreme value distribution representing peer-to-peer (P2P) traffic and gaming traffic are investigated in (Sung et al., 2010).

Switching delay in channel selection is taken into account in (Feng et al., 2009), where secondary users decide whether to switch the channel or not based on channel prediction and switching overhead. The exponential traffic pattern is considered. (Timmers et al., 2010 also study the same problem, showing that energy can be saved by buffering the packets during the primary user appearance compared to the case where the channel is always switched when the current channel is not available anymore. The same problem is studied in (Kahraman & Buzluka 2011) by proposing a channel switching strategy that balances the trade-off between the cost of the channel switch and cost of waiting until the end of the PU activity. The simulation results show that the proposed method can decrease the frequency of switches and increase the aggregated SU use especially in channels where PU activity is short-termed.

Use of radar spectrum is studied in (Tercero et al., 2011) and (Saruthirathana-worakun et al., 2012) showing that the deterministic radar pattern can be efficiently exploited by secondary wireless local area network (WLAN) users and cellular users. The radar pattern is formed by the periodic rotation of the radar antenna. However, one has to be careful also while sending between pulses to avoid interfering with the radar. Interference limits to be respected have been given by ITU in (ITU-R M.1461-1, 2009). (Song & Xie 2012) propose a fully distributed proactive channel selection approach for multiuser scenarios studying the operation under biased-geometric distributed and Pareto-distributed inter-arrival times. The inter-arrival time is the time between the arrival of one packet and the arrival of the next packet.

In (Wang et al., 2012), an extended data delivery time of the secondary connections is studied with the IEEE 802.22 standard-based always-staying and the always-changing channel sequences. Extended data delivery time is a metric that takes the number of interruptions during the data delivery into account. It is shown that if the secondary users can adaptively choose the better channel sequence

according to traffic conditions, the extended data delivery time can be improved significantly compared to the existing channel selection methods, especially for the heavy traffic loads of the primary users. The method is studied with the Pareto-distributed traffic patterns and exponential traffic patterns.

The prediction method taking switching delay into account (Kahraman & Buzluka 2011) is developed further in (Zhang & Shin 2013), where an adaptive sensing policy is developed to detect the primary user appearance as fast as possible. SUs may choose to stay silent in the evicted band for future reuse if the primary busy duration lasts relatively short. The paper derives the optimal time for the SUs to switch and proposes a learning strategy to estimate the primary's activity pattern while minimizing the disruption time of the SUs on-the-fly. Several stochastic traffic patterns modeled with exponential, Weibull, and gamma distributions are studied in the paper.

Clearly more work is needed on traffic pattern prediction. Methods that can learn the traffic patterns in different channels and optimize operation according to learned patterns would provide the best performance for cognitive users. The recent work in (Zhang & Shin 2013) is a promising step towards this direction.

## 2.3   Adaptive power allocation

Transmission power control is one of the key techniques in resource allocation in wireless systems. The use of power control prolongs the battery life, provides a means to manage interference, and together with diversity reduces the effects of multipath fading. Transmission power control can be classified using several different criteria such as centralized and distributed algorithms according to what is measured to determine power control commands such as channel quality, signal strength, and signal-to-interference ratio (SIR) (Chiang et al., 2007), (Novakovic & Dukic 2000) or, for example, by classifying the algorithms based on whether they consider pure power control task or the algorithm is combined with some other functionality such as beamforming (Rashid-Farrokhi et al., 1998).

A novel classification that takes two different aspects into account is presented in Figure 7. First, we will discuss how to determine the transmission power limit for a cognitive radio system. These methods are needed to determine the operational limits for a secondary system accessing the primary spectrum. Second, we divide adaptive power allocation strategies into two basic groups, namely the water-filling and inverse control approaches. The latter classification defines how the limited power is allocated when the wireless channel is available. Basically, the difference between these two approaches is that the water-filling approach allocates more power to the better channel instants whereas channel inversion aims at inverting the channel power gain while maintaining the desired signal strength at the receiver.
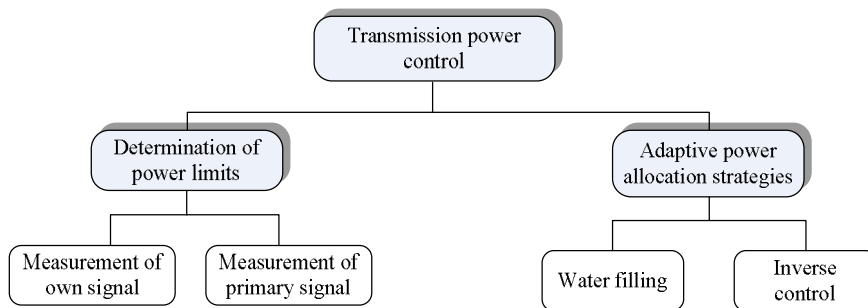
**Figure 7.** Classification of power control strategies.

### 2.3.1   Determining transmission power limits for CRSs

**Measurement of own signal**

To protect the primary users, the transmission power of the CRs should be limited based on their proximity to the PUs. The concept of interference temperature (Kolodzy 2006) discussed in the underlay channel selection section provides means to manage the transmission power of the CRS. Transmission power limit adjustments based on this concept have been described, for example, in (Wang et al., 2007) and (Zhang 2009), where peak and interference power constraints for SUs are considered. A defining feature for the interference temperature model is that the transmitter should be able to get information on the effect of its transmission at the primary receiver. Thus, the primary receiver or a very closely located measurement device should be able to provide interference information to the secondary system. Then, the secondary system could optimally set transmission power to the required level. This means that the operation would be based on the measurements of secondary signals and their effects on primary receivers. However, as pointed out in Section 2.2.2, the interference temperature model has many weaknesses and has already been abandoned by regulatory authorities such as FCC.

Numerical values for power limits have been provided for TV bands in the USA, where FCC conducted a series of tests with TV white space test devices from several companies such as Motorola, Adaptrum, Microsoft, Philips, and Institute for Infocomm Research ($I^2$R). Based on the tests, FCC adopted rules that allow unlicensed radio transmitters to operate in the broadcast television spectrum at locations where the spectrum is not used by licensed services. This unused spectrum is called "white spaces" and the devices operating under these rules are called TV bands devices (TVBDs). The rules are published by FCC in a compact form in (FCC 2011). Both fixed and portable TVBDs are considered. Fixed TVBD is a device that transmits and receives at a specified fixed location, for example, to provide wireless broadband access in urban and rural areas. A personal/portable

TVBD operates at unspecified locations or while in motion in the form of, for example, Wi-Fi-like cards in laptop computers.

The compliance requirements of all TVBDs include (FCC 2011): "A) Transmit power control has to be used. The transmission power needs to be limited to minimum necessary for successful communication. B) A TVBD is required to have the capability to display a list of identified available channels and its operating channel. C) A TVBD must comply with the limits that are set to in-band power, out-of-band emissions, and power spectral density at the antenna." The power limit is partly dependent on the time domain requirements, i.e., how often the device is updating the environment data. A personal and portable TVBD using geo-location needs to check its location at least once in every 60 s while in operation. The maximum transmission power is limited to 100 mW in a 6 MHz TV channel. Sensing-only TVBDs are limited to a maximum of 50 mW.

**Measurement of the primary signal**

In contrast to the interference temperature model, for example, (Hoven & Sahai 2005) and (Hulbert 2005) have proposed measurements of the primary signal to be used as a basis for adjusting own secondary transmitter signal power to a level that allows interference-free communication between the PUs. Either a signal from the PU transmitter (Hoven & Sahai 2005) or a so-called beacon signal transmitted from the receiver (Hulbert 2005) can be used to estimate the attenuation between the SU transmitter and PU receiver. The problem with the latter approach is that it cannot be used to primary receivers without modification.

The power level limits based on PU SNR measurement are discussed in (Hoven & Sahai 2005). Calculations for the power limit are provided for a single transmitter as well as for a network of transmitters. The work is extended in (Vu et al., 2008), where primary exclusive region defining the area inside which the secondary user is not allowed to operate is determined. Relationship between feasible signal-to-interference-and-noise ratios (SINRs) of cellular and femtocell users are investigated in (Chandrasekhar et al., 2009). The results are applicable to CRSs for determining the relationship between the feasible SINRs of the primary and CRS users.

Spectrum sensing can be used to define operational possibilities for the secondary users. However, the situation is partly dependent on the power level of the primary user compared to the secondary user (Mishra et al., 2007). For a large scale PU, an embedded sensor in the secondary transmitter might be enough. If the PU power level is close to the SU power level, a separate sensor network might be needed to reliably define whether the secondary user is allowed to allocate power in that band.

Spectrum sensing side information is used in power control in (Hamdi et al., 2007) and (Hamdi et al., 2013), where energy detection is used to estimate the path loss between the victim receiver and the cognitive transmitter and the power level is adjusted to keep the interference at a low enough level. Sensing information is used also in (Srinivasa & Jafar 2010) to adjust transmission powers

taking both the peak transmission power constraint as well as the interference constraint of primary users into account. Finally, sensing side information, i.e., probability of missed detections in a frame is used in power adaptation in (Peh et al., 2011) to protect the PUs. The authors maximize the average data rate and minimize the outage probability of the SU while ensuring that the probability of detecting the PU is above a pre-determined threshold such that the PU is sufficiently protected.

### 2.3.2  Adaptive power allocation strategies

Development of adaptive power control techniques started in the 1960s. (Hayes 1968) proposed adaptive transmitter power control over Rayleigh fading channel and derived an optimal strategy. The optimization criterion was to minimize the average probability of error subject to an average transmitted power constraint. (Cavers 1972) analyzed optimal data rate variation with constant transmission power by varying the transmission data rate optimally according to the channel gain. (Hentinen 1974) investigated simultaneous power and data rate control and showed that the rate control is more effective than pure power control. Simultaneous controlling further improves the performance of the system. (Srinivasan 1981) included pilot symbol estimation to adaptive transmission whereas the former works described above assumed ideal channel knowledge. Estimates were used for power and data rate control. Also impact of feedback delay was highlighted. (Vucetic 1991) and (Goeckel 1999) presented adaptive coding so that code rate varies based on channel state.

### Water-filling

(Webb & Steele 1995) proposed the variable rate *M*-ary quadrature amplitude modulation (MQAM) technique and (Goldsmith & Chua 1997) the variable rate variable power MQAM, where optimal adaptation rule, water-filling in time, was derived. In this work, channel state values were assumed to be known by the transmitter and both coding and modulation transmitted over the channels are optimized for instantaneous fade levels. The resulting water-filling strategy allocates more power to good channel states and, conversely, when the channel is not as good, less power is allocated. If the channel quality drops below a certain optimal threshold, the channel is not used for transmission. The proposed method achieves ergodic capacity for a fading channel. Capacity achieving method with maximal ratio combining diversity was presented in (Alouini & Goldsmith 1999). An important observation made in (Caire et al., 1999) was that the constant-rate variable power method is enough for achieving capacity if delay constraint is included in the analysis. No variable-rate coding is required.

The water-filling power control method can be applied also to the frequency domain. For example, (Yu et al., 2004) investigate iterative water-filling for Gaussian vector multiple access channels, providing an efficient numerical algorithm for

the problem. Iterative water-filling has been proposed for cognitive radio operation as well (Haykin 2005), (Setoodeh & Haykin 2009) because it can provide a distributed solution with low complexity and rather fast convergence speed. Each user acts greedily to optimize its own performance based on local information, and the users do not need to communicate with each other to establish coordination between themselves.

**Inverse control**

Inverse control has been used for several applications such as channel equalization (Widrow & Stearns 1985), (Proakis 2001), automatic gain control (AGC) (Meyr & Ascheid 1990), noise and interference cancellation (Widrow & Walach 1996), and transmission power control, which is the topic of this thesis. In addition to the capacity achieving water-filling strategy, also suboptimal policies, channel inversion and truncated channel inversion power control strategies were presented in (Goldsmith & Chua 1997). Inversion simplifies greatly the coding and modulation since channel with inversion appears to the encoder and decoder as an additive white Gaussian noise (AWGN) channel. Truncation improves energy and spectral efficiency and can also be used in a shadowing channel (Kim & Goldsmith 2000). (Saarinen 2000) derived an optimal BER minimizing policy with minimum mean square error (MMSE) estimation and showed that truncated channel inversion approximates the optimal rule in continuous transmission systems.

Several adaptive inverse control methods have been proposed in the literature for power control; see e.g., (Salmasi et al., 1991), (Pat. U.S. 5 056 109 1991), (Yang & Chang 1999), (Aldajani & Sayed 2003), (Frantti 2006), (Yang & Chen 2010), and (3GPP 2011). Inverse power control approaches have been proposed and used, for example, for code division multiple access (CDMA), LTE, and TV white space transmission. In the rules defined in (FCC 2011), the secondary device operating in the TV band needs to limit its transmission power to the minimum necessary for successful communication. A clear aim of the inverse control approaches is energy and interference reduction; to use only sufficient power to meet the transmission rate requirements.

The conventional 1-bit adaptive power control (CAPC-1) method from (Salmasi et al., 1991) and (Gilhousen et al., 1991) employs delta modulation, i.e., adjusts the previous transmission power up or down by a fixed step depending on whether the received power has been over or below a threshold value. The method is simple but not fast enough to compensate deep fades in the channel. In the literature, adaptive step sizes (Yang & Chang 1999), (Frantti 2006), (3GPP 2011) and predictive power control methods (Aldajani & Sayed 2003) are used to improve the performance of the conventional CAPC-1 algorithm. The basic idea is that when the power of the received signal is far from the desired, the control step is increased to reach the desired level faster.

The use of adaptive step sizes leads to a requirement of using more bits in the power control command. In practical systems, the implementation of the adaptive size algorithm has to be made with a limited feedback channel (Love et al., 2008).

For example, in CDMA systems, the typical control frequencies are 800 Hz and 1,500 Hz (Aldajani & Sayed 2003). If a simple 1-bit algorithm is used, the feedback control rate would be 800 bit/s and 1,500 bit/s, respectively. In the LTE system, the closed loop power control can be updated once in a millisecond (3GPP 2011). If 2 bits are used per power control command, the feedback rate is 2,000 bit/s. Thus, the adaptive algorithm needs to be designed to provide sufficient performance without requiring more than a few bits in the power control command.

There are several ways to manage dynamic range requirements with limited feedback. Nonlinear quantization of feedback signaling (Meyr & Ascheid 1990, Rabiner & Schafer 2007) and variable step algorithms (Yang & Chang 1999, Hwang & Li 2009, 3GPP 2011) are commonly used for this purpose. An interesting idea of a multiphase power control is introduced in (Frantti 2006). Since the CDMA system limits the size of the power control command into two bits, conventionally only four different commands are possible. Frantti proposes sending two bits in two consecutive control commands and then using four bits to increase the number of possible commands to sixteen. Simultaneously, the control frequency is reduced to half. Results show that a better performance can be achieved with the same control rate by the use of multiphase power control.

The performance of a power-controlled wireless system can be improved further by the use of interleaving, channel coding, and diversity (Stein 1987, Viterbi & Padovani 1992, Simpson & Holzmann 1993, Saarinen 2000). Power control and interleaving are complementary methods since with low velocities, power control operates accurately whereas interleaving operates more efficiently with high velocities. Diversity, on the other hand, reduces the dynamic range requirements of the power control.

## 2.4 Performance measures for adaptive transmission

### 2.4.1 Adaptive transmission over a wireless channel

Adaptive transmission systems should be analyzed based on the efficiency of the use of resources. Energy is a basic resource in digital transmission links. There are two alternative ways to measure the performance of the system in terms of energy. Either average transmitted or received energy per symbol is used, usually normalized by the receiver noise spectral density. This leads to the average transmitted SNR per symbol (Hayes 1968, Cavers 1972, Hentinen 1974, Srinivasan 1981) and the average received SNR per symbol (Ionescu & Boariu 2001, Proakis 2001), respectively. The performance of the system is partly dependent on the average received SNR because the achieved performance can tell how well the receiver is matched to the channel. However, transmitted energy is the basic system resource in adaptive transmission systems and should be used in comparing the different methods with each other (Mämmelä et al., 2006). The average received SNR can be used if the channels are properly normalized and the transmitters exploit no form of selectivity in space, time, or frequency domain.

Major approaches to normalization of the channel include average and peak normalization, i.e., normalizing either the average energy gain or the peak energy gain to unity, respectively (Xiang & Pietrobon 2003). Average normalization is used in most of the literature on fading channels. However, as was shown in (Xiang & Pietrobon 2003, Mämmelä et al., 2006), the approach has to be reconsidered when either the transmitted signal or the channel exhibits selectivity in time, space, or frequency. It was concluded in (Mämmelä et al., 2006) that by using the transmitted SNR and peak normalization, we can avoid confusing results and we know what the minimum transmitted SNR is.

In addition to the above-discussed issues, there are other things to be considered when selecting good performance measures to compare different adaptive transmission methods. In ergodic channels, the mean of some quantity such as link spectral efficiency, is a valid performance measure because one observes all possible channel states (Biglieri et al., 1998, Kotelba & Mämmelä 2008). In nonergodic channels, there is an uncertainty because only part of the channel states is observed. A common performance measure is then the outage probability, i.e., the probability that the performance is below a certain threshold. Transmission methods e.g. for optimizing capacity have been studied and reported in the literature with different system assumptions (Biglieri et al., 1998). So-called risk-reward theory from finance theory was proposed to be used in performance measurements of adaptive transmission systems in nonergodic channels in (Kotelba & Mämmelä 2008). The reward can be defined as the difference between the expected value of the link spectral efficiency, and the target link spectral efficiency for a given energy "investment". The risk can be measured, for example, with a second-order partial moment of the link spectral efficiency distribution. Basically, the proposed risk measure defines in a smooth way how far the system is from the desired value. The proposed approach jointly considers risk and reward provided by the adaptive transmission strategy and formulates the performance measure as a certain risk-reward ratio.

### 2.4.2 Channel selection in CRS

Performance measures for channel selection were discussed already in Section 2.2, where the existing methods were classified and reviewed. We will next briefly summarize the used criteria. A commonly used metric in the CRS literature is a binary decision criterion. A channel is regarded as busy or idle (Letaief & Zhang 2009), (Feng & Zhao 2010) and then an available channel is selected for transmission. Simplicity of this metric is targeting to decrease delays and minimize the control overhead. Other common metrics include selecting the channels with the lowest interference values (Jing et al., 2005) or with the widest bandwidth (Clancy et al., 2007).

Since simple metrics cannot measure the quality of the possible channels in more detail, several other criteria have been proposed for channel selection in order to support a more sophisticated resource allocation. However, gathering and

delivering more information increases the overhead. Thus, it was proposed in (Kim & Shin 2008) that a trade-off between the sensing frequency to find the best opportunities and the sensing overhead caused by frequent sensing should be considered when selecting the suitable channels for secondary transmission. Instead of considering a single criterion for the problem, multi-criteria selection has been recently studied, for example, in (Timmers et al., 2010) and (Sarvanko et al., 2012). Several parameters are jointly considered in the selection process to achieve a good trade-off between sometimes conflicting requirements.

In addition to the instantaneous information, metrics that need gathering data over time have also been investigated actively in the literature. Spectrum occupancy of a channel can be used as a metric in defining the suitability of a channel for CRS operation (Harrold et al., 2011, Wellens et al., 2008). It has been proposed that traffic models should be taken into account to obtain a more detailed view on the spectrum use over time (Haykin 2005). More detailed information on traffic patterns is used to capture spectrum availability as well as frequency of interruptions in the channel (Acharya et al., 2006, Wang et al., 2012). Detailed information on the primary user activity enables using predictive channel selection methods such as (Acharya et al., 2006), (Yang et al., 2008), and (Tercero et al., 2011) by selecting the channels with the highest probability of availability or with the longest idle times.

An important metric for secondary users is the delay in finding a suitable channel for transmission. Different approaches to delay minimization are considered in the literature. Delay reduction is achieved by focusing sensing on promising channels in (Vartiainen et al., 2010) while switching delay is avoided in (Feng et al., 2009, Timmers et al., 2010 Kahraman & Buzluka 2011, and Zhang & Shin 2013) by balancing the trade-off between the cost of channel switch and the cost of waiting until the end of the PU activity. Switching delays can also be reduced by reducing the switching frequency and simultaneously increasing the SU transmission time by favoring channels with the longest idle periods (Yang et al., 2008).

## 2.5   Learning

In addition to being able to gather information about its environment and adapt its operation based on that information, a real cognitive system is able to learn and thus improve its operation over time. Learning is included in the ITU-R definition (ITU-R SM.2152, 2009), which states that a CRS is able to learn from the results obtained. This is what separates the cognitive system from the adaptive system. According to (Claasen & Mecklenbräuker 1985), four features of the adaptive system include *a priori* knowledge, a quality criterion, an algorithm that determines the parameters, and a signal processing device using the parameters to achieve the goal set for the system. In learning systems, not only parameters but also the algorithm or even the criterion can be adapted to specific conditions (Claasen & Mecklenbräuker 1985). Machine learning can be defined as a process to improve the future performance of the system; i.e., things learn when they change their behavior in a way that makes them perform better in the future (Witten & Frank 2000).

Another definition of learning, adopted also in the thorough survey article on machine learning techniques for CRS in (Bkassiny et al., 2013), is given for intelligent systems in (Michalski 1995): "Learning is creating knowledge from the perceived information, i.e., the system can classify, organize, abstract, and generalize information obtained from the sensors." According to (Michalski 1995), intelligence can be described by an "equation" as information gathering + knowledge generation + knowledge utilization. Information gathering includes the ability to sense the surrounding environment and the internal states. Then learning is used to generate knowledge. Finally, knowledge is used to achieve certain goals through reasoning. Actually, learning can be described as a cycle that resembles the OODA loop described in Section 1.1.

Several learning techniques can be used to improve the performance of the CRS in various situations. According to (Duda et al., 2001), learning paradigms can be classified into supervised learning, unsupervised learning, and reinforcement learning (RL). In supervised learning, the training data is analyzed and a function that maps inputs to desired outputs is generated. Unsupervised learning techniques such as clustering aim at organizing the data and finding hidden structures in it. Reinforcement learning techniques aim at observing the impacts of the actions in the environment and using this feedback in adapting the learning algorithm. According to (Bkassiny et al., 2013), reinforcement learning can be seen as a subclass of the unsupervised learning paradigm because the agents can learn autonomously without supervision.

In order for learning to become necessary for CRS, the precise effects of the changing inputs on the outputs must not be known (Clancy et al., 2007). According to (Bkassiny et al., 2013), the main learning problems in CRS are decision making and feature classification. Classification problems often arise in spectrum sensing whereas decision making is often related to adaptive transmission or, for example, in determining the spectrum sensing policy (Bkassiny et al., 2013).

Several possible learning methods for improving decision making are discussed in (Bkassiny et al., 2013). Game theory has been applied for analyzing power control, rate adaptation, spectrum leasing, and spectrum allocation problems (Bkassiny et al., 2013). Learning in a game-theoretic framework provides potential solutions to multi-agent learning problems under partial observability assumptions. Learning is also applied in finding the optimal threshold for energy detection in a changing environment (Gong et al., 2009).

Reinforcement learning has been rather popular in the CR literature; see e.g., a review article (Yau et al., 2012), where application of RL techniques for routing, resource management and dynamic channel selection is reviewed. Distributed power control is studied in (Galindo-Serrano & Giupponi 2010) and (Chen et al., 2011). Learning enables the network to achieve equilibrium in a completely distributed way without any control from the centralized entity. The performance can be further improved if the nodes can share the information they have learned. The process of knowledge transfer, i.e., teaching, has been recently proposed to improve the learning process (Giupponi et al., 2010, Palazzo et al., 2012). The re-

sulting framework is referred to as docitive radios. Docition can significantly shorten the learning process for the system.

Classification increases the knowledge of the CRS about the surrounding radio environment. Learning can enable the CRS to detect the primary signals better and make decisions about the primary activity based on the observed and classified data. Learning is used, for example, in (Shetty et al., 2009) to identify and classify multiple wireless systems existing simultaneously in a certain frequency band such as industrial, scientific, and medical (ISM) band. Learning has also been applied to modulation classification (Ramkumar 2009, Petrova et al., 2010), MAC protocol classification (Yang & Chen 2010), and predicting the channel availability for secondary use (Tumuluru et al., 2010). Learning and prediction make the operation of cognitive radios more efficient compared to the case where only information available at the design time is possible. Ideally, the CRS should be able to use the information gathered during its lifetime.

# 3.  Summary of original papers

There are clear gaps in the literature regarding adaptive frequency and power allocation strategies. For example, a channel selection method that could learn and classify traffic patterns of the existing users could provide suitable operation possibilities to sensing based spectrum access users in any environment. In addition, the relation of the current inverse power control approaches to the traditional inverse control methods used, for example, for noise cancellation is missing. In the following, the contributions of the twelve original papers are summarized with respect to the prevailing gaps in the literature.

## 3.1  Overview of papers

Basic building blocks of a CRS (see Figure 1) include methods to gather information, use of learning to create knowledge from that information, decision making based on the obtained knowledge, and adapting transmission according to decisions. The original papers I–VII mainly investigate the adaptive transmission phase, but also decision-making aspects are included, e.g., regarding the maximum transmission power limit calculations. Papers VIII–XII consider the last three phases, starting from the assumption that there are spectrum sensors periodically producing information for knowledge generation.

Relations between the original papers are shown in Figure 8. The starting point for the thesis work was Paper I that studied the use of the FxLMS algorithm to adaptive inverse power control. Two different research directions arose from this: (1) we started to carefully consider performance metrics for adaptive transmission in Papers II and III, and (2) the FxLMS algorithm work was extended in Paper IV towards cognitive radio systems. The cognitive radio system research continued in two different areas: (1) predictive channel selection studies in Papers VIII–XII and (2) transmission power control in Papers V–VII. As shown in the figure, there were clear interrelations between the topics: for example, Paper V described a joint two-step approach to power and frequency allocations. The problems were studied with mathematical analyses, simulations, and measurements. In particular, network traffic measurements were used in the predictive channel selection work described in Paper XI.
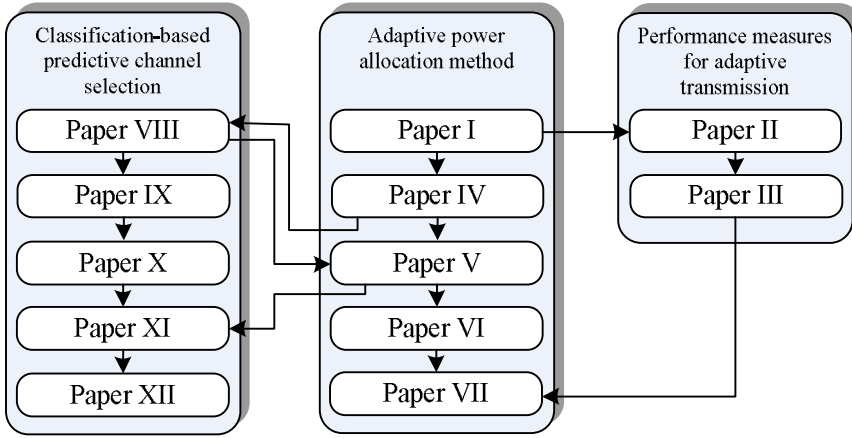
**Figure 8.** Relation of original papers.

## 3.2 Adaptive power allocation methods

### 3.2.1 FxLMS power control

The contribution of Paper I is to present the FxLMS method for adaptive inverse power control by introducing the analogy between the fixed-step CAPC method (Salmasi & Gilhousen 1991, Pat. U.S. 5 056 109 1991) and the well-known LMS algorithm. Since the LMS algorithm is not directly suitable for active control applications, a variant called the FxLMS algorithm has been developed for inverse control solutions (Widrow & Walach 1996). Paper I develops and describes a modified version of the FxLMS algorithm for inverse power control in a fading channel. The algorithm is presented in Figure 9. The algorithm updates the coefficient $c_k$ of a one-tap filter as

$$c_k = c_{k-1} + w_k \tag{1}$$

where $w_k = \mu x'_k \varepsilon_k$ is the correction term, $\mu$ is the adaptation step size of the algorithm that regulates the speed and stability of adaptation, and $\varepsilon_k = |x_k| - |h_k c_{k-1} x_k + n_k|$ is the error signal to be minimized. The filtered input signal for the conventional FxLMS algorithm is $x'_k = (\hat{x}_k \hat{h}_k)^*$, where $x^*$ is the complex conjugate version of $x$, $\hat{x}_k$ is the estimated input signal, and $\hat{h}_k$ is the estimated instantaneous channel gain. The filtered input signal is $x'_k = |\hat{x}_k \hat{h}_k|$ for the modified FxLMS algorithm and the parameter $n_k$ is additive white Gaussian noise.
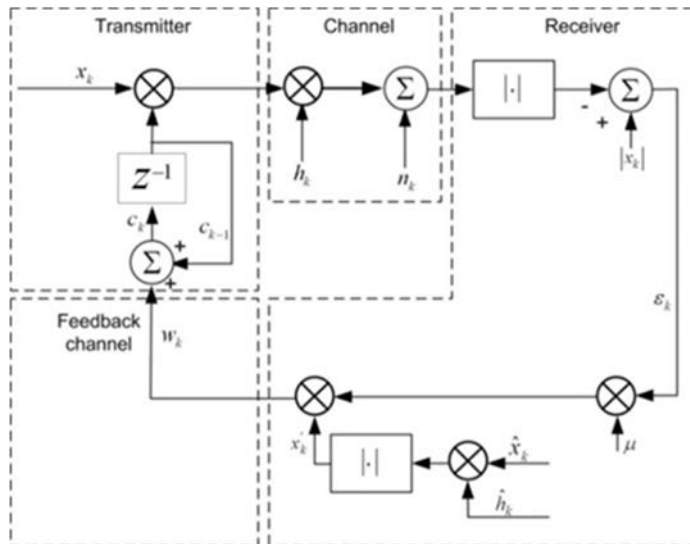
**Figure 9.** FxLMS algorithm-based power control, modified version.

In addition to the development of the FxLMS algorithm, another important novelty in Paper I is the method for modelling a time-variant fading channel. The model is a modification of Jakes' sum-of-sinusoids channel model (Jakes 1974). We have randomized frequency shifts in the model to avoid periodicity in the channel gain in the time domain and made the power spectrum flat and symmetric with respect to zero frequency. The performance of the modified FxLMS algorithm is compared to existing state-of-the-art algorithms with simulations in the proposed channel. The results show that the FxLMS algorithm can provide better accuracy and performance for the power control than the state-of-the-art methods.

Inverse power control is a suitable method for cognitive radio systems because it minimizes the interference that a secondary user creates to licensed users and allows more users to share the spectrum. A truncated version of the FxLMS algorithm is developed and studied in Paper IV for cognitive radio systems. Truncation, i.e., interrupting transmission and setting the transmission power to zero when the channel gain deteriorates under certain cutoff value, improves further the system performance. It reduces energy consumption of the CR node as well as interference to the primary users, improves capacity both under interference range and energy consumption constraint, allows more secondary users to share the spectrum and relaxes sensing requirements compared to full inversion. Since the interference range of the secondary user is smaller, there is no need to sense as weak signals as with the full inversion method.

A detailed comparison between the conventional FxLMS and the modified FxLMS algorithm using analyses and simulations is provided in Paper VII, justifying the used modifications. In addition, a convergence analysis for the modified FxLMS algorithm, providing new results for time-invariant and time-variant channels, is

provided. The modification in the algorithm is based on additional envelope detectors or absolute value blocks. The reason for this is that we are adjusting power levels and thus are interested only in amplitude values. Phases are not that important from the power control perspective and thus we can reduce the information to be carried in power control commands.

Paper VII includes a thorough comparison between the FxLMS and conventional state-of-the-art algorithms (Salmasi & Gilhousen 1991, Yang & Chang 1999, Frantti 2006, 3GPP 2011), showing that the FxLMS algorithm can be seen as a generalized inverse control to be used in the power control research. The development of a quantized version of the modified FxLMS algorithm is presented. Bit-error-rate simulations for the studied algorithms in a fading channel and in a diversity channel are provided and the results analyzed.

### 3.2.2   Transmission power limit for the secondary user

Sensing-based transmission power limit setting was proposed in (Hoven & Sahai 2005) using a simple channel model. Paper IV extends the idea by using link budget calculations for defining the transmission ranges and interference ranges in the primary-secondary system. The interference management method is described in more detail in Paper V, where analytical equations for transmission power limit calculations are given. It is shown that the allowed transmission power of the sensing-based secondary user scales linearly with increasing primary transmission power. The results also illustrate the effect of the antenna height on the transmission power limit. If the primary transmitter uses high antennas such as 50 m towers, it allows more powerful secondary users to operate in the same geographical area. The main reason for this is the fact that sensing the primary signal transmitted from a high tower can be made reliably also from a greater distance. The signal attenuates more rapidly between the secondary transmitter and the primary receiver both having low antennas, allowing larger transmission powers.

The general method developed in Paper V is applied to analyzing secondary use of the spectrum in a satellite band below 3 GHz in Paper VI. Application of cognitive radio techniques to satellite bands is a rather novel research area that has just started to attract attention at the time of writing this thesis. An interested reader may take a look at the topic, for example, in (Höyhtyä et al., 2012, Biglieri 2012). The primary system in Paper VI is a digital video broadcasting – satellite services to handheld devices (DVB-SH) hybrid network that is operating in the S band between 2170 MHz and 2200 MHz. The maximum transmission power is defined for a secondary user as a function of a detection threshold of a spectrum sensor, and results for several different indoor and outdoor scenarios are given. The results indicate that short-range communication is preferred for sensing-based access in the spectrum.

It is noted that energy detection cannot be used at all in many scenarios even when low-power short-range communication is considered. For example, in an urban environment where the sensor is located indoor, the detection threshold

allowing normal WLAN transmitters to transmit should be clearly below the noise floor. Implemented energy detection based sensors usually have thresholds 10–20 dB above the noise floor. Thus, sensors able to detect signals with clearly lower power levels are required. Matched filter detection and feature detection are needed, particularly when the secondary transmitters are using higher transmission powers. Based on the analysis and related uncertainties, it is proposed that the secondary system use database access or other passive spectrum awareness method whenever possible. This would guarantee the quality of service (QoS) of the both secondary and primary systems.

### 3.2.3 Performance measurements

Paper II studies analytically the relationship between the average transmitted and received energies under several transmission power control methods, including truncated channel inversion and water-filling. The paper shows that, in general, the average transmitted SNR should be used in performance measurement of an adaptive transmission system. Transmitted energy is the basic system resource. In addition, there is a correlation between the transmitted energy and the energy gain of the channel because of adaptive transmission, for example, when using transmitter power control. The use of transmitted energy leads to a normalization problem of the channel, which has been studied previously in (Xiang & Pietrobon 2003). Paper II generalizes the analysis from (Xiang & Pietrobon 2003) to include time, frequency and spatial domains. Peak normalization of the channel is needed to avoid confusion in performance comparison of energy-limited adaptive transmission systems.

We continued studies on performance measurements of adaptive transmission systems in Paper III by applying rational decision theory for that purpose. The concept was originally proposed in (Kotelba & Mämmelä 2008) by exploring similarities between the optimal portfolio selection problem in finance theory and the finding of a valid performance measure for adaptive transmission in nonergodic channels. The proposed approach jointly considers risk and reward provided by the studied adaptive transmission method. It formulates the performance measure as a certain risk-reward ratio that can be used in comparing different adaptive transmission strategies.

We extended the work in Paper III by developing and applying the metric to rank several practical adaptive transmission strategies, including the FxLMS power control strategy. An interesting result from the analytical studies in Paper III was related to the use of truncation in the power control strategy in a diversity channel. Even though the traditional maximum capacity scheme for a diversity channel requires the use of cutoff, the authors in (Alouini & Goldsmith 1999) suggest that based on intuition, with diversity, total channel inversion might be a better choice than truncated channel inversion. It does not achieve the highest capacity but is close enough to that. Rational decision making leads unambiguously to this solution because the optimal risk-reward ratio is achieved without the cutoff.

## 3.3 Classification-based predictive channel selection

A clear contribution of this thesis is related to the intelligent selection process described in Figure 3. The thesis proposes a novel classification-based predictive channel selection method that follows the intelligent selection principle. Classification of traffic patterns is needed to be able to estimate and predict idle times in different channels. Then, decision of a channel in which to transmit is made using the predicted idle times.

### 3.3.1 Predictive channel selection

Paper VIII started the predictive channel selection research. The main idea behind this concept is to be able to select not only the instantaneously best channels for secondary transmission but rather be able to learn and select channels that will remain good also in the future. Some papers had considered predictive spectrum access previously, see e.g., (Acharya et al., 2006, Yang et al., 2008), but they were restricted to a certain traffic model. To be really usable, the channel selection method should be able to classify traffic patterns of different channels and to predict the future use with different prediction methods for different traffic patterns. Traffic patterns can be classified, for example, by the use of the autocorrelation function. The main contribution of Paper VIII was proposing the classification-based method and providing prediction methods both for deterministic and for stochastic traffic patterns. Exponentially distributed traffic patterns were considered in stochastic traffic simulations. The system model used in the predictive channel selection studies is shown in Figure 10.
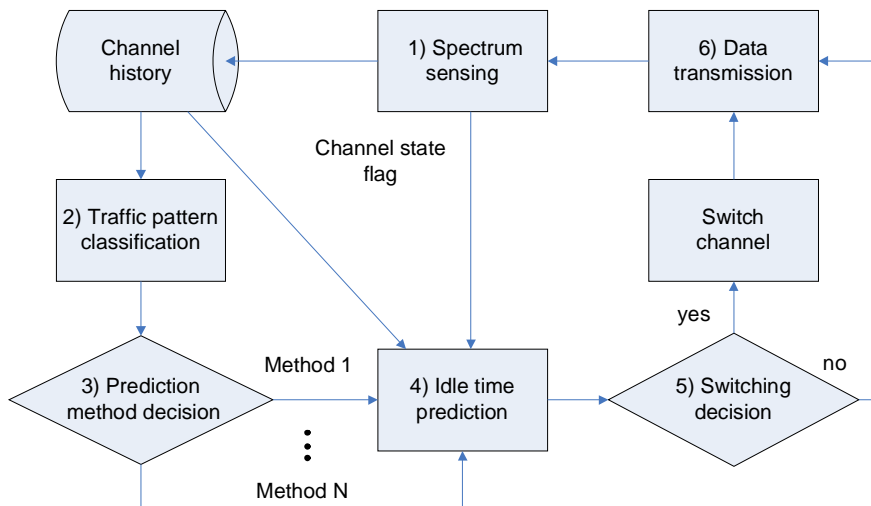


**Figure 10.** System model for predictive channel selection.

The method works as follows: (1) All channels are sensed and results stored in the channel history database. (2) Based on the collected history, the traffic patterns are classified into stochastic and deterministic ones. (3) The prediction method that is best suitable for a certain traffic type in a certain channel is selected. (4) The idle time prediction is made using history information and the selected prediction method. The channel state flag is used to define which channels are currently idle, and only those idle channels undergo the prediction phase. (5) A channel is used as long as it is free. After that, the channel with the longest predicted idle time is selected for data transmission. (6) Data is transmitted up to the maximum length of the interference time the PU can tolerate before the system goes back to state 1. If the tolerable interference time is 0, no CR operation is allowed in that band. The interference time is defined as a time period during which the CR transmission interferes with the PU. The secondary user could have *a priori* knowledge about the signal, e.g., from the standards to given licensed frequency bands. This information can be used additionally to assist the prediction.

The work continued in Paper V, where a maximum likelihood-based prediction rule for exponential traffic pattern was shown to be the mean idle time of previous idle periods. The rule was shown to provide good results for Weibull-distributed traffic patterns as well. Paper IX extended the previous works to analyzing how much classification helps to improve the performance of the system, measured by throughput and collision rate. The impact of sensing and switching times is taken into account in the analysis. Deterministic, exponentially distributed, and Pareto-distributed traffic patterns were used in the study. Throughput can be clearly improved by the use of the predictive channel selection method using history information compared to a channel selection that is based on instantaneous information. In addition, the number of collisions with a primary user can drop more than 60% compared to a predictive method operating without classification.

The main reason for a large reduction in the number of collisions is the ability to change the channel and or stop transmission in a current channel before the PU appears when the ON/OFF pattern is deterministic. The situation is shown in Figure 11 for a single channel operation. The dashed lines represent the sensing times of a CRS. The first row describes the PU transmission in a channel. The second row shows that when the system is operating reactively, collision occurs every time the primary user starts transmitting in a channel where a secondary user is active at that moment. The last row presents an alternative case where the secondary user operates proactively. The proactive method avoids the collisions due to the ability to predict the appearance of the PU.

Results of previous papers were extended and unified in Paper XI. The tests conducted with several different traffic models show the general applicability of the proposed classification-based method using mean time-based prediction to stochastic traffic patterns. With new simulations, the number of collisions with the primary user was shown to reduce up to 70% compared to the predictive system operating without classification. We used measurement data from the ISM band and from the 450 MHz band in Paper XI to verify the practicality of the proposed approach.
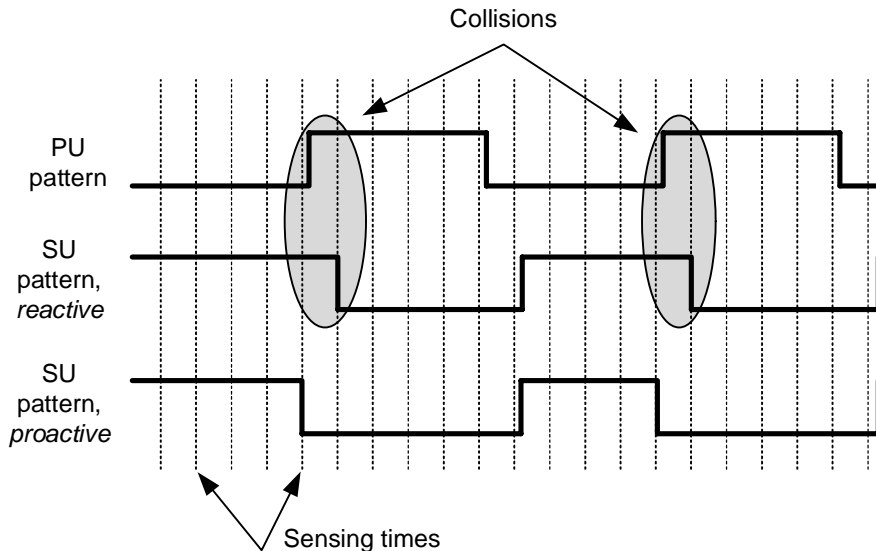
**Figure 11.** Impact of alternative reactive and proactive methods on collisions, single channel operation considered.

### 3.3.2   Classification of traffic patterns

Paper VIII was the first one in the literature to propose a traffic pattern classification in dynamic spectrum access networks. The autocorrelation function of the sensed signal was proposed to be used in the classification in Papers VIII and IX. Then, we improved the classification algorithm in Paper XII by reducing the errors that are caused by noise and incorrect spectrum sensing. The algorithm searches for the peaks in the autocorrelation function (ACF) to decide whether the signal is periodic or not. However, noise and incorrect sensing can cause additional peaks, so-called fake maximums, in the ACF. To be able to reliably classify the signals, the ACF signal needs to be smoothened by removing these fake maximums. It is described in the paper how a combination of median filtering followed by a mean filter is an effective way to do the smoothing. The procedure is shown in the Figure 12.

The resulting method was tested with Pareto, Weibull, and exponentially distributed stochastic traffic patterns and the deterministic traffic pattern. The method is able to classify the type of the traffic with a high probability when the channels of interest include both stochastic and deterministic traffic patterns and it is robust against noise and sensing errors. Probability of correct classification is more than 95% when the probabilities of missed detection and false alarms are below 10%. From the practical point of view, the proposed method is based on the autocorrelation function and thus can be used in real-time applications.
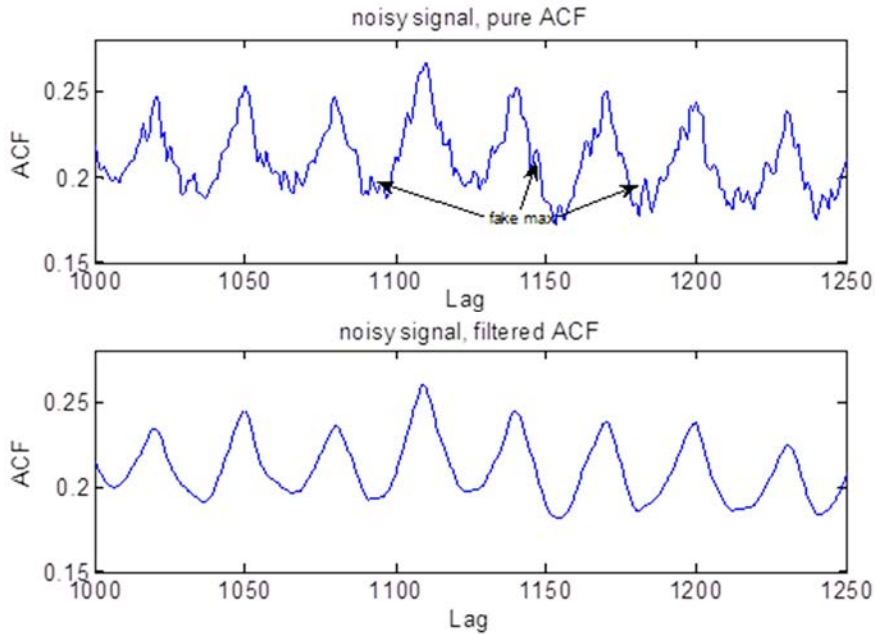
**Figure 12.** Smoothing the ACF by filtering.

### 3.3.3 Use of databases in channel selection

Paper X extends the predictive channel selection method further by joint long-term and short-term database use. Long-term (LT) database aids the operation of the CRS and reduces its sensing time by prioritizing the channels. Only the channels considered promising based on the detection history are selected to be sensed at the time of request (e.g., at 10 a.m. on Friday). Physically, the LT database needs to be local to its users to be able to provide relevant information to the channel selection process. It can be located. for example, in the base station of a cellular system. The request and feedback messages can include information about the needed availability time for the SU operation, enabling the channel allocation to support better the users requesting longer idle times.

Short-term (ST) database allows the classification of traffic patterns and more detailed prediction in the band of interest. The information about the local channel use is gathered with periodical sensing and stored in the ST database. Combining the LT and ST databases makes the operation faster and more efficient than either of these techniques alone. The contribution described in this paper lead to a patent application (Höyhtyä et al., 2010) on the topic before publishing the paper. The method both shortens the sensing time and reduces the number of channel switching, leading to an increase in the throughput for the secondary systems as well as reduced interference to the primary users. The idea can be extended to

consider several databases with different time and space resolutions even though the paper considers only two databases. A combination of the database and spectrum sensing seems to be a promising method for dynamic spectrum access. Spectrum sensing provides means to keep the spectrum data in databases up-to-date whereas the database can be used to assist the sensing of the resource-limited devices.

# 4.  Discussion and conclusions

The current view on the applicability of the CRS capabilities to real-world systems has concentrated on LSA type of concepts or database-based access to the spectrum. However, sensing-based access will also have a clear role, for example, in short-range communications or in military applications due to their ability to adapt to changing RF environments and find the needed spectrum whenever and wherever required. The current sensing-based Wi-Fi systems are very popular among end users, which can be seen as a clear signal of a need for sensing-based solutions in the future as well. This chapter discusses the main findings of the thesis, showing the main contributions to the CRS literature. In addition, the chapter presents the limitations of the work and suggestions for future research directions.

## 4.1  Main findings

Use of history information for predicting the future channel use enables selecting the best channels for secondary transmission. This leads to reduced energy consumption, higher throughput, and reduced delays and collisions. Long-term information can be used in spectrum sensing management to focus the sensing on the most promising channels. Then, short-term data over the promising channels help in classifying and selecting the actual transmission channel. Traffic classification can be made robust against sensing errors and noise by smoothing the autocorrelation function.

Transmission power limits can be set based on the spectrum sensing performance. We have shown the limit to be dependent on the height of the primary antenna. The allowed SU power increases linearly with the increasing PU power. The conducted simulations and calculations show that in many indoor and outdoor environments, only short-range communication is possible with spectrum sensing. This is particularly true when energy detection methods are used for sensing. Other concepts such as databases or LSA/ASA may be needed to achieve longer transmission ranges for spectrum sharing systems.

The developed FxLMS algorithm-based inverse power control is a new application of the algorithm widely used for other inverse control purposes. We have shown the convergence of the algorithm in a slowly fading channel through analyses and

simulations. The method is compared to other practical methods and a quantized version is developed. The algorithm provides a unified framework for many existing algorithms and links them to the LMS literature and theory.

Performance measurement of adaptive transmission methods differs from the traditional receiver-based thinking. Transmitted energy is the basic system resource, and transmitted SNR should be used in performance comparisons to obtain fair results due to covariance between the channel and the transmitted signal. We have also shown that rational decision theory can be used for designing adaptive transmission methods achieving an optimal trade-off between risks and rewards as well as for comparing the performance of different strategies with a simple risk-reward metric.

## 4.2 Limitations and future work

The results obtained in this thesis are promising but there are also limitations associated with the conducted research. For example, system level studies have not been conducted on the power allocation work. Instead, we have focused on investigations over a fading link. The obtained results show that the proposed FxLMS algorithm behaves in a rather similar way compared to state-of-the-art inverse power control algorithms. Thus, it seems to be a very promising method for adaptive transmission over fading links. More importantly, it provides a unified framework for inverse power control algorithms. A limiting factor in the development of the algorithm was related to limited feedback. The selection of the step size for the quantized FxLMS algorithm in a time-variant channel was made in the thesis using a heuristic method. Optimization of the step size remains an interesting future topic.

Another system level limitation can be seen in power limit calculations, where the work focused on the single user case. However, discussions are provided on how to take multiple users into account in calculations. Both the cooperative sensing gain resulting from the diversity effect (Mishra et al., 2006) and the constructive interference from multiple users affect the transmission power limit. This remains a good topic for future work. The obtained results show that sensing-based access should be used with caution already in the single user case; only short-range communications is possible in many environments. The multi-user situation would be even more challenging from the interference point of view.

We opened up a new research direction in *classification-based predictive channel selection*. The proposed classification method differentiates between deterministic and stochastic traffic patterns and the prediction rules are provided for both classes. A clear limitation in this method is that it cannot differentiate between different stochastic patterns. More accurate results could be obtained if specific methods could be applied to all different traffic patterns. However, this would require rather frequent sensing as well as a more complex classification method. The proposed method is simple to implement, rather robust with different sensing periods, and provides decent performance with several different stochastic

patterns. An interesting future topic would be to study the performance of classifiers and predictors with different time resolutions to see what are the circumstances, if any, where more complex methods provide reasonable performance gain to the system.

# 5.   Summary

The present thesis has presented adaptive frequency and power allocation strategies for CRSs. While it is more and more challenging to find new spectrum for coming wireless systems, the CRS technology enables spectrum sharing among several systems, increasing spectrum occupancy and supporting higher data rate demands. The largest challenge in the CRS is designing clever algorithms that will take all needed information that is available – including location of the CR nodes, sensing information, traffic patterns of the different users, regulations, etc. – and make decisions about where in the spectrum to operate at any given moment and how much power to use in that band. The realization of CRSs requires the use of adaptive transmission.

The thesis has reviewed the relevant literature on cognitive radio systems, providing a thorough review on the incentives for spectrum sharing as well. Channel selection methods and adaptive power control techniques were reviewed and classified. The thesis comprises a summary of results considering (1) channel selection in a CRS using history information and (2) power allocation in a selected frequency band assuming a fading channel. A novel FxLMS algorithm-based power control was proposed and studied in the thesis. It is a general inverse power control method that links the state-of-the-art algorithms to the LMS algorithm literature, providing a unified framework for many practical algorithms.

A method for calculating the transmission power limit for secondary transmission in sensing-based spectrum access has been developed. The results show that the allowed transmission power of the secondary user scales linearly with the increasing primary transmission power. The effect of the antenna heights of both primary and secondary systems was also studied and the thesis also provided numerical evaluations in the satellite bands. The results indicate that short-range communication is preferred for sensing-based access in the spectrum. We also noticed that in many scenarios, energy detection cannot support secondary operation in the spectrum. Instead, more sophisticated techniques such as matched filter detection or feature detection are required.

Selecting the proper performance measure to compare different adaptive transmission techniques fairly between each other is not a simple task. We propose using the average transmitted SNR in performance measurement of an adaptive transmission system to see how efficiently the basic energy resource

taken from the battery of the transmitter is used. The thesis also studied the use of rational decision theory in performance comparisons, jointly considering the risk and reward provided by the studied adaptive transmission method.

Intelligent use of history information in resource management was studied in the thesis, focusing on predictive channel selection. The thesis highlights the importance of classifying the traffic patterns in different channels and use of different prediction techniques for these channels based on the classification results. The classification based prediction reduces collisions and delays and increases the throughput of the secondary system compared to both random channel selection and pure predictive channel selection operating without classification. The thesis also proposes a robust autocorrelation-based method for traffic pattern classification. It is a practical method that provides decent performance in a noisy environment.

Finally, in order to use history information as efficiently as possible, the thesis presents a predictive channel selection method that uses both long-term and short-term database information in channel allocations. The long-term database aids the sensing process by prioritizing the channels and focusing the sensing on the most promising channels. Then, short-term information over these most promising channels allows classification and more detailed prediction in the band of interest.

The presented results can be applied to wireless systems operating in different frequency bands, for example, to mobile communication systems, short-range communications, or the satellite bands. In addition, the proposed techniques are useful when development and introduction and use of adaptive transmission techniques continues in the coming wireless systems. Adaptive and cognitive techniques will enable a more efficient spectrum use, providing means to respond to the growing capacity demands in the future.

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# Adaptive inverse power control using an FxLMS algorithm

# Adaptive Inverse Power Control Using an FxLMS Algorithm

Marko Höyhtyä and Aarne Mämmelä
VTT Technical Research Centre of Finland
Oulu, Finland

*Abstract*—**In this paper, a novel adaptive inverse power control method that is based on the filtered-x LMS (FxLMS) algorithm is introduced. Inverse power control minimizes the interference that a cognitive radio creates to licensed users and allows more users to share the spectrum. It is also needed in multi-access systems like code division multiple access (CDMA) to alleviate the near-far problem. The proposed variable step algorithm adjusts the step size in a nearly optimal way. Based on numerical analysis this new method clearly improves system performance compared to the algorithm where the well-known fixed or variable step adjustment power control is used. A normalized version of the FxLMS algorithm is needed in a fading channel. In a slowly fading channel (e.g., normalized Doppler frequency of 0.001) the FxLMS power control can keep the received signal-to-noise ratio (SNR) in the desired level with a good accuracy most of the time. The standard deviation of the received SNR is 1.92 dB when the received SNR is kept at 10 dB. The results with almost all different SNR values are better than the other methods can achieve.**

*Keywords-adaptive transmission; inverse control; FxRLS algorithm;*

## I. Introduction

The power control method that maximizes the capacity of a single user channel in the presence of fading is water filling [1]. However, in constant-rate transmission the performance of the water filling approach is inferior to that of truncated channel inversion. Inverse control is also a good choice for a cognitive radio network [2]. By using the minimum amount of transmission power needed to achieve prescribed requirements the cognitive radio minimizes the interference it creates to licensed users and allows more secondary users to share the spectrum. Furthermore, in multi-access systems like code division multiple access (CDMA) inverse power control is needed to alleviate the near-far problem.

A practical closed loop inverse power control method is fixed step adjustment power control (FSAPC) [3], known also as conventional closed loop power control (CLPC). When this method is used, transmission power is adjusted up- or downwards by a fixed amount (typically 1 dB/ms) depending on whether the received power has been over or below a threshold value. The FSAPC method is simple but not fast enough to compensate deep fades in the channel. In the literature adaptive step-size and also predictive power control methods are used to improve the performance of the conventional FSAPC algorithm [4]-[6].

An analogy can be seen between the FSAPC algorithm and the most well-known adaptive algorithm, the least-mean square (LMS) algorithm. Because of stability problems, the LMS algorithm is not directly suitable for active control application where the adaptive filter works as a controller for a time-variant system. Instead, the FxLMS algorithm is a good choice for that kind of applications [7]. It is essentially the LMS algorithm with a few little changes so that algorithm can remain stable.

The FxLMS algorithm is developed from the LMS algorithm by inserting the model of the controlled system between the input data signal and the adaptive algorithm that updates the coefficients of adaptive filter. The structure of an active control system using the algorithm is presented in Figure 1. The input signal is denoted by $x_k$, the controlled system is $P(z)$ and the model of it is $\hat{P}(z)$. The noisy plant output is compared to the desired response $d_k$ and error signal $\varepsilon_k$ is used when updating the filter coefficients.
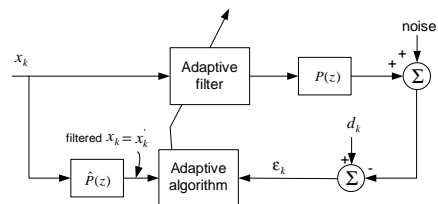


Figure 1. Active control system using the FxLMS algorithm.

The FxLMS algorithm is perhaps the most commonly used adaptive algorithm in active noise canceling applications. The structure and operation of the algorithm are ideally suited to the architectures of standard digital signal processing (DSP) chips and it behaves robustly in the presence of modeling errors and numerical effects caused by finite-precision calculations [8]. In addition, the algorithm is very well suited to adaptive inverse control solutions [9]. In this work we propose and demonstrate a new use of the FxLMS algorithm, namely power control.

Both open-loop and closed-loop methods are used in the power control. Typically the channel is not reciprocal, i.e., fading in up- and down-link correlate poorly and therefore a closed-loop control is required. Open-loop control can be used to compensate shadowing but in this work the main goal is the compensation of fast fading. Therefore only closed-loop methods are considered. Closed-loop FxLMS power control is employed by using noiseless and delayless feedback. The transmitter adjusts the transmission power according to the channel state information transmitted from the receiver. Using

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this novel power control method fast and accurate control can be achieved.

Usually the channel is slowly fading in the physical system. In addition to time-variance, many functions like for example automatic gain control (AGC) and open-loop power control have an effect on the performance of the whole system. In this work we concentrate on the closed-loop power control which is employed using the FxLMS algorithm.

In general, analysis of adaptive systems is not a simple task. In order to get an initial insight on the feasibility of the FxLMS algorithm in the power control loop, we carried out numerical analysis using accurate simulation models. The parts of the system have been tested to precisely respond the desired situation and the results of simulations have been compared to theoretical results presented in the literature.

This paper is organized as follows. Section II introduces the model used in power control simulations. Conventional power control is described in Section III. A novel FxLMS power control structure is introduced in Section IV. Section V provides the simulation results and performance comparison to FSAPC in time-variant channel. Section VI draws the conclusion.

## II. SYSTEM MODEL

The system model, which tranmits the input data $x[k]$ from the transmitter to the receiver, is illustrated in Figure 2. The data are assumed to be known in the receiver, and thus the system is data-aided (DA). The complex fading gain of the channel is $h[k] = \alpha[k]e^{j\theta[k]}$ and $n[k]$ is additive white Gaussian noise (AWGN) at time $k$. The amplitude of the fading gain is $\alpha[k]$ and $\theta[k]$ is the phase shift. The data are transmitted through the channel and the instantaneous transmit power $P[k]$ is allocated based on the channel gain estimate $\hat{h}[k]$ sent by the receiver. Direct LS estimation of $h[k]$ is made online. The transmission data are BPSK modulated with a rate of 10 kilobits per second.

### A. Channel modelling

A time-variant channel can be modelled using the Doppler power spectrum. Our channel is modelled with a flat Doppler power spectrum that corresponds to urban (where the transmitter is set above rooftop level) and indoor environments [10]. The rate of the channel variation can be characterized by Doppler frequency $f_d$. In Jakes' method sinusoids with different Doppler shifts are summed up [11]. Since a channel with a flat Doppler power spectrum is needed, $N$ equal amplitude sinusoids are summed. The time-variant channel gain can be written as

$$h[k] = \sum_{i=1}^{N} a e^{j(2\pi f_i k + \phi_i)} \qquad (1)$$

where $N$ is the number of multipath components, $a$ is the amplitude of every component, $f_i$ is the Doppler shift of the $i$th component, $\phi_i$ is the random uniformly distributed phase shift of the $i$th component in range $[0, 2\pi[$ and $k$ is time.
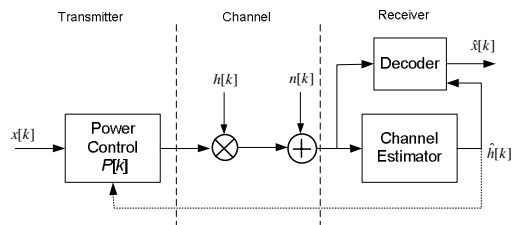


Figure 2. System model.

If the Doppler shifts of sinusoids are equally spaced between $[-f_d, f_d]$ the channel gain becomes periodic. Periodicity can be removed if the shifts are chosen so that the channel gain becomes quasi-periodic. The Doppler shift range is divided into $N$ parts with equal size. The first component lies at frequency $-f_d$ but the frequencies of other components differ a random amount from the equal space solution. With these selections we obtain the whole spectrum range to use in every simulation. The spectrum is made symmetric over zero frequency, which makes the autocorrelation function of the channel real. In this way the simulations are made faster.

### B. Method to compare performance

A good analytical way to investigate the accuracy of different power control methods is to use the concept of standard deviation, which is defined as the square root of variance. Because the aim of the control is to keep the received SNR in the desired level, we want to know the standard deviation of it. We have followed the common tradition that decibel values are used instead of absolute values in computations.

## III. CONVENTIONAL POWER CONTROL

The structure of the FSAPC control [3] is presented in Figure 3. The power of the received signal averaged over three ($m = 3$) symbols is compared to the reference power level $P_{ref}$ in the receiver. If the error signal $\varepsilon_k$ is positive, power is adjusted upwards while negative error causes downward adjustment. The power control algorithm can be written as

$$P_k = P_{k-1} + C_k \Delta P \text{ [dB]} \qquad (2)$$

where the power control command is $C_k = \begin{cases} +1, & \varepsilon_k \geq 0 \\ -1, & \varepsilon_k < 0 \end{cases}$. The

typical step size $\Delta P$ is 1 dB. If the step size is smaller, the control is slower, but it can be more accurate. With a larger step size the control is faster but it cannot achieve good accuracy. The power level is adjusted once in a millisecond.
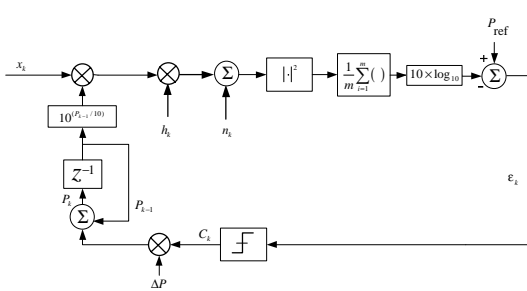
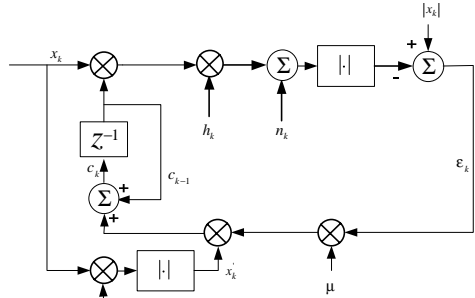3022

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Figure 3. FSAPC control structure.

The FSAPC method approximates the channel inversion. The weakness of this method is that closed loop control is too slow. The fading can typically be tens of dB even every half a carrier wavelength. If the mobile device moves fast (e.g. in a car), the controlling rate 1 dB/ms is not fast enough to compensate fading. Larger steps or diversity is required in such situations.

The control structure presented in Figure 3 can be used also in the variable step adjustment power control (VSAPC) [5]. The idea is that when the power of the received signal is far from the desired, the control step is increased to reach the desired level faster. When the error signal is small, the transmitted power is kept in the same level. The power control command for VSAPC is

$$C_k = \begin{cases} 3, & \text{when } P_{\text{err}} < -5\kappa \\ 2, & -5\kappa \le P_{\text{err}} < -3\kappa \\ 1, & -3\kappa \le P_{\text{err}} < -\kappa \\ 0, & -\kappa \le P_{\text{err}} < \kappa \\ -1, & \kappa \le P_{\text{err}} < 3\kappa \\ -2, & P_{\text{err}} \ge 3\kappa \end{cases} \quad (3)$$

where $P_{\text{err}}$ is the power of error signal in dB and $\kappa = 0.5\Delta P$.

## IV. FXLMS POWER CONTROL

### A. Control structure

The power control structure based on the FxLMS algorithm is introduced in Figure 4. It also approximates the channel inversion. The algorithm updates the coefficient $c[k]$ of a one-tap filter. The algorithm can be written as

$$c_k = c_{k-1} + \mu x'_k \varepsilon_k \quad (4)$$

where $\mu$ is the adaptation step size of the algorithm, the filtered input signal is $x'_k = |x_k \hat{h}_k|$ and $\varepsilon_k$ is the error signal to be minimized. If the variation of channel is slow enough, the algorithm can track the changes and invert the channel.



Figure 4. FxLMS power control.

### B. Convergence of the algorithm

The choice of initial conditions for the FxLMS algorithm is not critical [9]. The algorithm is stable if $\mu$ is small enough, and transients die out just as with the conventional LMS algorithm. In a slowly fading channel $h_k$ can be assumed constant over the memory of the LMS algorithm and the amplitude of the data is constant. Thus the stability condition to the structure when noise is neglected and the channel state is known is

$$0 < \mu < 2/(|x_k|^2 |h_k|^2). \quad (5)$$

An optimal step size can be found for each different $h_k$. The optimum value for the adaptation step size is in the middle of the defined range [12]. Therefore the optimum adaptation step size should be time variant. The optimum step size in a known channel can be defined as

$$\mu_{\text{opt}} = 1/(|x_k|^2 |h_k|^2). \quad (6)$$

When the channel gain is estimated, the system becomes unstable if this step size is used. To stabilize the control the optimum step size is given by

$$\mu_{\text{opt}} = \frac{1}{(|x_k|^2 |\hat{h}_k|^2) + c_{\text{term}}} \quad (7)$$

where $c_{\text{term}}$ is a small number that prevents the adaptation step size to grow to infinity when the estimated received power is very small [13].

Usually the adaptation step size of the FxLMS algorithm is not time-variant. However, the algorithm with a fixed adaptation step size corresponds to a first-order system. It cannot track the fastest changes in time-variant channel without lag error that can be quite large. The best performance is achieved by optimizing the adaptation step size with the instantaneous power of the input signal. It means that the FxLMS algorithm with a fixed step size is changed to the normalized version of it. The normalized version of the FxLMS algorithm corresponds to the filtered-x recursive-

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least-squares (FxRLS) algorithm [12] that can also be used in power control.

## V. PERFORMANCE IN TIME-VARIANT CHANNEL

It is very interesting to know how well the well-known FSAPC method performs in the channel defined in the system model. In this system $f_d$ is chosen to be 10 Hz and the normalized Doppler frequency is 0.001, which corresponds to a slowly fading channel. The number of multipath components, $N$, is chosen to be 12. The variance of $n_k$ is chosen so that the average received SNR is 20 dB. The performance with the step size of 1 dB is shown in Figure 5. The standard deviation of received SNR is now 1.24 dB. The control cannot compensate deep fades well. The received SNR is too low during a deep fade. Then the transmission power is adjusted upwards and because of lag error it is too high for a while after the fade. Clearly we need a faster power control method.
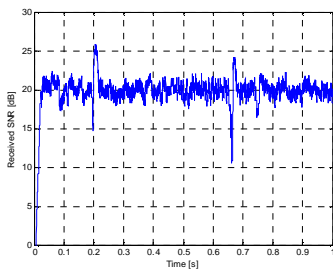


Figure 5. The received SNR with FSAPC power control when step size is 1 dB.

When the step size is doubled to 2 dB the tracking ability is improved and the method can compensate the deep fades in the channel quite well. The large deterioration following this selection is that the best achievable accuracy of control suffers significantly. It can be seen in Figure 6 that the level of received SNR fluctuates significantly all the time. As expected, the standard deviation is bigger with 2 dB step size than with 1 dB step size. The dB-scale value for it is 1.37 dB. This means that more accurate control is achieved with 1 dB step size. The main reason for that is that the received signal is kept in desired power level more accurately most of the time even though the performance during deep fades is worse.
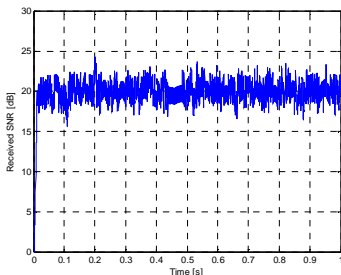


Figure 6. The received SNR with FSAPC when step size is 2 dB.

The performance of VSAPC method is shown in Figure 7. Clear improvement can be noticed when compared to the performance of FSAPC method. Deep fades can now be compensated and also between the deep fades the received signal is kept in the desired level quite accurately. The value of standard deviation is 0.78 dB.
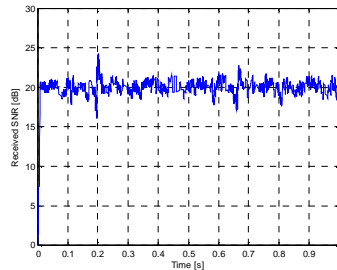


Figure 7. The received SNR with VSAPC power control.

When the normalized FxLMS algorithm is used in power control, the performance of the system is further improved. The power level is adjusted once in a millisecond as in the FSAPC and VSAPC methods. The value of $c_{term}$ was chosen to be 2/SNR, where SNR is the transmitted SNR [14]. The bigger SNR is used the more stable the control is and smaller correction term is needed. It can be seen from Figure 8 that with FxLMS power control the level of received signal-to-noise ratio can be held in the desired level with good accuracy.
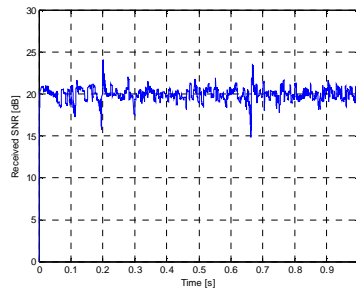


Figure 8. The received SNR with FxLMS power control.

During a deep fade in the channel the signal is a little bit weaker than it should be and after the fade the transmission power is too large for a while. When the results are compared to the results shown in the Figures 5-7 it can be seen that the system with FxLMS power control clearly outperforms the reference systems. The received SNR is held in the desired level with a better accuracy all the time. The value of standard deviation is 0.76 dB. Standard deviations for different SNRs are presented in Table 1. We can see that the accuracy of FxLMS power control is the best among the methods compared. Performance is only slightly deteriorated with an estimated channel.

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TABLE I
STANDARD DEVIATIONS OF DIFFERENT RECEIVED SNR VALUES (IN DECIBELS)

| Average received SNR | FSAPC (step size = 1 dB) | FSAPC (step size = 2 dB) | VSAPC | FxLMS, estimated channel | FxLMS, known channel |
|---|---|---|---|---|---|
| 5 dB | 3.49 | 4.35 | 3.44 | 3.03 | 2.93 |
| 10 dB | 2.02 | 2.29 | 1.95 | 1.92 | 1.90 |
| 15 dB | 1.44 | 1.58 | 1.18 | 1.22 | 1.12 |
| 20 dB | 1.24 | 1.37 | 0.78 | 0.76 | 0.68 |
| 25 dB | 1.13 | 1.25 | 0.60 | 0.51 | 0.48 |
| 30 dB | 1.11 | 1.22 | 0.51 | 0.39 | 0.37 |

The reason that makes the FSAPC control attractive in practical systems is that power control command is only one bit. Therefore the transmission rate of the feedback channel can be kept low. VSAPC and FxLMS algorithms need a higher bit rate in the feedback channel to achieve accurate control. But accuracy and fast control are required in many systems. Consequently, the methods with variable step size like the FxLMS power control are important to investigate.

## VI. CONCLUSIONS

The adaptive inverse power control employed with the normalized FxLMS algorithm is more accurate and faster than the conventional FSAPC method or the variable step method presented in [5]. These initial results using the proposed method are promising and encouraging. When the FxLMS algorithm is used, the power is adjusted up- and downwards in a linear scale. The algorithm is a variable step algorithm that adjusts the step size in a nearly optimal way. The authors do not know any algorithm that converges faster when the channel is assumed to be slowly fading. However, the approximations of the introduced method are needed for practical use. One possibility could be to put the method into practice in the dB domain like the FSAPC method. It would be interesting to study the performance of the FxLMS power control under practical assumptions, e.g., with delayed and noisy feedback. One problem to be solved is to analyze the needed amount of control information and to compare it to the VSAPC control.

A large part of the transmission power is now used to compensate the deepest fades. The performance of the proposed method can be further improved by using a cutoff that interrupts the transmission if the channel state deteriorates to bad enough. This kind of method is used in the well known truncated channel inversion [1]. The use of the cutoff could clearly improve the performance of the whole system. However, it should be noted that no data are transmitted below the cutoff.

## ACKNOWLEDGEMENT

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PAPER II

# Relationship of average transmitted and received energies in adaptive transmission

# Relationship of Average Transmitted and Received Energies in Adaptive Transmission

Aarne Mämmelä, *Senior Member, IEEE*, Adrian Kotelba, *Member, IEEE*, Marko Höyhtyä, *Student Member, IEEE*, and Desmond P. Taylor, *Life Fellow, IEEE*

*Abstract*—This paper studies the analytical relationship between the average transmitted and received energies under several adaptive transmitter power control methods, including water filling, truncated power inversion, and downlink beamforming. The study is applicable to many fading channel scenarios, including frequency-nonselective, frequency-selective, and multiple-input–multiple-output (MIMO) channels. Both the average transmitted and received energies are commonly used in performance comparisons, and the selection depends on what one wants to investigate. The transmitted energy is known to be the basic system resource. In the case of adaptive transmission, the average transmitted energy should, in general, be used instead of the average received energy. The use of transmitted energy leads to the normalization problem of the channel. The ratio of received energy to transmitted energy is the energy gain of the channel. All physical systems follow an energy-conservation law, which implies that the energy gain of the channel is less than or equal to 1. The major approaches for normalization include the setting of either the average energy gain or the peak energy gain to unity. In the normalization, the average energy gain is defined for a signal whose energy is uniformly distributed across the frequency and spatial dimensions. The peak energy gain of many mathematical fading models is not bounded, and those models cannot be normalized by the peak energy gain. We show that the proper normalization of the mathematical model and the selection of the correct performance measure are of critical importance in comparative performance analysis of adaptive transmission systems.

*Index Terms*—Energy-conservation law, multiantenna systems, multipath fading, multiple-input–multiple-output (MIMO) systems, transmitter power control.

## I. INTRODUCTION

ENERGY is a basic resource in digital transmission links, and systems should be analyzed on the basis of how efficiently it is used [1]. We divide systems into energy limited and power limited. In power-limited systems, such as a base station connected to the electrical network, the available power is limited, but energy is essentially unbounded. In energy-limited systems, such as a mobile terminal using a battery, the available energy is limited. In practice, to make the problem

analytically tractable, systems are usually optimized as if they were power limited, but performance is often measured as if they were energy limited by using the energy-to-noise power spectral density ratio.

There appear to be two alternative modes of performance measurement in terms of energy. Either the average transmitted or received energy per symbol is used, and both are usually normalized by the receiver noise spectral density. This leads to the average transmitted SNR per symbol [2, pp. 40–127], [3]–[6] and average received SNR per symbol [7], [8], respectively. The use of average transmitted and received SNRs was briefly discussed in [9, p. 2628], but no recommendation was made concerning their preferred usage.

It is known that system performance depends in part on the average received SNR. If we compare different receivers for the same transmitted signal and for the same channel, we can measure how well the receiver is matched to the channel. However, we do not necessarily know how well the transmitted signal is matched to the channel. In energy-limited systems, the transmitted energy is the basic system resource since it is the transmitted energy rather than the received energy that is taken from the battery and is necessarily limited. The actual received energy is typically a small fraction of the transmitted energy due to the finite effective aperture of the antennas. The authors of [7] and [8] optimize the use of the transmitted energy in adaptive transmission in a fading channel, but their numerical results show how efficiently the received energy is used. The reader is led to believe that the system is almost as good as if there were no fading at all, although significant improvement is actually possible. The use of the received SNR was emphasized in [10], but when the transmitter was optimized [10, p. 572], the transmitted power was fixed, following the theory presented in [2].

Since the average energy gain of the channel is a function of the transmitted signal, particularly in adaptive transmission systems, it is crucial to use the transmitted SNR rather than the received SNR for performance measurements. However, it is still possible to use the average transmitted SNR referred to the receiver, which is to be defined in Section III-E, provided that the channels are properly normalized. The average received SNR can be used if the channels are correctly normalized and the transmitters exploit no form of channel selectivity.

The major approaches for normalization of the channel include normalization of the average energy gain or the peak energy gain to unity [11]. For brevity, we call them average and peak normalization, respectively. In the normalization, the average energy gain is defined for a signal whose energy is uniformly distributed across the frequency and spatial dimensions.

We will refer to this specific average energy gain as the representative energy gain. Energy conservation is known to hold for all physical systems. Therefore, the output energy of a passive system cannot be larger than the input energy, and the peak energy gain should be less than or equal to 1 because a major part of the energy is lost in the channel from the receiver point of view. In most of the literature on fading channels, average normalization is used. However, as is shown in [11] and in the present paper, this approach must be reconsidered when either the transmitted signal or the channel exhibits selectivity in time, frequency, or space. The authors of [11] noticed that the peak energy gain of a linear time-invariant frequency-selective filter can be larger than unity if average normalization is used.

Our major contribution is to extend the results of [11] to a general class of linear vector channels. A linear vector model can represent a wide range of physical channels. These vector channels can be time variant or time invariant, frequency selective or frequency nonselective, and may have many inputs or outputs corresponding to, for example, multiple antennas. These systems are usually called multiple-input–multiple-output (MIMO) systems. Finally, the transmitter may use an arbitrary power control scheme. We show the analytical relationship between the average transmitted and received SNRs by using the covariance between the transmitted energy and the energy gain of the channel. The covariance specifies how well the transmitted signal is statistically matched to the channel. We also show that the conclusions from performance comparisons depend on whether the transmitted or the received SNR is used in the comparisons. In general, the transmitted SNR should be used, and the proper normalization method is shown to be peak normalization. We present novel bounds on the average received SNR that can be achieved with an adaptive power-control scheme and generalize previous analysis [11] to include time, frequency, and spatial domains.

Parts of this paper were presented in our earlier conference papers [12]–[14]. In the present combined paper, we have extended these results and have unified and elaborated the explanations and examples. We have made a clear distinction between power- and energy-limited systems. We have also derived analytical expressions for the distributions of the SNRs and shown the deviations if the channel is not peak normalized.

The remainder of this paper is organized as follows: In Section II, we introduce models of a linear vector channel and an adaptive transmitter. The basic concepts related to the transmission of energy through linear vector channels are covered in Section III. Section IV contains analysis for frequency-selective and frequency-nonselective fading channels with multiple antennas. Numerical results are presented in Section V and conclusions in Section VI.

*Notation:* Boldface lowercase letters $\boldsymbol{a}$ denote column vectors; $\boldsymbol{A} = [a_{ij}]_{i,j=1}^{m,n}$ denotes an $m \times n$ matrix whose $(i,j)$th entry is $a_{ij}$; $(\cdot)^*$ denotes the conjugate transpose of a matrix; $\text{tr}(\cdot)$ is the trace of a matrix; $\text{rank}(\cdot)$ is the rank of a matrix; $\text{diag}(d_{11}, \ldots, d_{kk})$ is a $k \times k$ diagonal matrix with entries $d_{ii}$, $1 \le i \le k$; $\boldsymbol{I}_m$ is the $m \times m$ identity matrix; $\{a_i\}_{i=1}^u$ denotes an ordered set of $u$ elements, $a_1 \le a_i \le a_u$; $\Pr[\cdot]$ denotes probability; $\mathbb{E}[X]$ and $\overline{X}$ denote expectation of a random variable $X$; $\mathbb{E}[X|Y]$ denotes conditional expectation of a random variable $X$ given a random variable $Y$; $\text{Var}[\cdot]$ denotes variance of a random variable; $\text{Cov}[\cdot, \cdot]$ denotes the covariance of two random variables; $f(x)^+ = \max[0, f(x)]$; and $\mathbb{C}$ and $\mathbb{R}$ denote the fields of complex and real numbers, respectively.

## II. SYSTEM MODEL

### A. Channel Model

We consider a discrete-time linear vector channel with $n$ inputs and $m$ outputs, where $n \le m$ for reliable detection. Let $\boldsymbol{y} \in \mathbb{C}^n$ denote a vector of complex input symbols, $\boldsymbol{n} \in \mathbb{C}^m$ denote a vector of complex noise samples, and $\boldsymbol{r} \in \mathbb{C}^m$ be a vector of complex output symbols. The output $\boldsymbol{r}$ and input $\boldsymbol{y}$ symbols are related by the matrix equation [15]–[18]

$$\boldsymbol{r} = \boldsymbol{H}\boldsymbol{y} + \boldsymbol{n} = \boldsymbol{z} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{z} = \boldsymbol{H}\boldsymbol{y}$ denotes the signal component of the received signal. The complex channel coefficients between the $j$th input and the $i$th output, which is denoted by $h_{ij}$, are assembled into a channel matrix $\boldsymbol{H} = [h_{ij}]_{i,j=1}^{m,n}$. We assume that the entries of $\boldsymbol{n}$ are complex zero-mean Gaussian random variables with variance $\sigma_n^2 = N_0/T_s$, where $N_0$ denotes the noise power spectral density, and $T_s$ is the sampling interval. Furthermore, we assume that the noise samples are uncorrelated, that is, $\mathbb{E}[\boldsymbol{n}\boldsymbol{n}^*] = \sigma_n^2 \boldsymbol{I}_m$.

The vector channel defined in (1) models a wide range of physical channels.

1) Frequency-nonselective fading channel with a single antenna—$\boldsymbol{H}$ is a random scalar.
2) Frequency-selective time-invariant channel with a single antenna—$\boldsymbol{H}$ is an arbitrary Toeplitz matrix that is fixed for the whole transmission duration.
3) Frequency-nonselective fading channel with multiple antennas—$\boldsymbol{H}$ is an arbitrary matrix that randomly changes from one channel use to another.
4) Frequency-selective block-fading channel with a single antenna—$\boldsymbol{H}$ is an arbitrary Toeplitz matrix that randomly changes from one transmission block to another.
5) Frequency-selective block-fading channel with multiple antennas—$\boldsymbol{H}$ is a block-Toeplitz matrix that randomly changes from one transmission block to another.

Frequency-selective fading can be modeled by (1), provided that the channel memory is assumed to be finite. The channel matrix $\boldsymbol{H}$ is then, as will be shown later, a convolution matrix with a Toeplitz or a block-Toeplitz structure.

The performance analysis is simplified if the channel model described by the matrix $\boldsymbol{H}$ is transformed into a virtual set of parallel orthogonal subchannels [15]–[18]. The transformation of the channel into its virtual structure is achieved with singular value decomposition. Let $\{\lambda_i\}_{i=1}^u$ be the nonzero eigenvalues of the matrix $\boldsymbol{A} = \boldsymbol{H}^*\boldsymbol{H}$. Then, we may write [19, p. 193]

$$\boldsymbol{H} = \boldsymbol{U}\boldsymbol{D}\boldsymbol{V}^* \tag{2}$$

where $\boldsymbol{U} \in \mathbb{C}^{m \times m}$ and $\boldsymbol{V} \in \mathbb{C}^{n \times n}$ are unitary, and the $m \times n$ diagonal matrix $\boldsymbol{D}$ has $\sqrt{\lambda_i}$ in the $(i,i)$ position ($1 \le i \le u$)
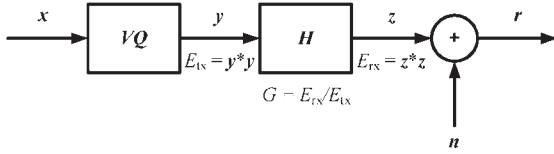
Fig. 1. Block diagram of the system.

and zeros elsewhere. The matrix equation (1) can then be rewritten as

$$r = UDV^*y + n. \tag{3}$$

Finally, the vector channel model is transformed into a set of orthogonal subchannels when the input and output vectors $y$ and $r$ are left multiplied by matrices $V^*$ and $U^*$, respectively. Thus, we obtain

$$\tilde{r} = U^*r = DV^*y + U^*n = D\tilde{y} + \tilde{n} \tag{4}$$

where $\tilde{y} = V^*y$, and $\tilde{n} = U^*n$.

The channel model described by $H$ and its virtual representation as specified by the unitary matrices $U$ and $V$ and the diagonal matrix $D$ are equivalent in the sense that the total input and output energies remain the same, i.e., $z^*z = \tilde{z}^*\tilde{z}$, $n^*n = \tilde{n}^*\tilde{n}$, and $y^*y = \tilde{y}^*\tilde{y}$. This is due to the fact that the inner product is invariant to unitary similarity transformations [19, p. 283].

### B. Transmitter Model

Typically, a transmitter includes some form of transmitter power control, which can be represented by the matrix equation [20]

$$\tilde{y} = Qx \tag{5}$$

which is equivalent to $y = VQx$, where $Q$ is the power control matrix, and $x$ is a vector of complex source symbols (see Fig. 1). The linear precoder formed by $VQ$ [20], [21] introduces correlation between the symbols. We assume that $Q \in \mathbb{R}^{n \times n}$ and $x \in \mathbb{C}^n$ with its last $n - w$ entries equal to zero, where $w = \text{rank}(Q) \leq \text{rank}(A)$ is the number of symbols actually transmitted within $n$ symbol intervals. Furthermore, we let the entries of $x$ be independent and identically distributed (i.i.d.) random variables with unit variance. This does not restrict our transmitter model in any way because the required transmission energy is achieved by properly scaling the entries of $Q$. Any channel coding, including space–time coding, is excluded from our system model.

In general, the power control matrix $Q$ may be nondiagonal. If the entries of $x$ are normal and our aim is to maximize channel capacity, the matrix $Q$ is diagonal [22]. In addition, in some simple suboptimal schemes for discrete signal constellations, the matrix $Q$ is diagonal [23]. Here, $Q$ is assumed to be a diagonal matrix whose entries are some function $f : \mathbb{R}^n \to \mathbb{R}$ of the energy gains $\lambda_i$ of the orthogonal subchannels, i.e., $q_{ii} = f(\lambda_1, \ldots, \lambda_n), 1 \leq i \leq n$.

A number of adaptive power control rules, together with corresponding mappings $f$, can be used in practical commu-

nication systems. For example, with the water-filling power control rule, the transmitted signal is controlled according to [9, p. 2827], [24]

$$q_{ii} = \sqrt{\left(\mu_{\text{wf}}^{-1} - \lambda_i^{-1}\right)^+}, \qquad 1 \leq i \leq n. \tag{6}$$

On the other hand, with truncated power inversion, the transmitted signal is controlled according to [9, p. 2629]

$$q_{ii} = \begin{cases} \sqrt{\beta/\lambda_i}, & \lambda_i > \mu_{\text{tci}} \\ 0, & \lambda_i \leq \mu_{\text{tci.}} \end{cases} \tag{7}$$

Furthermore, with a simple power control method, sometimes referred to as downlink beamforming [25], only the $u$th subchannel (that having the largest energy gain) is used for transmission, i.e.,

$$q_{ii} = \begin{cases} \delta, & i = u \\ 0, & i \neq u. \end{cases} \tag{8}$$

The scalars $\beta$ and $\delta$ and the cutoff values or transmission thresholds $\mu_{\text{wf}}$ and $\mu_{\text{tci}}$ are chosen such that the long-term average energy or power constraint is fulfilled [20, p. 2279]. In general, the average power constraint takes a simpler form because the average transmitted power per symbol $P_{\text{av}}$ is

$$P_{\text{av}} = \frac{\mathbb{E}[E_{\text{tx}}]}{nT_s} = \frac{\mathbb{E}[\tilde{y}^*\tilde{y}]}{nT_s} = \frac{\mathbb{E}[x^*Q^*Qx]}{nT_s} \tag{9}$$

where $T_s$ is the sampling interval. On the other hand, the average transmitted energy per symbol $E_{\text{av}}$ is

$$E_{\text{av}} = \mathbb{E}\left[\frac{E_{\text{tx}}}{w}\right] = \mathbb{E}\left[\frac{\tilde{y}^*\tilde{y}}{w}\right] = \mathbb{E}\left[\frac{x^*Q^*Qx}{w}\right] \tag{10}$$

because energy expenditure takes place only when it is used for transmission. The number $w$ of symbols actually transmitted can be a fixed number or a random variable. If the channel is time invariant or the power-control rule is such that the rank of $Q$ remains constant, then there is a simple relationship between the average transmitted power and energy. On the other hand, $w$ is likely to be a random variable when a power-control scheme with a transmission threshold $\mu$ is used. Hence, the exact relationship between average transmitted power and energy is difficult to establish. For those reasons, unless otherwise specified, in the remainder of this paper, we will consider only power-limited systems due to their analytical tractability. For a random $w$, the probability of outage or no transmission is

$$P_{\text{out}} = \Pr(w = 0). \tag{11}$$

### III. BASIC CONCEPTS

#### A. Energy Gain of the Channel

The *energy gain* of the channel is the ratio of the signal component of the received energy $E_{\text{rx}}$ to the transmitted energy $E_{\text{tx}}$ and is given by

$$G = \frac{E_{\text{rx}}}{E_{\text{tx}}} = \frac{z^*z}{y^*y} = \frac{y^*H^*Hy}{y^*y} \tag{12}$$

when $E_{\text{tx}} > 0$. On the other hand, when $E_{\text{tx}} = 0$, no transmission takes place, and the energy gain of the channel is defined to be zero.

The energy gain $G$ is in fact a Rayleigh quotient for an $n \times n$ Hermitian matrix $\boldsymbol{A} = \boldsymbol{H}^*\boldsymbol{H}$ [19, p. 282]. The form of the Rayleigh quotient is simplified if we use the virtual channel model [15]–[18] and take advantage of the invariance property of the Rayleigh quotient under unitary similarity transformations to obtain

$$G = \frac{\boldsymbol{z}^*\boldsymbol{z}}{\boldsymbol{y}^*\boldsymbol{y}} = \frac{\tilde{\boldsymbol{z}}^*\tilde{\boldsymbol{z}}}{\tilde{\boldsymbol{y}}^*\tilde{\boldsymbol{y}}} = \frac{\tilde{\boldsymbol{y}}^*\boldsymbol{D}^*\boldsymbol{D}\tilde{\boldsymbol{y}}}{\tilde{\boldsymbol{y}}^*\tilde{\boldsymbol{y}}} = \frac{\sum_{i=1}^n \lambda_i |\tilde{y}_i|^2}{\sum_{i=1}^n |\tilde{y}_i|^2} \qquad (13)$$

where $\tilde{y}_i$ is the $i$th element of vector $\tilde{\boldsymbol{y}}$. Let

$$\varepsilon_i = \frac{|\tilde{y}_i|^2}{\sum_{i=1}^n |\tilde{y}_i|^2}, \qquad i = 1, 2, \dots, n \qquad (14)$$

denote the fraction of the total transmitted energy allocated to the $i$th subchannel. Then, (13) can be rewritten as

$$G = \sum_{i=1}^n \lambda_i \varepsilon_i \qquad (15)$$

which shows that the energy gain $G$ depends on the distribution of the available energy among subchannels rather than its total amount. Furthermore, by the properties of a Rayleigh quotient [19, p. 285], the energy gain of the channel $G$ is bounded as

$$\lambda_l \le G \le \lambda_u \qquad (16)$$

where $\lambda_l$ and $\lambda_u$ are the minimal and the maximal eigenvalues of $\boldsymbol{A}$, respectively.

### B. Average Energy Gain of the Channel

In general, the *average energy gain* of the channel is

$$\overline{G} = \mathbb{E}[G] = \mathbb{E}[E_{\text{rx}}/E_{\text{tx}}] \qquad (17)$$

which is equal to $\mathbb{E}[E_{\text{rx}}]/\mathbb{E}[E_{\text{tx}}]$ if and only if $E_{\text{tx}}$ and $G$ are uncorrelated, for example, if $E_{\text{tx}}$ is fixed. By substituting (15) into (17), we obtain

$$\overline{G} = \sum_{i=1}^n \mathbb{E}[\lambda_i \varepsilon_i] = \breve{G} + \theta. \qquad (18)$$

The parameter

$$\breve{G} = \sum_{i=1}^n \mathbb{E}[\lambda_i]\mathbb{E}[\varepsilon_i] \qquad (19)$$

describes the average energy gain as if there was no correlation between the energy $\varepsilon_i$ allocated to the $i$th subchannel and the subchannel energy gain $\lambda_i$. On the other hand, the term

$$\theta = \sum_{i=1}^n \text{Cov}[\lambda_i, \varepsilon_i] \qquad (20)$$

in (18) describes how $\overline{G}$ changes when there is correlation between $\varepsilon_i$ and $\lambda_i$.

### C. Representative Energy Gain of the Channel

Our aim now is to find a representative energy gain of the channel that does not depend on the transmitted signal as do the energy gain in (13) and the average energy gain in (18). The average energy gain of (18) is independent of the transmitted signal if and only if the transmitted energy is uniformly distributed over all orthogonal subchannels associated with eigenvalues of the channel matrix, that is, $\varepsilon_i = 1/n$ for all $i$. Thus, the *representative energy gain* is uniquely defined to be

$$G_0 = \frac{1}{n}\mathbb{E}\left[\sum_{i=1}^n \lambda_i\right] = \frac{1}{n}\mathbb{E}[\text{tr}(\boldsymbol{A})]. \qquad (21)$$

The representative energy gain describes the average attenuation of the channel for a special transmitted signal. The definition in (21) is consistent with and is in fact a generalization of the one used, for example, in [11] in a frequency-selective channel. In fact, the representative energy gain is the energy of the impulse response of the channel [11]. In frequency-selective time-invariant or frequency-selective block-fading channels, distinct frequencies create orthogonal subchannels. In multiple-antenna channels, orthogonal subchannels are created by beamforming matrices. Thus, a uniform energy distribution over the orthogonal subchannels implies a uniform energy distribution across both the frequency and spatial dimensions.

### D. Average Transmitted and Received Energies

The average transmitted energy is

$$\mathbb{E}[E_{\text{tx}}] = \mathbb{E}\left[\sum_{i=1}^n |\tilde{y}_i|^2\right] \qquad (22)$$

whereas the average received energy is

$$\mathbb{E}[E_{\text{rx}}] = \mathbb{E}\left[\sum_{i=1}^n \lambda_i |\tilde{y}_i|^2\right]. \qquad (23)$$

When water filling, truncated channel inversion, or downlink beamforming are used, the power control matrix $\boldsymbol{Q}$ is diagonal. Then, the average transmitted and received energies, respectively, become

$$\mathbb{E}[E_{\text{tx}}] = \mathbb{E}\left[\sum_{i=1}^u q_{ii}^2 |x_i|^2\right] = \mathbb{E}\left[\sum_{i=1}^u q_{ii}^2\right] \qquad (24)$$

$$\mathbb{E}[E_{\text{rx}}] = \mathbb{E}\left[\sum_{i=1}^u \lambda_i q_{ii}^2 |x_i|^2\right] = \mathbb{E}\left[\sum_{i=1}^u \lambda_i q_{ii}^2\right]. \qquad (25)$$

To obtain the simplified forms of (24) and (25), we take advantage of the assumption that the entries of $\boldsymbol{x}$ are i.i.d. random variables with unit variance.

In the most general case, $q_{ii}^2$ follows a mapping $g : \mathbb{R}^n \to \mathbb{R}$, and the evaluation of (24) and (25) requires averaging over the joint probability density function (pdf) $p(\lambda_1, \dots, \lambda_n)$ of the eigenvalues of $\boldsymbol{A}$. However, in the special case where the $i$th

diagonal entry $q_{ii}$ is a function only of $\lambda_i$, i.e., $g : [0, \infty) \to \mathbb{R}$, we have

$$\mathbb{E}[E_{\text{tx}}] = \mathbb{E}\left[\sum_{i=1}^{u} g(\lambda_i)\right] = u \int_0^\infty g(\lambda) h(\lambda) \, d\lambda \qquad (26)$$

$$\mathbb{E}[E_{\text{rx}}] = \mathbb{E}\left[\sum_{i=1}^{u} \lambda_i g(\lambda_i)\right] = u \int_0^\infty \lambda g(\lambda) h(\lambda) \, d\lambda \quad (27)$$

where $h(\lambda)$ is the pdf of a single eigenvalue [26]. It can easily be verified that, under the long-term average energy or power constraint [20, p. 2279], the scalars $\beta$, $\delta$, $\mu_{\text{wf}}$, and $\mu_{\text{tci}}$ depend on the specific joint distribution of eigenvalues $(\lambda_1, \ldots, \lambda_n)$ rather than their instantaneous values. Consequently, water filling and the truncated channel inversion and downlink beamforming power-control schemes fall under this special case because, in all of them, $q_{ii}$, as (6)–(8) suggest, depends on only a single eigenvalue $\lambda_i$.

### E. Average Transmitted and Received SNRs

The average transmitted and received energies are usually normalized by the receiver noise spectral density $N_0$, leading to the *average transmitted SNR per symbol*

$$\overline{\gamma}_{\text{tx}} = \frac{1}{n} \frac{\mathbb{E}[E_{\text{tx}}]}{N_0} = \frac{1}{n} \frac{\mathbb{E}[\tilde{\boldsymbol{y}}^* \tilde{\boldsymbol{y}}]}{N_0} \qquad (28)$$

and the *average received SNR per symbol*

$$\overline{\gamma}_{\text{rx}} = \frac{1}{n} \frac{\mathbb{E}[E_{\text{rx}}]}{N_0} = \frac{1}{n} \frac{\mathbb{E}[E_{\text{tx}} \cdot G]}{N_0} = \frac{1}{n} \frac{\mathbb{E}[\tilde{\boldsymbol{z}}^* \tilde{\boldsymbol{z}}]}{N_0}. \qquad (29)$$

The *average transmitted SNR per symbol referred to the receiver* is defined as

$$\check{\gamma}_{\text{tx}} = \frac{1}{n} \frac{\mathbb{E}[E_{\text{tx}}] \cdot G_0}{N_0} = \overline{\gamma}_{\text{tx}} G_0 \qquad (30)$$

where $G_0$ is given by (21). The averages in (28)–(30) include outages. In [6, eq. (13)], the SNR corresponding to (30) was called the average transmitted energy-to-noise ratio. To avoid confusion, we have reserved the term average transmitted SNR per symbol for (28) because of the scaling by $G_0$ in (30). The scaling is used for convenience to take into account the average attenuation of the channel for a signal having a uniform distribution in frequency and spatial dimensions.

The relationship between the average transmitted SNR per symbol $\overline{\gamma}_{\text{tx}}$, the average transmitted SNR per symbol referred to the receiver $\check{\gamma}_{\text{tx}}$, and the average received SNR per symbol $\overline{\gamma}_{\text{rx}}$ can be established through the covariance of the transmitted energy $E_{\text{tx}}$ and channel energy gain $G$. In particular

$$\overline{\gamma}_{\text{rx}} = \overline{\gamma}_{\text{tx}} \mathbb{E}[G] + \frac{\vartheta}{nN_0} = \frac{\check{\gamma}_{\text{tx}}}{G_0} \mathbb{E}[G] + \frac{\vartheta}{nN_0} \qquad (31)$$

where

$$\vartheta = \text{Cov}[E_{\text{tx}}, G] = \mathbb{E}[E_{\text{tx}} \cdot G] - \mathbb{E}[E_{\text{tx}}] \cdot \mathbb{E}[G]. \qquad (32)$$

Mathematically, the covariance $\vartheta$ can be bounded as

$$-\sqrt{\text{Var}[E_{\text{tx}}]\text{Var}[G]} \leq \vartheta \leq \sqrt{\text{Var}[E_{\text{tx}}]\text{Var}[G]}. \qquad (33)$$

However, in the present system model, there is an alternative lower bound on the covariance. It is obtained by imposing the physical constraint on the received energy that it cannot be negative so that $\mathbb{E}[E_{\text{tx}} \cdot G] \geq 0$. After some algebra in (32), we obtain $\vartheta \geq -\mathbb{E}[E_{\text{tx}}] \cdot \mathbb{E}[G]$. Finally, the lower bound for the covariance is given by

$$\vartheta \geq -\min\left\{\mathbb{E}[E_{\text{tx}}]\mathbb{E}[G], \sqrt{\text{Var}[E_{\text{tx}}]\text{Var}[G]}\right\}. \qquad (34)$$

By substituting (18) into (31), we obtain

$$\overline{\gamma}_{\text{rx}} = \overline{\gamma}_{\text{tx}}(\check{G} + \theta) + \frac{\vartheta}{nN_0} = \frac{\check{\gamma}_{\text{tx}}}{G_0}(\check{G} + \theta) + \frac{\vartheta}{nN_0}. \qquad (35)$$

To summarize, we have defined three different averages of the energy gain $G$. The statistical average (17) is denoted by $\overline{G}$. If $\theta = 0$ in (18), we obtain $\overline{G} = \check{G}$. If, in addition, $\vartheta = 0$ in (35), we obtain $\overline{G} = G_0$. The covariance $\vartheta$ specifies how well the transmitted energy is statistically matched to the energy gain of the channel. The covariance $\theta$ specifies how well the energy allocations $\varepsilon_i$ are statistically matched to the energy gains $\lambda_i$ of the orthogonal subchannels. The covariances $\vartheta$ and $\theta$ describe the change of $\overline{\gamma}_{\text{rx}}$ due to power control in the transmitter. Since they can take negative and positive values, $\overline{\gamma}_{\text{rx}}$ could be smaller than or greater than $\check{G}\overline{\gamma}_{\text{tx}}$. The upper and lower bounds on covariance $\vartheta$, which lead to the respective bounds on $\overline{\gamma}_{\text{rx}}$ with respect to $\overline{\gamma}_{\text{tx}}(\check{G} + \theta)$, can be used in link budget calculations for adaptive links.

We want to emphasize that it would be misleading to refer to (30) as the average received SNR per symbol because the covariances $\theta$ and $\vartheta$ in (35) are, in general, nonzero and depend on the transmitted signal. Furthermore, if we want to know how efficiently the basic resource, i.e., transmitted energy, is used, we should not use (29) instead of (30) in performance comparisons.

So far, all the SNRs are presented as if the system were power limited. In energy-limited systems, we use the expurgated SNRs

$$\check{\gamma}_{\text{tx}}^{(e)} = \frac{1}{n} \frac{\mathbb{E}[E_{\text{tx}}|E_{\text{tx}} > 0] \cdot G_0}{N_0} = \frac{\check{\gamma}_{\text{tx}}}{1 - P_{\text{out}}} \qquad (36)$$

$$\overline{\gamma}_{\text{rx}}^{(e)} = \frac{1}{n} \frac{\mathbb{E}[E_{\text{tx}} \cdot G|E_{\text{tx}} \cdot G > 0]}{N_0} = \frac{\overline{\gamma}_{\text{rx}}}{1 - P_{\text{out}}} \qquad (37)$$

where the probability of outage $P_{\text{out}}$ is defined in (11). In a similar way, the transmitted SNR in (28) can be expurgated. A summary of the various SNRs is given in Table I. We have borrowed the term "expurgation" from the channel-coding literature [27]. The purpose of this expurgation process is to remove the effect of outage from the calculation of the average SNR values of (36) and (37). That is, we remove the effect of not transmitting during outage from the average SNR calculation.

TABLE I
SUMMARY OF THE DIFFERENT SNR CONCEPTS USED IN THIS PAPER

| Name | Nonexpurgated | Expurgated |
|---|---|---|
| Average transmitted SNR | $\overline{\gamma}_{\text{tx}} = \frac{1}{n}\frac{\mathbb{E}[E_{\text{tx}}]}{N_0}$ | $\overline{\gamma}_{\text{tx}}^{(e)} = \frac{1}{n}\frac{\mathbb{E}[E_{\text{tx}}|E_{\text{tx}}>0]}{N_0}$ |
| Average received SNR | $\overline{\gamma}_{\text{rx}} = \frac{1}{n}\frac{\mathbb{E}[E_{\text{tx}}\cdot G]}{N_0}$ | $\overline{\gamma}_{\text{rx}}^{(e)} = \frac{1}{n}\frac{\mathbb{E}[E_{\text{tx}}\cdot G|E_{\text{tx}}\cdot G>0]}{N_0}$ |
| Average transmitted SNR referred to the receiver | $\breve{\gamma}_{\text{tx}} = \frac{1}{n}\frac{\mathbb{E}[E_{\text{tx}}]\cdot G_0}{N_0}$ | $\breve{\gamma}_{\text{tx}}^{(e)} = \frac{1}{n}\frac{\mathbb{E}[E_{\text{tx}}|E_{\text{tx}}>0]\cdot G_0}{N_0}$ |

## IV. EXAMPLES

### A. Frequency-Nonselective Fading Channel

We consider a frequency-nonselective fading channel with $t$ transmitter and $r$ receiver antennas. The number of channel inputs $n$ is equal to $t$, and the number of channel outputs $m$ is equal to $r$. Furthermore, we assume that the entries of the channel matrix $\boldsymbol{H}$ are i.i.d. circularly symmetric complex Gaussian random variables with zero mean and variance $\sigma^2$. Consequently, the $n \times n$ matrix $\boldsymbol{A} = \boldsymbol{H}^*\boldsymbol{H}$ is a complex Wishart matrix, and the pdf of a single unordered eigenvalue of $\boldsymbol{A}$ is [28, eq. (15)]

$$h(\lambda) = \frac{e^{-\lambda/\sigma^2}}{u\sigma^2}\sum_{k=0}^{u-1}\frac{k!}{(k+\alpha)!}\left(\frac{\lambda}{\sigma^2}\right)^\alpha\left[L_k^{(\alpha)}\left(\frac{\lambda}{\sigma^2}\right)\right]^2 \quad (38)$$

where $u = \min(m,n)$, $v = \max(m,n)$, $\alpha = v - u$, and $L_k^{(\alpha)}(x)$ is the associated Laguerre polynomial of order $\alpha$. The cumulative distribution function (cdf) of the largest eigenvalue $F_\lambda(x)$ is [29, p. 421]

$$F_\lambda(x) = \frac{\Gamma_u(u)}{\Gamma_u(u+v)}\left(\frac{x}{\sigma^2}\right)^{uv}{}_1\text{F}_1\left(v;u+v;-\frac{x}{\sigma^2}\boldsymbol{I}_u\right) \quad (39)$$

where $\Gamma_u(\cdot)$ is the complex multivariate Gamma function [30, eq. (83)], and $_p\text{F}_q(\cdot;\cdot;\cdot)$ is the complex hypergeometric function of a matrix argument [30, eq. (87)]. These functions can efficiently be evaluated using algorithms developed in [31]. The representative energy gain of the channel is given by

$$G_0 = \frac{1}{n}\mathbb{E}\left[\text{tr}(\boldsymbol{A})\right] = \frac{1}{n}mn\sigma^2 = m\sigma^2. \quad (40)$$

A frequency-nonselective fading channel with a single transmitter and single receiver antennas is a special case of a frequency-nonselective fading channel where the channel matrix $\boldsymbol{H}$ is a random scalar. The entry $h_{11}$ simply describes the channel response at a given time instant, and $\lambda_1 = a_{11} = |h_{11}|^2$.

In our simulations, we use a channel whose fading gain is represented by the sum [32]–[34]

$$h_{11} = \frac{1}{N}\sum_{n=0}^{N-1}\exp\left(\sqrt{-1}\psi_n\right) \quad (41)$$

where $N$ is the number of complex equal-amplitude subpaths, and $\psi_n$ is the phase of the $n$th subpath. If the phases are all equal, the sum (41) is a coherent sum whose magnitude is equal to unity. Thus, peak normalization is used in (41). The

amplitudes of the subpaths in (41) are identical, which is only a convenient selection for our numerical results [32].

If the phases $\psi_n$ in (41) are random, independent, and uniformly distributed, (41) corresponds to a noncoherent sum. The pdf of the magnitude of (41) can be derived from the results presented in [34] for the values $N = 2$ and $3$. For large $N$, it can be approximated with a truncated Rayleigh distribution. The pdf of the squared magnitude of (41) can be derived from the work of [32]. For large $N$, it can be approximated with a truncated exponential distribution. Its peak value is unity, and the average value is $1/N$. We can alternatively use average normalization. In that case, we replace $1/N$ in (41) by $1/\sqrt{N}$.

### B. Frequency-Selective Block-Fading Channel

We next consider a frequency-selective fading channel with $t$ transmitter and $r$ receiver antennas. We assume that the matrix-valued channel impulse response is finite and spans $L + 1 < \infty$ symbol intervals. Furthermore, we assume that the channel is quasi-static[1] for $K \gg L + 1$ symbol intervals. Finally, we assume that symbols are transmitted in blocks of $K$ symbols and that there is no interblock interference.

Let $\boldsymbol{y}_k \in \mathbb{C}^t$ and $\boldsymbol{z}_k \in \mathbb{C}^r$ denote the transmitted and received vectors, respectively, at time instant $k$. The vector of received symbols at the $k$th time instant is then given as

$$\boldsymbol{z}_k = \sum_{l=0}^{L}\boldsymbol{H}_l\boldsymbol{y}_{k-l} \quad (42)$$

where $\boldsymbol{H}_l$ is a matrix-valued channel model corresponding to the $l$th tap. We assume that the matrices $\boldsymbol{H}_l$ are independently distributed complex Gaussian matrices with variance $\sigma_l^2$. By stacking the vectors $\boldsymbol{y}_k$ and $\boldsymbol{z}_k$, we obtain (43), shown at the bottom of the next page, where $\boldsymbol{H} \in \mathbb{C}^{Kr \times Kt}$ is a block-Toeplitz convolution matrix.

Block-Toeplitz matrices are asymptotically equivalent to block-circulant matrices, which implies that the eigenvalues of a block-Toeplitz matrix and a properly constructed block-circulant matrix asymptotically converge [35]. Since a block-circulant matrix can be block diagonalized by a block-Fourier matrix, the eigenvalues of the block-Toeplitz matrix can easily be approximated [35]. More precisely, for a sufficiently large ratio $K/L \gg 1$, we obtain

$$\boldsymbol{H} \approx (\boldsymbol{F}_K \otimes \boldsymbol{I}_r)^*\boldsymbol{D}(\boldsymbol{F}_K \otimes \boldsymbol{I}_t) \quad (44)$$

---

[1]That is, it remains constant for $K$ symbol intervals and randomly changes from block to block.

where $\otimes$ denotes the Kronecker product, $\boldsymbol{F}_K$ is the $K \times K$ Fourier matrix

$$\boldsymbol{F}_K = \frac{1}{\sqrt{K}} \left[ \omega^{(i-1)(j-1)} \right]_{i,j=1}^{K,K} \tag{45}$$

with $\omega = e^{-2\pi\sqrt{-1}/K}$, and $\boldsymbol{D} \in \mathbb{C}^{Kr \times Kt}$ is a block-diagonal matrix $\boldsymbol{D} = \text{diag}(\boldsymbol{D}_0, \boldsymbol{D}_1, \ldots, \boldsymbol{D}_{K-1})$ with $\boldsymbol{D}_k \in \mathbb{C}^{r \times t}$ given as

$$\boldsymbol{D}_k = \sum_{l=0}^{L} \omega^{kl} \boldsymbol{H}_l. \tag{46}$$

The entries of $\boldsymbol{D}_k$ are zero-mean complex Gaussian random variables as are the entries of $\boldsymbol{H}_l$. The variance of the entries of $\boldsymbol{D}_k$ is the sum of variances of respective entries of $\boldsymbol{H}_l$, i.e., $\sigma^2 = \sum_{l=0}^{L} \sigma_l^2$.

The joint pdf of the unordered eigenvalues of $\boldsymbol{A} = \text{diag}(\boldsymbol{A}_0, \ldots, \boldsymbol{A}_{K-1})$, where $\boldsymbol{A}_k = \boldsymbol{D}_k^* \boldsymbol{D}_k$ is a complex Wishart matrix, is unknown [36]. This precludes the derivation of the cdf of the largest eigenvalue. However, the average received energy can still be found approximately as

$$\mathbb{E}[E_{\text{rx}}] \approx \sum_{i=1}^{Ku} \int_0^{\infty} \cdots \int_0^{\infty} \lambda_i g(\lambda_i) p(\lambda_1, \ldots, \lambda_{Ku}) \, d\lambda_1 \cdots d\lambda_{Ku}$$

$$= K \sum_{i=1}^{u} \int_0^{\infty} \cdots \int_0^{\infty} \lambda_i g(\lambda_i) p(\lambda_1, \ldots, \lambda_u) \, d\lambda_1 \cdots d\lambda_u$$

$$= Ku \int_0^{\infty} \lambda g(\lambda) h(\lambda) \, d\lambda \tag{47}$$

where $u = \min(r,t)$, $v = \max(r,t)$, and $h(\lambda)$ is given by (38). The average transmitted energy can be obtained in a similar way. The representative energy gain of the channel is then

$$G_0 \approx \frac{\mathbb{E}\left[\text{tr}(\boldsymbol{A})\right]}{Kt} = \frac{1}{Kt}\mathbb{E}\left[\sum_{k=0}^{K-1} \text{tr}(\boldsymbol{A}_k)\right] = r \sum_{l=0}^{L} \sigma_l^2. \tag{48}$$

A frequency-selective block-fading channel with a single transmitter and single receiver antennas is a special case of a frequency-selective fading channel where $t = r = 1$. Consequently, $\boldsymbol{H} \in \mathbb{C}^{K \times K}$ is a Toeplitz matrix with the entry $h_{ij}$ being the $j$th sample of the channel impulse response at the $i$th time instant.
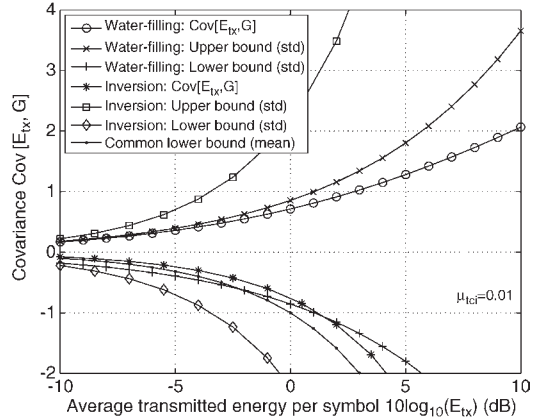


Fig. 2. Upper and lower bounds on the covariance value in a single-antenna channel with Rayleigh fading and $\sigma^2 = 1$.

## V. NUMERICAL RESULTS

### A. Covariance

The covariances in (35) are a measure of how well the transmitted signal is matched in a statistical sense to the channel: The larger the covariances $\theta$ and $\vartheta$, the larger the ratio $\overline{\gamma}_{\text{rx}}/\overline{\gamma}_{\text{tx}}$. In Fig. 2, we show a comparison of water filling and truncated channel inversion in a single-antenna channel with Rayleigh fading and $\sigma^2 = 1$. Since, in any single-antenna channel $\theta = 0$, the power control methods are compared according to the achievable covariance value $\vartheta$. The upper bound (33) and the lower bound (34) of the covariance are plotted for comparison.

The numerical results suggest that, in a single-antenna Rayleigh fading channel with low-power transmission, one approaches the covariance upper limit with water filling. On the other hand, with truncated channel inversion, one operates close to the covariance lower limit. In other words, water filling gives almost the highest possible average received SNR $\overline{\gamma}_{\text{rx}}$, whereas truncated channel inversion gives almost the lowest possible average received SNR $\overline{\gamma}_{\text{rx}}$, provided that $\overline{\gamma}_{\text{tx}}$ and $G_0$ are kept constant in comparisons. Truncated channel inversion remains useful because performance is improved by keeping the received SNR constant during transmission.

We plot the ratio $\overline{\gamma}_{\text{rx}}/\check{\gamma}_{\text{tx}}$ that can be achieved in a frequency-nonselective or a frequency-selective MIMO channel with water filling and truncated channel inversion in Figs. 3 and 4, respectively. The numerical results show that $\overline{\gamma}_{\text{rx}}$ is larger than $\check{\gamma}_{\text{tx}}$ when water filling is used. On the other hand, if truncated

$$\begin{bmatrix} \vdots \\ \boldsymbol{z}_0 \\ \boldsymbol{z}_1 \\ \boldsymbol{z}_2 \\ \vdots \end{bmatrix} = \underbrace{\begin{bmatrix} \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & & & \\ \cdots & \boldsymbol{0} & \boldsymbol{H}_L & \cdots & \boldsymbol{H}_1 & \boldsymbol{H}_0 & \boldsymbol{0} & \cdots & \\ & \cdots & \boldsymbol{0} & \boldsymbol{H}_L & \cdots & \boldsymbol{H}_1 & \boldsymbol{H}_0 & \boldsymbol{0} & \cdots \\ & & \cdots & \boldsymbol{0} & \boldsymbol{H}_L & \cdots & \boldsymbol{H}_1 & \boldsymbol{H}_0 & \boldsymbol{0} & \cdots \\ & & & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \end{bmatrix}}_{\boldsymbol{H} \in \mathbb{C}^{Kr \times Kt}} \underbrace{\begin{bmatrix} \vdots \\ \boldsymbol{y}_0 \\ \boldsymbol{y}_1 \\ \boldsymbol{y}_2 \\ \vdots \end{bmatrix}}_{\boldsymbol{y} \in \mathbb{C}^{Kt}} \tag{43}$$

$$\underbrace{\phantom{xx}}_{\boldsymbol{z} \in \mathbb{C}^{Kr}}$$

Fig. 3. Relationship between the average received SNR $\overline{\gamma}_{rx}$ and the average transmitted SNR referred to the receiver $G_0\overline{\gamma}_{tx}$ in a multiantenna channel with water filling and $\sigma^2 = 1$.


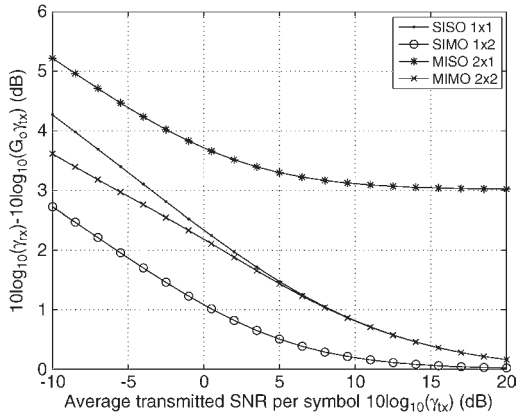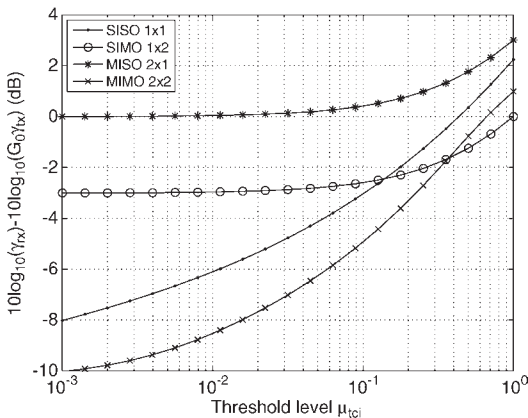
Fig. 4. Relationship between the average received SNR $\overline{\gamma}_{rx}$ and the average transmitted SNR referred to the receiver $G_0\overline{\gamma}_{tx}$ in a multiantenna channel with truncated channel inversion and $\sigma^2 = 1$.

channel inversion is used, $\overline{\gamma}_{rx}$ could be larger or smaller than $\check{\gamma}_{tx}$, depending on the threshold $\mu_{tci}$. The relationship between $\overline{\gamma}_{rx}$ and $\check{\gamma}_{tx}$ does not depend on the average transmitted SNR per symbol $\overline{\gamma}_{tx}$ when truncated channel inversion is used because $\beta$ cancels when dividing (27) by (26).

In a multiple-input–single-output (MISO) system with a two-transmitter/one-receiver antenna ($2 \times 1$) and a single-input–multiple-output (SIMO) system with one-transmitter/two-receiver antennas ($1 \times 2$), the average received SNR $\overline{\gamma}_{rx}$ is actually the same. It is because there is only one orthogonal subchannel, which implies that $\theta = 0$, and the distribution of the corresponding positive eigenvalue is the same in both cases. The difference in $\overline{\gamma}_{rx}/\check{\gamma}_{tx}$ shown in Figs. 3 and 4 comes from the fact that the representative energy gain differs. Specifically, in a MISO $2 \times 1$ system, $G_0 = 1$, whereas in a SIMO $1 \times 2$ system, $G_0 = 2$. Since $\overline{\gamma}_{rx}$ is equal to $\check{\gamma}_{tx}$ if $\theta = 0$ and $\vartheta = 0$, i.e., when there is no power control at the transmitter, the results in Figs. 3 and 4 demonstrate how beneficial power control is at the transmitter in a MISO system.
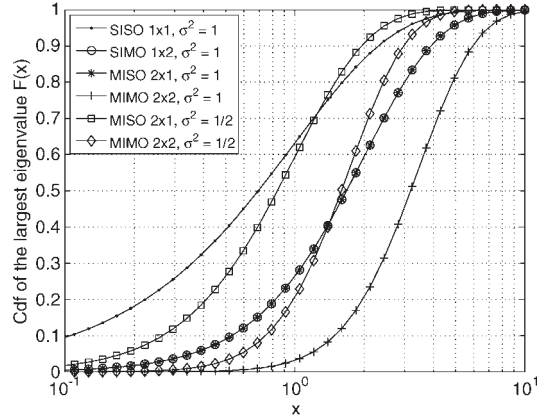


Fig. 5. Cdf of the largest eigenvalue $\lambda_u$ in a frequency-nonselective multiantenna channel.

The peak energy gain of the channel is bounded by the largest eigenvalue $\lambda_u$ of the matrix $\boldsymbol{A}$. The cdf of $\lambda_u$ in a number of frequency-nonselective multiantenna channels is shown in Fig. 5. For MISO and MIMO channels, we also plot the results in the case when average normalization is used, i.e., when $G_0 = 1$.

In general, the peak energy gain should be less than or equal to 1 to satisfy the energy-conservation law. The problem of the proper normalization of the peak energy gain does not normally arise if one includes path loss in the model, which scales down the maximum eigenvalue, and uses the average transmitted SNR $\overline{\gamma}_{tx}$ to compare different systems. However, a common practice is to use the average transmitted SNR referred to the receiver $\check{\gamma}_{tx}$ or the average received SNR $\overline{\gamma}_{rx}$ and compare different systems against each other or against a unit-gain additive white Gaussian noise (AWGN) channel.

The results in Fig. 5 suggest that, in all the considered channel models, there is a nonnegligible probability, even if the channels are normalized according to the representative energy gain, the peak energy gain exceeds 1. Consequently, a comparison of the performance attained by an adaptive system in the presented channel models and in a unit-gain AWGN can lead to erroneous conclusions. This effect could be particularly visible in adaptive systems that are able to take advantage of $\lambda_u > 1$.

A solution to the problem is to normalize the channel with respect to the peak energy gain. Unfortunately, this is not always possible because the peak energy gain could be unbounded as in the Rayleigh fading model. In this case, we propose to normalize the channel in a statistical sense, i.e., to normalize it such that the peak energy gain exceeds 1 only with some small probability $\zeta$. For instance, the actual value of $\zeta$ can be adopted from a "six sigma" rule in production quality assessment, where $\zeta = 3.4 \cdot 10^{-6}$ [37].

### B. SNR Distributions

We assume that both the receiver and the transmitter know the channel. The modulation method in the examples is binary antipodal. One sample is taken per symbol. We present the
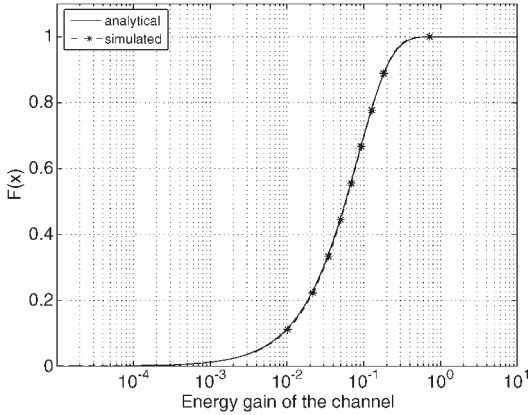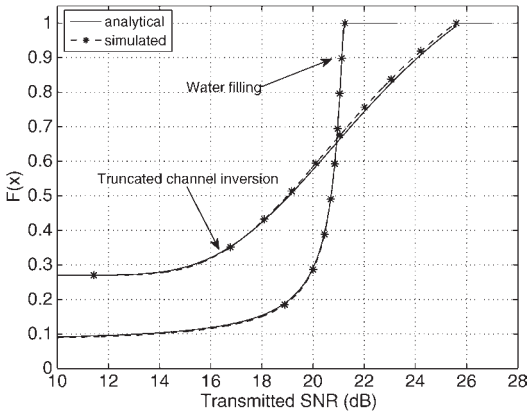
Fig. 6.   Cdf of the energy gain of the channel.



Fig. 7.   Cdf of the transmitted SNR in water filling and truncated channel inversion.



Fig. 8.   Cdf of the received SNR in water filling and truncated channel inversion.

analytical pdf's by assuming that the energy gain is exponentially distributed. We also present the simulated histograms by using the noncoherent sum of complex exponentials in (41) to represent a frequency-nonselective channel model. In the pdf's of the SNRs, there is an impulse at the origin corresponding to an outage with no transmission. When we include the impulse, the area under the pdf's is unity. We use the cdf's to illustrate the distributions.

In Fig. 6, we show the cdf of the energy gain of the channel when $E_{\text{tx}}$ is always positive. The cdf of the exponential distribution has the form

$$F(\lambda) = 1 - \exp(-\lambda/\sigma^2) \qquad (49)$$

for $\lambda \geq 0$, where $\lambda = |h_{11}|^2$. We can compare the cdf of (41) with peak normalization and (49) by setting $\sigma^2 = 1/N$. If $N \gg 1$, the cdf's are almost identical, except for $\lambda > 1$ [32]. If the transmission threshold is $\mu$, the probability of outage (11) for the exponential distribution is

$$P_{\text{out}} = \Pr(\lambda < \mu) = 1 - \exp(-\mu/\sigma^2). \qquad (50)$$

In Figs. 7 and 8, we present the cdf's for the transmitted and received SNRs for water filling and truncated channel
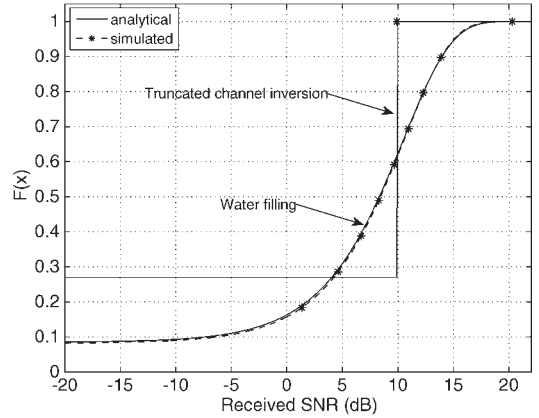
inversion when the average transmitted SNR is 20 dB, that is, $10 \log_{10} \overline{\gamma}_{\text{tx}} = 20$ dB, and we assume that the noise power spectral density is unity. The transmission thresholds are selected for water filling and truncated channel inversion by using [38, eqs. (8) and (47)], respectively. When the average transmitted SNR is 20 dB, the parameters are $\mu_{\text{wf}} = 0.0074$, $\mu_{\text{tci}} = 0.0271$, and $\beta = 9.871$. The theoretical probability of outage for the exponential distribution is with these parameters $P_{\text{out}} = 0.0853$ for water filling and $P_{\text{out}} = 0.2780$ for truncated channel inversion. Our aim is not to minimize the bit error probability but to demonstrate how the different power control rules behave. Corresponding analytical results for the SNR distributions are obtained from the results presented in [39, pp. 90–104] by using (6), (7), and (49). These results are summarized in the following sections.

*1) Transmitted SNR:* The cdf of the transmitted SNR is shown in Fig. 7. In water filling, the cdf has the form

$$F_{\text{wf}}(\gamma_{\text{tx}}) = \begin{cases} P_{\text{out}}, & \text{for } \gamma_{\text{tx}} = 0 \\ F\left(\frac{\mu_{\text{wf}}}{1 - \gamma_{\text{tx}}\mu_{\text{wf}}}\right), & \text{for } 0 < \gamma_{\text{tx}} \leq \mu_{\text{wf}}^{-1} \\ 1, & \text{for } \gamma_{\text{tx}} > \mu_{\text{wf}}^{-1} \end{cases} \qquad (51)$$

where $F(\cdot)$ is the cdf of the channel energy gain. In truncated channel inversion, the cdf is

$$F_{\text{tci}}(\gamma_{\text{tx}}) = \begin{cases} P_{\text{out}}, & \text{for } \gamma_{\text{tx}} = 0 \\ P_{\text{out}} + 1 - F(\beta/\gamma_{\text{tx}}), & \text{for } 0 < \gamma_{\text{tx}} \leq \beta/\mu_{\text{tci}} \\ 1, & \text{for } \gamma_{\text{tx}} > \beta/\mu_{\text{tci}}. \end{cases} \qquad (52)$$

*2) Received SNR:* In Fig. 8, we show the cdf of the received SNR for water filling. The analytical cdf is

$$F_{\text{wf}}(\gamma_{\text{rx}}) = F\left[\mu_{\text{wf}}(\gamma_{\text{rx}} + 1)/\overline{\gamma}_{\text{rx}}\right] \qquad (53)$$

where $\gamma_{\text{rx}} \geq 0$. For truncated channel inversion, the cdf of the received SNR is

$$F_{\text{tci}}(\gamma_{\text{rx}}) = \begin{cases} P_{\text{out}}, & \text{for } \gamma_{\text{rx}} \leq \beta \\ 1, & \text{for } \gamma_{\text{rx}} > \beta. \end{cases} \qquad (54)$$
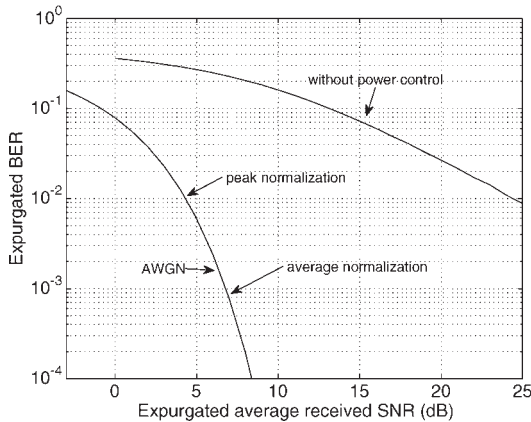
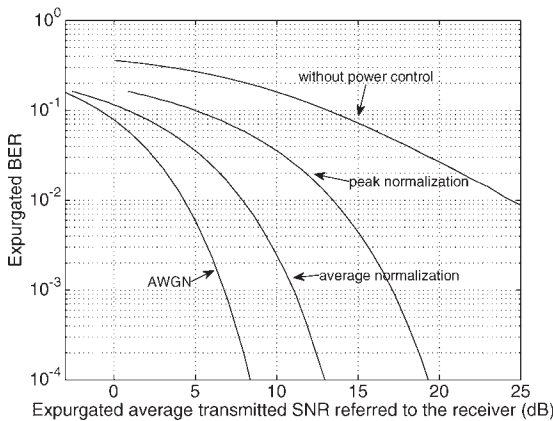Fig. 9. Expurgated BER as a function of expurgated average received SNR per bit (truncated channel inversion).



Fig. 10. Expurgated BER as a function of expurgated average transmitted SNR per bit referred to the receiver (truncated channel inversion).

### C. BER With Power Control

In our simulated system, the bit rate is constant above the threshold $\mu_{\text{tci}}$ in (7). We want to demonstrate how the bit-error-rate (BER) performance should be presented in an energy-limited system after we have analyzed the system as if it were power limited. The power-limited model has been used for mathematical tractability. We measure the BER only when we actually transmit energy in (7). Consequently, the average of the different SNRs is also measured under the condition that there is transmission. This implies that we use the expurgated SNRs defined in (36) and (37). Now, we are using the average energy actually transmitted per bit, but due to the outages, the average bit rates of different systems may be different, even in the same channel.

The BER performance for truncated channel inversion is presented in Figs. 9 and 10 by using either the expurgated average received SNR or the transmitted SNR referred to the receiver, respectively. We have used both peak and average

normalization. In Fig. 9, the normalization method does not have any effect on the performance. One could conclude that no performance gain can be obtained, but Fig. 10 shows that significant gain is possible, for example, by using diversity. Since the channel is assumed to be known, there is no performance loss in Fig. 9 compared with the AWGN channel. The BER curve with peak normalization in Fig. 10 does not go below the AWGN curve, although when using average normalization, it may happen. Thus, to avoid confusion in energy-limited adaptive transmission systems, we must use peak normalization of the channel, the expurgated average transmitted SNR referred to the receiver, and the expurgated BER.

### VI. CONCLUSION

Reliable and fair comparison of the performance of different systems that operate with different antenna configurations can be problematic. Both the average transmitted and received energies are used in performance comparisons, and the selection depends on what one wants to investigate. The transmitted energy is known to be the basic system resource. To avoid confusion in performance comparisons in energy-limited adaptive transmission systems, we must use peak normalization of the channel, the expurgated average transmitted SNR referred to the receiver, and the expurgated BER.

The whole idea of this paper is a generalization of the fact that, for correlated random variables $X$ and $Y$ and for $Z = XY$, we have the property $\mathbb{E}[Z] = \mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y] + \text{Cov}[X, Y]$. In our system model, $X$ corresponds to the transmitted energy, $Y$ corresponds to the energy gain of the channel, and $Z$ corresponds to the received energy. The random variables $X$ and $Y$ are correlated because of adaptive transmission, for example, when using transmitter power control. Therefore, the channel not only scales the transmitted energy, but the covariance $\text{Cov}[X, Y]$ also plays a crucial role. The covariance describes how well the transmitted energy is statistically matched to the channel. If there are several orthogonal subchannels, a second covariance is needed to show how well the transmitted energy is statistically matched to the energy gains of the subchannels. In addition, the expression $\mathbb{E}[X]\mathbb{E}[Y]$ should not be referred to as the average received energy because the latter has the form $\mathbb{E}[XY]$.

The systems under study should also be properly normalized. For example, it is reasonable to assume that a receiver equipped with two receiver antennas is able to receive twice as much energy as one with only one receiver antenna. The peak energy gains of the respective channel models should be scaled accordingly. Furthermore, the peak energy gain of the better channel should not exceed unity, or at the very least, the probability that the peak energy gain exceeds a respective limit should be the same for both channels.

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**Aarne Mämmelä** (M'83–SM'99) was born in Vihanti, Finland, in 1957. He received the M.Sc. (Tech.), Lic.Sc. (Tech.), and D.Sc. (Tech.) degrees (all with honors) from the University of Oulu, Oulu, Finland, in 1983, 1988, and 1996, respectively, all in electrical engineering. His main field of study was telecommunications.

From 1982 to 1993, he was an Assistant, Research Scientist, acting Associate Professor, and acting Professor with the Telecommunication Laboratory, University of Oulu, where he carried out research on adaptive algorithms in spread-spectrum systems. From 1990 to 1991, he was a Visiting Research Scientist with the University of Kaiserslautern, Kaiserslautern, Germany. In 1993, he joined VTT Technical Research Centre of Finland, Oulu, as a Senior Research Scientist. He has been a Research Professor of digital signal processing in wireless communications since 1996. From 1996 to 1997, he was a Postdoctoral Research Scientist with the University of Canterbury, Christchurch, New Zealand. He has been an Adjunct Professor with the Helsinki University of Technology, Espoo, Finland, since 2000 and with the University of Oulu since 2004. Since 2001, he has regularly organized a course and given some of the lectures on research methodology for doctoral students in engineering at the University of Oulu. His research interests are in adaptive and cognitive systems in telecommunications.

**Adrian Kotelba** (M'08) received the M.Sc. degree in electrical engineering from Poznan University of Technology, Poznan, Poland, in 2001. He is currently working toward the Ph.D. degree with the University of Oulu, Oulu, Finland.

He has been with VTT Technical Research Centre of Finland, Oulu, since 2000. His personal interests include communications theory, adaptive signal processing, adaptive modulation and coding, and cross-layer design.

**Marko Höyhtyä** (S'07) received the M.Sc. degree in information engineering in 2005 from the University of Oulu, Oulu, Finland, where he is currently working toward the Ph.D. degree. His M.Sc. thesis was on adaptive transmitter power control in multipath fading channels.

Since the beginning of 2005, he has been with VTT Technical Research Centre of Finland, Oulu, where he has been working on power control, beamforming, and cognitive radio technologies. Between February 2007 and February 2008, he made a one-year research visit to the Berkeley Wireless Research Center, Berkeley, CA. His research interests include adaptive algorithms, transmitter power control, and spectrally efficient communication. He is particularly interested in adaptive power and frequency-allocation strategies in a cognitive radio network.

**Desmond P. Taylor** (M'65–SM'90–F'94–LF'07) received the Ph.D. degree in electrical engineering from McMaster University, Hamilton, ON, Canada, in 1972.

From July 1972 to June 1992, he was with the Communications Research Laboratory and Department of Electrical Engineering, McMaster University. Since 1992, he has been with the University of Canterbury, Christchurch, New Zealand, where he is currently the Tait Professor of Communications.

He is the author or coauthor of approximately 230 published papers. He is the holder of two U.S. patents in spread-spectrum communications. His research is centered on digital wireless communications systems, with a primary focus on robust bandwidth-efficient modulation and coding techniques, and the development of iterative algorithms for joint equalization and decoding of fading dispersive channels. His secondary interests include problems in synchronization, multiple access, and networking.

Dr. Taylor is a Fellow of the Royal Society of New Zealand, the Engineering Institute of Canada, and the Institute of Professional Engineers of New Zealand.

# Practical adaptive transmission with respect to rational decision theory

# Practical Adaptive Transmission with Respect to Rational Decision Theory

Marko Höyhtyä, Adrian Kotelba, and Aarne Mämmelä

VTT Technical Research Centre of Finland
P.O. Box 1100, FI-90571 Oulu, Finland
firstname.surname@vtt.fi

*Abstract*—**In this paper we study the performance of adaptive transmission methods using the rational decision theory based concept. We introduce a channel model and a diversity model for simulations and develop a method for performance evaluation using the rational decision theory and the developed channel and diversity models. Optimal scheme based on this metric differs from the traditional capacity maximization scheme because the proposed metric takes transmission related risks into account. Several theoretical and practical power control methods are investigated through analysis and simulations. Both single-input single-output (SISO) and diversity channels are considered. The proposed filtered-x least mean square (FxLMS) algorithm outperforms other practical approaches and it can be actually seen as a generalization of practical algorithms.**

## I. INTRODUCTION

New generalized adaptive radios called cognitive radios (CRs) are using various sensors to estimate the status of the environment and making intelligent decisions based on the obtained information [1]. The aim of CRs is to improve the performance of the network; especially the efficiency of spectrum use has been under study. Realization of cognitive radios in practice requires use of adaptive transmission.

Finding good performance measures to compare different adaptive transmission methods and to determine best strategies e.g., for cognitive communication in the military environment is far from a trivial task. In ergodic channels, the mean of some quantity, for example link spectral efficiency, is a valid performance measure because one observes all possible channel states [2], [3]. In nonergodic channels, there is an uncertainty because only part of the channel states is observed. A common performance measure is then the outage probability, i.e., the probability that the performance value is below a certain threshold. Capacity maximization has been traditionally used in performance measurements and optimal transmission methods using this metric are provided e.g., in [2]. A new method for performance measurements was provided in [3] and [4] by exploring similarities between the optimal portfolio selection problem in finance theory and the finding of a valid performance measure for adaptive transmission in nonergodic channels. The proposed approach jointly considers reward and risk provided by adaptive transmission and formulates the performance measure as a certain risk-reward ratio. Optimal transmission strategy was also analytically derived. Another theory based on economics and used in communication systems is game theory [5].

In this paper we propose channel and diversity models for simulation studies and develop a performance metric taking into account both rewards and risks as well as the proposed models. Unlike in seminal studies in [3] and [4], we develop and apply the metric to rank several practical adaptive transmission strategies, including the recently developed FxLMS power control method [6]. The FxLMS algorithm was initially introduced in [7] for noise cancellation purposes. Channel and diversity models are tested with analysis and simulations and by comparing them with the literature. Several simulation studies are performed with the practical algorithms.

The paper is organized as follows. In Section II we present the channel and diversity models. Basic rational decision theory concepts and the performance metric are introduced in Section III. The power control methods under study are presented in Section IV. In Section V the performance of these methods are measured and discussed. Finally, the paper is concluded in Section VI with a summary of the main results.

## II. SYSTEM MODEL

Wireless links can be considered within the framework of individual rationality used in the decision theory. We consider a nonergodic slowly varying channel, corresponding to low mobility that can be modelled using the Doppler power spectrum [8]. The rate of the channel variation, i.e., the effect of mobility, can be characterized by Doppler frequency $f_d$. A flat Doppler power spectrum corresponds to urban, where the transmitter is set above rooftop level, and indoor environments [6]. To obtain flat Doppler power spectrum, the time-variant channel gain is written using sum of complex exponentials as

$$h[k] = a \sum_{i=1}^{N} e^{j(2\pi f_i k + \phi_i)} \qquad (1)$$

where $N$ is the number of multipath components, $a$ is the amplitude of every complex exponential, $f_i$ is the Doppler shift of the $i$th component, $\phi_i$ is the random phase shift of the $i$th component uniformly distributed in range $[0, 2\pi[$ and $k$ is time.

If the Doppler shifts of complex exponentials are equally spaced between $[-f_d, f_d]$ the channel gain becomes periodic. Periodicity can be removed if the shifts are properly chosen to make channel gain quasi-periodic. The Doppler shift range is divided into $N$ equal size parts. The frequencies of the components differ a random uniformly distributed amount from the equal space solution. With these selections, we obtain the whole spectrum range to use in every simulation. The

spectrum is made symmetric over zero frequency, which makes the autocorrelation function of the channel real. This selection makes simulations faster.

Major approaches for normalization of the channel include normalization of the average energy gain or the peak energy gain to unity, i.e., average and peak normalization, respectively [9]. When peak normalization is used, $a = 1/N$ in (1). If average normalization is used, $a = 1/\sqrt{N}$ .

In a diversity system the transmitter power control algorithm should control the power of the diversity combiner output in the receiver. The model for simulating diversity is shown in Fig.1. The proposed model is equivalent with the analysis done in [10]. Data can be added as shown when no intersymbol interference (ISI) is present and the system is coherent. ISI would make the noise correlated at separate sampling instants and thus the model would not be applicable. We assume linear, slowly fading, and frequency nonselective channel.
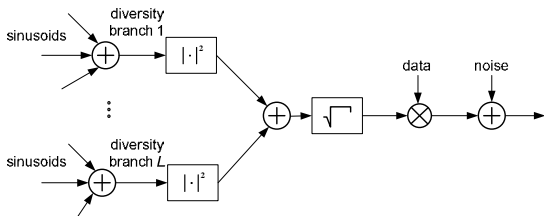


Figure 1.    Simulation model for diversity, coherent system.

### III.    RATIONAL DECISION THEORY CONCEPTS

In finance theory the *reward* is measured as an expected return $r$ on investment in excess of some predefined threshold $t$ [3]. In adaptive transmission, the return is the actual link spectral efficiency $r$ for certain energy "investment". The reward $d$ is the difference between the expected value of the link spectral efficiency $\mu_r = E[r]$, and the target link spectral efficiency $t$, $d = E[r - t] = \mu_r - t$.

The notion of *risk* is applied in economics as a property of uncertain options or lotteries, which affects decision-making. In adaptive transmission the risk can be measured with $n$th root of the $n$th order lower partial moment of the link spectral efficiency distribution $p_r(r)$ [3]

$$l_n^-(t) = \int_{-\infty}^{t} (t-r)^n \, p_r(r) dr, \quad n \geq 0 . \quad (2)$$

When $n = 0$, we have the outage probability. A risk measure with value $n = 1$ is called expected shortfall [11]. This meter is commonly used in nuclear engineering. In addition to the probability, the metric includes the magnitude of the potential shortfall. However, large infrequent losses represent the same risk as small and frequent losses. When $n > 1$, user's risk aversion can be used. The risk aversion means that a rational user, when offered several power control schemes with the same expected link spectral efficiency, prefers the scheme with the lowest risk. For analytical tractability, $n = 2$ is used in

[3] and [4]. The second order partial moment $l_2^-(t)$ is known as the below-target semivariance.

Basically, the proposed risk measure defines how far we are from the desired value. When probability of outage is used as a performance criterion, the performance of the link is good enough above the certain threshold and not working at all below the threshold. Proposed risk measure defines how badly fading affects the performance in a smoother way. The usability worsens when distance to the desired value increases. Video transmission is a good example of the phenomenon. The quality of the video becomes worse but still something can be seen and understood.

In decision theory, and especially in mean-risk models, the term "efficiency" refers to the *optimal trade-off* between mean performance and risk associated with a given mean performance. A trade-off between reward and risk is measured quantitatively by a reward-to-semivariability ratio. The most general reward-to-semivariability ratio is Kappa ratio, which is defined as the ratio of the reward to the $n$th root of the $n$th order partial moment,

$$\kappa_n(t) = \frac{E[r-t]}{\sqrt[n]{l_n^-(t)}}, \qquad n > 0 . \quad (3)$$

The optimal scheme is the one with the highest reward-to-semivariability ratio $\kappa_n(t)$ since it maximizes the reward per unit of risk taken. The optimal combinations of mean performance and risk are called efficient combinations [12]. The efficient frontier is the fundamental limit of the mean-risk performance because no other scheme can be constructed that achieves the performance above the efficient frontier.

### IV.    ADAPTIVE POWER CONTROL METHODS

#### A.    Theoretical methods

Power control algorithms can, in general, be divided into water filling and truncated channel inversion (TCI). If water filling is used the transmitted energy is $E_{tx} = \bar{E}_{tx}(1/ \gamma_0 - 1/ \gamma_H )$ for $\gamma_H \geq \gamma_0$ and zero otherwise where quality of the channel is defined as $\gamma_H = \bar{E}_{tx}|H|^2 / N_0$, $\gamma_0$ is a cut-off value, which is found by numerically solving (4.15) in [13]. $\bar{E}_{tx}$ is average transmitted energy per symbol, and $|H|^2$ is the instantaneous energy gain of the channel. If truncated channel inversion is used, the transmitted energy is

$$E_{tx} = \bar{E}_{tx}(\sigma_0 / \gamma_H ) \quad (4)$$

for $\gamma_H \geq \gamma_0$ and zero otherwise where $\sigma_0$ is a constant selected so that the average transmitted energy is $\bar{E}_{tx}$. The cut-off value is found by numerically maximizing (4.22) in [13]. The cut-off value is $\gamma_0 = 0$ for full channel inversion. $\bar{E}$ denotes expectation of a random variable $E$. Basically the difference between the described two approaches is that the water filling allocates more power to the better channel states whereas channel inversion aims at maintaining the desired signal strength at the receiver by inverting the channel power gain based on the channel estimates. Several practical approaches can be called inverse power control approaches.

## B. FxLMS algorithm

Filtered-x least-mean-square (FxLMS) algorithm was proposed for adaptive inverse power control in [6]. The algorithm updates the coefficient $c_k$ of a one-tap filter as

$$c_k = c_{k-1} + \mu x_k' \varepsilon_k \tag{5}$$

where $\mu$ is the adaptation step size of the algorithm, the filtered input signal is $x_k' = |x_k \hat{h}_k|$, $\hat{h}_k$ is the estimated instantaneous channel gain, and $\varepsilon_k$ is the error signal to be minimized. The optimum step size with estimated channel gain is given by

$$\mu_{\text{opt}} = \frac{1}{(|x_k|^2 |\hat{h}_k|^2) + c_{\text{term}}} \tag{6}$$

where $c_{\text{term}}$ is a small number that prevents the adaptation step size to grow to infinity when the estimated received power is very small. When we are using the FxLMS algorithm for power control, we can reduce the complexity of the transmitter by doing as much as possible calculations at the receiver. This reduces also information in the feedback channel since only signal $c_{k-1}$ is needed to be sent to the transmitter.

## C. Fixed and variable step adjustment power control

Typically the power control time interval in the code division multiple access (CDMA) system is around 1 ms [14]. CDMA power control employs both closed and open loop methods; we restrict our investigation purely on closed loop part and use the same 1 ms interval. Base station measures the signal-to-interference ratio (SIR) or the average received power over $m$ symbols and compares it to a reference power level $P_{\text{ref}}$. As a result of a comparison the base station tells mobile station to adjust its transmission power upwards or downwards by a control step size $\Delta P$. Practical fixed-step adjustment power control (FSAPC) method uses 1 dB steps. The power control algorithm can be written as

$$P_k = P_{k-1} + C_k \Delta P \ \ [\text{dB}] \tag{7}$$

where the power control command is $C_k = \begin{cases} +1, & \varepsilon_k \geq 0 \\ -1, & \varepsilon_k < 0 \end{cases}$. The

weakness of this fixed-step power control method is that it is still too slow for fast moving vehicles since the fading can be tens of dB even every half a carrier wavelength.

Variable step power control methods have been proposed to overcome the weakness of the fixed step solution. The basic idea is that when the power of received signal is far from the desired, the control step is increased to reach the desired level faster [15], [6]. The power control command for variable step adjustment power control (VSAPC) is [15]

$$C_k = \begin{cases} 3, & \text{when } P_{\text{err}} < -5\kappa \\ 2, & -5\kappa \leq P_{\text{err}} < -3\kappa \\ 1, & -3\kappa \leq P_{\text{err}} < -\kappa \\ 0, & -\kappa \leq P_{\text{err}} < \kappa \\ -1, & \kappa \leq P_{\text{err}} < 3\kappa \\ -2, & P_{\text{err}} \geq 3\kappa \end{cases} \tag{8}$$

where $P_{\text{err}}$ is the power of error signal in dB and $\kappa = 0.5\Delta P$. Thus, the control speed with this method is up to 3 dB/power control command.

A recently proposed adaptive closed loop power control (ACLPC) method is described in [16]. The uplink receiver estimates the signal-to-interference and noise ratio (SINR) of the received signal and compares it with the SINR target value. If the estimated value is below the target, transmission power is increased. Otherwise, the transmitted power will be decreased. TPC command is checked in every subframe whose duration is 1 ms. Thus, we use the same model as previously to see the performance of the closed loop part. Power control command $C_k$ values are $C_k = \{-4, -1, 1, 4\}$ (dB) which means that only two bits are needed for transmitter power control (TPC) command.

## V. RESULTS

Probability density function of the received SNR value using diversity is plotted in Fig. 2. The analytical result is plotted using (14.4–13) from [10] and the simulated result using our proposed model shown in Fig. 1. Number of diversity channels is $L = 4$. In simulations, a channel is modeled using (1). Simulated results match very well with the analytical ones. The results shown here verify that the channel model and the diversity model can be used in adaptive transmission technique studies.
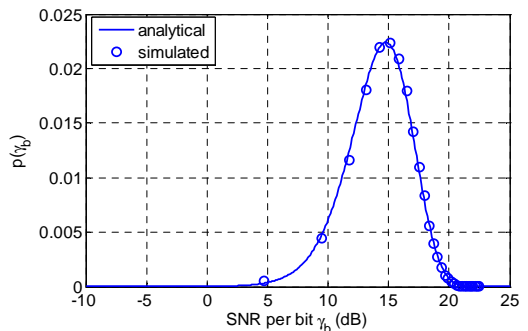


Figure 2.  Probability density function of SNR for diversity system.

We considered both single-input single-output (SISO) and diversity channels in TCI simulations. MRC diversity ($L = 2$ and $L = 4$) was considered in diversity experiments and the model proposed in Fig. 1 was used. The results are plotted in Figs. 3–5. The analytical Rayleigh channel results in Fig. 3 are plotted using (48) and (50) from [17] to define the value of $r$ for calculations. Target link spectral efficiency for the experiments was set to $t = 2$ bits/s/Hz. The mean link spectral efficiency is averaged over transmitted values, excluding the outages.

When SISO channel is considered, there is a clear turning point in the risk-return curve. The capacity of the Rayleigh fading channel with the total channel inversion is zero which means that the risk is very high. The risk is also high with sum-of-complex exponentials channel but the capacity is not zero.

The high risk comes from the fact that without any cutoff the transmitted signal has to be transmitted also during the deepest fades in the channel.
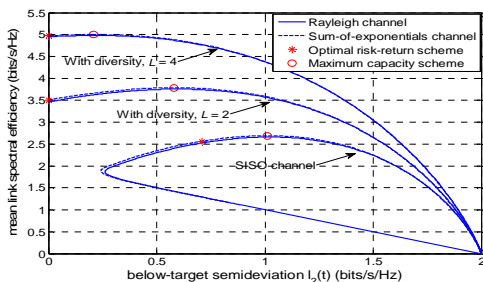


Figure 3.  Risk-return curves of truncated channel inversion over SISO and diversity channels

Total channel inversion can be used only with channels having $E[1/|h|^2] < \infty$ which is not valid for the Rayleigh channel [2]. Sum-of-complex exponentials channel achieves slightly better risk-reward performance since the model does not include zero gain and the peak gain is limited. In the following figures, only sum-of-complex exponentials channel is considered.
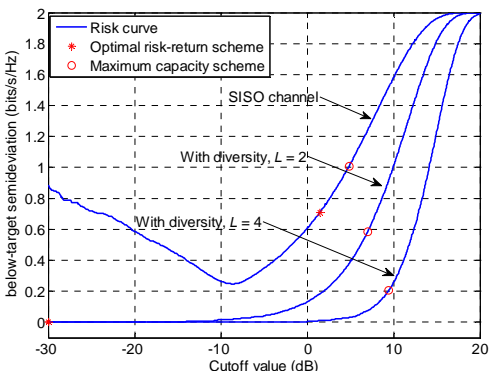


Figure 4.  Risk curves of truncated channel inversion over SISO and diversity channels.

When we start to increase the cutoff value from the zero in SISO channel the below-target semideviation reduces and at the same time the link spectral efficiency increases. Risk reduces since the power is not wasted in deepest fades. After a certain minimum-risk point, the risk starts to increase again because the probability of outage increases. The risk curve for all the cases can be seen in Fig. 4. The link spectral efficiency increases further when cutoff is increased until the maximum capacity scheme is achieved and after that increasing outage probability starts to reduce the return as seen in Fig. 5. With very high cutoff the risk is again very high and the link spectral efficiency approaches zero. When diversity is applied the risk is very small with low cutoff values and thus the risk-return

performance is also good. However, maximum capacity point is achieved with a higher cutoff than in the SISO channel.

Traditionally used maximum capacity approach gives different rules for power control than the rational decision theory. Actually, even though the maximum capacity scheme for diversity channel requires use of the cutoff, authors in [17] suggest that with diversity total channel inversion might be better choice than truncated channel inversion. The rational decision-making leads unambiguously to this solution.
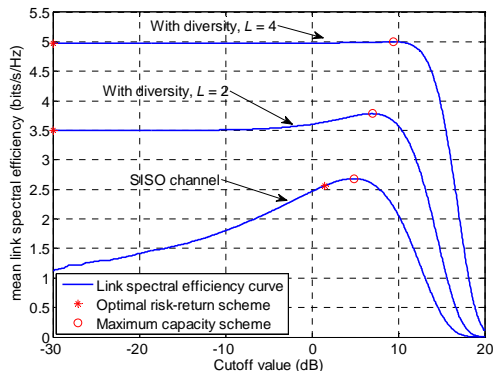


Figure 5.  Return curves of truncated channel inversion over SISO and diversity channels.

Results shown above suggest rethinking of optimal way to set thresholds for truncated channel inversion power control. Use of risk-reward approach gives lower threshold for SISO channel, leading to slightly lower link spectral efficiency but also with a lower probability of outage. This means that delays are shorter. When diversity is applied the proposed approach leads clearly to the conclusion of using full inversion for transmission, again with slightly lower reward but with no risk, i.e., without outages. The curves are mostly smooth but with low cutoff values there is small inaccuracy in SISO channel. This is due to the fact that we are operating with the tail values of the energy distribution. There are fewer samples in these values and thus the estimate of the average obtained with Monte Carlo method is not so accurate anymore. The problem disappears when diversity is applied.

Risk-reward performance of the practical full inversion power control algorithms cannot be measured using exactly the same method than above. The reason is that outage has to be defined in a different way and the average transmission power cannot be fixed if the aim is to keep the received SNR adaptively at the target level. We define an outage as a received signal level that is more than 2 dB below the target. Based on Vysochanskij-Petunin inequality and assuming 1 dB standard deviation, roughly 90 percent of cases are closer than 2 dB to the desired value. Now the risk-reward performance is given with one single point for each power control rule. The results are shown in Fig. 6. The result of a simulation with an optimal inversion is also provided and the risk of being 2 dB below the target is shown to be zero. Mean link spectral efficiency with the optimal inversion is slightly better than with the adaptive

approaches because it can keep the received SNR high enough also during the deep fades.
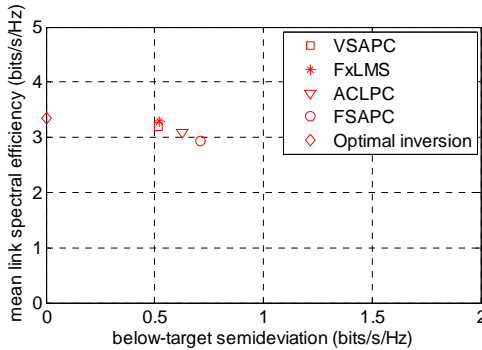


Figure 6. Risk-reward performance of practical power control rules in a SISO channel.

The FxLMS method gives the best performance and the FSAPC method is clearly the worst. FxLMS, VSAPC, and ACLPC methods have bigger step sizes which make adaptation faster. This can be seen in the rise times in Table 1. Rise time is the time required for the received signal to change from the initial value, when transmitted signal is 0 dB, to the required 10 dB value in a time-variant channel. The results shown are average values over several simulations. In addition, the system does not spend so much time during the deep fade than with smaller adaptation steps. That is the reason for the better risk performance. Since the FxLMS control is the best in reward and equally good with the VSAPC in risk performance, it achieves the best risk-reward values using the Kappa ratio defined in (3) as a measure. The risk-reward performance difference between methods is very clear when we look at the Kappa ratio values in Table I.

TABLE I.        PERFORMANCE OF THE PRACTICAL ALGORITHMS

| | Rise time (ms) | Standard deviation (dB) | Kappa ratio | Average transmitted SNR (dB) [9] |
|---|---|---|---|---|
| **FSAPC** | 19 | 1.48 | 1.32 | 25.71 |
| **ACLPC** | 7 | 1.09 | 1.66 | 26.75 |
| **VSAPC** | 9 | 1.04 | 2.30 | 26.68 |
| **FxLMS** | 4 | 1.03 | 2.48 | 26.65 |

There is a problem with the nonfixed average power constraint in the performance comparison since different methods use different amount of transmitted energy for communication. However, the difference is very small between ACLPC, VSAPC, and FxLMS methods as shown in Table 1. Thus, the performance comparison between these methods is pretty fair. FSAPC method suffers since it is spending more time during deep fades with a lower power and consequently the outage is also higher. Standard deviation of the received SNR, averaged in decibel domain, shows clearly the gain of using adaptive step sizes in control. Based on the achieved results, adaptive step sizes are much more preferable to be used in communication. The FxLMS algorithm achieves the best performance with a given fundamental metric.

## VI.  CONCLUSIONS

We have presented models for fading channel and diversity combining and verified the models with the simulations and results from the literature. Risk-reward performance metric is given for the developed channel and diversity models and used in the performance measurements. Both analytical and simulated results show that the proposed method leads to a solution that gives a slightly worse capacity with a better delay performance than the state-of-the art solution, giving new insights for the adaptive transmission strategy development. Our proposed FxLMS outperforms other practical methods in rise time, standard deviation of the SNR values, and in risk-reward performance. Actually, many practical algorithms can be seen as special cases of it. Use of the FxLMS algorithm makes general investigation of adaptive power control possible.

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PAPER IV

# Energy efficient inverse power control for a cognitive radio link

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# Energy Efficient Inverse Power Control for a Cognitive Radio Link

Marko Höyhtyä[1], Anant Sahai[2], Danijela Cabric[2], and Aarne Mämmelä[1]

[1]VTT Technical Research Centre of Finland
P.O. Box 1100, FI-90571 Oulu
Finland

[2]Berkeley Wireless Research Center
University of California, CA 94704
USA

*Abstract*—In this paper, a novel adaptive energy and spectrum efficient inverse power control method that is based on the truncated filtered-x LMS (FxLMS) algorithm is introduced. By truncated power control we mean power control where transmission is interrupted if the channel state deteriorates to bad enough. Inverse power control minimizes the interference that a cognitive radio (CR) creates to licensed users and allows more users to share the spectrum. To further reduce the transmission power and consequently the interference, truncation in power control is used. The performance of the system is improved and the amount of needed transmitted energy is smaller. Based on numerical analysis this new method offers energy efficient transmission, helps to minimize interference to the primary users, and allows even more users to share the same spectrum.

*Keywords-FxLMS algorithm; truncated power control; interference control;*

## I.    INTRODUCTION

Spectral efficiency plays a key role as future wireless communication systems will accommodate more and more users and high performance services. Nowadays the spectrum is used inefficiently. Cognitive radio technologies have been proposed to improve the spectral efficiency [1], [2]. The aim of cognitive radio system is very practical and concentrates on the efficient use of natural resources, which include frequency, time, and transmitted energy.

Spectrum awareness is a key requirement for a CR to operate [3]. However, dynamic spectrum management and power control are equally important functions as spectrum sensing. It is important to know how detected spectrum holes can be efficiently exploited while assuring the minimal interference to the primary users (PU) as well as to the other cognitive networks that share the same spectrum. Transmission parameters have to be adapted based on the sensed spectrum and the channel estimation. Inside the net, interference can be controlled with orthogonality principles whereas interference to the other networks is mainly controlled by reducing the transmitter power to the minimum. Because of interference, the cognitive radios have to adjust their power levels according to their potential proximity to a primary receiver [4]. In [5] the task of power control is presented as "to permit transmission at full power limits when necessary, but constrain the transmitter power to a lower level to allow greater sharing of spectrum when higher power operation is not necessary".

In active cognitive radio system, secondary users (SU) actively sense the surrounding radio environment and adapt their transmission based on the measurements. Spectrum sensing sensitivity can be used to calculate the potential proximity to the primary receiver and to estimate the power limit for secondary transmission. Given this power limit for transmission, can we use conventional adaptive power control methods to cope with multipath fading in a CR system? How can we efficiently use available spectral and energy resources and reduce interference to primary users and other secondary users sharing the same spectrum? What are the actual interference ranges of our own system? This paper addresses these questions, proposes a method for calculation of power limit and introduces a novel FxLMS algorithm based method to be used for power control over a cognitive link.

A very conventional approach for transmitter power control is to maintain desired signal strength at the receiver by inverting the channel power gain based on the channel estimates. Delay-sensitive applications require full inversion methods to be used in power control. However, in a cognitive radio network using active awareness principles, delays cannot be avoided because of periodical sensing. Such a network is not good for real-time communication. Thus, power control method does not need to assure delayless communication. A large part of the transmission power in continuous inverse control solutions is used to compensate the deepest fades in a fading channel. For energy or power efficiency, threshold policies have to be used. It has been recently proven in [6] that regardless of modulation and demodulation methods and taken general assumptions in wireless channel model into account, the optimal power control method is based on threshold policy. Power efficiency and throughput can be clearly improved when compared to continuous transmission schemes.

Link budget is an estimation technique for evaluating communication system performance [7]. The required bit error rate (BER) dictates the value of received signal-to-noise ratio (SNR) in order to meet that performance. In link budget calculations transmitter power, gains, and losses in the link are calculated with primary purpose of determination of actual operation point in the BER curve. However, conventional link budget calculations do not take effects of transmitter power control into account. We have shown in [8] that power control can improve or deteriorate the link budget depending on what kind of power control is used. Bit error rate depends both on the link budget and the distribution of the received signal.

Therefore, the link budget can be worse with inverse power control than without it because the distribution is better.

The amount of transmitted energy needed to achieve prescribed requirements is used as a metric for energy efficiency. Energy efficiency is an important metric for potentially mobile cognitive radios where energy is taken from battery and is therefore limited. Transmitter power level defines the interference level a CR creates to PUs. We use the interference range as a metric to compare different power control methods. Interference range is a range within which the interference level is more than the victim receiver can tolerate. This defines both how close to primary user we can operate and how well we can share the same spectrum with other secondary users. In addition, capacity under interference or energy constraint is one performance metric. Capacity can be improved either by using more bandwidth or with spectrally more efficient modulation method. The motivation for truncation in CR environment is that it

- Reduces energy consumption, battery lasts longer

- Reduces interference to the primary users

- Improves capacity both under interference range and energy consumption constraint

- Allows more secondary users to share same spectrum

- Relaxes sensing requirements; since the interference range is smaller, there is no need to sense as weak signals as with full inversion power control

This paper is organized as follows. Section II gives some background, and Section III introduces the method for power limit calculation and model used in simulations. Truncated inverse power control method is presented in Section IV. Numerical performance analysis with link budget and interference range calculations is provided in Section V. Section VI draws the conclusion.

## II. BACKGROUND AND BASIC CONCEPTS

Interference temperature concept has been proposed as a basis for power control adjustment for SUs. The interference temperature limit $T_L$ characterizes the maximum amount of tolerable interference for a given frequency band in a particular location where the receiver can operate satisfactorily [9]. CR terminals operating in licensed frequency bands have to measure the current interference temperature and adjust their transmission in a way that they avoid raising the interference temperature over the limit. Power control rules that takes $T_L$ into account are proposed in [2] and [9]. The fundamental problem with that approach is that cognitive radios cannot be aware of the precise locations of primary receivers and they cannot measure the effects of their transmissions on all possible receivers. In addition, regulation authorities have not provided actual numbers for $T_L$.

References [4] and [10] proposed measurements of primary signal to be used as a basis for adjusting own secondary transmitter signal power to a level that allows interference-free communication to the PUs. Either signal from the PU transmitter [4] or so called beacon signal from receiver, [10] can be used to estimate the attenuation between the SU transmitter and PU receiver. The problem with latter approach is that it cannot be used without modification to primary receivers. In addition, typically fast fading channel is not reciprocal, i.e., fading to opposite directions correlate poorly. Thus, measurements cannot give accurate information to the power control adjustment. In order to get the CR system working with wide variety of primary systems, we will take the same approach than [4]. The primary transmitter signal is detected with highly sensitive spectrum sensor and the decision about spectrum use with required power level is made based on that. When data transmission is on, transmitter power should be adjusted adaptively taking the changing channel conditions into account.

A practical closed loop inverse control method is fixed step adjustment power control (FSAPC), known also as conventional closed loop power control (CLPC) [11]. When this method is used, transmission power is adjusted up- or downwards by a fixed amount (typically 1 dB/ms) depending on whether the received power has been over or below a threshold value. The FSAPC method is simple but not fast enough to compensate deep fades in the channel. In the literature adaptive step size and also predictive power control methods are used to improve the performance of the conventional FSAPC algorithm [12]–[14].

The FxLMS algorithm is developed from the LMS algorithm by inserting the model of the controlled system between the input data signal and the adaptive algorithm that updates the coefficients of adaptive filter [15]. This makes the algorithm stable and suitable for active control applications. The FxLMS algorithm is perhaps the most commonly used adaptive algorithm in active noise cancelling applications. The structure and operation of the algorithm are ideally suited to the architectures of standard digital signal processing (DSP) chips and it behaves robustly in the presence of modeling errors and numerical effects caused by finite-precision calculations [15]. In addition, the algorithm is very well suited to adaptive inverse control solutions [15]. FxLMS algorithm can be efficiently used for power control [14]. It is a variable step algorithm that adjusts the step size in a nearly optimal way. In this paper, we investigate and propose a truncated FxLMS algorithm based power control algorithm to cope with fading in a CR environment.

Instead of interference temperature concept, 1 dB coexistence criterion is used in calculations to provide actual interference ranges with different receiver sensitivities. In [17], the fundamental criterion for coexistence in terms of acceptable interference in the victim receiver is defined as the interference level that causes 1 dB degradation in receiver sensitivity. This means that the interference power has to be 6 dB below receiver thermal noise. The interference range for secondary transmission can be defined as a range in which coexistence criterion stated above is not met.

## III. SYSTEM MODEL

### A. Basic scenario

Interference range can also be seen as a sensing range for a cognitive radio device. To be more exact, sensing range $r_s$ should be as much as the transmission range of primary transmitter $r_{pu}$ plus interference range of secondary transmitter $r_{int}$ to avoid interfering with primary user in the case the primary receiver is located in the edge of the transmission range. So the spectrum sensor should be highly sensitive. The scenario is shown in Fig. 1. Transmission range of the cognitive radio is $r_{cr}$.
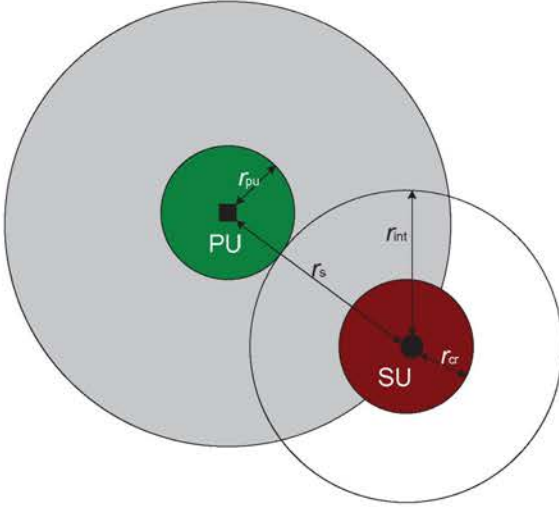


Figure 1. Sensing, interference, and transmission ranges.

So what is the rule for transmission power limit calculation? While it could be very helpful to know the location of PU receivers and the power loss gain of channel between them and secondary transmitters, neither of this information may be available in real systems. If the locations of primary receivers are available, e.g., in some database, this information should of course be used. But assuming fully active CR system we don't get information from primary users during operation. However, we could know something about primary users when we manufacture our cognitive radios. The receiver decoding sensitivity of the PU and the noise figure are the key issues to know. Knowing the decoding sensitivity of PU receiver and the spectrum sensing sensitivity of the cognitive radio we can calculate how much further a CR can detect the primary transmission than a primary receiver. Using worst case budgeting, i.e., assuming only the free space path loss between CR transmitter and PU receiver and large fading in a secondary link, and using 1 dB coexistence criterion, we can calculate how much power we can transmit and what could be the transmission range of the CR system.

Receiver sensitivity defines the minimum radio frequency (RF) signal power level required at the input of a receiver for a certain BER performance. This is a decoding sensitivity of receiver. It is defined as

$$S = N + N_F + \gamma_r \text{ [dB]}, \tag{1}$$

Where $N = kTB$ is the noise floor level in a band of interest, $k = 1.38 \cdot 10^{-23} J/K$ is the Bolzmann's constant, $T$ is the temperature in degrees Kelvin and $B$ is the bandwidth. The symbol $N_F$ is the noise figure and $\gamma_r$ represents required received SNR value. The decoding sensitivity and the spectrum sensing sensitivity are different things. While decoding sensitivity tells how much power is needed to decode the signal correctly, the sensing sensitivity defines the power level that can be detected. If the PU decoding sensitivity and noise figure are not known, they should be assumed to be as good as possible.

Rule above is for a single sensing device. More reliable sensing results can be achieved with collaboration and then worst case budgeting is not needed. The locally sensed spectrum information of nodes could be sent to the conscious node (CNode) that plays a role of spectrum coordination in the network [18] through a common control channel, combined, and then broadcasted to the CR terminals in the network. In the link level, spectrum has to be estimated periodically to obtain current spectrum use pattern. The system may also employ passive awareness principles and receive spectrum use information from e.g., servers, databases, or beacon signals. Based on the channel and spectrum estimates and the control channel information, operating frequency is selected and suitable power level adjusted to meet the prescribed requirements.

### B. Power control model

The system model used in power control simulations is presented as follows. The data are assumed to be known in the receiver, and thus the system is data-aided (DA). The data are transmitted through the channel and the instantaneous transmit power $P[k]$ is allocated based on the channel gain estimate $\hat{h}[k]$ sent by the receiver. The received complex baseband signal has the form

$$r[k] = x[k]\sqrt{P[k]}\,h[k] + n[k] \tag{2}$$

where the complex fading gain of the channel is $h[k] = \alpha[k]e^{j\theta[k]}$ and $n[k]$ is additive white Gaussian noise (AWGN) at time $k$. The amplitude of the fading gain is $\alpha[k]$ and $\theta[k]$ is the phase shift. Direct least-squares (LS) estimation of $h[k]$ is made online. The transmission data $x[k]$ are BPSK modulated with a rate of 10 kilobits per second.

**Signal-to-noise ratio definitions:** The average transmitted and the average received energy are usually normalized by the receiver noise spectral density $N_0$ leading to the average transmitted SNR per symbol [8]

$$\bar{\gamma}_{tx} = \bar{E}_{tx}/N_0 \tag{3}$$

and the average received SNR per symbol [8]

$$\bar{\gamma}_{rx} = \bar{E}_{rx}/N_0. \tag{4}$$

Transmitted energy is a basic system resource. In a mobile system it is taken from the battery of the transmitter and is therefore limited. Transmitted SNR should be used as a performance metric in order to obtain fair comparisons between different adaptive transmission systems.

**Channel modeling:** Our multipath channel is modeled by summing up equal amplitude sinusoids with different Doppler shifts. This gives us a flat Doppler power spectrum that corresponds to urban and indoor environments [19]. The time-variant channel gain can be written as

$$h[k] = \sum_{i=1}^{M} a e^{j(2\pi f_i k + \phi_i)} \tag{5}$$

where $M$ is the number of multipath components, $a$ is the amplitude of every component, $f_i$ is the Doppler shift of the $i$th component, $\phi_i$ is the random uniformly distributed phase shift of the $i$th component in range $[0, 2\pi[$ and $k$ is time.

## IV. TRUNCATED POWER CONTROL

Truncated channel inversion (TCI) compensates fading above a cutoff while meeting power constraint [20]. Transmission is interrupted and transmission power is zero when the channel gain deteriorates under certain cutoff value. Data are transmitted only when channel gain is above the threshold. The received SNR is kept in the level

$$\sigma_0 = 1/\overline{[1/\gamma]}_{\gamma_0}, \tag{6}$$

where

$$\overline{[1/\gamma]}_{\gamma_0} = \int_{\gamma_0}^{\infty} \frac{1}{\gamma} p(\gamma) d\gamma, \tag{7}$$

and cutoff value $\gamma_0$ is chosen by numerical root finding to maximize capacity per unit bandwidth [21]

$$\frac{C_{tci}}{B} = \log_2\left(1 + \frac{\overline{\gamma}}{E_1(\gamma_0/\overline{\gamma})}\right) e^{-\gamma_0/\overline{\gamma}} \text{ [bits/s/Hz]}. \tag{8}$$

Symbol $\gamma$ represents instantaneous received SNR value and $\overline{\gamma}$ is the average of it. $E_1(x)$ is the first order exponential integral. FxLMS power control structure can be modified to meet same constraint. Modified structure that approximates TCI is presented in Figure 2.

The algorithm can be presented with the equations

$$\varepsilon_k = |x_k| - \left| x_k c_{k-1} K_k / \sqrt{\sigma_0 \cdot N_0} h_k + n_k \right|, \tag{9}$$

$$c_k = c_{k-1} + \mu K_k \sqrt{\sigma_0 \cdot N_0} \varepsilon_k |x_k h_k|. \tag{10}$$
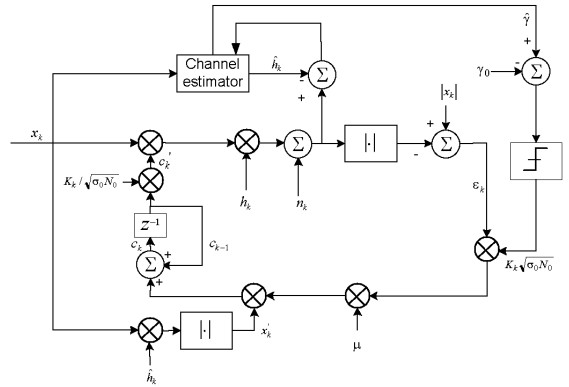


Figure 2.  Truncated FxLMS power control.

The algorithm updates the real coefficient $c_k$ of a one-tap filter, $\mu$ is the adaptation step size and $N_0$ is the noise spectral density. The optimal step size for multipath fading channel is given by [14]

$$\mu_{opt} = \frac{1}{(|x_k|^2 |\hat{h}_k|^2) + c_{term}}, \tag{11}$$

where $c_{term}$ is a small number that prevents the adaptation step size to grow to infinity when the estimated received power is very small. The parameter $K_k$ in equations is a factor that defines when the transmission is interrupted,

$$K_k = \begin{cases} 1, & \text{when } \hat{\gamma} \geq \gamma_0 \\ 0, & \hat{\gamma} < \gamma_0 \end{cases}. \tag{12}$$

Channel state estimate that is compared to cutoff value is

$$\hat{\gamma} = \overline{E}_{tx} \cdot (|\hat{h}_k|^2 / N_0), \tag{13}$$

where $\overline{E}_{tx}$ is the average transmitted energy. The transmitted energy is approximately $E_{tx} \approx \overline{E}_{tx} (\sigma_0 / \hat{\gamma})$ for $\hat{\gamma} \geq \gamma_0$ and zero otherwise.

If the data rate is kept constant during transmission above threshold and the aim is to keep overall data rate in the same level $R$ than in continuous transmission scheme, it has to be normalized with inverse of probability of outage $P_{out}$. Thus, the data rate will be

$$R_t = R/(1 - P_{out}). \tag{14}$$

Outage is the cutoff time when transmission is off, i.e., channel gain is below the threshold. Additional outage time in CR system comes from the fact that transmission has to be off during spectrum sensing to obtain reliable results about spectrum use. In addition, some time is needed also for spectrum allocation between users and also for time needed to reconfigure the transmitter after frequency shift.
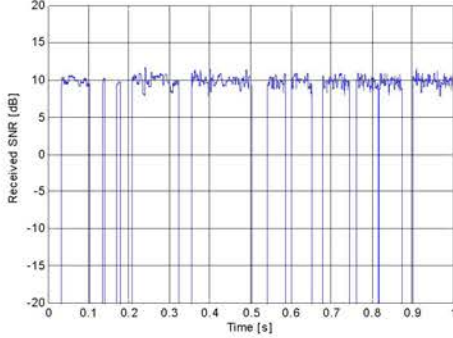
## V. RESULTS

### A. Energy efficiency



Figure 3. The received SNR with truncated FxLMS power control, average transmitted SNR = 20 dB.

Figure 3. shows the received SNR in a flat fading multipath channel with $M = 12$ when average transmitted SNR is set to 20 dB. In this system Doppler shift $f_d$ is chosen to be 10 Hz which corresponds to a slowly fading channel. Basically it tells how rapidly receiver is moving. 10 Hz corresponds to the walking speed 1.5 m/s when carrier frequency is 2 GHz. The target received SNR $\sigma_0$ is 9.9 dB and the probability of outage 27%. Delays caused by truncation are random.

To compare full inversion FxLMS method, FSAPC method, and variable step adjustment power control (VSAPC) [12] methods to truncated scheme we made simulations with same channel. Approximately same amount of energy is needed with every full inversion methods. As can be seen in Figure 4. the needed transmitted SNR to achieve received target SNR is clearly smaller with truncation. However, when the target SNR is increased, the lines get closer. When the difference is almost 9 dB with 6 dB target SNR, it is almost 3 dB smaller with 12 dB target. The reason for that is that more transmitted energy is allocated to deeper fades. This can be seen also from outage percentage. Probability of outage for three cases presented are 0.47/6 dB, 0.31/9 dB and 0.21/12 dB. Truncated scheme is clearly much more energy efficient. However, to achieve the same average throughput, data rate during the transmission has to be higher and this reduces the actual SNR difference.
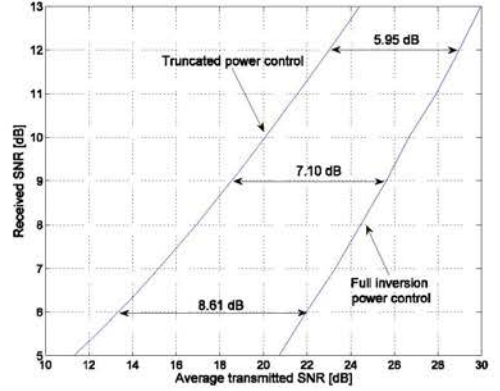


Figure 4. Transmitted SNR versus received SNR curves for truncated and full inversion power control.

To obtain results about interference range and more fair comparisons about transmitted SNR requirements that take data rate variation into account, we made link budget calculations that are offered in the next sections. Noise power in 10 kHz band is $N = kTB = 1.38 \cdot 10^{-23} J / K \cdot 290 K \cdot 1 \cdot 10^4 = 4.002 \cdot 10^{-17}$ W. In decibels it is $10 \lg(kTB) = -164$ dBW. Based on (14) and outage information we can compute data rate requirements and actual SNR differences between full and truncated inversion methods. Results are shown in Table 1.

TABLE 1. DATA RATES AND ACTUAL SNR DIFFERENCES BETWEEN FULL INVERSION AND TRUNCATED SCHEME

| Received target SNR | $R_t$ | Noise floor level $N$, $B = R_t$ | Actual SNR difference |
|---|---|---|---|
| 6 dB | 18.87 kbps | -161.22 dB | 8.61-(164-161.22)=5.83 dB |
| 9 dB | 14.49 kbps | -162.37 dB | 5.47 dB |
| 12 dB | 12.66 kbps | -162.95 dB | 4.90 dB |

Because of higher data rate, the noise floor changes and this reduces the actual SNR difference between truncated and full inversion power control schemes. However, it remains remarkable.

### B. Interference range

To obtain numerical results about the interference range variations, we made some calculations with a simple model. Node 1 and node 2 lie at the distance of $d$ from each other. We assume that signal propagates in line-of-sight (LOS) environment characterized by the two-slope path loss model which describes well the attenuation in short distance, low antenna height environment [22], [23] such that average received signal power $\overline{P}_{rx}$ [W] is

$$\overline{P}_{rx} = \frac{K}{d^a(1+d/g)^b}P_{tx},\qquad(15)$$

where $K$ is a constant, $a$ (usually two) is a basic path loss exponent for short distances, $b$ (between two and six) is an additional path loss exponent, and $P_{tx}$ [W] is the transmitted signal power. The parameter $g$ [m] is the break point of path loss curve and is given by $g = 4h_{tx}h_{rx}/\lambda_c$ where $h_{tx}$ [m] is the transmitter antenna height, $h_{rx}$ [m] is the receiver antenna height, and $\lambda_c$ [m] is the wavelength of the carrier. We use antenna heights $h_{tx} = h_{rx} = 2$ m, which are typical for mobile user [23]. When the carrier frequency $f_c$ is 2 GHz, we obtain break point at 106.67 m

The parameter $K$ in (15) depends on the used transmitter. The type of the antenna, use of beamforming etc. affects the constant value. When isotropical antenna is used, $K=1/(4\pi f_c/c)^2$. To find the maximal needed transmitted power we have to calculate the path loss with the distance $d = 200$ m, which we assume to be the maximal range for our cognitive link. With 2 GHz system the break point distance is 106.67 m. Let the path loss exponents to be $a = 2$ and $b = 4$. Then,

$$L_F = 10\log\left(\frac{d^a(1+d/g)^b}{K}\right) = 102.8\,\text{dB}.\qquad(16)$$

When we assume noise figure of 5 dB [24] and take into account that desired SNR in the receiver is 9 dB to achieve BER of $10^{-5}$ we obtain that receiver sensitivity is $(-134 + 5 + 9)$ dBm = -120 dBm. In Rayleigh fading channel, the probability of fade depth to be less than $F$ is simply $p = \exp(-1/F)$. Thus, for 99% coverage, fade margin of 20 dB is needed. The maximal needed transmitter power with the fading margin of 20 dB and shadowing margin of 10 dB which provides 90% successful communications at the fringe of coverage with 8 dB standard deviation [25] is $P_{tx} = P_{rx,\,desired} + L_F = -150$ dBW + 20 dB + 10 dB + 102.8 dB = -17.2 dBW = 19 mW.

Note that shadowing does not exceed the fade margin for 90% of locations at the maximal range (200 m from transmitter). When the receiver is nearer the value of the total path loss is less. Thus, clearly more than 90 percent of locations will have acceptable coverage. With truncation and with target SNR of 9 dB, the needed transmitted SNR is 5.47 dB smaller. We can calculate that maximal needed transmitter power is then only 5.4 mW. With 1 dB coexistence criterion and assuming that the required SNR for link we are interfering is 9 dB the interfering signal has to be 15 dB below the receiver sensitivity not to interfere. For example, with -85 dBm receiver sensitivity, the signal has to be below -100 dBm at this receiver.
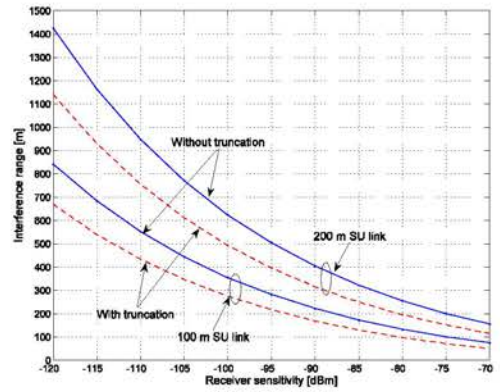


Figure 5.   Interference range with different receiver sensitivities for 100 m and 200m SU links.

To see the interference range in the highly improbable worst case situation, when 30 dB fading exists in SU link that uses maximum distance of 100 or 200 meters, and no fading at all exists between SU transmitter and PU receiver, we made calculations with different receiver sensitivities. We assumed that signal propagates according to (14). Results are shown in Figure 5. With 200 m link and sensitivity of -70 dBm, the range is 155 m with full inversion and 115 m with truncation. Thus, the interference area that is a circle with radius of interference range is reduced to the 55 % of the original. When sensitivity is -95 dB, ranges are 396 m and 504 m with interference area ratio of 61.7 %. If the system we are interfering with is equally sensitive cognitive radio system with -120 dBm sensitivity, the ranges are 1424 m and 1141 m with interference area ratio of 64.2 %. Thus, the gain of using truncated power control scheme is that interference area is reduced almost to the half from original. If path loss exponents would be smaller, the difference would be even larger. With 100 m SU link, 12.88 dB less power is needed and consequently the interference ranges are smaller as can be seen in Fig. 5. The interference area ratios with shorter link are even better because the attenuation mainly happens before the break point in the path loss curve. Thus, truncation improves the performance of low power transmitter even more. In addition to the interference reduction to the primary users, truncation improves the spectrum efficiency by allowing more secondary users to access the spectrum at the same time.

**Capacity.** How much better capacity can we achieve with same energy consumption? Since the difference in transmitted SNR is 7.10 dB when BER target is $10^{-5}$, we can raise the data rate with truncated scheme so that noise power becomes 7.10 dB higher. This happens with 51 kHz band which corresponds to $(51\,\text{kbps} \cdot (1-0.31)) = 35.2$ kbps average data rate. Thus, compared to full inversion scheme, we can achieve 3.5 times the throughput with the same energy consumption. If we are not allowed to raise our bandwidth, one option is to change the modulation to more efficient one. QPSK offers same BER performance than BPSK. If 16-QAM is selected, 3 dB larger SNR is needed to achieve same BER with double throughput.

This is less than the difference achieved with truncation. To achieve same throughput with full inversion, data rate during transmission should be 1.449 times higher. By changing the modulation we can double the data rate and still get clearly smaller interference range.

### C. Coexistence scenario with 1 Mbps secondary link

Assuming 1 Mbps QPSK transmission in 500 kHz band, 5 dB $N_F$ and 9 dB SNR to achieve required BER, the sensitivity of the receiver is S = -103 dBm. With 200 m link and 30 dB fading, transmitter power should be 29.8 dBm. If PU sensitivity is a realistic -90 dBm, interference ranges are approximately 845 m/670 m for full inversion/truncation. With 100 m link, transmission power should be 17 dBm and interference ranges are 490 m/383 m. Assuming PU link to be 200 m, spectrum sensor should sense signals 200 m farther than interference ranges mentioned above. With 30 dB fading, attenuations for cases mentioned are 170.2 dB/165.7 dB for 200 m link and 160.2 dB/157.0 dB for 100 m link.

When PU transmitter uses 40 dBm transmitted power, sensitivity of spectrum sensor should be -130.2 dBm/-125.7 dBm for 200 m link and -120.2 dBm/-117.0 dBm for 100 m link. Can we detect any of these signals when the noise floor is -117 dBm? Uncertainties in the noise and interference levels and the coherence time induce limits on how weak signals individual sensors can detect [26], [27]. The minimum power level is called SNR wall and cannot be overcome by increasing the sensing time. SNR wall with 1 dB noise uncertainty for energy detector is 3 dB below noise floor and can be further reduced by 20 dB by using feature detection. So the achievable sensing values are -120 dBm and -140 dBm for 500 kHz band. Only 100 m link with truncation can be used with energy detectors. All scenarios are achievable with feature detection. Assuming 10 dB gain for cooperative detection, also 200 m link with truncation can be used with simple energy detectors. Because the signal levels for detection with truncation are higher, faster sensing times and more efficient spectrum utilization can be achieved.

These calculations show that we can use highly sensitive cognitive radio system with relatively long transmission links inside the primary system even under worst case conditions. Interference can be controlled with transmitter power control together with reliable spectrum awareness method. However, if much higher data rate is needed, multi-carrier transmission over multiple spectral holes could be used. The other option is to cope multipath fading with diversity and use power control to mitigate the effects of path loss and shadowing. This would allow even better spectrum sharing and interference range reduction. Truncation offers much better energy efficiency also in shadowing channel [28].

## VI. CONCLUSIONS

Cognitive radio should minimize interference it creates to licensed users. This can be done by using minimum amount of transmitter power. In an active cognitive radio system, spectrum sensing sensitivity together with worst case link budgeting tells how much transmission power is allowed to use in order to avoid interfering with primary receivers. In a cognitive radio network using active awareness principles, delays cannot be avoided because of periodical sensing. Such a network is not good for real-time communication. Thus, power control method does not need to assure delayless communication.

A large part of the transmission power in continuous inverse control solutions is used to compensate the deepest fades in a fading channel. Truncation in power control reduces the energy consumption and transmission power. Thus, interference to primary users is reduced and more secondary users are allowed to share the spectrum. Both energy and spectrum efficiency are improved. In addition, sensing requirements can be relaxed because of shorter interference range. This means faster sensing times and better spectrum utilization. Drawback is that no data are transmitted below threshold which causes random delays to transmission. However, we can achieve much better average throughput with same interference range when compared to conventional full inversion scheme.

Truncation is a good choice for transmission in a CR system. When channel becomes bad enough, the secondary transmitter should stop transmitting and continue again when situation is better. Another option is to change frequency. Further work is still needed to investigate how the multipath fading affects the operation of a cognitive radio and what are the best methods to mitigate these effects. For example, an interesting research topic could be to investigate the effects of diversity and beamforming to the transmitter power needs and to the interference range. Intuitively, the combination of directional antennas, good diversity method and truncated power control method could offer very efficient spectrum sharing solution. In addition, experiments with multiple secondary users causing aggregate interference could be done.

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PAPER V

# Interference management in frequency, time, and space domains for cognitive radios

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# Interference management in frequency, time, and space domains for cognitive radios

Marko Höyhtyä, Tao Chen, and Aarne Mämmelä
VTT Technical Research Centre of Finland
P.O. Box 1100, FI-90571 Oulu
Finland

*Abstract*— In order to minimize interference with primary users (PU), cognitive radios should operate multidimensionally over time, frequency, and space. This paper addresses the problem with power control and predictive frequency selection. Both the methods are coupled with spectrum sensing. The proposed frequency selection method minimizes the amount of channel switches, which increases the capacity of the system and decreases the number of collisions with PUs. It is shown that the allowed transmission power of an SU scales linearly with increasing primary transmission power. The results illustrate the effect of the antenna height to the maximum power; a high-antenna PU transmitter allows more powerful SUs. Moreover, simulations indicate that the power control method reduces greatly the amount of interference imposed towards PUs.

## I. INTRODUCTION

Cognitive radio (CR) is not allowed to interfere with primary users while simultaneously offering good enough quality of service (QoS) for SUs [1], [2]. In frequency domain, a CR has to select frequencies that are not used by the PUs for secondary operation. Knowledge about spectrum use can be obtained with passive and active methods, for example using spectrum servers, beacons, or spectrum sensing.

Interference minimization is often treated as a spatial domain problem. To avoid interfering with PUs, the power of the cognitive radio should be limited based on locations of primary receivers [3]. Adaptive beamforming can be used to direct power only to the wanted direction [2]. In addition, prediction can be applied to find the best spectrum opportunities for secondary use in time domain [4], [5], [6]. This helps to avoid frequent service disruptions for secondary user as well as interference with PUs.

Interference minimization can be done separately in different domains but in order to work in a highly efficient way, a CR should operate multidimensionally over time, frequency, and space. Some authors have investigated joint power and channel allocation approaches for cognitive radios. Both centralized [7] and distributed methods [8], [9] have been proposed. In [8] power control aims at finding a topology that minimizes the maximum transmission power of nodes while transmission channel selection reduces the required bandwidth. In [7] and [9], the capacity of the system is maximized by water filling type of allocation while taking certain restrictions like signal-to-interference-plus-noise ratio (SINR) at each PU into account. In contrast to these joint approaches, we propose a sensing aided practical solution that will consider also the time aspect of PU operation.

Time is a very important resource for cognitive radios. In spectrum sensing CR seeks for spectrum holes, i.e., temporarily unused channels from the band of interest, for its own use. A CR has to sense every $\Delta\tau$ seconds for $\tau$ seconds to obtain reliable results about the spectrum usage. Parameter $\Delta\tau$ is the maximum length of interference the PU can tolerate. In addition, time is needed during every channel switch for resource allocation and transceiver reconfiguration. This limits the ability to utilize very short spectrum holes. To maximize time to be used for secondary transmission and minimize collisions with PUs, characteristics of the primary traffic in different channels should be taken into account. Secondary users should concentrate on the channels offering long enough idle time for communication.

We emphasize here the importance of multidimensional operation in interference management and propose sensing aided methods for power and frequency control. In addition to frequency domain operation, spectrum sensing gives valuable information for power adaptation. Spectrum sensing sensitivity, which is the detection limit of a sensor, can be used to calculate the potential proximity to the primary receiver and to estimate the power limit for secondary transmission.

We combine time domain aspect to frequency and power control. We propose a two-step approach in this paper: 1) Selection of operation frequency based on sensing and prediction and 2) Adaptive transmission power adjustment to meet required QoS. Frequency selection aims at finding frequencies that offer longest idle time into use to minimize the amount of collisions between primary and secondary user. We derive the optimal frequency selection method analytically and show the performance improvement with simulations.

Minimum transmission power to achieve required QoS is allocated which minimizes the interference range of a CR. The new practical method to calculate the maximum limit for secondary transmission power is presented based on knowledge about spectrum sensing sensitivity and known parameters from the primary system. The fundamental criterion for coexistence in terms of acceptable interference in the victim receiver is defined as the interference level that causes 1 dB degradation in receiver sensitivity [10]. This means that the interference power has to be 6 dB below receiver thermal noise. The interference range for secondary transmission can be defined as a range in which coexistence criterion stated above is not met. Simulations are conducted with different power control methods to see how the selection affects the performance.

This paper is organized as follows. System model is described in Section II. Section III describes the method for calculation of power limit for secondary use. Section IV describes the predictive channel selection approach and Section V discusses about transmission power control. Results are shown in Section VI and Section VII concludes the article.

## II. SYSTEM MODEL

### A. Interference model

We consider the coexistence of the primary and secondary system in the same area. The system model where both SUs and PUs form a transmitter-receiver pair is shown in Fig. 1. The figure illustrates the situation in the spatial domain. Cognitive radio uses sensing to obtain information about spectrum use. It can only detect local situation around it. Sensitivity of the sensor defines the sensing range $r_s$, i.e., how far a CR can detect PU transmission. On the other hand, transmission power of a CR defines its communication range $r_c$ and interference range $r_i$. Inside the communication range, the signal-to-noise ratio (SNR) is large enough to decode transmitted data. Interference range of the PU is marked as $d_i$.
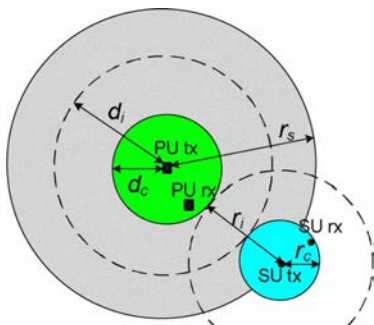


Figure 1. System model - ranges.

Since it is difficult to locate primary receivers nearby without any change to the primary system, the transmission power of the SU should be limited in a way that primary receivers in the edge of the communication range of the PU, $d_c$, do not experience more interference than they can tolerate. In reality, ranges around transceivers do not form circles. There is variation caused by fading and difference in signal strength at the same distance can be tens of decibels. To address the problem, worst case scenario is needed when primary and secondary systems do not cooperate at all. We assume a CR to have a single antenna. Thus, beamforming is not considered in this work.

### B. Dynamic spectrum management model

We assume that the total available spectrum is divided into multiple primary channels. Each channel has its own traffic pattern that defines the distribution of ON and OFF times of the traffic. Fig. 2 presents block diagram for the system. A CR senses the spectrum periodically and stores this information

into the database that includes parameters of the primary system like transmission power and noise figure. Information from sensing and database is used by the dynamic spectrum management (DSM) module. Channel history is used to predict future idle times in channels. The same channel is used as long as it is available, and when a CR has to switch channel it selects a free one with the longest predicted idle time. Power is controlled adaptively taking information from channel conditions as well as sensing and PU parameters into account.
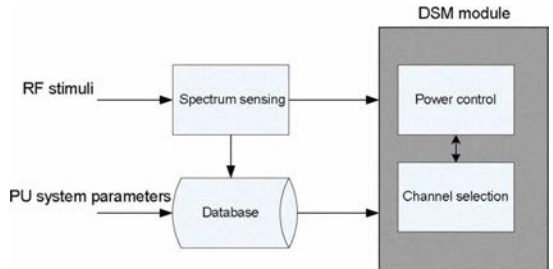


Figure 2. Block diagram for the system.

We propose here a two-step approach for interference management for cognitive radios. In the first step the aim is to reduce interference in time and frequency domains. Sensing is used to locate unused frequencies for secondary use. When the PU appears in the same band, prediction helps to switch to the channel with the longest idle time. In the second step, to keep the interference range as small as possible, an SU adjusts adaptively its transmission power to the minimum level that is still enough to meet QoS requirements and no more than transmission power limit for secondary use.

### C. Power control model

The instantaneous transmit power $P[k]$ is allocated based on the channel gain estimate $\hat{h}[k]$ sent by the receiver. The received complex baseband signal has the form

$$r[k] = x[k]\sqrt{P[k]}\,h[k] + n[k] \qquad (1)$$

where the complex fading gain of the channel is $h[k] = \alpha[k]e^{j\theta[k]}$ and $n[k]$ is additive white Gaussian noise (AWGN) at time $k$. The amplitude of the fading gain is $\alpha[k]$ and $\theta[k]$ is the phase shift. Direct least-squares estimation of $h[k]$ is made online. The transmission data $x[k]$ are BPSK modulated with a rate of 10 kilobits per second.

Our multipath channel is modeled by summing up equal amplitude sinusoids with different Doppler shifts. This gives us a flat Doppler power spectrum that corresponds to urban and indoor environments [11]. The time-variant channel gain can be written as

$$h[k] = \sum_{i=1}^{M} a e^{j(2\pi f_i k + \phi_i)} \qquad (2)$$

where $M$ is the number of multipath components, $a$ is the amplitude of every component, $f_i$ is the Doppler shift of the $i$th component, $\phi_i$ is the random uniformly distributed phase shift of the $i$th component in range $[0, 2\pi[$ and $k$ is time. The delays

of the components are assumed to be roughly the same to obtain flat fading in the frequency domain.

Transmitted energy is a basic system resource. In a mobile system it is taken from the battery of the transmitter and is therefore limited. Transmitted SNR should be used as a performance metric in order to obtain fair comparisons between different adaptive transmission systems. Therefore we define the SNR as follows: The average transmitted energy normalized by the receiver noise spectral density $N_0$ leads to the average transmitted SNR per symbol [17] $\bar{\gamma}_{tx} = \bar{E}_{tx} / N_0$.

## III. PREDICTIVE CHANNEL SELECTION

Sensing of primary channels is a periodic sampling process to determine the state (ON or OFF) of the channels at every sampling instant [5]. The outcome of sensing is a binary sequence of each channel. It has sufficient information to determine the periodicity, distribution of idle and busy times, and utilization of the channel.

When both ON and OFF times are random, we can calculate the expected remaining idle time after we detect the channel to become idle. Each CR stores the measurements of idle and busy times to a database. From the database, the probabilities that a channel will be available at least $X$ seconds can then be calculated as $P(t \geq X) = Q/G$, where $Q$ = amount of idle times $\geq X$ and $G$ = amount of all idle times.

A possible metric for channel quality is the median idle time. There is a 50% chance for the real idle time to be at least that long. The longer this time is the better. Using the database, a CR could also estimate the time to transmit under an interference constraint (i.e., $Y$ % guarantee not to interfere with PU). This means that it would transmit continuously without sensing certain amount of time and trust in the distribution. To achieve this, the CR should choose its transmission time $Z$ so that $P(t = Z) \leq 1 - Y$. In this way the CR could adaptively loosen its sensing period requirements. However, doing so the sampling process slows down and in the future the database cannot give as accurate information.

*Prediction analysis:*

Suppose we have a vector of $n$ samples of idle times from channel $i$, $\mathbf{X}^i = (x_1^i, x_2^i, ..., x_n^i)$. Assuming exponentially distributed OFF times with traffic parameter $\lambda_{OFF} > 0$ the probability density function (pdf) of the exponential function is

$$f(x; \lambda_{OFF}) = \begin{cases} \lambda_{OFF} e^{-\lambda_{OFF} x} & , x \geq 0 \\ 0 & , x < 0 \end{cases}. \qquad (3)$$

The maximum likelihood (ML) estimate for the traffic parameter is $\hat{\lambda}_{OFF} = 1/\bar{x}$, where $\bar{x} = (1/n) \sum_{j=1}^{n} x_j$ is the sample mean. Because of the invariance property of the ML estimator [12], ML estimate for idle time can be written as

$$\hat{T}_{OFF} = 1 / \hat{\lambda}_{OFF} = \bar{x}. \qquad (4)$$

This means that the optimal prediction of the next idle time is the average of the previous ones. In practice, traffic patterns of different channels might slowly vary over time. Thus, observation interval for average calculation should be restricted.

Exponential model have been traditionally used to model voice traffic. A better model to describe ON/OFF periods in real and possibly bursty network traffic is the Weibull distribution [13]. The pdf of a Weibull random variable $x$ is given by

$$f(x) = \begin{cases} \alpha\beta x^{\beta-1} e^{-\alpha x^\beta}, & x \geq 0 \\ 0, & x < 0 \end{cases} \qquad (5)$$

where scale and shape parameters are $\alpha > 0$ and $\beta \geq 0$. When $\beta < 1$, the Weibull distribution is heavy-tailed and can be used to model the ON/OFF period lengths of self-similar network traffic. The mean value for the distribution is

$$E[x] = 1/ \alpha \, \Gamma(1+1/\beta), \qquad (6)$$

where $\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt$ is a gamma function. If $z$ is a positive integer, then $\Gamma(z) = (z-1)!$. We consider here the case $\beta = \frac{1}{2}$ which leads to $E[x] = 2/ \alpha$.

SUs utilize the past channel observations to build predictive models of spectrum availability, and schedule their spectrum use in order to maximize spectrum utilization while minimizing the disruption rate to primary users. To do so, the CRs have to select the channel to switch to in an intelligent way. When switching channels, a user switches to the available channel $j$ with the largest expected remaining idle time $T_j$, chosen as $T_j = \arg\max_j T_j$, where $T_j$ is the calculated or estimated remaining idle time. Previous analysis supports mean time based selection. Predicted idle time is then

$$T_j = T_{mean}^j. \qquad (7)$$

When the distribution of idle times is memoryless, as is the case with exponential distribution, the consumed idle time does not affect the probability of the channel being idle in the future. Therefore, there is no need to subtract the consumed idle time from the prediction.

## IV. TRANSMISSION POWER LIMIT

While it could be very helpful to know the location of PU receivers and the power loss gain of the channel between them and secondary transmitters, neither of this information may be available in real systems. However, we could still know something about primary users that can aid the configuration of our cognitive radios. Sensing tells us about spectrum use. However, signal coming from primary transmitter attenuates

due to path loss and fading. Requirement to detect PU transmission is

$$P_{\mathrm{pu}} - \alpha_{\mathrm{ps}} \geq S_{\mathrm{s}} \ [\mathrm{dB}] \tag{8}$$

where $P_{\mathrm{pu}}$ is transmission power of the PU transmitter, $\alpha_{\mathrm{ps}}$ is attenuation between the PU transmitter and a sensing radio, and $S_{\mathrm{s}}$ is spectrum sensing sensitivity of the CR. If no detection occurs, there is no signal present or it is attenuated so much that it cannot be sensed.

Using 1 dB coexistence criterion [10] we can define that power received at PU receiver from secondary transmission should be 6 dB below the noise level

$$P_{\mathrm{sp}} \leq N + N_{\mathrm{F}} - 6 \ \mathrm{dB}, \tag{9}$$

where $N$ is noise floor and $N_F$ is noise figure of the primary receiver. Because we do not receive any information from other systems we assume the worst case scenario to guarantee interference-free communication for primary system. Thus, there is only path loss between secondary transmitter and primary receiver but heavy fading between primary transmitter and secondary receiver as well as in the secondary link.

Well known free space path loss equation is given as $L_F(d) = (4\pi f d/c)^2$, where $f$ is the signal frequency in hertz, $d$ is the distance from the transmitter in meters, and $c$ is the speed of light [16]. Path loss between primary transmitter and sensing radio is $\alpha_{\mathrm{ps}} - F_{\mathrm{m}}$, where $F_{\mathrm{m}}$ is fading margin. Assuming a CR lies just on the edge of the sensing range $r_s$ and using information given above we can calculate the range to be $r_{\mathrm{s}} = \sqrt{\mu} \cdot c/4\pi f$ where $\mu = 10^{(P_{\mathrm{pu}} - S_{\mathrm{s}} - F_{\mathrm{m}})/10}$. Attenuation between secondary transmitter and primary receiver in the worst case is given by free space path loss $\alpha_{sp} = L_F(r_s - d_c)$. On the other hand, inequality (9) can be written as

$$P_{\mathrm{sp}} = P_{\mathrm{su}} - \alpha_{sp} \leq N + N_{\mathrm{F}} - 6 \ \mathrm{dB}. \tag{10}$$

We can define the limit for secondary transmission power from equations (8)–(10),

$$P_{\mathrm{su}} \leq L_{\mathrm{F}}(r_s - d_c) + N + N_{\mathrm{F}} - 6 \ \mathrm{dB}. \tag{11}$$

Power, range, and noise figure parameters for working systems can be found easily and this information together with sensitivity information and 1 dB coexistence criterion defines how much power is allowed to use for secondary transmission. Another possible path loss model with more realistic features is a two-slope path loss model [14] which defines the average received signal power as

$$\overline{P}_{rx} = \frac{K}{d^a (1 + d/g)^b} P_{tx} \ [W] \tag{12}$$

where $K$ is a constant, $a$ (usually two) is a basic path loss exponent for short distances, $b$ (between two and six) is an additional path loss exponent, and $P_{\mathrm{tx}}$ is the transmitted signal power. The parameter $g$ $[m]$ is the break point of path loss curve and is given by $g = 4h_{\mathrm{tx}}h_{\mathrm{rx}}/\lambda_c$ where $h_{\mathrm{tx}}$ $[m]$ is the transmitter antenna height, $h_{\mathrm{rx}}$ $[m]$ is the receiver antenna height, and $\lambda_{\mathrm{c}}$ $[m]$ is the wavelength of the carrier. When this model is used, the ranges have to be solved numerically.

## V. TRANSMISSION POWER CONTROL METHOD

Transmission power control aims at fullfilling the QoS requirements of secondary users while keeping the produced interference in an acceptable level towards primary receivers. To minimize the interference, a CR should use minimum power to achieve QoS. This is a good method from energy conservation viewpoint. When transmission happens at the lowest power level, also energy consumption is at its minimum. Minimum power at link level is achieved by inverting the channel power gain based on the channel estimates while maintaining the desired signal strength at the receiver. A good practical adaptive inverse control method is variable step adjustment power control method (VSAPC) presented in [15] in which the power of the received signal averaged over three symbols is compared to the reference power level in the receiver. If the error signal is positive, power is adjusted upwards while negative error causes downward adjustment. The power control algorithm with power limit restriction can be written as

$$P_k = \begin{cases} P_{k-1} + C_k \Delta P, & P_k < P_{su} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

where the power control command is

$$C_k = \begin{cases} 3, & \text{when } P_{\mathrm{err}} < -5\kappa \\ 2, & -5\kappa \leq P_{\mathrm{err}} < -3\kappa \\ 1, & -3\kappa \leq P_{\mathrm{err}} < -\kappa \\ 0, & -\kappa \leq P_{\mathrm{err}} < \kappa \\ -1, & \kappa \leq P_{\mathrm{err}} < 3\kappa \\ -2, & P_{\mathrm{err}} \geq 3\kappa \end{cases} .$$

$P_{\mathrm{err}}$ is the power of the error signal in dB and $\kappa = 0.5\Delta P$.

To further reduce the produced interference and to make system more energy efficient, truncation can be used in power control. Truncated channel inversion (TCI) compensates fading above a cutoff while meeting power constraint [16]. Transmission is interrupted and transmission power is zero when the channel gain deteriorates under certain cutoff value. Data are transmitted only when channel gain is above the threshold. The received SNR is kept in the level

$$\sigma_0 = 1 / \overline{[1/\gamma]}_{\gamma_0} , \tag{14}$$

where $\overline{[1/\gamma]}_{\gamma_0} = \int_{\gamma_0}^{\infty} \frac{1}{\gamma} p(\gamma) d\gamma$ , and cutoff value $\gamma_0$ is chosen by numerical root finding to maximize capacity per unit bandwidth

$$\frac{C_{\mathrm{tci}}}{B} = \log_2 \left( 1 + \frac{\overline{\gamma}}{E_1(\gamma_0 / \overline{\gamma})} \right) e^{-\gamma_0 / \overline{\gamma}} \ [\mathrm{bit/s/Hz}], \tag{15}$$

where symbol $\gamma$ represents instantaneous received SNR value and $\bar{\gamma}$ is the average of it, $E_1(x)$ is the first order exponential integral. Adaptive power control structure can be modified to meet same constraint [17].

## VI. RESULTS

Numerical results for proposed interference management techniques are presented in this section. The intelligent channel selection method is compared with random selection that refers to the method making selection based on instantaneous information of channel conditions. With random selection, all available channels have equal probability to be chosen. Transmission power limits are investigated with different antenna heights and finally two different power control rules are compared in simulation study.

### A. Channel selection

Prediction based channel selection aims at finding channels offering longest idle times for operation. In order to see how well the proposed intelligent channel selection approach works when compared to random opportunistic channel selection, we made experiments with stochastic traffic patterns. Parameters for the simulation are shown in Table I.

TABLE I. SIMULATION PARAMETERS.

| Parameter | Value |
|---|---|
| Transmission period | 90 ms |
| Sensing period | 10 ms |
| Switching delay | 10 ms |
| Number of channels | 5, 10, 15, 20 |
| Primary user traffic models | Stochastic channels with Weibull distributed ON and OFF times |
| Utilization, mean idle times of stochastic primary traffic | Utilization of channels between [0.1, 0.9], mean idle times between [1 s, 10 s] |
| Simulation time | 10 000 s |
| Channel selection methods | Intelligent channel selection, random selection |

Learning and intelligence always seem to improve the efficiency of the system, measured by the number of channel switches. Results for Weibull traffic are shown in Fig. 3. The number of channels was as shown in Table I. Optimal selection shows the lower bound for switches in a situation where traffic is known perfectly.

The intelligent method can concentrate on the best channels and outperforms clearly the random method. The result shows significant gains for relatively simple prediction method. The reduction in channel switches ranges from 13% with 5 channels to 36% with 20 channels. Amount of switches with random selection remains the same since the average idle time is same for all number of primary channels whereas the intelligent method takes advantage of the increasing number

of good channels. Simulations with exponential, Pareto, and deterministically distributed traffic lead to the same kind of conclusion [18].
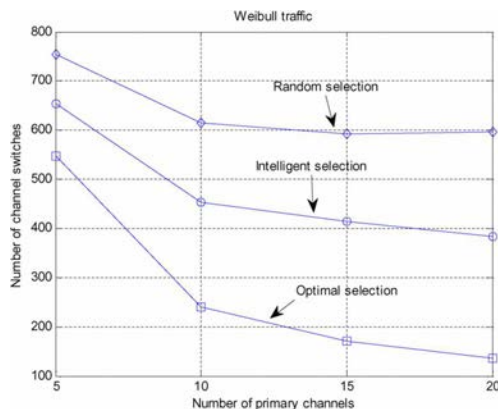


Figure 3. Amount of channel switches with stochastic traffic.

The effectiveness of the predictive approach depends heavily on the predictability of the traffic. With intelligent method we can always select best channels into use but to get a large performance gain out of it, there should be large variation in traffic at different frequencies. The more the traffic is varying across channels the better learning and prediction are working compared to methods based on instantaneous information. The reason behind that is the fact that with large variation the quality of best channels is much better than average channel quality.

### B. Transmission power control

After channel selection the CR transmits data in the channel. It has to adjust its power to be high enough for reliable communication. The power limit defined in (11) must be met, otherwise transmission is not allowed. The sensitivity of the sensor and the noise figure of the primary user define partly the range. We made calculations to see how the limit behaves with changing transmission powers of the primary user when the carrier frequency is 2 GHz. Parameters for calculations are shown in Table II. We used two slope path loss model in calculations. The same fading margin is used both for the primary link and between the primary transmitter and the sensing radio to define both the sensing range and the primary communication range. We assume that the sensor can detect signal 3 dB below thermal noise level. Analytical results for two different PU antenna heights, namely $h_{tx} = 1.5$ m and $h_{tx} = 50$ m are shown in Fig. 4. Selection refers to the cases where primary transmitter is either close to the ground, e.g, WLAN, or using high antennas, e.g., base station. Secondary transmitter and receiver are using antenna height of 1.5 m. Selected transmission power values cover practical systems from Bluetooth class 3 radio (0 dBm ) to WLAN (20 dBm) up to cellular base stations (40–50 dBm).

TABLE II.    POWER LIMIT CALCULATION PARAMETERS.

| Bandwidth | Noise figure | Fading margin | Sensing sensitivity | Required SNR, PU |
|-----------|--------------|---------------|---------------------|------------------|
| 1 MHz | 6 dB | 30 dB | -117 dBm | 10 dB |

Result shows that the more powerful the primary transmitter is, the more power is allowed to be used by secondary users. The transmission power limit of the secondary user scales almost linearly with increasing primary transmission power. We can see from the figure that the height of primary transmitter antenna has a significant impact on the allowed secondary power. Reason behind this is the fact that with a higher antenna the break point in the path loss curve is much farther and thus the attenuation is lower. This makes the sensing of primary signal easier and the detection can be made from a greater distance. The signal attenuates more rapidly between low secondary transmitter and primary receiver. This allows pretty strong secondary transmissions to be used though the assumption is that during the sensing there is large fading present and interfering signal from secondary transmitter is affected only by path loss. Worst case assumption is needed to protect primary receivers but in reality it may be unlikely to have the described situation.
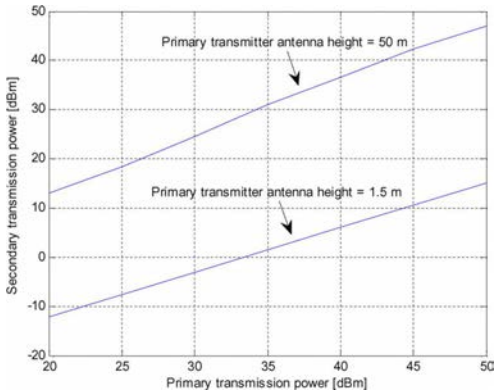


Figure 4.    Transmission power limit for secondary user.

From the interference viewpoint the approach of minimizing the maximum transmission power of cognitive radios is reasonable since that minimizes the interference range of the cognitive radio. The power control method aims at efficient use of energy while reducing interference also to other secondary users, thus allowing greater sharing of spectrum.

Table III shows simulated average and maximum transmitted SNR values for full and truncated inversion power control methods when received SNR was kept at the 10 dB level. Average value is a metric for energy efficiency while maximum value defines the worst case interference. Large

amount of power is needed to compensate deepest fades in multipath fading channel; maximum transmitted SNR value was between 41 and 48 dB in simulations with full inversion when $M = 12$ in equation (2). Power control method with truncation avoids deepest fades and allocates power for better time instants. The difference in average SNR values is around 7 dB while in maximum values the difference can be over 20 dB. The cutoff value in truncated method sets the upper limit for power and thus keeps the interference and energy consumption in a lower level.

TABLE III.    TRANSMITTED SNR VALUES FOR DIFFERENT POWER CONTROL METHODS

| Method | Average transmitted SNR | Maximum transmitted SNR |
|--------|-------------------------|-------------------------|
| full inversion | 25 – 29 dB | 41 – 48 dB |
| truncated inversion | 20.1 dB | 25.7 dB |

Average and maximum SNR values can be used to estimate average and maximum interference ranges of secondary transmission. Results for different communication ranges of the secondary link of the system are shown in Fig. 5. The chosen values correspond to the local area network. We used two-slope path loss model and 1 dB coexistence criterion in calculations. Maximum transmitted SNR for full inversion was chosen to be 45 dB. High instantaneous powers are needed with full inversion during deep fades and that makes the worst case interference range really large. When truncated method is used, even the worst case interference is smaller than the average value with full inversion method. Drawback of truncation is that no data are transmitted below threshold which causes random delays to transmission.
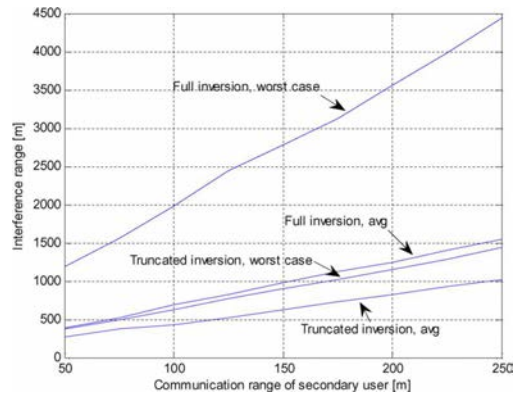


Figure 5.    Interference range with different communication ranges.

## VII. Conclusions

Cognitive radio should operate multidimensionally to avoid interfering with primary users while efficiently utilizing available radio resources. We proposed here models to avoid interfering with primary users in space, time, and frequency domain. Predictive channel selection helps to find best channels for control and data transmission. Allowed transmission power of secondary user was shown to scale linearly with increasing primary transmission power. The antenna height of primary transmitter was shown to greatly affect to the allowed power level. Truncation in power control offers energy efficient transmission and reduces the produced interference greatly compared to the full inversion based continuous communication.

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# Secondary terrestrial use of broadcasting satellite services below 3 GHz

# SECONDARY TERRESTRIAL USE OF BROADCASTING SATELLITE SERVICES BELOW 3 GHZ

Marko Höyhtyä

VTT Technical Research Centre of Finland, P.O.Box 1100, FI-90571 Oulu, Finland
`marko.hoyhtya@vtt.fi`

## ABSTRACT

*Secondary use of the satellite spectrum by a terrestrial system is studied in this paper, focusing on broadcasting satellite services. Both spectrum sensing based access and database based access are discussed. Link budget analysis is used to define operational limits for spectrum sensing and transmission power control when the primary system is a digital video broadcasting – satellite services to handheld devices (DVB-SH) system. The results show that cognitive radio techniques should be applied with caution in satellite bands. The energy detection method does not support well spectrum sharing in the studied band. Rather the sensing should be based on the feature detection or matched filter detection. The results show that only short-range transmission can be used on a secondary basis in many environments when the secondary spectrum use is based on the sensing.*

## 1. INTRODUCTION

Emergence of cognitive radio (CR) techniques has had a significant role in the wireless research during the last decade. CR techniques have been proposed to improve the spectrum occupancy by exploiting the unused parts of the spectrum without interfering with the primary users (PU) having either higher priority or legacy rights [1], [2]. The CR research work has focused strongly to the terrestrial systems, identifying solutions to spectrum awareness, resource management, and interference problems. Even though the work has progressed considerably, it is estimated that CRs will be adopted by mainstream only after 10+ years [3]. One of the key factors slowing down the adoption process is the difficulty in defining suitable bands for secondary operation.

There are several interesting spectrum band candidates for the secondary spectrum use, including e.g., TV bands due to the deterministic traffic and the suitable penetration characteristics. However, many other bands need to be studied carefully to find space for the ever-increasing demand for wireless services. Satellite communications and bands have not been explored much in the CR research literature. However, cognitive radio techniques could be applied in satellite communication systems in several different ways. A secondary system can operate at the satellite bands using the cognitive principles to avoid interfering with the primary satellite system. The satellite system itself can be made more intelligent by applying cognitive techniques in it. It is even possible that the satellite system accesses the band used by another communication system and operates as a secondary user in that band [4].

The purpose of our paper is to study the secondary terrestrial use of the satellite DVB-SH spectrum, focusing especially on the spectrum sensing requirements and transmission power limits for the secondary system while assuming realistic models for propagation. A part of our

1

work done in the satellite downlink is reported in [4]. However, our previous paper studies only satellite downlink sensing. Since spectrum sensing performance partly defines the transmission power of the secondary system, we consider here the research question: *What transmission power levels are supported by which spectrum sensing techniques/detection thresholds?* That information is used to define what kind of secondary systems could operate in this band.

The studied DVB-SH system can be seen as a general broadcasting scenario in frequencies below 3 GHz and thus the carried research provides useful information on the applicability of CR techniques in related scenarios as well. Both the indoor and outdoor scenarios in the urban and suburban environments are considered. The proposed estimation method does not require exact channel knowledge between the primary transmitter and the secondary sensor. We focus on the terrestrial part of the hybrid satellite-terrestrial system. In addition to sensing related investigation, we will also discuss about the possibility to use databases for spectrum sharing between systems.

The organization of the paper is as follows. Related work is presented in Section II and the system model in Section III. Achieved results concerning link budget and spectrum sensing ranges are shown in Section IV. Transmission power limits are estimated in Section V. The database approach is reviewed in Section VI and finally the paper is concluded in Section VII.

## 2. RELATED WORK

Spectrum sharing in satellite bands has been discussed by regulation authorities actively, e.g., in [5], [6] where Worldwide Interoperability for Microwave Access (WiMAX) and International Mobile Telecommunications-Advanced (IMT-Advanced) systems were considered. The results of [5] show that criteria where the fixed satellite services (FSS) antennas cannot co-exist with WiMAX systems range from 50 km to over 200 km. Use of adaptive antennas is shown to remarkably reduce the range requirements in [6].

There is a growing interest in spectrum sharing in satellite bands in the research community. Secondary use of terrestrial spectrum by a satellite system in the Ka band using highly directed antennas was considered in [4]. An extension of a terrestrial 3GPP Long Term Evolution (LTE) network by a satellite LTE system to provide coverage in areas where building infrastructure is too expensive was also investigated in [4]. Both the satellite and terrestrial components were operating in the 2.6 GHz band. Load-balancing in satellite-terrestrial wireless networks was investigated in [7]. Other hybrid satellite terrestrial systems have been proposed in [8] and [9]. The idea in these papers is to use the satellite to assist the terrestrial secondary network. In [8], the satellites are used to connect the terrestrial cells, which are operating as secondary users of the spectrum, to each other. The base station sends uplink data towards satellite. Downlink data are in both scenarios received by the base stations. In the architecture described in [9], the satellite is the central controller; i.e., it is in charge of the spectrum allocation and management.

It is shown in [10] that cyclostationary features of satellite signals help secondary operation in the same spectrum. Cyclostationarity affects both the secondary signal design and reliable detection of the satellite signals. A recent paper [11] proposes a satellite-based multi-resolution compressive spectrum detection algorithm to help the coexistence of a mobile satellite system and an infrastructure based wireless terrestrial network. Secondary use of satellite spectrum is considered also in [12]. The article investigates power allocation strategy for cognitive radio terminals which are using the spectrum of a primary DVB-SH system. In the proposed strategy it is assumed that the secondary system is able to collect all the relevant propagation information of both secondary and primary systems. In reality, the exact PU system information might not be available.
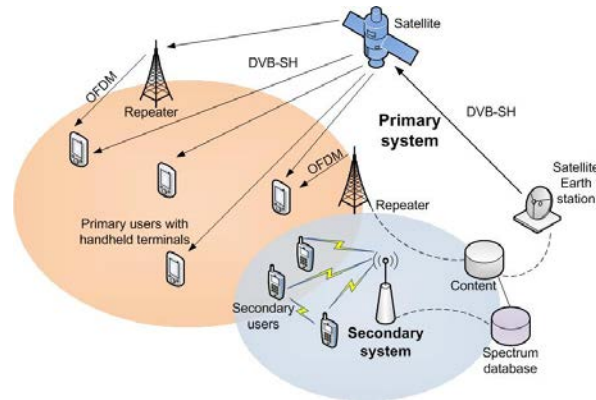
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Figure 1.  A secondary spectrum use scenario with a DVB satellite.

## 3. SYSTEM MODEL

Fig. 1 presents the system model for the studies. A terrestrial secondary system provides data transmission for its users. The secondary network operates in the same frequency band and geographical area with the primary DVB-SH satellite system. The primary system architecture is a hybrid one combining a satellite component and where necessary, terrestrial repeaters to complement reception in areas where the satellite reception is difficult. Repeaters may send information from the local content or from the satellite signal. The system can transmit either an orthogonal frequency division multiplexing (OFDM) or a time-division multiplexing (TDM) signal over the satellite link or an OFDM signal over the terrestrial link. The frequency band is the S band between 2.17 GHz and 2.2 GHz.

The secondary system is using the spectrum resources that are available, without interfering with the primary satellite system that is located in the geosynchronous earth orbit (GEO). The secondary network uses either spectrum sensing or database access to spectrum that it is using at times and locations where the primary user is not present. Fig. 2 describes the spectrum sensing task inside the satellite spot both for the terrestrial signal sent by the DVB-SH repeater and for the satellite signal. Sensing can be performed either via mobile devices or via fixed sensing stations with high-gain antennas.

Energy detection is a simple method that can be used to detect any signals in the band with a fast manner. However, it is not a suitable method for detection in the very low SNR regime. The limitations of the real energy detection equipment have been reported in the literature. For example, in the article [13] the sensing threshold of a commercial energy detection device is 10 dB above the noise floor that is already a rather sensitive threshold. Very low threshold causes significant amount of false alarms, i.e., the sensor claims that there is a user in the band even if there is no user at all. In addition, detection of weak signals requires a longer integration time than the detection of strong signals in the band. However, the sensor cannot detect signals below a fundamental limit called SNR wall, no matter how long it can observe the channel. The SNR wall for energy detection is -3.3 dB when the noise uncertainty is 1 dB [14].
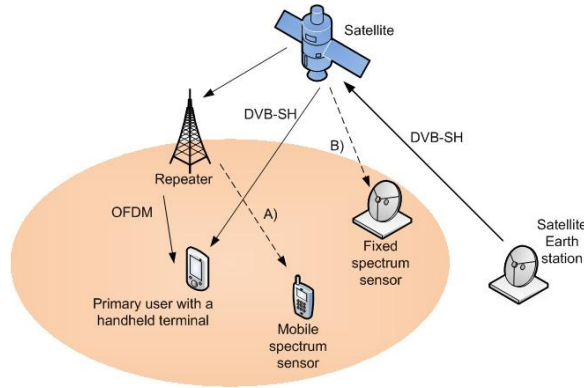
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Figure 2. Spectrum sensing of A) terrestrial signal and B) satellite downlink signal inside the satellite spot.

The performance of sensing can be increased with the knowledge of the primary signal. The feature detection requires partial knowledge of the signal whereas the matched filter detection needs a perfect knowledge on the signal. For example, reliable sensing of the DVB-T signal can be achieved at SNR = -20dB even with a hardware implementation [15]. The matched filter detection can provide even better performance since it is the optimal detection method for a known signal. The feature detection method seems to be very promising for the satellite DVB-SH signal detection as well.

It was shown in [4] that portable sensing devices can be used for downlink sensing only if the sensing method itself is good enough. The feature detection and especially matched filter detection can perform reliably in the satellite downlink signal sensing even with portable devices. Separate sensing stations with high gain antennas are required if energy detection is used for the same purpose. An interesting task then is to define requirements both for the sensing and transmission power of the secondary system when the terrestrial component of the DVB-SH system is considered as well.

## 4. SENSING RANGES OF DIFFERENT METHODS FOR TERRESTRIAL TRANSMISSION

The requirement to detect the terrestrial DVB-SH transmission in decibel domain is

$$P_{dvb} - \alpha_{rs} \geq S_s \qquad (1)$$

where $P_{dvb}$ is the transmission power of the terrestrial repeater, $\alpha_{rs}$ is the attenuation between the repeater and a sensing radio, and $S_s$ is the detection threshold of the CR. If no detection occurs, there is no signal present or it is attenuated so much that it cannot be sensed. From (1) we can define

$$\alpha_{max} = P_{dvb} - S_s \qquad (2)$$

for the maximum path loss. Usual transmission power $P_{dvb}$ for the repeater given in EIRP is 55.1 dBm [16]. Assuming shadowing margins calculated for the 95 % coverage in [16] we can now define the values for the sensing. Link budget for sensing is presented in the Table 1.

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Table 1. Terrestrial link budget with interference margins and spectrum sensing link budget for terrestrial signals.

| Parameters | Unit | Indoor with interference | | Outdoor with interference | |
| | | Urban | Suburban | Urban | Suburban |
|---|---|---|---|---|---|
| Useful bandwidth | MHz | 4.75 | 4.75 | 4.75 | 4.75 |
| Modulation | | QPSK | QPSK | QPSK | QPSK |
| EIRP | dBm | 55.1 | 55.1 | 55.1 | 55.1 |
| Required $C/N$ | dB | 2.8 | 2.8 | 2.8 | 2.8 |
| Rx antenna gain | dB | -3.0 | -3.0 | -3.0 | -3.0 |
| Noise figure | dB | 4.5 | 4.5 | 4.5 | 4.5 |
| Rx noise level | dBm | -102.7 | -102.7 | -102.7 | -102.7 |
| Minimum Rx level at the antenna, $R_s$ | dBm | -96.9 | -96.9 | -96.9 | -96.9 |
| Avg. building penetration loss | dB | 16.0 | 14.0 | 0.0 | 0.0 |
| Shadow fading margin | dB | 11.6 | 11.6 | 8.7 | 8.7 |
| SFN network gain, $G$ | dB | 4.7 | 0.0 | 4.7 | 0.0 |
| Minimum signal level | dBm | -74.0 | -71.3 | -92.9 | -88.2 |
| Maximum path loss, $L_m$ | dB | 129.1 | 126.4 | 148.0 | 143.3 |
| Interference margin | dB | 0.5 or 1.0 | 0.5 or 1.0 | 0.5 or 1.0 | 0.5 or 1.0 |
| Cell range, COST231-HATA model | km | 0.519 | 0.987 | 1.786 | 2.978 |
| Cell range, 0.5 dB margin | km | 0.502 | 0.955 | 1.727 | 2.882 |
| Cell range, 1.0 dB margin | km | 0.486 | 0.924 | 1.672 | 2.789 |
| Sensing parameters | | | | | |
| Detection threshold | dBm | $S_s$ | $S_s$ | $S_s$ | $S_s$ |
| Combined losses $L_c$ | dB | 27.6 | 25.6 | 8.7 | 8.7 |
| Maximum path loss, $L_m$ | dB | $55.1-27.6+G-S_s$ | $55.1-25.6+G-S_s$ | $55.1-8.7+G-S_s$ | $55.1-8.7+G-S_s$ |

5

The Cost231-HATA model that was also adopted in [16] has been used in calculations. The standard median path loss $L$ in urban areas is given by [17]

$$L_{50} \ (urban) = 46.3 + 33.9 \log f\ \text{-}13.82 \log h_B - a(h_R) + (44.9 - 6.55 \log h_B)\log d + C, \quad (3)$$

where $f$ is the frequency (in MHz), $h_B$ is the effective transmitter (base station) antenna height (in meters) ranging from 30 m to 200 m, $h_R$ is the effective receiver (mobile) antenna height (in meters) ranging from 1 m to 10 m, $d$ is the distance between the transmitter and the receiver (in km), and $a(h_R)$ is the correction factor (in dB) for an effective mobile antenna height which is a function of the size of the coverage area. The correction factor for a small to medium sized city is

$$a(h_R) = (1.1 \log f\ \text{-}0.7) \ h_R - (1.56 \log f - 0.8) \quad (4)$$

and for a large city, it is given as

$$a(h_R) = 8.29(\log 1.54 \ h_R)^2 - 1.1 \ \text{for} \ f \leq 300 \ \text{MHz} \quad (5a)$$
$$a(h_R) = 3.2(\log 11.75 \ h_R)^2 - 4.97 \ \text{for f} \geq 300 \ \text{MHz}. \quad (5b)$$

To obtain the path loss in a suburban area, the equation (3) is modified as

$$L_s = L_{50}(urban) - 2[\log (f / 28)]^2 - 5.4. \quad (6)$$

The factor $C = 0$ dB for a medium sized city and suburban areas and $C = 3$ dB for metropolitan areas. The building penetration loss and a larger shadowing margin are applied in the indoor environment scenarios.

The maximum median path loss $L_m$ for the signal to be detected in the urban environment, defining the attenuation to be used in the sensing range calculations is

$$L_m = \alpha_{max} - L_c + G \quad (7)$$

where $\alpha_{max}$ is defined in (2) and $L_c$ defines the combined losses in the signal path such as the building penetration loss and the shadowing margin. Parameter $G$ is the network gain that is 4.7 dB in case of a single frequency network (SFN) that is used in the urban area [16]. The same equation can be used in the cell range calculations when a small modification is made. Parameter $S_s$ in (2) needs to be changed to the minimum required power level at the receiving antenna of the primary node, parameter $R_s$, i.e., $\alpha_{max} = P_{dvb} - R_s$.

Fig. 3 shows the sensing results for the urban indoor scenario. Sensing thresholds exactly at the noise floor and -20 dB below the noise floor are set as examples in the figure. It can be seen that the energy detector able to operate exactly at the noise floor level would provide roughly 750 m sensing range. If the sensor can detect signals 20 dB below the noise floor, the sensing range is increased by 2 km. The lower threshold allows a better operational environment for the secondary system that starts to use the band when the DVB signal is not present at that location. Higher transmission powers can be used without interfering with the DVB-SH receivers.
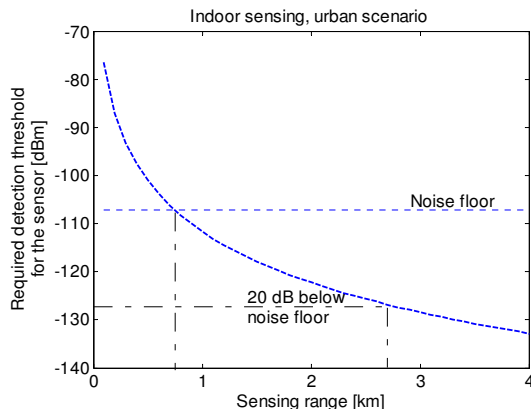
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Figure 3. Spectrum sensing of terrestrial DVB-SH transmission in urban environment, sensor located indoor.

## 5. TRANSMISSION POWER LIMITS

The interference caused by simultaneous transmission at the same band causes interference if the coexisting system is located too close. The interference management in the spatial domain in sensing-based system [18] is shown in Fig. 4. The red circle with a red receiver represents the primary DVB-SH system whereas the secondary system is shown with the blue colour. Communication ranges of the primary and secondary systems are marked with $r_t$ and $r_d$, respectively. Inside the communication range, the signal-to-noise ratio (SNR) is large enough to decode transmitted data. Transmission power of the transmitter, together with the channel, defines both the communication range and the interference range of the system. When the secondary transmitter is sending data, it is interfering with the victim receivers up to the interference range of $r_i > r_d$. The interference range of the primary system is $r_w$.

A cognitive radio can only detect the local situation around it. The sensing range of the secondary system, i.e., the maximum range to detect the primary transmission is $r_s$ and is defined using (2) and (3). The range should be $r_s \geq r_i + r_t$ to protect the PU from interference.

The Table I includes also estimates on the cell sizes for the different interference margins. The interference range of the secondary transmission system can be calculated using the 1 dB or 0.5 dB coexistence criterion, i.e., signal power received at the DVB-SH receiver by secondary transmission $P_{sp}$ should be 6 dB below the noise floor to decrease $C/N$ by 1 dB or 9 dB below the noise floor to decrease $C/N$ only by 0.5 dB. Now,

$$P_{sp} \leq N + N_F - X \text{ dB}, \tag{8}$$

where $N$ is the noise floor and $N_F$ is the noise figure of the primary receiver, and $X$ is either 6 dB or 9 dB. Because the CR system does not receive any information from other systems we assume the worst case scenario to guarantee interference-free communication for the primary system. Thus, there is only path loss between the secondary transmitter and the primary receiver but fading between the primary transmitter and the secondary receiver as well as in the secondary link. Inequality (8) can be written as

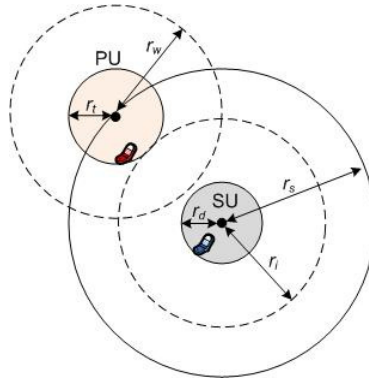$$P_{sp} = P_{su} - \alpha_{rs} \leq N + N_F - X \text{ dB}. \tag{9}$$

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Figure 4.  Interference, sensing, and communication ranges in a primary-secondary scenario.

We can now define the limit for the secondary transmission power as

$$P_{su} \le L_{50}(r_s - d_c) + N + N_F - X \text{ dB}, \tag{10}$$

where $r_s$ is the sensing range of sensor, $d_c$ is the cell range of the terrestrial DVB-SH repeater and the path loss $L$ is calculated using (3).

In order to allow 0.5 dB or 1 dB degradation to the SNR level, new cell ranges need to be calculated for the primary system. This means that in the edge of the cell, we allow either 0.5 dB or 1 dB attenuation to the signal due to interference. Calculations can be done with the modified version of (7) as discussed in the section below the equation. Now we will increase the minimum required power level at the receiving antenna by 0.5 dB or 1.0 dB for calculations. The estimated cell ranges are shown in the Table I. The results show that the reduction in the cell size is in the order of 3 % with the 0.5 dB margin and 6 % with the 1 dB margin.

Estimations for the transmission power limits for the secondary user are shown in Figs. 5–8. Typical transmission power levels of a WLAN access point (20 dBm) and the LTE base station (43-48 dBm) are marked in the figures as reference points. The results are calculated for a single transmitter in several different scenarios. Indoor and outdoor scenarios in urban and suburban environments are considered.

In Fig.5 the sensor is located indoor in the urban environment. The sensing threshold should be clearly below the noise level to allow even a WiFi type transmission on the same frequency band. The result means that energy detection cannot be used here but more powerful methods such as the matched filter detection are needed. The situation changes clearly when the suburban environment is considered as can be seen in Fig. 6. Now the sensor able to detect signals a few dB above the noise floor is enough for WLAN type transmission. Even LTE powers could be possible in the suburban indoor scenario with a sensor that can operate reliably more than 10 dB below the noise level. It should be remembered that the reported thresholds for implemented energy detectors are e.g., 10 dB above noise floor. Thus, these devices would not allow even short-range transmission in the studied scenario.
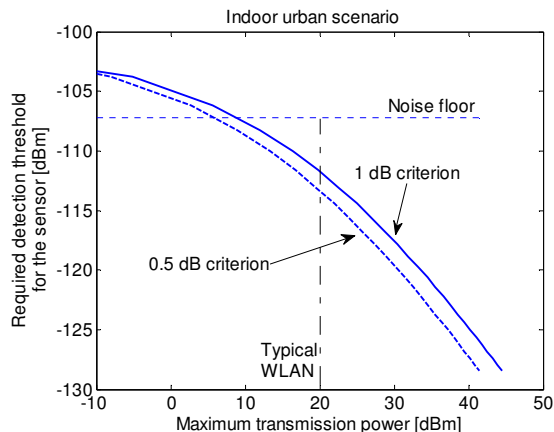
8

Figure 5.  Maximum transmission power of a secondary user in urban environment, sensor located indoor.
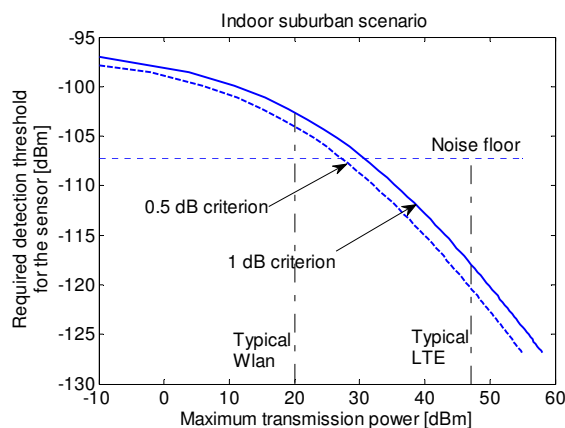


Figure 6.  Maximum transmission power of secondary user in suburban environment, sensor located indoor.

Fig. 7 and Fig. 8 show results for outdoor scenarios that are much easier for the spectrum sensing. In the suburban environment even the energy detectors with a sensing threshold 10 dB above the noise floor would allow WLAN type secondary transmission in the spectrum. In the urban environment the sensor has to be able to detect signals reliably 10 dB below the noise floor to make LTE type transmission possible. In the suburban case the threshold needs to be only slightly below the noise level.

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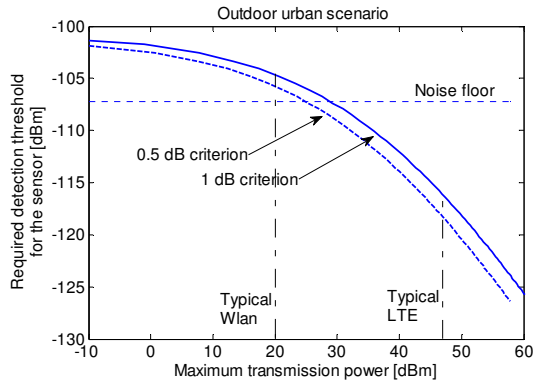
Figure 7.  Maximum transmission power of secondary user in urban environment, sensor located outdoor.

The most difficult environment is the urban case where the sensor is located indoor. The sensing threshold should be clearly below the noise level to allow even WiFi type transmission on the same frequency band. The only scenario where the conventional energy detector could support even the short range transmission is the suburban outdoor scenario. In other cases, more powerful sensing methods are needed. The difference between the transmission power limits is 3 dB with the same detection threshold for the two considered coexistence criteria (0.5 dB and 1.0 dB).
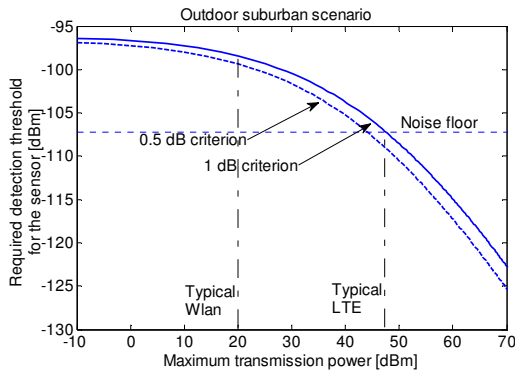


Figure 8.  Maximum transmission power of secondary user in suburban environment, sensor located outdoor.

The shown figures are restricted to a single secondary user case. Already these results show well that spectrum sensing should be used with caution for the spectrum access in the studied satellite band. In a more realistic situation, aggregate interference of several secondary users should be taken into account as well. A very rough estimate for the interference addition is to use constructive interference principle, i.e., assuming same parameters for all secondary transmitters and adding the interference powers together. The interference power is then increased by $10\log(N)$ dB where $N$ is the number of interferers. This means the correspondent reduction in the allowed transmission power for the secondary users.

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However, this is not a very realistic model. More accurate would be to use statistical models such as the Poisson-point process used in [19] for the secondary node placement and include the probability to sense the PU signal at certain location in the analysis. Cooperative sensing brings additional gain to the sensing, affecting also the aggregate interference value. Based on this discussion, we might assume that reduction of some decibels in the transmission power might be enough to handle the aggregate interference issue. This is a good topic for further studies.

## 6. DATABASE APPROACH

Other approaches for spectrum sharing need to be considered since spectrum sensing, especially if energy detection is used, cannot support well secondary operation. The database method is a promising approach for spectrum sharing between the hybrid DVB-SH system and a terrestrial secondary system. Frequencies used by the licensed system as well as unused frequencies can be seen from the database. Spectrum databases are currently heavily supported in many terrestrial scenarios, including TV white space operation [20].
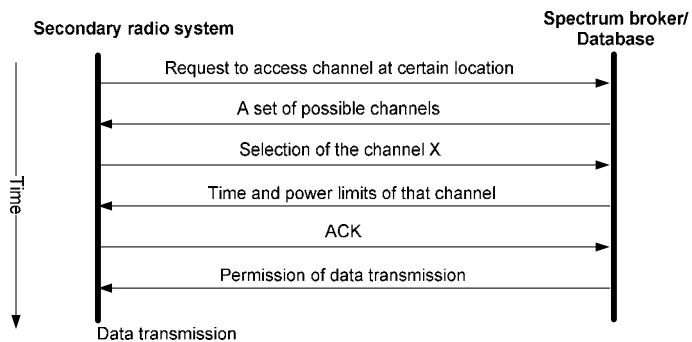


Figure 9. Spectrum access with a database.

When the secondary system needs to transmit, it requires spectrum from the spectrum broker that is governing the database, and available band is given for it. Other secondary users in the area can then see that this particular band is occupied. Thus, the method can be used to spectrum sharing among secondary systems as well. The proposed method for the spectrum access using a database is shown in Fig. 9. First the secondary system sends the request to access the spectrum to the spectrum broker governing the spectrum use in that area. The location information of the requesting device is attached. The spectrum broker sends back a set of possible channels that could be used in the secondary transmission. This set is idle at the request time.

Then, the secondary device selects a channel $X$ to be used in the transmission and informs the broker about the choice. This band is reserved to the secondary system in the database so that it will not be offered to other requesting secondary users. The broker sends information about the time and power limits of the channel. The secondary system acknowledges it has received the restrictions regarding the channel use. Finally, it receives permission to use that channel and starts data transmission.

Interference management and avoidance are easier with databases than with the spectrum sensing. However, the database method is not as dynamic and fast as sensing and this can restrict the way to operate. In addition, the use of this approach requires an extra infrastructure for the operation. Unlike spectrum sensing, it cannot be used straight away with the existing

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satellite systems. When the database operation is considered, the satellite system needs to play its part in sharing, i.e., provide the needed information for the operation.

A clearly advantageous feature of this type of spectrum sharing is the possibility to keep the situation in control. When the sharing of spectrum between the terrestrial and the satellite system is controlled, the systems can experience the predictable quality of service (QoS). The passive spectrum awareness helps the secondary system to avoid chaotic situations since the passively received spectrum use pattern shows the spectrum opportunities in advance. Instead on reactive operation, it helps the secondary user to be proactive.

In addition, leasing the spectrum enables the primary user to get financial advantage of the secondary operation at the same frequencies. Actually, guaranteed QoS requirements can be met for both primary and secondary users only if primary users promise not to interfere. This is most likely only true for a fee. All these features strongly support the use of database/broker based access to the spectrum.

The following requirements and open issues can be seen in this operation. 1) *Location awareness*. The secondary nodes need to have location information available. Otherwise they are not allowed to use the spectrum database for accessing the S band. 2) *Satellite system/operator provides information to spectrum broker*. Without the knowledge on the current spectrum use the broker cannot allocate resources to the users requesting it. 3) *Analysis and experiments are needed to provide time and power limits for secondary operation.* What are the acceptable transmission powers and continuous tranmission times when the database access is used? How much mobility affects to these in satellite bands? How often the secondary user needs to connect to the database to update the information?

## 7. CONCLUSIONS

We have investigated the secondary use of the spectrum in a satellite band below 3 GHz. Primary system is a DVB-SH hybrid network that is operating in the S band between 2170 MHz and 2200 MHz. Both a sensing based access method and a database based access method were described. We have calculated link budgets for the system in several different indoor and outdoor scenarios. Requirements for the spectrum sensing and transmission power control for the secondary system in these scenarios have been provided. Following conclusions can be drawn.

1) With sensing, short range communication is preferred, especially in the urban scenario.

   a. The sensing threshold and the environment where the secondary system is operating have significant effects to the allowed transmission power level.

   b. Energy detection with the same kind of devices that are used nowadays cannot be used at all in many scenarios even when low power short range secondary operation is considered.

   c. Matched filter detection and the feature detection are needed especially when the secondary transmitters are using higher transmission powers.

   d. Only a single secondary transmitter was considered. If the aggregate effect of several transmitters is considered, even better performing sensors are needed to fulfil the secondary power requirements. The effects might be different in each of the studied scenario.

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2) Based on the analysis and the related uncertainties, database information/passive spectrum awareness should be prioritized when possible.

   a. Use of these can guarantee the QoS of both the secondary and the primary systems.

   b. In addition, business models for this are easier to develop.

Several issues need to be still considered before the use of cognitive radios can be allowed in the satellite bands. Possible topics for future studies include: A) What bands are most promising for spectrum sharing? B) How the selection of terrestrial channel model affects the performance? C) How reliably the sensor needs to be able to detect transmission? We used 95 % value for the sensing analysis but higher values might be needed in practice. D) Open issues for the database approach described in Section V need to be investigated.

## ACKNOWLEDGEMENTS

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**Author**

**Marko Höyhtyä** obtained his M.Sc. degree in Information Engineering in 2005 from the University of Oulu. From the beginning of 2005 he has been at VTT Technical Research Centre of Finland where he has been working with power control, beam forming, and cognitive radio technologies. He is currently working towards the Ph.D. degree. In 2007–2008 he made one year research visit to the Berkeley Wireless Research Center, CA. His research interests include adaptive algorithms, transmitter power control, and spectrally efficient communication.

# Adaptive inverse power control using the modified filtered-x least mean square algorithm

# Adaptive Inverse Power Control Using the Modified Filtered-x Least Mean Square Algorithm

Marko Höyhtyä, *Member, IEEE* and Aarne Mämmelä, *Senior Member, IEEE*

*Abstract*— **In this paper, a modified filtered-x least mean square (MFxLMS) algorithm for closed loop power control is proposed and analyzed. A practical version of the algorithm is also developed. The FxLMS algorithm is widely used for inverse control such as noise cancellation. This is the first paper to apply the algorithm for power control. We have modified the conventional FxLMS algorithm by adding absolute value blocks since power control does not need phase information. The modification makes the algorithm more robust and requires fewer bits to be transmitted in the feedback link. The proposed algorithm can be seen as generalized inverse control to be used in power control research. It gives a unified framework for several existing algorithms, linking them to the LMS literature. Numerical results are provided, comparing the performance of the proposed algorithm to existing practical algorithms used e.g., in wideband code division multiple access (W-CDMA) systems.**

*Index Terms*—**Power control, feedback control systems, adaptive signal processing**

## I. Introduction

INVERSE control has been used for several applications such as channel equalization [1], [2], automatic gain control (AGC) [3], noise and interference cancellation [4], and transmission power control [5], which is the topic of this paper. Due to stability problems the least-mean square (LMS) algorithm is not directly suitable for active control applications where the adaptive filter works as a controller for a time-variant system. Instead, the FxLMS algorithm is a good choice for that kind of applications [4]. It is essentially the LMS algorithm with a few little changes so that algorithm can remain stable. The FxLMS algorithm is developed from the LMS algorithm by inserting the model of the controlled system between the input data signal and the adaptive algorithm that updates the coefficients of adaptive filter. The algorithm was introduced independently in [6], [7], and [8] for adaptive control and noise cancellation. We propose and demonstrate a new use of the FxLMS algorithm in this article, namely power control.

We described the FxLMS method initially for power control in [9] and compared it by numerical simulations to other practical algorithms in [9] and [10]. We developed also a truncated version of the algorithm in [11] to improve energy efficiency. Truncation means that the transmission is interrupted and transmission power is zero when the magnitude of the channel gain deteriorates under a certain cutoff value. Since transmission power control is a new application for the algorithm, new phenomena occur and modifications are needed. Fading in the wireless channel has a wide dynamic range and changes are fast compared to conventional control systems. In addition, wireless feedback channel limits the number of bits used in control commands [12].

In this paper, we show with analysis that the proposed algorithm converges exactly to the wanted solution in a noiseless channel. We restrict our investigation purely to the closed loop part, focusing on the algorithm and thus assuming ideal feedback [12]. Simulations show that the algorithm converges well also in a noisy channel. We create a unified framework for inverse power control for cellular systems. The proposed algorithm links the existing algorithms to LMS type of adaptive algorithms. The MFxLMS algorithm can be seen as a generalized adaptive inverse control method and several practical algorithms as special cases of it. In addition to theoretical analysis, we develop a practical quantized version of the algorithm and compare its performance to state-of-the-art algorithms. The proposed algorithm provides a fast adapting inverse power control solution that does not overshoot the power level as much after a fade as the conventional solution in [13]. Thus, it decreases interference to other users in these cases. We also propose an efficient way to implement the closed loop algorithm described in [14] as an enhanced version of the algorithm presented in [13].

Furthermore, we present novel fast simulation models for a fading channel and diversity. It was reported in [15] that Jakes' model [16] does not produce wide-sense stationary signals. The authors of [15] proposed to improve the model by randomizing the phase shifts of the low-frequency oscillators. We have modified Jakes' model further by randomizing also the frequency shifts in the model. Several simulation studies are performed with the practical power control algorithms both in additive white Gaussian noise (AWGN) and fading channels.

The organization of the paper is as follows. Section II discusses related literature and Section III presents the system model. Performance metrics are introduced in Section IV. The MFxLMS algorithm with the convergence analysis is presented with other adaptive inverse power control schemes in Section V. Achieved results are provided in Section VI and conclusions with recommendations for further work are drawn in Section VII.

## II. RELATED LITERATURE

Power control methods can in general be divided into water filling and channel inversion [5]. Basically the difference between these two approaches is that the water filling allocates more power to the better channel instants whereas channel inversion aims at inverting the channel power gain while maintaining the desired signal strength at the receiver.

Several adaptive inverse control methods have been proposed in the literature for power control, e.g., [13], [14], [17]–[20]. The conventional 1-bit adaptive power control (CAPC-1) method [13], [17] employs delta modulation, i.e., adjusts the previous transmission power up or down by a fixed step. In this paper, the acronym CAPC-*x* refers to conventional power control using *x* bits in the power control command. Conventional inverse power control approaches have been proposed and used e.g., for CDMA, 3GPP Long Term Evolution (LTE), and TV white space transmission. A clear aim of these approaches is energy and interference reduction; to use only sufficient power to meet the transmission rate requirements. For example, CDMA power control employs both closed and open loop methods. In the open loop method, the mobile station measures the average received total power by an AGC circuit and adjusts its transmission power so that it is inversely proportional to the received power [21]. Nonlinear control is used to allow fast response to the reduced channel attenuation with a maximum of 10 dB/ms but slow response to increased attenuation. This is to avoid additional interference to other users.

Required dynamic range with a limited feedback can be achieved by nonlinear quantization of feedback signalling [22] and variable step (VS) algorithms [23]–[25]. Nonlinear AGC control can be exponential or approximately exponential [3]. A simple way to compress power control commands is to operate the algorithm in decibel domain [18]. Logarithmic quantization such as *μ*-law and *A*-law companding are used in speech codecs [22]. Companding amplifies weak input signals and compresses strong signals to save the needed number of bits to be transmitted. Companding is applied also for reducing peak-to-average power ratio (PAPR) in orthogonal frequency division multiplexing (OFDM) signals [26].

Many variable step size LMS algorithms have been proposed in order to improve the performance of the LMS algorithm by using large step sizes in the early stages of the adaptive process, and small step sizes when the system approaches convergence [23]–[25]. The step size can be adapted e.g., based on the received signal power [9] or the squared error signal [17]–[18]. Optimization of the step size has been studied in [27], where lag error of an adaptive system is also considered. This error is caused by the attempt of an adaptive system to track variations of the nonstationary input signal.

## III. SYSTEM MODEL

The system model for adaptive transmission is illustrated in Fig. 1. The input data $x_k$ are binary phase shift keying (BPSK) modulated and transmitted from the transmitter to the receiver
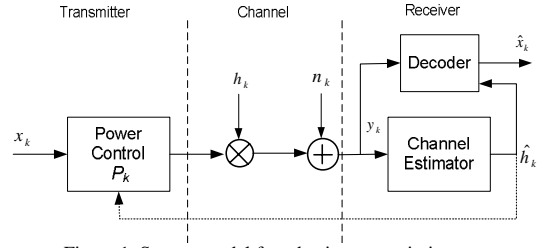


Figure 1. System model for adaptive transmission.

over a fading channel. The received signal $y_k$ can be given as

$$y_k = x_k P_k h_k + n_k. \qquad (1)$$

The complex gain of the channel is $h_k = \alpha_k e^{j\theta_k}$ and $n_k$ is additive white Gaussian noise at time $k$. The amplitude of the fading gain is $\alpha_k$ and $\theta_k$ is the phase shift. The data are transmitted through the channel and the instantaneous transmit power $P_k$ is allocated based on the channel gain estimate $\hat{h}_k$ sent by the receiver. LMS estimation of the channel gain is done as

$$\hat{h}_{k+1} = \hat{h}_k + \vartheta e_k x_k \qquad (2)$$

where $\vartheta$ is the step size of the algorithm and $e_k$ is the estimation error [1]. A typical value for the step size $\vartheta$ is $0 – 0.99$. Larger values lead to faster convergence with the cost of reduced accuracy since noise averaging does not work so well [28].

We consider a slowly varying channel that can be modelled using the Doppler power spectrum [15], [16]. The rate of the channel variation, i.e., the effect of mobility, can be characterized by the Doppler frequency $f_d$. We are using a flat Doppler power spectrum that corresponds to an urban environment where the transmitter is set above rooftop level [29].

### A. Sum-of-sinusoids fading channel

To obtain a flat Doppler power spectrum, the time-variant channel gain of a channel with index $l$ is represented by the sum of complex exponentials as

$$h_l(k) = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} e^{j(2\pi f_{i,l}k + \phi_{i,l})} \qquad (3)$$

where $N$ is the number of subpaths with the same delay, $f_{i,l}$ is the Doppler shift of the $i$th subpath, $\phi_{i,l}$ is the random phase shift of the $i$th subpath uniformly distributed in the range [0, $2\pi$[ and $k$ is time. The amplitudes of the subpaths in (3) are identical due to the flat spectrum. The average energy gain of the channel is normalized to unity [30]. The model is straightforward to generalize to multiple delays.

If the Doppler shifts of the complex exponentials are equally spaced in the interval [-$f_d$, $f_d$], the channel gain (3) becomes periodic in time. Sampling in time domain corresponds to periodicity in frequency domain and vice versa

[31]. Periodicity can be removed if the shifts are properly chosen. The Doppler spread is divided into $N$ equal size frequency bins. Within these bins the frequencies $f_{i,l}$ differ a random uniformly distributed amount from the equal space solution. Thus, we obtain the whole Doppler spread to use in every simulation. The power spectrum is made symmetric with respect to zero frequency, which makes the autocorrelation function of the channel real. This selection also makes simulations faster. The random phases $\phi_{i,l}$ are not symmetric with respect to the zero frequency.

### B. Diversity channel

A time-variant frequency selective channel model can be represented with a tapped delay line as

$$\beta(l,k) = \frac{1}{L}\sum_{l=1}^{L} h_l(k)\delta(\tau - \tau_l) \qquad (4)$$

where $L$ is the number of tap weights and $\tau_l$ is the delay of $l$th tap generated using (3). Now we have a flat impulse response instead of usual exponentially decreasing model. However, from power control point of view this does not affect since the optimal demodulator for this signal is a coherent demodulator that collects the signal energy from all the received signal paths within the delay span 0 to $\tau_L$ [2]. In a diversity system, the transmitter power control algorithm should control the power of the diversity combiner output in the receiver. There is no loss in performance in dividing the total transmitted signal energy differently among the $L$ channels and thus the model does not change the comparison between the selected power control algorithms. Actually the time-variant channel gain of the diversity channel can be given as

$$H(k) = \sqrt{\frac{1}{L}\sum_{l=1}^{L}|h_l(k)|^2} \qquad (5)$$

where $h_l(k)$ is the channel gain of the $l$th diversity branch, generated using (3), and $L$ is the number of diversity branches. Equation (5) corresponds to the ideal maximal-ratio combining. The channel can thus represent also a frequency selective channel. From the subcarrier point of view, frequency selective channel looks frequency nonselective in an OFDM system [2]. We assume that no intersymbol interference (ISI) or interpulse interference (IPI) is present since we use compressed pulses [2].

### IV. PERFORMANCE METRICS

Suitable performance metrics are needed to fairly compare the performance of the adaptive algorithms. One of the most important ones to consider is the signal-to-noise ratio (SNR) concept. The average transmitted and the average received energies are usually normalized by the receiver noise spectral density $N_0$ leading to the average transmitted SNR per symbol [30]

$$\bar{\gamma}_{\text{tx}} = \bar{E}_{\text{tx}}/N_0 \qquad (6)$$

and the average received SNR per symbol [30]

$$\bar{\gamma}_{\text{rx}} = \bar{E}_{\text{rx}}/N_0. \qquad (7)$$

The parameter $\bar{E}_{\text{tx}}$ is the average transmitted energy per symbol and $\bar{E}_{\text{rx}}$ is the average received energy per symbol. Transmitted energy is a basic system resource. In a mobile system it is taken from the battery of the transmitter and is therefore limited. Transmitted energy or equivalently transmitted SNR should be used as a performance metric in order to obtain fair comparisons between different adaptive transmission systems. In adaptive transmission the average energy gain of the channel is a function of the transmitted signal due to correlation between the instantaneous transmission power and the instantaneous energy gain of the channel. The use of the received SNR as a performance criterion in adaptive transmission system studies can lead to misleading results as was shown in [30].

Learning curve, i.e., plotting the mean square error (MSE) against the number of iterations, can be used to measure the statistical performance of adaptive algorithms [1], [2]. The MSE $J(k)$ can be approximated as

$$J(k) = \frac{1}{\eta}\sum_{i=0}^{\eta-1}|\varepsilon_{k-i}|^2 \qquad (8)$$

where $\varepsilon_k$ is the error signal measured as a difference between the output of the adaptive algorithm and the desired signal. Parameter $\eta$ defines the number of samples used for averaging. Usually MSE is compared to signal power, in this case transmission power.

### V. ADAPTIVE POWER CONTROL METHODS

### A. Theoretical inverse control methods

If the truncated channel inversion is used, the transmitted energy is [32]

$$E_{\text{tx}}(k) = \bar{E}_{\text{tx}}(\sigma_0/\gamma_{\text{H}}(k)) \qquad (9)$$

for $\gamma_{\text{H}}(k) \geq \gamma_0$ and zero otherwise where $\sigma_0$ is a constant selected so that the average transmitted energy is $\bar{E}_{\text{tx}}$. The quality of the channel is defined as $\gamma_{\text{H}}(k) = \bar{E}_{\text{tx}}|H(k)|^2/N_0$, $\gamma_0$ is a cut-off value, which is found by numerically maximizing (4.22) in [32], and $|H(k)|^2$ is the instantaneous energy gain of the channel. The cut-off value is $\gamma_0 = 0$ for full channel inversion. Channel inversion aims at maintaining the desired signal strength at the receiver by inverting the channel power gain based on the channel estimates.

### B. Adaptive FxLMS algorithm

The power control structure based on the MFxLMS algorithm is introduced in Fig. 2. It approximates the channel inversion. In the following, we will present both original and modified versions of the algorithm.
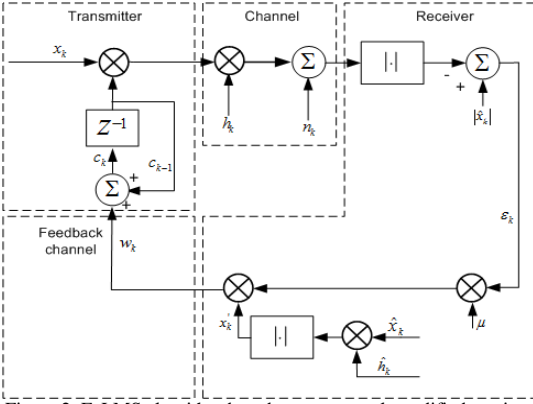
Figure 2. FxLMS algorithm based power control, modified version.

The FxLMS algorithm updates the coefficient $c_k$ of a one-tap filter as

$$c_k = c_{k-1} + w_k \qquad (10)$$

where $w_k = \mu x'_k \varepsilon_k$ is the correction term, $\mu$ is the adaptation step size of the algorithm that regulates the speed and stability of adaptation, and $\varepsilon_k$ is the error signal to be minimized. The filtered input signal for the FxLMS algorithm is $x'_k = (\hat{x}_k \hat{h}_k)^*$, where $x^*$ is the complex conjugate version of $x$, $\hat{x}_k$ is the estimated input signal, and $\hat{h}_k$ is the estimated instantaneous channel gain. The filtered input signal is $x'_k = |\hat{x}_k \hat{h}_k|$ for the MFxLMS algorithm and the parameter $n_k$ is additive white Gaussian noise. The channel can be modelled using (3) – (5).

We have modified the conventional FxLMS structure by adding the absolute value blocks to the algorithm and having a wireless channel as a system to be controlled and inverted. In addition, a large difference in our system to conventional control systems comes with a separate receiver and transmitter. The main reason for the addition of absolute value blocks is that we are adjusting power levels and thus interested only in amplitude values, similarly to AGC circuits [3]. Phases are not important from the power control point of view, and in this way we can reduce control information to be carried. This also makes the system more robust since phases can change fast during deep fades and thus cause problems to the adaptive algorithm [33].

The model is discretized using a matched filter [2], assuming slow changes compared to the symbol rate. Thus we can use one sample of a symbol in the system model. When we are using the MFxLMS algorithm for power control, we can reduce the complexity of the transmitter by doing the main part of the calculations at the receiver. This reduces also information in the feedback channel since only the correction term $w_k$ is sent to the transmitter. The filtered input signal $x'_k$ affects the operation of the algorithm. Thus, the control structure is decision directed (DD) [2]. Error propagation is known in DD approaches and remedy strategies have been

developed [34], [35]. It was proposed in [35] that pilot on request training (PRQT) is used to mitigate the error propagation. The pilot is requested when error propagation is detected in the system. We assume our system to operate with the PRQT principle. When the error probability is very small, we can assume $\hat{x}_k$ to be $x_k$.

### 1) Convergence analysis for the MFxLMS power control algorithm:

The choice of initial conditions for the FxLMS algorithm is not critical [4]. The algorithm is stable if $\mu$ is small enough, and transients die out just as with the conventional LMS algorithm. A primary concern with the MFxLMS algorithm is its convergence to the optimal solution where $E[\varepsilon_k^2]$ is minimized. Since absolute value blocks make the analysis of the algorithm very complicated in a noisy channel, we will first analyse the conventional FxLMS algorithm that can also be used in power control. A general analysis for the FxLMS algorithm can be found in [37].

#### a)     Coherent case

Let us assume a time-invariant channel with perfect channel estimation, i.e., $\hat{h}_k = h$. The error signal is now

$$\varepsilon_k = x_k - (hc_{k-1}x_k + n_k), \qquad (11)$$

leading to

$$E[c_k] = (1 - \mu|h|^2 R)E[c_{k-1}] + \mu h^* R \qquad (12)$$

where $R = E[|x_k|^2]$. The white noise $n_k$ is assumed to be uncorrelated with the input $x_k$. In addition, we assume that the input $x_k$ is independent of the weight $c_k$ as in the analysis of the LMS algorithm in [4]. The first part of the function in the right-hand side will clearly form a geometric series that will converge only if the geometric ratio has a magnitude of less than unity,

$$|1 - \mu|h|^2 R| < 1. \qquad (13)$$

Therefore, we can define

$$c_\infty = \lim_{k \to \infty}(1 - \mu|h|^2 R)^k c_0 + \frac{\mu R h^*}{1 - (1 - \mu|h|^2 R)} = \frac{h^*}{|h|^2} = \frac{h^*}{hh^*} = \frac{1}{h}. \qquad (14)$$

Since the first part of the sum in (14) will approach zero, the algorithm converges exactly to the inverse of the channel gain. We can see from (14) that in order to keep the algorithm stable, the step size for updating the algorithm coefficients should be

$$0 < \mu < \frac{2}{R|h|^2}. \qquad (15)$$

The optimal step size for the FxLMS algorithm lies in the middle of stability interval [36], [37]. The convergence will be

fastest with this selection. Thus, the optimal step size is now

$$\mu_{\text{opt}} = \frac{1}{R|h|^2}. \qquad (16)$$

With this selection the fixed step FxLMS algorithm is changed to the normalized version of it.

*b)      Non-coherent case*

From the power control point of view we would only need the inverse of the absolute value of the channel gain instead of the result of (14) since we are interested in inverting the power level to maintain the received signal power at a constant level. Thus, let us now consider the MFxLMS algorithm with absolute value blocks in a time-invariant, noiseless channel, assuming perfect channel estimation, i.e., $\hat{h}_k = h$. The error signal is given as

$$\varepsilon_k = |x_k| - |hc_{k-1}x_k|. \qquad (17)$$

Thus, (10) becomes

$$c_k = c_{k-1} + \mu|h|^2|x_k|^2 - \mu|c_{k-1}||x_k|^2|h|. \quad (18)$$

In general we should consider two separate cases: $c_k > 0$ and $c_k < 0$. However, there is no need to use negative values in power control since the solution we want to achieve is to maintain certain SNR at the receiver. The case $c_k < 0$ leads to the converged solution that is a negative version of the solution for the case of $c_k > 0$. When $c_k > 0$, $|c_k| = c_k$. Now,

$$c_k = (1 - \mu|x_k|^2|h|^2)c_{k-1} + \mu|x_k|^2|h|. \quad (19)$$

Convergence conditions for the MFxLMS algorithm can be found from this version quite straightforwardly, leading to the same solution as is shown in (13). Therefore, we can write

$$c_\infty = \frac{1}{|h|}, \quad c_k > 0. \qquad (20)$$

The algorithm converges exactly to the inverse of the absolute value of the channel gain. We can see from the results above that in order to keep the algorithm stable, the step size for updating the algorithm coefficients should be exactly in the same interval as the one shown in (15). Thus, the optimal step size for the MFxLMS algorithm in a noiseless channel is given in (16).

Convergence of the MFxLMS algorithm when noise is present in the system becomes mathematically intractable due to the absolute value blocks. Now, (10) can be rewritten as

$$c_k = c_{k-1} + \mu|h||x_k|^2 - \mu|hx_k||hx_kc_{k-1} + n_k|. \quad (21)$$

The algorithm cannot be analysed straightforwardly due to absolute value of the term that includes noise. Simulations are also used instead of analysis in reference state-of-the art algorithm developments due to mathematical intractability

[13], [14], [17] – [19]. Based on simulations the MFxLMS algorithm behaves and converges almost identically with the algorithm without absolute blocks in a fading channel when the transmitted SNR is high enough. Actually, the MFxLMS algorithm is more robust since fast phase changes do not affect its performance. Nonlinearity causes threshold phenomenon for the modified algorithm in low SNR regime that is always a problem in noncoherent systems using some combining or averaging.

*2) Time-variant channel:*
Usually the adaptation step size of the FxLMS algorithm is not time-variant. The algorithm with a fixed adaptation step size corresponds to a first-order system. It cannot track the fastest changes in the time-variant channel without a lag error [27] that can be quite large. A better performance is achieved by optimizing the adaptation step size with the instantaneous power of the input signal. It means that the FxLMS algorithm with a fixed step size is changed to the normalized version of it. The normalized version of the FxLMS algorithm corresponds to the filtered-x recursive-least-squares (FxRLS) algorithm when $\mu = 1 - \lambda$ where $\lambda$ is the forgetting factor which gives exponentially less weight to older samples.

In a slowly fading channel $h_k$ can be assumed to be constant over the memory [4] of the MFxLMS algorithm. Thus the stability condition to the structure when noise is ignored and the channel state is known is the same as presented in (15) when $h$ is replaced by $h_k$. The optimal step size can be found for each different $h_k$ in (16) by replacing $h$ by $h_k$. Therefore the optimal adaptation step size should be time variant. When the channel gain is estimated in (16), the system becomes unstable if this step size is used due to errors in the estimate [38]. To stabilize the control, the step size is given by

$$\mu_{\text{s}} = \frac{a}{R|\hat{h}_k|^2 + b} \qquad (22)$$

where $b$ is a small real number that prevents the adaptation step size to grow uncontrollably when the estimated received power is close to zero. Parameters $a$ and $b$ are dependent e.g., on SNR and $L$ but the values need to be found experimentally to optimize the trade-off between lag error and noise averaging for different channel dynamics. Default values for these parameters can be given as $a = 1/\sqrt{L}$ and $b = 0.2/\bar{\gamma}_{\text{rx}}$ where $\bar{\gamma}_{\text{rx}}$ is the received SNR defined in (7). Smaller $a$ means slower convergence, better noise averaging, and a larger lag error while the parameter $b$ has an opposite effect.

*3) Quantized MFxLMS power control:*
In the following sections, only the MFxLMS algorithm is considered. In practice, the power control command has to be quantized while still obtaining a decent performance. In the case of the MFxLMS algorithm, the signal $w_k$ has to be fed back to the transmitter as shown in Fig. 2. With a limited number of quantization levels, it is good to quantize frequently occurring small values of the signal in more detail and then use coarser steps for the less frequent large signal levels [22].
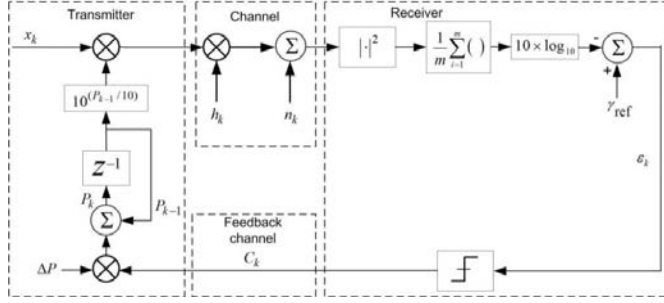
Figure 3. Conventional power control structure.

This preserves needed information to be used when adapting the system. The signal $w_k$ is first compressed, then quantized uniformly, and sent to the channel. The received signal is expanded to get close to the original version of the power control command.

The $\mu$-law compression is defined for real input signal $w_k$ as

$$v_k = F(w_k) = \text{sgn}(w_k) \frac{V \ln(1+\mu_q |w_k|/V)}{\ln(1+\mu_q)}. \quad (23)$$

where $V$ is the peak magnitude of the input signal. This is also peak value of the output. A typical value for the compression parameter $\mu_q$ is between 50 and 300. In our case we have quantized the signal in the range [-1, 1] to be able to effectively combat the deep fades even though the average power of the signal $v_k$ is roughly 0.1. The maximum value is close to unity during the deepest fades. We have not scaled the signal before quantization. If the signal is scaled up, the clipping is increased while the quantization noise is reduced. Scaling down reduces clipping but increases noise. Received quantized signal $q_k$ is expanded using

$$\widehat{w}_k = F^{-1}(q_k) =$$
$$sgn(q_k)\left(\frac{V}{\mu_q}\right)\left(e^{|q_k|\ln(1+\mu_q)/V} - 1\right), \ 0 \leq |q_k| \leq 1. \quad (24)$$

The proposed practical version of our MFxLMS algorithm allows fair comparison with other practical algorithms presented in the literature.

### C. Conventional adaptive power control

Typically the time interval between power control commands in CDMA systems is around 1 ms [13]. The method is shown in Fig. 3. The base station measures the average received power over $m$ symbols and compares it to a reference signal to interference plus noise (SINR) level $\gamma_{\text{ref}}$. As a result of a comparison the base station tells the mobile station to adjust its transmission power upwards when the error signal $\delta_k$ is positive or downwards with negative error by a control step size $\Delta P$. Practical CAPC-1 method [13], [17] uses 1 dB steps. The power control algorithm can be written as

$$P_k = P_{k-1} + C_k \Delta P \ [\text{dB}] \quad (25)$$

where the power control command is

$$C_k = \begin{cases} +1, & \delta_k > 0 \\ -1, & \delta_k \leq 0 \end{cases}. \quad (26)$$

The weakness of this fixed-step power control method is that it is too slow to track changes in a fading channel.

### D. Variable step adjustment power control

Variable step power control methods have been proposed to overcome the weakness of the fixed step solution. The basic idea is that when the power of received signal is far from the desired, the control step is increased to reach the desired level faster. A recently proposed 2-bit version of the CAPC (CAPC-2) method is described in [14] where power control command $C_k$ values are $C_k = \{-4, -1, 1, 4\}$ (dB). In the mentioned document [14] only step sizes are given. No rules how to use them in practice are included. Based on the simulation studies we have conducted the following rule that was found to achieve a good performance:

$$C_k = \begin{cases} 4, & \text{when } \delta_k < -5\kappa \\ 1, & -5\kappa \leq \delta_k < 0 \\ -1, & 0 \leq \delta_k < 5\kappa \\ -4, & \delta_k > 5\kappa \end{cases} \quad (27)$$

where $\kappa = 0.5\Delta P$. An asymmetric 3-bit version of the conventional adaptive power control (CAPC-3) proposed in [18] is

$$C_k = \begin{cases} 3, & \text{when } \delta_k < -5\kappa \\ 2, & -5\kappa \leq \delta_k < -3\kappa \\ 1, & -3\kappa \leq \delta_k < -\kappa \\ 0, & -\kappa \leq \delta_k < \kappa \\ -1, & \kappa \leq \delta_k < 3\kappa \\ -2, & \delta_k \geq 3\kappa \end{cases} \quad (28)$$

Variable step algorithms can be implemented with the structure depicted in Fig. 3. The only difference to the 1-bit CAPC method is in the quantization, i.e., more bits are used for power control commands in CAPC-2 and CAPC-3.
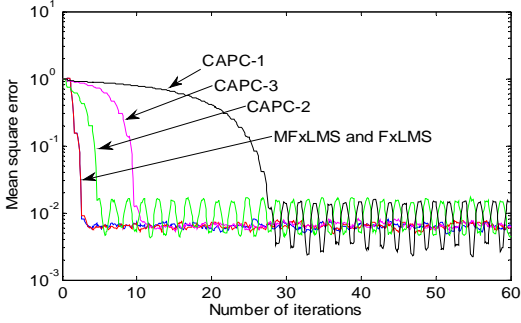
Figure 4. Learning curves for studied algorithms in an AWGN channel.

*E.  Comparison between the FxLMS and conventional algorithms*

The idea to use the FxLMS algorithm started from the observation that analogy can be seen between the control structure in Fig. 3 and the LMS algorithm. Actually the conventional algorithms can be seen as a special case of the FxLMS algorithm. Following modifications are needed from the MFxLMS structure in Fig. 2 to the CAPC structure in Fig. 3: 1) First, the CAPC structure uses square-law detection instead of envelope detection used in the MFxLMS structure. These have shown to provide comparable performance but the former is usually easier to analyse [39] while the latter allows a larger dynamic range [40]. 2) The CAPC method uses averaging to remove noise. The LMS algorithms are in principle based on exponential averaging [1]. An additional averaging block could be used as well, but it does not provide additional performance gain for the algorithm [41]. Instead, it can slow down the adaptation loop due to additional delay and the achieved gain is overridden [42]. It is better to use instantaneous gradient estimates as is used in our power control structure. 3)  Companding, i.e., going first to decibel domain (compressing) and then back to linear domain (expanding) is used in the CAPC algorithm. Compressing is used to cover the large dynamic range in a fading channel. In the practical MFxLMS structure, companding focuses on the task of nonlinear quantization, i.e., to reduce the number of bits in the power control command.  4) 1 bit quantization is used in the CAPC-1 method to simplify feedback signalling. The MFxLMS method is using quantization as in (23)-(24). Power control command needs to be more than 1 bit for variable step power control. That is true also for the variable step algorithms that are based on the structure shown in Fig. 3. 5) The CAPC-1 method uses a fixed scaling factor $\Delta P$ whereas in the MFxLMS method the step size scales based on the channel state. However, the similarities between the investigated practical methods and the LMS method are so clear that the MFxLMS method can be seen as a generalization of inverse power control approaches.

VI.  RESULTS

*A.  Power control over an AWGN channel*

We made simulations for FxLMS variants with a fixed channel gain $h = 1$. The error signal $\varepsilon_k$ used in the MSE calculations is given in (11) with $c_0 = 0$, leading to $\varepsilon_0 = 1$ that is set as the first value to (8). The parameter $\eta$ used in the simulations was $\eta = 6$, increasing from $\eta = 1$ in the beginning until enough samples for $\eta = 6$ were achieved. Ensemble averaging over 100 independent trials was performed to obtain the results for the FxLMS and the MFxLMS algorithms. We used BPSK signal in transmission and thus the choice of $\mu = 1$ corresponds to the normalized algorithm using the optimum step size defined in (16). As expected, the larger the step size is the higher the converged mean squared error is. The performance of the algorithms is almost identical in the AWGN channel.

Learning curves for the practical algorithms are shown in Fig. 4 together with the normalized MFxLMS algorithm and the normalized FxLMS algorithm, using 20 dB received SNR. Numbers of iterations to the convergence are 28, 10, 5, and 4 for the CAPC-1, CAPC-3, CAPC-2, and MFxLMS algorithms, respectively. Used error signal in simulations for CAPC-x algorithms was $e_k = x_k - (P_{k-1}h_k + n_k)$ to obtain a fair comparison with the MFxLMS results. The step sizes for CAPC-*x* algorithms are defined in (26) – (28) and the parameter $\gamma_{\mathrm{ref}} = 20$ dB. For the criterion for the convergence we used 10 % misadjustment [4].

The CAPC-1 is the slowest one due to fixed step size and the variable step size algorithms clearly outperform it. The CAPC-2 is faster than CAPC-3 since it uses a larger maximum step size for fast adaptation. CAPC-1 and CAPC-2 algorithms adapt the power up and down all the time. Other variable step algorithms can set the power to the wanted level and keep it there.

*B.  Power control over a fading channel with the non-quantized MFxLMS algorithm*

Both conventional and modified versions of the FxLMS algorithm operate well in the AWGN channel as expected. However, robustness of the FxLMS is not as good as the robustness of the MFxLMS algorithm when we look at the performance in the fading channel modelled with (3). Two different channel realizations are considered in Fig. 5. It shows the received SNR levels for the simulations over a fading channel modeled using (3) with value of $N = 12$ and $f_{\mathrm{d}} = 10$ Hz. The LMS channel estimation with parameter value of $\vartheta = 0.1$ is used in the FxLMS simulations. In addition, the values of $a = 1$ and $b = 0.2/\bar{\gamma}_{\mathrm{rx}}$, where $\bar{\gamma}_{\mathrm{rx}}$ is the received SNR, were chosen for (22). The larger SNR is used, the more stable the control is and the smaller correction term is needed. In all the shown simulations the power control update rate was 1000 Hz.

In the first row in Fig. 5, the channel variations both in phases and amplitudes are not too fast for the algorithms to make inversion accurately. The performance of the conventional and modified FxLMS algorithms is almost identical. However, in the second row the faster phase
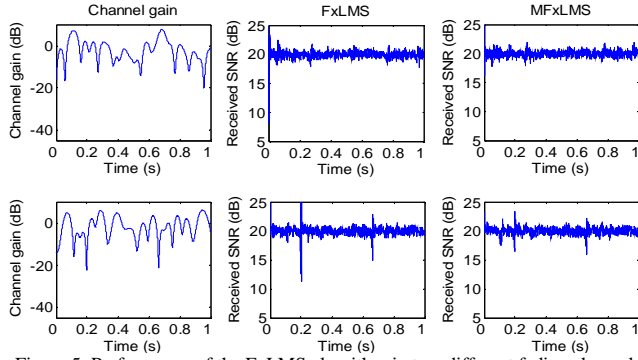
Figure 5. Performance of the FxLMS algorithm in two different fading channels.
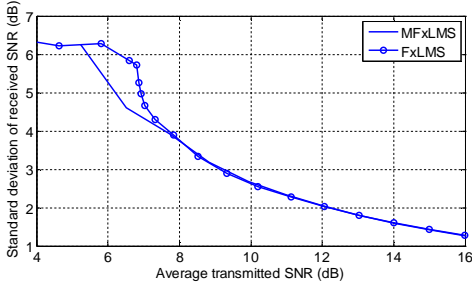


Figure 6. Performance of the FxLMS algorithm in low and medium SNR regimes.



Figure 7. Received SNR values with different power control methods.

variations during deep fades [33] cause clearly problems to the conventional FxLMS algorithm. The MFxLMS algorithm performs robustly and the received SNR variation remains at an acceptable level since it follows the amplitude variations rather well also during the deep fades.

Fig. 6 presents performance of the FxLMS and the MFxLMS algorithms in a fading channel in low and medium SNR regimes when the channel realization of row 1 of the Fig. 5 is used. When the transmitted SNR is above 8 dB, the performance of the algorithms measured with standard deviation of received SNR is almost identical. The more robust MFxLMS obtains better performance than the conventional FxLMS below 8 dB due to problems caused by rapid phase variations to the latter. However, the performance of the MFxLMS collapses when the transmitted SNR drops below 5 dB while the FxLMS operates also below this limit. The reason for the collapse is the inclusion of noise term in (21) inside the last absolute value term. When the noise term is strong enough compared to the signal power the algorithm cannot converge anymore. Above this performance limit the MFxLMS is more robust and provides either equal or better performance compared to the conventional FxLMS. Thus, in all the remaining results, only the MFxLMS algorithm is considered in comparison with the CAPC-*x* algorithms.

Results with the channel model shown in the row two of the Fig. 5 are presented in Fig. 7. With the CAPC-1 method the received SNR is too low during a deep fade. Then the
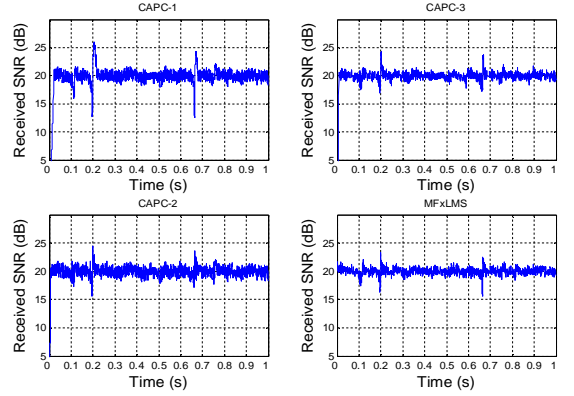
transmission power is adjusted upwards and because of lag error the power is too high for a while. The variable step methods perform better. The CAPC-3 and MFxLMS methods can keep the received signal close to the desired value. The CAPC-2 and CAPC-1 methods are changing the power by 1 dB up and down even when they are close to the target level.

Variable step size methods have larger step sizes which make adaptation faster. This can be seen in the rise times in Table I. The rise time is the time required for the received signal to change from the initial value, when transmitted signal is 0 dB, to the required 20 dB value in a time-variant

Table I. Performance of the practical algorithms

|  | Rise time (ms) | Standard deviation (dB) | Average transmitted SNR (dB) |
|---|---|---|---|
| **CAPC-1** | 19 | 1.186 | 25.46 |
| **CAPC-2** | 7 | 0.798 | 26.25 |
| **CAPC-3** | 9 | 0.613 | 26.31 |
| **MFxLMS** | 4 | 0.573 | 26.18 |
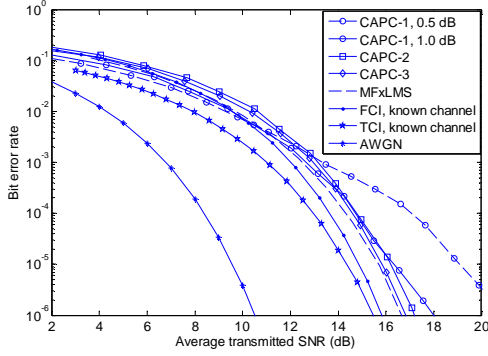
Figure 8. The bit error rate as a function of average transmitted SNR in channel (5), $L=1$.



Figure 9. Bit error rate performance comparison in a diversity channel ($L = 2$).

channel (3) using the same parameters as for generating the Fig. 5. The results are average values over several simulations. The MFxLMS algorithm sets the transmission power to the required level fast. In addition, the system is able to compensate deep fades without suffering lag error. That is the reason for the better performance for adaptive step size algorithms.

It is impossible to obtain identical received and transmitted SNRs since different algorithms use different amount of transmitted energy for communication due to their different adjustment methods. However, the difference is very small between CAPC-2, CAPC-3, and MFxLMS methods as shown in Table I. Thus, the performance comparison between these methods is fair. The performance of the CAPC-1 method is decreased since it is spending more time during deep fades with a lower power and consequently the outage time is also higher. Standard deviation of the received SNR, averaged in the decibel domain, shows clearly the gain of using adaptive step sizes in control with the studied control command rate. Standard deviation is measured after the rise time to exclude large differences between the required SNR and the actual signal level at that time. The MFxLMS algorithm achieves the best performance among the compared algorithms.

The bit error rate (BER) performance of the studied algorithms in the channel (5) when $L = 1$ is considered in Fig. 8. The same metric was applied in [43] to compare fixed step and adaptive step power control. Simulations are carried out to establish the effect of power control step size (variable versus fixed) on the average BER performance. BPSK modulation is used in the simulations. The performance of the full channel inversion (FCI), referring to (9) with $\gamma_0 = 0$, and the optimal TCI in a known channel are plotted as references to show the effect of adaptation in the BER performance. The difference of roughly 5 dB between the FCI and AWGN curves is caused by fading. The difference can be reduced with diversity. In the low SNR regime the noise error is the dominating source of errors and the variable step algorithms are not performing better than the CAPC-1 method that was studied with 2 different step sizes, $\Delta P = 0.5$ dB and $\Delta P = 1$ dB. The crossing in the BER curves between the MFxLMS and CAPC-1
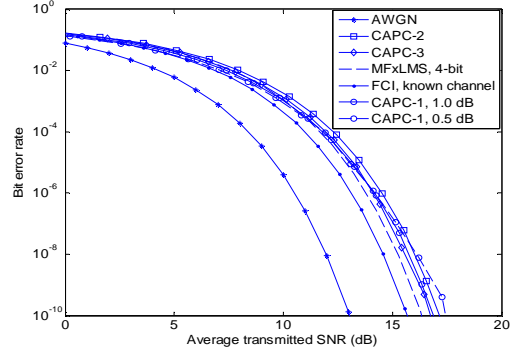
methods around 12 dB SNR is due to effect of noise. When the SNR is higher, the standard deviation of the MFxLMS and the corresponding BER values are smaller. Variable step methods are using larger step sizes to correct the errors caused by the noise and that makes their performance worse in the low SNR regime. Smaller step sizes are better for noise averaging.

Also the theoretical FCI method is worse than the CAPC-1 method in the low SNR regime since it allocates more power to the deep fades whereas the CAPC-1 method cannot invert the channel totally, making it actually a truncated algorithm. When the SNR is increasing, the variable step methods can follow better the channel fading. The CAPC-1 method is too slow to invert the channel during fast changes especially with the smaller step size and the lag error makes the performance of it worse when SNR is increasing. The FxLMS method outperforms the other algorithms in the high SNR regime when the fastest converging step size defined in (22) is used, i.e., with $a = 1$. However, during low SNR values, the smaller step size is better due to better noise averaging properties. The FCI performance approaches the TCI curve when SNR increases since the probability of outage of the TCI method is reducing.

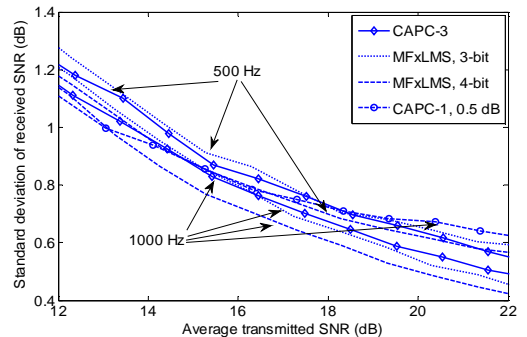### C. Power control over a diversity channel with the quantized MFxLMS algorithm

The previous results are provided for the nonquantized MFxLMS algorithm to see its capabilities. Quantized version is needed to verify the practicality of the algorithm. The experiments were made over the diversity channel since that would be an obvious feature to be used in practical systems. The diversity channel with $L = 2$ branches for simulation studies was generated using (5) and parameter values $N = 12$ and $f_d = 10$ Hz. In order to see the effect of companding in the results, we made several simulation runs where we used either companding or pure quantization the feedback channel. The standard deviation of the received SNR of the algorithm with quantization was significantly lower with companding. Thus, we use companding in the following simulations. In addition to the proposed use of sending the correction term (10) in the feedback channel, we made experiments by sending the signal
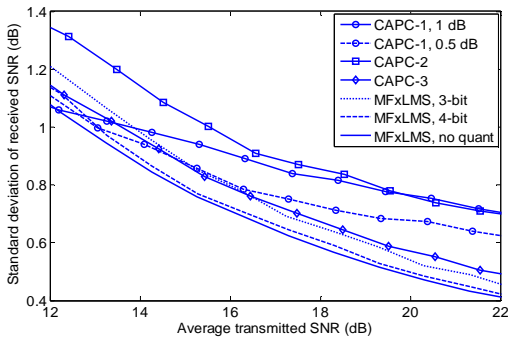
Figure 10. Performance comparison in a diversity channel ($L = 2$).



Figure 11. Performance comparison in a diversity channel ($L = 2$) with different control rates.

$c_{k-1}$ in the feedback channel to minimize calculations at the transmitter. However, the signal level variation using the correction term $w_k$ is smaller in the diversity channel, providing better performance with the quantization. Simulation results using the quantized correction term are shown in Figs. 9–11.

The bit error rate performances of the studied algorithms are shown in Fig. 9 as a function of transmitted SNR. The performance of the full channel inversion in a known channel is plotted as a reference. It is actually a better reference in a diversity channel than in a channel without diversity where truncation gives a clear advantage. Full channel inversion without cutoff is the optimal inversion method in a diversity channel [10]. Control rate of the adaptive algorithms is 1000 Hz. Control step size of the MFxLMS algorithm in a diversity channel was experimentally found to provide good tradeoff between lag error and noise averaging when the parameters in (22) were $a = 1/\sqrt{L}$ and $b = 0.2/\bar{\gamma}_{rx}$. With higher SNRs the inversion is more accurate due to reducing effect of the noise error. All the tested algorithms work rather well in a diversity channel. The MFxLMS algorithm needs less SNR than other adaptive algorithms to achieve BER < $10^{-4}$ due to accuracy of the adaptation. Very close to the performance of the nonquantized MFxLMS algorithm is achieved already with a 4 bit power control command. The performance of the MFxLMS algorithm approaches the ideal inversion when the channel is changing more slowly. The performance differences between the algorithms in the high SNR regime can be well understood when we look at the accuracy of the algorithms measured with the standard deviation of received SNRs.

It can be seen from the results shown in Fig. 10 that the 3-bit MFxLMS control achieves comparable performance to the best earlier algorithm studied, i.e., the CAPC-3 method. Accuracy of the CAPC-1 and CAPC-2 algorithms is restricted due to the minimum step size of 1 dB. When the step size of the CAPC-1 algorithm is set to 0.5 dB, the performance is clearly better. The crossing in the BER curves between the MFxLMS and CAPC-1 methods around 12 dB SNR is seen also in Fig. 10. When the SNR is higher, the standard deviation of the MFxLMS and the corresponding BER values

are smaller. In a diversity channel, the additional larger step size of the CAPC-2 decreases the accuracy of the control compared to the simple CAPC-1 control since the fading can be controlled with smaller steps. Variable step size algorithms are still outperforming fixed step algorithms in a diversity channel in the high SNR regime. However, the gain is achieved by using a higher feedback channel rate.

In order to see the effect of control rate to the accuracy of the control, simulations were performed with two different control rates, 1000 Hz and 500 Hz. Results are shown in Fig. 11. Main comparison is made between the most accurate variable step algorithms, the MFxLMS and the CAPC-3 algorithm. CAPC-1 results with 1000 Hz control rate using 0.5 dB step size are provided as a reference curve. The results show that reduction in the control rate causes the accuracy of variable step algorithms to drop roughly to the same level with a 1-bit algorithm with 1000 Hz rate. Still the number of control bits needed to send over the feedback channel is 1500 bits/s and 2000 bits/s for variable step CAPC and MFxLMS algorithms, respectively. CAPC-1 with a higher control rate requires only 1000 bits/s, i.e., with a proper step size selection it gives rather good performance with a low feedback control rate. The rate depends on the fading rate of the channel and can be decreased e.g., when higher order diversity is applied.

## VII. CONCLUSIONS

In centralized wireless systems the transmission power control is often based on inverse control. We have developed the MFxLMS algorithm for power control. We analyzed the algorithm in a noiseless channel and simulations show that it converges well also in a noisy channel. The proposed algorithm provides a unified framework for many existing practical algorithms and can be seen as a generalization of inverse power control algorithms. We compared the proposed method to the well-known CAPC-1 method and its variable step variants. Simulations in fading channels with diversity show that the best conventional algorithms give comparable performance to the theory based MFxLMS solution. An interesting future topic would be to study the optimization of the step size (22) of the MFxLMS algorithm in a timevariant

channel. Some related work has been done for direct estimation and decision feedback equalization in [27] but more investigation is needed to find solutions for inverse control. Another interesting problem to study would be the development of the algorithm to handle vector type signals. The algorithm could be able to take into account correlation between subcarriers in the OFDM system.

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# Performance improvement with predictive channel selection for cognitive radios

# Performance Improvement with Predictive Channel Selection for Cognitive Radios

Marko Höyhtyä[1], Sofie Pollin[2], and Aarne Mämmelä[1]

[1]VTT Technical Research Centre of Finland
P.O. Box 1100, FI-90571 Oulu
Finland

[2]Berkeley Wireless Research Center
University of California, Berkeley CA 94704
USA

*Abstract*—**Prediction of future availability times of different channels based on history information helps a cognitive radio (CR) to select the best channels for control and data transmission. Different prediction rules apply to periodic and stochastic ON-OFF patterns. A CR can learn the patterns in different channels over time. We propose a simple classification and learning method to detect the pattern type and to gather the needed information for intelligent channel selection. Matlab simulations show that the proposed method outperforms opportunistic random channel selection both with stochastic and periodic channel patterns. The amount of channel switches needed over time reduces up to 55%, which reduces also the delay and increases the throughput.**

## I. Introduction

Cognitive radio should be more than only an adaptive opportunistic radio. In order to be called intelligent, it should have the ability to learn from experiences. However, a huge majority of cognitive radio research is focused on methods that use only instantaneous information about the environment as a basis for dynamic operation. Available channels for selection can be assumed to be equally good [1]–[3] or characterized based on interference level [4] or bandwidth [5]. Secondary users sense their environment and react to detected changes in spectrum availability in an opportunistic way. Such an approach results in a bad channel selection for secondary users since the system randomly selects channels that may be heavily utilized by primary users (PU). This may cause frequent service disruptions for secondary users since they have to refrain from transmission, and result in interference to primary users. In addition, every channel switch causes a non-negligible delay for the transmission. If a single channel can be used over a long period, such delays can be avoided and the capacity is improved.

The problem has not been explored much in the literature. However, there are a couple of papers that present some possible solutions to the problem. The seminal paper [6] emphasized that a dynamic spectrum management algorithm should include information about the traffic pattern of the primary user occupying the channel. In a wireless environment, two basic classes of traffic patterns exist [6]: 1) Deterministic patterns where the PU transmission is ON, then OFF during a fixed time slot. 2) Stochastic patterns where traffic can be described only in statistical terms. Poisson distributed traffic is one example of stochastic traffic.

Perfect knowledge of traffic patterns in different primary channels would make spectrum sharing easy. We could plan our spectrum usage including routing and frequency switches in a non-interfering manner. The capacity could be maximized and the control would be extremely robust. However, we cannot know exactly what is going on around us and it is especially hard to know how things will be in the future.

In order to plan the secondary use of the spectrum better without cooperation with the primary user, some authors have proposed predictive models to be used in spectrum sharing [7]–[9]. These papers propose prediction models for specific types of primary traffic patterns. Reference [7] investigates the predictability when the primary traffic is assumed to be representable by a cyclostationary random process. In [8], the authors propose a proactive access method to utilize holes in TV broadcast channels. The main goal of paper [9] is to minimize interference to primary users by predicting the future idle times and by changing to better channels before the primary user appears on the currently used channel. The authors investigate specifically the usability of prediction under exponential ON-OFF traffic models, and also periodic-exponential models where the duration of either ON or OFF times is fixed and only the other period is exponentially distributed.

One limitation of the mentioned papers is that the proposed method should not be restricted to one possible traffic model only. It should work with a variety of traffic classes and thus, a general model would be needed. Basically, a CR should characterize whether the traffic is deterministic or stochastic and based on that it should use different methods for selecting the channel.

Our contributions are a simple classification and learning method to detect the pattern type (periodic or stochastic) and to gather needed information, a method for availability time prediction both for periodic and stochastic traffics and a rule for intelligent channel selection for data transmission and control exchange. We tested our method with different traffic patterns using Matlab simulations in comparison with an opportunistic random selection approach and achieved very encouraging results. Focus in this paper is on the prediction; the classification method will be covered more thoroughly in the future.

The organization of the paper is as follows. Section II presents the model used in simulations. The prediction method is introduced in Section III and results are presented in Section

IV. Discussion of the topic is provided in Section V and conclusions with recommendations for further work are drawn in Section VI.

## II. System Model

Availability time prediction helps to choose the best channels to use. In addition, temporal history information gives valuable information to the sensing process. A CR system can abandon some channels after a certain learning time if it seems that the band is used almost all the time. It is not reasonable to waste resources for the bands that cannot offer communication possibilities. Energy efficiency is better if the system concentrates only on channels that seem to have potential idle times.

### A. System model
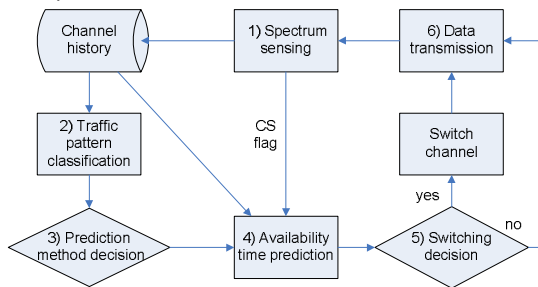


Figure 1.   System model for predictive transmission.

Fig. 1 represents the architecture for a predictive cognitive radio system. 1) First, the CR collects information about spectrum use in different frequency channels through spectrum sensing and stores this information into the channel history database. The last spectrum sensing result tells what the current situation in a particular channel is. If the channel is free, the channel state (CS) flag is set to 0 and if not, CS = 1. 2) Based on the collected history, the traffic patterns of different channels are classified into stochastic and periodic ones by using the autocorrelation function (see Section B). 3) Different prediction methods apply for different traffic patterns and the selection is made by classification. 4) The availability time prediction uses information from three sources. The CS flag of channels is checked first. If CS = 1, the predicted availability time is 0 s. If CS = 0, the remaining idle time of these channels is estimated based on the channel history and selected prediction method for that particular channel. 5) If the channel used currently is still free, continue transmission. If not, switch to the channel with longest expected remaining idle time. 6) Data transmission and then back to the point 1) after $\Delta t$ seconds where $\Delta t$ is the maximum length of interference the PU can tolerate.

### B. Classification of traffic pattern

The goal of traffic prediction is to forecast future traffic rate variations as precisely as possible, based on the measurement history [10]. In a cognitive radio context the prediction aims to determine idle times in PU traffic that can be utilized by

secondary transmissions. The first thing to learn from the traffic before making actual predictions is the traffic type.

There are different types of traffic appropriate for prediction:
1) periodic traffic with fixed ON+OFF time,
2) fixed OFF times, random ON times,
3) fixed ON times, random OFF times,
4) both ON and OFF times are random.

In each of the cases, the exact ON and OFF times can vary across channels. In fact, the goal of the prediction is then to choose the channel with the largest predicted OFF time. However, for each of the cases the prediction algorithm should be different.

Sensing of primary channels is a sampling process to determine the state (ON or OFF) of the channels at every sampling instant. The outcome of sensing is a binary sequence for each channel as shown in Fig. 2. This sequence tells us about the traffic that is ongoing. It has sufficient information to determine the periodicity, distribution of idle and busy times, and utilization percentage of the channel. As you can see from Fig. 2, the detected pattern can differ from the actual one; the starting and ending times of ON and OFF times are slightly shifted because of the limited sensing resolution.
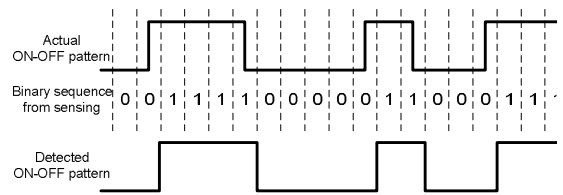


Figure 2.   Detection of primary traffic.

Since the traffic patterns in different channels can be anything from the 4 types mentioned above, it would be desirable if the cognitive radio could identify the type of traffic after a short learning period from the binary sequences gathered during that period. ON and OFF times can be assumed to be random in each channel before learning period is over.

First, the periodicity is searched from the binary sequence. Authors in [7] proposed to use the global maximum of the autocorrelation function for detection of the period length. Actually, this does not work if the period is fixed and the ON and OFF times are not. The discrete autocorrelation function at lag $m$ over $N$ samples for discrete signal $x[n]$ is

$$R_{xx}[m] = \sum_{n=0}^{N-m-1} (x[n]x[n+m]) . \qquad (1)$$

Computing the autocorrelation function over many periods gives several peak values. Identical periods give us identical peak values. When the ON and OFF times can vary within the period, the peak values are not constant anymore. However, one can use local maximums when calculating the period

length. We define the period so that there is only one ON time followed by one OFF time. This pseudocode can be used to check if the binary sequence is periodic or not:

1. Computation of parameters
   1. Compute autocorrelation $R_{xx}$ of the input sequence
   2. Search global (*tau_max*) and local maximums of $R_{xx}$
   3. Check if the local maximum is too local, not showing the place of a real period. It should be larger than value of $R_{xx}$ a few samples away.
   4. Calculate average separation between consecutive local max values, *tau_ave*
   5. Calculate standard deviation of separations, *std*

2. Traffic type classification: Traffic is periodic if separation between consecutive local max values is constant enough. Limit value for *std* should be chosen based on *tau_ave* to allow larger deviation for longer periods.

```
if tau_ave = = tau_max,
        Period length  is tau_max,
        Sequence is periodic = TRUE
elseif std is smaller than limit value
        tau = round(tau_ave)
        sequence is periodic = TRUE
else
        sequence is stochastic
```

The autocorrelation function is sensitive to the sampling rate and therefore the sensing resolution restricts the ability to detect very short periods. Traffic patterns can change over time and thus we have to limit the time horizon by using a moving time-window for collecting samples and making estimations.

## III. PREDICTION OF IDLE TIMES

### A. Periodic traffic

Statistics about the length of ON and OFF times gives valuable information about how the channel has been utilized in the past. This information helps us to predict future idle times. In the fixed period case, it is possible that ON and OFF times are fixed or random. In the first case, we can make exact predictions about the future and fully utilize all available resources for secondary transmissions. For the first case, the starting point of the OFF time for $M$ consecutive periods is

$$T_{s,n} = t_n + T_{ON} , n = 1,\ldots,M, \qquad (2)$$

where the beginning time of period $n$ with length $\tau$ is $t_n$. The length of period is

$$T_l = T_{OFF} = \tau - T_{ON} , \qquad (3)$$

where $T_{ON}$ and $T_{OFF}$ are the lengths of the ON and OFF times. In the latter case, after the channel becomes idle at time $t_o$, we know exactly how long it will be available before the PU appears again, namely

$$T_{idle,n} = \tau - (t_o - t_n) , n = 1,\ldots,M. \qquad (4)$$

When the period length is not fixed, we have to make our decisions based on the statistics gathered. In case of fixed OFF times, we know the remaining idle time after the channel becomes available at time $t_o$.

### B. Random traffic

When the ON time is fixed and the OFF time random, we know the starting time of the idle time but the length can be only estimated in a probabilistic way. When both times are random, we can calculate the expected remaining idle time after we detect the channel to become idle. To be usable with a wide variety of traffic patterns, the prediction should be simple and general.

Each cognitive radio stores the measurements of idle and busy times to the database and constructs a histogram from them. One good thing to look at is the average utilization over the time window. It tells us how heavily the channel is used on average. However, to know more exactly what kind of traffic is going on, one should look at the distribution of idle and busy times. From the database, the probabilities that different channels will be available at least $X$ seconds can then be calculated as

$$P(t \geq X) = \frac{amount\ of\ idle\ time\ values \geq X}{amount\ of\ all\ idle\ time\ values} \qquad (5)$$

A good metric for channel quality is the median availability time that is met with 50% probability. There is a 50% chance for the real idle time to be at least that long. The longer the time the better. Using the database, a CR could also estimate the time to transmit under an interference constraint (i.e., $W$% guarantee not to interfere with PU). This means that it would transmit continuously without sensing certain amount of time and trust the distribution. To achieve this, the CR should choose transmission time $Z$ so that

$$P(t \leq Z) = 1 - W . \qquad (6)$$

In this way the CR could adaptively loose its sensing period requirements. However, doing so the sampling process slows down and in the future the database cannot give as accurate information.

### C. Intelligent channel switching

Secondary users utilize the past channel observations to build predictive models of spectrum availability, and schedule their spectrum use in order to maximize spectrum utilization while minimizing the disruption rate to primary users. To do that, the CRs have to select the channel to switch to in an intelligent way.
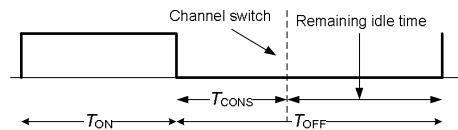


Figure 3.   Different times of signal.

When switching channels, a user switches to the available channel $j$ with the largest expected remaining idle time $T_j$, chosen as

$$\arg \max_{j} T_j \,, \tag{7}$$

where $T_j$ is the calculated remaining idle time. Below, we specify the prediction rules for different traffic types based on different times that are defined in Fig. 3. In the case of periodic signals, the prediction is

$$T_j = \tau_j - T_{ON}^{j} - T_{CONS}^{j}. \tag{8}$$

For stochastic signals we estimate the remaining idle time with the probability of 0.5,

$$T_j = T_{50}^{j} - T_{CONS}^{j}. \tag{9}$$

This means that from the predicted idle time for the channel the consumed idle time is subtracted (i.e., the time when CR was operating in a different channel) and then the channel with the longest idle time is selected. To avoid time-consuming median search in case of stochastic traffic, also the mean time of idle times could be used.
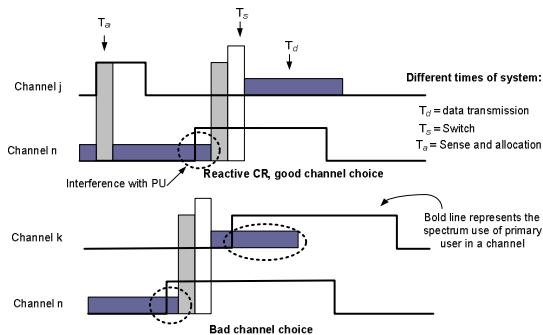


Figure 4. Different channel switching schemes.

Fig. 4 shows different channel selection possibilities. A CR can select the next channel randomly or based on prediction. The next channel should be selected based on the predicted value: channel $j$ is a much better choice than channel $k$ because it offers a longer time for CR operation and helps to avoid interference with a PU.

## IV. RESULTS

In order to see how well the proposed intelligent channel selection approach works when compared to random opportunistic channel selection we made experiments with periodical and stochastic traffic patterns. Parameters for the simulation are shown in Table 5. We tested the classification method with stochastic and periodic traffic with parameter values mentioned in Table 5. Stochastic pattern was always classified right. With the periodic traffic where the amount of possible ON times was limited as is the case of packet-based network, the classification made right decision in 80 % of tests.

TABLE 5. SIMULATION PARAMETERS

| Parameter | Value |
|---|---|
| Transmission period | 90 ms |
| Sensing period | 10 ms |
| Switching delay | 10 ms |
| Number of channels | 5-20 |
| Primary user traffic models | Stochastic channels with exponentially distributed ON and OFF times Periodic channels with fixed ON and OFF times |
| Utilization, mean idle times, and period lengths of primary traffic | Almost uniformly distributed utilization [0.1, 0.9], mean idle times between [1s, 10s], period lengths [2s, 20s] |
| Simulation time | 10 000 s |
| Channel selection methods | Intelligent channel selection , random selection |

We examined the number of channel switches during the simulation time when either the random or intelligent channel selection method was used. For simplicity, the classification was assumed to work perfectly. Intelligent selection procedure then took the exact traffic type into account.

Learning and intelligence always seem to improve the efficiency of the system. When stochastic traffic over 8 primary channels with exponentially distributed idle and busy times was used, the number of switches with the intelligent method was 17% smaller than with random selection. With periodic traffic the difference was 43%. When both periodic channels and stochastic channels were used, the improvement was around 20%.

We made simulations with different channel selection methods to see how the number of channels affects the performance. The number of channels varied from 5–20. Both exponential and periodic traffic patterns were examined. Since the search of the median time for stochastic traffic can be time-consuming, we tried also a method were the expected time is the mean idle time of the channel. Results for exponential traffic are shown in Fig. 5.

With 5 channels the methods are almost equally good since there are not many channels to choose from. When the amount of primary channels is increased, the difference between intelligent and random selection increases. The intelligent method can concentrate on the best channels. Quite interestingly, the mean idle time based selection outperformed slightly the median based selection in every case. Reason for this is the fact that median time is smaller than mean time in exponential traffic and the subtraction of $T_{CONS}$ affects more to the median based selection. This means more conservative approach and probable abandoning of good channels. The result is good since it shows significant gains for relatively simple prediction method. The gain in channel switches ranges from 6% with 5 channels to 39% with 20 channels while the average number of available channels increases approximately linearly as [2.2 4.7 7.4 9.4]. The mean average idle times for

channels were [3.5 3.2 3.5 3.6] s. Random selection follows approximately the average idle time distribution with more switches with lower average idle times whereas the intelligent method takes advantage of the increasing number of good channels.
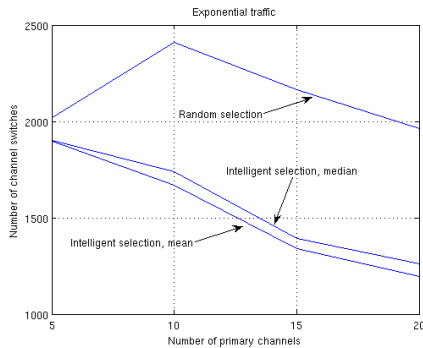


Figure 5.    Amount of channel switches with stochastic traffic.

The performance with periodic traffic patterns is shown in Fig. 6. The intelligent selection method can predict the idle times almost perfectly and can select the best channels very well. The gain compared to the random method is large all the time. With 15 and 20 channels, the amount of switches with intelligent selection is 55% lower than with random selection. The average mean idle times for channels are now [7.0 6.1 6.6 6.5] s. Again, the performance of random selection depends on the average values of channels whereas the intelligent selection method concentrates to good channels and can take advantage of an increasing number of them.

## V.    DISCUSSION

A reactive CR switches to different channel after a PU is sensed to appear in the same channel. To reduce the interference with PUs, a CR could switch proactively to a new channel before the PU appears in the current band. It can change the channel when the predicted $T_j$ is over, and it does not wait until the PU appears. Especially with deterministic traffic this proactive method is preferred.

In some cases the prediction of busy times in addition to idle times could make sense. Depending on the application used and its QoS requirements, this allows estimating if we could stay and wait for the channel to become idle instead of frequency hopping. Multi-hop ad hoc networks are possible target systems for this kind of operation. In multi-hop networks, every frequency change causes a need for an update of the routing table. If this happens very frequently, a large amount of energy and bandwidth resources are consumed to keep those tables up-to-date and as a result, the capacity of the system decreases.

## VI.    CONCLUSIONS

Intelligent channel selection helps to select the best channels for control and data transmission. Even with totally random exponential traffic patterns the amount of switches reduces clearly when using intelligence which improves the efficiency of the spectrum use. Cognitive radios should have learning abilities to be able to intelligently select channels for secondary use in a way that minimizes delays and maximizes throughput.
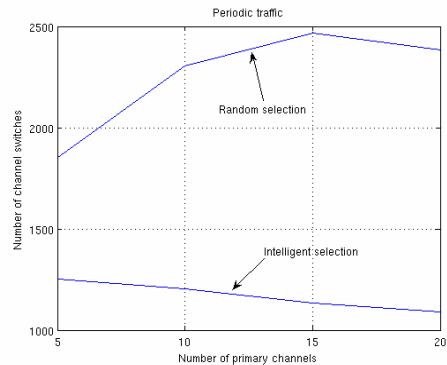


Figure 6.    Amount of channel switches with periodic traffic.

However, more work is needed in this area. Interesting things to look at are the use of intelligent selection models with a wide variety of primary traffic patterns and the reliability of the classification method. Also we can test the approach with real measured network traffic. We should also investigate the effect of proactive channel selection on the amount of switches, delays and throughput. In addition, the case with multiple secondary users sharing the spectrum would be interesting to look at since a channel may now become busy also by CR activity. These things will be investigated in future.

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# Classification-based predictive channel selection for cognitive radios

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# Classification-based predictive channel selection for cognitive radios

Marko Höyhtyä[1], Sofie Pollin[2], and Aarne Mämmelä[1]

[1]VTT Technical Research Centre of Finland
P.O. Box 1100, FI-90571 Oulu
Finland

[2]Interuniversity Microelectronics Center (IMEC)
Kapeldreef 75, B-3001 Leuven
Belgium

*Abstract*—**The proposed method classifies traffic patterns of primary channels in cognitive radio systems and applies different prediction rules to different types of traffic. This allows a more accurate prediction of the idle times of primary channels. An intelligent channel selection scheme then uses the prediction results to find the channels with the longest idle times for secondary use. We tested the method with Pareto and exponentially distributed stochastic traffic and with deterministic traffic. The predictive method using past information improves the throughput of the system compared to a system based on instantaneous idle time information. The classification-based predictive method improves the performance compared to pure prediction when the channels of interest include both stochastic and deterministic traffic. The amount of collisions with a primary user can drop 60 % within a given interval compared to a predictive system operating without classification.**

## I. INTRODUCTION

A cognitive radio (CR) should have the ability to learn from past experiences to improve future performance compared to the case where only instantaneous information is taken into account. This implies the need of prediction algorithms, and most importantly, it assumes that the future can actually be predicted from past observations. In this paper, we consider the channel selection problem for secondary users, and study how to improve that channel selection based on sensed past information about the channel use. For channels where the activity of the primary users (PU) is varying much over time, instantaneous sensing information might become obsolete in the near future, causing frequent service disruptions for secondary users since they have to refrain from transmissions and search for new available channels. Frequent channel switching causes delays and reduces throughput. In addition, interference is produced towards PUs. Therefore, the channel selection algorithm should take into account the cost or probability of such future change in channel availability when selecting a channel.

As was emphasized in [1], the dynamic spectrum management algorithm should include information about the traffic pattern of the PU occupying the channel. In a wireless environment, two basic classes of traffic patterns exist: 1) Deterministic patterns where the PU transmission is ON, then OFF during a fixed time slot; 2) Stochastic patterns where the traffic can be described only in statistical terms. Poisson distributed traffic is one example of stochastic traffic. Frame structures make traffic patterns fully or partially deterministic. Partially deterministic means that the ON time starts periodically but its length can vary while the period $T_p$ is fixed as illustrated in Fig. 1. A period consists of one ON time followed by one OFF time. This definition covers also the

deterministic periodic case where ON and OFF times are fixed. In our study, the traffic patterns are either stochastic or partially deterministic, and we will loosely use the term deterministic from now on for the latter. The terms OFF time and idle time as well as ON time and busy time are used interchangeably in this paper.
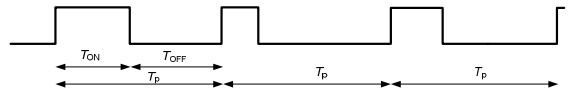


Figure 1. Partially deterministic traffic pattern.

Predictive models have been proposed for cognitive radios to make channel selection more intelligent [2]–[5]. However, these approaches have a common problem of restricting the prediction to the known traffic model only. In [2] the exponential weighted moving average based method is proposed to use idle times in TV broadcast channels. Exponential ON-OFF traffic models and periodic-exponential models are investigated in [3]. Reference [4] investigates the predictability when primary traffic is assumed to be a cyclostationary random process. Traffic prediction in [5] is performed using binomial distributed call arrival times and gamma distributed call holding times. We proposed a more general method that works with a variety of traffic classes in [6]. The method classifies the traffic in the sensed PU channels as deterministic and stochastic and uses specific prediction methods for different types of traffic to estimate what the expected idle times in the different channels will be. We have also analytically shown the optimal prediction rule for exponential traffic in [7]. The rule is shown also to work well with a Weibull distributed stochastic pattern.

Previous work does not show how much classification helps to improve the performance of the system, measured by throughput and collision rate. This work extends the work presented in [6] and shows how classification-based predictive method works with various traffic models and analyses the impact of sensing and switching times on the throughput. Proposed classification-based prediction decreases the amount of collisions with PUs greatly compared to the pure prediction based selection when the channels of interest include both stochastic and deterministic traffic. Analysis, simulations, and following discussions define how different parameters affect the performance and what scenarios are most useful for predictive operation. We verified our method with numerical analysis and careful simulations with different traffic patterns.

Organization of the paper is as follows. Section II presents the system model. The classification and prediction methods and used traffic patterns are introduced in Section III. Results

are shown in Section IV and finally Section V concludes the paper.

## II. SYSTEM MODEL

We use the same system model as in our previous paper [6]. The total available spectrum is divided into multiple primary channels to be sensed and used by cognitive radios. Each channel has its own independent traffic pattern. Fig. 2 represents the architecture of our predictive cognitive radio system. The CR collects information about spectrum use in the different channels through spectrum sensing and stores this information into the channel history database in binary format. Since the traffic patterns of channels might slowly vary over time the database should include information only over limited time interval. The method works as follows. 1) All channels are sensed and the channel history database is updated with the most recent sensing information. The last spectrum sensing result is used to define the current situation in a particular channel. If the channel is free, the channel state (CS) flag is set to 0 and if not, CS = 1. 2) Based on the collected history, the traffic patterns of different channels are classified as stochastic or deterministic. 3) Different prediction methods apply to different traffic patterns and the method selection is made following the traffic type classification.
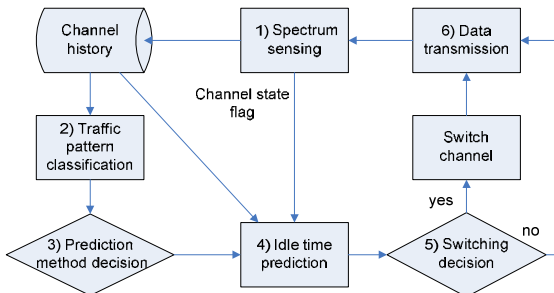


Figure 2. System model for predictive transmission.

4) The idle time prediction uses information from three sources. The CS flag of channels is checked first. If CS = 1, the predicted idle time is 0 s. If CS = 0, the remaining idle time of these channels is estimated based on the channel history and selected prediction method for that particular channel. 5) If the channel used currently is still free, secondary transmission continues. If not, the CR switches to the channel with the longest expected remaining idle time. 6) Data is transmitted and the system goes then back to the task 1) after $\Delta t$ seconds to check and update the channel state and improve the channel selection. $\Delta t$ is the maximum length of interference the PU can tolerate. It is a system dependent parameter that should be known for licensed systems operating on the same frequency band as the cognitive radio. Requirements from standards and manufacturers together with interference measurement studies can be used to define numerical values for the parameter.

## III. TRAFFIC MODELS AND PREDICTIVE CHANNEL SELECTION

The sensing of primary channels is a periodic sampling process to determine the state (ON or OFF) of the channels at every sampling instant. The outcome of sensing is a binary sequence for each channel. When a sufficiently long history of traffic patterns of channels is stored to the database, patterns can be classified and appropriate prediction performed. For stochastic and deterministic cases the prediction algorithm should be different. The goal of the prediction is to find the channel with the largest predicted OFF time. First we discuss the range of traffic models considered, then the classification and finally the prediction algorithms per class.

### A. Traffic models

The (partially) deterministic traffic was already fully defined in Section I. Deterministic traffic can be observed e.g., in TV transmission, where the periods can be long such as hours, days, or weeks. Moreover, the traffic in a network can be regulated periodic ON–OFF traffic with fixed ON and OFF times [8]. In addition, we define two types of stochastic models. A Poisson model with exponentially distributed ON and OFF times has traditionally been used to model voice traffic and is often used also in other network traffic studies. Suppose we have a vector of $n$ samples of idle times from channel $i$, $\mathbf{X}^i = (x_1^i, x_2^i, ..., x_n^i)$. Assuming exponentially distributed OFF times with traffic parameter $\lambda > 0$ the probability density function of the exponential distribution is

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & , x \geq 0 \\ 0 & , x < 0 \end{cases}. \tag{1}$$

The model is analytically tractable but does not fit so well to bursty data traffic carried in a network. A model that has been found to model nicely ON/OFF periods in real network traffic is the Pareto distribution [9]. The probability density function of this distribution is given by

$$f(x) = \begin{cases} \beta \dfrac{\alpha^\beta}{x^{\beta+1}}, & x > \alpha \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $\beta > 0$ and $\alpha > 0$ are the shape and scale parameters of the distribution. The mean value of the distribution is defined as $E[x] = \alpha\beta/(\beta - 1)$ for $\beta > 1$. If $\beta \leq 1$ the expected value is infinite. Another important characteristic of the distribution is that the variance of a random variable $x$ is infinite if $\beta \leq 2$. The degree of self-similarity [9] is measured by Hurst parameter given by $H = (3 - \beta)/2$. Traffic is self-similar if $0.5 < H < 1$.

### B. Classification of traffic

Since the traffic patterns in different channels differ from each other, it would be desirable if the cognitive radio could identify the type of traffic even after a short initial learning period from the binary sequences gathered during that period. Initially the CR works under the assumption that the ON and OFF times are stochastic in each channel. After the learning

period is over, the CR has made a decision about the determinism or randomness of the traffic and can adapt the prediction method. The length of the learning period depends on the ON and OFF times of the traffic. With perfect sensing only few traffic periods is needed but if there are errors in the sensing the learning period has to be longer.

A very distinctive feature for classification in our case is the periodicity. First, the periodicity is searched from the binary sequence. We can use the autocorrelation function [6] to find out the length of $T_\mathrm{p}$ in different channels. First the discrete autocorrelation function (ACF) at lag $m$ for a discrete signal $x[n]$ of length $N$ is calculated as

$$R_{xx}[m] = \sum_{n=0}^{N-m-1}(x[n]x[n+m]) . \qquad (3)$$

Computing the autocorrelation function over many periods gives several periodic peak values. The average separation of the peak values $\tau$ can be used for estimation of the deterministic period length, and the standard deviation of separations tells whether the traffic can be seen as deterministic or not. When the standard deviation is zero or smaller than some predefined value $\sigma$ that is set trough experiments, the traffic is classified as deterministic. Otherwise, it is stochastic. However, as shown in Fig. 3, when the ON and OFF times are not fixed, i.e., for partially deterministic traffic, there will be small peak values or fake maximums between real maximum peaks that have to be filtered away before averaging. These small peaks can be difficult to detect and remove in many situations. To circumvent this limitation of the ACF method we propose an alternative method based on the use of edge detection. These edges or starting points of the ON times are found from input sequence where '0' turns to '1'. The average separation of the raising edges and the standard deviation of the separations tell whether the traffic is deterministic or not.
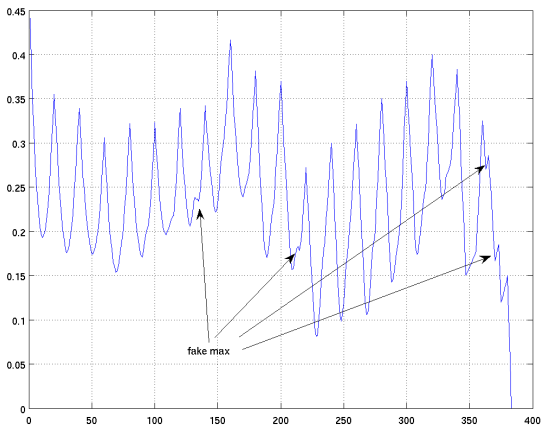


Figure 3. Autocorrelation sequence for partially deterministic traffic.

### C. Predictive channel selection

With random selection, a CR senses the spectrum and picks up randomly one channel. The same channel is used as long as it is available. When switching is required, the channel selection is done randomly using a uniform distribution across channels. If prediction is used for channel selection, the CR can select those channels offering the longest idle times. When switching channels, a user switches to the available channel $j$ with the largest expected remaining idle time $T_j$, chosen as $T_j = \arg\max_{j} T_j$, where $T_j$ is the calculated or estimated remaining idle time.

The prediction method for this idle time is selected based on the classification. As we proved in [7], the maximum likelihood (ML) estimate of the idle time in the case of stochastic traffic is the average of idle times in the channel. This is optimal for exponential traffic and leads almost equally good improvements in channel switching also with Pareto and Weibull distributed traffic. Thus, the best prediction is then the average of the previous idle times,

$$T_j = T^j_\mathrm{mean} . \qquad (4)$$

In practice, the observation interval for average calculation should be restricted. One potential way to do calculation is to use the exponential weighted moving average method that has been shown to be a very good choice for prediction purposes in business and economic time series [10]. It calculates the weighted averages of previous data samples which in our case may be idle times of the channel. The weighting of each older data sample decreases exponentially, giving more importance to the recent observations.

In the case of deterministic signals, the prediction is

$$T_j = T_\mathrm{p} - T^j_\mathrm{ON} - T^j_\mathrm{CONS}. \qquad (5)$$

This means that from the predicted idle time for the channel the consumed idle time $T^j_\mathrm{CONS}$ is subtracted, i.e., the time when the channel was already idle while the CR was operating in a different channel, and then the channel with the longest idle time is selected.

Since deterministic traffic can be predicted very accurately, weighting can be used in channel selection to favor deterministic channels when the estimated idle times of stochastic and deterministic channels are close to each other. The prediction of the OFF time in deterministic traffic is then as shown in (5) but the prediction of the stochastic traffic is weighted as $w \cdot T_j$, $w \le 1$. Furthermore, deterministic traffic makes proactive operation proposed in [2] possible. Proactive means that the channel is switched before a PU is predicted to appear on the current channel. In reactive operation, channel switching is performed after the PU appears only.

## IV. RESULTS

### A. Classification

The simulation results shown in this section validate the performance improvement achieved by using the classification-based prediction. We tested both ACF based and

edge detection based classification methods with stochastic and deterministic traffic with parameter values mentioned in Table 1. We assumed that the traffic has been sensed perfectly. In practice, noise is always present and causes problems to detection and classification; results shown here provide an upper bound of the performance for the methods. The value of $\sigma$ was set to $\tau/10$. Exponentially distributed and Pareto distributed stochastic patterns were always classified right with both methods. With the deterministic traffic both methods found patterns with fixed ON and OFF times without problems. When ON and OFF times can vary inside the period, the ACF method is not working so reliably anymore due to fake maximums that cannot always be filtered away. Success percentage was around 70 %. The edge detection method classified also this type of partially deterministic traffic perfectly.

TABLE 1. SIMULATION PARAMETERS

| Parameter | Value |
|---|---|
| Transmission period $T_d$ | 90 ms |
| Sensing period $T_s$ | 10 ms |
| Switching delay $T_w$ | 10 ms |
| Number of channels | 5, 10, 15, 20 |
| Primary user traffic models | Stochastic channels with exponentially or Pareto distributed ON and OFF times Deterministic channels |
| Spectrum occupancy | Between [0.1, 0.9] in different channels |
| Simulation time | 10 000 s |
| Channel selection methods | Intelligent channel selection, random selection |

### B. Prediction: Impact on channel switching and throughput

A first performance metric we consider is the number of channel switching that is required by the cognitive radio. When there are not many channels to choose from (5 channels), the gain obtained with intelligent channel selection is smaller, as seen in Fig. 4. When the amount of primary channels is increased, the difference between intelligent and random selection increases. The intelligent method can concentrate on the best channels and outperforms clearly the random method.

Fig. 4 shows the situation for Pareto distributed traffic for the parameter value $\beta = 2.2$ that is chosen to be over 2 to keep variability at a finite level. Intelligent selection clearly outperforms the random selection also in this case. The difference in channel switching is 30 % when 20 primary channels are considered. The optimal selection refers to the situation when we have perfect information about traffic patterns in the future.

A good performance metric for the cognitive radio system is the percentage of time during which it can successfully transmit without colliding with the PU [11]. We call this metric throughput. Assuming that on average a collision takes half of the transmission time of the CR away between sensing instants and following transmission time is shorter by
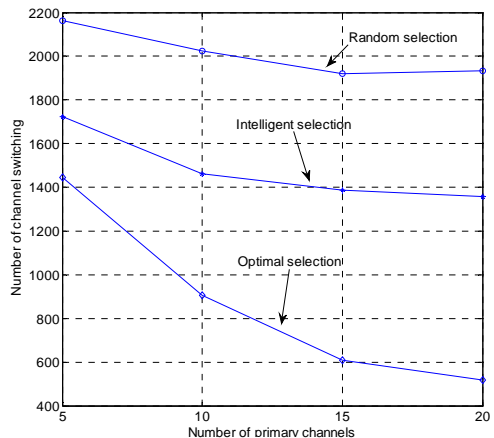


Figure 4. Number of channel switching with Pareto traffic.

switching time, throughput over time interval $[0, T]$ including $m$ transmission and sensing periods is

$$C_{CR} = \frac{T - m \cdot T_s - \delta \cdot T_d / 2 - \theta \cdot T_w}{T} \qquad (6)$$

where $\delta$ is number of collisions, $\theta$ is the number of switching events, $T_d$ is the transmission time of a CR packet, $T_s$ is the sensing time, and $T_w$ is the switching delay. With the reactive channel selection method the number of collisions equals the number of channel switching events.

Simulations above were made with transmission period length of 100 ms and idle times of channels were between [1 s 10 s]. We made experiments to see how changing of them affects the performance of the system. We used 10 primary channels having idle times uniformly distributed between [0.5 s, 2 s]. Transmission period length was 100 ms, 200 ms, and 500 ms in different simulations. The throughput results for exponential and Pareto traffic are shown in Fig. 5.
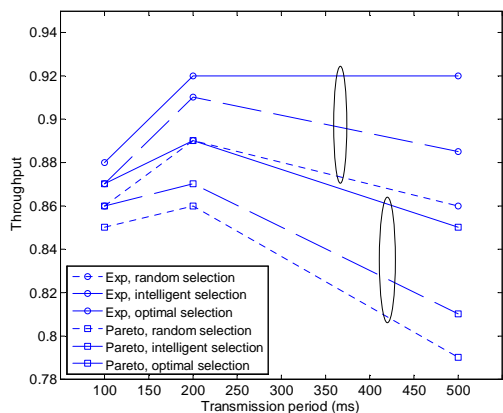


Figure 5. Throughput with different transmission period lengths when idle times of PU traffic between [0.5 s, 2 s].

The result shows that throughput increases when $T_d$ increases from 100 ms to 200 ms. When $T_d$ is 500 ms, the throughput is clearly smaller since the amount of collisions becomes higher and thus decreases the efficient transmission time. Intelligent selection outperforms the random selection in all cases and the largest gain is achieved with larger $T_d$ since decreasing the amount of collisions affects the throughput more in this case.

Fig. 6 shows the situation when the idle times of primary traffic are distributed in the range of [1 s, 5 s]. The trend is almost the same here. However, throughput is now better when $T_d$ is 500 ms compared to the 100 ms case with both traffic models. This is due to longer idle times than in the Fig. 5. Frequent sensing affects more the performance than collisions that do not occur so often. The performance variations between the different transmission lengths are now smaller since longer idle times mean smaller amount of collisions and channel switching.
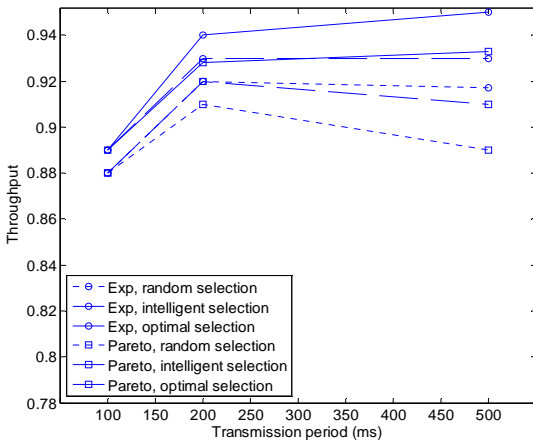


Figure 6. Throughput with different transmission periods when idle times of PU traffic between [1 s, 5 s].

We then also change the sensing and switching times from 10 ms to 20 ms or to 50 ms. Especially with shorter $T_d$ the increase of $T_s$ decreases the throughput remarkably as shown in Fig. 7. Since the CR senses the spectrum periodically, the lower the $T_d$ is the more time is consumed sensing. When the same parameters as in Fig. 5 are used, the increase of $T_s$ from 10 ms to 20 ms decreases the throughput by 0.1 when $T_d = 100$ ms and only 0.02 when $T_d = 500$ ms. The difference decreases with larger $T_d$ since the sensing is not performed so often.

Changing the switching time does not have such a large effect to the total performance when $T_d$ is small since the sensing time always dominates. With higher values of $T_d$ the effect of switching is close to the effect of sensing. The throughput decreases drastically if $T_s$ is set to remarkably higher values, e.g., to 50 ms. When $T_d = 100$ ms, this would mean that half of the potential transmission time is spent for sensing.
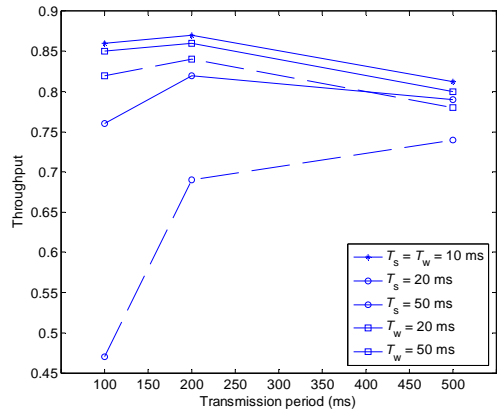


Figure 7. Throughput with different sensing and switching times.

Overall, the sensing time dominates the switching time in impact on the achieved throughput when stochastic traffic patterns are considered. This is especially true when the transmission period is short. The time spent for switching channels has a significant effect when the used idle periods of primary traffic are short and frequent switching is performed. Compared to the sensing time, another significant effect comes when the transmission period is not very short. Tolerable interference time $\Delta t$ of the PU sets limits for the length of transmission period since sensing has to be performed periodically in order to notice whether there is primary transmission on or not. In addition, the more the traffic is varying across the channels the better learning and prediction are working compared to the method based on instantaneous information.

### C. Classification-based prediction

Previous results basically show the benefit of prediction in the channel selection as well as the effect of the sensing and switching times to the performance. When classification is included in the prediction, there is even more gain. Fig. 8 shows the number of channel switching as well as number of collisions for situation where there are 10 primary channels including 5 stochastic and 5 deterministic ones. The stochastic traffic is Pareto distributed. Idle times of channels are between 1 s and 10 s. Results are shown for mean time based prediction and for classification based prediction with weightings of $w = \{1\ 0.7\ 0.5\}$. The smaller the value the more deterministic traffic is favored.

Results show that the intelligent mean-time based prediction already improves both channel switching and collision results significantly. When classification and more accurate predictions with deterministic traffic are employed the situation becomes even better. With all values of $w$ the number of switching is slightly lower than without classification. But the true difference comes in collisions. When classification is employed, the CR knows when it is

using a deterministic channel and can switch to the new channel just before collision. The amount of collisions drops by 35 % already when $w = 1$ and the reductions are 54 % and 62 % when $w = 0.7$ and $w = 0.5$, respectively. The results lead to a conclusion that weighting is preferred in channel selection to favor deterministic channels.
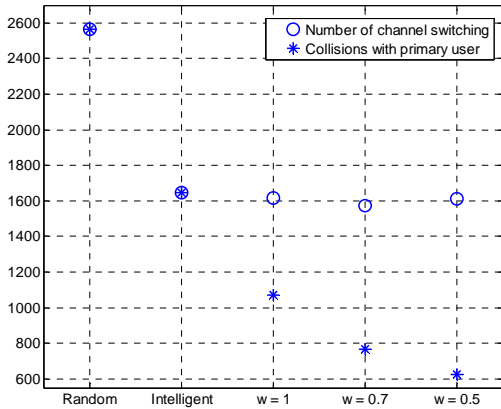


Figure 8. Performance results for classification-based prediction.

The proactive method is only worth to be used with predictable traffic. Since the expected idle time of stochastic traffic does not depend on the currently consumed idle time of the channel, there is no use to switch the channel before the PU appears. If the longest idle time offering channel was already selected and it is still available it should be used since it most probably offers longest idle time for secondary operation. Thus, either the proactive CR system has to be restricted to work inside certain primary system transmitting deterministic traffic or it has to have ability to classify the traffic. The classification makes prediction more accurate increasing the throughput and decreasing collisions with primary user. A CR system employing classification is able to work efficiently with variety of primary systems.

## V. CONCLUSIONS

Learning and classification methods improve the performance of a cognitive radio system. Classification divides traffic patterns into stochastic and deterministic ones, both needing own prediction rules. The intelligent channel selection scheme uses prediction results to find out channels offering the longest idle times for secondary use. The proposed method was verified by simulations with different traffic patterns. Prediction reduces the number of channel switching and increases throughput. An even higher gain is achieved with classification-based prediction since there it is possible to adapt the prediction to deterministic traffic and take advantage of the improved predictability when possible. Especially classification helps in reducing the collisions with primary users. Classification makes proactive operation possible also in the case where both stochastic and deterministic traffic

patterns exist together in primary channels. It was shown that sensing time has a larger effect on the performance than channel switching time when the transmission period is short. The prediction based method is most useful when there is a high variability in the traffic across the channels.

However, more work is needed in this area. An interesting thing to look at is the application of the method with real traffic measurements. Classification method should be further tested and developed for a noisy environment where sensing would work imperfectly. In addition to traffic patterns, learning and prediction could be incorporated in the spatial domain. Sensing results stored in the database together with geolocation information could give valuable information about spectrum use in different locations. CR nodes could possibly use beamforming antennas together with sensing to get even more detailed information about spatio-temporal use. This spatio-temporal use can also have some patterns over time and space which could be used in predicting where and when to operate with cognitive radio system.

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PAPER X

# Combination of short term and long term database for cognitive radio resource management

# Combination of short term and long term database for cognitive radio resource management

## *Invited paper*

Marko Höyhtyä[1], Johanna Vartiainen[2], Heli Sarvanko[1], and Aarne Mämmelä[1]

[1]VTT Technical Research Centre of Finland
P.O. Box 1100, FI-90571 Oulu
Finland

[2]University of Oulu, Centre for Wireless Communications
P.O. Box 4500, FI-90014 University of Oulu
Finland

*Abstract*—**We propose a method that uses long term information on the use of primary channels to select the most auspicious ones to be sensed and exploited by cognitive radios at the requesting time. These channels are investigated in more detail over the short term. Sensing results are stored in the short term database and used to predict which channels are best for data transmission. The method makes the operation of cognitive radios more reliable and efficient in terms of delay and throughput, and decreases collisions with primary users.**

## I. INTRODUCTION

The radio frequency spectrum bands are mostly allocated to licensed users but many bands are used only part of the time in a certain geographical location. Future wireless systems will accommodate more and more users and high performance services, thus needing more spectrum that is a scarce natural resource. Therefore, cognitive radios (CR) have been proposed for lower priority secondary systems aiming at improving spectral efficiency by sensing the environment and filling the discovered gaps of unused licensed spectrum by their own transmission. However, there are problems to be solved.

Spectrum sensing of all licensed channels consumes a lot of time that could be used for cognitive radio operation. In addition, channel switching based on instantaneous channel occupancy information may result in poor channel selection since the selected channel might be heavily utilized by primary user even though it happened to be available during the sensing time. This may cause frequent service disruptions for secondary users, thus resulting in interference to primary users. That would also increase delays of transmission and limit the capacity of the system. To solve the described problem, a CR could use databases including history information and prediction to make operation more efficient.

Predictive models have been proposed for spectrum sharing in [1]-[4] but these approaches have a common problem of restricting the prediction to a certain traffic model only. Exponentially weighted moving average based method to utilize idle times in TV broadcast channels is proposed in [1]. Exponential ON-OFF traffic models and periodic-exponential models are investigated in [2]. Reference [3] investigates the predictability when primary traffic is assumed to be representable by cyclostationary random process. Traffic prediction in [4] is performed using binomial distributed call arrival and gamma distributed call holding times. This method uses long term information in 24 hour periods in prediction.
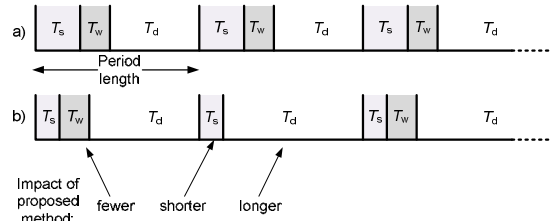
Figure 1. Impact shown in frame structure: a) original frame b) with the proposed method.

Long term information was proposed to be used to guide sensing in [5]. We proposed more general method that works with a variety of traffic classes in [6], [7]. The method classifies the traffic in different channels to deterministic and stochastic and uses specific prediction methods for different types of traffic to estimate what the following idle times in different channels will be. In addition, a recent patent [8] considers the use of database and prediction for cognitive radios for exploiting idle periods of TV channels.

The proposed method brings new aspects to the prior work by joint long term and short term database use. The proposed method is not limited to a certain type of traffic, but works with a variety of traffic patterns. Long term (LT) database aids the operation of cognitive radio system and reduces its sensing time by prioritization of channels. Short term (ST) database allows classification and prediction in the bands of interest. This leads to intelligent channel selection for data and control transmission and thus improves the system performance both by increasing the throughput of the secondary system and also reducing interference caused towards primary users. Combination of the LT and the ST database makes the operation faster and more efficient than either of these techniques alone. The combination seems to be unique in cognitive radio environment. The method is flexible and independent of the used frequencies and CR types. During the normal operation the LT database cooperates with CRs but if the connection to the LT database is lost, CRs can continue operating independently.

Impact and motivation of the proposed method in a simple way to the operation of cognitive radios is shown in Fig. 1. The use of the LT database shortens the sensing time $T_s$ because number of the channels to be sensed reduces.
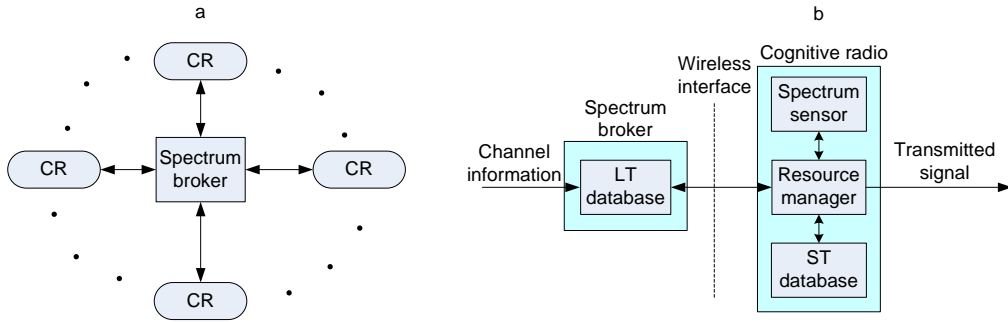
Figure 2. a) An example of the network and b) Block diagram of the system.

The use of the ST database reduces the channel switching rate. Thus, fewer reconfigurations consuming each $T_w$ from the operation time are needed. These both affect so that more time is left for data transmission, making data period $T_d$ longer. For that reason, capacity is increased and due to proper channel choices interference with primary users is reduced.

## II. System description

### A. Long term database and network model

A long term database aids and speeds up the sensing process by prioritizing the channels so that only most auspicious ones will be considered, thus reducing time needed for sensing. The LT database includes information about activities over different channels over long time period, e.g., a week. When access to primary channel is required, long term database could be used to check what the most auspicious bands are at that time (e.g., on Monday at 2 pm).

An example of the operating network and the block diagram of the system are shown in Figs. 2a and 2b, respectively. The spectrum broker includes the long term database in the example. However, the LT database can be included, e.g., in the base station or even exist separately. The LT database includes information from the channels of interest over the long term. Physically the LT database has to be local to its users since otherwise it cannot offer relevant information. It can be shared with several CRs located near each other, for example, in a campus area or in a company. Only the spectrum use spatially close to requesting cognitive radios is important to be known to assist the operation of them. Channel information can be gathered to the LT database with various approaches, including spectrum sensing and obtaining the spectrum knowledge through beacons or control channels or by sharing databases with licensed users. The LT database can also include policy database, which includes information about different quality of service (QoS) parameters for the channels to be used in channel selection, e.g., interference levels and parameters for different licensed systems. The LT database should be immobile to offer relevant information over its serving area.

Cognitive radio has a wireless interface to the LT database to change information with it. When a CR wants to access channel to send its data, it first connects to the LT database to ask what the most auspicious channels are. The LT database sends back $N$ channels to be sensed. In addition to frequency information such as centre frequency and bandwidth of the channel, the request and feedback includes information about how long channels are needed or predicted to be available. Thus, if a CR does not need spectrum for a long time, such channels can be offered to those users requesting longer times.

### B. Short term database and short method description

Short term database gives more detailed information over the bands of interest. The information about local channel use is gathered by periodical sensing and stored into the ST database. Every CR has its own ST database. Using pattern recognition and classification techniques that are crucial parts of an intelligent system, a cognitive radio can recognize and classify traffic patterns in different channels. This allows the system to use specific prediction methods for different types of traffic to make idle time prediction of channels as accurate as possible. Channels with the longest idle times are selected for operation. Mathematically the method works in a following way:

1) Pre-selection of $N$ out of $M$ channels using the LT database, $N < M$.

2) Final selection of $P$ out of $N$ channels using the ST database and sensing, $1 \leq P < N$

3) Returns $N - P$ channels into use of others.

Thus, the method uses three different timescales in the operation; long term, short term and instantaneous. Long term database includes information which is collected, e.g., over a day or a week. Short term information covers the channel use concerning current data transmission, e.g., over a few seconds or minutes. Spectrum sensing gives instantaneous information about channel use. Sensing can be performed cooperatively with other CRs to improve the detection probability [9]. Sensing information stored in the ST database can be just own sensing results or cooperative sensing data.

Periodically, a CR stops transmission to perform sensing to check the availability of channels, selects the channel, and continues transmission until all the needed data are sent. Only part of the $N$ given channels is used in the current transmission. Rest are returned to the LT database to be shared again.

## III. DETAILED DESCRIPTION OF THE METHOD

More detailed description is provided with Fig. 3 that is a flow chart diagram for the proposed method. Operation of the different blocks is described below.
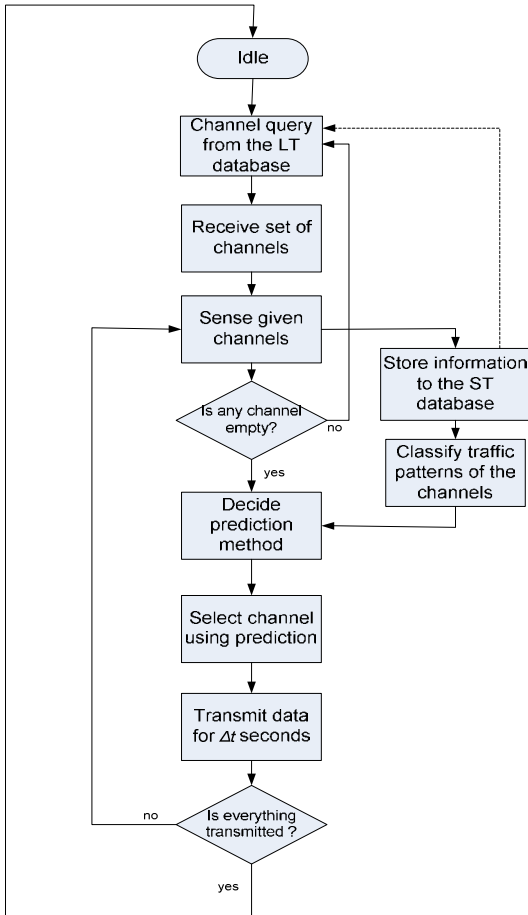


Figure 3. Flow chart of the proposed method.

**Channel query from the LT database:** A CR needs spectrum for data transmission and sends query to the LT database to get information about the most auspicious channels to sense and exploit. The query can be aimed to obtain only information about available channels or it can also include some additional information, e.g., estimated time for the total data transmission or needed capacity so that the LT database can response based on additional information.

**Receive set of channels:** LT database sends back information about suitable and auspicious channels, giving $N$ channels to be investigated, where $N > 1$. Time and capacity estimations can be used to define channels that are wide enough and offer needed time for transmission.

**Sense given channels:** Given $N$ channels are sensed to know whether they are now free or not.

**Store information to the ST database:** Sensing information of $N$ channels is stored into the short term database to be used in predictive channel selection. Dashed line connection between the ST and the LT database means that there is an option that the ST database can give feedback to the LT database especially when the given channels are not good for secondary use to update the situation. The spectrum use at the same area can change time to time and thus, LT database need to be updated.

**Classify traffic patterns of the channels:** It takes some time from the start of the operation to collect information to the ST database for prediction purposes. After the learning period the ST database has enough history information about given $N$ channels to analyze the traffic patterns of the channels. Prediction of future idle times depends on the pattern of the traffic. Thus, classification enables the use of specific prediction method for specific type of the traffic, making the prediction more accurate. A CR classifies the traffic patterns of all $N$ channels.

**Decide prediction method:** A CR decides the prediction method based on the classification. Prediction using short term information aims at finding most suitable channels for transmission, offering longest idle times to maximize the capacity of the secondary user as well as to reduce interference towards primary users. Short term information makes it possible to find the best ones from the list of channels provided by the LT database.

**Select channel using prediction:** Future idle times of the channels are predicted taking into account the classification result and the history from the ST database. The channels estimated to offer the longest idle times are selected into use. $P \geq 1$ channels are to be used in data transmission and the rest $N - P$ channels are returned to be offered to others requesting access to the spectrum.

**Transmit data for $t$ seconds:** After channel selection is done, the CR sends data for $t$ seconds in the channel. The parameter $t$ is the maximum tolerable interference time for the primary system which can, in practice, be a rather short period. If there are still data to be sent, the CR senses again the channels and continues transmission on an available channel. The parameter $t$ is a system dependent parameter that should be known for licensed systems operating on the same frequency band as the CR. Value for the parameter could be stored in the LT database and given to the requesting CRs simultaneously with other information of the set of $N$ channels.

After data transmission is over, $P$ channels are returned to the LT database. The LT database has to be updated regularly in order to keep the database up to date since radio environment and traffic patterns in different channels may change over time. Timescale for updating the information in the database needs to be carefully considered to avoid unnecessary overhead while offering valuable data for spectrum sharing purposes. However, this is a topic itself for research and is not covered in this paper.
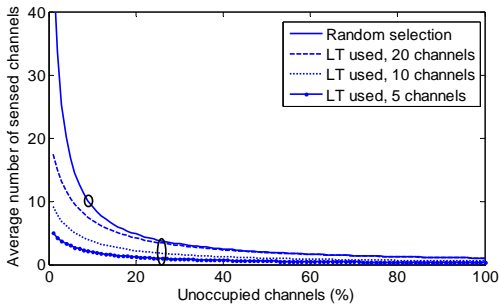
Figure 4. Number of channels to sense before an unoccupied one is found.

## IV. CHALLENGES AND POSSIBILITIES

Disadvantage of the solution is that complexity increases compared to the cognitive radio operating purely based on instantaneous sensing information. The proposed method requires also infrastructure for the database. However, there are several possible cases where the proposed method could be exploited, and the infrastructure itself can exist already. For example, to mention a few network models, *spectrum brokers* or *spectrum servers* can be used to enable coordinated dynamic spectrum access in a certain region [10], [11]. The server could include an LT database to make the spectrum use very efficient. When part of the decision making would be included in the cognitive radio side, the control signalling would not consume so much spectrum, allowing more time to cognitive radios for data transmission. Therefore, a CR including ST database would do intelligent decisions among the proposed resources from the server.

Another case is clustering that is a concept for network formation [12]. Clusters in the network are formed by connecting neighbour nodes sharing common channels that are locally available, and the network by interconnecting clusters through gateway nodes. *Clustered mesh networks* have been interesting in many commercial and military applications. The proposed system could be used in this kind of networks, each cluster including their own local LT database and devices having their ST databases. Applications that could be used with the proposed system are, for example, different wireless devices and wireless Internet access, e.g., for data downloading. The method could improve the performance and reliability of different CR systems used for military, emergency, and commercial purposes.

## V. PERFORMANCE ANALYSIS

### A. Sensing time with the LT database

The performance of the LT database can be measured with the sensing time that depends on the amount of channels needed to be sensed before an unoccupied one is found. As it was mentioned in [13], average number of sensed channels in random search is

$$m = \frac{N+1}{K+1}, \qquad (1)$$

where $N$ is the total number of channels and $K$ is the number of unoccupied channels. On average, this leads to the total sensing time to be $T_s = m t_s$, where $t_s$ is the sensing time of a single channel.

Assuming our system to cover 100 channels we can estimate the number of sensed channels depending on the way the LT database operates. This covers only the LT part, short term operation is not considered. The Fig. 4 shows that if all the 100 channels have to be covered, tens of channels are needed to be sensed in high occupancy situation. When the LT database proposes lower amount of channels, time needed to find a channel reduces. Parameter $N$ will have a smaller value and parameter $K$ will have proportionally higher value. However, the difference e.g., with 100 and 20 channels is very small when percentage of unoccupied channels is over 20 %.

However, in addition to smaller number of channels, the percentage of unoccupied channels is higher when the channels are selected by the LT database. Thus, one should compare random method with the LT one with a clearly higher percentage of unoccupied channels. One example is marked with ovals in Fig. 4. When percentage in random selection is 10 %, it can be clearly more than 20 % in the channels proposed by the LT database. This would mean that required number of sensed channels to find an available one drops down to a fraction of the original. As an example, if there are 10 available channels originally among 100 possible ones, these 10 available channels can be included in the set of 50 channels proposed by the LT database. In that case the percentage of unoccupied channels is doubled. The results indicate that the LT information always improves the performance, especially when the number of channels is restricted to 10 or below.

### B. Throughput performance with the combination of the LT and the ST database

Throughput values for the random, pure ST, and both methods combined with the LT database are shown in Fig. 5. Primary traffic is purely deterministic. Throughput is defined as the percentage of time during which the CR system can successfully transmit without colliding with the primary user. Assume that on average a collision takes half of the transmission time of a SU away between sensing instants as is the case with exponential traffic, and the following transmission time is shorter by a switching time. Then, throughput over a time interval [0, $T$] including $n$ transmission and sensing periods is

$$C_{CR} = \frac{T - n \cdot T_s - \delta \cdot T_d / 2 - \theta \cdot T_w}{T}, \qquad (2)$$

where number of collisions is , is the number of switching, $T_d$ is the transmission time of SU, $T_s$ is the sensing time, and $T_w$ is the switching delay.
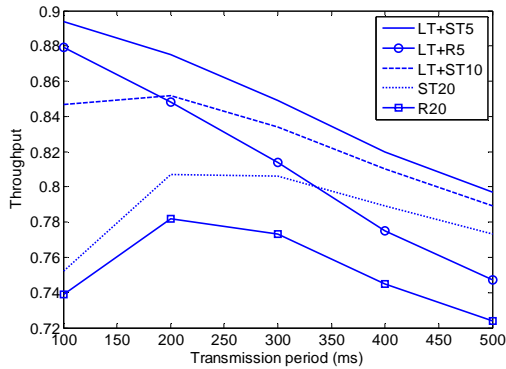
Figure 5. Throughput performance for the used methods.

We used 20 channels in simulations. Traffic in the channels has exponentially distributed ON and OFF times, and average OFF times in the traffic are distributed between 0.5 s and 2 s. Occupancy of the channels is uniformly distributed between 10 % and 90 %. As shown in Fig. 5, the worst performance is achieved with the pure random method. Inclusion of the ST database improves the performance clearly and with the longer transmission periods the improvement is higher.

The numbers in the figure legends tell how long the sensing periods are, e.g., R20 means random selection with 20 ms sensing time. We assume that both the pure ST and the pure random methods need 20 ms sensing time to go through all the channels. When the LT is applied, sensing time is smaller. We have tried sensing time values 5 ms and 10 ms in our simulations, meaning that 25 % or 50 % of channels are sensed after pre-selection made by the LT database. Switching time is fixed to 10 ms.

With low transmission period values the LT database gives a large performance improvement comparing to the methods without it. Reason for the behaviour is that with short transmission periods sensing time dominates in (2). A CR stops frequently data transmission to perform sensing. The LT based method enables shorter sensing times and thus the throughput is high when transmission period is short.

In addition to sensing, another significant effect comes with collisions when transmission periods are longer. As shown in (2), every collision takes half of the transmission period away. Thus, the longer the transmission period is the more a collision affects the throughput. Collision rate is decreased when the ST database is applied in channel selection process which improves clearly the situation.

When the LT with random short term selection is used, the performance is worse than with a pure ST method with longer transmission periods. Clearly the best performance with any transmission period is achieved with a combination of the ST and the LT database.

## VI. CONCLUSIONS

A cognitive radio system needs history information to operate efficiently in a heterogeneous radio environment. In this paper we present a method using both long and short term history information in radio resource management. Pure long term information improves the performance of cognitive radios in terms of sensing time. However, a lot of channel queries are needed when used channel changes frequently if the only source of information is a centralized LT database. When more detailed information locally is offered via an ST database, it becomes easier to avoid congested channels and use the ones offering good transmission opportunities. This reduces query delays in transmission. The results indicate that a hybrid system combining both long term and short term history information increases throughput of a CR system and decreases interference towards primary users of the spectrum.

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PAPER XI

# Improving the performance of cognitive radios through classification, learning, and predictive channel selection

# Improving the Performance of Cognitive Radios through Classification, Learning, and Predictive Channel Selection

Marko Höyhtyä, Sofie Pollin, and Aarne Mämmelä

*Abstract*—**Prediction of future idle times of different channels based on history information allows a cognitive radio (CR) to select the best channels for control and data transmission. In contrast to earlier work, the proposed method works not only with a specific type of traffic but learns and classifies the traffic type of each channel over time and can select the prediction method based on that. Different prediction rules apply to partially deterministic and stochastic ON-OFF patterns. New prediction methods for both traffic classes are developed in the paper. A CR predicts how long the channels are going to be idle. The channel with the longest predicted idle time is selected for secondary use. Simulations show that the proposed classification method works well and predictive channel selection method outperforms opportunistic random channel selection both with stochastic and deterministic ON-OFF patterns. Weibull, Pareto, and exponentially distributed traffic patterns are used in stochastic simulations to show general applicability of the proposed method. The classification-based method has even a higher gain when channels of interest include both stochastic and deterministic traffic. The collision rate with primary user over a given time interval can drop by more than 70% compared to the predictive system operating without classification.**

*Index Terms*—**Spectrum access, prediction, history information**

## I. INTRODUCTION

**A** cognitive radio should be more than a radio taking immediate advantage of spectrum opportunities. It should have the ability to learn from experiences. Learning makes the operation of cognitive radios more efficient compared to the case where only information available at the design time is possible. Ideally, information gathered during the lifetime of the radio should be used. However, the majority of cognitive radio research is focused on methods that use only instantaneous information about the environment as a basis for dynamic operation. Available channels for selection can be assumed to be equally good [1]–[3] or characterized based

on the interference level [4] or bandwidth [5] to prefer the ones with the lowest interference levels or the ones with the widest bandwidths. Secondary users sense their environment and react to estimated changes in spectrum availability in an opportunistic way. Such an approach can result in a bad channel selection since the system randomly selects channels that may be heavily used by primary users (PU) if that channel happened to be available during the sensing time. This may cause frequent service disruptions for secondary users since they have to refrain from transmission, and result in interference to primary users. In addition, every channel switch causes a non-negligible delay for the transmission. If a single channel can be used over a long period, such delays can be avoided and the capacity is improved.

The problem of using learning in channel selection has not been explored much in the literature. The seminal paper [6] emphasized that a dynamic spectrum management algorithm should include information about the traffic pattern of the primary user occupying the channel. The durations of ON and OFF times of the traffic are random variables determining the traffic pattern i.e., the ON-OFF pattern. In a wireless environment, two basic classes of traffic patterns exist [6]: 1) Deterministic patterns where the PU transmission is ON, then OFF during a fixed time slot; 2) Stochastic patterns where the traffic can be described only in statistical terms. Frame structures make traffic patterns fully or partially deterministic. Partially deterministic means that the ON time starts periodically but its length can vary while the length of the period, $T_{\mathrm{p}}$, is fixed as illustrated in Fig. 1. A period consists of one ON time followed by one OFF time, i.e., a time interval from the raising edge of the signal to the next raising edge. This definition covers also the deterministic periodic case where ON and OFF times are fixed. In our study, the traffic patterns are either stochastic or partially deterministic ones, and we will loosely use term deterministic from now on for the latter. Terms OFF time and idle time as well as ON time and busy time are used interchangeably in this paper.

In order to plan the secondary use of the spectrum better without cooperation with the primary user[1], some authors have proposed predictive models to be used in spectrum sharing [9]–[11]. One limitation of the mentioned papers is that the proposed method should not be restricted to one possible traffic model only. It should work with a variety of

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[1]In addition to the primary/secondary model, prediction can also be applied to systems relying cognitive techniques for recognition of radio resource availability in a heterogeneous environment [7]– [8].
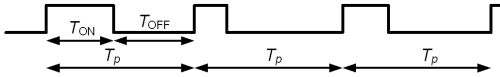
Fig. 1.   Partially deterministic traffic pattern.

traffic classes and thus, a general model would be needed. A radio can determine the modulation type from the incoming signal [12], [13] or classify jammers in spread spectrum burst transmission systems [14]. In order to work with a variety of traffic classes, a CR should recognize traffic patterns in different channels to be able to improve the use of the OFF times. Basically, a CR should characterize whether the traffic pattern is deterministic or stochastic and based on that it should use different methods for idle time prediction before selecting the channel.

Our contributions are an idea of using classification in the prediction, a simple classification and learning method to detect the pattern type and to gather needed information, an analytically derived method for idle time prediction both for deterministic and stochastic traffic patterns, and a rule for smart channel selection for data transmission and control exchange. In contrast to methods from [9]–[11], [15], the proposed method works not only with a specific type of traffic but learns and classifies the traffic type of each channel over time and can select the prediction method based on that. We verified our method with the measurement studies and tested it with different traffic patterns using simulations in comparison with an opportunistic random selection approach and achieved very encouraging results. The proposed classification-based prediction decreases the collision rate with the PUs greatly compared to the pure prediction based selection when the channels of interest include both stochastic and deterministic traffic. Actually, a recent article shows using extensive set of measurements that spectrum use in several different frequency bands is well modeled using the geometric distribution [16]. Thus, our proposed prediction method for stochastic traffic that is developed using maximum likelihood (ML) estimate for exponential distribution, continuous counterpart of geometric distribution, is close to optimal in many cases. Conducted tests with several different traffic models show the general applicability of the method.

Parts of this paper were presented in our earlier conference papers [17]–[19]. In the present combined paper we have extended the results and unified and elaborated the explanations and examples. Extended simulations with various traffic models have been conducted. In addition, we have made measurement studies both with 802.11 traffic and in the 450 MHz band to verify the practicability of the proposed approach. The classification is discussed with more details.

The organization of the paper is as follows. Section II presents the system model. The prediction method and traffic models are introduced in Section III. Channel switching schemes are presented in Section IV and performance metrics are defined in Section V. Measurement studies are discussed in Section VI and simulation results in Section VII. Applicability of the method in different situations is discussed in Section

VIII and the conclusions are drawn in Section IX.

## II. System model

Traffic prediction aims at forecasting future traffic as precisely as possible, based on the measurement history [20]. In a CR context the prediction aims at determining idle times in PU traffic to be used by secondary transmissions. In addition, history information gives valuable information to the sensing process. A CR system can abandon some channels after a certain learning time if it decides that the band is used almost all the time. It is not reasonable to waste resources to the bands that cannot offer communication possibilities. The energy efficiency is better if the system concentrates only on channels that seem to have long enough idle times.

### A. System model

We assume that the total available spectrum is divided into multiple primary channels to be sensed and used by cognitive radios. Each channel has its own independent traffic pattern. Fig. 2 represents the architecture for a predictive cognitive radio system. The CR collects information about the spectrum use in the different channels through spectrum sensing and stores this information into the channel history database in a binary format. Since the traffic patterns of the channels might slowly vary over time, the database should include information only over a limited time interval. Cooperative sensing may be needed to detect primary users reliably in the same area. The performance improvement of the cooperative spectrum sensing results from the exploitation of spatial diversity. The method works as follows.

1) All channels are sensed and the channel history database is updated with the most recent sensing information. The last sensing result is used to define the current situation in a particular channel. If the channel is free, the channel state (CS) flag is set to 0 and if not, CS = 1.
2) Based on the collected history, the traffic patterns of different channels are classified as stochastic and deterministic ones (see Section B).
3) Different prediction methods apply to different traffic patterns and the method selection is made following the traffic type classification.
4) The idle time prediction uses information from three sources. The CS flag of channels is checked first. If CS = 1, the predicted idle time is 0 s. If CS = 0, the remaining idle time of these channels is estimated based on the channel history and selected prediction method for that particular channel.
5) If the channel used currently is still free, secondary transmission continues. If not, the CR switches to the channel with the longest expected remaining idle time.
6) Data is transmitted and the system goes then back to the task 1) after $\Delta t$ seconds where $\Delta t$ is the maximum length of interference the PU can tolerate. It is a system dependent parameter that should be known for licensed systems operating on the same frequency band as the cognitive radio. If $\Delta t = 0$, CR operation is not allowed
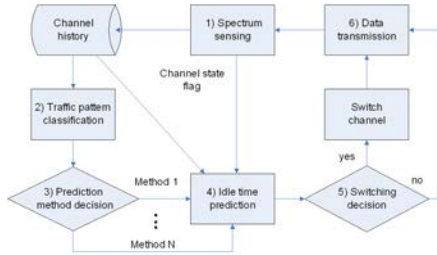
Fig. 2. System model for predictive transmission.

in that band. Requirements from standards and manufacturers, and interference measurement studies can be used to define numerical values for the parameter. However, this part is a research area on its own and out of scope of this paper.

### B. Classification of the traffic pattern

Sensing of primary channels is a periodic sampling process to determine the state (ON or OFF) of the channels at every sampling instant. The outcome of sensing is a binary sequence for each channel. This sequence tells us about the traffic that is ongoing. It has sufficient information to determine the periodicity, distribution of idle and busy times, and occupancy of the channel. Occupancy defines the fraction of the time that the primary user is transmitting in a channel. We assume perfect sensing in this paper. We do not consider the case where the primary users' ON or OFF times are shorter than the sampling interval which in our case equals to $\Delta t$. The real detected pattern is noisy and if the signal is weak that can cause some changes to the detected pattern.

Cognitive radio should identify the type of the traffic after a short learning period from the binary sequences gathered during that period. There are different types of traffic appropriate for prediction but basically they can be divided into two basic groups as discussed in the introduction. For stochastic and deterministic cases the prediction algorithm should be different. Initially the CR works under the assumption that the ON and OFF times are random in each channel. After the learning period is over, the CR has made a decision about the determinism or randomness of the traffic and can adapt the prediction method.

A very distinctive feature for classification in our case is the periodicity. We propose an edge detection based method, given as a pseudocode in Table I, for period search. The edges are found from input sequence where '0' turns to '1'. The average separation of these raising edges and the standard deviation of the separations tell us whether the traffic is deterministic or not.

### III. PREDICTION OF IDLE TIMES

### A. Deterministic traffic

Deterministic patterns can be found from different channels and with different timescales. In TV transmission periods can be really long, e.g., a day or a week. Shorter periods can be found e.g., from air-traffic control radar and weather radars [21]. In the fixed period case, it is possible that ON and OFF times are fixed or random. In the first case, we can make exact predictions about the future and fully use all available resources for secondary transmissions. For this case, the starting point of the OFF time for $M$ consecutive periods with length $T_\mathrm{p}$ is $T_{s,m} = t_m + T_\mathrm{ON}$, $m = 1, 2, \ldots, M$ where the beginning time of the period $m$ is $t_m = m \cdot T_\mathrm{p}$. The length of the OFF time is $T_\mathrm{OFF} = T_\mathrm{p} - T_\mathrm{ON}$ where $T_\mathrm{ON}$ and $T_\mathrm{OFF}$ are the lengths of the ON and OFF times. In the second case, the ON time is not fixed. When the channel becomes idle at time $t_0$, we know exactly how long it will be available before the PU appears again, namely

$$T_{\mathrm{OFF},m} = T_\mathrm{p} - (t_0 - t_m) \, m = 1, 2, \ldots, M, t_0 \geq t_m. \quad (1)$$

### B. Stochastic traffic

When the ON time is fixed and the OFF time random, we know the starting time of the idle time, but the length can be only estimated in a probabilistic way. In the case of fixed OFF times, we know the remaining idle time after the channel becomes available at time $t_0$. If both times are random, we estimate the expected remaining idle time after detecting the channel to become idle.

Each cognitive radio stores the measurements of idle and busy times in the database and constructs a histogram of them.

Average occupancy over the observation interval tells us how heavily the channel is used on average. To know more exactly what kind of traffic is going on, one should look at the distribution of idle and busy times. From the database, the probabilities that different channels will be available for at least $X$ seconds can then be calculated as

$$P(t \geq X) = \frac{\text{The number of idle time values} \geq X}{\text{The number of all idle times}}. \quad (2)$$

Using the database, a CR could estimate the time to transmit under an interference constraint, i.e., $W$ % guarantee not to interfere with PU. This means that it would transmit continuously without sensing a certain amount of time and trust in the distribution. To achieve this, the CR should choose its transmission time $Z$ so that $P(t \leq Z) = 1 - W/100$. Probability for real idle time to be smaller than $Z$ would then be $(100 - W)$ %. Using this approach the CR could adaptively loosen its sensing period requirements. However, doing so the sampling process slows down and in the future the database cannot give as accurate information.

*1) Prediction analysis::* Suppose we have a vector of $n$ samples of idle times from the channel $i$, $\mathbf{X}^i = (x_1^i, x_2^i, \ldots, x_n^i)$. Assuming exponentially distributed OFF times with traffic parameter $\lambda_\mathrm{OFF} >$ the probability density function of the exponential distribution is

$$f(x) = \begin{cases} \lambda_\mathrm{OFF} e^{-\lambda_\mathrm{OFF} x}, & x \geq 0 \\ 0, & x < 0 \end{cases}. \quad (3)$$

The maximum likelihood (ML) estimate for the traffic parameter is $\hat{\lambda}_\mathrm{OFF} = 1/\bar{x}$, where $\bar{x} = (1/n) \sum_{j=1}^{n} x_j$ is the sample mean. Because of the invariance property of the ML estimator

TABLE I
PSEUDOCODE FOR CLASSIFICATION

1. Computation of parameters
   1.1. Search edges from the input sequence
   1.2. Calculate average separation between consecutive raising edges, *tau_ave*
   1.3. Calculate standard deviation of separations, *std*
2. Traffic type classification
     if std = 0 or smaller than limit     % When the period length is constant,
        sequence is periodic = TRUE     % the sequence is periodic
        tau = round(tau_ave)          % The estimated traffic period length is tau_ave rounded
                                      % an integer
     else
        sequence is periodic = FALSE    % If standard deviation is too large, the sequence is not periodic

[22], ML estimate for idle time can be written as

$$\hat{T}_{\text{OFF}} = \frac{1}{\hat{\lambda}_{\text{OFF}}} = \bar{x}. \tag{4}$$

This means that, using the ML criterion, the best prediction of the next idle time is the average of the previous ones. In practice, traffic patterns of different channels might slowly vary over time. Thus, the observation interval for average calculation should be restricted. One possible way to do the calculation is to use the exponential weighted moving average (EWMA) method.

*2) Other distributions to describe wireless traffic:* **Weibull process:** Poisson model with exponentially distributed ON and OFF times has traditionally been used to model voice traffic and is often used in other network traffic studies. It is analytically tractable but does not fit so well to a bursty data traffic carried in a network. There are many different models where the burstiness of the traffic is taken into account [23]. Two widely used models, Weibull and Pareto processes, will also be under study.

The probability density function of a Weibull random variable $x$ is given by

$$f(x) = \begin{cases} \alpha\beta x^{\beta-1}e^{-\alpha x^{\beta}}, & x \geq 0 \\ x, & x < 0 \end{cases}, \tag{5}$$



Fig. 3.   Probability density functions of the distributions

where the scale and shape parameters are $\alpha > 0$ and $\beta \geq 0$. When $\beta < 1$, the Weibull distribution is heavy-tailed and can model the ON/OFF period lengths of self-similar network traffic [23]. The mean value for the distribution is $E[x] = 1/[\alpha\Gamma(1 + 1/\beta)]$, where $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}$ is the gamma function. If $z$ is a positive integer, then $\Gamma(z) = (z-1)!$. We consider here the case $\beta = 1/2$ which leads to $E[x] = 2/\alpha$.

**Pareto Process:** Another model that has been found to model nicely ON/OFF periods in the real network traffic is the Pareto distribution [23]. The probability density function of this distribution is given by

$$f(x) = \beta\frac{\alpha^{\beta}}{x^{\beta+1}}, \; x > \alpha \tag{6}$$

where $\beta > 0$ and $\alpha > 0$ are the shape and scale parameters of the distribution. The mean value of the distribution is $E[x] = \alpha\beta/(\beta - 1)$ for the shape parameter value of $\beta > 1$. The expected value is infinite if $\beta \leq 1$. Other important characteristic of the distribution is that the variance of a random variable $x$ is infinite if $\beta \leq 2$. The degree of self-similarity is measured by the Hurst parameter given by $H = (3 - \beta)/2$. Traffic is self-similar if $0.5 < H < 1$.

The probability density functions of the three discussed distributions are shown in Fig. 3. The mean value for the distributions is fixed to 3 and the parameter $\beta$ in Pareto distribution is 2. The tails of the distributions can be seen in the lower part of the figure, showing the heavier tails of the Weibull and Pareto distributions compared to the exponential distribution.

## IV. CHANNEL SWITCHING SCHEMES

### A. Predictive channel switching

Secondary users use the predictive models of spectrum availability, and schedule their spectrum use in order to maximize spectrum occupancy while minimizing the disruption rate to primary users. To do that, the CRs have to select the channel to switch to in a smart way.

When switching channels, a user switches to the available channel $i$ with the largest predicted remaining idle time $T_i$, chosen from the set of the $m$ channels as
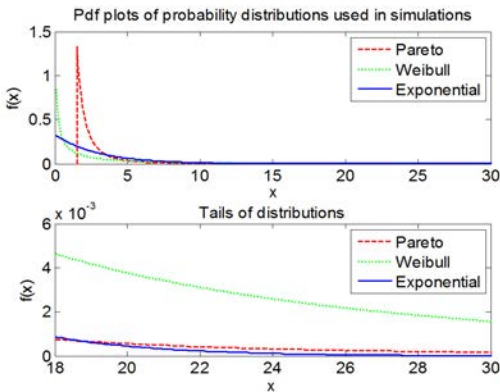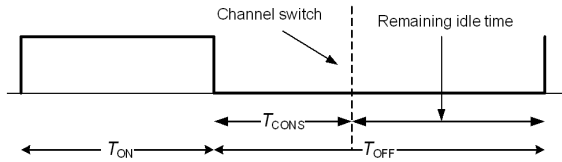
$$T_i = max_j T_j \tag{7}$$

Fig. 4.    Different times of channel usage.

where $T_j$ $j = 1 \ldots, m$, is the calculated or estimated remaining idle time of the channel $j$. Below, we specify the prediction rules for different traffic types based on different times that are defined in Fig. 4. In the case of the deterministic signals, the prediction is

$$T_j = T_p - T_{ON}^j - T_{CONS}^j. \tag{8}$$

This means that from the predicted idle time for the channel the consumed idle time $T_{CONS}^j$ is subtracted, i.e., the time when the channel was already idle while the CR was operating in a different channel. For stochastic signals we estimate the remaining idle time with the mean idle time due to previous analysis and the measurement study provided in Section 6. The predicted idle time is $T_j = T_{mean}^j$, i.e., the mean idle time of the channel.

When the distribution of idle times is memoryless, as is the case with the exponential distribution, the consumed idle time does not affect the probability of the channel being idle in the future. With memoryless property we mean that observations from the past do not affect the recent situation. If the channel was idle in the previous time instant, it will be idle at the next instant with a constant probability that only depends on the parameters of the distribution. Therefore, there is no need to subtract the consumed idle time from the prediction.

Since a deterministic traffic can be predicted very accurately, weighting can be used in channel selection to favor deterministic channels. The deterministic channel is selected if the estimated idle times of stochastic and deterministic channels are close to each other. The prediction of the OFF time in a deterministic traffic is then as shown in (8) but the prediction of the stochastic traffic is weighted as $w \cdot T_j$, $w \leq 1$, i.e.,

$$T_j = \begin{cases} T_j = T_p - T_{ON}^j - T_{CONS}^j, & \text{if traffic is deterministic} \\ w \cdot T_{mean}^j, & \text{if traffic is stochastic.} \end{cases} \tag{9}$$

### B. Random channel switching

A random channel selection scheme corresponds to a situation when only instantaneous information of the channel conditions is known. A cognitive radio senses the spectrum and picks up randomly one channel among all available ones into use. The same channel is used as long as it is available. When switching is required, the next channel selection is done randomly using the uniform distribution. Suppose the sensing gives a vector of $m$ samples $C = (c_1, c_2, \ldots, c_m)$ showing the current channels available for secondary use, lowest frequencies first. Random selection happens by rounding $m \cdot U$ into the nearest greater integer and selecting the corresponding channel

from $C$. Symbol $U$ is a random number that is uniformly distributed in the interval $(0, 1)$.

### C. Optimal channel switching

Optimal channel selection could be done if all the traffic patterns with exact ON and OFF times in different channels were known in detail also in the future. When switching is required, the channel that is free and offers longest remaining idle time at the moment of switching is selected. Ideal switching scheme is used in simulations to show the lower bound for the channel switching rate, i.e., number of channel switching in a time unit.

Fig. 5 shows channel selection possibilities. Sensing is done through all channels and during sensing the cognitive radio is not transmitting. A CR can select the next channel randomly or based on prediction. Prediction improves selection: channel $j$ is a much better choice than channel $k$ because it offers a longer time for CR operation. CR can select the next channel reactively or proactively. The reactive method switches to a different channel after the PU is sensed to appear in the same channel. The proactive method changes the channel before collision. It predicts that the PU will appear soon and switches to the next channel.

## V. PERFORMANCE MEASURES

*Channel switching rate*: Every channel switch causes some delays for the transmission and frequent switching decreases the capacity and makes the network management more difficult. Thus, a good metric for the frequency control is the channel switching rate, i.e., the number of channel switching in a second. Minimization of the switching rate decreases also the probability for collisions with primary user since the switching rate is partly dependent on the collisions.

*Throughput*: A good performance metric for the cognitive radio system is the percentage of time during which it can successfully transmit without colliding with the PU. Throughput of each SU over a time interval $[0, T]$ is defined now as

$$C_{CR} = \lim_{T \to \infty} \frac{\text{Successful transmission time in } [0, T]}{T}. \tag{10}$$

Assuming that on average, collision takes half of the transmission time of a SU away between sensing instants as is the case with exponential traffic, and following transmission time is shorter by a switching time, throughput over a time interval $[0, T]$ including $n$ transmission and sensing periods is

$$C_{CR} = \frac{T - n \cdot T_s - \delta \cdot \frac{T_d}{2} - \theta \cdot T_w}{T} \tag{11}$$

where number of collisions is $\delta$, $\theta$ is the number of switching, $T_d$ is the transmission time of SU, $T_s$ is the sensing time, and $T_w$ is the switching delay. With the reactive channel selection method the number of collisions equals to the number of channel switching.

*Collision rate*: Collision happens when both primary and secondary users simultaneously transmit on the same channel. Collision rate between SUs and PUs can be used as a PU protection metric since one aim of cognitive radio networks is
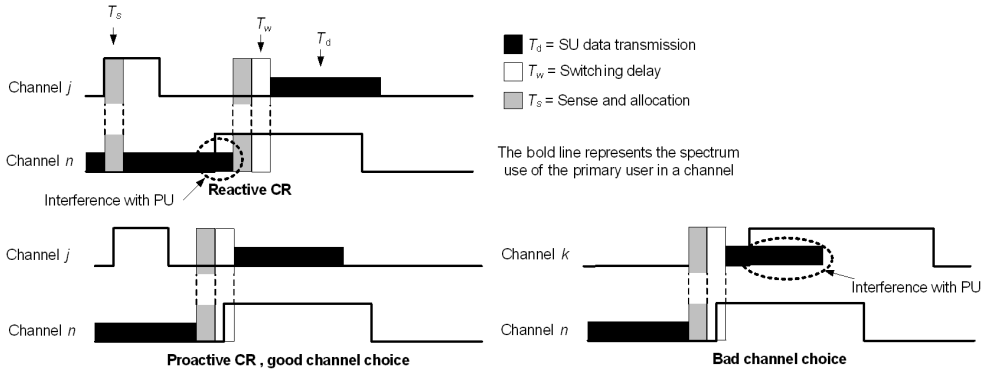
Fig. 5.   Different channel switching schemes.

to keep interference with primary users in a minimum level. The collision rate $R_C$ can be defined as

$$R_C = \lim_{T \to \infty} \frac{\text{The number of PUs collided packets in } [0, T]}{T}.$$
(12)

## VI. Measurement Studies

### A. The 802.11 traffic

We tested the proposed mean time based prediction with the exponential weighted moving average (EWMA) method using real 802.11 traffic measured at the University of California, Berkeley. ON/OFF patterns were derived from the timestamps of reception and the length of packets. The mean OFF time for traffic was 5.6 ms which is roughly speaking ten times longer than the usual packet size 0.5 ms. Idle time values were between $[2.07 \times 10^{-4} \text{ms}, 97.6 \text{ms}]$. Most idle times were very short. EWMA method was tested with different $\mu$ values to see if we can predict next idle times based on history. The method is given as

$$T_{n+1} = \mu \cdot I_n + (1 - \mu) T_n$$
(13)

where $T_{n+1}$ is the new estimated idle time, $T_n$ is the last estimated idle time, $I_n$ is the latest real idle time, and $\mu$ is a constant attenuation factor between 0 and 1. Time-window for estimation is selected with the parameter $\mu$, which defines the weighting for time samples. Weighting decreases exponentially for each older sample. When $\mu$ is close to 1, recent samples are heavily weighted, and older history does not affect much. With small $\mu$ older samples get more weight.

The prediction was done over a set of $M = 27000$ samples and the accuracy was measured with average squared prediction error $\varepsilon$

$$\varepsilon = \frac{1}{M} \sum_{n=1}^{M} (I_n - T_n)^2$$
(14)

where $I_n$ is the real idle time and $T_n$ the predicted idle time. Small values of $\mu$ give the best performance as can be seen from Table II. Actually the best "prediction" was achieved with

averaging over all values ($\varepsilon = 2.37 \times 10^{-4}$) which confirms the stochastic prediction rule.

It is sufficient to know the probability distributions of the idle and busy times to characterize random traffic. If idle times are exponentially, or in the discrete analogous case, geometrically distributed, the mean is a sufficient characterization of the whole probability distribution. In reality, we do not know exact lengths of idle times as we are sensing every $\Delta t$ seconds for $Y$ seconds to obtain reliable results, which limits our ability to measure and detect short times. In addition, every channel switch can take several milliseconds with today's equipment. Thus, CR should concentrate on using channels that offer longer OFF times. Also, to use OFF times efficiently, they should rather be tens of times longer than the switching times, i.e., times needed to reconfigure transceivers for new frequency and to continue transmission.

### B. 450 MHz band

To see whether we can find deterministic patterns from real traffic we investigated also spectrum measurements conducted in Netherlands in 2007 around 450 MHz band. The measurement set was performed over frequency range [459.62 MHz, 467.82 MHz] with a bandwidth resolution of 100 kHz. The band of interest is allocated to several wireless systems including intercom connection and land mobile services. Measurement had 10 000 samples of data with an intersample period of 120 ms for all 500 channels. To reduce the impact of noise we filtered the measured data with a moving average filter with window of 5 samples before performing the analysis. The window size has been experimentally shown to represent the optimal relation between noise filtering and a possible information loss in [24] where more details in the measurement setup can be found. Binary ON-OFF patterns for all channels

TABLE II
MEAN SQUARED PREDICTION ERRORS WITH DIFFERENT VALUES OF $\mu$

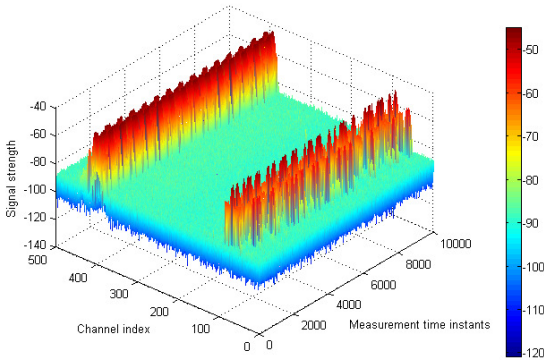| $\mu$ | 0.1 | 0.3 | 0.5 | 0.7 | 0.9 | 1.0 |
|---|---|---|---|---|---|---|
| $\varepsilon$ | $2.48 \times 10^{-4}$ | $2.92 \times 10^{-4}$ | $3.40 \times 10^{-4}$ | $3.93 \times 10^{-4}$ | $4.58 \times 10^{-4}$ | $5.00 \times 10^{-4}$ |

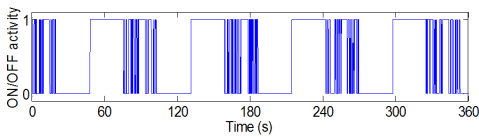Fig. 6.   3D surface spectrogram of the measurement set



Fig. 7.   Traffic pattern from the measurements.

were extracted using the same threshold as the one used in [24], i.e., -80 dBm. The spectrogram of the measurement set is shown in Fig. 6.

The mean spectrum occupancy over the band is only about 7 % which means that roughly 93 % of spectrum is available for spectrum use. It is easy to see the areas that can be efficiently used by a CR. However, also the parts of the spectrum that have wireless transmission on have lots of opportunities for secondary operation, especially using the proposed classification-based method. We were interested in looking at the patterns in the channels having both ON and OFF periods.

For example, a channel shown in Fig. 7 included determin-istic traffic pattern that is used approximately 50 % of time. Long periodically repeating idle periods in this channel are slightly more than 28 seconds long which means that they are very well suitable for secondary use by cognitive radios.

## VII. CLASSIFICATION AND CHANNEL SELECTION SIMULATIONS

We made experiments with deterministic and stochastic traffic patterns in order to see how well the proposed predictive channel selection approach works when compared to the random opportunistic channel selection. Parameters for the simulation are shown in Table III. The chosen parameter values correspond to the maximum tolerable interference time of a PU to be 100 ms. Actual transmission time $T_d$ of the SU in one transmission period is 100 ms $- (T_s + T_w)$. Latter is dropped out if channel switching is not needed. We tested the edge detection based classification method with noiseless

TABLE III
SIMULATION PARAMETERS

| Parameter | Value |
|---|---|
| Transmission period | 100 ms |
| Sensing period | $T_s$ |
| Switching delay | $T_w$ |
| Number of channels | 5, 10, 15, 20 |
| Primary user traffic models | Stochastic channels with exponen-tially, Pareto, and Weibull dis-tributed ON and OFF times Deterministic channels with fixed ON and OFF times |
| Occupancy, mean idle times of stochastic, and period lengths of deterministic primary traffic | Occupancy of channels between [0.1, 0.9], mean idle times [1 s, 10 s], period lengths [2 s, 20 s] |
| Simulation time | 10 000 s |
| Channel selection methods | Predictive channel selection, random selection |
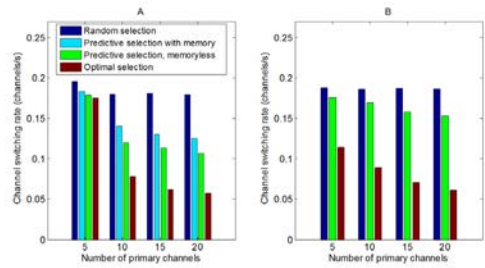


Fig. 8.   Channel switching rate with exponential traffic: two different idle value distribution sets (A and B)

stochastic and deterministic traffic and the method classified patterns without problems. In practice, noise is always present and causes problems to detection and classification; results shown here provide an upper bound of the performance for the method.

### A. Prediction: Impact on channel switching

We examined the channel switching rate with the presented methods. For simplicity, the classification was assumed to work perfectly. Every simulation was conducted 10 times and the results were averaged. Results for exponential traffic are shown in Fig. 8.

Fig. 8a shows the situation with the parameters in Table II. In Fig. 8b the mean idle time of channels were between 4 s and 6 s. Regarding Fig. 8a, with 5 channels the methods are almost equally good since there are not many channels to choose from. When the number of primary channels is in-creased, the difference between the predictive and the random selection increases since the former can concentrate on the best channels.

As can be expected with distribution having memoryless property, a better performance is achieved without subtracting the consumed idle time away from the prediction. The reduc-tion in channel switching ranges from 9 % with 5 channels to 39 % with 20 channels while the average number of available
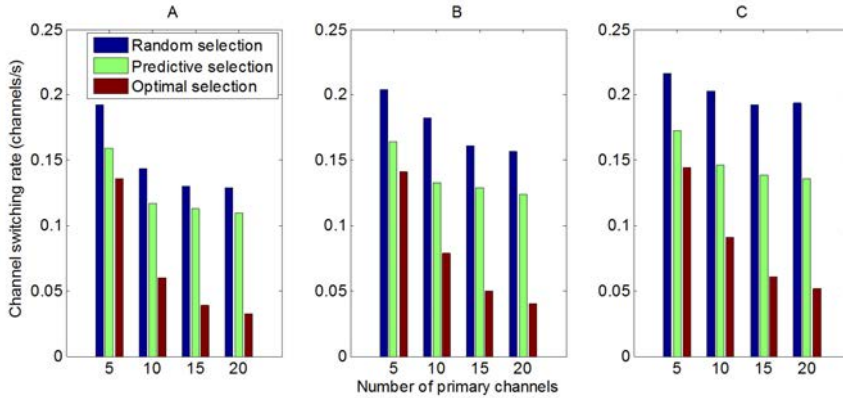
Fig. 9. Channel switching rate with Pareto traffic. The subfigures show results with parameter values $\beta = 1.8$, $\beta = 2$, and $\beta = 2.2$.

channels increases approximately linearly as {2.5, 5.8, 8.1, 9.7} when number of primary channels are {5, 10, 15, 20}. The mean idle times for the channels were 5.5 s.

With lower variation the gain of prediction is smaller as can be seen in Fig. 8b. The reason is the fact that the quality of good channels is not much better than the average quality of the channels. In the previous results the average value for mean idle times of all channels was 5.5 s while the best channels had almost two times larger value. Now the average value is 5 s and the best channel offers only 1 s longer mean idle time.

The difference between the proposed predictive method and the optimal selection can be quite large since the optimal method can take advantage of long idle time values that come from the tail of the distribution. Predictive method makes the decision based on the average time. The random selection follows approximately the average idle time distribution with more switches with lower average idle times whereas the predictive method takes advantage of the increasing number of good channels. The more the traffic is varying across the channels the better learning and prediction are working compared to methods based on the instantaneous information.

Weibull traffic simulations lead to the same kind of results as the exponential traffic simulations, as shown in Table IV, even though the distribution has a long, heavy tail. The number of switching is always lower with the predictive method and the difference gets larger as the number of channels increases. The reduction in channel switching ranges from 13 % with 5 channels to 36 % with 20 channels. The bigger average idle time value determines the better channel well also in this case.

Pareto simulations were done with different values of the parameter $\beta$. Very interesting values are around 2 since the variance of Pareto distributed random variables is infinite when $\beta \leq 2$. When $\beta$ is larger than 2 and becomes smaller, the variability increases. The same limit also defines the self-similarity of the traffic. When $\beta = 2$, the Hurst parameter value is $H = 0.5$. It is larger with the lower values of $\beta$ and vice versa.

Results with the parameter values $\beta = 1.8$, $\beta = 2$, and $\beta = 2.2$ are shown in Fig. 9a, 9b, and 9c, respectively. The

TABLE IV
REDUCTION IN CHANNEL SWITCHING

|  | 5 channels | 10 channels | 15 channels | 20 channels |
|---|---|---|---|---|
| **Exponential** | 9 % | 33 % | 35 % | 39 % |
| **Weibull** | 13 % | 26 % | 30 % | 36 % |

predictive selection offers better performance than random selection with all parameter values. Interestingly the difference in performance between different selection methods is smaller when the number of channels increases with parameter values $\beta \leq 2$. One reason behind this phenomenon is the fact that the quality of the available channels measured by mean values is closer to each other with higher number of channels. This together with high variability leads to the situation where the mean time based selection does not offer great advantage over the random selection. The channel with a lower mean value can easily have a longer idle time to offer. The optimal selection curve shows that with a lower value of $\beta$ the number of optimal switches is lower due to higher variability inside the channels. There are more long idle times in the traffic. When the value of $\beta$ increases, the variability decreases, and the gain of using the predictive selection method increases compared to the random selection. The performance gain, measured in reduction of channel switching, of using the predictive method is up to 30 % with 20 channels. The largest gains are achieved with the parameter value $\beta = 2.2$.

The performance with deterministic traffic patterns is very good since the predictive selection method can predict the idle times perfectly to select the best channels for secondary use. The method is identical to the optimal selection method when the traffic is deterministic. The gain compared to the random method is large all the time. With 20 channels, the switching rate with the predictive selection is 64 % lower than with the random selection. Deterministic traffic is more deeply covered in Section 7C.
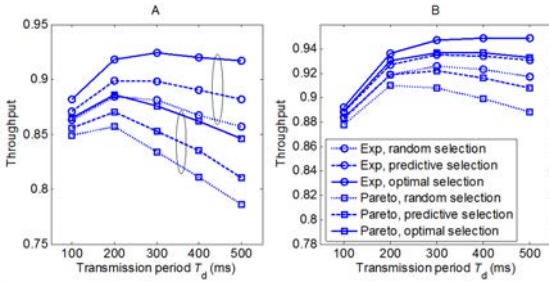
Fig. 10.  Achievable throughput with two different idle value distribution sets (A and B).



Fig. 11.   Throughput with different sensing and switching times.

## B. Impact on throughput and collision rates

Throughput results for various transmission period values with the exponential and Pareto traffic are shown in Fig. 10. PU idle times of the 10 primary channels are uniformly distributed in the range of [0.5 s, 2 s] in Fig. 10a and in the Fig. 10b the idle times are between [1 s, 5 s]. Same legends apply for both. We used period lengths from 100 ms to 500 ms.

The results show that throughput increases in both figures when $T_d$ increases from 100 ms since larger proportion of time is used for data transmission instead of sensing. In Fig. 10a the increase of $T_d$ up to 500 ms clearly reduces the throughput since the collisions decrease more the efficient transmission time. The main reason is that it takes longer to find a new available channel for transmission when the time between two consecutive sensing is longer. When the situation in Fig. 10b is considered the throughput with $T_d = 500$ ms is actually better compared with the 100 ms case with both traffic models. This is due to longer idle times since frequent sensing affects more the performance than collisions that do not occur so often. The performance variations between the different transmission periods are now smaller since longer idle times mean smaller collision and channel switching rates. Predictive selection outperforms the random selection in all cases and the largest gain is achieved with larger $T_d$ since decreasing the collision rate affects the throughput more in this case.

Fig. 11 represents the situation where sensing and switching times can be 10 ms, 20 ms, or 50 ms. Especially with shorter $T_d$ the increase of $T_s$ decreases the throughput remarkably. Since the CR senses the spectrum periodically, the lower the $T_d$ is the more time is consumed in sensing. When the same parameters as in Fig. 10a are used, the increase of $T_s$ from 10 ms to 20 ms decreases the throughput by 0.1 when $T_d = 100$ ms and only 0.02 when $T_d = 500$ ms since sensing cuts away part of the transmission time, i.e., loss is $T_s/T_d$. The difference decreases with larger $T_d$ since the sensing is not performed so often. Changing the switching time does not have such a large effect on the total performance when $T_d$ is small since the sensing time always dominates. With higher values of $T_d$ the effect of switching is close to the effect of sensing. The throughput decreases drastically if $T_s$ is set to a remarkably higher value, e.g., to 50 ms. When $T_d = 100$ ms this would mean that half of the potential transmission time
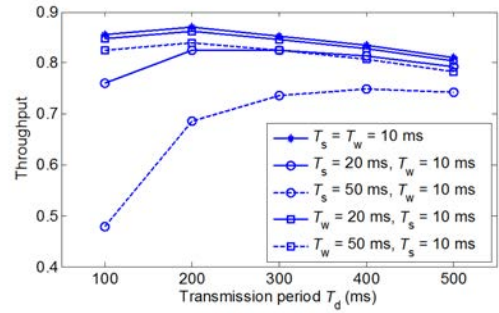
is spent for sensing.

Sensing time dominates the switching time $T_w$ in impact on the achieved throughput when stochastic traffic patterns are considered. This is especially true when $T_d$ is short. The time spent for switching channels has a significant effect when the idle periods of the primary traffic are short and frequent switching is performed. Compared to the sensing time, another significant effect comes when the $T_d$ is not very short. Tolerable interference time $\Delta t$ of the PU sets limits for the length of the transmission period since sensing has to be performed periodically in order to notice whether there is primary transmission on or not.

## C. Classification-based prediction

As shown in Fig. 5, a reactive CR switches to a different channel after a PU is sensed to appear in the same channel. To reduce the interference with the PUs, a CR could switch proactively to a new channel before the PU appears in the current band. Previous results basically show the benefit of the prediction in the channel selection as well as the effect of the sensing and switching times to the performance. Now, classification and proactive operation are also considered. Fig. 12 shows the channel switching rate as well as the collision rate for a situation where there are 10 primary channels including 5 stochastic and 5 deterministic ones. The stochastic traffic is Pareto distributed. Idle times of the channels are between 1 s and 10 s. Results are shown for random selection, for the mean time based prediction, and for the classification-based prediction with weightings of $w$ in (9). The smaller the value $w$ is, the more the deterministic traffic is favored. Reactive channel selection is used with the random and predictive methods, i.e., the channel switching rate equals the collision rate.

Results show that the predictive mean-time based prediction already improves both channel switching and collision results significantly. When classification and more accurate predictions with deterministic traffic are employed the situation becomes even better. With all values of $w > 0$, the switching rate is close to the result without classification. Smallest values are achieved when $w = 0.5$. But the true difference comes in collisions. When classification is employed the CR knows when it is using a deterministic channel and can switch to
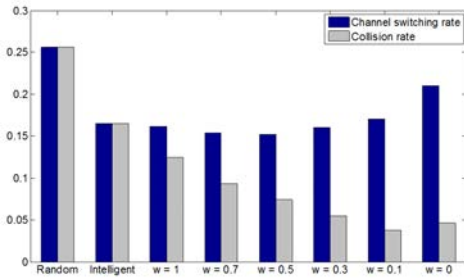
Fig. 12. Performance results for classification-based prediction.

a new channel just before a collision. The collision rate drops by 25 % already when $w = 1$ and the reductions are 44 %, 55 %, 67 %, and 77 % when $w = 0.7$, $w = 0.5$, $w = 0.3$, and $w = 0.1$, respectively. When $w = 0$, both the channel switching rate and also the collision rate increase. The reason is that the parameter $w$ should be $> 0$ to be able to select good stochastic channels if deterministic ones are not available. If $w = 0$, the system cannot differentiate quality of stochastic channels and thus can select bad channels for use. The collision rate would be zero only if during every time instant a deterministic channel would be available. This was not the case here.

The results lead to a conclusion that weighting is preferred in the channel selection to favor the deterministic channels. However, in order to find good channels among stochastic ones when needed, parameter $w$ should be positive.

## VIII. APPLICATION OF THE METHOD IN DIFFERENT SITUATIONS

One clear conclusion drawn here is that a proactive method is only worth to be used with the predictable traffic. Since the expected idle time of a stochastic traffic does not depend on the currently consumed idle time of the channel, there is no use to switch the channel before the PU appears. If the longest idle time offering channel was already selected and it is still available it should be used since it most probably offers longest idle time for secondary operation. Thus, either the proactive CR system has to be restricted to work inside a certain primary system transmitting deterministic traffic or it has to have an ability to classify the traffic.

The method can be used also when many SU users or even several SU systems are active simultaneously at the same geographical area. One way to do that is to have additional governing entity i.e., spectrum broker, operating at the same area. This entity gives permission to the SU to operate over a set of channels, different systems having their own sets. Then, predictive method is applied in these channels. Actually the set of channels could be selected so that only the most promising ones would be given to the SU systems to reduce the sensing time and be able to operate on the channels offering good possibilities for secondary use. This would require measurements and analysis over a long term. The topic is discussed in [25].

## IX. CONCLUSIONS

We investigated both classification and prediction methods separately. Simulations and measurements were used to verify methods. The proposed prediction method is a general one, applicable to a variety of traffic models unlike the previous proposals. With all investigated traffic models the number of channel switching reduces and throughput increases when prediction is applied. An even higher gain is achieved with the classification-based prediction since there it is possible to adapt the prediction to deterministic traffic and take advantage of improved predictability when possible. Especially classification helps in reducing the collisions with primary users. Classification makes proactive operation possible also in the case where both stochastic and deterministic traffic patterns exist together in primary channels. It was shown that the sensing time has a larger effect on the performance than the channel switching time when the transmission period is short. The more the traffic is varying across the channels the better learning and prediction are working compared to the method based on instantaneous information.

However, more work is needed in this area. Studies here were made assuming perfect detection and a delayless channel. Classification method should be further tested and developed for a noisy environment. In some cases the prediction of busy times in addition to idle times could make sense. Depending on the application used and its quality of service requirements, this allows estimating if we could stay and wait for the channel to become idle instead of frequency switching. Multi-hop ad hoc networks are possible target systems for this kind of operation. In multi-hop networks, every frequency change causes a need for an update of the routing table that is a database that stores the routes to particular network destinations. If this happens very frequently, a large amount of energy and bandwidth resources are consumed to keep those tables up-to-date and as a result, the capacity of the system decreases.

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**Marko Höyhtyä** obtained his M.Sc. (Tech.) degree in information engineering in 2005 from the University of Oulu. From the beginning of 2005 he has been at VTT Technical Research Centre of Finland where he has been working with power control, beamforming, and cognitive radio technologies. He is currently working towards the D.Sc. (Tech.) degree. In 2007–2008 he made a one year research visit to the Berkeley Wireless Research Center, CA. His research interests include adaptive algorithms, transmitter power control, and spectrally efficient communication. He is especially interested in adaptive power and frequency allocation strategies in a cognitive radio network.

**Sofie Pollin** received a degree in electrical engineering in 2002 and a Ph.D. degree in 2006 (with honors) from the Katholieke Universiteit Leuven, Belgium. Since October 2002 she has been a researcher at the Wireless Research group of the Interuniversity Microelectronics Center (IMEC). In the summer of 2004 she was a visiting scholar at National Semiconductor, Santa Clara, California. In the summer of 2005 she was a visitor at the UC Berkeley. In 2006, she started as a post-doctoral researcher at the UC Berkeley working on coexistence issues in wireless communication networks. Since 2008, she has been a senior researcher at IMEC working on cognitive radio.

**Aarne Mämmelä** received the degree of D.Sc. (Tech.) (with honors) from the University of Oulu, Finland in 1996 in the field of telecommunications. From 1982 to 1993 he was with the University of Oulu and in 1993 he joined VTT Technical Research Centre in Oulu. Since 1996 he has been a research professor of digital signal processing in wireless communications at VTT. Since 2004 he has also been a docent at the University of Oulu. He is interested in digital signal processing in adaptive, cognitive, and nonlinear systems in wireless communications.

# Autocorrelation-based traffic pattern classification for cognitive radios

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# Autocorrelation-Based Traffic Pattern Classification for Cognitive Radios

Marko Höyhtyä, Heli Sarvanko, Marja Matinmikko, and Aarne Mämmelä

VTT Technical Research Centre of Finland

P.O. Box 1100, FI-90571 Oulu, Finland

Marko.Hoyhtya@vtt.fi

*Abstract*—**This paper proposes a autocorrelation-based method to classify traffic patterns of primary channels in cognitive radio systems to allow a more accurate prediction of the future idle times. The classification algorithm uses binary information collected by spectrum sensing. It searches periodicity from the sensed binary pattern using a discrete autocorrelation function. Errors that are caused by noise and possible false sensing reports are filtered away from the autocorrelation function. We tested the method with Pareto, Weibull, and exponentially distributed stochastic traffic, and with deterministic traffic. The proposed method finds the type of traffic with a high probability when the channels of interest include both stochastic and deterministic traffic. Stochastic traffic is always classified right and regarding the deterministic traffic the probability of correct classification is over 95 % when the probability of missed detection or probability of false alarms is below 10 %.**

## I. INTRODUCTION

Predictive models have been proposed for cognitive radios (CR) to make channel selection more intelligent, and to improve the performance of CR systems [1]–[4]. The proposed approaches have had a common problem of restricting the prediction to the known traffic model only. We proposed a more general method that works with a variety of traffic classes in [5] and made a more detailed investigation of this approach in [6]. The method classifies the traffic in the sensed primary user (PU) channels as deterministic and stochastic and uses specific prediction methods for different types of traffic to estimate what the expected idle times in the different channels will be. It was shown in [6] that classification-based predictive channel selection method works well with various traffic models. The classification makes prediction more accurate increasing the throughput and decreasing collisions with the PU. A CR system employing classification is able to work efficiently with variety of primary systems. However, the paper did not consider the classification problem very deeply.

Classification of signals in CR environment has been considered in different studies. The classification has usually meant modulation classification. A good example of this kind of study is presented in [7]. However, good traffic pattern classification studies do no exist. It was emphasized already in [8] that a CR should know about the traffic pattern of the PU occupying the channel. In a wireless environment, two basic classes of traffic patterns exist: 1) Deterministic patterns where the PU transmission is ON, then OFF during a fixed time slot; 2) Stochastic patterns where the traffic can be described only in statistical terms. Poisson distributed traffic is one example of stochastic traffic. Prediction of future idle times for the stochastic signals can be made using the mean values of previous idle times [6]. Frame structures make traffic patterns fully or partially deterministic. Deterministic traffic can be observed e.g., in TV transmission, where the periods can be long such as hours, days, or weeks. The terms OFF time and idle time as well as ON time and busy time are used interchangeably in this paper.

Following the discussion above, it is useful to develop a classification method to distinguish between stochastic and deterministic patterns. Periodicity search has been proposed in [3] using the maximum value of the autocorrelation function. However, this method has clear restrictions as is shown in Section III. Thus, we have proposed modifications for the method in our previous papers in [5] and [6]. To extend the previous work, we investigate now the classification part in detail. We show the performance of classification under noisy or unreliable sensing and compare our modified method to the one proposed in [3]. We verified our method with numerical analysis and careful simulations with different traffic patterns. The developed algorithm is shown to work reliably under imperfect detection.

Organization of the paper is as follows. Section II presents the predictive channel selection model. The classification method and used traffic patterns are introduced in Section III. Performance metrics are presented in Section IV, classification results in Section V and finally Section VI concludes the paper.

## II. SYSTEM MODEL FOR PREDICTIVE TRANSMISSION

The system model for predictive channel selection is the same as considered in our previous papers [5], [6]. The total available spectrum is divided into multiple primary channels to be sensed and used by CRs. Each channel has its own independent traffic pattern. Initially the system operates using instantaneous sensing information. Prediction can be applied after a short initial learning period. Fig. 1 represents the architecture of our predictive cognitive radio system.

The CR collects information about spectrum use in the different channels through spectrum sensing and stores this information into the channel history database in a binary format. Since the traffic patterns of the channels might slowly vary over time the database should include information only over a limited time interval. The predictive transmission works as follows. 1) All channels are sensed and the channel history database is updated with the most recent sensing information. The last spectrum sensing result is used to define the current situation in a particular channel. If the channel is free, the channel state (CS) flag is set to 0 and if not, CS = 1. 2) Based on the collected history, the traffic patterns of different channels are classified as stochastic or deterministic. 3) Different prediction methods apply to different traffic patterns
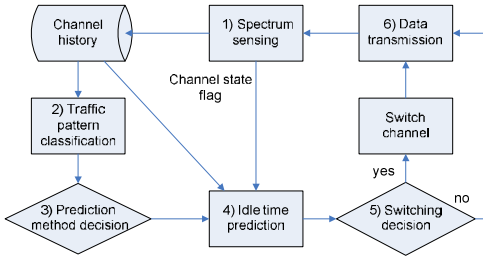
Figure 1. System model for predictive transmission.

and the method selection is made following the traffic type classification. 4) The idle time prediction uses information from three sources. The CS flag of channels is checked first. If CS = 1, the predicted idle time is 0 s. If CS = 0, the remaining idle time of these channels is estimated based on the channel history and selected prediction method for that particular channel.

5) If the channel used currently is still free, secondary transmission continues. If not, the CR switches to the channel with the longest expected remaining idle time. 6) Data is transmitted and the system goes then back to the task 1) after $\Delta t$ seconds to check and update the channel state and improve the channel selection. $\Delta t$ is the maximum length of interference the PU can tolerate. It is a system dependent parameter that should be known for licensed systems operating on the same frequency band as the cognitive radio. Requirements from standards and manufacturers together with interference measurement studies can be used to define numerical values for the parameter.

## III. TRAFFIC CLASSIFICATION

### A. Traffic models

The sensing of primary channels is a periodic sampling process to determine the state (ON or OFF) of the channels at every sampling instant. The outcome of sensing is a binary sequence for each channel. When a sufficiently long history of traffic patterns of channels is stored in the database, the patterns can be classified and appropriate prediction performed. A couple of periods is enough for deterministic traffic.

Frame structures make traffic patterns fully or partially deterministic. Partially deterministic means that the ON time starts periodically but its length can vary while the length of the period, $T_p$, is fixed as illustrated in Fig. 2. A period consists of one ON time followed by one OFF time, i.e., a time interval from the raising edge of the signal to the next raising edge. This definition covers also the deterministic periodic case where ON and OFF times are fixed.

In addition to the deterministic traffic, we use also stochastic traffic models in our study. This covers the use of exponential, Pareto, and Weibull distributed traffic. Exponentially distributed ON and OFF times have traditionally been used to model voice traffic and is often used in other network traffic studies. However, Weibull and Pareto distributions match better to packet traffic that consists of bursts of packets [10]. The mean idle time is an optimal prediction for exponential traffic. It is shown to be a good prediction also for

the other mentioned stochastic traffic patterns [6]. In practice, prediction is made as an average of the previous idle times.
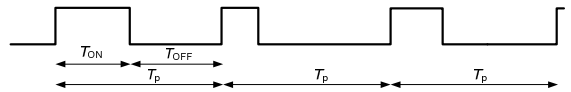


Figure 2. Partially deterministic traffic pattern.

### B. Classification method

Initially the CR works under the assumption that the ON and OFF times are stochastic in each channel. After the short learning period is over, the CR has made a decision about the determinism or randomness of the traffic and can adapt the prediction method. The length of the learning period depends on the ON and OFF times of the traffic. With perfect sensing only few traffic periods is needed but if there are errors in the sensing the learning period has to be longer.

#### a) Autocorrelation computation

A very distinctive feature for classification in our case is the periodicity. First, the periodicity is searched from the binary sequence. We can use the autocorrelation function [5] to find out the length of $T_p$ in different channels. First the discrete autocorrelation function (ACF) at lag $m$ for a discrete signal $x[n]$ of length $N$ is calculated as

$$R_{xx}[m] = \sum_{n=0}^{N-m-1} (x[n]x[n+m]) . \tag{1}$$

Authors in [3] proposed to use the global maximum of the ACF for detection of the period length. The problem is that this does not work if the period is fixed and the ON and OFF times are not. It works well only if all the times are fixed. When the ON and OFF times can vary within the period, the peak values are not constant anymore. In addition, a variation in the lengths of ON and OFF times inside the fixed period creates random local maximums in the autocorrelation function that are much smaller [6]. We call these fake maximums. In order to calculate the period based on the maximums in the ACF, one has to filter fake maximums away to obtain correct results. We propose a modified ACF based binary classifier to detect deterministic and stochastic traffic patterns from the binary sensing information. A pseudocode for the algorithm is given in the Table I.

#### b) Fake maximum filtering

Filtering of fake maximums as well as noise reduction is done with a median filter [11]. The window size we experimentally found good for our purposes is 5, i.e., the entry itself and two preceding and two following entries are considered in filtering. Thus, median filtered signal is

$$R_{xm}[m] = \text{Median } (R_{xx}[m\text{-}2], R_{xx}[m\text{-}1],..., R_{xx}[m+2]) \tag{2}$$

The window size is enough to smooth the signal efficiently but not too large to avoid losing useful information. Even though the median filter itself is a pretty powerful technique for noise reduction, additional processing using a mean filter is required for the signal to enable more reliable classification, i.e.,

TABLE I. Classification algorithm as a pseudocode.

| |
|---|
| 1. Computation of parameters<br>   1.1. Compute autocorrelation of the input sequence<br>   1.2. Filter fake maximums away using median and mean filtering<br>   1.3. Calculate average separation between consecutive local max values, $\tau_{av}$<br>   1.4. Calculate standard deviation of separations, *std*<br><br>2. Traffic type classification<br>       if $\sigma = 0$ or smaller than limit $\eta$     % When the period length is constant,<br>           sequence is periodic = TRUE   % the sequence is periodic<br>           $\tau$ = round($\tau_{av}$)          % The estimated traffic period length is $\tau_{av}$ rounded<br>                                        % an integer<br>     else<br>           sequence is periodic = FALSE   % If standard deviation is too large, the sequence<br>                                    % is not periodic |

$$R_{mm}[m] = ( R_{xm}[m\text{-}2]+ R_{xm}[m\text{-}1]+...+ R_{xm}[m\text{+}2])/5. \tag{3}$$

Combination of median filtering followed by a mean filter smoothes the ACF defined in (1), filtering out both the noise and fake maximums from it. The peaks of the smoothed signal (3) can then be used by the classification algorithm shown in Table I both to detect the traffic type and in case of deterministic signal to define the period $T_p$.

The smoothing of the signal is shown in Fig. 3. Original ACF of the noisy signal is shown in Fig 3a and the modified filtered ACF signal in Fig 3b. As can be seen from the figure, the filtering smoothes the signal very well which makes it applicable for further analysis.
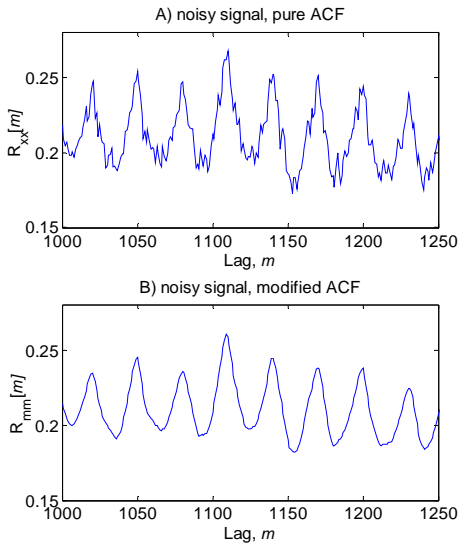


Figure 3. Autocorrelation sequence for noisy signal, before (a) and after (b) filtering.

However, some small peaks can still exist in the valleys of the signal. A simple additional filtering can be done to remove them by comparing a value of the peak to the value of the

previous peak. When the difference is too high, i.e., the new peak $\kappa$ is under $\beta$ % of the previous one, we can conclude that this is not the real maximum, i.e., if $\kappa(i) < \beta/100 \cdot \kappa(i\text{-}1)$.

*c) Calculation of average separation of peaks*

From the filtered signal, average separation between peaks is calculated. First, local maximums are searched using an algorithm that exploits the following information: Local maximum $\kappa$ is the point $m^*$ if there is some $\varepsilon > 0$ such that $R_{mm}(m^*) \geq R_{mm}(m)$ when $|m - m^*| < \varepsilon$. The average separation of $N$ consecutive peaks can be calculated as

$$\tau_{av} = \frac{1}{N-1}\sum_{i=2}^{N} d(i-1) \tag{4}$$

where $d(i\text{-}1) = \kappa(i) - \kappa(i\text{-}1)$.

*d) Calculation of standard deviation and final decision*

To make the classifier even more robust to small errors, minor deviations in the peak separation is allowed. The concept of standard deviation

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} (d(i) - \tau_{av})^2} \tag{5}$$

is used before the final decision is made. For the classification decision, i.e., Part 2 in Table I, the limit for standard deviation is set to $\sigma < \eta$, where $\eta$ is a value that is proportional to $\tau_{av}$. The longer the period is the bigger the deviation is allowed to be.

## IV. PERFORMANCE METRICS

The reliability of the classification is partly dependent on the sensing. Classification works very well with perfect sensing. However, there are always errors affecting the sensing performance. Let us check the sensing process.

The goal of the spectrum sensing is to decide between the two hypotheses, namely

$$x(t) = \begin{cases} n(t) & , H_0 \\ h(t)s(t)+n(t) & , H_1 \end{cases} \tag{6}$$

where $x(t)$ is the complex signal received by the cognitive radio, $s(t)$ is the transmitted signal of the primary user, $n(t)$ is the additive white Gaussian noise (AWGN) and $h(t)$ is the complex amplitude gain of the channel. $H_0$ is a null hypothesis, which states that no licensed user signal is present. $H_1$ is the alternative hypothesis which indicates that a primary user signal exists.

The following metrics can be used to measure the performance of a spectrum sensor. Probability of missed detection is defined as the probability that an occupied spectrum is sensed to be idle, while the probability of false alarm is the probability that an idle spectrum is sensed to be occupied by a licensed user. To define more formally, the probability of missed detection is

$$P_{md} = P\{Y < \lambda \mid H_1\} \tag{7}$$

where $Y$ is a decision statistic and $\lambda$ the decision threshold. The probability of false alarm can be defined as

$$P_f = P\{Y > \lambda \mid H_0\}. \tag{8}$$

Both of these metrics affect to the performance of the classifier. Probability of incorrect detection [12] is defined as

$$P_{id} = P(H_1)P_{md} + P(H_0)P_f. \tag{9}$$

This metric takes both false alarms and missed detections into account. From the classification point of view, any deviation in an estimated binary pattern to the real situation is significant. Thus, $P_{id}$ is a natural performance metric for the study. There are clear causes for the incorrect detection. When the signal-to-noise ratio is not high enough, errors occur in detection. An example of this kind of situation is shown in Fig. 3a. Another source for errors is malicious operation by other wireless users. For example, sensing targeted attacks [9] can cause problems for sensing. Thus, it is important that the classifier works well under non-ideal circumstances.

The performance of a classifier itself is most straightforwardly measured by the probability of correct classification

$$P_c = P\{\hat{c} = c\} \tag{10}$$

where $\hat{c}$ is the estimated traffic class and $c$ is the real traffic class. In words, it is defined as the probability that the traffic pattern is classified as deterministic when it is actually deterministic and for stochastic when it actually is stochastic.

## V. CLASSIFICATION RESULTS

We tested the classification method with different stochastic and deterministic traffic patterns. We investigated both the case of perfect sensing and a more practical approach where noise is present and causes problems for detection and classification. Perfect sensing results provide an upper bound of the performance for the methods. The stochastic patterns, including Weibull, exponentially distributed, and Pareto distributed stochastic patterns were always classified right in

the simulations, also in the noisy situation. The classifier recognizes this without problems. The fact that the classification is based on the periodicity search explains this well. Stochastic patterns are not periodic. The parameter value $\beta$ for simulations was 0.7 and $\eta = \tau_{av}/10$. We had 5 primary channels with stochastic traffic and 5 channels with deterministic traffic in our simulations. A single simulation covered 300 seconds time. The period length $T_p$ for the deterministic traffic varied between 3 s and 20 s, sensing period $\Delta t$ was 100 ms. All the simulations were done 100 times and the results are shown as averages of all the simulations as well as averaging over the channels. Thus, a deterministic result means that the result is an average classification result of 5 channels over 100 hundred simulations.
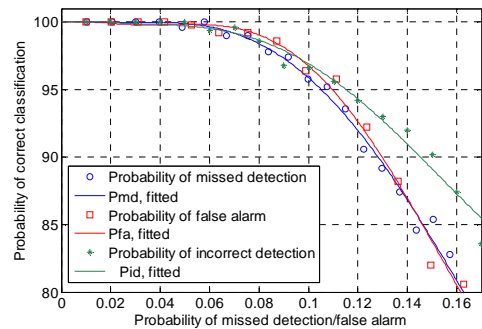


Figure 4. Probability of correct classification using the modified ACF based method, deterministic traffic.

With a deterministic traffic the proposed method found patterns with fixed ON and OFF times without problems when perfect sensing results are used. The situation changes when the method is tested with a noisy deterministic traffic. The results are shown in Fig. 4. The probability of correct classification is presented in terms of the sensing performance that is measured both with the probability of missed detection, with the probability of false alarms, and with the probability of incorrect detection. In the experiments, either missed detections or false alarms occur, or both of them. For example, when the $P_{md}$ is 0.05, it means that 5 percent of the bits '1' in the binary pattern have been changed to '0'. When probability of incorrect detection is considered, any bit is changed with a given probability. The selected bits have been randomly chosen using uniform distribution. The aim was to see whether the algorithm is more sensitive to missed detections or to false alarms. However, no large differences can be seen. The achieved performance is very good with low probability of missed detection as well as with the low probability of false alarms. The probability of correct classification is more than 95 % when the probabilities of missed detection and false alarms are below 10 %.

When the probability of sensing errors increases, performance drops down. The reason is the fact that it becomes harder and harder to search periodicity from the binary sequence and the classification method is not anymore

capable of filtering the effect of sensing errors out. Regarding the probability of incorrect detection curve, we can see that when the errors can be caused both by missed detection and false alarms as is the case in reality, the classifier is even more robust. Probability of correct classification is almost 95 % when the $P_{id}$ is 12 %. The performance gap to the other curves increases after this point. From the classification algorithm point of view, it is better that errors are spread randomly throughout the sequence. Pure missed detections or false alarms hide the periodicity more efficiently. Actually probability of incorrect classification figure is the most interesting one, since the false alarms and missed detections affect the performance equally, depending partly on the values of $P(H_1)$ and $P(H_0)$. In the realistic systems both of these are present.

The results indicate that the proposed classifier can work well under sensing errors and even tolerates some sensing targeted attacks [9] when stochastic and purely deterministic signals are considered. The acceptable values for $P_{fa}$ and $P_{md}$ in real systems are below 10 % to keep interference towards PUs low enough and the throughput in an acceptable level. Especially the values of $P_{md}$ are needed to be low in CR systems to avoid interference toward PUs. The results indicate that the proposed classifier suits very well for a practical system.

When ON and OFF times can vary inside the period, the ACF method is not working so reliably anymore due to additional fake maximums that cannot always be filtered away. We present only the most interesting results for the partially deterministic traffic, i.e., probability of correct classification as a function of probability of incorrect detection. The results are presented in Fig. 5.
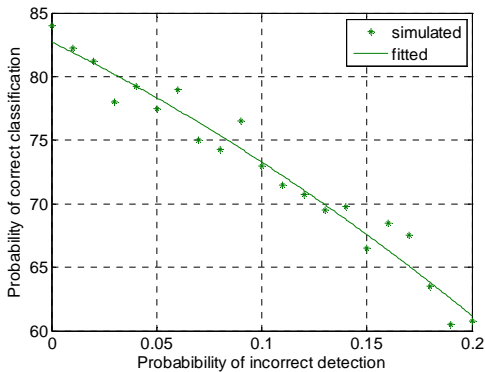


Figure 5. Probability of correct classification, partially deterministic traffic.

The performance results show that even with the perfect detection the classification method cannot always make right decisions when partially deterministic traffic is considered. Compared to the full deterministic signal results, we can see for example that when the $P_{id} = 10$ %, the $P_c$ is below 75 %. This is more than 20 percent units lower than in the previous case. However, this means that most of the time the system is able to use more accurate prediction algorithms in these channels to estimate precisely the idle times. As mentioned previously, the results are averaged over several channels. Short periods were found clearly more efficiently than the long ones. When $P_{id}$ was set to 0.15, the $P_c$ was 0.97 when $T_p$ was 3 s while the $P_c$ was 0.47 with the $T_p = 16$ s. The longer the periods are the more the sensing errors there are and especially the varying ON and OFF times hide the correlation between consecutive periods.

## VI. CONCLUSION

Learning and classification methods are essential for a cognitive radio system, improving the performance in terms of throughput and delay. We proposed a classification method that divides traffic patterns into stochastic and deterministic ones, both needing own prediction rules. The method can be used by CR systems to allow more accurate predictive channel selection. Furthermore, traffic classification can enable a good resource management tool for optimization of the network. From the practical point of view the proposed method is based on autocorrelation function that can be used in real-time applications. The results indicate that the proposed method works reliably in the presence of sensing errors. However, more testing with real measured data for the method is still needed and we plan to continue the work in this area.

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| Title | **Adaptive power and frequency allocation strategies in cognitive radio systems** |
|---|---|
| Author(s) | Marko Höyhtyä |
| Abstract | This doctoral thesis comprises a summary of novel results considering (1) channel selection in a cognitive radio system (CRS) using history information and (2) power allocation in a selected frequency band assuming a fading channel. Both can be seen as methods to manage interference between in-system users as well as to the users of other systems operating in the same geographical area and frequency band. Realization of CRSs that are using various methods to obtain information about environment and making intelligent decisions based on that information requires the use of adaptive transmission. Adaptive techniques proposed in this thesis enable efficient operation of CRSs in varying radio environment.<br><br>History information and learning are essential factors to consider in the CRS design. Intelligent use of history information affects throughput, collisions and delays since it helps to guide the sensing and channel selection processes. In contrast to majority of approaches presented in the literature, this thesis proposes a classification-based prediction method that is not restricted to a certain type of traffic. Instead, it is a general method that is applicable to a variety of traffic classes. The work develops an optimal prediction rule for deterministic traffic pattern and maximum likelihood prediction rule for exponentially distributed traffic patterns for finding channels offering the longest idle periods for secondary operation. Series of simulations were conducted to show the general applicability of the rule to a variety of traffic models. In addition, the thesis develops a method for traffic pattern classification in predictive channel selection. Classification-based prediction is shown to increase the throughput and reduce the number of collisions with the primary user up to 70% compared to the predictive system operating without classification.<br><br>In terms of the power allocation work, the thesis defines the transmission power limit for secondary users as a function of the detection threshold of a spectrum sensor as well as investigates theoretical water-filling and truncated inverse power control methods. The methods have been optimized using rational decision theory concepts. The main focus has been on the development and performance comparison of practical inverse power control methods for constant data rate applications. One of the key achievements of the work is the development of the filtered-x LMS (FxLMS) algorithm based power control. It can be seen as a generalized inverse control to be used in power control research, giving a unified framework to several existing algorithms as well. |
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| Nimeke | **Adaptiiviset tehon ja taajuuden allokoinnin strategiat kognitiivisissa radiojärjestelmissä** |
|---|---|
| Tekijä(t) | Marko Höyhtyä |
| Tiivistelmä | Tämä väitöskirja sisältää yhteenvedon tuloksista koskien 1) historiatietoa käyttävää kanavanvalintaa kognitiiviradiojärjestelmässä ja 2) tehon allokointia valitulla taajuuskanavalla häipyvässä kanavassa. Molemmat menetelmät auttavat häiriönhallinnassa sekä järjestelmän omien käyttäjien välillä että muiden samalla alueella toimivien järjestelmien suhteen. Ympäristötietoa useilla eri menetelmillä keräävien ja tämän tiedon mukaan älykkäitä päätöksiä tekevien kognitiiviradiojärjestelmien toteuttaminen vaatii adaptiivisten lähetystekniikoiden käyttöä. Väitöskirjassa ehdotettujen adaptiivisten menetelmien käyttö mahdollistaa kognitiiviradiojärjestelmien tehokkaan toiminnan vaihtuvassa radioympäristössä.<br><br>Historiatiedot ja oppiminen ovat olennaisia kognitiiviradiojärjestelmän suunnittelussa huomioitavia asioita. Älykäs historiatietojen käyttö vaikuttaa kapasiteettiin, törmäyksiin ja viiveisiin, koska se auttaa ohjaamaan sensorointia ja kanavanvalintaprosessia. Toisin kuin valtaosa kirjallisuuden menetelmistä, väitöskirja ehdottaa luokitteluun perustuvaa menetelmää, joka ei rajoitu tiettyyn liikennemalliin. Ehdotettu menetelmä on yleinen ja toimii useiden liikenneluokkien kanssa. Työssä on kehitetty optimaalinen ennustussääntö deterministiselle liikenteelle ja suurimman uskottavuuden estimaatti eksponentiaalisesti jakautuneelle liikenteelle, kun tavoitteena on löytää lähetyskanavat, jotka tarjoavat mahdollisimman pitkät vapaat ajat sekundääristä käyttöä varten. Väitöskirja osoittaa simulointien avulla sääntöjen soveltuvan myös muille malleille. Lisäksi työssä on kehitetty luokittelumenetelmä liikennemalleille ja osoitettu luokitteluun perustuvan ennustavan kanavanvalinnan lisäävän kapasiteettia ja vähentävän törmäyksiä primäärisen käyttäjän kanssa jopa 70 % verrattuna luokittelemattomaan ennustavaan kanavanvalintaan.<br><br>Tehoallokointityössä on määritelty lähetystehorajoja sekundäärisille käyttäjille spektrin sensoroinnin ilmaisukynnyksen funktiona ja tutkittu teoreettista täyttömenetelmää ja katkaistua kanavainversiomenetelmää. Menetelmiä on optimoitu käyttäen rationaalista päätösteoriaa. Pääfokus tehonsäätötyössä on ollut käytännöllisten vakiodatanopeutta käyttävien inverssimenetelmien kehittämisessä ja suorituskykyvertailuissa. Yksi väitöskirjatyön pääsaavutuksista on ollut FxLMS-algoritmiin perustuvan tehonsäätömenetelmän kehittäminen. Sen voi katsoa olevan yleinen inverssisäätöalgoritmi, jonka erikoistapauksina saadaan määriteltyä monet käytännölliset algoritmit. |
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| Julkaisija | VTT<br>PL 1000, 02044 VTT, puh. 020 722 111 |

# Adaptive power and frequency allocation strategies in cognitive radio systems

This thesis studies (1) channel selection in a cognitive radio system (CRS) using history information and (2) power allocation in a selected frequency band assuming a fading channel. Both can be seen as methods to manage interference between in-system users as well as to the users of other systems operating in the same geographical area and frequency band. Adaptive techniques proposed in this thesis enable efficient operation of CRSs in varying radio environment.

Intelligent use of history information affects throughput, collisions and delays since it helps to guide the sensing and channel selection processes. This thesis proposes a classification-based prediction that is applicable to a variety of traffic classes. Classification-based prediction is shown to increase the throughput and reduce the number of collisions with the primary user up to 70% compared to the predictive system operating without classification.

In terms of the power allocation work, the thesis defines the transmission power limit for secondary users. The main focus has been on the development and performance comparison of practical inverse power control methods. One of the key achievements of the work is the development of the filtered-x LMS (FxLMS) algorithm based power control that can be seen as a generalized inverse control to be used in power control research.