Advanced coexistence technologies for radio optimisation in licensed and unlicensed spectrum

(ACROPOLIS)

Document Number D8.2

Machine Learning and Information Theoretic Techniques for Cognitive Radio and Networks

Contractual date of delivery to the CEC:	30/09/2012
Actual date of delivery to the CEC:	30/09/2012
Project Number and Acronym:	257626 - ACROPOLIS
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Participants:	TUD, RWTH, KTH, CTTC, PUT
Workpackage:	WP8
Security:	Public (PU)
Nature:	Report
Version:	1.0
Total Number of Pages:	70

Abstract:

This deliverable provides a brief review and survey of applications of selected Artificial Intelligence techniques, including popular Machine Learning methods, which can be applied to cognitive radio and wireless networking. Moreover, it contains an overview over recent research on Cognitive Radio Networks from an information theoretical point of view.

This deliverable discusses on a role that popular types of machine learning and artificial intelligence methods can play in wireless networking. Alongside it accommodates for a representative list of references that explains these algorithms and techniques in more detail, surveys or provides stand along examples of applications of these methods in cognitive, as well as traditional, wireless networking. In particular, we discuss supervised, unsupervised and reinforcement machine learning methods on examples of such popular methods such as artificial neural networks, Q learning, etc. These methods are useful in modelling of various networking aspects. We also introduce a range of metaheuristics, including genetic and particle swarm optimization algorithms that are often applied to search for an optimal solution in the irregular with multiple local extrema state space of a problem. Finally, we discuss fuzzy logic that is a form of probabilistic reasoning, which is used for formulation, representation and reasoning on cognitive radio systems' objectives and knowledge that are formulated in value, imprecise way; it is also applied as part of modeling, decision making and optimization conducted by these systems.

The most important models and tools that are provided by the information theory literature are summarized to describe the key aspects of spectrum sharing and cognitive radio. The results in two-user SISO interference channel are summarized, followed by literature survey in MISO interference channels and the more recent interference alignment technique. Moreover, we give examples for how the results summarized can be applied and specialized to the cognitive radio scenarios. The results in (extended) cognitive radio channel are summarized, followed by literature survey in MISO/MIMO cognitive radio systems, and the time sharing technique and two cognitive relay scenarios are also introduced.

Keywords: machine learning, fuzzy logic, metaheuristics, information theory, interference channel, cognitive radio channel, survey

Document Revision History

Version	Date	Author	Summary of main changes
0.1	04.11.2011	TUD	Initial structure of the document
0.2	12.12.2011	TUD	TOC on machine learning added
0.3	13.12.2011	TUD	TOC on information theory updated
0.31	16.04.2012	RWTH	TOC on machine learning updated
0.32	30.05.2012	TUD	Contribution from CTTC added
0.4	11.07.2012	TUD	Contribution from KTH added
0.5	23.07.2012	TUD	Contribution from TUD added
0.6	27.07.2012	TUD	Contribution from RWTH added
0.7	18.08.2012	KTH	Update from KTH added
0.8	20.08.2012	TUD	Contribution from PUT added
0.9	03.09.2012	RWTH	Update from RWTH added
0.91	15.09.2012	TUD	Editing
1.0	28.09.2012	TUD	Revision after review

Executive Summary

Deliverable 8.2 serves as the survey of the fundamental theoretical tools which can be applied to specific cognitive radio scenarios in the ACROPOLIS project. It provides a review of selected Artificial Intelligence techniques, including popular Machine Learning methods, which can be applied to cognitive radio and wireless networking. It concentrates on a genetic review and survey of applications of the selected machine-learning and other artificial intelligence approaches, whereas in Deliverable 11.3 of WP11 detailed examples of application of these methods as part of the overall network management and optimization solutions are provided. Moreover, it contains an overview over recent research on Cognitive Radio Networks from an information theoretical point of view, including the results in interference channel and specific cognitive radio systems.

Machine learning methods, as well as other artificial intelligence techniques play an important role in modelling and optimization of cognitive wireless networks and their operational environments in noisy and only partially observable context. In this report we shortly introduce the basics and survey applications of several important machines learning techniques currently utilized in cognitive radio networks. Supervised learning mostly deals with building models based the known input-output relations or labelled samples. We consider supervised learning on examples of support vector machines and artificial neural networks. Unsupervised learning mechanisms typically perform regression analysis, clustering, or otherwise help selecting the most appropriate model based on unlabeled observed data. These mechanisms can also help in establishing dependencies between observed inputs. Examples of considered unsupervised methods and models that can result from application of these techniques are self-organizing maps, Bayesian networks and hidden Semi-Markov models. Reinforcement learning deals with run-time model development and system optimization that aims at maximization of its performance in a given environment. Reinforcement learning techniques primarily operate on a set of observed performance metrics and try to find sequence of actions that would maximize these criteria. We consider this class of methods on example of Q-learning. In this report we also discuss on applications of two other classes of artificial intelligence techniques, namely metaheuristics and fuzzy logic. Metaheuristic methods search for the near-optimal solution of an optimization problem by traversing the state space of possible solutions. These methods are typically applied to large irregular search spaces that are explored iteratively applying some heuristics. Though these methods are known to be efficient even when almost no information on the structure of the problem is available, they do not guarantee convergence to the optimum in limited amount of iterations. As examples of metaheuristics we consider genetic algorithms, particle swarm and ant colony optimization, simulated annealing and tabu search. Fuzzy logic is a form of probabilistic logic, which reasons on approximate, vague, representation of knowledge and objectives. As not all data operated by a cognitive wireless system, e.g., user data, can be or needs to be formulated in definite precise values, fuzzy logic is a promising approach for some tasks in future networks.

Within information theory, research on cognitive radio focuses mainly on fundamental limitations of cognitive radio networks expressed by upper bounds on capacity and achievable rates or rate regions. It is based on simple models which are adapted to different

combinations of aware/unaware, cooperative/non-cooperative primary and secondary systems, where a fundamental building block is given by the framework of interference channels. Information-theoretic studies of the interference channel have provided various achievable rate regions, which can be applied and specialized to the cognitive radio scenarios. We summarize the most important models and tools that are provided by the information theory literature to describe the key aspects of spectrum sharing and cognitive radio. The results in two-user SISO interference channel are summarized, including different strategies resulting in different rate regions. Then starting with two-user MISO interference channels, we have a literature survey on multi-user MISO interference channels and the more recent interference alignment technique. The results in (extended) cognitive radio channel are summarized, followed by literature survey in underlay/overlay MISO/MIMO cognitive radio systems. Moreover, the time sharing technique and its application in the secondary interference channel, and two cognitive relay scenarios are introduced.

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1. Introduction

This deliverable provides a brief review and survey of applications of selected Artificial Intelligence techniques, including popular Machine Learning methods, which can be applied to cognitive radio and wireless networking. Moreover, it contains an overview over recent research on Cognitive Radio Networks from an information theoretical point of view.

Following the Introduction, Section 2 of the deliverable discusses on a role that popular types of machine learning and artificial intelligence methods can play in wireless networking. Alongside it accommodates for a representative list of references that explains these algorithms and techniques in more detail, surveys or provides stand along examples of applications of these methods in cognitive, as well as traditional, wireless networking. In particular, in Section 2 we discuss supervised, unsupervised and reinforcement machine learning methods on examples of such popular methods such as artificial neural networks, Q learning, etc. These methods are useful in modelling of various networking aspects. We also introduce a range of metaheuristics, including genetic and particle swarm optimization algorithms that are often applied to search for an optimal solution in the irregular with multiple local extrema state space of a problem. Finally, we discuss fuzzy logic that is a form of probabilistic reasoning, which is used for formulation, representation and reasoning on cognitive radio systems' objectives and knowledge that are formulated in value, imprecise way; it is also applied as part of modeling, decision making and optimization conducted by these systems.

In Section 3, we summarize the most important models and tools that are provided by the information theory literature to describe the key aspects of spectrum sharing and cognitive radio. Specifically, the results in two-user SISO interference channel are summarized, followed by literature survey in MISO interference channels and the more recent interference alignment technique. In Section 4, we give examples for how the models summarized in Section 3 can be applied and specialized to cognitive radio networks. Specifically, the results in (extended) cognitive radio channel are summarized, followed by literature survey in MISO/MIMO cognitive radio systems, and the time sharing technique and two cognitive relay scenarios are also introduced.

Section 5 concludes this deliverable.

2. Selected Artificial Intelligence Techniques in Cognitive Wireless Networks

In this section we consider application of selected artificial intelligence techniques, including some of the machine learning methods, for modeling and optimization of various aspects of cognitive wireless systems and their operational environment. We also mention on how the resulting models could be further applied for decision-making in Cognitive Wireless Networking (CWN), though the decision-making itself is mostly discussed in D8.3 and the WP12. We concentrate on the basics of the selected statistical machine-learning, metaheuristics search and fuzzy logic methods, and survey their applications for wireless networking, and specifically CWNs[1]. We also shortly discuss on role of modeling in cognitive radio and wireless networking and connection of modeling to machine learning methods.

2.1 Introduction

Application of Machine-Learning (ML) and other Artificial Intelligence (AI) techniques [2]-[4] for cognitive wireless networking are gaining momentum, with several recent survey on the topic being already produced both in the domain of cognitive radio communications [5]-[8], as well as wireless networking in general [9]-[12]. (In this deliverable we will not explicitly duplicate papers cited in these surveys, as interested reader may always consider them. We rather provide additional selected references illustrating diversity of applications of the machine learning methods and other artificial intelligence techniques for cognitive radio and, generally, wireless networks.) A big advantage of models and other modules concerned with controlling of cognitive radios that can obtained using machine learning and other relevant AI techniques is that they often allow circumventing dynamics, uncertainty and noisiness typical for wireless environment. They enable, for example, efficient search of the optimization state spaces of irregular landscapes, post-processing and classification of observed data in noisy conditions, and corresponding derivation of effective decision metrics and algorithms. In the next sections we review several key machine-learning, metaheuristics and fuzzy logic methods and survey their application for cognitive wireless networking. First, in Section 2.2, we shortly recap on role of modeling for cognitive wireless networking and give overall comments on key features that machine-learning techniques should in application to different modeling tasks. Then we processed with the overview of with probabilistic supervised machine learning techniques that are kernel methods, and artificial neural networks in Section 2.3. We also consider unsupervised classification and regression methods in Section 2.4. We explain principle of Q-Learning and reinforcement learning in Section 2.5, followed by an overview of selected metaheuristics in Section 2.6. Finally, we discuss on fuzzy logic and its sample applications to CWNs in Section 2.7 with conclusions following in Section 2.8.

[1] Clearly, there exist numerous enhancements of the methods we survey, other machine learning techniques, as well as solutions based on combination of these algorithms or application of one ML method for improvement of the other. There are also more applications of machine learning to cognitive wireless networking than we cite. However, the main aim of this section is to provide the initial background of the readers on the topic of applicability of machine-learning to modeling in cognitive radio networking, rather than provide exhaustive survey were individual details would cloud the overview of the field.

Before proceeding further we consider it useful to mention popular tools and packages that implement many of the discussed ML and AI methods. Some of the standard relevant libraries for MATLAB are Neural Network, Bioinformatics, Global Optimization, Statistics and Fuzzy Logic Toolboxes. For R there is list of maintained machine learning packages under the link http://cran.r-project.org/web/views/MachineLearning.html. Otherwise, the complete list of R packages that can be browsed for the required AI library is available at http://cran.r-project.org/web/packages/available_packages_by_name.html.

2.2 Modeling and Machine Learning in Cognitive Wireless Networking

Cognitive wireless networking relies on the concept of self-awareness of networked systems that allows them to conduct self-optimization decision in timely and effective manner. One can view Cognitive Wireless Networks (CWNs) as systems that are continuously solving the performance optimization tasks. The abstraction can be taken that these systems rely on a notion of a feedback loop (a cognitive cycle [1]), where sensory inputs are processed through in-built models by relevant optimization and decision-making algorithms to result, if required, in certain network management and reconfiguration actions. Modeling, i.e., “understanding of the world and yourself”, plays a crucial role in the overall operation of a cognitive wireless system. Inaccurate models prevent correct optimization decisions and, thus, almost guarantee suboptimal network performance. Models can capture the vital aspects of an operation context and the system itself that might range from the propagation environment to user and application behavior. We believe that it is important to acknowledge for different types of models and their classifications, as this allows for more informed choices and application of methods and algorithms used for this task. When classifying models we also comment on how their key characteristics influence applicability of machine-learning techniques. For example, if model aims at temporal prediction it is likely that some form of Markov models or time-series regression analysis would be suitable. If a cognitive wireless network employs distributed optimization models from the game theory might become useful [13].

Models can be classified according to multiple criteria. For example, *descriptive* models aim only to capture key observed or expected features of the operational environment, without understanding of the causality relations. Examples of these constructs are radio propagations, spatial network topology, traffic, user/application arrival, and mobility models. Often these models take form of probability distributions, function fits or classifications, and are used to simulate, study and predict changes in operational environments. *Explanatory* models try to establish *causal* relation between either registered events or action/observation pairs. For example, they try to capture protocol parameter / Key Performance Indicator (KPI) relations, or detect causes for network failures. Many of the supervised and unsupervised techniques pass for derivation of both descriptive and explanatory models. Unsupervised learning can be used for performing regression and classification analysis with minimal developer involvement, who mostly should correctly specify initial inputs for the machine learning techniques. Supervised methods are often useful to train a model for detection and identification of specific events, features, contexts. For explanatory models their inner structure are often of a particular interest, as it often reflects the degree of connection between specific inputs and outputs.

Models can be used to *predict* future events, as well as to *process* already registered data to extract useful information. Predictive models require explicit feedback of historical information, with complexity of a model being often dependent on number of prior historical states being taken into the account simultaneously. For example, Markov Models are widely used to predict user mobility [14] and spectrum occupancy [15]. Another example are models used to estimate subjective voice and video quality received over a network based on transport and application-layer KPIs [16][17]. However, many of these belong to processing rather than predictive class of models, as they do not make predictions based on historical data, rather combine multiple performance metrics into the one, like Mean Opinion Score (MOS), comfortable for further processing.

Decision models serve as in-built part of network decision making algorithms. For example, decision trees could be statistically derived as models that record optimal sequence of test and actions for optimization in cognitive wireless networks [18]. Models of relating KPIs and tunable optimization parameters are inherent part of evolutionally, genetic, algorithms that are popular tools for network planning and management [19],[20].

It is useful to distinguish models based on imposed processing and communication overheads, as well as applicability to different optimization strategies. For instance, not all types of models and corresponding derivations tools (such as specific machine-learning and AI techniques) are suitable for both centralized and distributed optimization. For centralized solutions optimization actions are structured and probability of deployment of contradictory decisions is low. For distributed systems there exist multiple agents, which might act both towards one or multiple goals. In any case there actions are often unsynchronized and might even contradict each other leading to system instability and suboptimal performance. At the same time distributed optimization algorithm can lead for faster local. Also the amount of available information and its trustworthiness is different in case of cooperative and un-cooperative networks operations.

There is also a considerable difference between offline and run-time training and utilization of models. The main specifics of online solution of the optimization problem is the necessity to gather inputs, solve and execute solutions online, with each of this actions having a direct influence of network stakeholders. Online network (self-)optimization always carries the trade-off between the exploration and the exploitation phases. This trade-off, when understood broadly, deals with every aspect concerning performance improvements gained by users at a price of additionally spent resources, which include additional control and computational overheads, longer network setup times, certain instabilities caused by reconfigurations, etc. Therefore, as opposed to offline processes for run-time optimization tasks should consider for both long-term and well as momentary stakeholders' satisfaction.

When designing a model one should also account for the amount of noise, uncertainty and hidden influence factors in the system and its environment. While generally machine-learning and fuzzy logic methods are good at handling those, one still should specifically account for designated adjustments of AI models, or additional application of pre-processing techniques. For example, hidden nodes could be added to probabilistic graphical models to indicate presence of unregistered factors that could influence the observed metrics. Various forms filtering can be used to reduce noise in observations, though some methods, such as neural network can successfully operate even on very noise data, if their structure is sufficiently complex and a large number of training samples is available.

2.3 Supervised Machine Learning

In machine learning under *supervised learning* we classify methods that learn a function (model) relating inputs and outputs from *labeled* training data. Supervised learning methods produce classification or regression models that aim to relate a set of incoming sensory inputs to one or more of the *predefined* outputs. Examples of common types of supervised learning techniques are decision trees and random forests, artificial neural networks, and support vector machines. In this deliverable we consider two of these techniques, namely support vector machines, which also belong to the class of kernel methods, and multi-layer feedforward neural networks, which are one of the types of artificial neural networks.

2.3.1 Support Vector Machines

Support Vector Machines (SVMs) are one of the types of the *kernel machines* [21] that are often used for classification and pattern recognition. These methods have efficient training algorithms and can represent complex nonlinear functions. The core of this method is transformation of the studied data into new, often higher dimensional, space so that this data is *linearly separable* in this new space and, thus, classification would be possible. Representation of data using high-dimensional space carries the risk of overfitting. Kernel machines avoid this by finding optimal linear *separator, a hyper-plane,* that is characterized by the largest *margins* between itself and data samples from both sides of the separator (see Figure 2-1). A separator is obtained though solution of a quadratic programming optimization problem, which is characterized by having a global maximum, and is formulated using dot products. More formally, if formulating a problem for *linear support vector machines* in the dual form, we need to find the parameters α_i through which $\sum_{i}\alpha_i - 0.5\sum_{i,j}\alpha_i\alpha_j y_i y_j(\bar{x}_i \cdot \bar{x}_j)$ is maximized with $\alpha_i \geq 0$ and $\sum_i \alpha_i y_i = 0$, where $\bar{x}$ define a vector of real-valued attributes of a data point, and y can take values of -1 and 1 indicating to which class the point x_i belongs. The coefficients α_i associated to each data point are zero except for the points which are closest to the separator. Thus, these points with non-zero coefficients form a *support vector* of a classification hyper-plane. As said it is rare that a linear separator cannot be found in the original input space $\bar{x}$, but in the high dimensional feature space $F(\bar{x})$ it is possible, if the dot product $\bar{x}_i \cdot \bar{x}_j$ is replaced with $F(\bar{x}_i) \cdot F(\bar{x}_j)$. The speciality of the dot (scalar) product as a mathematical expression is that the latter expression $(F(\bar{x}_i) \cdot F(\bar{x}_j))$ can be calculated without computing the function F for each data point, which greatly simplifies the task. Therefore, when applying support vector machines we can substitute the expression $F(\bar{x}_i) \cdot F(\bar{x}_j)$ with the *kernel function* $K(\bar{x}_i, \bar{x}_j)$ that needs to be computed instead of the full list of features for each data point. Generally optimal linear separators are obtainable in feature spaces with even billions, or, sometimes infinitely many, dimensions [2].

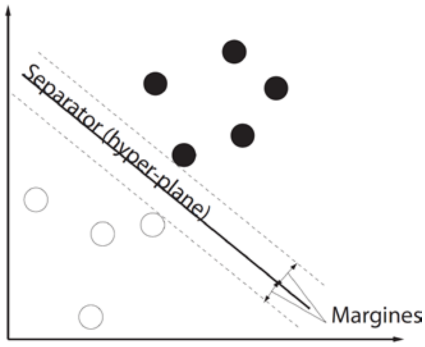

Figure 2-1: Linear classification in the feature space by Support Vector Machines.

Kernel machines are gaining popularity in machine learning, especially for the data with many input features. Developments in kernel machines introduced methods to work with non-numerical data types, such as strings or trees. Moreover, non-linear kernel machines also exist. In cognitive wireless networking kernel machines and specifically support vector machines have been successfully applied for signal classification, especially estimation of modulation technique [22]-[24]. Furthermore, these were employed as part of solutions for the problems of dynamic channel selection joint with simultaneous assignment of a modulation technique [25], improvement of (cooperative) spectrum sensing [26][27], and anomalous signal detection [28]. There even exist first attempts for classification of between TDMA and CSMA/CA MAC protocols based on energy samples [29]. Additionally, among others, SVMs have been successfully applied for localization [30], advanced signal processing [31] including application to adaptive modulation and coding [32], security threads detection [33][34], traffic prediction [35], and latency prediction in Internet [36].

2.3.2 Artificial Neural Networks

Artificial Neural Networks (ANN) emerged in an effort of mimicking neural networks that exist in real biological systems. There are many different ANN models that are widely used for speech and image recognition, pattern matching and search engines [37]. Artificial neural networks are utilized in cognitive radio networking and generally wireless networking to solve such problems as signal classification [38], including detection of a transmission technology [39] and modulation detection [40], wireless performance prediction [41], and localization (indoor positioning) [42]. As we see the tasks for which artificial neural networks and kernel machines are applied generally overlap. Which of the alternative algorithms would cope better with the problem depends on the specific characteristics of the problem.

Among all ANN models, Multi-layer Feed-forward Neural Networks (MFNNs) are very successful in statistical pattern recognition applications, and are widely applied for other types of information processing [43]. In the following, we will concentrate on this type of ANN, providing a brief overview of MFNNs and explaining their current utilization in the cognitive radio context. For a more detailed description, the reader is referred to the abundant literature on Neural Networks, e.g., [3] and [4].

2.3.2.1 Multi-layer Feedforward Neural Networks

The basic element of an MFNN is the neuron. A generic neuron has inputs $x_i\left(i=1,\ldots,M\right)$ and a single output y that are related as $y(x,\omega)= f(a)$ with $a=\sum_{i=1}^{M}\omega_i x_i+\theta$, where ω_i is the weight associated with the input x_i, θ is the bias, and $f(a)$ is a differentiable, nonlinear, activation function, which is in general chosen to be a sigmoid function. A neural network is composed of neurons that are connected in a feed forward fashion and organized in a multilayer topology, see Figure 2-2. Each MFNN has only one input and one output layer, and any number of hidden layers. In order to use such a network as a function approximation for pattern recognition purposes, it is necessary to determine the values of the weights and biases, which is done in a process that is called *training*. The commonly adopted strategy for training is the *back propagation algorithm* [3].

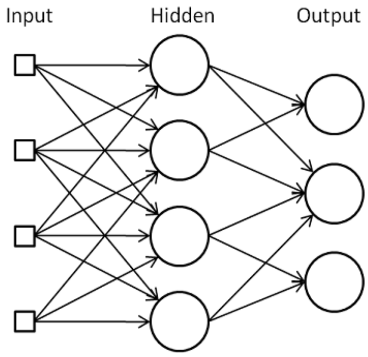

Figure 2-2: Two-layer feed-forward neural network.

2.3.2.2 MFNNs in Cognitive Radio Context

In recent years MFNNs got popular as general-purpose function approximations, especially for modeling dynamic systems. Many studies have been done on the subject of MFNN application in a cognitive radio context. For example, the author of [3][43] recommends MFNNs as they provide more compact models than other prediction techniques with the same generalization performance, such as support vector machines (SVMs). Furthermore, the authors of [44] did a study on the network traffic prediction using MFNN and Auto Regressive Integrated Moving Average (ARIMA), and as a result they recommend the use of a MFNN as a prediction technique with less complexity and better results. The authors of [45] review the application of this technique to cognitive radio control. Additionally, the authors of [46] consider MFNNs as promising tool in a CR context, because MFNNs can be efficiently used even when number of inputs and outputs to the system is relatively high, as such models are computationally light and, therefore, well-suited for real-time systems. For neural networks the major overhead is imposed during the training process, which is computationally demanding, but it does not have to be repeated frequently, and can be postponed till the time when computational resources are available.

In [47],[48] and [49] it is shown that the use of MFNNs for the estimation of wireless network parameters, such as application throughput, QoS and QoE, gives significant improvements comparing to state-of-the art techniques that are typically based on an analytical model and do not use machine learning techniques. In those studies are considered two different wireless network scenarios: access point selection problems for IEEE 802.11 networks and Radio Admission Control (RAC) in Long Term Evolution (LTE) system. Both systems are motivated by the assumption that theoretical models might not always be sufficient to solely guide the optimization process in wireless networks. Therefore, models connecting the current observations on state of the environment and the surrounding networks with the expected performance estimates in case of certain network reconfiguration actions are needed. The models have to learn from past experience, and adjust themselves during run-time to account for the changes in the operational environment, i.e., they should display some reinforcement features, see Section 2.5. Suggested solutions apply MFNN to model non-linear relations between an operational environment as observed by an IEEE 802.11 mobile station and expected performance obtained gains in case of reconnection to another access point [48].

In the first approach, an MFNN is used to model the non-linear relation between the wireless network environmental conditions and the application throughput of a mobile station in an access point selection scenario. In this case the MFNN is used for the estimation of the application throughput. In this approach, first the relevant metrics that represent the environmental conditions that may affect the application throughput are selected. In the second step, by using the experimental measurements of these metrics and of the application throughput, the MFNN is trained. In the process of training the weights of the inputs to neurons in the hidden layers and the output layer of the MFNN are adjusted. In the third step, the comparison of MFNN performance for different training parameters is done, such as the learning rate, the number of hidden layers and the maximum number of epochs. Finally, the MFNN is configured to use the combination of training parameters that give the minimum error in estimation of application throughput. In this approach, the Access point selection procedure relies on MFNN estimation of throughput and in that way uses the past experience which includes context specific information of the environment in which the MFNN is trained. This approach based on machine learning gives better performance than traditional analytical approaches [47],[48].

Another approach guides the RAC of a certain eNodeB that need to determine if a new session can be supported with sufficient service quality (mostly with regard to the Voice over IP (VoIP) traffic) without degrading the quality of already established connections. The proposed cognitive RAC scheme is able to cope with the non-ideal conditions which are present in real scenarios, such as changes in radio environment due to mobility or eventual inter-cell interference which influence performance of ongoing sessions, but which can be complex to account for by using traditional analytical approaches. The scheme implements a MFNN on top of the QoS aware RRM algorithm proposed in [49] which is based on prioritizing using the head of line delay. The works are conducted using the ns-3 simulator, its LTE extension LENA, and the EXTREME Testbed. For the implementation of the MFNN, the FANN software library is used, which implements iRPROP-batch training algorithm. The discussed works demonstrate effectiveness and high potential of neural networks in application to admission control and access selection problems for wireless and cellular networking.

2.4 Unsupervised Learning

Unsupervised learning methods try to establish patterns in data when no specific outputs explaining these data are supplied. These methods try to establish structure of the *unlabeled* data. Unsupervised learning methods are often applied to conduct clustering, dimensionality reduction, explain hidden causes or model data density. Examples of widely known methods being considered as unsupervised are factor and principal component analysis, k-means clustering, techniques that allows to learn parameters and structure graphical models, such as Bayesian networks or hidden Markov models, and self-organized maps. In this deliverable we consider two of these techniques, namely self-organized maps that employ artificial neural networks, and the Expectation-Maximization (EM) algorithm that is applied to learn parameters of Bayesian graphs and hidden Markov models.

2.4.1 Self-organized Maps

Self-Organizing Maps (SOM) [50] are artificial neural networks [51] that belong to the class of unsupervised learning methods and are especially useful in application to clustering/classification and high-dimension data projection. They do not require data labeling or human intervention, besides initial parameter settings, for training. Self-organizing maps have a very desirable property of topology preservation, which allows similar input patterns to be represented by the same or the nearby outputs of the map. In other words, nearby multi-dimensional data points are mapped into nearby regions of the SOMs, which are typically 2D grids. This makes these models to be a valuable data mining and visualization tools. A self-organizing map algorithm maps a continuous input vector space onto a discrete space of neurons.

A SOM can be seen as a certain type of competitive learning networks that has a well-defined spatial neighbourhood structure. At initialization a SOM algorithm builds a discrete map of neurons, which gets adjusted under the influence of input data. A multi-dimensional input vector *x* incoming at a time or sequence number *t*, *x(t)*, is mapped to the neuron that suits the best for its representation. In other words the (Euclidean) distance between this vector x(t) and the vector of synaptic weights of chosen neuron $w_c(t)$ is minimal as compared to other neurons. After the winning neuron is determined the synaptic weights of this neuron and its neighbourhood neurons are getting adjusted to better match the encountered input. The neighbourhood function *h(t)* that determines the range of affected neurons is typically monotonically decreasing as the distance from the winning neuron is growing. The rate of adjustment of synaptic weights *a(t)* also depends on the distance from the winning node. Furthermore these functions also depend on the number of inputs, or time *t*, the network has been trained. This parameter influences the convergence of the algorithm. Generally the new value of the weights of a neuron is determined as

$$w_i(t+1) = w_i(t) + \; a(t)h_{ci}(t)[x(t) - w_i(t)]\,, \tag{2.4.1}$$

where w_i denote weights of a neuron under consideration and w_c is the neuron and its weights with minimal distance to the input vector *x*.

Self-organized maps have been widely applied in many engineering domains [52][53]. Notable application in fixed and wireless networking include, traffic classification [54], including anomaly traffic detection [54], security threats detection [54], signal processing

[51], and localization [54]. In wireless sensor networks this artificial neural networks were applied for optimization of sensing strategies [58] and abnormal behaviour detection [59], as well as cluster election and routing [60]. Additionally, in context of cognitive wireless networking SOMs have been used for signal clustering in application to transceiver reconfiguration [61][62], and dynamic spectrum management [63].

2.4.2 Learning of Graphical Models

Graphical models [64] are a general class of probabilistic tools for reasoning about the dependencies of random variables. The common feature of graphical models is the assumption that these dependencies can be described using different types of graph structures, with vertices corresponding to random variables or events, and edges denoting different types of relationships between the vertices. The type of graph structure used further distinguished between different graphical model families. For example, Bayesian networks are recovered by assuming that the graph structure is directed and acyclic, whereas Markov random fields are obtained by letting the graph structure be undirected and allowing for cycles.

In typical applications the graph structure defining the model is fixed, and “learning” consists of estimating the various probabilities associated to the edges from a given data set. Techniques such as maximum likelihood estimation or expectation-maximization algorithm are often used for this purpose. The result of this process is a fitted model from which answers to various probabilistic questions can be extracted. In simple cases such inference can be carried out by analytical means, but for more complex problems numerical techniques such as belief propagation or stochastic simulation are needed. Graphical models form a very rich set of tools for dealing with problems in which the overall probabilistic structure is known, but details need to be estimated. Even in the cases in which the structure of the model is not known, machine-learning techniques can be applicable. In particular, research on structure learning aims to develop methods for joint inference of model structure together with the different probabilities involved from the data. Of course, a major challenge for structure learning is the rapidly increasing amount of data required for reliable estimation and inference.

While most of the classical graphical models are static in nature, applications for modeling dynamical systems are also possible. Examples of the appropriate methods include dynamic Bayesian networks, and graph-based Markov and Semi-Markov models. These are used, for example, versatile tools for modeling queuing systems [65], the usage of radio spectrum [66]-[68], or localization [69].

2.5 Reinforcement Learning and Q-learning

Reinforcement Learning (RL) [2],[70] typically deals a process of derivation of *actions* or sequence of actions that maximize the *reward* of the system in the environment under study. A RL mechanism typically does not have accurate estimated of the effects of its action. It also might not immediately know if the right action was performed that would lead to the desired result, thus exploration of a state space of an optimization problem is natural part of reinforcement learning. Additionally, some RL methods can also deal with uncertainty on their own state. Reinforcement learning as compared to supervised learning does not rely on training, where correct actions, input-output pairs, are explicitly presented. Instead, sub-optimal actions are accepted and only their reward is send to the RL mechanism. Reinforcement learning is often applied for online problems, often where operational conditions are changing dynamically. Thus, *exploitation-exploration* trade-off is common and important for these methods. (This trade-off is very important for any runtime learning and online adaptation processes, which in context of CWNs is, for example, discussed in [71] in application to multi-antenna PHY-layer adaptation). Further, as an illustration of basics of reinforcement learning, we will outline the basic Q-learning technique that is classical for this field.

As evident form the name, the Q-learning algorithm learns relations between actions, the resulting system states and their utilities [70]. It relies on choosing the next action to be performed based on the estimated utility function Q that is a weighted sum of an immediate reward taking an action and the utility to be achieved if getting (taking path) through the new state. This is a recursive function that gets updated with each action taken, as new information on utilities of the states might become available. Only the asymptotic convergence of the estimated Q-function to the real one is proven. Therefore, for the basic version of the algorithm it might take a really large number of steps to learn the impact of actions in the operational environment sufficiently good. There have been multiple proposals on improvement of the basic Q-learning, also with techniques from supervised learning, such as neural networks, where relations between states and actions are represented using separate NNs. Original Q-learning is also not designed to handle system dynamics, so the mechanism should be modified accordingly as well.

Reinforcement learning is an actively developing and much anticipated field of research as it gives a promise of elimination of hand coded control strategies even in the high-dimensional partially observable environment to which cognitive wireless networks belong. By a popular definition [2], the reinforcement learning can operate with three main designs, model-based design, model-free design, and a reflex design. The Q-learning falls in the area of model-free design, where action-value functions (Q-functions) are learned without relying on models, which generally simplified the learning problem, but restricts its applicability to complex environments, as such learning techniques in their pure form cannot simulate the results of courses of actions. *Adaptive dynamic programming* methods, though much more complex, are capable of learning both a model and a reward functions, thus they are suitable to operate in very complex environments, where a sequence of optimization actions is to be planned. *Temporal difference* learning utilizes a combination of Monte Carlo and dynamic programming techniques. It requires no model, as it relies on both already observed results of its previous actions and *predictions* about the future states. This method can be quite successful in practice, and can be seen as an approximation of the adaptive dynamic programming approaches. Finally, the reflex design is based on utilization of the *policy* search, where a policy is seen as a function that maps states to actions. Contrarily to the Q-learning, which aims to find an estimate close to the original Q-functions, the policy search simply aims to find the functions that would lead to the best reward (which might obviously differ from the original action-value dependency). Reinforcement learning additionally distinguishes between the tasks that aim to learn the affect of sequential decisions, such as done by Q-learning, and exploration of non-sequential decision, which is done, e.g., though formulation of bandit problems [2].

Q-learning as well as other reinforcement learning methods have been successfully in cognitive networking as a solution for such tasks as the interference management [72], secondary transmission strategies [73], and estimation of spectrum availability [74]. Q-learning was also applied in cellular networking, for example, to improve throughput multimedia application in WCDMA system, while complying to QoS requirements [75], or to perform admission control [76]. Additionally, reinforcement learning schemes have been applied for energy-aware management and routing [77][78].

2.6 Metaheuristics

Heuristics plays an important role in the field of Artificial Intelligence [10][79]. Heuristics can be seem as theoretically unverified/unproven metrics or methods, basically “rules of thumb”, that in most cases can, but do not guarantee, fast finding of a near-optimal solution to a problem. For example, there exist a large range of heuristic searches for exploration or finding of a near-optimal solution in state spaces, where application of classical mathematical, e.g., convex, optimization techniques is not possible, and utilization of the exhaustive search is not desirable [10]. Compared to classical optimization algorithms, such as convex optimization, heuristics methods do not impose specific requirements of the relief of the search, e.g., ask for its convexity. They can be applied on problems that are characterized by both on continues and discrete search space structures. Many of heuristics methods, especially the ones of the iterative nature, can avoid local minima and, thus, search in highly irregular reliefs. In case of cognitive wireless networking heuristics or metaheuristics searches are often used to investigate a state space of an optimization problem, for example, to find an optimum network configuration in a given operational context.

Machine learning techniques are useful to find good heuristics for the search algorithms [80]-[83]. They can be also directly incorporated in a search mechanism to serve as *metaheuristics*, which evolves iteratively when the search is executed to provide presumably improving heuristics [84]-[86]. In cognitive radio networking and generally wireless networking different search mechanisms based on heuristics, e.g., variants of greedy searches [87], have been widely applied [88][89]. Metaheuristic optimizations [90] are also very popular in the networking for such applications as network planning, low- and cross-layer self-optimization, etc.

Often metaheuristics techniques are used as parts of *hybrid* solutions to improve the search in the particular area of interest [91]. For example a combination of particle swarm optimization and simulated annealing is used improve network coverage as part of the dynamic network planning problem [92]. The term “hybrid” is also used when metaheuristics machine-learning methods are combined together. Metaheuristics and machine learning share a lot in common [93]. Machine-learning models incorporate inside a metaheuristics search can sometimes be extracted and re-used to direct another optimization searches. Other way round, good heuristics can sufficiently improve the convergence rate and quality of models produced by machine learning [94][95]. For example, Meshkova et al. studied effect of adding structure to simulated annealing using simple probabilistic dependencies, as well as Bayesian graphs [96]. Pendharkar has used a popular concept of using metaheuristics to improve the training rate of supervised algorithms, by using genetic algorithms to train neural networks that can predict customer churn cellular systems [97]. Similarly hybrid metaheuristics to train neural networks for channel prediction in application the MIMO scenarios have been proposed as well [98].

2.6.1 Genetic Algorithm

Genetic algorithms [99] are, probably, the most well know representatives of the family of evolutionary methods. The algorithms mimic the process of natural evolution and are known to be efficient for solving a wide range of optimization and search problems. These algorithms typically operate on parameter-based representation of the optimization state space with imposed additional constraints. A genetic algorithm relies on strings of chromosomes with each of them encoding one candidate solution to a problem, so called individual. Individuals form a population on which operations inspired by biological processes. These are inheritance, selection, crossover, and mutation. Each individual is assessed according to its fitness function, i.e., utility functional. Bases on this assessment the individual as a whole (elite individual) or its chromosomes participate into formation of new population (generation). This process of evaluation of individual and their evolutionary-inspired adaptation for a new population is repeated multiple times, which typically leads to gradual improvement of the solution quality. One of the popular criteria for algorithm termination is absence of significant performance improvement of new solutions as compared to the one already found for a preset number of generations. Other common criterion is a maximum number of generations reached. Genetic algorithms are very flexible. They have a lot of tunable parameters, as well as possibilities for adaptation of its basic mechanisms, thus providing possibilities for incorporation of machine learning models. Wide applicability and good performance of genetic algorithms lead to development of the concepts of genetic programming, where tree-like representations of the state-space are explored, which gives possibility of the search space structuring in more program-like (if-then) manner. Graph form state representations are explored in evolutionary programming. A mixture of both linear chromosomes and trees is explored in gene expression programming.

Genetic algorithms and other evolutionary computing methods have been widely applied in the domain of cognitive wireless networking and generally wireless networking. The survey by Kampstra and et al. provides a review on application of evolutionary techniques to the field of telecommunications in general, structuring it after the application problems, which range from network planning to dimensioning, routing, and dynamic spectrum access/frequency assignment [100]. Genetic algorithms were explored for the task in wireless sensor network design [101], which is, after slight adaptations, is also relevant for cognitive radio networking. Genetic algorithms have also been used to solve joint network planning and power assignment problems in wireless networking [102]. Specifically to cognitive wireless networks one of the first applications of genetic algorithms was their utilization to find optimum PHY settings at part of SDR reconfiguration [103]. Further this line of research lead to application of genetic algorithms for online multicarrier transceiver configuration [104], runtime cross-layer reconfigurations [105], and spectrum management [106].

2.6.2 Particle Swarm Optimization and Ant Colony Optimization

Particle swarm optimization (PSO) is a popular metaheuristics operating belonging to the class of *swarm intelligence methods* [107]. The algorithm mimics social behavior of large gatherings of animals or birds, where behavior of an individual (a potential solution, a *particle*) is influenced by other individuals already residing at better positions. The PSO similarly genetic algorithms also rely on multiple copies of potential solutions, i.e., it forms a population, to avoid stacking in local minimum. However, instead of relying on the crossover or mutation operations, the PSO particles (individual potential solutions) rely on their own best known positions in the search space, as well as on the the entire swarm's best known position in order to probabilistically decide the “speed” and “direction” of its further “movement” in the state space. This iterative metaheuristics has been a successfully applied to many research problems; however it, as many other methods of its kind, is dependent of initial choice of parameters. As this other methods discussed in this section, there also exist multiple variations of the basic particle swarm optimization metaheuristics.

Ant colony optimization is another metaheuristics belonging to the class of swarm intelligence methods [108]. It is inspired by the behavior of ants in finding paths from the colony to food sources. The algorithm to avoid getting stuck in local minima uses multiple ants (or agents) to traverse the solution space and find locally productive areas. The strategy usually does not perform as well as simulated annealing and other forms of local search, but it can solve tasks where no global or up-to-date perspective can be obtained, and therefore the other, in general more effective methods cannot be applied. Ant colony optimization outperforms simulated annealing, tabu search and genetic algorithms in dynamic environments, as it can adapt continuously to the changes in real time.

In wireless networking swarm intelligence methods have been applied to problems ranging from network planning [109] and its dynamic deployment [110], to mobile ad-hoc routing [111], spectrum and other radio resource allocation problems [112][113]. These techniques are especially popular in application wireless sensor networking, with a sample survey on application of PSO given in [114]. The variants of PSO techniques have also been employed to optimize radio or sensory coverage of the network [114], perform cross-layer and PHY layer optimization [118][119], localization [120], cooperative sensing [121]. Ant colony optimization methods are very often applied for the routing tasks [115], and, along with particle swarm optimization for choosing appropriate cluster heads [116][117].

2.6.3 Simulated Annealing and Tabu Search

Simulated annealing [122] is one of the oldest probabilistic metaheuristics that can be loosely described as a heating and controlled cooling process of a metal, which aims to improve its quality by affecting its microstructure. It belongs to the class of *local* neighborhood searches [90]. Simulated annealing can in some sense be viewed as a subset of a genetic algorithms with only one generation present, which undergoes continues mutations. However, simulated annealing in contrarily to the genetic algorithm introduces the concept of temperature and reheating. Temperature controls the processes of adaptation of configuration parameters (“genes”, “electrons in an atom”) that define the optimization state space of a problem. The higher is the temperature the more actively gene values are changing and the “further” (in terms of considered distance metrics) values from each other they can take. When the temperature drops very few of the parameters can change and these changes would not be significant. Therefore, when temperature is high the optimization state space is searched aggressively, and when it drops the local neighborhood of the best solution obtained so far is primarily searched. At the temperature of zero the search stops. Simulated annealing *probabilistically* accepts newly found solutions, which allows the system to move consistently toward lower energy states, yet still jump out of local minima. The algorithm also foresees the mechanisms of reheating, such as the temperature could be raised again, which allows escaping local minima. Simulated annealing allows to flexibly defining the function of temperature cooling as functions of, typically, number of iterations or performance improvement, and the function of “mutation” of its state space parameters, which depend of the current temperature. Another specifics of the simulated annealing is that these mechanisms make decisions based only on a single sample of the explored state space, which can be especially useful for situations when long exploration phases may have sufficient negative performance impacts, e.g., in cases of run-time optimization with active users.

In cognitive radio networking the algorithm was successfully applied to similar problems as other metaheuristics. These include parameter-based cross-layer optimization [96], power control [123], localization [124], and network/radio resource planning [125][126]. In all these problems repeatedly the question is raised concerning the randomness of the solution, i.e., how similar would be the delivered results after running the metaheuristics multiple times, and what is the desirable number of iterations, and if other less “heuristics-base” alternatives exist. This is a common problems for all (meta-)heuristics approaches. Their strength is that they are likely to find a good result in sufficiently high number of iterations in even nothing about the problem and the corresponding utility of its search space is known. As soon as more about the structure of the problem is learned and utilized in metaheuristics by some sort of hybrid solutions, the faster typically would be the convergence and solutions quality provided. Even simple the better metaheuristics and evolutionary mechanism can be chosen. From the other side in this case it can be that with sufficient approximations classical mathematics optimization techniques can be applied [127] and then metaheuristics is not needed at all.

Tabu search [128] is another example of the local search metaheuristics. The algorithm uses memory structures, tabu-lists, forbidding the use of certain values of attributes in the search. Typically formation of the tabu-lists is based on the search history. One example of a prohibitive rule is a tabu imposed on visiting the state spaces that were traversed very recently. Tabu lists containing the prohibited values are very effective, though a very good solution that just happens to have this value might be missed. To overcome this problem aspiration criteria are introduced. They allow overriding the tabu state of a solution and including the solution in the allowed set. Tabu search algorithms can vary primarily by the way in which the tabu criteria and aspiration are defined. In wireless networking the Tabu search has been applied, for example, to perform clustering in wireless sensor networks [129], or wireless sensor network planning [130].

2.7 Fuzzy Logic

Fuzzy Logic is a technique originally aimed at reproducing the human reasoning. In its most basic form, it is used to represent the expert knowledge that has been gathered by humans on a specific topic, to implement it on a machine and use it for realizing, for example, automated control and decision making systems. In such basic form, it is normally considered an artificial intelligence technique, but not a machine learning technique, since the knowledge is only transferred to the machine upon initial configuration, and the machine does not perform any further learning on its own. However, more advanced Fuzzy Logic techniques, such as for example Neuro-Fuzzy systems, feature an automated learning process that complements and refines the initial knowledge possessed by the machine; such techniques can therefore be also considered a form of machine learning.

2.7.1 Fuzzy Logic Theory

We hereby provide a brief summary of the most important concepts of fuzzy logic, in order to make it easier for the unfamiliar reader to understand how they can be applied to Cognitive Radio and Networks. For an exhaustive presentation of fuzzy logic theory, the reader is referred to the abundant literature on this topic (e.g., [131]). Fuzzy Logic extends the traditional Boolean logic in that a variable is not limited to being either true or false, but rather can have varying degrees of truth. Similarly, Fuzzy Set Theory differs from traditional set theory in that partial membership is allowed, i.e., an element can belong to a set only to a certain degree. Both truth values and membership values are commonly represented using real values in [0, 1]. Fuzzy Numbers are a particular kind of fuzzy sets that carry information which is both quantitative and qualitative at the same time. Thanks to the *extension principle*, the standard arithmetic operations can be applied to them. Due to their peculiarity, Fuzzy Numbers play an important role in many applications such as fuzzy control, fuzzy decision making and approximate reasoning. A Predicate in Fuzzy Logic is expressed in the form "X is A" where X denotes a variable defined over a domain U (also referred to as the *universe*) and A is a fuzzy set defined over U. Hence, also Fuzzy Predicates have partial degree of truth, represented using a real number in [0, 1]. The traditional logic operators NOT, OR, AND, IF…THEN are redefined in terms of how they modify the truth value of the predicate(s) they are applied to in order to produce the truth value of the final statement.

A fuzzy control system is a controller whose control actions are determined using fuzzy logic reasoning. Since the inputs and outputs of the system are commonly crisp in nature, a "fuzzification" and "defuzzification" process is needed in order to translate them to and from fuzzy representation. The architecture of a fuzzy controller is depicted in Figure 2-3. The heart of a fuzzy logic controller is composed by a set of IF…THEN rules which is used to determine the value of the output variables.

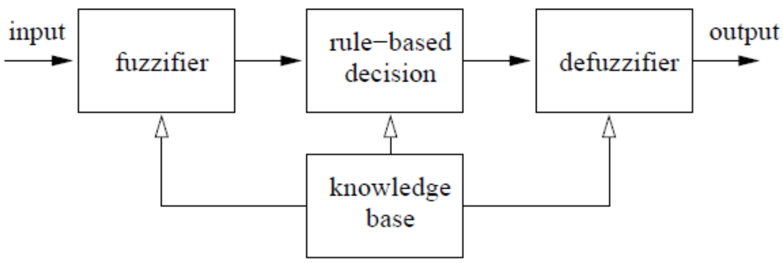

Figure 2-3: Fuzzy controller.

2.7.2 Fuzzy Knowledge Representation for Cognitive Radios and Networks

Over the last 20 years, Fuzzy Logic has been selectively adopted for solving very specific networking and communication problems. For example, fuzzy logic has been applied to QoS-aware routing in wired networks [132], route caching decisions in wireless ad hoc networks [133], radio resource management [134], channel selection in cellular networks [135], and mobility management [136]. An interesting survey on the usage of Fuzzy Logic techniques in the telecommunication field can be found in [137]. It is to be noted that most of these proposals consider a Fuzzy Controller to implement a simple input-output relationship using logic inference. As such, they embed some expert knowledge in the system, but do not qualify as Cognitive Radio or Cognitive Networking systems.

The concept of using Fuzzy Logic for the realization of a Knowledge Representation Base for Cognitive Radios and Networks is first discussed in [138]. This proposal takes partially inspiration from the Radio Knowledge Representation Language introduced by Mitola in [140], to which it adds the use of a Fuzzy representation with the aim of enhancing the interpretability of the knowledge possessed by the cognitive radio. In detail, in [138] it is proposed that, for each layer in the protocol stack, a set of fuzzy variables and fuzzy control parameters are identified. These variables and parameters must be representative of the functionality provided by the layer, and should be generic enough to accommodate different implementations and technologies for the same layer. It is said that the set of fuzzy variables and parameters should not contain technology-dependent items, and that their fuzzification/defuzzification process should be kept confined within the component that exports them. The aim is that cross-layer information exported by one layer can be interpreted easily by other layers not possessing the technology-specific knowledge of that layer. For example, a PHY layer could exploit knowledge of the modulation and coding schemes being used to translate SNR measurements in dB into more abstract fuzzy attributes *bad SNR* and *good SNR*. The result of this fuzzification is that the fuzzy SNR bad/good characterization can be correctly interpreted even without explicit knowledge of the modulation and coding in use by the PHY layer.

2.7.3 Fuzzy Controllers for the Implementation of Cognitive Radio Engines

Again in [138], it is suggested that Fuzzy Logic Controllers are a good choice for the implementation of Cross-layer Cognitive control schemes, especially in the case where heterogeneous components (e.g., different access technologies, protocols, applications) are being used. A fuzzy controller can either be embedded into a specific component, or implement a centralized cognitive engine. In the first case, it is used to tune some private and possibly technology-specific control parameter of the layer. In the second case, its output variables are the fuzzy control parameters exported by all layers.

As an example, the following approach is considered in [138]. Both link, routing and transport layers could be assumed to be satisfactorily characterized by just using reliability, congestion, bandwidth and delay as the knowledge representation base. The first two variables can be purely qualitative fuzzy variables, i.e., expressing just the concept of high and low. By contrast the last two, due to their quantitative nature, are better represented by fuzzy numbers with layer-dependent landmark values; for example, a linguistic attribute for the bandwidth could be “about 100 kbps”, and for the delay “less than 150ms” or, alternatively, “excellent for interactive communications”. All information concerning the link layer is well suited to be determined by measurements, while upper layers might need to interpret cross-layer information before being characterized. For instance, a WLAN layer could easily determine channel reliability and congestion by evaluating SNR measurements and frame statistics; a TCP layer might exploit link layer information to better distinguish between congestion and error status of a connection, and a routing layer could exploit information from both the link layer and the transport layer to assess route characteristics. In this example, cross-layer optimization strategies could be implemented in different ways. The TCP layer could export no control parameters, using just an embedded fuzzy controller to optimize its own throughput; this would make sense since in TCP it is not possible to trade off throughput for delay and/or reliability. By contrast, an RTP layer could export two fuzzy control parameters, reliability and throughput, determining (after defuzzification) the amount of FEC to be used. These fuzzy parameters would allow an application or a centralized cognitive engine to increase/decrease throughput and reliability in order to improve the QoS perceived by the user.

2.7.4 Fuzzy Arithmetic for Modeling Cross-layer and Inter-node Interactions

In [139] the authors propose a generic knowledge representation framework using Fuzzy Numbers with the aim of enabling a generic representation of the most relevant performance metrics of different applications in a Cognitive Network. This representation is then used to build a Cognitive Network Knowledge Database, which has the aim of collecting service quality information fed back by all users. The aim of this proposal is to allow users to perform network access selection by leveraging information provided by other users about the network performance and comparing it with its own application requirements and radio link performance measurements, in order to assess the expected service quality for each access point that is in range. In this process, both Fuzzy Logic Inference and Fuzzy Arithmetic are used. Finally, the most suitable network access opportunity is selected by the user by using Fuzzy Decision Making techniques.

Unlike other works which consider a Fuzzy Controller implementing a simple input-output relationship using logic inference, this proposal works on top of a rather complex performance evaluation framework based on Fuzzy Arithmetic which spans across the whole protocol stack. In particular, the use of Fuzzy Arithmetic allows modeling variations in the uncertainty of information due to 1) the estimation of cross-layer interactions among variables, and 2) the aggregation of measurements provided by multiple users.

2.7.5 Use of Fuzzy Logic as Part of Machine Learning Techniques

Fuzzy Logic has also been used as part of machine learning techniques for applications that fit into the definition of cognitive radio and networks. In particular, Neuro-fuzzy systems have been considered in a number of cases. For instance, in [141] the authors propose a Joint Radio Resource Management (JRRM) framework for multicell and multi-RAT scenario that leverages on a Fuzzy Neural Network (FNN) system. The authors choose a fuzzy logic methodology since it allows making suitable radio resource management decisions from imprecise and dissimilar information, while also allowing for considering the non-specificity of human preferences in the decision-making. The choice of a FNN system is motivated by the fact that the behavior of a traditional FLC is highly dependent on the particular membership functions, which are often chosen arbitrarily, thus leading to potential performance degradations; on the other hand, in a FNN neural networks are used to automatically tune the membership functions in an appropriate way. In [143] the authors use a Fuzzy Q-Learning (FQL) approach for performing link adaptation (i.e., selection of the MIMO transmission mode and modulation and coding scheme) in a 3GPP HSPA system; the authors compare the performance of the proposed solution with respect to a traditional (non-fuzzy) Q-Learning system, and show that a faster and better learning performance is obtained thanks to the addition of Fuzzy Logic that complements the learning system with the inclusion of expert knowledge provided by the algorithm designer. In [144], the authors propose a solution for self-organized femtocells which is also based on FQL; the benefits that they claim with respect to other Reinforcement Learning (RL) techniques is that FQL allows to generalize the state space and to generate continuous actions, besides significantly speeding up the learning process.

2.8 Conclusions

In this section we have reviewed selected Artificial Intelligence methods, including several key classes of machine learning algorithms, with their application to wireless cognitive networking. The results of the survey are summarised in Table 2-1. Classical machine-learning techniques are often used to create, refine, and train various models that can improve design, planning and self-optimization in cognitive wireless networks. In particular we discussed selected supervised, unsupervised, and reinforcement machine learning methods. Metaheuristics search techniques, including genetic algorithms that also belong to evolutional methods, are applied to avoid the exhaustive search in large irregular state spaces of optimization problems. Network planning and network-wide run-time optimizations are often characterized by such state spaces. Moreover metaheuristics are often used to speed up training of supervised machine learning methods. From the other side they can also benefit from knowing additional structure of the problem that could also be obtained using machine learning methods. At last we have also considered applications of fuzzy logic that find its strength in non-strict statement and goal definitions, and can often be integrated as part of decision-making process. Further in Deliverable D11.3 of WP11, we discuss in detail on how ML algorithms can be used as part of the complete solutions to enhance the operation of CWNs based on the work conducted by the ACROPOLIS partners.

Name	Sample techniques	Application domains	Sample applications	Refs.
Supervised machine learning	Support vector machines (kernel methods), artificial neural networks	Model construction based on labelled data	Statistical pattern recognition applied to • advanced signal processing • signal classification; • transmission technology detection; • modulation detection; • anomalous signal detection; • prediction of performance, traffic and latency; • localization; • security threads detections ; • admission control	[21]-[49]
Unsupervised machine learning	K-means clustering, self-organized maps, Bayesian networks, hidden (Semi)-Markov models	Model construction using unlabelled data	Clustering/categorization, data mining • abnormal event and input detections in traffic analysis, security, WSNs; • signal categorization in application to dynamic spectrum management; • clustering as part of routing and sensing aggregation	[50]-[69]
Reinforce-ment learning	Q-learning, adaptive dynamic programming methods, temporal difference, policy search	Finding sequence of actions that maximizes the objective function	• Interference management • secondary transmission strategies; • estimation of spectrum availability; • admission control; • network resource management; • routing	[70]-[78]
Meta-heuristics	Genetic algorithms, simulated annealing, particle swarm optimization	Search of a state space for near-optimal solution	• Network planning and design, including dimensioning; • (radio) resource management • spectrum management; • cross-layer optimization; • run-time PHY, MAC re-configuration; • multicarrier transceiver configuration; • routing and cluster heads election; • localization; • cooperative sensing; • hybrid schemes, e.g. application of metaheuristics for training of a neural network for MIMO channel prediction	[79]-[130]
Fuzzy logic	Fuzzy logic	Operation on fuzzy, vaguely defined data	• Radio resource management; • mobility management; • routing and route caching; • part of cross-layer and other network optimization schemes especially to reason upon fuzzy data, especially when dealing with user feedback and objectives; • part of hybrid schemes with machine learning methods for cellular networks	[131]-[144]

Table 2-1: Summary of machine learning and other artificial intelligence methods and their application to (cognitive) wireless networking reviewed in Section 2.

3. Information Theoretical Models and Tools

In this section, we summarize the most important models and tools that are provided by the information theory literature to describe the key aspects of spectrum sharing and cognitive radio. The results in two-user SISO interference channel are summarized, followed by literature survey in MISO interference channels and the more recent interference alignment technique.

3.1 Prerequisites

In the discussion of the most relevant concepts that follows, we consider mainly channels where the channel outputs are distorted by additive white Gaussian noise (AWGN). For a point-to-point link with channel input symbols X, an average input-power constraint $\mathrm{E}\{\mathrm{X}^2\} \leq \mathrm{P}$, additive white Gaussian noise Z with zero mean and unit variance (i.e., $\mathrm{Z} \sim \mathrm{N}(0;1)$), it is known that a Gaussian input distribution (i.e., $\mathrm{X} \sim \mathrm{N}(0;\mathrm{P})$) maximizes the channel capacity which is the supremum of all achievable rates for which error free communication can be guaranteed in the limit of infinite block length. The channel capacity for the AWGN point-to-point channel is given under these conditions as (see, e.g., [145])

$$C_{AWGN} = \frac{1}{2}\log(1+P)\,. \tag{3.1.1}$$

3.2 Two-user Interference Channel

In this section, we discuss the most basic example of an interference channel, the two-user single-antenna interference channel. We start with the general model and discuss then important transmission strategies, which are of practical relevance and for which achievable rates are known.

3.2.1 Overview

The general model for the two-user single-antenna interference channel is given in Figure 3-1. The model consists of two transmitter-receiver pairs that communicate using the same resources (e.g., the same frequency bands) at the same time. This model is well suited to describe both coordinated and uncoordinated coexistence of a primary system and a secondary system or coexistence of multiple secondary systems.

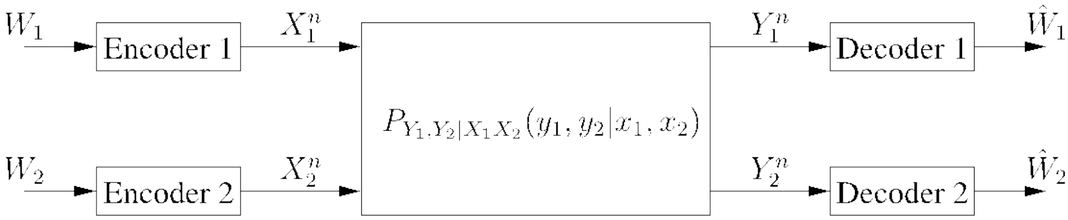

Figure 3-1: Two-user interference channel.

In the model given in Figure 3-1, each user wishes to transmit a message $\mathrm{W_i}$, which is encoded by a length-n codeword $\mathrm{X_i^n}$. The messages $\mathrm{W_1}$ and $\mathrm{W_2}$ are typically assumed to be independent. The input-output relation of the channel is modelled by the stochastic mapping $\mathrm{P}_{\mathrm{Y_1,Y_2|X_1,X_2}}(\mathrm{y_1,y_2|x_1,x_2})$ of the symbols $\mathrm{X_1, X_2}$ at the channel input to the symbols

Y_1, Y_2 at the channel outputs2, and it is assumed that the channel is memory-less. That is, symbols at the channel outputs Y_1, Y_2 at a given time instant depend only on the symbols X_1, X_2 at the channel inputs at the same time instant.

The additive white Gaussian noise interference channel is probably the most relevant special case of the two-user interference channel. It is shown in Figure 3-2. The relation between the channel input and output symbols are given by

$$Y_1 = h_{11}X_1 + h_{21}X_2 + Z_1\,, \tag{3.2.1}$$

$$Y_2 = h_{12}X_1 + h_{22}X_2 + Z_2\,, \tag{3.2.2}$$

where Z_1 and Z_2 are a real-valued additive white Gaussian noise samples with zero mean and unit variance and the real-valued coefficients h_{ij} describe the fading on the link from transmitter i to receiver j. In this model, it is commonly assumed that the transmitted real-valued codewords X_i^n fulfil the average power constraints

$$\frac{1}{n}\sum_{j=1}^{n} E\{X_{i,j}{}^2\} \leq P_i\,. \tag{3.2.3}$$

If we now assume that the noise processes Z_1 and Z_2 are independent and denote their probability density functions as $p_{Z_i}(z)$, we can rewrite the channel transmission probability as

$$p_{Y_1,Y_2|X_1,X_2}(y_1,y_2|x_1,x_2) = p_{Z_1}\big(y_1 - (h_{11}x_1 + h_{21}x_2)\big)\cdot p_{Z_2}\big(y_2 - (h_{12}x_1 + h_{22}x_2)\big), \tag{3.2.4}$$

which relates the model shown in Figure 3-2 to the model introduced in Figure 3-1.

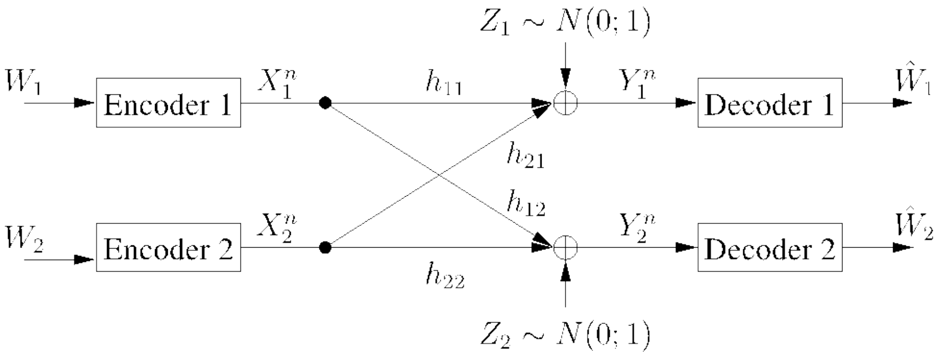

Figure 3-2: Two-user Gaussian interference channel.

As we will see in the following sections, the strengths of the cross-channel gains h_{12}^2 and h_{21}^2 and especially the ratios of the cross-channel gains to the direct channel gains h_{ij}^2/h_{ii}^2 have a strong impact on the transmission strategies of the two transmitters and the achievable rates. For that reason, it is convenient to consider a normalized version of the interference channel, which is referred to the interference channel in standard form, and shown in Figure

[2] Note that $P_{Y_1,Y_2|X_1,X_2}$ is given by a probability density function $p_{Y_1,Y_2|X_1,X_2}$if Y_1, Y_2 are continuous random variables, and by a probability mass function $P_{Y_1,Y_2|X_1,X_2}$ otherwise.

3-3. Here, the direct channel gains are normalized to one and the cross-channel gains a and b can be obtained from the more general model in Figure 3-2 as follows (assuming positive real-valued channel coefficients h_{ij})

$$a = \frac{h_{21}}{h_{22}} \text{ and } b = \frac{h_{12}}{h_{11}}. \quad (3.2.5)$$

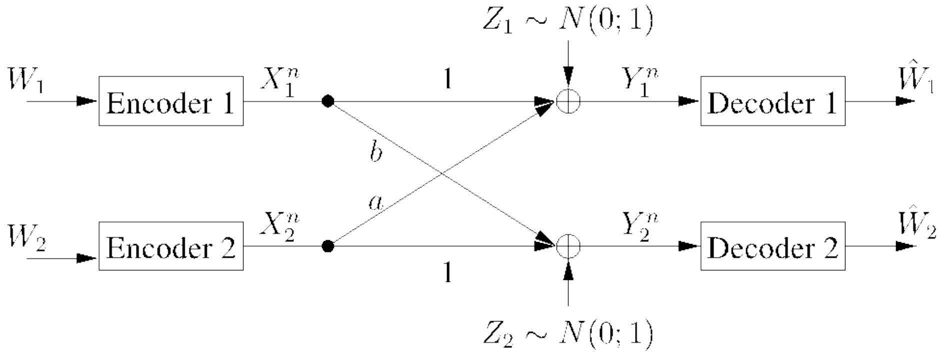

Figure 3-3: Gaussian interference channel in standard form.

While the channel model in Figure 3-2 is convenient to establish a direct connection to path-loss and propagation models, its representation in standard form is better suited to classify different interference regimes such as

- Weak interference: $a^2 < 1$ and $b^2 < 1$
- Strong interference: $a^2 \geq 1$ and $b^2 \geq 1$
- Very strong interference: $a^2 \geq P_1 + 1$ and $b^2 \geq P_2 + 1$

For illustration purpose, the contour plot in Figure 3-4 shows regions for which we have weak or strong interference over the cross links, assuming that the primary transmitter is located at position $(0,0)$, the primary receiver is located at position $(1,0)$, the secondary transmitter is located at position (x, y), and secondary receiver is located at position $(x + 1, y)$. In the left plot, we assumed that the fading coefficients take only into account a simple path-loss model with path-loss coefficient $p = 3$. In the right plot, the effect of Rayleigh fading is considered as well assuming one particular realization of the fading process. As we can see, both systems are in a weak interference regime if the links are sufficiently far apart, and we get different combinations of weak and strong interference on the links if the links are close to each other. Since the performance of the different transmission strategies depends on the interference regime, maps as shown in Figure 3-4 can be used by a cognitive-radio system for strategy selection if positioning information is available.

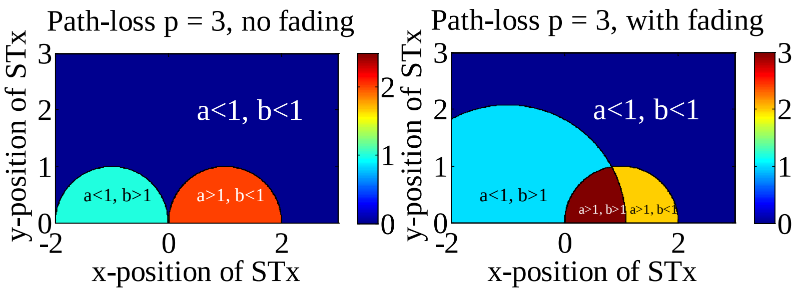

Figure 3-4: Regions of weak and strong interference for a primary transmitter and receiver located at (0,0) and (1,0), respectively, a secondary transmitter located at position (x, y), and a secondary receiver located at position $(x + 1, y)$.

For the channel model discussed in this section, we are now interested in transmission strategies that ensure reliable communication such that the joint error probability of the two receivers tends to zero as the block length n becomes large

$$\lim_{n\to\infty} P^{(n)}(W_1 \neq \widehat{W}_1, W_2 \neq \widehat{W}_2) \to 0\,. \tag{3.2.6}$$

For this purpose, we introduce different fundamental transmission strategies in the following sections and evaluate their performances in terms of achievable rates. That is, for a given transmission strategy, we are interested in the boundary of the achievable rate region which is given by the union of all achievable rate pairs $(\mathrm{R}_1, \mathrm{R}_2)$ for which reliable communication with diminishing error probability can be ensured.

3.2.2 Orthogonal Transmissions

The simplest approach to establish reliable communication is to split the resources into two portions and to allow each user to use one of the two portions exclusively. In this way, the two concurring links are orthogonalized and interference is completely avoided. This is equivalent to TDMA if the available time slots are split among the users, and it is equivalent to FDMA if the available frequency bands (or sub-carriers in a multi-carrier system) are split among the users.

Assume now that User 1 gets a fraction α of the resources and that User 2 gets the remaining fraction $\bar{\alpha} = (1 - \alpha)$ of the resources. For the AWGN channel model, the achievable rate tuples $(\mathrm{R}_1, \mathrm{R}_2)$ are now bounded by the respective channel capacities for the AWGN point-to-point channel

$$0 \leq R_1 \leq \frac{\alpha}{2} \log\left(1 + \frac{P_1}{\alpha}\right), \tag{3.2.7}$$

$$0 \leq R_2 \leq \frac{\bar{\alpha}}{2} \log\left(1 + \frac{P_2}{\bar{\alpha}}\right). \tag{3.2.8}$$

Here, only a fraction of the point-to-point capacity of the respective link is achieved by each user since User 1 and User 2 have only access to fractions α and $\bar{\alpha}$ of the available resources, respectively. Since we are furthermore considering an average power constraint as introduced in the previous section, the transmit powers of the two users are scaled by the fraction of the utilized channel uses.

The rate region is illustrated in Figure 3-5 (solid line), which includes as well the case of time-sharing without power control (dashed line). In this case, the power is kept constant at power level P_i for User i regardless of the time-sharing parameter α. It is important to notice that the rate region does not depend on the cross-channels since interference is avoided. This becomes relevant if comparisons to other schemes are considered in the following sections.

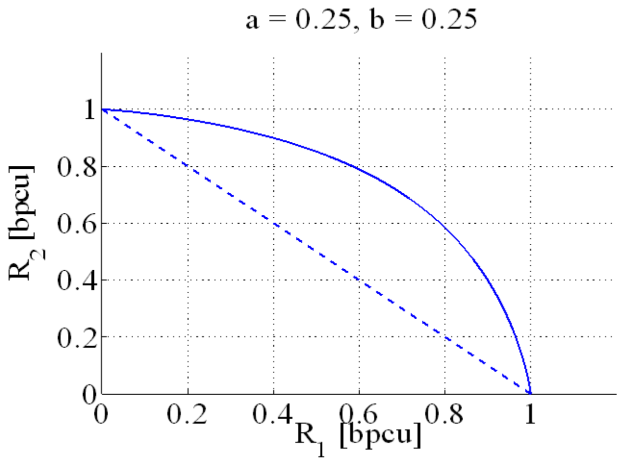

Figure 3-5: Rate region for orthogonalized resources: with power control (solid line) and without power control (dashed line).

As mentioned above, the rate region given in this section gives the performance for strategies that try to avoid interference by distributing the resources in an orthogonal way. In a cognitive radio context, a similar situation occurs when the interweave spectrum-sharing paradigm is considered such that the channel is only entered if the channel is known to be free and interference is avoided. While in a conventional system the time-sharing parameter α is the system parameter that can be chosen appropriately to control the distribution of the resources, it is in the cognitive radio case a function of the activity level of the primary user and the reliability of the employed spectrum awareness mechanism.

3.2.3 Treating Interference as Noise

As we have seen in the previous section, the price for orthogonalizing the channels is a loss in degrees of freedom. That is, only fractions of the resources are used by the users, which become visible in the rate equations by factor in front of the *log* term. An alternative approach is to let both users enter the channel at the same time. In this setup, different rates can be achieved depending on the capabilities of the receivers.

Let us assume the simplest case, in which the receivers treat the interfering signals as an additional noise term. In this case reliable transmission is possible as long as the rate of transmission is low enough such that the additional "noise" can be compensated by the employed code. The achievable rates can hence be obtained from the point-to-point capacity of the AWGN channel by considering the additional interference power in the denominator in the argument of the *log* term

$$0 \leq R_1 \leq \frac{1}{2}\log\left(1 + \frac{P_1}{1 + a^2 P_2}\right), \tag{3.2.9}$$

$$0 \leq R_2 \leq \frac{1}{2}\log\left(1 + \frac{P_2}{1 + b^2 P_1}\right). \tag{3.2.10}$$

We can see that full degrees of freedom are preserved. However, we can observe as well that the interference reduces the effective signal-to-noise ratio in the argument of the *log* term. Since the interference powers are proportional to the gains of the cross-links, it is clear that this will become a drawback if the strong and very strong interference regimes are considered. This is illustrated in Figure 3-6 (black lines) where the region defined by the rate constraints above is illustrated for different choices of the cross-channel coefficients (left: weak interference; middle: strong interference; right: very strong interference). In Figure

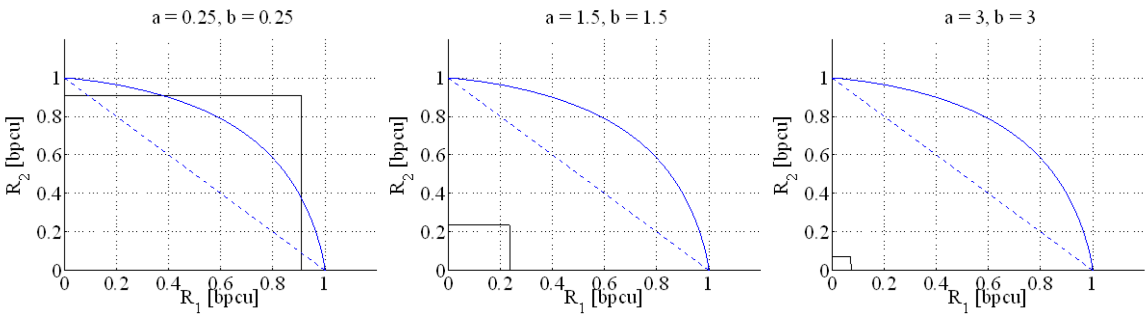

Figure 3-6: Rate region if interference is treated as noise (black lines).

3-6, it is assumed that the transmitters use full power and do not optimize their transmit powers. Accordingly, Figure 3-6 does not show the complete region of achievable rates. For comparison purpose, the rate region that is achieved by time-sharing is included as well. We can see that treating interference as noise is only beneficial if we are in the weak interference regime. For the strong and very strong interference regime, only small rates are obtained.

The transmission strategy considered in this section is a good model for a setup in which competing transmissions are allowed. It is the simplest model for this regime since we assumed that the users do not decode the messages from the interfering users (see the following section). This can be the best thing to do if

- The channel gains do not permit decoding of the interference,
- The required codebook of the interfering signal is not known to the receivers, or
- Complexity does not permit multi-user processing.

This model is well suited to describe underlay spectrum sharing where secondary users are allowed to enter the channel uncoordinated as long as the interference caused to the primary is bounded. It can be as well applied in a coordinated setup where the users perform a joint power allocation to maximize their rates.

3.2.4 Interference Decoding

As indicated above, treating interference as noise is only wise as long as the interference is low and it will lead to diminishing rates if interference is strong. However, if interference is strong, an alternative strategy may be to decode and remove interference instead of treating it as noise. As we will see in the following, significant gains can be obtained.

As an example to illustrate the idea, let us assume in the following that we are in a strong interference regime such that $a^2 \geq 1$ and $b^2 \geq 1$, and let us assume furthermore that codebook knowledge for the interfering signals are available at the receiver. In this setup, the two receivers can first decode the interfering messages treating the desired messages as interference, given that the rates of the interference transmitters support this. In a second set, assuming that the first decoding step was successful, the receiver can remove (i.e., subtract) the decoded interference from the received channel output samples and decode the desired signal based on an interference free signal.

The following rate conditions need to be fulfilled to make this strategy work in a general setup: Consider decoding at User 1. First, the sum rate $R_1 + R_2$ of both users needs to be supported by the receiver of User 1, i.e.

$$0 \leq R_1 + R_2 \leq \frac{1}{2}\log(1 + P_1 + a^2 P_2)\,. \tag{3.2.11}$$

This constraint is necessary to ensure that the received superposition of signals can be recovered in presence of the receiver noise. From the MAC channel, it is further known that both messages can be decoded at the receiver of User 1 if

$$0 \leq R_1 \leq \frac{1}{2}\log(1 + P_1)\,, \tag{3.2.12}$$

and

$$0 \leq R_2 \leq \frac{1}{2}\log(1 + a^2 P_2)\,. \tag{3.2.13}$$

Three similar bounds on R_1, R_2, and the sum rate $R_1 + R_2$ can be obtained for User 2. By combining all bounds we get

$$0 \leq R_1 \leq \min\left\{\frac{1}{2}\log(1 + b^2 P_1)\,, \frac{1}{2}\log(1 + P_1)\right\}, \tag{3.2.14}$$

$$0 \leq R_2 \leq \min\left\{\frac{1}{2}\log(1 + a^2 P_2)\,, \frac{1}{2}\log(1 + P_2)\right\}, \tag{3.2.15}$$

$$0 \leq R_1 + R_2 \leq \min\left\{\tfrac{1}{2}\log(1 + P_1 + a^2 P_2)\ , \tfrac{1}{2}\log(1 + b^2 P_1 + P_2)\right\}. \tag{3.2.16}$$

For the weak-interference case, where we have $a^2, b^2 \leq 1$, the first terms in the minimum dominates the constraints on the rates R_1 and R_2, and it becomes inactive as soon as we are in the strong interference regime. For the very-strong interference regime, where $a^2, b^2 \geq 1 + P_{i/j}$, it can be shown that the sum-rate constraint becomes inactive and the highest achievable rates for R_1 and R_2 equal the capacity of the interference-free point-to-point channels. That is, in this regime, spectrum sharing does not lead to any rate loss for any user. The achievable rate region is illustrated in Figure 3-7 (red lines). It includes again the previously discussed rates for comparison purpose.

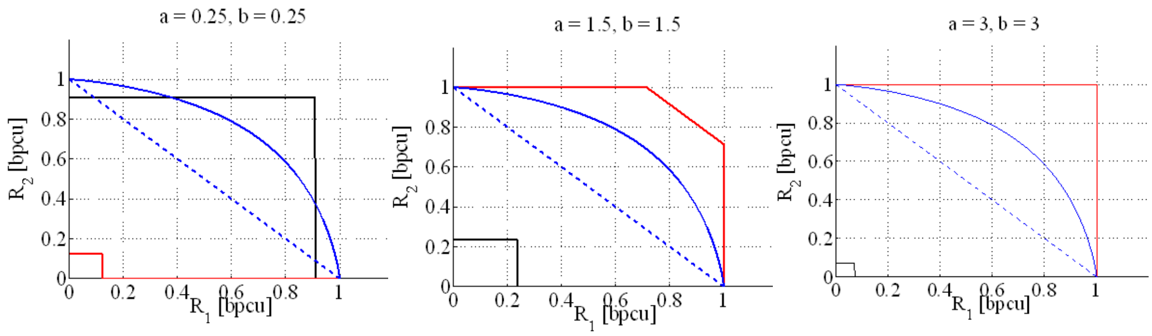

Figure 3-7: Rate region with interference decoding (red lines).

As it can be seen from Figure 3-7, interference decoding requires strong and very strong interference to lead to an improvement in rate. However, as a comparison to treating interference as noise shows, significant rate gains can be obtained if both users decided to cooperate by exchanging their codebooks. From a CR perspective, this is relevant, for example, in a setup where the cognitive receiver is close to the primary transmitter and has codebook knowledge. If the primary receiver is furthermore flexible and agrees to perform interference decoding, both users will benefit from this strategy.

3.2.5 The Han-Kobayashi Scheme

As we saw in the previous section, interference decoding, if applied in beneficial channel conditions, can be a powerful approach to improve rates in the interference channel. However, in less beneficial setups, forcing the receivers to decode the entire interfering message first, turned out to be inefficient. A more flexible solution, in which the receivers are only required to partially decode the interfering messages, was proposed by Han and Kobayashi [146]. The encoder structure that was suggested by Han and Kobayashi to enable partial decoding of the interfering message is illustrated in Figure 3-8. Encoding proceeds in two steps: in a first step, the encoder uses rate splitting to subdivide the message W_i at User i into two messages W_i' and W_i'' with rates R_i' and R_i'', respectively, such that $R_i = R_i' + R_i''$. The sub-messages W_i' and W_i'' are then encoded by two codewords U_i^n and V_i^n, respectively, with average power constraints

$$\frac{1}{n}\sum_{j=1}^{n} E\{U_{i,j}{}^2\} \leq P_i' \quad \text{and} \quad \frac{1}{n}\sum_{j=1}^{n} E\{V_{i,j}{}^2\} \leq P_i'' \tag{3.2.17}$$

and superposed to form the codeword $X_i^n = U_i^n + V_i^n$ with average power constraint fulfilling $P_i = P_i' + P_i''$.

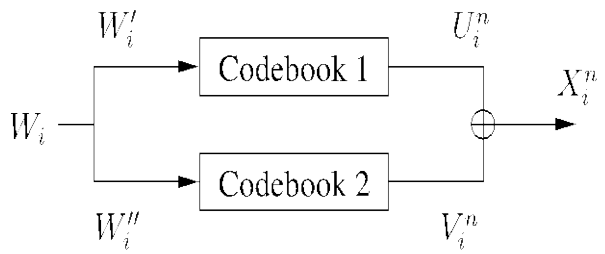

Figure 3-8: Superposition coding.

The rate and power allocation at the two users are now optimized such that the receivers can decode both messages from the designated transmitters and one of the two messages from the interfering transmitter. To illustrate the key idea of this strategy, consider as an example the receiver of User 1 and assume that rates and powers are set such that the following decoding strategy becomes beneficial for User 1 and a similar strategy can be applied at User 2.

1. Decode U_1^n, treating V_1^n as well as U_2^n and V_2^n as interference.
2. Subtract U_1^n from the channel output Y_1^n, and decode the interfering codeword U_2^n, treating V_1^n and V_2^n as interference.
3. Subtract U_1^n and U_2^n from the channel output Y_1^n, and decode V_1^n treating V_2^n as interference.

The rate region that follows from the constraints that have to be satisfied to make the scheme work is complex; it consists of seven rate constraints and it relies on time-sharing parameters that are not covered in this report. The Han–Kobayashi region is tight for the class of discrete memory-less interference channel with strong and very strong interference, but not for the case of weak interference.

Due to its complexity, we skip a detailed discussion of the Han-Kobayashi region in this port. Explaining the underlying transmission strategy is however relevant for our work in this project since it provides us with a blueprint for a sophisticated underlay strategy. This strategy has been used in the PUT/TUP/KTH cooperation as a reference scheme for benchmarking the performance of the developed overlay strategies.

3.3 Multiple-antenna Interference Channel

3.3.1 Overview

Multiple antennas can be deployed at the transmitters or receivers or both in an interference channel. The (multiple-input and single-output) MISO IC describes, for example, the downlink communications of cochannel cells in which the base stations have multiple antennas and the mobile stations have single antennas. Less well understood is the downlink transmission in the presence of interference, both in terms of its fundamental performance limits (i.e., capacity region), as well as in practically feasible transmission schemes. The assumption of multi-antenna transmitters and single-antenna receivers is motivated by the real world constraints in which miniaturization of mobile units limits the number of antennas. In addition, the asymmetry in available resources at base and mobile stations favors systems in which transmitters are tasked with heavy processing in exchange for reduced complexity at mobile units. Assume that each receiver implements single-user decoding (SUD), i.e., it treats interference as channel noise.

3.3.2 Two-user MISO Interference Channel

For information theoretical analysis of IC, two definitions are provided in the literature. One is achievable rate region, which is the set of all rates that can be achieved using beamforming vectors that satisfy the power constraint, and the other is Pareto boundary, which is the outer boundary of this region. For the special two-user case, it is shown that the optimal transmit beamforming vector to achieve a Pareto-boundary rate-pair for the MISO-IC can be expressed as a linear combination of the zero-forcing (ZF) and maximum-ratio transmission (MRT) beamformers, i.e. a real number between 0 and 1 is needed to parametrize the beamforming vector [147].

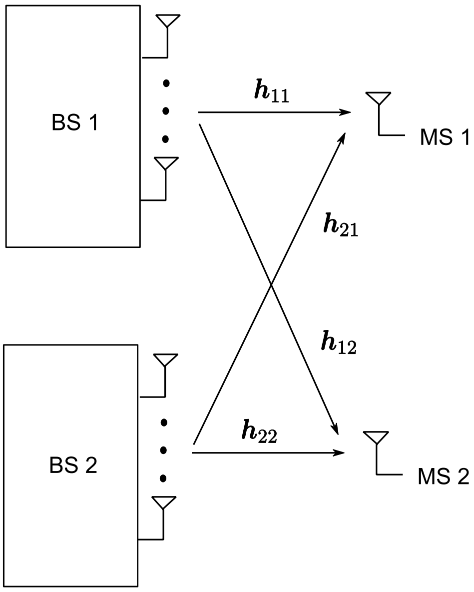

Figure 3-9: Two-user MISO interference channel.

As in Figure 3-9, the beamforming vectors can be parametrized as

$$\mathbf{w}_1(\lambda_1) = \sqrt{\lambda_1}\frac{\Pi_{\mathbf{h}_{12}}\mathbf{h}_{11}}{\|\Pi_{\mathbf{h}_{12}}\mathbf{h}_{11}\|} + \sqrt{1-\lambda_1}\frac{\Pi^{\perp}_{\mathbf{h}_{12}}\mathbf{h}_{11}}{\|\Pi^{\perp}_{\mathbf{h}_{12}}\mathbf{h}_{11}\|}, \tag{3.3.1}$$

$$\mathbf{w}_2(\lambda_2) = \sqrt{\lambda_2}\frac{\Pi_{\mathbf{h}_{21}}\mathbf{h}_{22}}{\|\Pi_{\mathbf{h}_{21}}\mathbf{h}_{22}\|} + \sqrt{1-\lambda_2}\frac{\Pi^{\perp}_{\mathbf{h}_{21}}\mathbf{h}_{22}}{\|\Pi^{\perp}_{\mathbf{h}_{21}}\mathbf{h}_{22}\|}, \tag{3.3.2}$$

where $\Pi_{\mathbf{a}} \triangleq \mathbf{a}\left(\mathbf{a}^H\mathbf{a}\right)^{-1}\mathbf{a}^H$ denotes the orthogonal projection onto the space of $\mathbf{a}$, $\Pi^{\perp}_{\mathbf{a}} \triangleq \mathbf{I}-\Pi_{\mathbf{a}}$ denotes the orthogonal projection onto the orthogonal complement of the space of $\mathbf{a}$, $\lambda_1 \in [0,1]$ and $\lambda_2 \in [0,1]$. λ_1 and λ_2 can be varied from 0 to 1 to get the achievable rate region and the corresponding pareto boundary. More efficient computation methods of the pareto boundary can be found in [148] and [149], and closed-form solutions can be found in [150] and [151].

3.3.3 Multi-user MISO Interference Channel

For the multi-user case, the beamforming vectors that correspond to a rate point on the Pareto boundary can be parametrized by $K(K-1)$ complex numbers, where K is the number of transceiver pairs [147]. In [149] [152] [153], the authors independently prove that beamforming is optimal for the entire SUD rate region for a multi-user MISO IC. In [149], the authors characterize the Pareto boundary of the MISO IC through controlling interference temperature constraints (ITC) at the receivers. Each Pareto-boundary rate-tuple of the MISO-IC can be achieved in a decentralized manner when each of the BSs attains its own channel capacity subject to a certain set of interference-power constraints at the other MS receivers. It is shown that $K(K-1)$ real valued parameters, each between zero and a value depending on the channel vectors, are needed to achieve all Pareto optimal points. ITC is a terminology used in cognitive radio scenarios under the underlay paradigm, which quantifies the amount of interference from the secondary transmitters that is tolerated by the primary users. In [152], the K-user MISO IC is considered with the capabilities of time sharing the resources between the links. All points on the Pareto boundary of the MISO IC rate-region are achieved with $K(K-1)$ real valued parameters each between 0 and π.

In [153], a general framework is proposed for parametrizing the transmission strategies of each transmitter which are relevant to achieve Pareto optimal points. This framework is applicable to settings where the utility functions of the systems are monotonic in the received power gains. Firstly, the properties of efficient transmission of a single transmitter are investigated. These properties are acquired on studying the transmitter's power gain-region. The power gain-region is composed of all jointly achievable power gains at the receivers. Of interest are the transmission strategies which achieve its boundary part in a specific direction. It is proved that the boundary of the power gain-region is convex and always achieved with rank-1 transmit covariance matrices. Due to these properties, the corresponding beamforming vectors are characterized by real-valued parameters. When power control is needed for efficient transmission, an additional real valued parameter between zero and one is needed that varies the power level at the transmitter. Then the developed single-transmitter framework is utilized for the multiple-transmitter case. Based on the network setting and the monotonicity properties of each receiver's utility function, the boundary part which is relevant for Pareto optimal operation is determined for each transmitter's gain-region. Consequently, each transmitter's efficient strategies are parametrized.

In [154], joint linear precoding is investigated taking into account the signaling overhead between the transmitters. The rate region achieved with joint precoding is larger than the MISO IC rate-region, and all Pareto optimal beamforming vectors are parameterized by $K(K-1)$ complex-valued parameters. For the same setting, a recent result in [155] reduces the number of parameters to $K+L$ real-valued scalars, each between zero and one, where L is the number of linear constraints on the transmission.

3.4 Interference Alignment

Interference Alignment was introduced by Cadambe and Jafar in their landmark paper [156], where a K-user interference channel was considered. As pointed out above for the two-user case (see Section 3.2.2), if a transmit strategy is employed that divides the resources (e.g., time, frequency, spatial dimensions) equally among the users, then each transmitter-receiver receiver pair will get a fraction $1/K$ of the total resources. With interference alignment, however, it can be shown that every user can achieve *1/2* of the channel resources, regardless of the number of users. This is made possible by having every transmitter sacrifice half of its maximum signaling dimensions (time, frequency bands, spatial dimensions). The transmission scheme is then designed such that at every receiver, the signal from the desired transmitter occupies half of the maximum available dimensions and the signals from the interfering transmitters are aligned in the remaining. As result, each transmitter-receiver pair can communicate over an interference-free link, regardless of the number of number of interferers [158].

3.4.1 State of the Art

Although the original scheme presented in [156] is an elegant solution to the interference alignment problem, it is unsuitable for practical implementation, as it requires global channel knowledge. That is, every transmitter needs to know all the $K(K-1)$ channels. It is furthermore complex, and most importantly, it does not apply to scenarios with more than 3 users and multiple antennas. Finding closed-form solution for interference alignment is impossible in this setting.

To overcome this problem, numerical solutions have been proposed to extract the maximum possible DoFs from a given setting. However, instead of achieving the promised *K/2* DoF gain, they provide only a suboptimal performance. We can distinguish centralized interference alignment algorithms, where all the processing is done by some central entity, from distributed interference alignment approaches, which try to solve the problem in a decentralized manner.

The centralized solutions (such as [164]) shift the computational burden to the transmitters; that is, the underlying algorithm is transparent to the receivers. However, they require global channel knowledge at all the transmitters, which raises the issue of CSI acquisition and overhead. However, it was shown in [162] and [163] that interference alignment with limited feedback can still achieve the full promised DoFs.

A good example for a distributed interference alignment scheme is presented in [157] where the authors tried to solve the alignment problem by having the algorithm run at both the transmitters and receivers in an alternating and distributed fashion. Although many other algorithms have been proposed in the literature, they are structurally similar; i.e., they operate by trying to minimize some interference cost function [160], [161]. Note that the latter is a non-convex function, thus, global convergence of the algorithm has never been proved so far. Other algorithms operate by trying to maximize some network utility functions. For instance, in [165] the authors adopt the sum-rate as utility function and try to maximize it by moving along its gradient. A similar approach was adopted by [166] and [167]. Although the algorithms that fall under this umbrella get around the need for global channel knowledge (only local CSI is required at every transmitter / receiver), they suffer from several practical limitations that are inherent to the fact that they operate at both the transmitters and receivers. For instance, to efficiently run the algorithms in an alternating fashion on the transmitter and receiver sides, synchronization is required which might be hard to maintain especially at the receivers' side. Furthermore, the limited computational capability of the receivers (for example in a down-link scenario) might be a bottleneck for the execution time of the algorithm. Finally, the assumption of channel reciprocity is central and thus limits the applicability of such algorithms to TDD systems only.

3.4.2 Challenges

From theoretical point of view, the gains promised by interference alignment are unprecedented. However, these promising gains come with a few challenges.

- Solving the issue of global channel knowledge, either by CSI acquisition or by bypassing it using distributed algorithms, has been at the heart of the research effort. As mentioned earlier, both approaches have inherent obstacles and limitations.
- None of the iterative algorithms presented so far, whether centralized or distributed, has been shown to be globally convergent; i.e., when minimizing their cost functions, they can easily get stuck in local minima, that do not correspond to the interference alignment solution. This is due to the fact that cost/utility functions are non-convex. With this in mind, the global convergence of interference alignment algorithms is still an open problem.
- The feasibly of interference alignment was only shown for a very limited number of cases. Recently, more light has been shed on that matter. The first attempt was made by [168] to characterize the feasibility of interference alignment by using arguments from Bernstein's theorem; however, the applicability of the result was somewhat limited. The authors in [169] proved a stronger result by settling the feasibly conjecture, although in one way only. However, conjecture was settled both ways in [165]. Furthermore, the authors provided a polynomial-time feasibility test for interference alignment problems.
- In addition, the authors in [171] showed that interference alignment belongs to the class of NP-hard problems. More specifically, they show that the problem of maximizing the total degrees of freedom for a given interference channel is NP-hard. Furthermore, they show that even checking the achievability of a given DoF assignment among the users is NP-hard.
- Recent works address the inherent trade-off of interference alignment from a practical perspective; for example, by studying whether the overhead required by interference alignment might destroy the promised gains. Such works include [172] and [173] where the authors tackle issues like overhead along with the optimal performance tradeoff. Furthermore, the authors in [174] establish a generic but extremely interesting result: cooperation in general (including, but not limited to interference alignment) has fundamental limits. In that sense, the authors show that linear scaling of the capacity, captured by the DoF metric is not accurate in the high SNR regime. As a result, the sum-rate curve saturates at SNR levels of operational relevance to cellular networks.

3.4.3 Applications

Although theoretically speaking the concept of interference alignment can be applied to any interference-limited network (cellular networks, WLANs, sensor networks, etc.), due to the limitations and practical issues that were reported earlier, the envisioned applications of interference alignment have been limited to cellular networks, so far. Even so, very little work addressed the system wide performance of interference alignment, taking into account the overhead that is required. In [175] the authors simulated the system wide performance of IA in a conventional 3G cellular network, and reported modest overall gains of 20% to 30% - much less that what the theory predicts. This suggests the existence of fundamental discrepancies in the system model.

3.4.4 Summary

Summing up, IA seems to be an extremely promising technique that has the potential to deliver capacity gains large enough to cope with the exponential increase in market demand for mobile data. However, as we mentioned before, there are still many non-trivial technical issues that need to be addressed, if the idea should ever see the light in a real systems. But most importantly, before any realizable gains can be extracted from the application of such a technique, the research effort in the near future has focus on bridging the relatively large gap between the theoretical and practical aspects of IA.

4. Information Theoretical Techniques in Cognitive Radio Networks

In this section, we give examples for how the models summarized in the previous section can be applied and specialized to the cognitive radio scenarios. The results in (extended) cognitive radio channel are summarized, followed by literature survey in MISO/MIMO cognitive radio systems, and the time sharing technique and two cognitive relay scenarios are also introduced. In this deliverable, the information theoretical results in the underlay/overlay MISO cognitive channels is introduced in Section 4.3, while the optimal overlay transmission strategy is detailed in Section 4.1 of Deliverable 13.1 and compared with the optimal underlay transmission strategy, and the decision-making framework for the transmission strategy selection is included in Deliverable 12.3, which results from the joint research among KTH/PUT/TUD in WP8/12/13.

4.1 Cognitive Radio Channel

An extension of the two-user interference channel is given by the so-called cognitive radio channel, which was introduced in the information theory literature as a model to describe a special class of spectrum overlay strategies, where the secondary transmitter acts as relay for the primary system (see e.g. [176]-[179]). To model this situation, it is assumed in the cognitive radio channel model that the secondary transmitter knows the message W_1 of the primary user ahead of its transmission. The resulting channel model is illustrated for the Gaussian case in Figure 4-1.

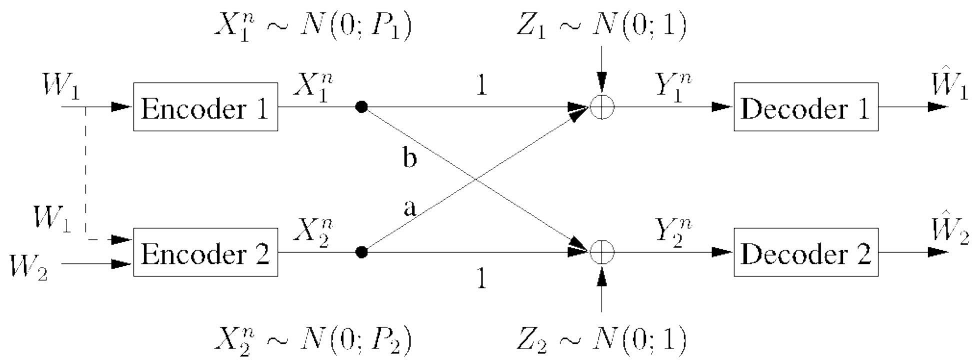

Figure 4-1: Gaussian cognitive radio channel.

The knowledge of the primary's message can be used in different ways at the secondary transmitter: it can be used for relaying to compensate the primary system for the interference caused by the secondary transmitter, and it can be used to pre-cancel the interference from the primary transmitter received at the secondary receiver. Two strategies based on these ideas are summarized in the following.

4.1.1 Weak Interference to the Primary Receiver

In the first example, we consider the special case where we have weak interference from the secondary transmitter to the primary receiver (i.e. $|a| < 1$). We assume furthermore that the primary user uses a point-to-point code for encoding its message and transmits at capacity of the interference-free primary link, i.e.

$$R_1 = \frac{1}{2}\log(1 + P_1). \quad (4.1.1)$$

In this case, any interference that further increases the signal-to-interference-plus-noise ratio (SINR) at the primary receiver will lead to a breakdown of the primary link.

The optimal transmission strategy, that achieves capacity in this special setup, was developed in [177], [178]. In a first step, the secondary transmitter employs superposition coding and transmits

$$X_2^n = X'^n_2 + X''^n_2, \quad (4.1.2)$$

where $X'^n_2 = \sqrt{\beta P_2/P_1} \cdot X_1^n$ is used to relay the primary's message with a fraction β of the secondary's power and the remaining power $(1-\beta)P_2$ is used to encode the secondary's message. The resulting SINR at the primary receiver is given by

$$SINR_p = \frac{\left(\sqrt{P_1} + a\sqrt{\beta P_2}\right)^2}{1 + a^2(1-\beta)P_2}. \quad (4.1.3)$$

The optimal power allocation β^* can now be obtained from the fact that $\mathrm{SINR_p} \geq P_1$ has to be ensured to maintain the primary link, and it follows by solving $\mathrm{SINR_p} = P_1$ for β.

Assuming that the secondary transmitter has as well knowledge of the cross-link channel coefficient b, it can pre-cancel the interference $\left(b + \sqrt{\beta^* P_2/P_1}\right) \cdot X_1^n$ received by the secondary system by using Gelfand-Pinsker coding (known as well as dirty-paper coding or Costa pre-coding in the Gaussian case) at the secondary transmitter when encoding W_2 by X''^n_2. The rate obtained for the secondary link equals then

$$R_2 = \frac{1}{2}\log(1 + (1-\beta^*)P_2). \quad (4.1.4)$$

4.1.2 Strong Interference to the Primary Receiver

In the strong interference case (i.e. $|a| > 1$), it is no longer beneficial to compensate the primary system for the interference caused by the secondary. Instead, if the primary system agrees to change the receiver and employs a multi-user decoding with successive decoding (see as well Section 3.2.4), the following strategy can be employed. The secondary transmitter uses again superposition coding as described above and encodes the primary message in X'^n_2 using a fraction β of its power such that $X'^n_2 = \sqrt{\beta P_2/P_1} \cdot X_1^n$. Instead of using pre-cancelation techniques as in the previous section it encodes the secondary message directly in X''^n_2 using the remaining fraction $(1-\beta)$ of its power.

The rate of the secondary transmission and the power allocation are now optimized to make the following decoding strategies at the primary and the secondary receivers are possible.

- *Decoding at the primary receiver*: The secondary message is decoded first, treating the primary message as interference. After subtracting the secondary message from the channel output, the primary message is decoded based on interference-free channel observations.

- *Decoding at the secondary receiver*: The secondary message is decoded, treating the primary message as interference.

Since the secondary message has to be decoded at both receivers, we get two different rate constraints limiting the secondary rate R_2. The primary rate R_1 on the other hand benefits from this strategy (i.e., it is increased compared to the primary link an absence of the secondary) since all interference is removed by successive decoding and the power of the desired signal component is increased.

4.2 Extended Cognitive Radio Channel

In the classical cognitive radio channel model it is assumed that the secondary transmitter has non-causally access to the primary's message. This implies however that resources were used beforehand, which are not considered in the rate expressions of the classical model. We can therefore expect that achievable rates promised in the classical model are too optimistic. To quantify how much rate is lost if we consider the resources that are required to convey the primary's message to the secondary transmitter, we proposed in this project an extended model that combines the cognitive radio channel model with decode-and-forward relaying. The resulting model is illustrated in Figure 4-2, and the general idea of this model is summarized in the following.

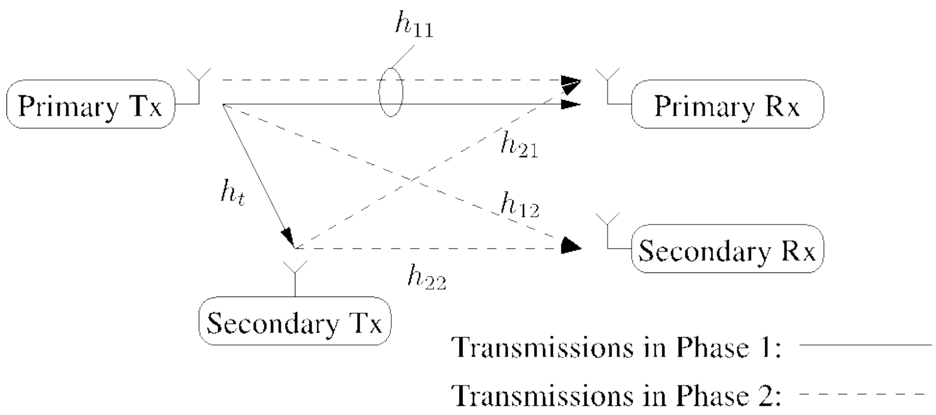

Figure 4-2: Extended cognitive radio channel model.

To account for practical constraints we assume that the secondary transmitter cannot transmit and receive at the same time using the same frequencies. Accordingly, conveying the message from the primary transmitter to the secondary transmitter and carrying out a cooperative transmission as described in the cognitive radio channel have to happen in two consecutive transmission phases using different portion of the available resources. In the following, we assume that the entire transmission (considering both phases) is carried out using n channel uses in total. A fraction α of the channel uses is allocated to the first phase, and the remaining fraction $(1-\alpha)$ is used for the second phase.

In the first phase (bold lines in Figure 4-2), the primary broadcasts a codeword carrying the primary message to the primary transmitter and the secondary receiver. The code rate R_0 of this initial transmission is set such decodability at the secondary transmitter is ensured, i.e.

$$R_0 \leq \frac{1}{2}\log\left(1 + h_t^2 P_1^{(1)}\right), \tag{4.2.1}$$

where $P_1^{(1)}$ is the power spent by the primary during the first transmission phase. Note that this cooperative scheme is only reasonable if the secondary transmitter can decode before the primary receiver, i.e. we require $h_t^2 > h_{11}^2$.

After successful decoding, the secondary transmitter employs a binning strategy similar to the so-called decode-and-forward binning. That is, it splits the codewords of the code used by the primary transmitter into sub-codes of equal size and with rates R_0' satisfying

$$R_0' \leq \frac{1}{2}\log\left(1 + h_{11}^2 P_1^{(1)}\right). \tag{4.2.2}$$

The rate is set such that each sub-code is decodable based on the information received by the primary receiver during the first phase. That is, knowing the sub-code that contains the transmitted codeword from the first phase would enable the primary receiver to decode the primary's messages (based on the channel observation from the first phase). The goal of the second phase is therefore to inform the primary receiver about the sub-code that contains the transmitted codeword from the first phase.

Since the initial code contains $2^{n\alpha R_0}$ codewords that are split into $2^{n\alpha R_0'}$ sub-codes, it is clear that each sub-code can be labelled by an integer number $i \in \{0, \dots, 2^{n\alpha(R_0 - R_0')}\}$ using $m = n\alpha(R_0 - R_0')$ bits. The goal of the second phase is therefore to transmit the m-bit index i reliably to the primary receiver while using an overlay strategy as described in Section 4.1 to simultaneously convey the secondary message. If we denote the rates obtained from the cognitive-radio channel model for the primary and the secondary link as $R_1^{CR}(P_1, P_2, \beta)$ and $R_2^{CR}(P_1, P_2, \beta)$, parameterized by the transmit powers P_1 and P_2 and the power allocation at the secondary transmitter β, and assume that the primary link requests a target rate R_1^*, then we can characterize the rates that are achievable by the extended cognitive radio model as follows

$$R_1^* \leq \frac{\alpha}{2}\log\left(1 + h_{11}^2 P_1^{(1)}\right) + (1-\alpha) R_1^{CR}(P_1^{(2)}, P_2/(1-\alpha), \beta), \tag{4.2.3}$$

$$R_1^* \leq \frac{\alpha}{2}\log\left(1 + h_t^2 P_1^{(1)}\right), \tag{4.2.4}$$

$$R_2 \leq (1-\alpha) R_2^{CR}\left(P_1^{(2)}, \frac{P_2}{1-\alpha}, \beta\right), \tag{4.2.5}$$

where the power constraint for the primary system requires $P_1 = \alpha P_1^{(1)} + (1-\alpha) P_1^{(2)}$. The first constraint gives the mutual information that is received by the primary receiver using this strategy. The second constraint is needed to ensure decodability at the secondary transmitter. The last constraint bounds the rate achieved by the secondary user. Compared to the classical cognitive radio channel, the rate expression is reduced by a factor $(1-\alpha)$ since only the second phase is used for the secondary transmission. The secondary power is scaled by a factor $(1-\alpha)$ for the same reason in order to satisfy the average power constraint. In this project, we have generalized this model further to the MISO case. The optimization of the beamforming vectors was discussed in part in WP13 while the overall optimization and the evaluation is treated in WP12.

4.3 MISO Cognitive Radio Systems

As in Section 3.3.2, the optimal beamforming to achieve a Pareto-boundary rate-pair for the two-user MISO-IC can be expressed as a linear combination of the ZF and MRT beamformers. As in Figure 4-3, in an underlay cognitive radio setting, the primary link is unaware of the existence of the secondary link, and MRT is deployed at the primary transmitter. The secondary transmission subjects to the satisfaction of the interference temperature constraint (ITC) at the primary receiver.

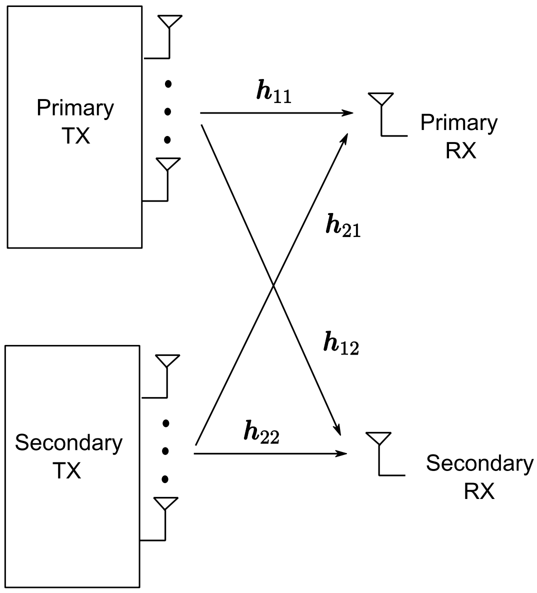

Figure 4-3: MISO cognitive channel with ITC.

With beamforming vector $\mathbf{w}_2$ ($\|\mathbf{w}_2\| = 1$) and power p_2 ($0 \le p_2 \le P_2$) at the secondary transmitter, the achievable secondary rate is

$$R_2 = \log_2\left(1 + \frac{\left|\mathbf{h}_{22}^H \mathbf{w}_2\right|^2 p_2}{\left|\mathbf{h}_{12}^H \mathbf{h}_{11}\right|^2 P_1 + 1}\right), \tag{4.3.1}$$

and the achievable primary rate becomes

$$R_1 = \log_2\left(1 + \frac{P_1 \left\|\mathbf{h}_{11}\right\|^4}{\left|\mathbf{h}_{21}^H \mathbf{w}_2\right|^2 p_2 + 1}\right), \tag{4.3.2}$$

where P_1 and P_2 are the primary and secondary power constraint, respectively. To enable the coexistence of the primary and secondary links, certain ITC, or equivalently primary rate, has to be satisfied. It results that the optimal beamforming that maximizes the achievable secondary rate can be parametrized as [180]

$$\mathbf{w}_2(\lambda) = \sqrt{\lambda}\,\frac{\Pi_{\mathbf{h}_{21}} \mathbf{h}_{22}}{\|\Pi_{\mathbf{h}_{21}} \mathbf{h}_{22}\|} + \sqrt{1-\lambda}\,\frac{\Pi_{\mathbf{h}_{21}}^{\perp} \mathbf{h}_{22}}{\|\Pi_{\mathbf{h}_{21}}^{\perp} \mathbf{h}_{22}\|}, \tag{4.3.3}$$

and the optimal power is

$$p_2 = P_2. \tag{4.3.4}$$

When the primary interference is strong enough, rate splitting and successive decoding can be deployed at the secondary link to achieve a higher secondary rate.

When the secondary transmitter has noncausal knowledge of the primary message, it can relay the primary message to maintain or improve the primary rate requirement. The primary transmitter uses a Gaussian codebook and deploys MRT. The primary receiver has knowledge of the codebook for d_1. The secondary transmitter uses the same codebook for d_1 as the primary transmitter, and encodes d_2 into u_2 by dirty-paper coding (DPC) to protect it against the interference created due to the transmission of the message intended for the primary receiver. The secondary receiver has knowledge of the codebook for d_2.

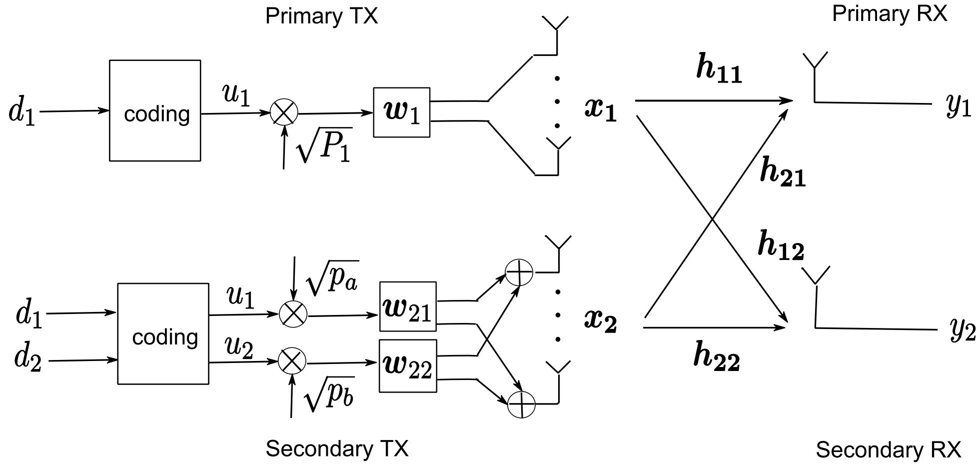

Figure 4-4: MISO cognitive channel with noncausal primary message and ITC.

The achievable primary and secondary rates are

$$R_1 \le \log_2\left(1 + \frac{\left|\sqrt{P_1}\|\mathbf{h}_{11}\|^2 + \sqrt{p_a}\mathbf{h}_{21}^H\mathbf{w}_{21}\right|^2}{1 + p_b\left|\mathbf{h}_{21}^H\mathbf{w}_{22}\right|^2}\right), \tag{4.3.5}$$

$$R_2 \le \log_2\left(1 + p_b\left|\mathbf{h}_{22}^H\mathbf{w}_{22}\right|^2\right), \tag{4.3.6}$$

where $\|\mathbf{w}_{21}\| = \|\mathbf{w}_{22}\| = 1$ and $0 \le p_a + p_b \le P_2$. It results that the optimal beamformers that maximize the achievable secondary rate are written as [181]

$$\mathbf{w}_{21} = \mathbf{h}_{21}/\|\mathbf{h}_{21}\|, \tag{4.3.7}$$

$$\mathbf{w}_{22}(\lambda) = \sqrt{\lambda}\frac{\Pi_{\mathbf{h}_{21}}\mathbf{h}_{22}}{\|\Pi_{\mathbf{h}_{21}}\mathbf{h}_{22}\|} + \sqrt{1-\lambda}\frac{\Pi_{\mathbf{h}_{21}}^{\perp}\mathbf{h}_{22}}{\|\Pi_{\mathbf{h}_{21}}^{\perp}\mathbf{h}_{22}\|}, \tag{4.3.8}$$

and the optimal power is

$$p_a + p_b = P_2. \tag{4.3.9}$$

4.4 MIMO Cognitive Radio Systems

Several woks have been done for the MIMO underlay cognitive radio systems. In [182], the channel capacity of a MIMO secondary link is studied, under both its own transmit-power constraint as well as a set of interference-power constraints each imposed at one of the primary receivers. Multi-antennas are deployed at the secondary transmitter to effectively balance between spatial multiplexing for the secondary transmission and interference avoidance at the primary receivers. Convex optimization techniques are used to design algorithms for the optimal secondary transmit spatial spectrum that achieves the capacity of the secondary transmission. Suboptimal solutions for ease of implementation are also presented. For the special two-antenna case, a closed form expression for a linear precoding and linear reception scheme, which guarantees to meet the achievable rates and no mutual interference between primary and cognitive terminals, is obtained in [183]. The coexistence of a MIMO primary link and a MIMO secondary link is studied in [184]. To maximize the achievable secondary rate with primary rate requirement, the problem is shown to be non-convex due to primary rate constraint. By approximating this rate constraint by the method of Taylor series expansion, an iterative algorithm is proposed. In [185], jointly-optimized beamforming algorithms is proposed to maximize the achievable secondary rate, where single stream transmission in both primary and secondary links is considered and no coordination is required between the primary and secondary users and the interference cancellation is done at the secondary user. Specifically, the beamforming vector of the secondary link is designed to maximize the achievable rate under the condition that the interference both at the primary and secondary receivers is completely nullified. In the overview paper on resource allocation in cognitive radio networks [186], a cognitive MIMO link with power constraint and ITC is studied. There, the solution is characterized using Lagrangian duality. The optimal transmit strategy is given by a singular value decomposition strategy and it is parameterized by the Lagrangian multipliers corresponding to the constraints. A suboptimal heuristic algorithm is proposed and compared to the optimal solution. The extension to the cognitive MIMO MAC/BC/IC scenario is briefly discussed. In [187], opportunistic transmission methods are proposed to exploit spatial holes in secondary MIMO multiple access or broadcast channel. The proposed methods determine a precoding matrix for each secondary transmitter as well as a post processing matrix for each secondary receiver. [188] studies the coexistence of secondary MIMO MAC system with a SISO primary link which has a rate requirement. The primary rate constraint is transformed into an interference constraint profile with individual ITC for the secondary transmitters. By spatial shaping (transmit covariance matrix optimization, linear precoding), an iterative algorithm is proposed to optimize the sum capacity of the secondary MIMO MAC system, in which each user updates its transmit strategy with the transmit strategies of the other users fixed. The optimal single-user transmit strategy is obtained by comparing the achievable rate of two iterative algorithms, where transmit covariance matrix with either rank-one or rank-larger-than-one is optimized.

In the MIMO overlay cognitive radio systems, the secondary transmitter has knowledge of the primary message. An achievable region and an outer bound is derived for the coexistence of one primary MIMO link and one secondary MIMO link in [189]. It is shown that under certain conditions, the achievable region is optimal for a portion of the capacity region that includes sum capacity. With one primary SISO link and partial channel state information such that each transmitter knows its channel to its own receiver but has no information about its channel to the other receiver, two simple transmission strategies for the overlay CR system [190]. In the first strategy, the primary message is independently encoded at the two transmitters, whereas the same primary message encoding is used in the second strategy which not only allows the coherent signal combining at the primary receiver but also the possibility of complete interference cancellation at the secondary receiver even in the limiting case when the secondary receiver is equipped only with two antennas. The simulation results demonstrate that the proposed strategy with same primary message encoding shows considerable performance benefit over the strategy where the primary message is independently encoded at the two transmitters. [191] investigates the achievable secondary rate with one MISO primary link. The covariance matrix for the primary message is chosen according to beamforming strategy. An iterative method for determining the optimum covariance matrix is proposed.

4.5 Time Sharing

The idea of time-sharing is often treated as an alternative to the pure power control approach [192][193]. In the latter, the goal is to find such power distribution among e.g. antennas or subcarriers that allows the considered terminal to transmit in the continuous fashion, i.e. without any pauses, utilizing all or at least most of its resources for data transmission. Let us consider the case where *L* users will work continuously in the same geographical area, thus will interfere with each other. The idea behind the power control is to find such power distribution that allows *i*-th user to maximize its expectations not harming other users at the same time. In general, final power distribution is derived in such a way that some predefined criterion, such as total rate or amount of introduced interference, is optimized. One of the main drawbacks of such solution is relatively often high complexity of the algorithm used for finding the optimal power distribution. It is also worth mentioning that although we limit ourselves to the power distribution, similar analysis can be done for resource allocation among wireless users, e.g. in OFDMA systems in downlink transmission.

Contrarily, the goal of time-sharing is to avoid highly complicated derivation of the optimal or suboptimal power distribution and to assume that not all of the users have to transmit continuously. It is further agreed that the users will apply uniform power distribution among antennas or subcarriers, or at least the power will be adopted to the actual channel characteristics. The influence of the given user to the other users will be not included in the process of power distribution derivation. In order to reach the same effectiveness as in the power-control approach the users will split the assumed transmit period of the duration *T* into smaller sub-periods and transmit with one of the predefined strategies in each of these smaller periods. The exemplary transmit strategy can be to be silent (one strategy), to transmit with the half or maximum power (two additional strategies). The goal now is to find the schedule of playing optimal strategies by all users in each sub-period such that the global requirement (e.g. sum rate) is fulfilled. Let us consider the simple example of two SISO user interference channel, for which the corresponding rate region $\mathcal{R} = \{(R_1, R_2): R_i \in\ < 0, R_{i,\max} >, i = 1{,}2\}$ has been presented in Figure 4-5.

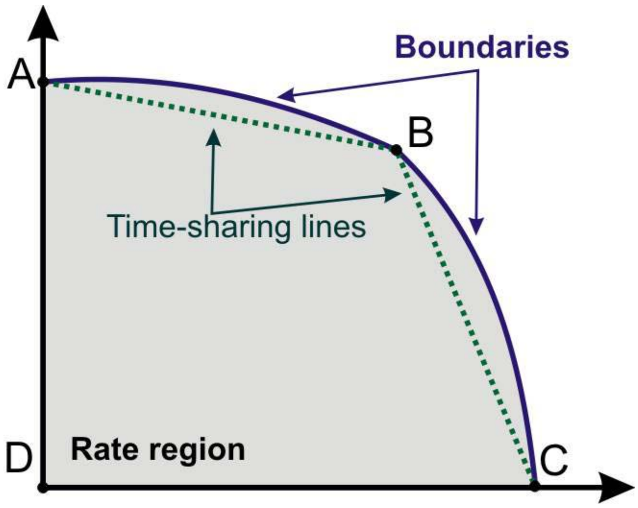

Figure 4-5: Rate region of the two-user interference channel.

It has been assumed that *i*-th user can transmit with the maximum power $T_{i,\max}$, achieving maximum theoretical rate $R_{i,\max}$, when no interference is observed. The boundaries of the rate region are obtained in such a way that one of the users transmits with its maximum power and the other user change its transmit power from zero to the maximum value. Four characteristic points can be identified on the rate region boundaries denoted as A, B, C, and D. These points correspond to the specific transmit strategies:

- Point A – user 1 transmits with the maximum power and user 2 is silent;
- Point B – both users transmit with the maximum power;
- Point C – user 2 transmits with the maximum power and user 1 is silent;
- Point D – both users are silent.

As it has been stated, the idea of time-sharing is to limit the set of all transmit possibilities in each sub-period to the specific set of predefined strategies. In the considered case each user can choose one of two possible strategies, i.e. to be silent or to transmit with the maximum power. Thus, the rate region can be bounded by straight lines connecting the neighboring points, as it has been shown in Figure 4-5. The solution obtained after application of the time-sharing procedure will be the guidelines how many sub-periods should be defined and how long should they last, as well as the indications for each users which strategies should be selected in each sub-period. The difference between the time-sharing and power control approach in the two-user interference channel has been shown in the Figure 4-6. As in the latter case both users transmit with the maximum power during the whole transmission period, appropriately distributed among antennas or subcarriers. In the time sharing approach each user can be either silent (white areas on the plot) or transmit data (grey areas).

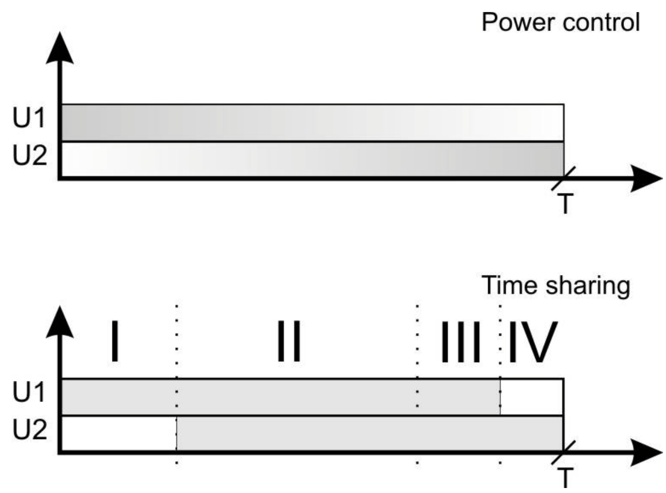

Figure 4-6: Illustration of the power-control and time-sharing concepts.

The above analysis can be extended to other cases, e.g. to the MIMO users [194], to the femtocell scenario [195] and can be applied for cognitive radio [196]. In the last case, the time-sharing approach can be applied in the overlay scenario, when both primary and secondary users cooperate, as well as in the secondary interference channel, where two secondary users have to optimize their transmission not causing harmful interference to the other users. Clearly, when the simple example of SISO interference channel will be extended to other scenarios, the set of new possible playing strategies will be defined accordingly.

Example – an application of the time-sharing approach to the secondary interference channel

Based on [196], let us shortly analyze the opportunities of application of the time-sharing approach in the secondary interference channel presented in Figure 4-7.

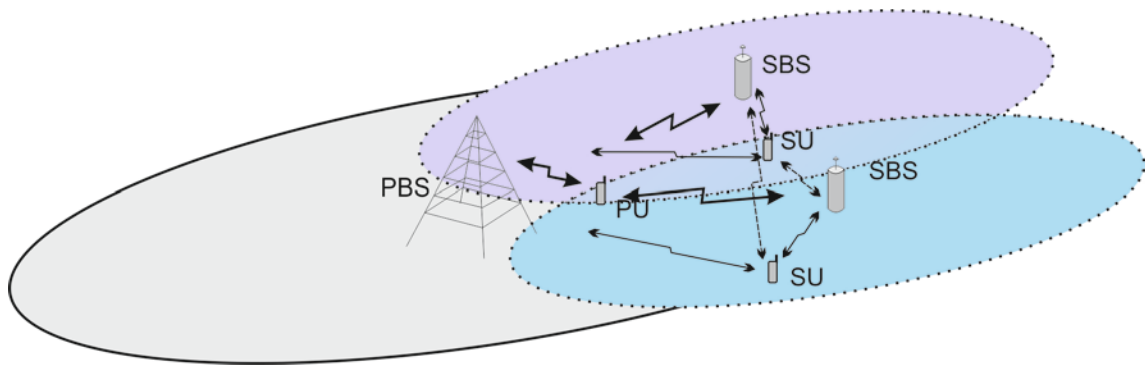

Figure 4-7: Secondary interference channel.

Two secondary users case (which corresponds to the two cognitive cells case as well) has been analyzed, in which each of the two SU's mobile terminals (SMT) communicates with his own secondary base station (SBS) causing interference to the neighboring cell as well as to the Primary User (PU). Each SMT has N_t transmit antennas, each SBS has N_r receive antennas and ith SU can transmit data with the maximum total power equal to $P_{i;max}$. It is also assumed that the Primary Mobile Terminal (PMT) and primary base station (PBT) have also N_r and N_t transmit and receive antennas, respectively. Intentionally, we do not consider the situation that the PU uses any technique to suppress the harmful interference.

Moreover, perfect channel knowledge in all SMT's has been also assumed. In order to ease the analysis, we limit our derivation to case where 2 SU and one PU exist. In the considered scenario the multipath channel $\mathrm{H} \in \mathbb{C}^{3\mathrm{N_r} \times 3\mathrm{N_t}}$ can be defined as follows

$$\mathrm{H} = \begin{pmatrix} \mathrm{H}_{11} & \mathrm{H}_{12} & \mathrm{H}_{1\mathrm{P}} \\ \mathrm{H}_{21} & \mathrm{H}_{22} & \mathrm{H}_{2\mathrm{P}} \\ \mathrm{H}_{\mathrm{P}1} & \mathrm{H}_{\mathrm{P}2} & \mathrm{H}_{\mathrm{PP}} \end{pmatrix} \text{ where } \mathrm{H}_{\mathrm{ij}} \in \mathbb{C}^{\mathrm{N_r} \times \mathrm{N_t}}. \quad (4.5.1)$$

The channel matrix $\mathrm{H}_{\mathrm{ij}} = \left\{\mathrm{h}_{\mathrm{kl}}^{(\mathrm{i,j})} \in \mathbb{C}, \mathrm{i}, \mathrm{j} \in \{1,2,\mathrm{P}\}, \mathrm{k}, \mathrm{l} \in \mathbb{N}\right\}$ consists of the actual values of channel coefficients $\mathrm{h}_{\mathrm{kl}}^{(\mathrm{i,j})}$, which define the channel between transmit antenna *k* at the *i*-th mobile terminal and the receive antenna *l* at the *j*-th base station. In the considered case of 2-user 2×2 MIMO secondary interference channel with one neighboring PU, six channel matrices are defined, i.e. $\mathbf{H}_{11}$, $\mathbf{H}_{22}$ (which describe channel between the first SMT and first SBS or second SMT and second SBS, respectively), $\mathbf{H}_{12}$ and $\mathbf{H}_{21}$ (which describe the interference channel between first SMT and second SBS and between second SMT and first SBS, respectively); furthermore, the matrices $\mathbf{H}_{1P}$ and $\mathbf{H}_{2P}$ denote the channel between the first and second SU and the PBS, the matrices $\mathbf{H}_{P1}$ and $\mathbf{H}_{P2}$ denote the channel between the PMT and the first and second SBS. Finally, $\mathbf{H}_{PP}$ corresponds to the channel of the primary user. Additive White Gaussian Noise (AWGN) of zero mean and variance σ^2 is added to the received signal. Each user transmits the signal vector $\mathrm{X_i} =\in \mathbb{C}^2, \mathrm{i}, \mathrm{j} \in \{1,2,\mathrm{P}\}$ through the multipath channel. Receiver *i* observes the desired useful signal, denoted as $\mathbf{Y}_\mathrm{i}$, coming from the *i*-th user. Moreover, in the interference scenario, receiver *i* (SBS_i or PBS_i) receives also interfering signals from other users located at the neighboring cell. When interference is treated as noise, the achievable rates for 2-user secondary interference MIMO channel with the presence of one PU Access Point (AP) are defined as follows

$$\mathrm{R}_1(\mathrm{Q}_1, \mathrm{Q}_2) = \log_2(\det(\mathrm{I} + \mathrm{H}_{11}\mathrm{Q}_1\mathrm{H}_{11}^*)(\sigma^2\mathrm{I} + \mathrm{H}_{\mathrm{P}1}\mathrm{Q}_\mathrm{P}\mathrm{H}_{\mathrm{P}1}^* + \mathrm{H}_{21}\mathrm{Q}_2\mathrm{H}_{21}^*)^{-1}), \quad (4.5.2)$$

$$\mathrm{R}_2(\mathrm{Q}_1, \mathrm{Q}_2) = \log_2(\det(\mathrm{I} + \mathrm{H}_{22}\mathrm{Q}_2\mathrm{H}_{22}^*)(\sigma^2\mathrm{I} + \mathrm{H}_{\mathrm{P}2}\mathrm{Q}_\mathrm{P}\mathrm{H}_{\mathrm{P}2}^* + \mathrm{H}_{12}\mathrm{Q}_1\mathrm{H}_{12}^*)^{-1}). \quad (4.5.3)$$

Clearly, the rate for the primary user can be found based on the formula

$$\mathrm{R}_\mathrm{P}(\mathrm{Q}_\mathrm{P}) = \log_2(\det(\mathrm{I} + \mathrm{H}_{\mathrm{PP}}\mathrm{Q}_\mathrm{P}\mathrm{H}_{\mathrm{PP}}^*)(\sigma^2\mathrm{I} + \mathrm{H}_{1\mathrm{P}}\mathrm{Q}_1\mathrm{H}_{1\mathrm{P}}^* + \mathrm{H}_{2\mathrm{P}}\mathrm{Q}_2\mathrm{H}_{2\mathrm{P}}^*)^{-1}). \quad (4.5.4)$$

In the above formulas R_1, R_2, and R_P denote the rate of the first and second secondary user and primary user, respectively, (A^*) denotes transpose conjugate of matrix **A**, det(**A**) is the determinant of matrix **A**, and $\mathrm{Q_i}, \mathrm{i}, \mathrm{j} \in \{1,2,\mathrm{P}\}$ is the *i*th user data covariance matrix i.e. $\mathrm{E}\{\mathrm{X_i}\mathrm{X_i^*}\} = \mathrm{Q_i}$ and $\mathrm{tr}\{\mathrm{Q_i}\} \leq \mathrm{P_{i,max}}$. Let us note that the power of interference observed by the PU $\Omega = \mathrm{tr}\{\mathrm{H}_{1\mathrm{P}}\mathrm{Q}_1\mathrm{H}_{1\mathrm{P}}^* + \mathrm{H}_{2\mathrm{P}}\mathrm{Q}_2\mathrm{H}_{2\mathrm{P}}^*\}$ has to be lower than the allowable level ξ_P, i.e. $\Omega \leq \xi_\mathrm{P}$.

The exemplary achieved rate region and the corresponding crystallized rate regions for the time selection diversity 2×2 MIMO [194] secondary interference channel is presented in Figure 4-8.

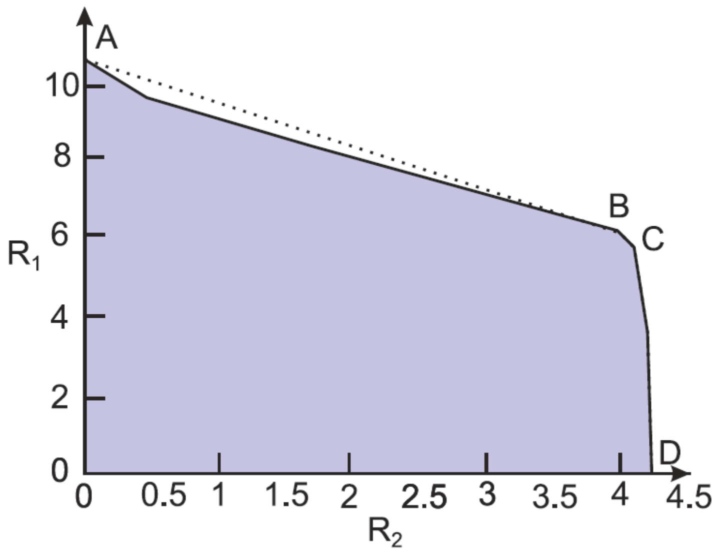

Figure 4-8: Exemplary rate region for time selection diversity 2×2 MIMO secondary interference channel.

The theoretical rate region is illustrated using the violet area, while the boundaries of the crystallized rate-region are represented as the dotted lines. One can observe, that these lines connect the so-called characteristic points, i.e. A, B, C and D (together with the (0,0) point), creating a convex area. All of these points correspond to a specific strategy of signal transmission, for example point A stands for the situation, when the user 1 transmits with the max allowed power during the whole transmission period, while the second secondary user is silent. Let us stress one more time that the idea behind the application of the crystallized rate region is to maximize the sum-rate of the two secondary users through switching only between the characteristic points.

In order to verify the effectiveness of the proposed solution extensive computer simulations have been carried out. The so-called regret matching algorithm [196] has been used in order to find the best playing strategy. Moreover, the setup of the considered system was as follows: number of transmit and receive antennas of PU and SU was equal to 3, application of the time selection diversity MIMO techniques at the SU transmitter have been assumed, while the transmit power of the PU was assumed to be equally distributed among all antennas. Three values of the scaling parameterδ have been considered, i.e. $\xi_{\mathrm{P}} \in \{0; 0.5; 1\}$ (δ is the parameter defining the impact of the interference introduced to the other users on the behavior of the regret matching algorithm, for details please see [196]) The maximum allowable ratio between total induced power of interferences to the PU and the total transmit power of PU has been set to $\xi_{\mathrm{P}} = 0.2$. Analyzing the obtained results one can observe that the proposed regret-matching procedure applied with the time-sharing approach finds the solution close to optimal one, i.e. the algorithm proposes to play all the time the strategies corresponding to the point near to points B and C on the exemplary rate region.

Rate of the first SU					
δ	$\xi_P = 0$	$\xi_P = 0.04$	$\xi_P = 0.08$	$\xi_P = 0.12$	$\xi_P = 0.16$
0	0	4. 988	9.8184	10.4545	10.4545
0.5	0	5.3374	9.9068	10.4545	10.4545
1	0	5.3436	7.6047	9.19	9.635
Rate of the second SU					
0	0	6.1176	8.3656	10.5373	10.5373
0.5	0	6.2514	8.7324	10.5373	10.5373
1	0	6.0537	6.3508	8.7254	8.8368
Total interference induced to PU					
0	0	0.0832	0.0861	0.1064	0.1064
0.5	0	0.09	0.0992	0.1064	0.1064
1	0	0.0852	0.0871	0.1042	0.1032

Table 4-1: Achieved rates for both SUs, total interference induces to the primary user and the exemplary selected strategies for N_t = N_r = 3.

One of the main drawbacks of the time-sharing approach, but also crucial in the power control case, is that the algorithm works fine when all of the users possess various, often detailed information about the channel of other users. It has been however verified, that the proposed time-sharing solution works well also in the case when only the data about the quantized channel are circulated among users.

4.6 Cognitive Relay

The basic ideas behind cooperative communication can be traced back to the work of Cover and El Gamal on the information theoretic properties of the relay channel with additive white Gaussian noise (AWGN) [196]. However, the relays aims to only assist the source transmission, whereas the users in cooperative communication systems can act as both information sources and relays. Combining cognitive radio (CR) with cooperative communications can further improve the spectrum utilization and enhance the network performance by obtaining more space diversity gain. In cooperative cognitive networks, CR nodes are collaborating in the sensing process to detect the spectrum holes left by the primary user (PU). Afterwards, the different relays assist the source to destination transmission over the detected spectrum holes.

Generally, there are two basic models considered in the cooperative cognitive networks depending on the behaviour of the secondary network with respect to the primary network transmission and can be classified as follows

- **Cooperative CR network with ability to assist the primary network transmission:** in this model, the cognitive network can access the primary system channels only when they are idle (inactive). Moreover, the secondary network nodes can assist the primary network transmission by forwarding the primary transmitter messages to the primary receiver as depicted in Figure 4-9.

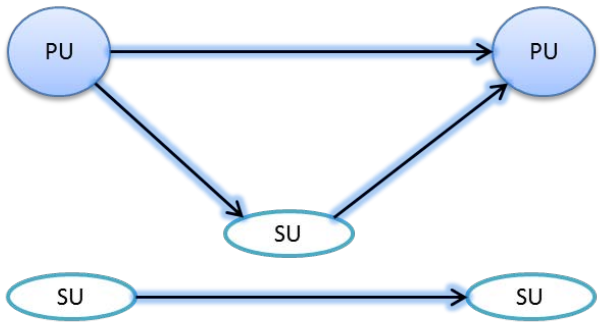

Figure 4-9: Cooperative CR network model with the ability of the secondary user to assist the primary network transmission.

By this transmission assistance, the secondary network improve the performance of the primary network which helps in satisfying the rate constraints in the primary network which will generate more transmission opportunities for the secondary network. The information theoretic framework of this model is analysed in [198][199]. The system performance from MAC layer point of view is analysed in [200]. The authors show that benefits of relaying strongly depend on the topology (i.e., average channel powers) of the network. Khuzani et al. in [201] studied the effect of this type of cooperation on the PU in terms of outage probability and 'probability of error' and on the cognitive user in terms of outage probability in orthogonal frequency division multiple access (OFDMA) based networks. They showed that cognitive user cooperation has been shown to improve the outage and probability of error performance of PU whereas the outage probability of cognitive users has not been changed significantly. This model is extended to consider multi-hop transmission in [202].

- **Cooperative CR network without primary network assistance:** in this model, the CR doesn't assist the primary network transmission and can access the spectrum in underlay/overlay way under the condition of not disturbing the operation of the primary system or negatively altering its performance as depicted in Figure 4-10.

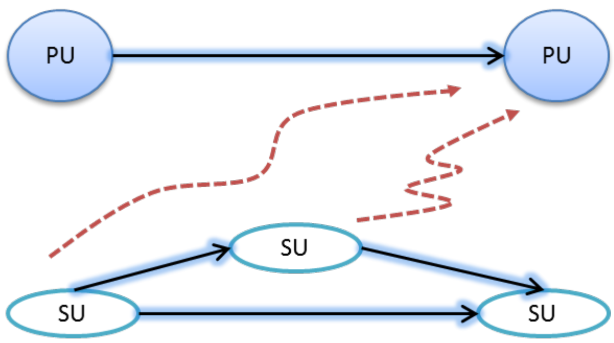

Figure 4-10: Cooperative CR network model with the ability of the secondary user independent from the primary network transmission. The CR transmission causes interference to the primary system.

The CR network can work in either the half-duplex mode or in the full-duplex mode depending whether the cognitive relays transmit data themselves or not. Time-division multiple access (TDMA) is often used with the half-duplex transmission while code-division multiple access (CDMA) is used the full-duplex mode. Mietzner et al. developed in [203] a fully decentralized and a distributed feedback-assisted power allocation schemes to maximize the output signal to interference plus noise ratio (SINR) or minimize the overall transmit power subject to predefined SINR target. Jia et al. proposed in [204] a centralized heuristic algorithm to select the most profitable pair of nodes and to allocate the different channels based on the availability of the spectrum. The interference to the primary system was not considered. In [205], a power allocation algorithm in a single relay decode-and-forward (DF) orthogonal frequency division multiplexing (OFDM) based CR system has been proposed. Under the assumption of prior perfect subcarrier matching in the two hops, the authors treated the optimization problem in the source and the relay individually. The algorithm performance degrades significantly if the relay has to forward the receiving message on the same subcarrier, i.e. there is no subcarrier pairing. The work is developed in [206] to deal with the bit loading problem in relay. In [207], the CR network uses the same spectrum of the primary network so that the transmission time and power of relay-assisted CR network is optimized to reduce its generated interference while still guaranteeing its quality-of-service (QoS) level. Additionally, the authors of [208] proposed a distributed relay selection and power control algorithm. A stochastic optimization formulation is used where the tradeoff between the achievable rate and the network life time is considered. Liying et al. presented in [209] a joint relay selection and power allocation algorithm where the cognitive relay system is prevented from inducing severe interference to the primary system by limiting its maximum transmission power. In [210], the authors proposed an algorithm to select the best transmit way between the network nodes. The algorithm can select direct, dual or diversity transmission based on the available spectrum as well as the maximum allowable transmission powers. In [211], the problem of resources allocation in DF relayed OFDM based cognitive system is considered. The dual decomposition technique is adopted to obtain an asymptotically optimal subcarrier pairing, relay selection, and power allocation. The resources are optimized under the individual power constraints in source and relays so that the sum rate is maximized while the interference induced to the primary system is kept below a pre-specified interference temperature limit.

Glossary and Definitions

Acronym	Meaning
AI	Artificial Intelligence
AWGN	Additive White Gaussian Noise
BC	Broadcast Channel
CDMA	Code-Division Multiple Access
CR	Cognitive Radio
CRN	Cognitive Radio Network
CSI	Channel State Information
CWN	Cognitive Wireless Networking
DF	Decode-and-Forward
DoF	Degree of Freedom
DPC	Dirty Paper Coding
FDMA	Frequency-Division Multiple Access
IA	Interference Alignment
IC	Interference Channel
ITC	Interference Temperature Constraint
KPI	Key Performance Indicator
LTE	Long Term Evolution
MAC	Multiple Access Channel
ML	Machine Learning
MFNN	Multi-layer Feed-forward Neural Network
MISO	Multiple Input and Multiple Output
MIMO	Multiple Input and Multiple Output
MRT	Maximal Ratio Transmission
NN	Neural Network
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
PSO	Particle Swarm Optimization
PU	Primary User
QoE	Quality-of-Experience
QoS	Quality-of-Service
RAS	Radio Access Control

RL	Reinforcement Learning
RRM	Radio Resource Management
SDR	Software Designed Radio
SINR	Signal to Interference plus Noise Ratio
SISO	Single Input and Single Output
SOM	Self-Organizing Maps
SU	Secondary User
SUD	Single-User Decoding
SVM	Support Vector Machine
TDMA	Time-Division Multiple Access
WCDMA	Wideband Code-Division Multiple Access
WLAN	Wireless Local Area Network
ZF	Zero Forcing

5. Conclusions

In this deliverable, we introduce the basics and survey applications of several important machines learning techniques currently utilized in cognitive radio networks. In particular, we discuss supervised, unsupervised and reinforcement machine learning methods on examples of such popular methods such as artificial neural networks, Q learning, etc. We also introduce a range of metaheuristics, including genetic, particle swarm optimization algorithms, ant colony optimization, simulated annealing and tabu search. Finally, we discuss fuzzy logic.

Moreover, we summarize the most important models and tools that are provided by the information theory literature to describe the key aspects of spectrum sharing and cognitive radio. The results in two-user SISO interference channel are summarized, including different strategies resulting in different rate regions. A literature survey is done on MISO interference channels and the more recent interference alignment technique. The results in (extended) cognitive radio channel are summarized, followed by literature survey in underlay/overlay MISO/MIMO cognitive radio systems. The time sharing technique and its application in the secondary interference channel, and two cognitive relay scenarios are introduced.

6. References

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