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Cognitive Radios and Networks

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Abstract

In recent years, the Cognitive Radio and Cognitive Network paradigms have received significant attention by the research community. Cognitive Radios and Networks, in their initial formulation, are characterized by the addition of cognition capabilities such as reasoning and learning to wireless devices and networks, with the aim of providing enhanced adaptability and reconfigurability to cope with the ever-growing challenges of radio communications. The concepts of Cognitive Radio and Network have actually been interpreted in several different ways. In this thesis, we will first of all provide an overview of the different interpretations of Cognitive Radios and Networks, as appeared in the recent literature. We will then focus on the cognitive adaptation and reconfiguration of devices and networks by means of Artificial Intelligence (AI) techniques. In this respect, we will discuss how two well-known AI techniques, i.e., Fuzzy Logic and Neural Networks, can be used within a cross-layer and cross-device knowledge representation and reasoning architecture to become major enabling technologies for Cognitive Radios and Networks. For each technology we will discuss how it can be effectively adopted to implement key functionalities of cognitive systems, and we will present and discuss example applications such as cross-layer parameter optimization, wireless network access selection and channel assignment. For all the discussed applications, we will present performance evaluation results showing the advantages that the proposed techniques provide with respect to state-of-the-art approaches.

Sommario

Negli ultimi anni, i concetti di Radio e Reti Cognitive hanno ricevuto una notevole attenzione da parte della comunità scientifica. Nella loro formulazione originale, questi concetti consistono nell'addizione a dispositivi radio e reti di calcolatori tradizionali di capacità cognitive, come ad esempio la capacità di ragionare e di imparare, con l'obiettivo di ottenere una adattabilità e riconfigurabilità più elevata che consenta di affrontare le sempre più difficili sfide poste dal progresso delle comunicazioni radio.

I concetti di Radio e Reti Cognitive sono stati in realtà interpretati in tanti modi differenti. In questa tesi, forniremo dapprima una visione generale delle diverse interpretazioni apparse nella recente letteratura scientifica. In seguito ci concentreremo sulla riconfigurazione e ottimizzazione di dispositivi e reti radio effettuata tramite tecniche di Intelligenza Artificiale (IA). A questo proposito, discuteremo come due particolari tecniche di IA, cioè la Logica Fuzzy e le Reti Neurali, possono essere utilizzate all'interno di un'architettura cross-layer per la rappresentazione della conoscenza e il ragionamento, e consentire così la realizzazioni di Radio e Reti Cognitive. Per ognuna di queste tecniche discuteremo come può essere utilizzata in pratica per implementare funzionalità chiave di sistemi cognitivi; presenteremo inoltre alcune loro applicazioni pratiche, come ad esempio l'ottimizzazione cross-layer di parametri, la selezione del punto di accesso e la selezione del canale in reti radio. Per ognuna delle applicazioni discusse sarà fornita una valutazione delle prestazioni che mostrerà i vantaggi ottenuti rispetto allo stato dell'arte.

Contents

Chapter 1

Introduction

Trying to mimic the human behavior has been one of the most appealing research areas since the birth of Artificial Intelligence, and the word *cognitive* has always made researchers enthusiastic. Recently, the communications research field has experienced the same excitement. Stimulated by the progress in wireless communications and electronics, the concepts of Cognitive Radios and Networks have attracted a lot of attention in the last decade.

Cognitive Radios and Networks do not represent well-defined areas; the initial definition of Cognitive Radio as a wireless communication devices with cognitive capabilities that can "*detect user communications needs as a function of use context*" and "*provide radio resources and wireless services most appropriate to those needs*"[1] is very generic, and has actually been interpreted in several different ways; similarly, the definition of Cognitive Networks is rather broad in nature [2]. The reason for this generality is due to the fact that they represent more a vision for future communications, rather than a technology which is ready right now or is going to be ready in the near future.

Unfortunately, there has been a rather big hype around these visions, as if they were going to become reality in a few years. On one hand this brought a fast increasing interest in the area, which can be regarded as a positive effect; however, several downsides also came at the same time. The quickness with which Cognitive Radio came to the attention of the research community caused a lot of confusion on the term Cognitive Radio itself, to the point that the initial broad definition of Cognitive Radio got confused with one of its applications, i.e., Dynamic Spectrum Access, which currently represents the most commonly used interpretation for Cognitive Radio. In doing so, unfortunately, the focus shifted to spectrum access and physical layer issues, while the cognitive and cross-layer nature of Cognitive Radios was lost. The definition of Cognitive Networking, in spite of being more recent, faces the similar risk of being restricted to a "*network of devices*
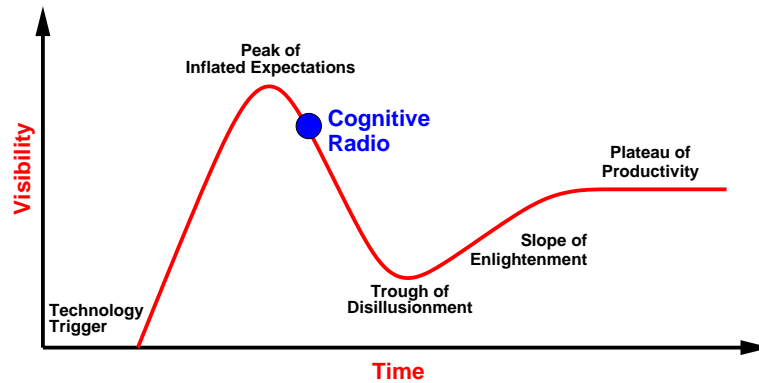
Figure 1.1: Estimated current position of Cognitive Radio in the Hype Cycle

performing dynamic spectrum access". Of course, we believe that Dynamic Spectrum Access is an interesting and promising field, worth a lot of investigation. However, the point is that when we look at the recent proliferation of publications labeled as being about Cognitive Radios or Networks, it is somewhat sad to see that, while "cognitive capabilities" were at the beginning the most exiting feature expected from these systems, most of this work actually does not deal with anything related to cognition. Furthermore, in conversation with other communications researchers, it happens often to hear that a non negligible fraction of the research labeled as "*cognitive*" is actually very similar to rather "traditional" approaches to communications, such as frequency allocation, cross-layer optimization or ad hoc networking, disguised as cognitive by using the proper keywords.

To summarize, the exaggeration with which Cognitive Radios have been presented after their introduction, together with the failure to present practical solutions for their implementation, has caused a significant degree of disillusionment. This can been interpreted as an occurrence of Gartner's Hype Cycle [3], according to which the "peak of inflated expectations" which follows the initial discussion around new technology always results in disillusionment and loss of visibility. Hopefully, when the hype has gone, the technology can finally, and more quietly, find its way to the real world. Cognitive Radio is now believed to be past its peak of visibility, on the way to disillusion, as discussed in [4] and represented in Figure 1.1.

We believe, however, that there is a lot of good potential in the original formulation of Cognitive Radios and Networks, and that the recent hype and the consequent disillusion should not be regarded as a reason to drop research effort on the topic. Rather, it should be seen as a motivation to push firmly Cognitive Radios and Networks out of the hype into their realization. All the work presented in this Ph.D. thesis was done with a clear goal in mind: trying to make Cognitive Radios and Networks happen in their original formulation of wireless communications devices and networks which

leverage on cognitive capabilities to react to changes in the communications environment in order to provide enhanced service to the users. With the aim of giving a concrete contribution towards the realization of this vision, the chosen line of research has been to identify Artificial Intelligence techniques which could fit this purpose, and to actually test the fitness of these techniques in real communication scenarios. While we are still far from being able to claim that we realized Cognitive Radios and Networks, we hope that at the end of our thesis the reader will agree that we have been able to bring them closer to reality.

The rest of this thesis is organized as follows. In Chapter 2 we will provide a detailed overview of the state of the art in Cognitive Radio and network research, as appeared in the recent literature. The purpose of this chapter will be to make the reader familiar with all the different interpretations that have been given to the Cognitive Radio and Network concepts, and also to examine what has been done from a practical point of view with respect to each definition. In the subsequent two chapters we will present the major contribution of this thesis: the investigation and experimentation of Artificial Intelligence techniques for the purpose of introducing real cognitive capabilities into radios and networks. In particular, Chapter 3 will deal with Fuzzy Logic and Chapter 4 with Neural Networks. We will provide a generic overview for each of these techniques, discussing the benefits of their application in a Cognitive Radio and Network context, and presenting experimental applications including performance evaluation. Finally, in Chapter 5 the conclusions will be drawn.

Chapter 2

Cognitive Radios and Networks: a survey

The original definition of the term *Cognitive Radio* was introduced by Mitola in [1] and refers to a *communicating device* which is able to:

- detect user communications needs as a function of use context

- provide radio resources and wireless services most appropriate to those needs.

It is to be noted that this definition is very generic. Mitola used the term *radio* to identify a generic mobile terminal, such as a PDA, laptop or smartphone, used for communication purposes by a human being. The term *cognitive* provides a further connotation of the mobile terminal as an *intelligent agent*: a cognitive radio device is expected to act both *humanly* and *rationally*[1] in its attempt to satisfy the needs of the user, observing the environment, evaluating possible strategies, making decisions, performing actions and learning from experience.

As pointed out in [6], in telecommunication research, as well as in many other fields, the choice of metaphors plays a key role in how the ideas which should be conveyed by these metaphors are actually interpreted by others. Cognitive Radio is probably a case in which the choice of metaphors has led to a deviation of the common interpretation of the term from its original intended meaning. The use of the term *radio* has been in most cases interpreted in a fairly reductive fashion as referring almost exclusively to the lower-layer characteristics of wireless communications, in particular the PHY layer. It is probably for this reason that the most popular interpretation of Cognitive Radio is currently that of a *spectrum-agile* device performing Dynamic Spectrum Access [7, 8]. On the other hand, there is no prevailing

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[1]It is to be noted that Acting Humanly and Acting Rationally are two commonly adopted definitions of Artificial Intelligence. For a detailed discussion, see [5]

interpretation of the term *cognitive*. In some cases, as for Dynamic Spectrum Access, it is interpreted more in the sense of *acting humanly*. The Game-theoretic approach to Dynamic Spectrum Access, for example, fits into this category, since it consists of analyzing the problem by comparing the possible strategies that could be adopted by the cognitive radio to human-like behaviors such as competition and cooperation. Similarly, the concept of Cognitive Network, as formulated by Thomas et al. [2], is heavily based on the metaphor of the networking devices as a human society in which all individuals interact among themselves to pursue the wealth of the society.[2] In other cases, the term *cognitive* has been interpreted more in the sense of acting rationally, i.e., the Cognitive Radio is seen as an Intelligent Agent performing its actions to pursue the goal of providing satisfactory communication services; in this respect, Artificial Intelligence techniques are expected to be used to solve the evaluation, optimization, decision and learning problems that arise.

In this chapter we will discuss the most common interpretations of the Cognitive Radio and Network concept, as appeared in the literature.

2.1   Dynamic Spectrum Access

One of the applications proposed by Mitola [1] for cognitive radios was *spectrum pooling*, i.e., the possibility for a mobile user to overcome traditional spectrum licensing schemes and to directly negotiate the needed spectrum depending on his communication needs. The rationale for this application is the observation that the continuously increasing demand for wireless connectivity has led to a shortage of available spectrum: the majority of the usable spectrum (i.e., upper limited by present-day technology) is already allocated to specific services, and the room for additional services is scarce. On the other hand, the few frequency ranges which do not require licence and can be used freely are overcrowded by different services: a notable example is the 2.4 GHz ISM band which hosts several popular protocols such as 802.11, Bluetooth, Zigbee and WiMAX.

As a consequence of these fact, Dynamic Spectrum Access techniques descending from the one proposed by Mitola for Cognitive Radios have received a lot of interest in subsequent years, to the point that nowadays the most commonly referred to interpretation of Cognitive Radio is that of a device performing Dynamic Spectrum Access, as per the formal definition of Cognitive Radio by the Federal Communications Commission [8].

Due to the popularity of Dynamic Spectrum Access, even though it is not the main focus of the work presented in this thesis, we will cover it in the next sections, outlining the major research directions in which it has

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[2]An example is the capitalistic system in which individuals, by pursuing their own interests, contribute to the wealth of the nation [9]

been investigated in recent years.

2.1.1 Spectrum Regulation

The shortage of available spectrum which has been experienced in recent years has brought the problem of spectrum regulation to the attention of the research community. Several reports (e.g., [10, 11]) showed that the spectrum usage in most licensed frequency bands is actually very low (below 10%). This was recognized to be due to the fixed and long-term licensing scheme imposed by the radio regulation in force in most countries, commonly referred to as the *Command and Control model*. As a consequence, it was proposed by both the Federal Communication Commission in the US [12] and the European Parliament in Europe [13] to investigate alternative means of spectrum regulation and access in order to use spectrum more efficiently, thereby overcoming the shortage currently being experienced.

Since then, several spectrum regulation strategies have been discussed. The most important are:

- **Spectrum leasing**, where the license holders (*primary users*) can rent spectrum to other users (*secondary users*) for a limited amount of time;

- **Spectrum trading**, in which spectrum is dealt with as private property, and as such can be sold, thereby enabling dynamic spectrum ownership;

- **Spectrum commons**, according to which all users are allowed to use the spectrum provided that they respect some constraints, such as maximum transmit power. It is the same approach currently in use for the ISM bands;

- **Unlicensed use of licensed spectrum**, i.e., allowing unlicensed secondary users to use licensed spectrum provided that the primary users are not using it, or that transmission by secondary users does not cause harmful interference to primary users.

The perspective of the introduction of these spectrum regulation policies has caused a significant research effort in order to develop practical schemes by means of which they could be implemented. The Spectrum Commons approach is interesting from a political and economical point of view, and for this reason it is often advocated [14]; however, it is not investigated much by the communications research community, since it can be seen as the extension of the policy adopted for the ISM bands to other bands, and therefore most likely the same technologies currently used for the ISM bands could be reused. Researchers in Economics focus much more on the Spectrum

Leasing and Trading approaches, in particular on which market interactions could take place between the different players (spectrum licensee, secondary users and spectrum brokers) in order to make Dynamic Spectrum Access viable. Communication research focuses mainly on the Unlicensed Reuse of Licensed Spectrum, whose realization poses significant technical challenges; for this reason, we will deal mainly with this approach in the next subsections.

2.1.2   Channel Sensing

When designing solutions for unlicensed access of licensed spectrum, a key problem is how to detect the presence of a primary (licensed) user to determine if the secondary (unlicensed) user is allowed to use the spectrum. The problem has been extensively studied in recent years, and several approaches have been proposed.

In [11,15,16] the best-known sensing techniques are described and analyzed with respect to sensing performance and implementation complexity. Among these techniques, it is worth mentioning energy detection, matched filter, and cyclostationary feature detection. Of these techniques, cyclostationary feature detection seems to be the most promising, as several proposed sensing strategies rely on it [17,18]. A good primer on cyclostationary feature detection can be found in [19].

In [20] the authors propose the use of neural networks for signal classification: the provided results show that this technique is effective in enhancing sensing reliability, while at the same time keeping run-time complexity low since most computationally demanding tasks are performed offline.

A number of papers [21–23] propose collaborative sensing performed by a network of secondary users, in order to improve detection performance and to avoid issues related to the hidden terminal problem.

Some other authors [24,25] propose the use of a dedicated wireless sensor network for spectrum sensing purposes. The strength of this approach is that sensors are inexpensive when compared with cognitive radio devices, and thus can be deployed with higher density in order to provide better sensing performance. Furthermore, with this architecture the secondary users are not required to perform the sensing themselves, which in turns lowers their requirements in terms of computational power.

2.1.3   Modeling of Dynamic Spectrum Access Networks

Several techniques have been adopted to investigate and study the dynamics of Dynamic Spectrum Access devices and networks. Game Theory is one of the most popular modeling strategies. In the game-theoretic approach to Dynamic Spectrum Access, cognitive radio devices are viewed as independent actors facing decision problems such as channel selection or parameter

tuning. The choice made by each actor influences the performance – i.e., the reward – which can be achieved by other actors. Game Theory is used to analyze how different behaviors and policies, such as competition and cooperation, affect the performance seen by each radio device and by the cognitive network as a whole. In [26], the authors discuss the fitness of Repeated Games, S-modular Games and Potential Games for generic decision problems in cognitive radio networks. In [27] Game Theory is applied to the case of an M-user Gaussian interference channel to derive a Pareto-optimal spectrum allocation. A similar approach is also proposed in [28].

Other authors [29] use an information-theoretic approach to spectrum management. In this type of approach a key concept is the *interference temperature*, which describes the amount of interference caused by secondary users to primary users. Calculating interference temperature allows the determination of channel capacity using Shannon's Theorem. One example of this is [30], where both the interference temperature model and the Game-theoretic approach are used.

An analysis of the performance limits achievable by Cognitive Radios is presented in [31, 32]. In this approach, radio devices are cognitive in that they are expected to have perfect knowledge of the messages being transmitted by other radio devices, as well as perfect knowledge of the wireless channel. In this situation, the Cognitive Radio can exploit MIMO techniques such as *dirty paper coding* to overcome the interference and achieve successful transmission, or can act as a cooperator and aid the other on-going communications; also, a mixed combination of the two strategies is proposed. In the papers, theoretical performance bounds for this approach are derived.

The authors in [33] use color sensitive graph colouring to solve the Spectrum Allocation problem. This approach yields an optimal solution, but it is computationally intractable (NP-hard) and moreover requires a centralized spectrum management. To overcome this issue, in the same paper a near-optimal heuristic is proposed which is both computationally lighter and well-suited to distributed spectrum management.

In [34] a distributed solution to the problem of spectrum management is proposed. The solution consists of a bargaining algorithm which provides local optimization of channel assignment in response to changes in topology due to user mobility. The algorithm is claimed to provide nearly optimal spectral efficiency while requiring a lower communication overhead and computational effort compared to traditional centralized algorithms using graph coloring techniques.

The same authors present in [35] another method of performing distributed spectrum management. This method consists of having each node perform spectrum decisions independently by following pre-defined spectrum access rules, and relying on minimal information exchange with other users. Several rules are discussed in the paper, which differ on the type of channel

assignment considered (conflict-free vs contention-based) and on the degree
to which fairness issues are considered. The reported performance evalua-
tion shows that the proposed solution has significantly lower complexity and
communication overhead compared to the solution in [33], while achieving
slightly lower performance.

In [16] the authors propose a Cognitive Radio approach for usage of Vir-
tual Unlicensed Spectrum (CORVUS). The proposal consists of a spectrum
pooling framework by means of which licensed bands which are not being
used by primary users are gathered together to form a Virtual Unlicensed
Band. In CORVUS, dedicated control channels are exploited by secondary
users to communicate spectrum sensing information as well as link manage-
ment and medium access control messages.

The authors of [36] discuss a Primary-prioritized Markov approach to
dynamic spectrum access. Interactions between the primary users and the
unlicensed users are modeled as continuous-time Markov chains; this model
is then used to design appropriate access probabilities for the unlicensed
users with the aim of achieving the desired tradeoff between spectrum effi-
ciency and fairness.

2.1.4 Multi-channel Medium Access Control

Medium Access poses significant challenges in a Dynamic Spectrum Access
system, due to the difficulties in handling multiple channels. To cope with
this issue, several solutions have been proposed in the recent literature.

In [37] the Dynamic Channel Access (DCA) scheme is proposed: it is a
modification of the 802.11 MAC tailored to multi-channel ad hoc networks.
The DCA scheme introduces modifications to the RTS/CTS mechanism
to include channel availability and preference information. The solution
requires terminals to have two separate wireless interfaces, since one of them
must transmit and receive on a fixed control channel, while the other is to
be used for data transmission on dynamically selected channels.

The solution proposed in [38] is based on the DCA scheme in [37], with
the addition of neighbor information reports which are used to exchange
information on the presence of primary users and, hence, provide enhanced
support for unlicensed access to unused licensed spectrum.

Another modified version of 802.11 targeting unlicensed reuse of licensed
spectrum is KNOWS [39]. The main features in KNOWS are cooperative
sensing among ad-hoc nodes to identify unused spectrum bands, and re-
source advertising and reservation performed by means of the newly defined
RTS/CTS/DTS handshake in place of the traditional 802.11 RTS/CTS.

A new multi-channel medium access protocol for ad hoc networks named
C-MAC is proposed in [40]. C-MAC exploits a dynamically determined
rendez-vous channel together with a slotted beaconing approach in order to
exchange channel availability and selection information for data transmis-

sion. The rendez-vous channel is also exploited for broadcast and multicast transmissions.

Another multi-channel MAC protocol is proposed in [41]. This proposal considers the case in which a dedicated control channel exists.

In [42], the authors propose a distributed scheme with the aim to dynamically allocate frequencies to access points in infrastructured 802.11 WLANs. In [43], the performance of an experimental implementation of the same scheme is reported.

In [44], the Single-Radio Adaptive Channel algorithm is presented. An interesting contribution of this work is the notion of cross-channel communication, i.e., allowing a sender to transmit even if the channel is being interfered, provided that the receiver is simultaneously not hit by the same interference.

2.1.5 Channel Selection and Routing for Multi-hop Wireless Networks

Some recent work goes beyond the type of approaches outlined in the previous section, and tries to design Dynamic Spectrum Access solutions which take care both of Medium Access and Routing.

In [45], routing policies for multi-channel multi-hop wireless networks are examined. The authors deal with the case of mobile terminals equipped with a single radio interface; furthermore, they assume that a centralized *spectrum manager* is providing information on the spectrum resources (e.g., unused licensed spectrum) which are available to mobile terminals. The authors consider two different solutions: a *decoupled approach*, in which channel assignment and routing are performed separately, and a *collaborative approach*, in which channel assignment and routing decisions are performed jointly by solving a scheduling problem on a conflict graph.

In [46] the author proposes a spectrum-aware, data-adaptive routing scheme for multi-channel, multi-hop dynamic spectrum access networks. The scheme selects the Pareto fastest paths from a source to a destination by accounting for the quantity of data to be transmitted, the channel capacities, spectrum availability, the link propagation time and the secondary user link occupancy. In the same paper, the author also proposes a solution to the broadcast and multicast problem in the same scenario.

In [47], a spectrum-aware on-demand routing solution for multi-hop wireless networks is defined. Spectrum opportunities are identified according to an approach previously outlined in [48]; this information is then exploited within a modified version of AODV to perform both route selection and channel allocation.

In [49] the authors propose a cluster-based solution according to which each cluster is dynamically formed and allocated a channel; a hierarchical network is then defined over cluster heads. Furthermore, a superframe-based

MAC protocol is defined, which uses a TDMA period for data transmissions and an ALOHA period for control message exchange; two more periods in the superframe are reserved for spectrum sensing and neighbor discovery, respectively.

In [50] an algorithm based on interference temperature model is proposed for channel allocation in mesh networks. Interference temperature is used to model occupancy and availability of a channel. Link and end-to-end routing metrics are then proposed to select appropriate channels from the computed set of available channels.

2.1.6   Standards related to Dynamic Spectrum Access

Some IEEE standards are related to Dynamic Spectrum Access:

- IEEE 802.22 [51, 52] is an emerging standard for Wireless Regional Area Networks which aims at exploiting unlicensed access to unused licensed TV channels.

- IEEE 802.16H [53] considers cognitive radio techniques for network coexistence in license-exempt bands.

- IEEE 1900, which includes the following:

  - IEEE 1900.1: Standard Definitions And Concepts For Spectrum Management And Advanced Radio System Technologies
  - IEEE 1900.2: Recommended Practice for Interference and Coexistence Analysis
  - IEEE 1900.3: Recommended Practice for Conformance Evaluation of Software Defined Radio Software Modules
  - IEEE 1900.4: Coexistence Support for Reconfigurable Heterogeneous Air Interfaces

2.2   Cognitive Cross-layer Optimization

A typical communication system is composed of various layers, such as physical, medium access, network, transport and application. Each layer supports different configurations and modes of operations, which determine the communication performance of that layer. The overall end-to-end performance of an application is determined by the combination of the performance of each single layer in the protocol stack; in other words, in order to improve end-to-end performance, the configuration parameters of each layer should be tuned.

It is rather intuitive that separate optimization of each component of a system is likely to yield sub-optimal performance with respect to what

could, in theory, be achieved by a joint optimization of all components. This practice in communication systems is commonly known as cross-layer optimization: breaking the traditional encapsulation of the communication protocol stack to enable a more effective optimization of the overall communication quality. Cross-layer optimization solutions need to be designed very carefully, in order to avoid subtle interactions that could result in degraded performance, as discussed in [54]; however, a cross-layer optimized communication system is nowadays commonly expected to be able to provide significant performance enhancements over a traditional system [55, 56]

Because of potentially superior performance, Cross-layer Optimization is expected to be extensively used in Cognitive Radio and Networks. The Cognitive Engine at the heart of the Cognitive Radio or Network system will leverage on cross-layer information exchange and interactions to exploit different wireless interfaces and protocol stack configurations, in order to achieve the best service quality for all communications.

Unfortunately, the current state of the art in wireless communication systems research is still quite far from an effective formulation of the ultimate Cognitive Cross-layer Architecture. In the last decade, cross-layer optimization strategies have been widely studied and adopted, but in most cases the aim was to achieve performance enhancements in specific scenarios. For instance, a vast number of those cross-layer solutions had the aim of improving the performance of a particular multimedia application or transport protocol over a given radio link such as 802.11 or UMTS. In most cases these solutions cannot be reused for different wireless technologies or applications without a significant re-design effort. This unfortunately makes them unsuitable for highly reconfigurable devices such as Software Defined Radios upon which Cognitive Radios are based.

In more recent years, much effort has been put by the research community in trying to synthesize all this experience on cross-layer optimization into a more generalized, universal cross-layer architecture, with the aim of enabling the exchange of information and interactions to arbitrary combinations of applications, protocols and wireless technologies [57–59]. However, although the awareness of the need for a generic and universal cross-layer framework coexisting with the traditional protocol stack is fairly well established in the research community, a definitive formulation for it is still lacking.

We believe that such envisioned "ultimate cross-layer optimization architecture" matches very well with the original Cognitive Radio definition by Mitola [1], and is very interesting to investigate. For this reason, in this thesis, we refer to Cognitive Cross-layer Optimization as the particular interpretation of Cognitive Radio as an intelligent agent whose purpose is to carry out a cross-layer optimization of the whole communication system in order to achieve satisfactory communication performance for the end user. The difference with traditional cross-layer optimization is that its design

and scope should be by no means restricted to a particular scenario or application, but rather should exhibit the highest possible degree of technology and application independence, and that Artificial Intelligence techniques are adopted with the aim of achieving more effective solutions which can also adapt to heterogeneous and dynamically varying scenarios. In the rest of this section we will summarize the current state of the art in Cognitive Cross-layering.

In [60], the authors propose an architecture for Cognitive Radios which is based on the encapsulation of different elements which are responsible for well-distinct functionalities, such as Reasoning, Learning, Knowledge Representation, and System Reconfiguration. However, there is no hint to how to actually implement the proposed architecture.

The possibility of using Genetic Algorithms for implementing the brain of a Cognitive Radio has also been investigated [61–63]. The major benefit of GAs is that they are well-suited for solving optimization problems with a very large number of parameters, as is typical in cross-layer optimization for Cognitive Radio devices, for which other approaches are not feasible due to the overwhelming complexity. The main issue with GAs is that the time required to converge to the optimal solution can be very long; however, this latency is greatly reduced for the case in which a nearly optimal solution is acceptable.

Artificial Neural Networks have been proposed, among other things, for channel assignment [64–66], routing [67] and, more recently, for signal classification [68,69]. However, no work dealt with the use of Artificial Neural Networks to design a general purpose Cognitive Radio Engine. In this thesis we present our work on this approach, which has been in part published [C6].

Similarly, also Fuzzy Logic has been proposed several times as a particular solution to very specific problems in communications systems, e.g., for QoS routing in wired networks [70], route caching decisions in wireless ad hoc networks [71], radio resource management [72], channel selection in cellular networks [73], and mobility management [74]. An interesting though not very recent survey on the usage of Fuzzy Logic techniques in the telecommunication field can be found in [75]. However, we note that in all these proposals a Fuzzy Logic system is tailored to a specific problem, and no attempt is made to identify a generic Cross-layer architecture based on Fuzzy Logic which can fit different wireless technologies and applications, as envisioned in the Cognitive Radio paradigm.
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2.3   Cognitive Networks

The concept of a Cognitive Network was already foreseen by Mitola, when in [1] he suggested that his cognitive radios could interact within the system-

level scope of a Cognitive Network. However, the contribution of Mitola to Cognitive Networking does not go much beyond Cognitive Radio.

A significant step forward towards the concept of Cognitive Networking was performed by Clark and Partridge: in [76] they propose the introduction of a Knowledge Plane in the Internet, to complement the Data Plane, i.e., the current Internet infrastructure which takes care almost exclusively of data delivery. This Knowledge Plane is conceived as a distributed architecture which is responsible for collecting and making available information regarding the status of the Internet, and at the same time has cognitive capabilities (e.g., reasoning and learning) which allow it to provide services such as fault diagnosis, automatic reconfiguration, and enhanced QoS support. It is to be noted, however, that Clark and Partridge never mention the term *Cognitive Network*.

Between 2003 and 2004 Cognitive Networking is repeatedly cited as a promising technology [77, 78], but we have to wait until 2005 for a formal definition of Cognitive Networks. In [79] (and, with minor differences, in [2] one year later) Thomas et al. define a Cognitive Network as possessing a "*cognitive process that can perceive current network conditions, and then plan, decide and act on those conditions*", and which can "*learn from these adaptations and use them to make future decisions, all while taking into account end-to-end goals*".

Another highlight of [79] is that similarities and differences between Cognitive Radio, Cross-layer Optimization and Cognitive Networks are analyzed; among the similarities, it is to be noted the fact that Cognitive Networks are foreseen to be based on the so-called Software Adaptable Network, in exactly the same way in which Cognitive Radio is based on Software Defined Radio. Almost simultaneously to the work by Thomas et al., Lake [80] proposed a similar approach; in particular, he defined his Software Programmable Intelligent Network which turns out to be very similar to Thomas' (and, in turn, to Clark and Partridge's) proposal.

An overview of Cognitive Networking can be found in [81].

A very generic overview of Machine Learning issues for Cognitive Networks is found in [82]. The authors discuss different aspects of learning in Cognitive Networks, namely Classification, Interpretation/Understanding and Acting/Planning. Moreover, several issues concerning the current practice in Machine Learning for Cognitive Networks are analyzed. The particular use cases examined in this work are mainly focused on traditional networking issues, such as Parameter Optimization, Anomaly and Fault Detection, and Intruder Prevention, and consequently are not explicitly targeted to wireless communications. However, it is to be noted that the considerations can be applied to wireless networks as well.

Concrete proposals concerning aspects of Cognitive Networking today are still being awaited for. It is however to be noted that a significant part of the research effort in the field of autonomic networks, such as [83–

86], has a significant overlap both in goals and strategies with Cognitive Networking, even though the term *Cognitive Network* is not commonly used in this context. Moreover, we note that Cross-layer Optimization is relevant to Cognitive Networks as well, and so many of the considerations that we made in the previous section for Cognitive Radios apply here to.

2.4   Conclusions

In this chapter we have surveyed the state of the art in Cognitive Radios and Networks, highlighting in particular the various interpretations that have been given to these concepts. From this survey, it emerges clearly that Dynamic Spectrum Access and the related subtopics discussed in Section 2.1 have received most of the attention in recent years, while Cognitive Cross-layer Optimization and Cognitive Networks, discussed respectively in Section 2.2 and 2.3, still remain relatively unexplored. In the next chapters of this thesis we will outline the research activity that we carried out during our Ph.D. in an effort to fill this gap by investigating practical techniques for Cognitive Cross-layering and Cognitive Networking. In particular, in Chapter 3 we will describe our effort in the definition of a Knowledge Representation Base and Information Processing Architecture for Cross-layer Optimization in Cognitive Radios and Networks which leverages on Fuzzy Logic; in Chapter 4 we will show how Neural Networks can be exploited to provide Learning and Adaptation capabilities to Cognitive Radio and Network systems.

Chapter 3

Fuzzy Logic for Cognitive Radios and Networks

As we clearly stated in the previous chapters, we refer to the definition of Cognitive Radio and Network as an entity that has the primary objective of providing wireless communication capabilities which are able to adapt to the needs of the user(s) in face of varying environmental conditions. In particular, we are interested in investigating Artificial Intelligence (AI) techniques in order to carry out Cognitive Cross-layer Optimization of wireless devices and networks in order to fulfill this objective.

In this chapter, we argument that the design of such intelligent systems is very challenging due to complexity, modularity, information imprecision and interpretability issues. Following these considerations, we then propose a Cognitive Cross-layer Knowledge Representation Base with the aim of meeting these challenges by leveraging on Fuzzy Logic. As an incomplete knowledge representation technique, Fuzzy Logic is well-suited for addressing imprecision issues; in addition to this well-known peculiarity of Fuzzy Systems, we will show how the process of translating information into a fuzzy representation can be exploited, together with an appropriate architecture design, to address also the modularity, complexity and interpretability issues. In order for the reader to better understand our proposal, we will also provide a brief overview of Fuzzy Logic, including aspects such as Fuzzy Arithmetic and Fuzzy Controllers. We will then present two particular applications of the proposed Fuzzy Knowledge Representation Base for Cross Layer information. The first one belongs more to the Cognitive Radio field, in that it deals with the Cross-layer Optimization of the transport layer behavior using PHY and MAC information. The second one, on the other hand, represents a Cognitive Networking approach to wireless network access selection, based not only on cross-layer information processing but also on knowledge sharing among users.

3.1 Challenges of Cognitive Cross-layer Optimization

We hereby describe the main challenges that the design of the ultimate Cognitive Cross-layer Architecture shall meet. Although these challenges can be considered as generic system design issues, in the following we will discuss in particular how they relate to cognitive radio and network design. After this discussion, we will evaluate to what degree existing proposals are successful in meeting them.

3.1.1 Modularity

Traditionally, protocol encapsulation has always been effective in providing modularity, i.e., in allowing independent implementation of all layers (e.g., wireless interfaces, drivers, protocol stacks, applications). In the definition of a cross-layer framework, care should be taken in preserving the modularity of the architecture, in order to allow components with cross-layer capabilities to be designed independently of each other, and to be used interchangeably [54].

Abstracting from the underlying technology is a key prerequisite to this concept of modularity. As an example, suppose we are designing a cognitive transport protocol implementation which can exploit link state information from the link layer to provide enhanced performance. If we can get the necessary information from the link layer in an abstract way, say channel error and congestion status, we can succeed in designing a modular transport layer which will work with different technologies. If, on the other hand, we are forced to rely on technology-specific information, e.g., the value of 802.11 Network Allocation Vector as a measure of link congestion, our design will be unusable when we switch to a different link layer technology such as UMTS or WiMax.

3.1.2 Information interpretability

As stated above, in order to achieve modularity it is necessary to choose a knowledge representation base which can accommodate different implementations of layer modules. While necessary, this practice brings further design challenges related to information interpretability. Suppose for instance that we identify SNR as being a generic and useful information shared by all wireless technologies, and as such we include it as a relevant link-layer information in the cross-layer knowledge base. The interpretation of SNR by other layers or entities would be misleading, since it is impossible to, e.g., infer the goodness of a wireless link from SNR without technology-specific knowledge such as the type of modulation and FEC/ARQ schemes used.

3.1.3 Imprecision and uncertainty

Most information to be exported by the different layers is obtained from measurements, which are affected by errors in precision and accuracy. These issues can often be properly dealt with by jointly designing all layers of a specifically targeted cross-layer optimization system. Unfortunately this is not feasible in a modular cross-layer system where all components are designed independently. Data can be easily misinterpreted if precision and accuracy are not known.

The example of SNR is once again enlightening. Suppose that upper layers (transport, application) possess the technology-specific knowledge (BER curves, etc.) needed for a correct interpretation of SNR measurements, and use this information for cross-layer optimization. In most consumer devices SNR measurements are very inaccurate, and in many systems, such as 802.11, BER performance has a very sharp transition (within a few dBs) from excellent to bad performance. As a consequence, if a SNR measurement is considered as an exact value, a bad channel might be misinterpreted as good and vice versa.

3.1.4 Complexity and scalability

The ultimate Cognitive Radio is required to be able to span over all available resources (e.g., available wireless interfaces and protocols, with all possible parameter configurations) in order to find the best solution to meet the user's needs. Cross-layer optimization is often a computationally intensive task even in fixed scenarios; as the number of layers involved in the optimization process increases, the computational load can easily become unbearable. Moreover, if the information and parameters exported by each layer are high in number and very different in nature, the complexity of designing optimization or AI algorithms can make Cognitive Radio impractical. This issue is of course taken to the limit in Cognitive Networks, where optimization is to be performed not only across the different layers in the protocol stack, but also across different devices.

3.2 Related Work

Mitola, who is generally acknowledged as the father of Cognitive Radio, proposed in [87] the adoption of a cross-layer knowledge representation base named Radio Knowledge Representation Language (RKRL). This language is a collection of micro-worlds, each one representing a particular technology; for example, we have separate semantics to talk about GSM, UMTS, and 802.11 links, as well as for different transport protocols and different applications. The consequence of this type of approach is that performing Cross-layer Optimization requires a full understanding of the semantics of

each separate world in order to operate effectively. This implies that the Cognitive Engine must be designed with explicit knowledge of the different technologies that it needs to support, which is clearly against the modularity and scalability constraints.

As far as complexity is concerned, jointly optimizing a lot of technology-specific information and parameters is non-trivial even for a fixed combination of layers in the protocol stack, and becomes much harder if the cognitive radio is supposed to be able to span over all possible combinations of wireless technologies, links, routes and protocols. Moreover, a knowledge representation approach like Mitola's also has scalability issues, since adding more protocols or wireless interfaces to the system can easily bring to an overwhelming computational load to the cognitive engine responsible for cross-layer optimization.

Actually, the majority of existing cross-layer architecture proposals (e.g., [56, 58, 88]) mainly rely on technology-specific information, and therefore share the same drawbacks of Mitola's proposal as far as modularity, information interpretability and complexity are concerned. A remarkable exception is [59], in which an object-oriented model is used to allow both generic and technology-specific information and commands to be exchanged with the link layer, but no attempt is made to extend the same approach to the whole protocol stack.

Finally, in a few works [72, 74, 89, 90] Fuzzy Logic is used for Cross-layer optimization. These proposals, however, are targeted to specific scenarios: in all these works a fuzzy logic controller is used to implement a technology-specific cross-layer solution. No effort is made to generalize the proposed approach to different Cross-layer Optimization problems, and therefore the design constraints we described in the previous section of this paper are not met. To the best of our knowledge, our approach is novel, as there is no previous work proposing Fuzzy Logic as a generic Knowledge Representation Base for Cross-layer Optimization in Cognitive Radios and Networks.

3.3   Fuzzy Logic

We will now provide a very brief overview of Fuzzy Logic, introducing the concepts of Fuzzy Sets, Fuzzy Logic Inference and Fuzzy Control System.

We point out that all notions provided within this section are well-established in the Fuzzy Logic community. The purpose of this overview is to help the reader unfamiliar with Fuzzy Logic understand our proposal; however, an exhaustive presentation of Fuzzy Logic is clearly beyond the scope of this paper, and for this purpose the reader is referred to the abundant literature on this topic (see for instance [91]).

3.3.1 Fuzzy Sets

Traditional set theory has a crisp[1] concept of membership: an element either belongs to a set or it does not, *tertium non datur*. 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. This degree of membership is commonly referred to as the *membership value* and is represented using a real value in $[0, 1]$, where 0 and 1 correspond to full non-membership and membership, respectively. Formally, a fuzzy set A in a universe U is defined by the membership function

$$A : U \to [0, 1] \tag{3.1}$$

so that for each $u \in U$ its grade of membership to A is given by $A(u)$. Commonly, triangular or trapezoidal functions are used as membership functions, because of their simplicity; however, more smooth or complex shapes can be used if necessary.

For fuzzy sets, the standard complement, union and intersection operators are defined as

$$\begin{align} \overline{A}(u) &= 1 - A(u) \tag{3.2} \\ (A \cap B)(u) &= \min(A(u), B(u)) \tag{3.3} \\ (A \cup B)(u) &= \max(A(u), B(u)) \tag{3.4} \end{align}$$

These operators are of particular importance since they correspond, in predicate logic, to the $\neg$ (NOT), $\wedge$ (AND) and $\vee$ (OR) operators, which in turn are widely used in AI techniques such as Fuzzy Control and Fuzzy Decision Making.

3.3.2 Fuzzy Logic Inference

Predicates in Fuzzy Logic can have partial degree of truth, in the same way as elements can have partial membership in Fuzzy Set Theory. The grade of truth of a predicate is represented using a real number in $[0, 1]$. The grade of truth of a generic predicate P in the form "u is A", where u is an element in the universe U and A is a fuzzy set over U, is given by $P(u) = A(u)$. The traditional logic operators $\neg$ (NOT), $\vee$ (OR) and $\wedge$ (AND) 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:

$$\begin{align} (\neg P)(u) &\triangleq 1 - P(u) \tag{3.5} \\ (P_1 \wedge P_2)(u) &\triangleq \min(P_1(u), P_2(u)) \tag{3.6} \\ (P_1 \vee P_2)(u) &\triangleq \max(P_1(u), P_2(u)) \tag{3.7} \end{align}$$

---

[1] In Fuzzy Logic the term *crisp* is used to indicate variables having exact values, as opposed to the term *fuzzy* which indicates a qualitative rather than quantitative method of representation.

We note that, as anticipated, there is a correspondence between the logical and the set operators.

In addition to the traditional logic operators, other operators can be introduced, which are commonly associated with linguistic modifiers. Classical examples are the concentrator and the dilution operators, which can be associated with the linguistic modifiers *very* and *somewhat*:

$$(\text{CON}\,P)\,(u) \quad \triangleq \quad (P(u))^2 \tag{3.8}$$

$$(\text{DIL}\,P)\,(u) \quad \triangleq \quad \sqrt{P(u)} \tag{3.9}$$

Using these operators makes it possible to evaluate the truth of predicates like "u is very A" and "v is somewhat B", thus providing enhanced support for qualitative reasoning.

3.3.3   Extension Principle

Ordinary functions can be extended to act on fuzzy sets by means of the *extension principle* [91, Sec. 2.3]. Let U and V be ordinary sets, and let A and B be fuzzy sets defined over U and V respectively. For a generic function $f : U \rightarrow V$ the extension principle defines its fuzzy counterpart $f : A \rightarrow B$ as

$$[f(A)]\,(v) = \sup_{u|v=f(u)} A(u) \tag{3.10}$$

3.3.4   Fuzzy Numbers

A fuzzy set is said to be normal if $\sup_{u\in U} A(u) = 1$. Finally, $\forall \alpha \in [0,1]$, the α-cut ${}^{\alpha}A$ of a fuzzy set A is defined as

$${}^{\alpha}A \quad = \quad \{u \in U : A(u) \geq \alpha\} \tag{3.11}$$

α-cuts are important because of the so-called *decomposition theorem* [92], which states that a fuzzy set is uniquely identified by the family of its α-cuts.

A fuzzy set X is said to be a Fuzzy Number if the following conditions are satisfied: 1) its universe is $\mathbb{R}$; i.e., $X : \mathbb{R} \longrightarrow [0,1]$; 2) X is a normal fuzzy set; 3) $\forall \alpha \in (0,1]$, the α-cut ${}^{\alpha}X$ is a closed interval; 4) the support of X is bounded, i.e., $\exists a, b \in \mathbb{R}$ such that $\forall u \notin [a,b]\ \ X(u) = 0$.

Fuzzy Numbers are particularly interesting since they provide information which is both quantitative and qualitative at the same time, and also because the standard arithmetic operations can be applied to them. Due to this peculiarity, Fuzzy Numbers play an important role in many applications such as fuzzy control, fuzzy decision making and approximate reasoning.

3.3.5   Fuzzy Arithmetic

The arithmetic operations on fuzzy numbers can be defined thanks to the property that each α-cut of a fuzzy number is a closed interval. Arithmetic
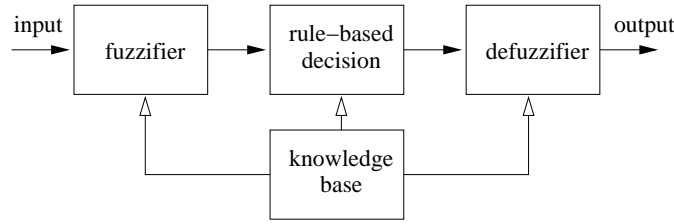
Figure 3.1: Basic architecture of a fuzzy controller

operations on closed intervals $[a, b], [c, d] \subset \mathbb{R}$ are defined as follows [93]

$$[a, b] + [c, d] = [a + c, b + d] \, ; \qquad [a, b] - [c, d] = [a - d, b - c]$$
$$[a, b] \times [c, d] \quad = \quad [\min(ac, ad, bc, bd), \max(ac, ad, bc, bd)]$$
$$[a, b] \, / \, [c, d] \quad = \quad \left[\min(\frac{a}{c}, \frac{a}{d}, \frac{b}{c}, \frac{b}{d}), \max(\frac{a}{c}, \frac{a}{d}, \frac{b}{c}, \frac{b}{d})\right] \tag{3.12}$$

Let now A and B be fuzzy numbers. $\forall \alpha \in [0, 1]$, using interval arithmetic we can then define

$$\begin{aligned}
{}^{\alpha}(A + B) &= {}^{\alpha}A + {}^{\alpha}B & {}^{\alpha}(A - B) &= {}^{\alpha}A - {}^{\alpha}B \\
{}^{\alpha}(A \times B) &= {}^{\alpha}A \times {}^{\alpha}B & {}^{\alpha}(A/B) &= {}^{\alpha}A/{}^{\alpha}B
\end{aligned} \tag{3.13}$$

Thanks to the decomposition theorem, the definition of a family of α-cuts for the result of each arithmetic operation on fuzzy numbers uniquely identifies the result as a fuzzy set. It can be proved that this fuzzy set satisfies the necessary requirements to be a fuzzy number.

Using a similar approach, if we define the MIN and MAX operators for closed intervals $[a, b], [c, d] \in \mathbb{R}$ as

$$\text{MIN}([a, b] \, , [c, d]) = [\min(a, c), \min(b, d)] \, ; \quad \text{MAX}([a, b] \, , [c, d]) = [\max(a, c), \max(b, d)] \tag{3.14}$$

we can then define the MIN and MAX operators for fuzzy numbers A and B using α-cut decomposition:

$${}^{\alpha}(\text{MIN}(A, B)) = \text{MIN}({}^{\alpha}A, {}^{\alpha}B); \qquad {}^{\alpha}(\text{MAX}(A, B)) = \text{MAX}({}^{\alpha}A, {}^{\alpha}B) \tag{3.15}$$

3.3.6 Fuzzy Controllers

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 3.1. The modules composing a fuzzy controller are described in the rest of this section.

Knowledge base

the knowledge base characterizes the vision that the fuzzy logic has of the outside world, defining the relationship between crisp input/output parameters and their fuzzy representation understood by the fuzzy controller. From a practical point of view, each input/output variable is characterized by the following items in the knowledge base:

- its universe, i.e., the domain over which the variable can assume values;

- the set of linguistic attributes ("labels") which compose its qualitative representation;

- for each label, the membership function defining it.

As an example, suppose SNR in dB is an input variable of our control system. The corresponding universe is $\mathbb{R}$, since in theory dB values can assume any real value. We can choose the attributes *good* and *bad* to represent SNR qualitatively; the membership function of each attribute $(\mathrm{SNR}_{good}, \mathrm{SNR}_{bad} : \mathbb{R} \longrightarrow [0,1])$ will be strictly related to the receiver performance with respect to SNR, e.g., taking into account modulation performance, receiver sensitivity, etc.[2]

Fuzzification

this is the process of translating crisp input measurements into their fuzzy representation. This process is carried out for each input variable at every control cycle, by evaluating the membership value of each attribute characterizing it. Following the above mentioned SNR example, at each control cycle a new SNR value x will be available to the fuzzifier, which will determine how likely the channel is to be considered good and bad by evaluating $\mathrm{SNR}_{good}(x)$ and $\mathrm{SNR}_{bad}(x)$ respectively.

Rule-based control and decision making

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. IF conditions are composed using the predicates and logic connectors discussed in Section 3.3.2, while THEN statements are commonly basic predicates indicating the fuzzy attribute which is more appropriate for the output variables involved.

The process of rule evaluation is easier to explain by an example. Let X,Y be input variables and Z be an output variable. Let X,Y and Z be

---

[2]For an example of possible membership functions for the 6 Mbps modulation scheme in 802.11g, see Figure 3.3 in Section 3.5.

represented by the linguistic attributes X_1 and X_2, Y_1 and Y_2, Z_1 and Z_2 respectively. Suppose we have the following rule set:

Rule 1: IF X is X_1 and Y is Y_1 THEN Z is Z_1
Rule 2: IF X is X_2 or Y is Y_2 THEN Z is Z_2

Finally, let x and y be the current crisp values for X and Y. First of all, the truth value α_i for each rule i is calculated:

$$\alpha_1 = (X \text{ is } X_1) \wedge (Y \text{ is } Y_1) = \min\left(X_1(x), Y_1(y)\right) \qquad (3.16)$$

$$\alpha_2 = (X \text{ is } X_2) \vee (Y \text{ is } Y_2) = \max\left(X_2(x), Y_2(y)\right) \qquad (3.17)$$

then a modified membership function μ' is calculated for the control output recommended by each rule by taking the minimum (fuzzy $\wedge$ operator) of its membership function and the truth value of the IF clause:

$$Z_1' = \alpha_1 \wedge \mu_{Z_1} = \min\left(\alpha_1, Z_1(z)\right) \qquad (3.18)$$

$$Z_2' = \alpha_2 \wedge \mu_{Z_2} = \min\left(\alpha_2, Z_2(z)\right) \qquad (3.19)$$

The effect of the $\wedge$ operation in (3.18) and (3.19) is that the membership function of each control action (THEN clause) is limited to the truth value of each antecedent (IF clause); in other words, a rule which is "more true" yields a stronger contribution to the output of the Fuzzy Controller.

Finally, the membership function $Z(z)$ for the control output of variable Z is calculated by taking the maximum (fuzzy $\vee$ operator) of the modified membership μ' of all control actions referring to Z:

$$Z(z) = Z_1 \vee Z_2 = \max\left(Z_1'(z), Z_2'(z)\right) \qquad (3.20)$$

Defuzzification

the rule evaluation and decision making process has produced, for each output variable, a membership function $\mu_Z(z)$ representing the appropriateness of each output value z. Defuzzification is the process of determining an appropriate crisp value $\overline{z}$ to be used as the actual output. One of the most commonly used techniques for this purpose is the Center Of Area (COA) method:

$$\overline{z} = \frac{\int z\, Z(z)\, dz}{\int Z(z)\, dz} \qquad (3.21)$$

3.4 Fuzzy Cross-Layer Knowledge Representation Base

3.4.1 Design principles

First of all the knowledge representation base of the Cross-layer architecture needs to be defined. For each layer in the protocol stack, a set of variables

and parameters should be identified. 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. The set of variables and parameters should be kept to a minimum, without duplication of information in different forms if possible, and most importantly should not contain technology-dependent items. All variables are intended to be fuzzy variables, and all parameters are intended as fuzzy control variables. Both variables and parameters should have a standardized meaning and interpretation.

For status variables to be determined from crisp measurements, we propose to keep the fuzzification process of the status variables confined within the layer that exports them. Technology-specific knowledge is needed for a correct design of the fuzzifier; this however poses no problem, since the needed knowledge is normally possessed by the designers/manufacturers of each layer. Moreover, we suggest the fuzzy representation of each variable to be chosen such that part of the technology-specific knowledge is embedded into the fuzzy representation, so that cross-layer information can be interpreted more easily by layers not possessing the same technology-specific knowledge. 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* or *good*; the result of this fuzzification is that the fuzzy SNR *bad/good* characterization can be correctly interpreted even without explicit knowledge regarding modulation an coding, since we can rely on the fact that they have been taken into account for the fuzzification process.

3.4.2   Benefits

It is our opinion that using the above mentioned principles for the design of a Fuzzy Cross-layer architecture can be a significant step forward in meeting the challenges described in Section 3.1. First of all, such an architecture is modular by definition. Keeping technology-specific information processing within each layer allows independent implementation of the layers themselves, while representing cross-layer information using generic status variables with standardized meaning ensures that the information itself is consistent and usable for cross-layer optimization, independently of the underlying technology. One should note that achieving this modularity in practice will require a significant standardization effort.

Using fuzzy variables also brings improved information interpretability: e.g., information represented in the form "link reliability is high" is much easier to interpret correctly than "SNR is 6 dB". This is again a consequence of having removed the need for possessing technology-specific knowledge.

As far as precision and accuracy of measured information are concerned, the obstacle has been avoided by using an imprecise knowledge representa-

tion base. Fuzzy Logic is intrinsically suited to represent the likelihood of information, in other words how precise and accurate a measurement is. Accomplishing this in practice requires proper design of the fuzzification phase; in our architecture, this phase is confined within the layer performing the measurements, which is likely the place where accuracy and precision are known best.

Finally, the complexity of our cross-layer framework is very low compared to other proposals. By mapping technology-specific information available at the various layers to a small and generic knowledge base, we keep a considerable fraction of the system complexity distributed, thus making the design of AI-based and optimization algorithms more manageable. As far as computational power is concerned, Fuzzy Logic systems typically require low computational resources when implemented in general purpose processors; alternatively, dedicated Fuzzy Logic chips are available on the market for use in critical scenarios.

3.5   Application to Cognitive Cross Layer Optimization

In this section we investigate the use of the just introduced Fuzzy Knowledge Representation Base for the realization of a Cognitive Cross Layer Optimization strategy for Cognitive Radios. We design a Fuzzy Logic Controller to realize a Cognitive Cross-layer Engine which is to carry out cross-layer optimization of transport layer parameters in order to adapt to varying network and propagation conditions.

3.5.1   Fuzzy Controllers for Cognitive Cross-layer Optimization

Since Fuzzy Logic has been chosen for the knowledge representation base, Fuzzy Logic Controllers are the natural choice for the implementation of Cross-layer control schemes. A fuzzy controller can either be embedded into a layer 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, we propose the following approach. 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. By contrast, 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
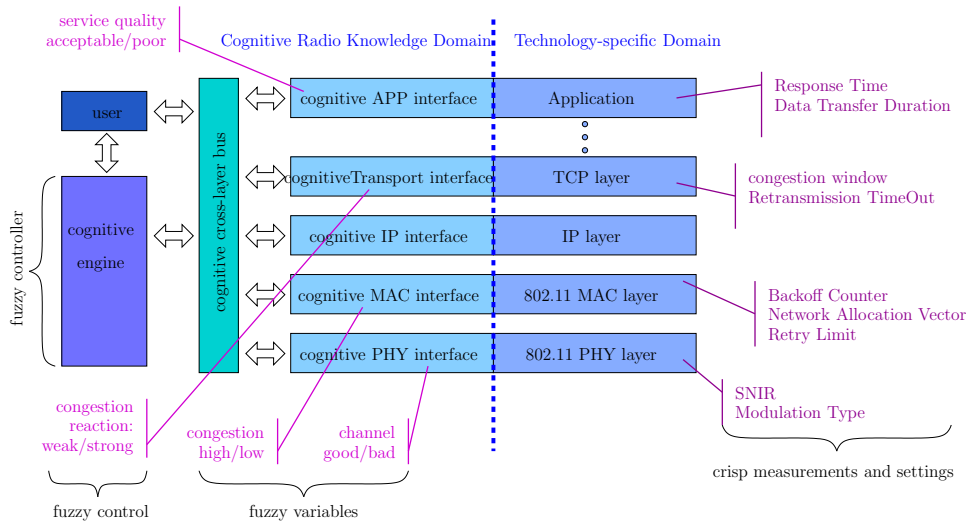
Figure 3.2: Example of Fuzzy Cognitive Cross-layer Architecture

allow an application or a centralized cognitive engine to increase/decrease throughput and reliability in order to improve the QoS perceived by the user. In other words, embedded controllers are more suitable for layers which can be optimized independently of others; for the general case in which this separate optimization might lead to suboptimal performance, a centralized controller performing joint optimization may be preferred.

3.5.2 Case study: TCP Fuzzy

As a proof of concept for our proposal, in this section we present a cross-layer optimization scheme for TCP which uses fuzzy logic for the representation of relevant cross-layer information, and a fuzzy controller for the implementation of the optimization engine.

Many solutions have been proposed in the literature to improve the performance of TCP over error-prone links by differentiating packet losses due to congestion and errors, and by setting TCP's congestion control parameters accordingly [94]. For TCP Fuzzy we use a similar approach, except that the optimization engine leverages on cross-layer information provided by the knowledge representation base described earlier in this chapter, and is implemented using a fuzzy controller.

Design

We associate the increment and decrement value of TCP's congestion window to the fuzzy variables *cwndIncr* and *cwndDecr*, respectively. The value of these variables is determined as the output of a Fuzzy Controller using the following rule set:

```
IF (linkCongestion is high)
    THEN (cwndIncr is weak AND cwndDecr is strong)
IF (linkCongestion is low)
    THEN (cwndIncr is strong AND cwndDecr is weak)
```

linkCongestion is a cross-layer information provided by the MAC layer in the form of a fuzzy variable. If the MAC layer possesses some measurement which is directly related to congestion, then *linkCongestion* can be determined by proper fuzzification of that measurement. Alternatively, if the MAC only possesses some measurement related to reliability, the congestion level can be determined using a cross-layer approach, provided that the PHY layer possesses some other measurements related to the status of the channel, e.g., a signal strength indicator. Let *linkReliability* and *channel* be fuzzy variables obtained by fuzzification of the above mentioned measurements; the value of *linkCongestion* is determined using fuzzy inference:

```
IF (linkReliability is low AND channel is good)
    THEN linkCongestion is high
IF (linkReliability is high OR (linkReliability is low AND channel is bad))
    THEN linkCongestion is low
```

The rule sets just provided result in a conservative management of the TCP congestion window when the link is affected by congestion, and in a more aggressive behavior when the link is not congested and the channel is affected by errors.

The cross-layer architecture used by TCP Fuzzy is clearly technology-independent and therefore is suitable for use with different wireless technologies. For instance, a plain 802.11b/g device could exploit the MAC counters to derive *linkReliability* and RSSI measurements to determine *channel*. Alternatively, an 802.11e or 802.11k device could exploit cell load measurements provided by the AP to derive *linkCongestion* directly, and a UMTS device could possibly use interference power measurements for the same purpose.

Performance evaluation

Performance evaluation has been carried out for the 802.11g case using the NS-Miracle simulator [C7]. The simulated scenario is an infrastructured 802.11g cell with different numbers of users placed at a varying distance from the AP. All nodes used the 6 Mbps modulation scheme and performed a bulk data transfer for a duration of 300s to a fixed host connected to the AP with a wired link with 10 Mpbs bandwidth and 0.1s one-way delay. Transmission errors were determined using a Packet Error Rate vs. SINR relation which was derived offline for the modulation scheme in use; SINR was calculated at runtime using path loss and a gaussian interference model. Simulations were
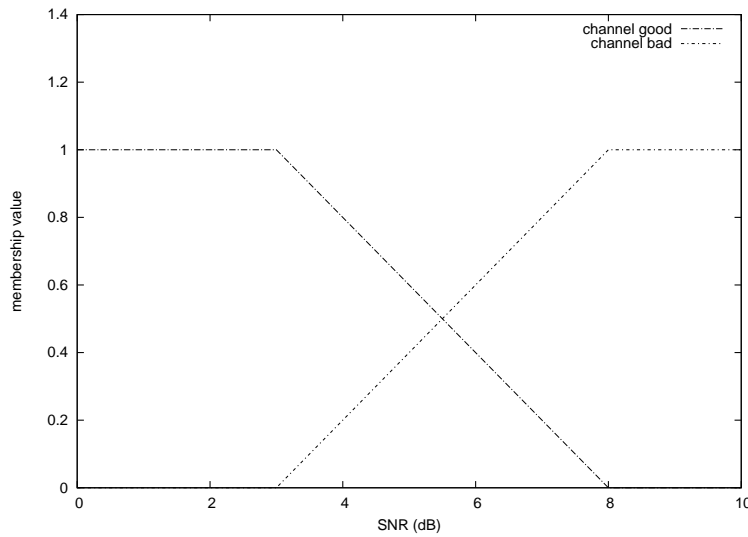
Figure 3.3: Membership functions of channel attributes for the 6 Mbps modulation scheme of 802.11g

conducted using alternatively TCP Reno (which is one of the most widely used versions of TCP) and TCP Fuzzy which was implemented by modifying TCP Reno according to the above described algorithm. For both TCP schemes a 64 kB window limit was used. The membership functions used for the input variables of the fuzzy controller are reported in Figures 3.3 and 3.4, and were designed specifically for the 802.11g PHY and MAC used for the performance evaluation, thus following the design principles introduced in Section 3.4.1. The membership functions used for the output variables, reported in Figure 3.5, were chosen to make TCP Fuzzy behave the same as TCP Reno when the channel is good, thus exhibiting the same congestion control and fairness behavior, while being more aggressive when the channel is bad in order to provide improved performance.

Simulation results are reported in Figure 3.6, averaged over 100 iterations per point. TCP Fuzzy can achieve significantly better throughput performance than TCP Reno at critical SNR values; moreover TCP Fuzzy tends to achieve similar performance to TCP Reno as the number of users increase, showing that the more aggressive management of the congestion window performed by TCP Fuzzy is mitigated as congestion becomes relevant.

These results confirm that our Fuzzy Logic solution can achieve the performance improvements provided by cross-layer optimization, while at the same time being much more modular and reuseable than traditional cross-layer solutions, and is therefore a promising approach for cognitive radio networks, worth of further investigation.
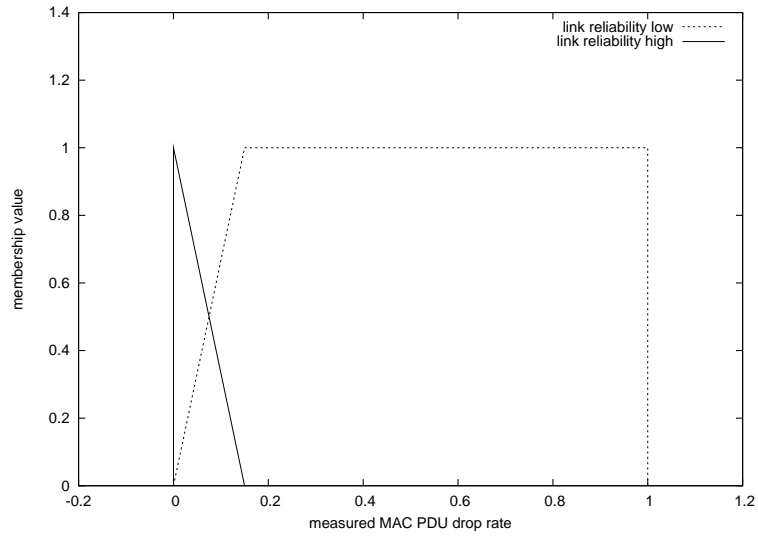
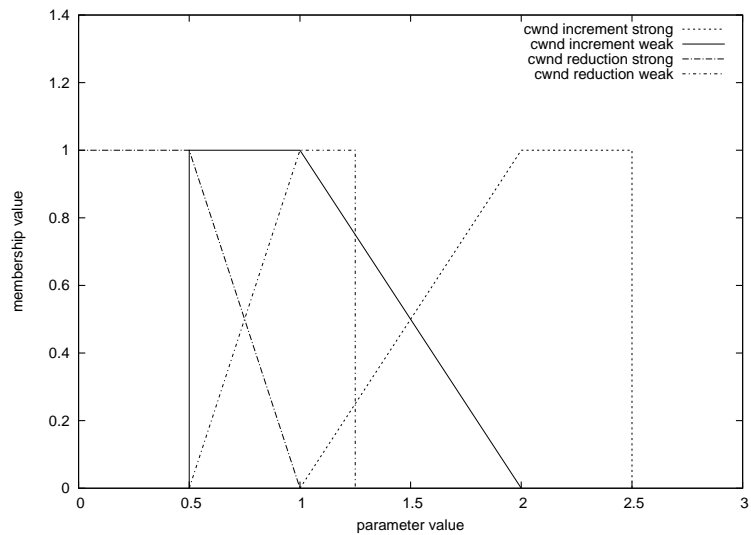Figure 3.4: Membership functions of link reliability attributes for 802.11 MAC

Figure 3.5: Membership functions of the output variables of the Fuzzy controller
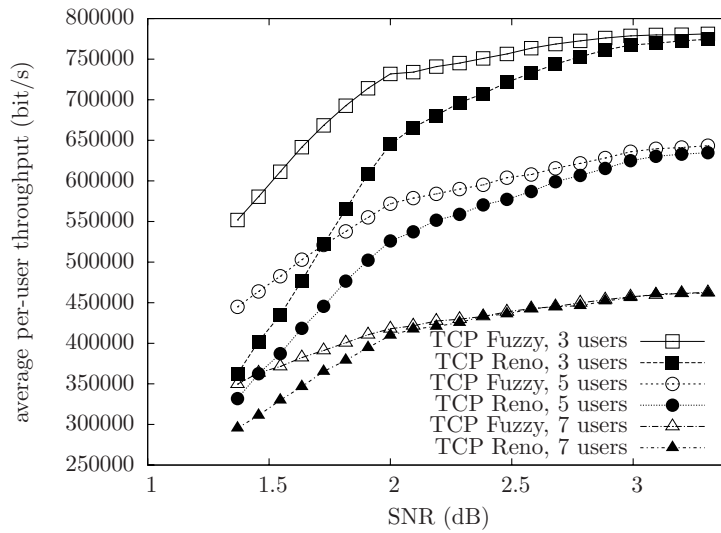
Figure 3.6: Performance of TCP Fuzzy compared to TCP Reno

3.6   Application to Wireless Network Access

The recent progress in radio communications today provides several network access technologies for wireless connectivity, e.g., IEEE 802.11, WiMAX and UMTS. At the same time, advances in microelectronics allow all these technologies to be exploited within a single mobile device equipped with multiple radio interfaces. As a consequence of these facts, many new challenges have arisen for the telecommunication research community. The one we focus on in this section is wireless network access, i.e., how a user who wants to connect to the Internet can select, among all the available opportunities, the one which yields the best performance.

Most previous work dealing with this problem considers only a specific wireless technology. The most notable example is 802.11: several valuable solutions have been proposed to solve the problem of Access Point selection [95–97], but all of them rely on 802.11-specific metrics. The consequence is that these solutions cannot be used with other wireless technologies and, most importantly, the obtained performance metrics cannot be compared to the ones obtained by different solutions designed for other types of radio interfaces. Moreover, while it is possible to design network access schemes to handle a particular set of existing technologies, an ideal network access solution would be required to be generic and modular enough so as to accommodate even new wireless technologies as they are introduced.

Another issue in wireless network access is that an ideal solution should be optimal with respect to the end-user perspective. In particular, two key aspects should be considered. First, user-perceived service quality depends on end-to-end performance, in which the wireless link plays an important role without however being the only issue. Previous work on access point selection targeted only scenarios in which the wireless link is the bottleneck, while in many real life scenarios also the core network can exhibit non-ideal performance, thus having a non-negligible effect on end-to-end network performance. Second, the optimization of the end-to-end network performance should take the Quality of Service (QoS) requirements of different applications into account. Much previous work on Access Point Selection focuses on the maximization of network throughput only; however, applications such as VoIP and gaming are more strongly affected by other factors such as network delay and reliability. In recent years, interest in providing satisfactory service quality for these applications has grown considerably, due to their increased popularity; this in turn has promoted a significant effort by the research community to find methods and solutions able to enhance the QoS of multimedia applications on various wireless technologies, most notably 802.11 [98–100] and UMTS [101–103]. Unfortunately, this QoS-related research has focused almost exclusively on optimizing the performance of an already established multimedia communications, and the problem of performing a QoS-aware network access decision has not been dealt with so

far.

To summarize, the problem of identifying an algorithm for wireless network access selection which 1) is independent of the radio technology, 2) can accommodate the QoS requirements of different applications, and 3) can account not only for wireless link performance, but also for possible non-ideal conditions of the entire end-to-end path, is a very challenging and still open issue.

From this perspective, the recently proposed Cognitive Network paradigm seems to be a very promising approach. In [2], a Cognitive Network is defined as "*a network with a cognitive process that can perceive current network conditions, and then plan, decide, and act on those conditions*". Cognitive Networking implies the presence of a cognition process which spans both all the layers of the protocol stack and all the network components of end-to-end communication; this cognition process is distributed among the different nodes composing the network, which share their knowledge and cooperate among themselves. This architecture is promising in that it is potentially able to solve problems which are too complex to be handled within a traditional cross-layer approach, while at the same time being capable of learning the behavior of different wireless technologies and applications.

In this section, we propose a Cognitive Network approach to the Wireless Network Access problem. In particular, we propose a knowledge representation framework based on Fuzzy Logic which enables the implementation of a cognition process which is both cross-layer and network-aware; furthermore, we exploit knowledge sharing among different devices with the purpose of achieving a more complete and reliable characterization of the performance of the whole network. Subsequently, we define a network access scheme based on Fuzzy Decision Making which allows each user to choose the Access Point which best satisfies its QoS requirements. We stress that the modularity of the architecture and the generality of the chosen knowledge representation allow our solution to easily provide optimized network access policies for new wireless technologies and applications which outperform state-of-the-art schemes while at the same time minimizing the effort required to accommodate different wireless technologies and applications.

3.6.1   Cognitive Network Access

It is worth mentioning that the original definition of Cognitive Radio by J. Mitola [87] already tries to address the problem of wireless network access. Mitola's Cognitive Radio has the explicit purpose of "*detecting user needs, and providing wireless services most adequate to meet them*". The use of the term *cognitive* highlights the fact that some Artificial Intelligence (AI) needs to be at the heart of the device which is to choose and adapt its services to the user's needs. One of the most quoted definitions for AI is "*how to make machines do things at which, at the moment, humans are better*" [104]. So,

in the context of wireless network access, the goal of a cognitive radio would be to relieve the mobile users from having to figure out themselves which is the most satisfactory access opportunity. The key motivation behind the approach proposed in this section directly follows from these considerations: our goal is to replace user's decisions trying to mimic the actual decision strategies that a typical human user would adopt.

As an example, consider a cafe with a nearby 802.11 hotspot, in an area covered by a UMTS provider. A single user comes in with his laptop, orders a coffee and looks for an Internet connection to do some web surfing. He might try UMTS first, maybe just to realize that it is too slow for what he pays for it. Then he might realize that there is an 802.11 hotspot nearby, connect to it and finally surf the web happily with high throughput. A second user comes in, orders another coffee, and turns on his mobile device to watch a TV program via video streaming from the Internet. Instead of figuring out the quality of the available networks by himself, he might just notice the first user who is surfing happily, and query him about the best connection available. Based on this knowledge of the previous experience of the first customer, he would likely connect to the hotspot, and be satisfied by enjoying video streaming with high throughput connectivity. Then a third user comes in and, under advice from the previous users, connects to the hotspot for a VoIP conversation. It could happen, however, that she is not satisfied because, e.g., the wired network serving the hotspot has a considerably high delay, or the hotspot itself has become congested; consequently, she might try out UMTS, and possibly be more satisfied because of the lower Round Trip Time. Finally, a last user might come in with his laptop to play some highly interactive online game. He asks all previous customers about the performance they experienced, and he decides to use the UMTS connection, since he understands that his application requirements (low latency) are much closer to the requirements of the VoIP user rather than to those of the other two.

Although very simple, this example highlights some important facts. First of all, while direct experience is an effective means of inferring the quality of several connection opportunities, exploiting knowledge previously gathered by other users may be a quicker and easier way. Second, the choice of a suitable knowledge representation base for performance evaluation metrics becomes crucial: on one hand it is impossible to find a unique definition of quality, since different applications can have even conflicting performance requirements, and so we need different metrics; on the other hand, we cannot rely on too fine-grained and technology-specific metrics, since this could possibly make information gathered by some users difficult to interpret by others having similar but not identical needs. Furthermore, we point out that the performance seen by each user is actually made up of two components, i.e., radio link and core network performance, and that these aspects should be evaluated jointly. In the example above, suppose the first user

leaves the cafe and goes and sits on a bench in a nearby park. Previous experience still indicates the hotspot as the most suitable choice. However, current link quality metrics (e.g., the RSSI indicator) might show that he is too far from the hotspot to get an acceptable throughput. Finally, it should be noted that all the available information should be interpreted *cum grano salis*, i.e., not only quantitatively but also qualitatively, because performance reports by other users might be biased, measurements might be affected by errors, and all this information might be partial and/or old. [3]

Based on the above discussion, we consider here a scheme in which prospective users have access to a shared knowledge base that contains information about the service quality experienced by past and present active connections. To overcome the above mentioned issues, we define 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. We propose the use of this knowledge representation to build a Cognitive Network Knowledge Database, which is to be filled with service quality information fed back by all users actively using the network. A user willing to set up a new connection can then retrieve such information and compare it to both application requirements and other measurements, in order to assess the expected service quality for each access opportunity; in this process, both Fuzzy Logic Inference and Fuzzy Arithmetic are used. Finally, the most suitable network access opportunity must be selected using Fuzzy Decision Making techniques. The presence of a knowledge representation base including information belonging to different components of the communication system, the cross-layer processing of this information, the mechanism by which a node learns from its neighbors' experience as well as its own history, the use of Fuzzy Logic for incomplete knowledge representation, and the use of Fuzzy Decision Making to select among access opportunities clearly identify our proposed scheme as belonging to the Cognitive Network Paradigm.

We note that Fuzzy Logic has been already proposed for use in the context of telecommunication system, e.g., for QoS routing in wired networks [70], route caching decisions in wireless ad hoc networks [71], radio resource management [72] and channel selection in cellular networks [73]. An interesting survey on the usage of Fuzzy Logic techniques in the telecommunication field can be found in [75]. The main difference of our approach is that, unlike previous work, we do not consider a Fuzzy Controller implementing a simple input-output relationship using logic inference, but rather a Fuzzy Decision Making scheme which works on top of a rather complex performance evaluation framework based on Fuzzy Arithmetic which spans

---

[3]An important aspect ignored in this section is how to deal with users that maliciously provide wrong information to influence other nodes' decisions. This issue is left for future research.

across the whole protocol stack; moreover, we propose the adoption of Fuzzy Logic not only to design a decision strategy which can take into account imprecision and uncertainty issues, but also as a technology-independent knowledge representation which can fit different radio technologies, network protocols and user applications.

3.6.2   Knowledge Representation, Cross-layer Information Processing and Information Sharing

Following the approach described in Section 3.6.2, we characterize performance in terms of *throughput*, *delay* and *reliability* (defined as the success ratio of packet transmissions), where each of these items is represented using a fuzzy number. This characterization is applied to different components of the communication performance: wireless link quality measurements performed by each user, wired network performance reported by all users to the Cognitive Network Database, estimation of end-to-end network-layer and transport layer performance, and QoS requirements of user applications.

We introduce the notation beforehand, in order to make the discussion easier to understand in spite of the heterogeneity and vast number of variables used. We denote throughput, delay and reliability metrics with t, d and r; the subscripts l, n, e, t and a denote respectively radio link, core network, end-to-end, transport and application metrics. Finally, for a generic metric x, we denote its measured value with $\check{x}$, its estimated value with $\hat{x}$, and its fuzzy representation with $\tilde{x}$.

Our knowledge representation and cross-layer information processing architecture is represented in Figure 3.7. Some modules are expected to make use of technology-dependent information to measure and/or estimate communication quality, and represent it using the technology-independent throughput, delay and reliability metrics. One of such modules is the radio link module, which is in charge of providing the radio link performance measurements $\check{t}_l$, $\check{d}_l$ and $\check{r}_l$ for ongoing communications, and of expressing the estimated radio link performance for access point selection using the fuzzy metrics $\tilde{t}_l$, $\tilde{d}_l$ and $\tilde{r}_l$. Another use of technology-dependent information is within the transport module, where a characterization of the performance provided to the application by the transport layer as a function of the end-to-end network layer performance is needed; we suppose this characterization can be expressed using the three functions $f_t(d_e, r_e, t_e)$, $f_d(d_e, r_e, t_e)$ and $f_r(d_e, r_e, t_e)$, which provide respectively application layer throughput, delay and reliability as a function of end-to-end network-layer performance (either measured or estimated). Finally, application QoS requirements are represented using fuzzy sets. We denote with $\tilde{t}_a$, $\tilde{d}_a$, $\tilde{r}_a$ the fuzzy sets representing respectively satisfactory throughput, delay and reliability for a particular application; the membership functions of these sets are to be determined *a priori* using application-specific knowledge.
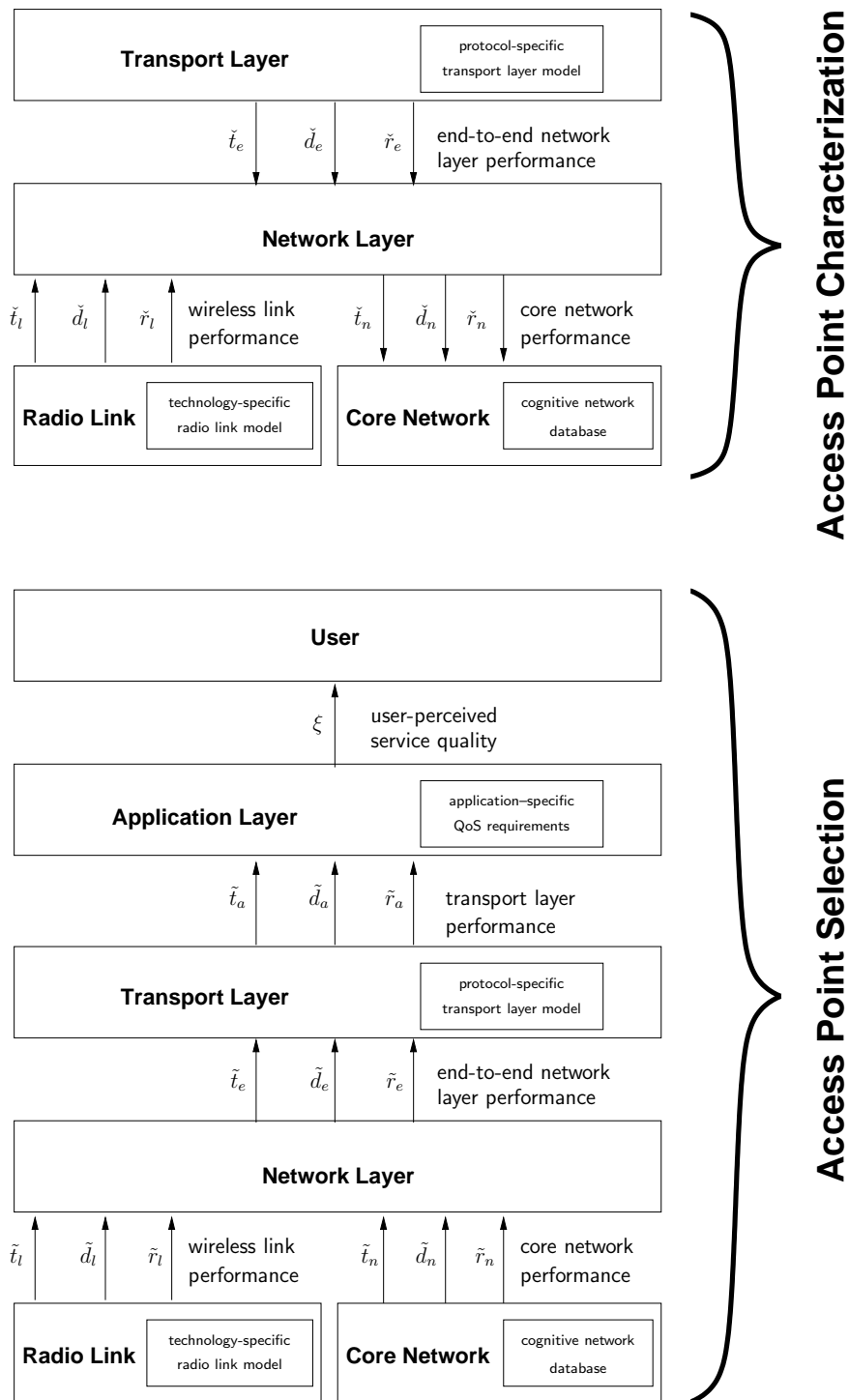
Figure 3.7: Knowledge representation and cross-layer information processing for Cognitive Network Access

According to the principles discussed in Section 3.6.2, while technology-specific knowledge is needed to design these modules properly, the overall architecture is technology-independent, thanks to its modularity and to the use of an abstract and generic knowledge representation base in the definition of the interfaces between modules. In the rest of this section, we discuss the technology-independent architecture; an example implementation of the technology-dependent components will be provided in Section 3.6.3.

Each cognitive user performs at a given time one of two cognitive activities. The first one, Access Point Characterization, is carried out by users having ongoing communications, and consists in processing radio link and end-to-end performance measurements to obtain an estimate of the core network performance for the access point in use; this information is shared with other users by means of the cognitive network database. The second activity is Access Point Selection, which is performed by users willing to start a new communication; it consists of estimating the application-layer communication performance by combining the estimated performance at the radio link with the Access Point Characterization obtained from the Cognitive Network Database, and subsequently selecting the Access Point which is expected to better satisfy the application requirements. Each of these activities will be explained in the following subsections.

Access Point Characterization

This process is represented in the left side of Figure 3.7. When a communication is being performed over the radio link, the radio link module provides instantaneous measurements for the metrics $\check{t}_l$, $\check{d}_l$ and $\check{r}_l$. For the same communication, the transport layer module measures the end-to-end network layer performance it is perceiving, which we denote with $\check{t}_e$, $\check{d}_e$ and $\check{r}_e$. We define core network performance as the performance of the part of the network beyond the Access Point. In our architecture, this is the information which is to be shared among users to support cooperative access point characterization effectively. Unfortunately, core network performance cannot be measured directly. For this reason, we propose to measure the core network throughput, delay and reliability ($\check{t}_n$, $\check{d}_n$ and $\check{r}_n$, respectively) by comparing the measured end-to-end network-layer performance with the performance at the radio link layer and at the transport layer. In detail, the delay and reliability are calculated as $\check{d}_n = \check{d}_e - \check{d}_l$ and $\check{r}_n = \check{r}_e/\check{r}_l$, respectively. For the core network throughput, the most reasonable way to measure it is by evaluating the measured end-to-end network-layer throughput $\check{t}_e$. However, we must consider that if the core network is not the bottleneck this method can result in a severe underestimation; this can happen, for instance, when the bottleneck is at the wireless link, or when throughput is limited by the transport layer (e.g., due to high round trip time in TCP) or the application layer. To overcome these issues, we define the following estimate of core

network throughput:

$$\check{t}_n = \begin{cases} \check{t}_e & \text{if } \check{t}_e < \check{t}_l \text{ and } \check{t}_e < f_t(\check{d}_e, \check{r}_e, \check{t}_l) \\ T_{max} & \text{otherwise} \end{cases} \qquad (3.22)$$

where T_{max} is a suitably large number. Using all these calculations, users with ongoing communications can periodically compute core network performance measurements and upload them to the Cognitive Network Database. The database will therefore be populated with a performance characterization of all available access networks.

Access Point Selection

This process is represented in the right side of Figure 3.7. When a user wants to start a new communication, it estimates the service quality which can be provided by all the available access points, and selects the most suitable one. This estimation is obtained for each AP by processing the shared access point performance characterization provided by the cognitive network database, and the radio link performance estimation provided by the relative radio link module within the particular user being considered. Radio link performance metrics are represented using the fuzzy numbers $\tilde{t}_l$, $\tilde{d}_l$ and $\tilde{r}_l$; these metrics are to be provided by the radio link module based on technology specific measurements (such as RSSI, interference, mobility...), and the fuzzification process is intended to account for imprecision and inaccuracy in the measurements. Core network performance metrics are represented by the fuzzy numbers $\tilde{t}_n$, $\tilde{d}_n$ and $\tilde{r}_n$; the fuzzification process is intended to represent the uncertainty due to differences in the measurements performed by different users. To this aim, we chose to represent the resulting metrics using triangular fuzzy numbers, where maximum membership is attained by the mean μ of the available measurements, and the support of the membership function is $[\mu - 2\sigma, \mu + 2\sigma]$, where σ is the standard deviation of the measurements [105]. A rectangular sliding window is used to select only the more recent measurements, so that in the fuzzification process older measurements are discarded.

All the fuzzy performance metrics just introduced are processed using Fuzzy Arithmetic in order to evaluate the communication quality expected from each AP. From now on, we explicitly include the index of the AP in the notation whenever needed to avoid confusion.

First of all, the expected network-layer end-to-end performance $\hat{t}_e(i)$, $\hat{d}_e(i)$ and $\hat{r}_e(i)$ for each Access Point i is determined by combining radio

link and core network performance as follows:[4]

$$
\begin{aligned}
\tilde{t}_e(i) &= \mathrm{MIN}(\tilde{t}_l(i), \tilde{t}_n(i)) \\
\tilde{d}_e(i) &= \tilde{d}_l(i) + \tilde{d}_n(i) \\
\tilde{r}_e(i) &= \tilde{r}_l(i) \times \tilde{r}_n(i)
\end{aligned}
\tag{3.23}
$$

Then, transport-layer performance is derived applying (3.10) to the functions f_t, f_d and f_r:

$$
\begin{aligned}
\tilde{t}_t(i) &= f_t(\tilde{d}_e(i), \tilde{r}_e(i), \tilde{t}_e(i)) \\
\tilde{d}_t(i) &= f_d(\tilde{d}_e(i), \tilde{r}_e(i), \tilde{t}_e(i)) \\
\tilde{r}_t(i) &= f_r(\tilde{d}_e(i), \tilde{r}_e(i), \tilde{t}_e(i))
\end{aligned}
\tag{3.24}
$$

The fuzzy metrics just defined provide an estimate of the communication performance which will be provided to the application. By comparing them with $\tilde{t}_a$, $\tilde{d}_a$, $\tilde{r}_a$ we can derive the values $\zeta_t(i), \zeta_d(i), \zeta_r(i) \in [0,1]$, which represent to what degree the connection through Access Point i is expected to satisfy each performance requirement of the application. Different techniques can be used for this purpose, the most straightforward being maximum membership [105]:

$$
\begin{aligned}
\zeta_t(i) &= \max_{x \in \mathbb{R}}(\tilde{t}_t(i) \cap \tilde{t}_a)(x) \\
\zeta_d(i) &= \max_{x \in \mathbb{R}}(\tilde{d}_t(i) \cap \tilde{d}_a)(x) \\
\zeta_r(i) &= \max_{x \in \mathbb{R}}(\tilde{r}_t(i) \cap \tilde{r}_a)(x)
\end{aligned}
\tag{3.25}
$$

We obtain an overall measure of the fitness ξ_i of Access Point i to meet the user needs, by calculating the highest degree to which all application requirements are jointly satisfied, i.e.,

$$
\xi_i = \min(\zeta_t(i), \zeta_d(i), \zeta_r(i))
\tag{3.26}
$$

and choose the access opportunity for which ξ_i is maximum.

3.6.3 Case study: File Transfer and VoIP over WLAN and UMTS

In this section, we described how our proposed scheme can be implemented in some practical cases. In particular, we will consider the scenario of file transfer and VoIP applications over WLAN and UMTS radio links. For this scenario, we will provide a possible implementation of the technology-specific components which are present in our proposed framework. For the

---

[4]we note that (3.23) is based on the assumption that the radio link and the core network performances are independent.

majority of the fuzzy metrics, we adhere to the wide-spread practice of using triangular membership functions [91], since they provide a good trade-off between expressivity and simplicity. We note that the characterization provided in the following sections are not intended to be the best possible; rather, our focus is on showing the implementability of our architecture, and to provide support for the performance evaluation which will be presented in Section 3.6.5.

Application requirements

For file transfer, the membership function $\tilde{t}_a(u)$ we use for the throughput requirement is logarithmically increasing from 0 to 1 in $(10^3, 10^8)$; we preferred a logarithmic increase over a linear increase since it yields a more meaningful representation of how user satisfaction increases with throughput. Furthermore, we assume that file transfer poses no delay constraints $(\tilde{d}_a(u) = 1 \ \forall u)$ but requires strict reliability $(\tilde{r}_a(u) = 1$ for $u = 1$, and 0 otherwise). For VoIP, we adopt the commonly recognized reference values for G.711 speech quality. In particular, the one-way delay is considered excellent if < 0.15 s and poor if > 0.45 s, so we define the round-trip delay requirement $\tilde{d}_a(u)$ as linearly decreasing from 1 to 0 in $(0.3, 0.9)$; the packet loss rate is considered acceptable if < 0.05, and consequently we define $\tilde{r}_a(u)$ as linearly increasing from 0 to 1 in $(0.95, 1)$; finally, the throughput requirement $\tilde{t}_a(u)$ is chosen as linearly increasing from 0 to 1 for throughput ranging from 64000 (G.711 bitrate) to 80000 in order to provide some margin. We note that, thanks to the expressivity of the proposed fuzzy knowledge representation base, it is straightforward to provide support for other applications: all that is needed is to provide a proper fuzzy definition of their QoS requirements.

Radio link performance

For 802.11 access, we propose the following characterization derived from the AP capacity metric presented in [95] which refers to the case where the downlink communication path is the bottleneck of the ongoing communications in the cell (a realistic assumption for most 802.11 scenarios). In these conditions, it has been shown [106] that in the long term each user gets a fair share of the available cell capacity, due to the fact that the AP is almost the only node contending for the channel. Let A be the set of users already associated with the AP, and let τ_j be the time required for the transmission of a packet from the AP to user $j \in A$. If we make the further assumption that packet losses are negligible, a lower bound for τ_j can be easily calculated once the packet size and the modulation scheme used by each user $j \in A$ are known. Supposing that the AP uses a simple round-robin scheduling policy, it will serve all its users in an interval $T = \sum_{j \in A} \tau_j$, and the average throughput t_l experienced by a particular user is given by

$t_l = s/T$, where s is the payload size of the packets addressed to the user being considered. In the case of a user which is not already associated with the AP, we redefine t_l as the throughput he might expect when associated with the AP as $t_l = s/(T + \overline{\tau})$, where $\overline{\tau}$ is the transmission time of the user under consideration. Due to the assumptions made, t_l is an optimistic estimate of the radio link throughput. To account for this estimation bias, we define the fuzzy metric $\tilde{t}_l$ as having a triangular membership function with support $(0.5t_l, t_l)$ and peak at $0.75t_l$. Using the same assumptions, we can determine a lower bound on the radio link contribution to the average round trip time as $\underline{d_l} = 0.5T + \overline{\tau}$, where we have accounted for the average waiting time for a random packet arrival at the AP in the downlink, and for the lowest possible transmission time (no contention, no retransmissions) in the uplink. Again, to account for the estimation bias we define the fuzzy metric $\tilde{d}_l$ with a triangular membership function with support $(\underline{d_l}, 1.5\underline{d_l})$ and peak at $1.25\underline{d_l}$.

For the reliability metric, we consider the error probability of a SDU frame, for which we calculate the lower bound $\underline{p_l} = p^{(r_{max}+1)}$ and upper bound $\overline{p_l} = (p+q)^{(r_{max}+1)}$, where p is the frame error rate (due to SNR only) for the modulation scheme being used, r_{max} is the MAC retransmission limit and q is a worst case estimate of the collision probability (in our simulations we used the fixed value $q = 0.3$; more accurate estimators could be used, such as the one in [C4]. We then define the lower and upper reliability bounds as $\underline{r_l} = 1 - \overline{p_l}$ and $\overline{r_l} = 1 - \underline{p_l}$, respectively. Finally we define the fuzzy metric $\tilde{r}_l$ using a symmetric triangular membership function with support $(\underline{r_l}, \overline{r_l})$.

We point out that the type of information needed for this scheme is likely to be possessed by the Access Point, and can be forwarded to the clients, e.g., using information frames such as those specified in the 802.11k and 802.11e protocols [107, 108]. Alternatively, each user could privately monitor each wireless channel and get equivalent performance metrics by direct measurements, though at a higher computational cost.

For UMTS access, we consider a Release 4 system in which data transmission is performed over a Dedicated Channel (DCH) using Acknowledge Mode (AM) at the Radio Link Control (RLC) layer. For convenience we define the following: K is the number of PDUs per SDU, I is the length of the interleaving, T_{PDU} is the duration of a PDU transmission, $T_{RLC} = 2(2I + T_{PDU})$ is the RLC Round Trip Time, $m = \lfloor T_{RLC}/T_{PDU} \rfloor$ is the number of PDUs per RLC Round Trip Time, L is the maximum allowed number of transmission attempts for a single PDU. Furthermore, we suppose an estimate of the PDU error probability p to be available[5] with a known confidence interval of σ_p. We define $\underline{p} = \max(p - \sigma_p, 0)$ and $\overline{p} = \min(p + \sigma_p, 1)$. For a

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[5]We note that in a real system p can be evaluated as a function of the SINR measurements which are commonly performed by UMTS devices as part of the inner loop power control.

given spreading factor x and link direction y (uplink/downlink), a DCH has a well-defined data throughput $t_l(x, y)$ [109]. This is the maximum throughput which can be achieved in ideal conditions; however, in typical conditions the actually achieved throughput can be slightly lower due to PDU losses and the Selective Repeat ARQ used in AM. To account for this factor, we define the fuzzy metric $\tilde{t}_l$ as having a triangular membership with support $((1-\overline{p})t_l, (1-\underline{p})t_l)$ and peak at $(1-p)t_l$. For the reliability, we consider the widely adopted block-fading model, according to which SDU losses occur with probability $f(z) = 1 - (1 - z^L)^K$, where z is a given PDU error probability. Consequently, for the fuzzy reliability metric $\tilde{r}_l$ we use a triangular membership function with support $(f_r(\overline{p}), f(\underline{p}))$ and peak at $f(p)$.

Finally, for the delay, we use the heuristic proposed in [110] which provides a very good approximation of the complementary cumulative distribution function $ccdf(t, z)^6$ of the SDU delay t as a function of the PDU error probability z. Let $d_l = \{t \mid ccdf(t, \underline{p}) = 0.5\}$, $\underline{d_l} = \{t \mid ccdf(t, \underline{p}) = 0.95\}$ and $\overline{d_l} = \{t \mid ccdf(t, \overline{p}) = 0.05\}$. The fuzzy delay metric $\tilde{d}_l$ is defined as having a triangular membership with support $(\underline{d_l}, \overline{d_l})$ and the peak at d_l.

Transport layer performance

Since the applications considered in this case study are file transfer and VoIP, we need to provide a proper characterization of the impact on performance of the TCP and UDP/RTP transport protocol. For RTP/UDP we suppose that no particular ARQ/FEC scheme is in place; this choice yields $f_r(d_e, r_e, t_e) = r_e$, $f_d(d_e, r_e, t_e) = d_e$ and $f_t(d_e, r_e, t_e) = \eta t_e$, where $\eta \leq 1$ accounts for protocol overhead. For TCP, we have $f_r(d_e, r_e, t_e) = 1$ thanks to TCP's reliability; for the throughput we adopt the formulation in [111], i.e.,

$$f_t(d_e, r_e, t_e) = \min\left(t_e, \eta L \min\left(\frac{W_0}{d_e}, \frac{1}{d_e\sqrt{\frac{2p_e}{3}} + \alpha d_e \min\left(1, 3\sqrt{\frac{3bp_e}{8}}\right)} \right) \right) \tag{3.27}$$

where W_0 is the maximum window size, $p_e = 1 - r_e$ is the end-to-end packet error rate, L is the packet size, b is the delayed ACK parameter, and αd_e is an estimate of the retransmission timeout obtained by scaling the end-to-end delay. Furthermore, since we did not impose any delay constraints for the file transfer application, we provide no formulation of $f_d(d_e, r_e, t_e)$ for the TCP case, as it is not needed for our implementation. Finally, we note that the model in [111] might not be very accurate in wireless scenarios. However, the use of a fuzzy representation and processing of the inputs of the model ensures that our transport layer characterization is able to provide an effective and meaningful representation of the range and likelihood of

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[6]i.e., the probability that a SDU experiences a delay greater than t

the performance experienced on top of TCP, even in scenarios in which the model itself might not be very accurate.

Cognitive Network Database Implementation

It is to be noted that in this work we do not make any assumption on the type of architecture to be used for data upload and retrieval; instead, we just assume that the Cognitive Network Database is available to all users. In practice, different approaches could be adopted, each one having its own benefits and drawbacks[7] [81]. This assumption is justified by the need to validate the proposed cognitive network approach while not precluding any possible implementation. A detailed study of the architecture of the Cognitive Network Knowledge Base and the related trade-offs is left as a future research topic.

3.6.4   Other Network Access Decision Schemes

In this section we introduce other network access schemes for comparison purposes. The first two schemes, Highest RSSI and Link Capacity, represent the current state-of-the-art in wireless network access; however, as we will discuss in this section and show in Section 3.6.5, they present some obvious sub-optimality with respect to our cognitive scheme – e.g., they do not consider the performance of the part of the network beyond the AP – and therefore they cannot provide any insight on how close the performance of our cognitive scheme is to a hypothetical optimal performance. To address this issue, we introduce two additional schemes, Network Capacity and Low Delay, that we explicitly design for comparison purposes. These two last schemes are application-specific, and exploit *a priori* knowledge of the network topology as well as of the characteristics of the traffic generated by the users. This prior knowledge is rarely available, if ever, in practice, so the Network Capacity and Low Delay strategies we will describe in this section are not very well suited for implementation. This particular design choice was made in order for the performance of these schemes to be as close to the optimal as possible, so that it is possible to evaluate the degree of sub-optimality of the cognitive scheme due to 1) its independence from the particular application being used, and 2) the usage of access point characterization by means of information sharing performed by the users, instead of *a priori* knowledge of the network characteristics.

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[7]For example, a centralized approach such as storing the information related on each access opportunity on the Access Point itself could be very efficient; however this approach may have serious security problems, since a malicious operator could deliberately alter the information in the database to get more subscribers and increase its own revenue. Keeping the Cognitive Network Database distributed among users would be more robust in this sense, though at an increased computational/storage cost and communication overhead.

Highest RSSI scheme

This access scheme is very often implemented in real devices, due to its simplicity. The fundamental assumption behind it is that a higher RSSI allows a higher rate modulation scheme to be used, and therefore yields higher throughput and lower communication delay. Let ρ_i be the Received Signal Strength Indicator (RSSI) seen from Access Point i by the user under consideration. The Highest RSSI approach consists of choosing the access opportunity which maximizes ρ_i.

For the multi-technology case, we consider the case in which one or more 802.11 APs are present together with at most one UMTS AP. A simple but reasonable policy would be to prefer 802.11 whenever available, following the common sense that 802.11 provides a higher throughput and lower price connection. In this case, we assume a SNR threshold Δ is defined, representing the minimum SNR required for successful communication with an 802.11 AP. If no 802.11 AP is reachable with SNR $> \Delta$, then the UMTS AP is selected, otherwise one of the 802.11 APs is selected using the Highest RSSI selection method.

Link Capacity scheme

Using the throughput estimate given in Section 3.6.3, a new user k can evaluate the throughput $t_l(i)$ he could get from each available AP i. It has been proposed in [95] to perform 802.11 AP selection based exclusively on this metric, which aims at achieving an even load balancing between different APs. This is clear once we note that, with reference to the expression of t_l for 802.11 provided in Section 3.6.3, s does not depend on the AP being considered, and the chosen AP is the one that minimizes $T + \overline{\tau}$. If $\overline{\tau} \ll T$, this is the AP with the lowest load, and hence highest residual capacity. For this reason we refer to this scheme as *Link Capacity*.

Network Capacity scheme

The Network Capacity access scheme is explicitly designed to maximize TCP throughput. We adopt the same metrics used for our Cognitive scheme, except that explicit knowledge of core network performance is employed instead of measurements retrieved from the Cognitive Network Database. More in detail, suppose we known *a priori* the nominal bandwidth $B(i)$, delay $D(i)$ and packet error rate $P(i)$ of the link between the fixed host and AP i. Let $t_l(i)$, $\underline{d_l}(i)$ and $\underline{p_l}(i)$ be the expected radio link throughput and lower bounds for the delay and packet error rate, as defined in Section 3.6.3. Furthermore, let $N_{i,\mathrm{TCP}}$ and $N_{i,\mathrm{CBR}}$ be the number of TCP and CBR users associated with AP i, respectively, and let the generic CBR application $k = 1 \ldots N_{i,\mathrm{CBR}}$ have bandwidth $B_{\mathrm{CBR},k}$. For each access opportunity i, the

end-to-end network-layer performance can be estimated as

$$
\begin{aligned}
\hat{t}_e(i) &= \min\Big(t_l(i), \Big(B(i) - \sum_{k=1}^{N_{i,\mathrm{CBR}}} B_{\mathrm{CBR},k}\Big)/N_{i,\mathrm{TCP}}\Big) \\
\hat{d}_e(i) &= \underline{d_l}(i) + D(i) + B(i)/s \\
\hat{r}_e(i) &= 1 - (P(i)\underline{p_l}(i))
\end{aligned}
\tag{3.28}
$$

where s is the packet size in use by the user performing the access decision. Then, using (3.27), we can calculate the expected TCP throughput from AP i as $t_t(i) = f_t(\hat{d}_e(i), \hat{r}_e(i), \hat{t}_e(i))$, and select the AP which maximizes $t_t(i)$.

Low Delay scheme

This scheme is explicitly geared towards real-time applications, such as Voice over IP, Video Conferencing, and other interactive applications whose service quality is heavily influenced by packet errors and communication delays. As before, we use the same radio link performance metrics used for the Cognitive scheme, and we replace the role of the Cognitive Network Database by explicit knowledge of core network performance. In particular, we reuse the end-to-end network performance metrics derived in (3.28) for the Network Capacity scheme, and we choose the access opportunity which satisfies the following minimization problem:

$$
\min_i \hat{d}_e(i) \qquad : \qquad \hat{r}_e(i) \geq 1 - E_{\mathrm{CBR}}
\tag{3.29}
$$

The solution of (3.29) is not necessarily optimal for all real-time communications, since a certain amount of delay might be tolerable and throughput requirements are not considered. However, this scheme is reasonably efficient for applications such as VoIP, which have very low throughput requirements together with a well-defined maximum packet error rate for acceptable service quality (typically, 0.05 for the G.711 codec), and in which the satisfaction level of the end user is inversely related to the experienced end-to-end delay.

3.6.5 Performance Evaluation

Performance evaluation of the proposed access scheme was carried out using NS-Miracle [C7], which is a multi-interface cross-layer extension of the well-known NS simulator [112]. We simulated a square area of 30×30 m^2 with two Access Points placed on one side of the square, and n randomly placed users. Each AP is connected to a fixed host with a dedicated symmetrical link, whose bandwidth has a specified fixed value according to the considered scenario. Depending on the scenario, either two 802.11 APs or one 802.11 and one UMTS AP were used.[8] For 802.11 communications, both

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[8]We actually carried out performance evaluation for scenarios with 3 and 4 APs as well. In general, the behavior of the Access Schemes under evaluation was very similar

the wireless users and the APs use 802.11g with a rate adaptation scheme which consists of selecting the modulation scheme based on the experienced SNR in order to achieve a target Packet Error Rate ≤ 0.01. For UMTS, we used a spreading factor of 8 in both downlink and uplink, which corresponds to a bit rate of 456 kbps in downlink and of 240 kbps in uplink.

In the following, we present simulation results highlighting the different performance of the schemes outlined in the previous section. We consider several scenarios in order to evaluate different issues relevant to the network access selection problem, such as load balancing on the radio link, core network performance degradation, satisfaction of QoS requirements, and interactions in mixed traffic situations. All reported results, unless explicitly stated, have been obtained averaging 100 independent simulation runs in order to achieve the necessary statistical confidence. In several cases, we will be interested in the fairness of a metric x_i for the set of users $i = 1, \ldots, n$; for this purpose, we use Jain's index, defined as $(\sum_i x_i)^2 / (n \sum_i x_i^2)$

Scenario 1: Load balancing on the radio links

The purpose of this scenario is to evaluate the load balancing capabilities of the different access schemes being considered. We simulated a scenario in which the links connecting the two APs with the fixed host have the same bandwidth (10 Mbps). The APs are placed so that the RSSI seen by all users from one AP is always slightly better than from the other AP. The results, reported in Figure 3.8 for different numbers of TCP users, show that in such a situation the Highest RSSI scheme suffers a severe performance degradation due to unbalanced load at the APs. All other schemes achieve a similar performance, with the Cognitive scheme achieving a slight throughput improvement over the others when there are enough users ($n \geq 6$) to provide sufficient statistical confidence for the performance estimation provided by the Cognitive Network Database. The performance improvement is due to the fact that using network performance measurements fed back from all users allows to account for events such as, for instance, increased Round Trip Time due to downlink congestion at the AP; this type of performance degradation is neglected by the other schemes because they consider *a priori* knowledge only (Network Capacity scheme) or they do not consider core network performance at all (Highest RSSI, Link Capacity).

Scenario 2: Asymmetric core network performance

In this scenario we examine the performance of the different access schemes in response to asymmetries in core network bandwidth: the bandwidth of

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to the one observed in the two AP scenarios, but the analysis of the results is much more complex due to the higher number of environmental variables to consider. To summarize, scenarios with more than 2 APs do not give any significant insight compared to scenarios with 2 APS, and have therefore been omitted for the sake of brevity.
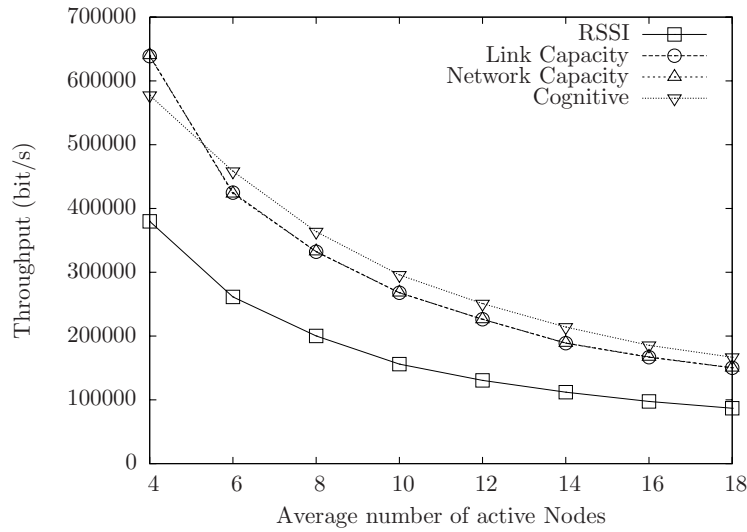
Figure 3.8: Throughput for Scenario 1

the link connecting the second AP to the fixed host is only a fraction of the 10 Mbps bandwidth which is available to the first AP. In each simulation, we have n TCP users uniformly distributed with respect to the APs. We show only the results for $n = 15$, as a qualitatively similar behavior was observed for other values of n. The obtained behavior for different bandwidth ratios is reported in Figures 3.9 and 3.10: although the throughput averaged among all users seems similar across the different schemes, in asymmetric situations (low bandwidth ratio) the RSSI and Link Capacity schemes exhibit a significantly lower degree of throughput fairness compared to the other schemes. Both the Cognitive and the Network Capacity scheme provide good throughput and good fairness in all cases. As evident from Figure 3.11, this is due to the fact that the RSSI and Link Capacity schemes assign on average half of the users to AP2 in spite of the fact that it can offer significantly lower throughput compared to AP1, whereas the Network Capacity and Cognitive schemes are able to properly adapt to the bandwidth differences.

We also examined other types of asymmetries in core network performance, e.g., in terms of delay or packet error rate. The obtained performance is similar to what observed for the varying bandwidth case: the Highest RSSI and Link Capacity schemes fail to recognize core network performance degradation and result in severe throughput differences among users, while the Cognitive and Network Capacity schemes provide significantly better fairness.
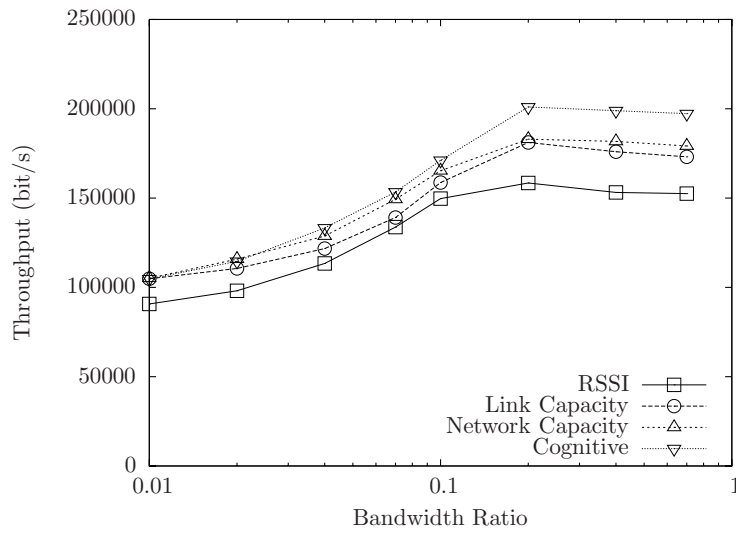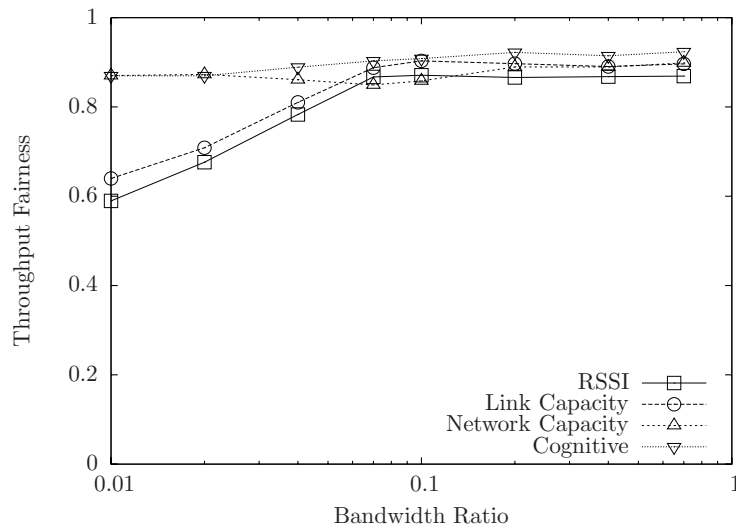
Figure 3.9: Average Throughput for Scenario 2

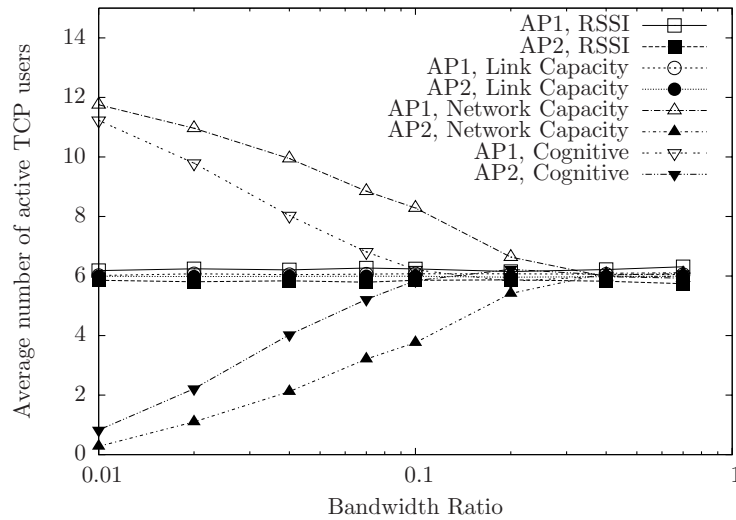Figure 3.10: Throughput Fairness for Scenario 2

Figure 3.11: AP usage for Scenario 2

Scenario 2b: Multi-technology load balancing

For this scenario, we used an 802.11 AP and a UMTS base station co-located in the center of one of the sides of the square area in which 15 users are randomly placed. The backhaul link of the UMTS AP was configured with a bandwidth of 100 Mbps. We ran several simulations varying the backhaul link bandwidth of the 802.11 AP.

The key point of this scenario is that the performance of the UMTS access is radio-link limited, while for the 802.11 access it is core-network limited; in particular, when the backhaul link of the 802.11 AP is not a bottleneck, the overall throughput achievable with 802.11 is greater than with UMTS due to the greater radio link capacity. Moreover, while UMTS can offer almost the same performance regardless of the number of users (as long as they are not located at the border of the cell and their number is below the interference-limited capacity of the cell), the performance in an 802.11 cell and in its backbone is heavily influenced by the number of users, due respectively to the contention-based medium access and the limited bandwidth available.

The performance obtained by the different schemes in this scenario is reported in Figure 3.12. The RSSI and Link Capacity schemes always select the 802.11 AP, resulting in poor throughput performance as the bandwidth of the backhaul link becomes low. The behavior of the RSSI scheme is due to the fact that in the chosen topology the 802.11 AP is always reachable with sufficient RSSI to perform communication, while the Link Capacity scheme always chooses the 802.11 AP because the expected radio link throughput is always higher for 802.11 than for UMTS. On the other hand, the Network
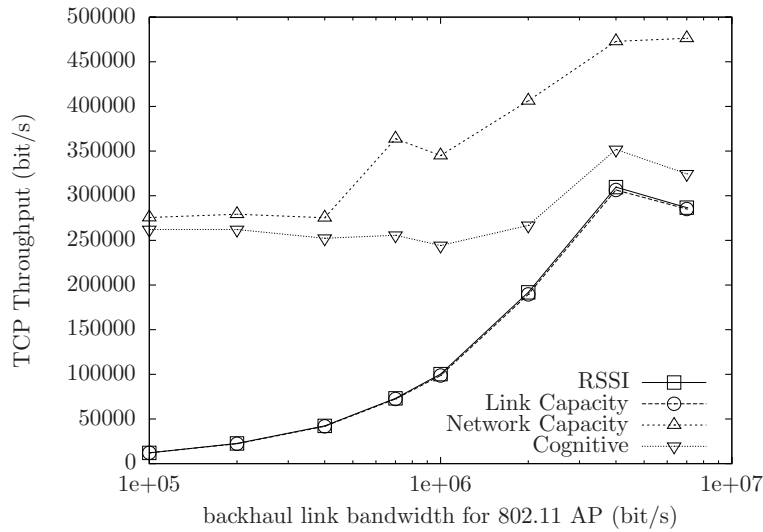
Figure 3.12: Throughput for Scenario 2b

Capacity and Cognitive schemes are successful in progressively preferring the UMTS AP as the 802.11 AP backhaul link bandwidth becomes lower.

Scenario 3: Real-time applications

This scenario is designed to compare the performance of the access schemes with respect to real-time applications. The topology of this scenario is the same as in Scenario 2 as far as the asymmetry in core network performance is concerned; the only difference is the use of VoIP connections instead of TCP file transfers. The results, reported in Figure 3.13, show again that the RSSI and Link Capacity schemes provide poor delay performance, due to their inability to choose the AP based on the bandwidth of the backhaul link. On the other hand, the Cognitive scheme achieves almost the same performance as the Low Delay scheme, which achieves the best performance among all schemes thanks to its perfect knowledge of the network parameters. (In this scenario, where delay rather than throughput is the main application constraint, we use Low Delay instead of Network Capacity.)

Scenario 4: Mixed traffic types

In this scenario, we consider the case in which the two traffic types coexist in the same area (6 TCP users and 7 VoIP users in the results shown), and share the same access resources. The purpose of this study is to investigate the interactions between the two traffic classes and to understand how the transmission resources are shared. Figures 3.14 and 3.15 show the TCP throughput and VoIP delay performance of the two classes of users. As
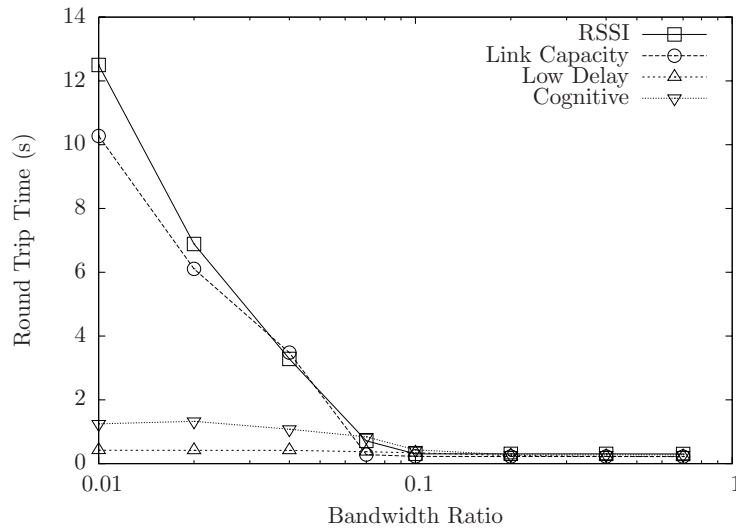
Figure 3.13: Average Round Trip Time for Scenario 3

expected, the Highest RSSI scheme performs poorly in both cases, due to its complete unawareness of the core network asymmetries, as in scenarios 2 and 3. The other schemes trade off the throughput of TCP users and the delay of VoIP users in different ways. For example, the Cognitive scheme tends to keep a sufficiently low delay, at the expense of a somewhat lower TCP throughput for data users. On the other hand, the Link Capacity scheme provides better TCP throughput but totally unacceptable VoIP delay.

The behavior of the centralized schemes (Network Capacity for TCP users and Low Delay for VoIP users, according to the performance requirements of the two applications) needs some more detailed explanation. For extreme asymmetry, all users are connected to the "good" Access Point, AP1 (see Figures 3.16 and 3.17). As the bandwidth of AP2 increases, at some point (400 kbps in the Figures) there is a sharp increase of the TCP throughput. In fact, such bandwidth value can serve very well a single VoIP connection, and therefore each VoIP user decides to move from AP1 to AP2 (note that these decisions are made simultaneously with no awareness of other users' intentions). The result is that much more bandwidth becomes available to TCP users (who stay at AP1) whereas AP2 becomes congested, which leads to unacceptable VoIP performance. This is a result of the blindness of the Low Delay strategy that, while knowing the network parameters *a priori*, is unable to react to events such as sudden increases in delay due to the AP queues being filled by the relatively aggressive behavior of TCP flows. As the bandwidth of AP2 is further increased, congestion at AP2 is relieved, and VoIP performance significantly improves. At this point, some TCP users also try to move towards AP2, but this in fact results in poorer
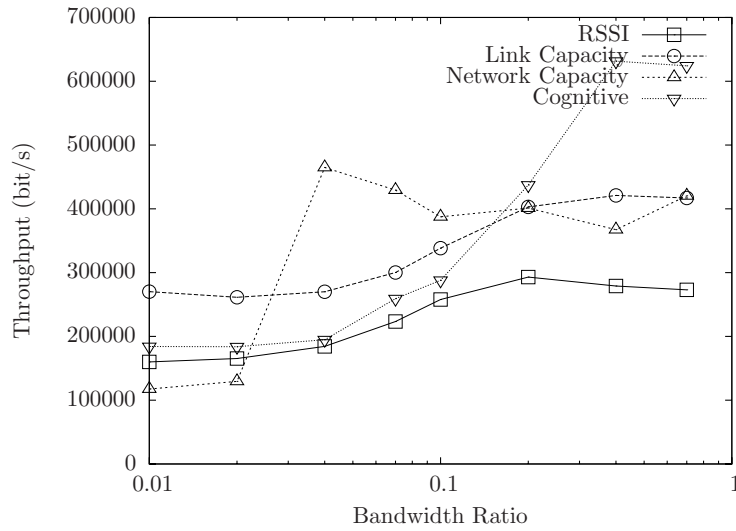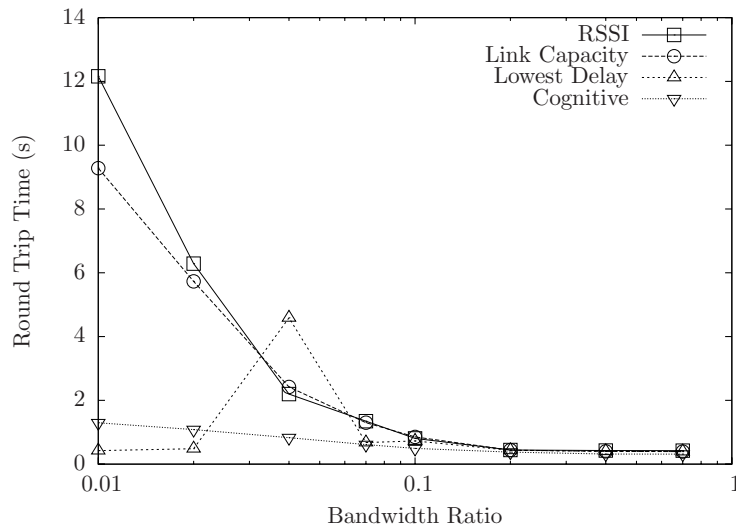
Figure 3.14: TCP throughput for Scenario 4

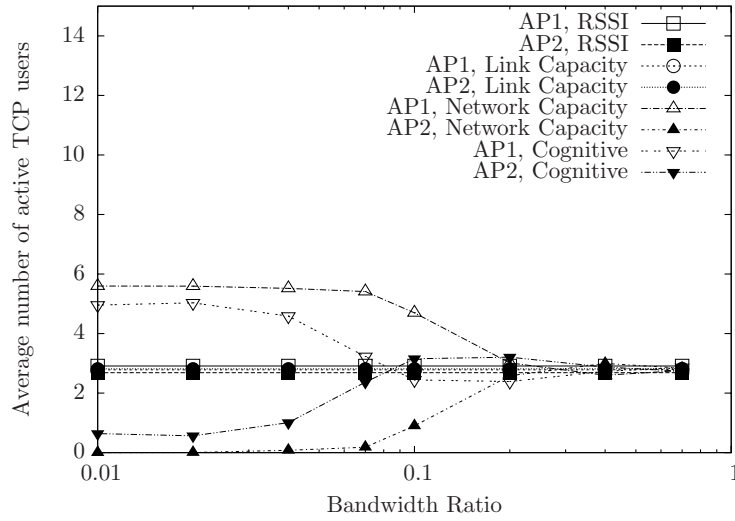Figure 3.15: VoIP Round Trip Time for Scenario 4

Figure 3.16: AP usage for Scenario 4 (TCP users)

overall performance due to the complex interactions among the coexisting traffic flows. On the other hand, the Cognitive scheme, while possibly showing a slightly inferior overall performance for some classes of users, has a much more stable behavior and a significantly better fairness than the other schemes.

Scenario 4b: Multi-technology multi-application

This is similar to Scenario 4 but with a UMTS AP in place of one of the 802.11 APs, as done for Scenario 2b. The results are reported in Figures 3.18 and 3.19. As expected, the RSSI and Link Capacity schemes always choose the 802.11 AP, thus resulting in poor performance for both TCP and VoIP flows. The joint usage of the Network Capacity and Low Delay scheme results in the VoIP flows always selecting UMTS to minimize the communication delay, and in the TCP flows distributing between UMTS and 802.11 to maximize throughput performance. The Cognitive scheme has a similar behavior, with the difference that for high values of the backhaul link bandwidth a small fraction of VoIP users select the 802.11 AP; this results in some fluctuations in the AP usage by TCP users which resembles the one already observed in Scenario 4, although smaller in magnitude, and has the same explanation provided in the previous section.

Control traffic overhead

To evaluate the entity of the control traffic overhead for the Cognitive scheme, we consider a simple implementation with a centralized Cognitive
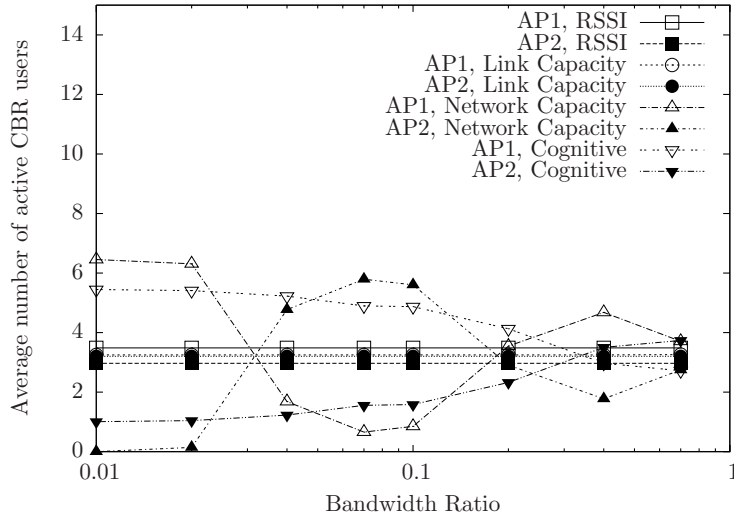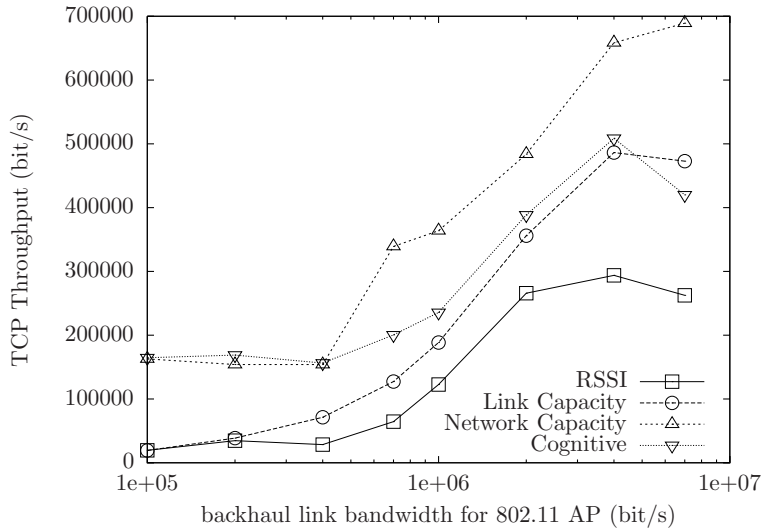
Figure 3.17: AP usage for Scenario 4 (VoIP users)

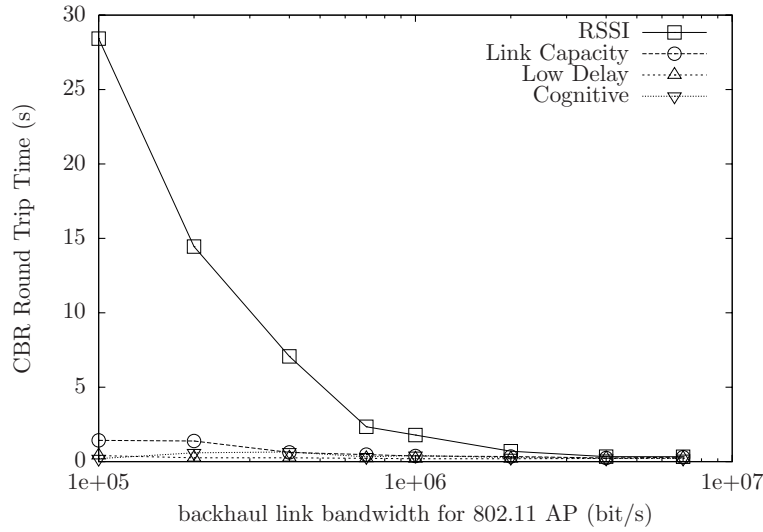Figure 3.18: TCP Throughput for Scenario 4b

Figure 3.19: VoIP RTT for Scenario 4b

Network Database reachable through any of the APs. We assume that a QoS report consists of a 20 byte packet, 12 of which are used for the throughput, delay and reliability metrics (a 32 bit floating point number for each, just to be very conservative), 32 bytes to identify the AP (i.e., interface type, operating frequency, network name, and so on) and 8 bytes reserved for protocol-related information. Such a report protocol would likely work on top of UDP/IP, which requires additional $20 + 8$ byte headers. Consequently, a QoS report packet just below the IP layer consists of 80 bytes. A query to the Cognitive Network Database could consist only of the 8 bytes of protocol-related information. The response provided by the Cognitive Network Database would include a 72 byte field for each AP being reported, plus the 8 bytes of protocol-related information. If we suppose that the performance of at most 10 APs can be included for each response, we obtain a packet size of 36 bytes for the query and of 756 bytes for the response. In our simulations we used a report interval of 2 s, and an average data flow duration of 12.5 s. As a consequence, for each user, the bandwidth required is 352 bit/s for QoS reports and 506.88 bit/s for queries/responses to and from the Cognitive Network Database. Although these figures do not take into account the overhead introduced by the MAC and PHY layers, it is clear that an implementation of the solution proposed here would require almost negligible control traffic overhead.

3.6.6   Conclusions

In this section we have proposed a Cognitive Network Access scheme in which the network performance reported by all previous users is compared

to application requirements and expected radio link performance in order to help new users to choose the best access opportunity. The framework features a modular design and a generic and technology-independent knowledge representation based on fuzzy logic, which together facilitate the integration of different wireless technologies and applications.

The performance of the proposed scheme has been evaluated by means of simulation and compared with both state-of-the-art access schemes known from the literature and omniscient application-specific schemes that we introduced as performance benchmarks. The performance evaluation involved scenarios explicitly designed to highlight specific issues, in particular load balancing on the radio link, load balancing in the whole network, satisfaction of real-time QoS requirements, and coexistence of different traffic types. Both single radio technology (802.11) and multi-technology scenarios (802.11 and UMTS) were considered to evaluate the capability of the different schemes to cope with heterogeneous wireless technologies.

The results have shown that the Cognitive access scheme proposed in this section performs significantly better than state-of-the-art schemes, in terms of both overall performance and fairness. Also, in most cases, the Cognitive scheme has proven capable of achieving similar performance to the reference omniscient application-specific schemes. The fact that the Cognitive scheme achieved this by exploiting information shared by users rather than omniscience, while at the same time offering a modular and flexible design which can easily integrate new wireless technologies and applications, confirms that the cognitive network approach we proposed in this section for wireless network access is effective, and worthy of further investigation.

Chapter 4

Neural Networks for Cognitive Radios and Networks

4.1 Orientation and Learning in Cognitive Radios and Networks

In [1], Mitola describes the fundamental activities that a CR should perform in order to meet this goal: *observing* the environment, *orienting* itself, making *decisions*, performing *actions* and *learning* from experience; this set of activities is referred to as the Cognition Cycle, and has been proposed for use in Cognitive Networks as well [2].

There is a very common practice of interpreting the Cognition Cycle as an optimization problem [62, 113], as represented in Figure 4.1. According to this interpretation, the different phases assume the following form:

- the *action* phase consists of (re)configuring the CR to provide enhanced communication quality with respect to user-defined goals. Such configuration can be, for instance, the choice of the wireless radio interface to be used for communication, or the tuning of the communication system's parameters;

- the *observation* phase implies collecting sensorial information about the surrounding communication environment. This sensorial information is expected to be available in the form of measurements of different types, e.g., traffic information, signal and noise power measurements, as well as time and location coordinates.

- the *orientation* phase consists of identifying and understanding the status of the network and the impact on communication performance of the external environment and of possible system configurations. This
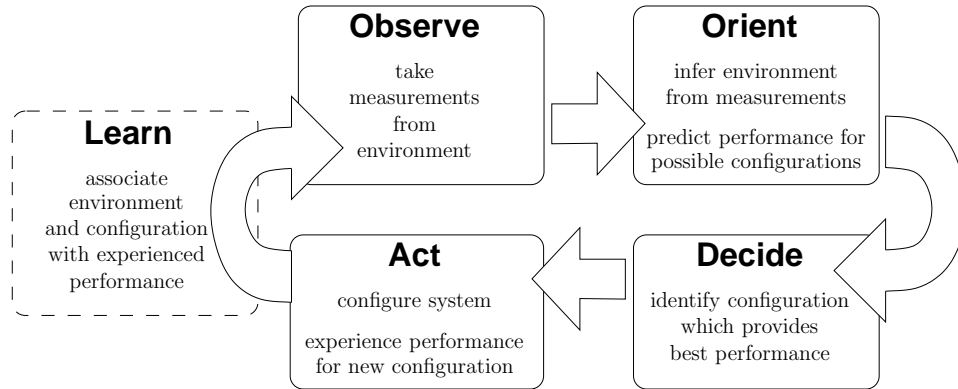
Figure 4.1: The Cognitive Radio's Cognition Cycle as an optimization problem

is achieved by identifying a functional relation between measurements and configuration parameters and different aspects of communication performance (e.g, throughput, delay, reliability). Also part of the orientation phase is the prediction of the evolution of the state of the network;

- the *decision* phase is the solution of the performance optimization problem, i.e., it is a search in the space of possible configurations which aims at finding the one that best satisfies user-defined goals, which are expressed in terms of high-level performance metrics such as application-layer throughput, delay and reliability, as well as cost, power consumption, etc.

- finally, the *learning* phase consists of evaluating the outcome of the decisions which have been made, thereby gathering knowledge to be exploited in future *orientation* phases with the aim of being more effective in the *decision* phase.

While a significant research effort has been put into examining suitable *decision* strategies, i.e., effective search algorithms to solve the optimization problem, very little research has been done on the *orientation* phase, i.e., to analyze suitable approaches for the determination of the performance metrics to be used in the optimization process and their dependence on environmental factors and configuration parameters. Many CR proposals, such as [62, 114], rely on a priori characterizations of these performance metrics, which are often derived from analytical models. Unfortunately, as we will discuss in Section 4.2, this approach is not always practical due to, e.g., limiting modeling assumptions, non-ideal behaviors in real-life scenarios, and poor scalability. Further, the use of analytical models often provides no means to actually include learning from experience in the performance

characterization; thus, the aspect of learning, though repeatedly claimed to be one of the fundamental features of CRs, has often been overlooked.

In this chapter, we propose Multilayered Feedforward Neural Networks (MFNN) as a convenient techniques to synthesize performance evaluation functions in CRs. The major benefit of using MFNNs is that they provide a general-purpose black-box modeling of the performance as a function of the measurements collected by the CR; furthermore, this characterization can be obtained and updated by a CR at run-time, thus effectively implementing some learning capabilities. In the next sections we will discuss how MFNNs can be used to achieve accurate performance modeling of the components of a CR system. We will compare the features offered by MFNNs with respect to other modeling approaches, including analytical models and black-box modeling techniques such as regression and linear dynamic systems. We will also present practical examples of applications of the MFNN approach to Cognitive Radios and Networks.

4.2   Related Work

As we mentioned in Section 4.1, in many Cognitive Radio and Network proposals analytical models have been used for performance characterization. For instance, in [113] analytical models for the bit error rate performance of different modulation schemes are used to derive some objective functions, which are then evaluated in the process of optimizing the chosen PHY layer configuration; in [115] a generic framework for cross-layer optimization of multimedia communications is described, in which analytical models are used to define objective functions; in the approach we presented in Section 3.6.3, analytical models for MAC-layer and transport-layer performance are used to derive the performance of the available wireless network access opportunities.

There are, however, several problems associated with analytical models in this context:

- they are based on some modeling assumptions (traffic load, topology, channel idealization, etc.) which may not apply in real life scenarios;

- the results of the model might be biased with respect to real performance due to, e.g., non-ideality of the device, failure of some components, or unexpected environmental factors. Analytical models typically provide no explicit means for dealing with these issues;

- in several situations an analytical model might not be available and/or practical to use;

- every time a new component is added to the CR system, a new analytical model needs to be developed off-line and loaded into the system.

This is a major drawback if we consider that a CR is expected to be highly reconfigurable and modular, and that developing a new analytical model may require significant human effort.

An alternative approach to analytical models is *black-box modeling*, which consists of analyzing input-output relations of the system under consideration, and trying to build a predictor with the purpose of estimating output values for unknown combinations of the inputs. Unlike analytical models, black-box models exploit almost no a priori knowledge of the laws driving the real system; as a consequence, this approach has the following benefits:

- it poses no issues concerning simplifying assumptions which could not be verified in practice;

- it can account for non-idealities in parameters (tolerance of components, device failures, etc.) since the measurements are also affected by them;

- there exist several well-known general purpose models that can be *trained* for different particular systems.

An example of black-box modeling can be found in [61], where the author proposes the use of a Hidden Markov Model (HMM) trained by a Genetic Algorithm to model the channel response. The choice of HMM for system modeling makes sense in this case: in fact, modeling the wireless channel using Markov Models, such as the Gilbert-Elliot model and its derivatives, is a widely accepted practice. However, HMMs cannot be considered to be in general suitable for performance modeling in CRs, primarily for the difficulty of representing the type of input/output relation needed for *orientation* which we discussed in Section 4.1.

Linear Models (FIR, ARX, ARMAX, Kalman filters) [116] are often used to model dynamic systems for control purposes. The major issue with these models is that in most practical cases the system being modeled is non-linear in nature, and consequently the input-output relation cannot be reproduced with accuracy. Linear models are often still suitable for control systems, where system dynamics are the main concern, and in which a quantitatively accurate output of the predictor is not of primary importance as long as an effective control action can be achieved. Unfortunately, using linear models for performance characterization in CRs is in general not very effective, since this lack of accuracy can severely impact the results of the optimization process.

Another possibility is to apply regression techniques to non linear models, which are defined in terms of some parametric function (polynomials, exponentials, etc.). These approaches can achieve a better approximation of the input-output relation of the system with respect to linear models. However, the choice of the parametric function is critical, and has often to be

performed exploiting some a priori knowledge about the system; moreover, these types of models can be very complex to handle as the number of input and output variables of the system grows [116].

In recent years, Multilayer Feedforward Neural Networks (MFNNs) have become increasingly popular as general-purpose function approximators and, in particular, for modeling dynamic systems [116]. In this paper, we investigate and discuss the use of MFNNs for modeling the performance characteristics of the components of a CR system. It is our opinion that using MFNNs for this purpose is a promising approach for the following reasons:

- MFNNs provide black-box modeling, thus offering the above discussed benefits with respect to analytical models;

- MFNNs provide a non-linear input-output relation with superior function approximation capabilities with respect to what can be achieved with state of the art linear regression techniques [116, 117];

- the CR can effectively *learn* as we train the MFNNs characterizing system performance with data obtained from real-time measurements (*observations*) performed by the CR itself;

- the process of training a MFNN has been deeply investigated in recent years, and several techniques have proven to be very effective for this purpose [118];

- MFNN can be effectively used even when the number of both inputs and outputs is high;

- the output evaluation of a MFNN is computationally very light and therefore well-suited for real-time systems[1];

- training is computationally much more intensive than output evaluation; however, we note that training does not need to be performed frequently, and it is reasonable for a CR device to perform it when computational resources are available (e.g., the device is idle, perhaps attached to a power source).

A limited number of publications on this subject appeared in recent years. The authors of [119], dealing with the problem of network traffic prediction, evaluate the effectiveness of traditional prediction techniques such as Auto Regressive Integrated Moving Average (ARIMA) and Fractional Auto Regressive Integrated Moving Average (FARIMA), and compare them with Multilayer Feedforward Neural Networks (MFNNs), concluding that

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[1]This statement is significant for the case in which the MFNN is implemented in software, as is often seen in applications. We also note that hardware implementations of MFNNs can be completely parallelized, and thus can offer almost instantaneous output calculation.

MFNNs are more practical due to lower complexity and the ability to model non-linear relationships. In [120] the authors compare the performance of linear regression models with that of MFNN for the purpose of building models of the performance in mobile ad hoc networks as a function of external factors such as traffic load and configurable parameters such as the routing protocol being used; again, the authors conclude that MFNNs are the best choice for modeling in the considered scenario. The key difference with our work lies in the scope of application. The authors of [121] aim primarily at replacing the need for extensive simulation campaigns to characterize the performance of a MANET for design purposes; on the contrary, we focus on exploiting the capabilities of MFNNs for real-time learning within a real system. Furthermore, the authors of [121] consider the dependence of end-to-end metrics on just a few very specific parameters they are interested in, and therefore do not attempt to model the whole complexity of the system. On the other hand, we propose a divide-and-conquer approach to handle the complexity of a communication system: we use several MFNNs to separately model smaller components, e.g., single protocol layers, which are less complex and therefore can be more easily modeled taking into account all the relevant parameters that determine the performance.

4.3   Multilayer Feedforward Neural Networks

We will hereby provide a very brief overview on MFNNs. For a more detailed description, the reader is referred to the abundant literature on Neural Networks (for instance, see [116–118, 122]).

The basic element of a MFNN is the single neuron or *perceptron*, which implements the following relation between its inputs x_i, $i = 1, \ldots, M$, and its output y:

$$y = f(a), \qquad a = \sum_{i=1}^{M} w_i x_i + \theta \qquad (4.1)$$

where w_i are the *weights* associated with each input, θ is the *bias* and $f(a)$ is the activation function, which is in many applications a sigmoid function, e.g., $f(a) = 1/(1 + e^{-a})$.

A MFNN is composed of several neurons connected in a feedforward fashion and arranged into L layers. Let N_l be the number of neurons at layer l. Each neuron in a layer $l = 2, \ldots, L$ has $M_l = N_{l-1}$ inputs, each of which is connected to the output of a neuron in the previous layer. Each of the M_1 inputs of the MFNN is connected to each neuron in the first layer. The outputs are obtained from the output of each neuron at layer L (i.e., the *output* layer), so the MFNN provides N_L outputs. Layers $1, \ldots, L - 1$ are referred to as *hidden* layers. An example of a two-layer ($L = 2$) MFNN is depicted in Figure 4.2, where it can be noted that layer $l = 1$ is the hidden
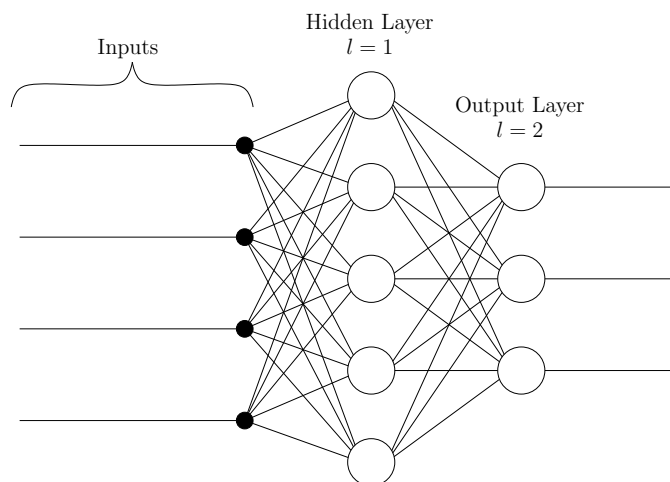
Figure 4.2: Example of a two-layer MFNN

layer, layer $l = 2$ is the output layer, and the number of inputs of each neuron in the output layer is equal to the number of neurons in the hidden layer (i.e., $M_2 = N_1 = 5$).

It can be proven [118] that a two-layer MFNN can approximate arbitrary continuous functions defined over compact subsets of $\mathbb{R}^{M_1}$, provided that a sufficient number of neurons is used at the hidden layer. From a practical point of view, in order to achieve this it is necessary to determine the values of the weights and biases which provide the desired approximation; this operation is referred to as *training*.

MFNNs are typically used with *supervised learning*, in which a set of sample input-output tuples is used to train the MFNN. This is done by applying in sequence all input tuples to the MFNN and at each step adjusting the weights and biases to reduce the error between the known output tuples and the output values provided by the MFNN; the process is repeated until the error falls below a certain threshold. The most commonly adopted strategy for this purpose is the *backpropagation algorithm* [118].

4.4 MFNNs for Cognitive Radios and Networks

As we anticipated in Section 4.2, we propose to use the function approximation capabilities of MFNNs for the performance characterization of the components of a Cognitive Radio system. The key prerequisite is that, for each component of which performance modeling is desired, the Cognitive Radio be able to obtain the following:

- *environmental measurements*, i.e., some measurements which can con-

vey information on the external factors which might affect performance; [2]

- *performance measurements*, i.e., measurements of the performance which is to be modeled, such as throughput, delay or reliability.

- *Parameter Settings*: the values of the configurable parameters of the system which have been used in the past;

As we stated in the previous section, the key point of our design is that we require the cognitive controller to be able to learn how performance depends on both environmental conditions and network configuration. We train a MFNN-based predictor using Environmental Measurements and Parameter Settings as inputs, and Performance Measurements as known output values. The purpose of this component is to predict the performance that will be experienced in the future for different values of the configurable parameters in different environmental settings, so that the optimal configuration can be chosen. This is done by solving an optimization problem using the predicted performance as a cost function and the parameters as the variables.

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[2]We note that it is not necessary to actually know the exact relation between the measured variables and the external factors we want to consider; it is sufficient that they are directly related. For example, if we consider performance modeling of an 802.11 cell, the number of users is clearly an environmental factor that impacts the performance, and which unfortunately cannot be measured directly. However, as we will show in Section 4.5, it is sufficient to consider the number of detected transmissions together with the fraction of idle channel time as environmental measurements for the MFNN to be able to learn the impact on performance of a different number of users.

4.5 MFNNs for 802.11 performance characterization

In this section we show in some case studies how MFNN can be effectively used for performance characterization of the components of a CR system. For each case study, we identify the relevant environmental factors and measurements to be used to characterize the performance. We run several simulations using the NS-Miracle simulator [C7] to obtain a set of data characterizing the performance with respect to these measurements. We use a subset of this data to train a MFNN; afterwards, we use the rest of the data set to compare the performance of the prediction provided by the trained MFNN with the actually experienced performance. We also report the prediction obtained by means of some well-known analytical models for comparison purposes.

4.5.1 802.11 with ideal channel

As a first case study, we consider the problem of predicting the throughput performance of an infrastructured 802.11 cell. For simplicity, we consider the case of saturation traffic in uplink, with all mobile terminals near the Access Point (SNR = 30 dB, losses due to collision only) and using a fixed modulation scheme of 54 Mbps; furthermore, we consider single-hop communications only. Under these assumptions, the achievable throughput performance depends on the traffic load in the cell; more precisely, it is a function of the number of users, which is an environmental factor. Unfortunately, the number of users is not a measurement commonly available from a real device; so, to characterize this environmental factor, we consider the following environmental measurements:

- *ReceivedFrames*, i.e., the number of data frames sensed on the channel (regardless of their destination) which are correctly received;

- *ErroneousFrames*, i.e., the number of frames for which a failed checksum indicated an incorrect reception;

- *IdleTime*, i.e., the fraction of time in which the channel was sensed idle;

We use these metrics as the input variables to a MFNN whose output variable is the expected throughput. We note that all these metrics can be expected to be exported by a real 802.11 card, so implementation of this scheme is actually feasible.

In our simulations, the measurements were collected by a single node interpreting the role of the CR. We ran several simulations varying the number of nodes to evaluate whether the MFNN was able to model the
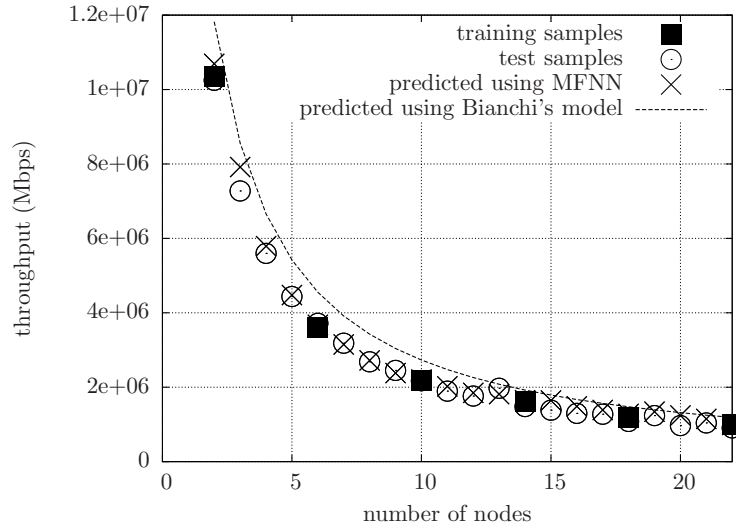
Figure 4.3: Comparison of the MFNN predictor with Bianchi's model

throughput performance with respect to the traffic load. We used a two-layer MFNN with 6 neurons in the hidden layer, which was trained using 6 data samples obtained from simulations with 2, 6, 10, 14, 18 and 22 nodes. Then we verified the performance prediction capabilities of the MFNN by applying some test data (i.e., environmental measurements obtained from more simulations with different number of users) as input, and comparing the output of the MFNN with the expected throughput associated with the test input data. The results are reported in Figure 4.3, and show that the the MFNN is able to successfully predict the performance.

We note that, in the conditions considered above, one could use Bianchi's model [123] to calculate the expected throughput, which, as reported in Figure 4.3, would result in a predicted performance very close to that provided by the MFNN. These values were obtained evaluating Bianchi's model with the actual number of users which, as we already mentioned, is not commonly available in real devices. To estimate it, Bianchi proposed the use of a Kalman filter [124]; this practice, however, requires additional complexity, and is expected to reduce the accuracy of the throughput performance prediction. Most importantly, as we will discuss in the next section, the usability of Bianchi's model in practical cases is severely limited by the fact that it only applies to the ideal case we have considered, and cannot be used in more realistic scenarios.

4.5.2   802.11 with channel errors

One of the major drawbacks of analytical models is that it can be very difficult to extend a given model to include new factors, i.e., new input vari-
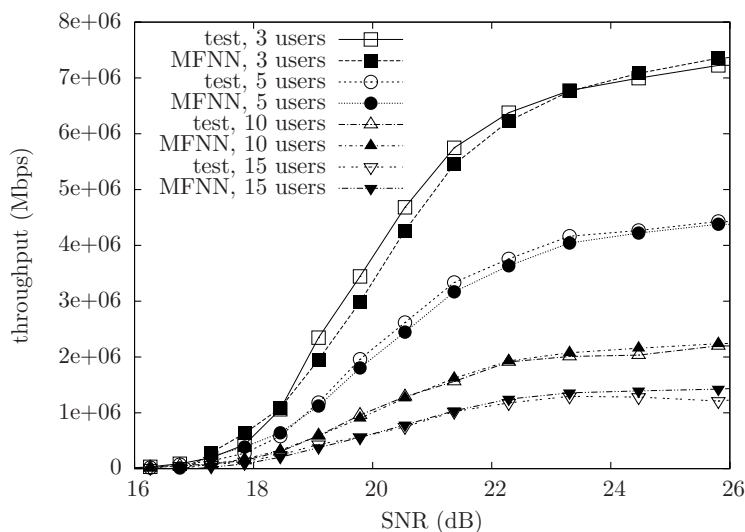
Figure 4.4: MFNN predictor performance with varying SNR

ables. For instance, Bianchi's model does not take into account losses due to non-ideal propagation conditions. Some attempts have been made to extend the model in this direction, unfortunately with little success; for instance, in [125] the authors propose the addition of a packet error probability term to the collision probability variable; however, in doing so the authors assume that all users in the 802.11 cell undergo the same packet error rate, which may severely limit the usability of the model for performance estimation in real scenarios.

On the other hand, adding new input variables to a MFNN performance predictor requires little effort, apart of course from re-training the MFNN. For instance, we added to the MFNN described in the previous section a Signal-to-Noise Ratio (SNR) environmental measurement, with the aim of accounting for the propagation conditions as a new environmental factor. We ran several simulations varying both the number of nodes and the distance of the test node from its destination. We used 30 performance samples as training data to characterize the bi-dimensional environmental factor space. The other samples obtained from the simulations were used to test the prediction capabilities of the trained MFNN. The obtained prediction accuracy is very good, as shown in Figure 4.4. We also note that, as expected, the asymptote for SNR$\longrightarrow \infty$ corresponds to the throughput performance predicted by Bianchi's model, which on the other hand cannot be used for finite SNR values.
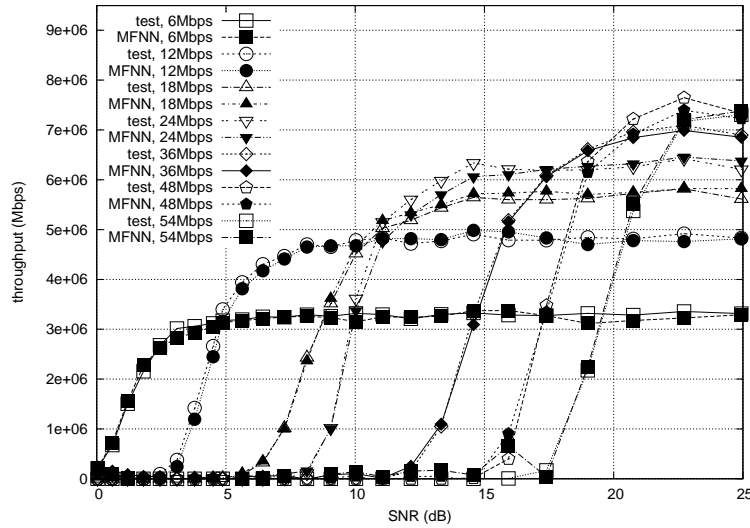
Figure 4.5: MFNN predictor performance with different PHY modes in a scenario with 2 interferers

4.5.3   802.11 multirate

As we discussed in Section 4.4, environmental measurements are not the only type of input which can be applied to the MFNN. It is indeed feasible and of great interest to also use configuration parameters as input variables in order to provide support for the optimization process which is to be performed by the CR. As an example, consider the problem of evaluating the performance of the different PHY modes available in 802.11g. For this purpose, we added to the MFNN described in the previous section a new input representing the modulation scheme being used. We ran several simulations varying the number of users, the distance of the test node and the modulation scheme which was kept fixed for the whole duration of the simulation. Of the data resulting from the simulations, 210 samples were used for training, and the others were used for testing purposes. The results are reported in Figure 4.5: the trained MFNN is able to predict the performance of different modulation schemes even in face of conditions (traffic load, SNR) which differ from what experienced during the training.

Once trained, the MFNN predictor can be used to optimize the configuration of the CR. In the example just presented, the presence of the PHY rate as an input parameter makes the MFNN predictor suitable, for instance, for the implementation of a rate adaptation algorithm. We studied the performance of a scheme which evaluates exhaustively the performance of all available PHY modes with respect to the current environmental conditions, and selects the PHY mode which, according to the MFNN predictor, will yield the best performance. We ran some simulations varying
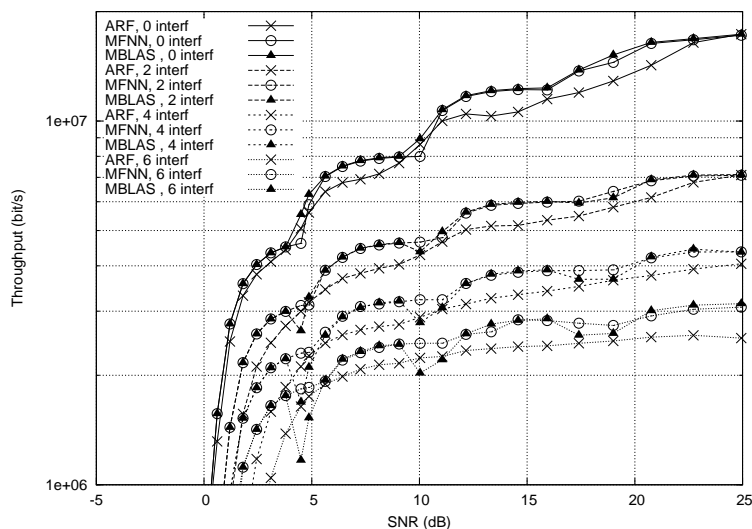
Figure 4.6: Performance of a rate adaptation scheme using the MFNN predictor

the distance of the node from the AP as well as the number of interfering nodes, in order to compare the MFNN-based rate adaptation with the well-known Auto Rate Fallback (ARF) [126] and MPDU-Based Link Adaptation Scheme (MBLAS) [127][3]. In Figure 4.6 we report the obtained results: the MFNN-based scheme always outperforms ARF, and also achieves better performance with respect to MBLAS in the presence of interferers, as evident for SNR values in the intervals $[4, 5]$, $[10, 11]$ and $[17, 19]$ where a throughput improvement of up to 20% can be observed. This is explained observing that MBLAS chooses the optimal PHY mode based on the throughput performance expected in the absence of interference, and this choice becomes increasingly sub-optimal as the number of users that contend for the medium grows. We also note that MBLAS and the MFNN-based scheme achieve the same (optimal) performance when interference is not present.

4.5.4 Some implementation issues

So far we have demonstrated the features of performance prediction using MFNN; however, the discussion would not be complete if we did not talk about some implementation issues related to this approach.

The first and most obvious is the number of samples required for a proper training of the MFNN. This is actually an issue which is not exclusively rel-

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[3]The MBLAS scheme selects the optimal PHY mode with respect to an analytical model of the throughput performance accounting for the SNR at the receiver, the MPDU size, and the 802.11 MAC backoff mechanism. It is to be noted that the adopted analytical model is valid only for scenarios with a single transmitter/receiver pair.

evant to MFNN, but rather appears in all statistical learning methods. The fact is that the training data needs to be sufficiently representative of the performance variations with respect to the environmental factors which need to be accounted for. For a single environmental factor, i.e., when the environmental factor space is one-dimensional, a few samples might be enough – as an example, we recall that for the case discussed in Section 4.5.1, where the only environmental factor was the number of users, 6 samples already provided a quite accurate model. Unfortunately, the number of required samples grows in principle exponentially with the number of dimensions in the environmental factor space – for instance, in the example provided in 4.5.2 we added one environmental factor (SNR) and we found that about 30 samples were needed for a proper training of the MFNN.

Another issue is the size of the hidden layer. More hidden layer neurons allow the representation of more complicated functions; however, too many of them can result in overfitting the training data and consequently in poor generalization of the performance prediction. This issue, however, can be dealt with by means of network pruning strategies such as the Optimal Brain Surgeon [128].

Finally, we observe that it is of primary importance to verify that the training of the MFNN has been successful. This is commonly accomplished by testing the MFNN with a set of test samples which have not been used for training, and then evaluating the prediction error.

4.6 MFNNs for Dynamic Channel Selection in 802.11 networks

We now apply the MFNN approach to the problem of Dynamic Channel Selection in IEEE 802.11 networks.[4] The reasons for this choice are many. First of all, channel selection in 802.11 systems is an interesting and challenging topic, due to the ubiquity of 802.11 networks and due to the well-known overcrowding of the 2.4 ISM bands in which 802.11b/g operates. Second, 802.11 is a very well known and studied technologies; as such, its behavior in different operating conditions is very well understood, and in particular the problem of channel allocation has already been studied in the past, so that we have some legacy channel allocation strategy to use as a performance reference. Last, commercial 802.11 devices, in particular those supporting the MadWiFi Linux driver [129], offer a very flexible and cost-effective solution for the implementation of a Cognitive Network testbed.

4.6.1 Related Work

Traditionally, Channel Assignment in 802.11 infrastructured networks has always been performed in a static fashion, allocating the APs with techniques such as graph coloring [130]. More advanced proposals use a more theoretical approach, in which several pieces of information are supposed to be known a priori, such as the number of users in the network, the amount of traffic they generate, and the propagation characteristics of the network; with this information it is in theory possible to calculate the amount of interference generated by the users in one cell to the users in other cells, and therefore to determine the channel assignment for each cell which maximizes some metric such as the cumulative throughput or the fairness among users. Several publications follow this approach in the literature; however, while being a reasonable strategy from a theoretical point of view, in real deployments it suffers from some major issues. First, the propagation and interference models commonly used have some subtle differences from propagation in a real environment, and as a consequence the theoretical model for inter-cell interference and the resulting optimization model for channel allocation could fit poorly in a real deployment. Second, a typical assumption which is made is that there are few access points which have a very high

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[4]The work presented in this section was done during the visit to the California Institute for Telecommunications and Information Technology, UCSD division, under supervision by prof. Ramesh Rao and in collaboration with B. S. Manoj and B. R. Tamma. It is to be noted that the the deployment of the wireless network infrastructure and the multi-channel sensing system was mainly performed by the collaborators. The contribution of the author in this work the design of the MFNN-based Cognitive Controller for Dynamic Channel Selection, the development of the client performance measurement system which was needed for its implementation but was not available previously, and finally the implementation and performance evaluation of the MFNN-based Cognitive Controller.

load, while in many urban scenarios there are even tens of APs within range of each other, and the traffic per AP can be rather low; as a consequence, while many theoretical proposals focus prominently on load balancing issues among APs in the same network, in a real deployment other issues may be more relevant, such as interference from other wireless networks or microwave ovens. Third, the presence of users and the amount of traffic they generate varies significantly not only with respect to time, but also with respect to space; for this reasons, taking into account the instantaneous variations of load at all access points to do a joint channel assignment, while straightforward in theoretical approaches where everything is assumed to be known, is not practical in real scenarios.

4.6.2   Application of MFNN to channel assignment in 802.11 networks

In order to apply the proposed approach to the particular problem of channel assignment in an 802.11 wireless network, we need to identify what particular pieces of information available in a real 802.11 system can be conveniently used for each of the categories introduced in the previous subsection.

For the *Parameter Setting* we obviously use the channel setting $(1, 2, \ldots, 11)$. For the training, this is the channel for which some particular measurement data has been obtained. At run time, this is the channel whose performance the Cognitive Controller wants to predict.

Since the objective of our cognitive controller will be to provide the channel assignment which maximizes the throughput of the users, for the *Performance Metrics* we use the application layer throughput of the mobile users. For the training phase, we exploit measurements performed by a test client node; alternatively, other techniques could be used, such as throughput estimation based on traffic sensing [131], or QoS reports fed back by real clients as we discussed in Section 3.6. During the evaluation phase, the estimated application layer throughput is provided as the output of the predictor.

Finally, the most relevant environmental factor determining the performance of an 802.11 cell with respect to a particular channel is how much interference is present in the cell on that channel.

Interference actually comes in two forms: interference in the form of radio power added to noise which negatively affects the success probability of frame receptions, as generated by far away 802.11 transmitters as well as by non-802.11 devices such as bluetooth and microwave ovens, and interference in the form of 802.11 transmissions contending for the medium, which trigger the transmission deferral and backoff freeze procedures as per the 802.11 standard, and result in increased medium access times. To characterize both these aspects, we use as *Environmental Measurements* the following metrics:

- the Packet Rate, defined as the number of valid IEEE 802.11 frames received per unit time;

- the Data Rate, defined as the value of the PHY data rate averaged over all successful IEEE 802.11 receptions;

- the CRC Error Rate, defined as the number of incoming IEEE 802.11 transmissions for which the link-layer CRC check failed;

- the PHY Error Rate, defined as the number of times acquisition was triggered at the PHY layer but reception was aborted because of a failure in the PLCP header check.

- the Packet Size, defined as the average size of valid IEEE 802.11 frames.

Furthermore, some other *Environmental Measurements* are exploited, in particular information used to characterize the behavior of the system with respect to time:

- The Day of Week, ranging from 0 (Monday) to 6 (Sunday)

- The Hour of Day, ranging from 0 to 23

We note that every Cognitive Access Point in the network will collect the above mentioned measurements, and thus the characterization will be specific to the position of each cell, thus effectively modeling the dependency of the performance of the communication system on location.

For the implementation of the MFNN-based predictor, the simplest way would be to assume that the environmental conditions vary only slowly, and therefore using only the last measurement as input of the neural network is sufficient for an accurate prediction. This was the approach we followed in the work we presented in Section 4.4. However, this solution is not expected to be effective when the environmental conditions vary significantly between subsequent optimization periods. This aspect has actually been investigated in the past in the context of both generic and MFNN-based control systems [116]. To cope with this issue, we feed past measurements to a delay line with k taps prior to applying them to the MFNN, and feed simultaneously all the measurement values obtained at all the taps of the delay line to the MFNN for prediction. In this way, the MFNN predictor is expected to be able to identify and learn regular behaviors in the training data, thereby providing a more accurate prediction.

4.6.3   Implementation

The system described in the previous section was implemented on a testbed deployed in the Calit2 building at the University of California, San Diego,
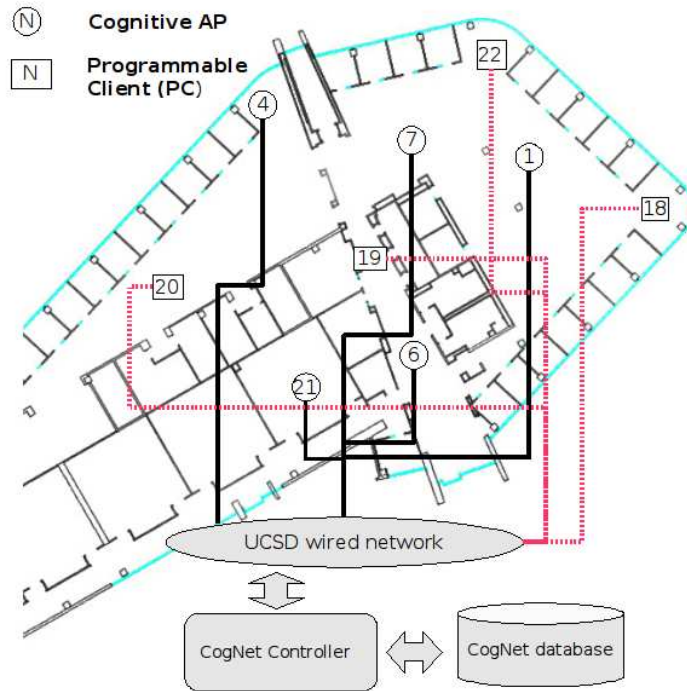
Figure 4.7: Diagram of the Cognitive Wireless Network Testbed used for the experiment.

which is represented in Figure 4.7. A collection of Cognitive APs forms the basis of our system. Each Cognitive AP consists of a Soekris Engineering net4521 system board, equipped with two 100 Mbps Ethernet interfaces and two Ubiquity 802.11a/b/g cardbus wireless interfaces based on Atheros AR5213 chipset with external antenna connectors. Of the two wireless NICs, one acts as an AP and provides network access to wireless client nodes, while the other is configured in monitor mode to capture all 802.11 packets on the air, thereby acting as a wireless network traffic sensor. The testbed is facing two main sources of interference: the production wireless service in the building, made up of Avaya APs configured for 802.11b/g service, and several experimental ad-hoc and mesh networks on the sixth floor of the building. For the experiment described in this paper, we have deployed 5 Cognitive APs on the 6th floor of the building among the production APs. Each Cognitive AP runs Voyage Linux [132], and uses the MadWiFi driver [129] for driving the Atheros-based wireless interfaces. Each Cognitive AP is connected to the campus intranet via one of its Ethernet interfaces.

The Cognitive APs also feature a time-based sensing control module,

which uses the STT sampling scheme described in [131], with a sampling period of 11s and a sampling duration of 1s. As discussed in [131], this allows accurate measurement across all 11 channels using a single wireless NIC. The synchronization and control module, on the other hand, performs synchronization of the Cognitive APs with the Cognitive Controller using NTP [133] over the wired network.

Using the capture-to-file functionality of the open source `tcpdump` packet sniffer, the traffic sensor module creates capture files and remits them to the Cognitive Controller (Dell PowerEdge 1900 server with two Dual Core Intel Xeon processors operating at 2 GHz with 4 GB RAM and 7.2 TB of storage) via the data transfer module. To further reduce the storage cost, `tcpdump` is configured to capture only the first 250 bytes of each sampled packet. This is a reasonable solution, since all protocol headers we are interested in are located at or near the start of the packet. At the Cognitive Controller, a modified version of `tcpdump` is employed to read the capture file to extract Prism monitoring header fields and header field values from the MAC through transport layers of the TCP/IP protocol stack. These values are stored in our Cognitive Network Database, implemented using MySQL server, from which they can be queried to extract the training and test data used for this work, as well as for generic analysis purposes. The Cognitive Controller stores the information in two separate forms: (i) instantaneous traffic records and (ii) historical traffic records. The instantaneous traffic records contain large amounts of wireless network data traffic tagged with space and time information. The historical traffic records are created from instantaneous traffic records, by averaging data referring to the same location and channel over one-minute intervals. The purpose of having historical traffic records is to speed up subsequent reprocessing of information by not needing to process the complete traffic records every time (which is a very costly operation).

In addition to traffic samples, we gather other measurements which can be used to better characterize the conditions of the wireless medium. In particular, the MadWIFI driver has a tool (`athstats`) which provides additional statistics like the number of CRC errors (i.e., receptions failed due to bad CRC in the MAC trailer) and PHY errors (receptions failed due to the CRC failure on the PLCP header). This information is transferred periodically to the Cognitive Controller and is stored in a dedicated record.

Implementation of the time-based sensing module is done using a combination of shell scripts running `wireless-tools` [134] and MadWiFi tools. These are used to periodically switch the wireless NIC's channel setting in order to gather traffic samples from all 802.11 b/g channels; channel switching is done in parallel to the traffic sensing activity. In order to report additional information about the packet currently being captured, the MadWiFi driver generates the Prism monitoring header, 144 bytes in length, and adds it to the packet. The Prism monitoring header contains, among
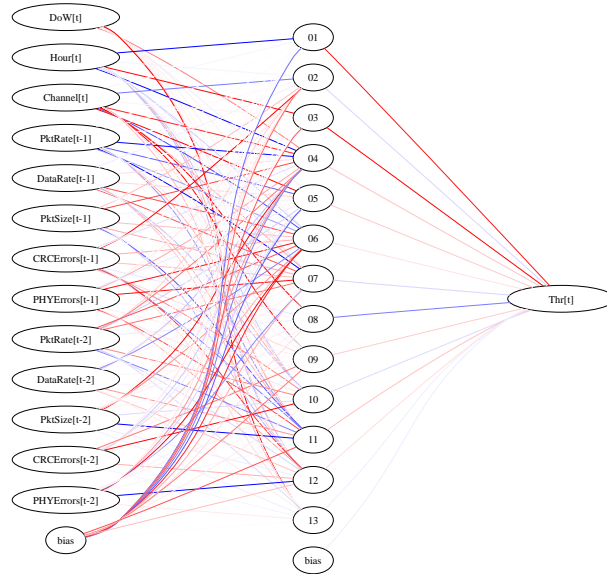
Figure 4.8: A realization of the MFNN predictor.

other information, the Received Signal Strength Indicator (RSSI), channel and data rate of the packet. The data transfer module takes care of transferring the sensed traffic information files from a large number of wireless traffic sensors to the Cognitive Controller in an automated way; this module is implemented using the File Transfer Protocol (FTP).

We complement the set of Cognitive APs with a number of nodes built using the same hardware, with a single wireless NIC in managed mode, and configured as Programmable Clients (PCs). The Cognitive Controller interacts with the PCs, so that each PC is periodically associated with a different Cognitive AP, and runs a modified version of the `iperf` software [135] to carry out active measurements by performing TCP data transfers both in the uplink and in the downlink direction. In this way application-layer performance metrics, such as throughput, delay, jitter, and packet loss ratio, are collected by the Cognitive Controller.

The MFNN-based Cognitive Controller described earlier in this section was implemented using the Fast Artificial Neural Network library [136]. In Figure 4.8 we represent a realization of the predictor with $k = 2$ delay line taps and $H = 13$ neurons at the hidden layer.

4.6.4   Performance Results

We used data gathered by the Cognitive Network testbed described in the previous section for the performance evaluation of the proposed Cognitive Controller. This data consists of the measurements described in Section 4.6.2 collected by the Cognitive APs of the testbed described in 4.6.3 and averaged
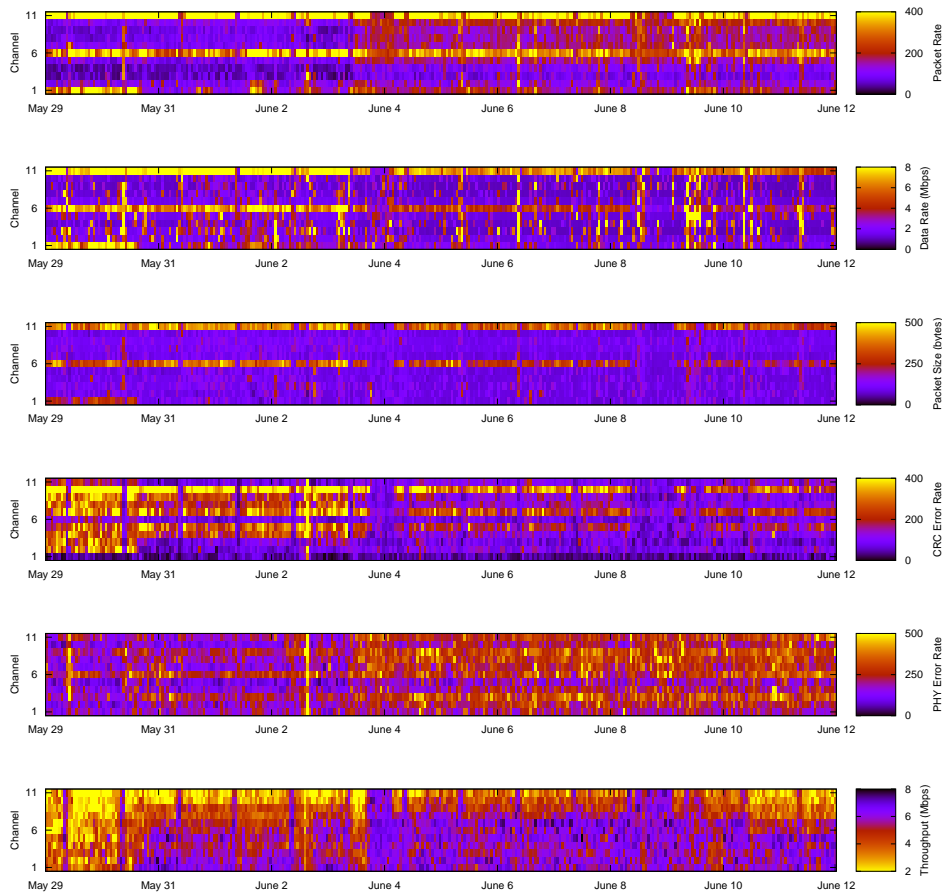
Figure 4.9: Subset of the training data for node006 over a two week period from May 29 to June 12, 2008. The first five spectrograms represent environmental measurements which are used as input data to the MFNN predictor. The last spectrogram represent the performance measurements which are used as the known values of the output of the predictor.

over one-hour intervals. Data gathered from April 1 to July 15, 2008 was used as the training set, while data gathered from July 16 to September 15 was used as the testing set; the former set was used to train the Cognitive Controller, while the latter was used to test the accuracy of the prediction by calculating the mean square error between the predicted value and the known output value, and also to evaluate the performance achieved by both the MFNN-based channel selection scheme and other comparison schemes. A small subset of the data collected by node006 from May 29 to June 12 is shown in Figure 4.9. We note that some correlation is evident between environmental measurements (first five spectrograms) and performance (last spectrogram). This is exactly the type of correlation that we want the MFNN predictor to learn. Representation of other data is omitted due to space constraints.

Training procedures were performed using the backpropagation algorithm [122] with a learning rate of 0.7 and a number of epochs of 1000. We tested different types of MFNNs predictors varying the number of neurons H at the hidden layer and the number of delay taps k; we achieved the best prediction performance with $H = 13$ and $k = 2$, and therefore used these MFNN parameter values for the MFNN predictor to be used for channel selection.

For every Cognitive AP, the Cognitive Controller performed channel selection at the beginning of every hour in the test period using the measured data in the preceding hours. This was performed by applying, for every channel, the environmental data relative to that channel to the inputs of the MFNN predictor, and retrieving the predicted performance for that channel in the next hour as the output of the MFNN. The channel providing the highest expected performance was then selected.

We compare the performance of the MFNN-based channel selection scheme with the performance obtained by two channel allocations obtained as valid solutions of the graph coloring approach described in [130] on the set of Cognitive APs. We also report the performance obtained by randomly selecting a different channel every hour, and the best *a posteriori* performance determined by measuring the throughput performance on all channels and selecting the highest value.[5]

The throughput performance we obtained for the channel selection schemes just mentioned is reported in Figure 4.10, for every AP considered, and averaged over the whole testing period. We note that the graph coloring approach does not perform very well: the first allocation performs very poorly, while the second allocation has rather good performance for node001 and performance close to random on the other nodes. This poor performance of

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[5]This can be done in our setup since we always measure the performance of all channels for evaluation purposes. However this is not a feasible channel selection scheme, since channel selection needs to be done before channel usage, and therefore has to be based on past measurements only.
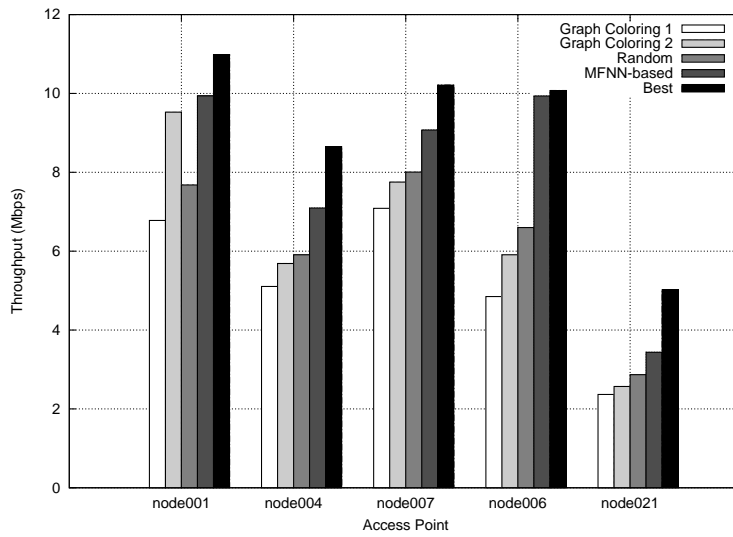
Figure 4.10: Performance of different Channel Selection schemes

graph coloring is due to its staticity, combined with its inability to consider external interference in the determination of valid solutions. The MFNN-based scheme achieves a performance improvement which ranges from roughly 13% to 50% over the random scheme, and is even more significant in several cases with respect to the graph coloring approach. We note that in the case of AP node006 the performance achieved by the MFNN scheme is almost equal to the best performance, while in the other cases it is lower. In this respect, we note that the "best" performance can be better than the one achievable by any possible predictor, especially when there is a high short-term variance in the network conditions and/or in the performance measurements.

These results show that the MFNN-based channel selection scheme was able to provide significant performance improvements over legacy techniques such as graph coloring, thus proving that the MFNN-based approach to Cognitive Networking is practical and effective.

Chapter 5

Conclusions

In this thesis, we have discussed the application of two well-known Artificial Intelligence techniques, i.e., Fuzzy Logic and Neural Networks, to Cognitive Radio and Network systems. We have explained how Fuzzy Logic can be conveniently adopted for Knowledge Representation in a cognitive system, providing benefits such as an enhanced interpretability of information, the ability to represent imprecise and uncertain data, and the applicability of control techniques such as Fuzzy Controllers and Fuzzy Decision Making. Furthermore, we have shown that the learning capabilities of Multilayer Feedforward Neural Networks can be very effective in providing Cognitive Radios and Networks with the ability to characterize the surrounding environment, enabling them to understand how the changes in the configuration of the communication system affect its performance, and therefore to be able to choose the configuration which is expected to provide the best service quality to the user.

Of course, we cannot claim that, thanks to our contribution, Cognitive Radios and Networks have now become practical; many aspects are still left to be investigated. We would like to stress, in particular, that while each of the discussed techniques has its own merits, none of them can actually be considered to be sufficient alone for the realization of Cognitive Radio and Networks systems. One example for this is the application of Fuzzy Logic to Wireless Network Access that we presented in Section 3.6.3: in this section, in order to implement the design that we had introduced in 3.6.2, we have been forced to rely massively on analytical models, thus introducing in our implementation the drawbacks that we discussed later on in Section 4.2, and that could have been overcome by the use of Neural Networks for system modeling. Another example is in our implementation of the Neural Network based cognitive system that we discussed in Chapter 4. The point here is that the considered optimization problems (Rate Adaptation, Channel Selection) are characterized by a solution space which is monodimensional, discrete and has very low cardinality. It would not be straightforward to

extend this work to problems with more complex solution spaces without introducing adequate search strategies. To summarize, our understanding is that the simultaneous adoption of several Artificial Intelligence techniques – not only of Fuzzy Logic and Neural Networks, but also of other techniques, such as Genetic Algorithms, Learning Automata, Bayesian Networks – is the way to go for the realization of Cognitive Radio and Network systems.

Finally, we would lik to stress that we are convinced that Dynamic Spectrum Access is a very promising research area, even though in this thesis we did not propose any advancement explicitly addressed to it. For this reason, we believe that the application to the field of Dynamic Spectrum Access of the AI techniques that we investigated in our work would be extremely interesting as a future line of research.

Appendix A

Other research activities

We hereby briefly describe other research activities carried out during the Ph.D. which were not explicitly related to Cognitive Radio and Networks.

A.1 Cross-layer Optimization for IEEE 802.11 communications

This activity was carried out as part of a research project involving the University of Padova and STMicroelectronics. The objective of this study is to design and test suitable optimization techniques for multimedia communications over 802.11 WLAN which can be implemented on an embedded device. The work was done under supervision by prof. Michele Zorzi and in collaboration with Andrea Zanella, Federico Maguolo and Simone Merlin; the contribution of the author of this thesis spanned across all aspects of the project, from system design to performance evaluation.

With this respect, we designed an optimization framework consisting of two separate components: a network status estimator, which has the role of assessing the performance of the 802.11 wireless link, and a parameter optimization block, which evaluates the impact of different parameter settings at the various layers (e.g., PHY rate, MAC retransmission limit, application packet size) on end-user perceived quality, thus allowing the selection of the settings expected to yield the best performance.

The proposed solution has been applied in two different use cases: optimal PHY Rate Adaptation for throughput-intensive applications, and PHY and MAC optimization for VoIP communications. Both these studies have been published [C4,C5].

A.2 Underwater Acoustic Communications

Radio signals cannot be used effectively underwater, and therefore underwater communications are commonly performed by means of acoustic waves.

Underwater Acoustic Communications, however, are very challenging due to the long propagation delay of acoustic signals, the scarce bandwidth available for communication, and the complex dependency on frequency of both propagation and noise.

Our research activities in this area focused on the design of MAC and Routing schemes which are effective in these challenging conditions. In particular, Cognitive[1] FDMA medium access techniques have been investigated, in order to overcome the delay issues that make TDMA-based and contention-based techniques scale poorly with the size of the network; this study has been already published in [C3]. At the routing layer, energy-efficient routing algorithms have been designed; the results of this work have been accepted for publication [J2]. These activities were carried out under supervision by prof. Michele Zorzi and in collaboration with Paolo Casari. The author's contribution was the design of the Cognitive FDMA system, and the performance evaluation by means of network simulation for both the Cognitive FDMA system and the energy-efficient routing schemes.

A.3   Network Simulation Tools

This activity is centered around the development of NS-Miracle, which is a set of libraries designed to enhance the functionalities provided by the Network Simulator ns-2. NS-Miracle provides an efficient and embedded engine for handling cross-layer messages and, at the same time, enables the coexistence of multiple modules within each layer of the protocol stack. For instance, multiple IP, link, MAC or physical layers can be specified and used within the same node, and can exchange arbitrary control information using cross-layer messages. In addition, dedicated modules and APIs provide an enhanced support for the development of PHY, MAC and Routing implementations. Overall, the NS-Miracle framework facilitates the simulation of modern communication systems in ns2; moreover, due to its modularity, the code is portable, re-usable and extensible. The features of the NS-Miracle simulator are described in two conference papers [C1,C7]. Finally, NS-Miracle also features detailed implementations of the 802.11, UMTS and WiMAX radio technologies, as well as a set of modules for the simulation of Underwater Acoustic Communications. The author of this thesis had a major role in the design and development of NS-Miracle, and of several of its extension modules. It is to be noted that all the performance evaluation carried out by means of simulation which is reported in this thesis has been done with NS-Miracle, and in most cases it would have not been straightforward or even possible to do it with other network simulators due to their limitations.

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[1]We note that the term "cognitive" in this case refers to the intelligent usage of the available spectrum.

Appendix B

Full list of publications

Papers published on journals

[J1] Nicola Baldo, Michele Zorzi, "*Fuzzy Logic for Cross-layer Optimization in Cognitive Radio Networks*", IEEE Communications Magazine, April 2008.

[J2] Michele Zorzi, Paolo Casari, Nicola Baldo and Albert F. Harris III, "*Energy-efficient routing schemes for underwater acoustic networks*", IEEE Journal on Selected Areas in Communications, accepted for publication.

Papers published on conference proceedings

[C1] Nicola Baldo, Federico Maguolo and Marco Miozzo, "*A new approach to simulating PHY, MAC and Routing*", ACM Second International Workshop on NS-2, Athens, October 2008

[C2] Nicola Baldo, Paolo Casari, Paolo Casciaro, Michele Zorzi, "*Effective Heuristics for Flexible Spectrum Access in Underwater Acoustic Networks*", MTS/IEEE Oceans 2008, Quebec City, September 2008

[C3] Nicola Baldo, Paolo Casari, Michele Zorzi, "*Cognitive Spectrum Access for Underwater Acoustic Communications*", IEEE CogNet Workshop, Beijing, China, May 2008

[C4] Nicola Baldo, Federico Maguolo, Simone Merlin,Andrea Zanella, Michele Zorzi, Diego Melpignano, David Siorpaes, "*GORA: Goodput Optimal Rate Adaptation for 802.11 using Medium Status Estimation*", IEEE International Conference on Communications, Beijing, China, May 2008

[C5] Nicola Baldo, Federico Maguolo, Simone Merlin,Andrea Zanella, Michele Zorzi, Diego Melpignano, David Siorpaes, "*APOS: Adaptive Parameters Optimization Scheme for Voice over IEEE 802.11g*", IEEE International Conference on Communications, Beijing, China, May 2008

[C6] Nicola Baldo, Michele Zorzi, "*Learning and Adaptation in Cognitive Radios using Neural Networks*", 5th IEEE Consumer Communications and Networking Conference, Las Vegas, USA, January 2008, accepted for publication.

[C7] Nicola Baldo, Federico Maguolo, Marco Miozzo, Michele Rossi, Michele Zorzi, "*NS2-MIRACLE: a Modular Framework for Multi-Technology and Cross-Layer Support in Network Simulator 2*", ACM NSTools, Nantes, France, 22 October 2007, accepted for publication.

[C8] Nicola Baldo, Michele Zorzi, "*Cognitive Network Access using Fuzzy Decision Making*", IEEE CogNet 2007 Workshop, Glasgow, June 24th, 2007.

[C9] Nicola Baldo, Michele Zorzi, "*Fuzzy Logic for Cross-layer Optimization in Cognitive Radio Networks*" 4th IEEE Consumer Communications and Networking Conference, Las Vegas, USA, January 2007

Papers submitted for publication

[S1] Nicola Baldo, Michele Zorzi, "*Cognitive Network Access using Fuzzy Decision Making*", IEEE Transactions on Wireless Communications, submitted for publication.

[S2] Nicola Baldo, Bheemarjuna Reddy Tamma, Paul Baumgart, B. S. Manoj, Ramesh Rao, and Michele Zorzi "*A Neural Network based Cognitive Controller for Dynamic Channel Selection*", IEEE International Conference on Communications, May 2009

[S3] Nicola Baldo, Bheemarjuna Reddy Tamma, Paul Baumgart, B. S. Manoj and Ramesh Rao, "*Multi-Channel Wireless Traffic Sensing and Characterization for Cognitive Networking*", IEEE International Conference on Communications, May 2009

[S4] Nicola Baldo, Bheemarjuna Reddy Tamma, Paul Baumgart, B. S. Manoj and Ramesh Rao, "*A Cognitive Network Architecture for Autonomic Control of Wireless Networks*", IEEE Transactions on Computers

Papers published prior to Ph.D.

[R1] Nicola Baldo, Andrea Odorizzi, Michele Rossi, "*Buffer Control Strategies for the Transmission of TCP Flows over Geostationary Satellite Links Using Proxy-Based Architectures*", IEEE VTC Spring 2005. Stockholm, Sweden, May 2005

[R2] Markus Kampmann, Nicola Baldo, "*Adaptive Wireless Video Streaming Using Transmission Rate Control and Packet Scheduling*", Packet Video Workshop 2004, California, USA, December 2004

[R3] Nicola Baldo, Uwe Horn, Markus Kampmann, Frank Hartung, "*RTCP feedback based transmission rate control for 3G wireless multimedia streaming*", IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, Barcelona, Spain, September 2004

Patents

[P1] *Method, apparatus and computer program product for controlling data packet transmissions*

- *Patent number:* WO2005081465
- *Publication date:* 2005-09-01
- *Inventors:* Kampmann Markus (DE); Horn Uwe (DE); Hartung Frank (DE); Baldo Nicola (IT); Lundberg Jonas (SE); Westerlund Magnus (SE); Stille Mats (SE)
- *Applicant:* Ericsson Telefon Ab L M (SE);
- *International classification:* H04L12/56; H04L12/56; (IPC1-7): H04L12/56

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