Cognition procedures for optical network design and optimization

by

Luis David Notivol Calleja

UNIVERSITAT POLITÈCNICA DE CATALUNYA (UPC)

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Luis David Notivol Calleja

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Advisors: Dr. Salvatore Spadaro and Dr. Jordi Perelló Muntan

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Abbreviations and Symbols

Abbreviations

APD	Avalanche Photodiode Device
ASE	Amplifier Spontaneous Emission
ASON	Automatically Switched Optical Network Architecture
AWG	Array Waveguide Gratings
BER	Bit Error Rate
BOL	Beginning-Of-Life
BPSK	Binary Phase Shift Keying
CAPEX	Capital Expenditures
CBR	Case-Based Reasoning
CD	Chromatic Dispersion
CFP	Centum Form Factor Pluggable
CHRON	Cognitive Heterogeneous Reconfigurable Optical Network
CML	Chirp Managed Lasers
CL	Channel Net Losses
CO	Central Office
CWDM	Coarse Wavelength Division Multiplexing
DCM	Dispersion Compensation Management
DD	Direct Detection
DEMUX	Demultiplexer

DGD	Differential Group Delay
DML	Direct Modulation Device
DPSK	Differential Phase Shift Keying
DP-QPSK	Dual-Polarization Quadrature Phase Shift Keying
DQPSK	Differential Quadrature Phase Shift Keying
DSF	Dispersion Shifted Fiber
DSP	Digital Signal Processing
DWDM	Dense Wavelength Division Multiplexing
EAM	Electro-absorption Modulators
EDFA	Erbium Dropped Fiber Amplifier
EM	Expectation-Maximization
EML	External Modulators
EOL	End-Of-Life
ERM	Electro-Refraction Modulators
FBG	Fiber Bragg Gratings
FEC	Forward Error Correction
FTTC	Fiber To The Curb
FTTH	Fiber To The Home
FWM	Four Wave Mixing
GMPLS	Generalized Multi-Protocol Label Switching
GVD	Group-Velocity Dispersion
IBL	Instance Based Learning
IETF	Internet Engineering Task Force
IM-DD	Intensity Modulation / Direct Detection
IP	Internet Protocol
ITU-T	International Telecommunication Union-Telecom Standardization
KB	Knowledge Base
k-NN	k-Nearest Neighbors

M	System Margin
MAN	Metropolitan Area Networks
MDS	Multidimensional Scaling
MEMS	Micro-Electro-Mechanical Systems
MUX	Multiplexer
MZM	Mach-Zehnder Modulator
NF	Noise Figure
NN	Nearest Neighbors
NLI	Non-linear impairments
NZ-DSF	Non-Zero Dispersion Shifted Fiber
LO	Local Oscillator
LOOSNR	Link Operational OSNR
LP	Lightpath
LTP	Long Term Potentiation
LWR	Locally Weighted Regression
OA	Optical Amplifier
OADM	Optical Add/Drop Multiplexer
OBS	Optical Burst Switching
OCS	Optical Circuit Switching
ODB	Optical Duo Binary
OF	OpenFlow
OOK	On-Off Keying
OPEX	Operational Expenditures
OPM	Optical Power Meter
OPS	Optical Packet Switching
OSA	Optical Spectrum Analyzer
OSNR	Optical Signal-to-Noise Ratio
OTN	Optical Transport Network
OXC	Optical Cross Connect

PCA	Principal Component Analysis
PDM-QPSK	Polarization Division Multiplexing Quadrature Phase-Shift Keying
PDL	Polarization Dependent Losses
PMD	Polarization Mode Dispersion
PLC	Photonic Lightwave Circuits
Pol-Mux	Polarization Multiplexing
Ptx	Transmission power
SDN	Software Defined Networks
Srx	Sensitivity of the receiver
QAM	Quadrature and Amplitude Modulation
QoE	Quality of Experience
QoS	Quality of Service
QoT	Quality of Transmission
QPSK	Quadrature Phase Shift Keying
RBF	Radial Basis Functions
RIN	Relative Intensity Noise
ROADM	Reconfigurable Optical Add/Drop Multiplexers
SBS	Stimulated Brillouin Scattering
SDH	Synchronous Digital Hierarchy
SFP	Small Form Factor Pluggable
SOA	Semiconductor Optical Amplifiers
SOM	Self-Organizing Maps
SPM	Self-Phase Modulation
SRS	Stimulated Raman Scattering
STM	Synchronous Transfer Mode
SVM	Support Vector Machines
TFF	Thin Film Filters
TRX	Transceiver
XFP	10G Small Form Factor Pluggable

XPM	Cross-Phase Modulation
WAN	Wide Area Networks
WDM	Wavelength Division Multiplexing
WRON	Wavelength-Routed Optical Networks
WSS	Wavelength Selective Switches

Symbols

D	Dataset of information
H	Set of hypothesis
$d()$	Distance function
$f()$	Target function
$h()$	Hypothesis function
$\boldsymbol{x}$	Instance or vector of data
x_n	n-th attribute of the instance
x'_k	normalized n-th attribute of the instance
$\overline{x_k}$	mean of the k^{th} attributes
σ_k	standard deviation of the k^{th} attributes

Summary

Telecom operators have to compete in a dynamic and fierce market where offered services and Quality of Experience (QoE) will be the key to capture new customers, while retaining the existing ones with high level of satisfaction. The offer of services is continuously changing and telecom carriers have to quickly adapt and react to the new market demands, following proactive strategies. Optical transmission capacity has dramatically increased from the initial optical transport network solutions. Thus, network structures shall accommodate a growing volume of users, devices and services, such as the emerging 5G, virtual reality, ultra-high definition experiences, mobility and ubiquity.

To admit and distribute these volumes of information, telecom carriers have to adapt their networks, increasing the existing capacity and deploying new standards. This fact implies an enormous investment on capacity that financial departments will have to know how to drive in order to make benefits grow up. In this way, any efficiency and reduction on the required investments or costs is searched.

The architecture of the solution proposed in the present thesis is based on how humans learn, at least one of the processes, and an approach trying to simulate a part of it has been developed. Importance of data and how it interacts in precedent situations is key, in the era of big data and machine learning, which allows to manage huge volume of information and mainly to combine these enormous sets of data to discover patters enabling to take decisions. It is in this direction that the cognitive proposal has been developed.

In this thesis, an opportunity to improve efficiency and reduce investments has been identified and a solution is proposed. When designing an optical transport network, telecom operators shall ensure the quality of the end-to-end communications. To this end, an over-dimensioning policy is commonly applied, in terms of both network equipment and devices, and operational margins used.

This thesis introduces and evaluates a cognitive approach to reduce one of these margins, the System Margin, based on controlling and applying more efficiently the optical power budget and the optical transmission power. From an operational perspective, margin reduction will lead to a fall of the required investments on transceivers in the whole transport network.

The System Margin takes into account, among other constraints, the long-term ageing process of the network infrastructure. Its conservative and fixed value is established during the design and commissioning phases. The cognitive approach considers the possibility that this operational margin has a flexible and variable value, adapted to the network conditions. To this aim, the cognitive solution proposes a new lower launched power guaranteeing the quality of service of the new incoming lightpath. To this end, it relies on transmission values applied in past and successful network situations. All the previous knowledge is stored in the memory of the cognition system. First, a static knowledge base is considered, initially populated offline with test lightpaths allowing to record real measurements. This knowledge is not replaced by a newer one. In this context, several novel cognitive schemes are presented and discussed. Among all of them, that one allocating the minimum launched power in similar precedent situations provides the best performance, achieving 48% in transmission power savings and the consequent System Margin reduction. Furthermore, no remarkable differences can be noted when applying the cognitive solution in different network load situations, although higher performances are normally provided in lower mean load situations. Second, even though the static approach leads to savings to the telecom operator, the performance of the cognitive solution is improved by means of a dynamic learning approach. Hence, this thesis introduces and evaluates a dynamic knowledge base. An online replacement of the recorded lightpaths takes place, by applying dynamic learning algorithms. The knowledge base is dynamically updated with new information more adapted to the current network conditions. Five new active algorithms are presented and assessed. Among them, that one leveraging in the combination of several characteristics of the stored lightpaths, such as previous usefulness, transmission power used and age on the knowledge base, provides the best performance. By renewing the knowledge base of the system, the operator is able to improve savings in launched power, with gains raising up to +7% or +18% with respect to the static approach, depending on the path. Moreover, it can be stated that there is not a unique and common best cognitive parameter combination solution, valid for all lightpaths in all network situations. By selecting intermediate values in terms of past, similar and successful network situations, the best performance is reached. In light of this, the cognitive approach appears as useful to be applied in commercial optical transport networks with the aim of reducing the operational System Margin.

Dedicated to my oncle Feliciano, my aunt Tere, Loïc, Pilar, Ana, María, mum, dad, granny and all my family.

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Chapter 1

Introduction

1.1 Optical transport networks environment and historical evolution

Optical transmission capacity has dramatically increased from the initial optical transport network solutions. Network structures shall be simple to accommodate a growing volume of users, devices and services, such as the emerging 5G, virtual reality, ultra-high definition experiences, mobility and ubiquity. One of the main objectives for a transport network is that any service within the whole portfolio of services should map into a simple and more efficient convergence layer. Optical networks evolved from using optical fibers merely as a high capacity physical media, a kind of dark fiber, until Photonic Networks and the All Optical Network paradigm, with switching and routing occurring in the optical domain.

The Photonic Transport Layer concept was already introduced in 1999 in [1], where authors present and address emerging scenarios towards photonic access and transport networks. In the initial stages, the optical network architecture was a model composed of several layers, each one of them dedicated to manage a specific type of traffic and to provide some explicit services, as indicated in Figure 1.1. Each one of these layers was made up of several network elements or nodes particularly dedicated to the corresponding layer. This line of network architecture allowed an easy node design but inevitably required a complex global management network, regarding the management itself as well as the maintenance. Each layer, conceived separately from the others had to be managed independently. This complexity was multiplied when a new service had to be introduced in the network. For this reason, new approaches to consolidate the different layers and flatten the optical transport network architecture were investigated, with the aim of enhancing and aggregating functionalities, removing those that were redundant and reducing the number of different network nodes, which shall benefit the telecom carrier in terms of Capital Expenditures (CAPEX) investments and the associated Operational Expenditures (OPEX). The analysis naturally tended to a two-layer model. In this scenario a control plane, common to all the layers, had to be developed.

Due to industry and market evolution but also to tackle scalability issues and costs, development of layer consolidation on optical networks was addressed as an IP over Dense Wavelength Division Multiplexing (DWDM) model, with photonic switching and the Generalized Multi-Protocol Label Switching (GMPLS) series of protocols [2] and other related standards, as the Internet Engineering Task Force (IETF) [3] and [4] recommendations, conceived to supply a common control plane to all layers and network elements of the emergent photonic optical transport networks. Thus, the desired network management, service multiplexing and layer administration and protection, with the aim of reducing costs on equipment and network operation [5] [6] became a reality:

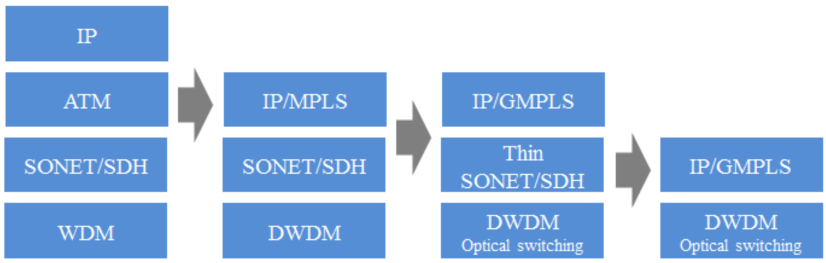

Figure 1.1. Evolution of optical networks model

The available paths between nodes can be considered as a concatenation of point-to-point links between them; then, new approaches in the transport optical network design were necessary. For this reason, Optical Transport Network (OTN) [7] [8] standard was introduced, incorporating the concept of wavelength-routed optical networks (WRON).

Optical Transport Network is the recommendation for DWDM transparent networks following an optical circuit switching (OCS) approach and allowing and easing the interconnection between operators.

Parallel to the introduction of the WDM technology and OTN standards, the Automatically Switched Optical Network architecture (ASON) [1.9] [1.10] was also proposed. An ASON is an OTN network offering dynamic connection establishment and releasing capabilities [11] through a properly defined control plane. The provisioning of leased connections or optical paths can normally take weeks, especially when several network operators were involved. These leased optical paths are normally kept established for several months or years. Therefore, the ASON architecture may reduce provisioning time of the requested lightpaths to several minutes or seconds, opening a new era of possibilities for business cases for telecom operators.

Thus, the evolution of the optical networks focused on a simpler and flatter OTN DWDM infrastructure, based on GMPLS/ASON, with IP protocol on top. The final objective is to reach the All-Optical Switching paradigm.

In parallel to legacy and mainly deployed OCS approaches, other paradigms allowing efficiency packet switching in the optical domain emerged in the scientific community, such as Optical Packet Switching (OPS) [12] and Optical Burst Switching (OBS) [13]. Both of them, however, have been left out of the scope of the present thesis.

1.2. Objectives of this thesis

Telecom operators have to compete in a dynamic and fierce market where offered services and Quality of Experience (QoE) will be the key to capture new customers, while retaining the existing ones with high level of satisfaction. The offer of services is continuously changing and telecom carriers have to quickly adapt and react to the new market demands, following proactive strategies. Among others, the arrival of 5G will involve an important increase of traffic volume of information among sites; the security of communications will also represent a key factor of differentiation. For instance, connected car manages today around 500 gigabytes; an autonomous car shall process about 50 terabytes of information [14]. In order to ensure that these autonomous cars are well connected and they are able to drive and navigate appropriate and safely, 5G mobility networks will be required. Such 5G networks will create an ecosystem where the road and environment conditions, the vehicle infrastructure and mapping software interact among them.

To accommodate and distribute these volumes of information, telecom carriers have to adapt their networks, increasing the existing capacity and deploying new standards. This fact implies an enormous investment on capacity that financial departments will have to know how to drive in order to make benefits grow up. In this way, any reduction on the required investments or costs is searched.

Most of the efforts are concentrated in trying to solve the issue of how to help telecom carriers to save costs. The architecture of the solution proposed in the present thesis is based on how humans learn, at least one of the processes, and an approach trying to simulate a part of it has been developed. Importance of data and how it interacts in precedent situations is key, in the era of big data and machine learning, which allows to manage huge volume of information and mainly to combine this enormous sets of data to discover patters enabling to take decisions. It is in this direction that the cognitive proposal has been developed: memories are a key data base enabling humans to learn and past experiences contribute to it. Artificial intelligence is helping to better understand how human brain works.

In the present thesis, an opportunity to improve efficiency and reduce investments has been identified and a solution proposed. When designing an optical transport network, telecom operators shall ensure the quality of the end-to-end communications. To this end, an over-dimensioning approach is commonly applied, in terms of both network equipment and devices, and operational margins used.

This thesis develops and presents a cognitive solution to reduce one of these margins, based on controlling and applying more efficiently the optical power budget and the optical transmission power. Margin reduction will lead to a fall of the required investments on transceivers in the whole transport network.

Some error situations can occur when the presented cognitive solution is applied in a commercial context. The proposal tries to minimize and handle them. However, the key question: *may the learning systems learn all the possible scenarios*?, is difficult to be answered. Today is complex, but cognitive knowledge and technology will evolve allowing to improve results and be closer to human learning processes.

1.3 Thesis outline

This thesis is structured into two introductory chapters (2 and 3) and three chapters dedicated to the research that has been conducted (chapters 4, 5 and 6).

Chapter 2, *Design and configuration processes in long-haul optical transport networks*, is dedicated to provide a basic view of the main design, deployment and commissioning processes followed by telecom operators. As mentioned, over-dimensioning is a typical policy applied in these stages, in several aspects addressed during the implementation of the optical transport network. The second part of the chapter presents the network elements making up the optical links of the transport network, the main parameters characterizing them, and typical values used in the design and commissioning phases.

Chapter 3, *Machine learning fundamentals and case-based reasoning*, presents the main machine learning methodologies and techniques. A special attention is paid to the case-based reasoning approach, which is the selected foundation to build the solution developed in this thesis.

Chapter 4, *Cognitive science applied to reduce optical network operational margins and work scenario*, presents the network model used to develop the cognitive proposal and the proposed approach regarding the criteria, parameters and observed rules. Results obtained are presented in the next two chapters.

Chapter 5, *Cognitive approach evaluation to reduce the system margin over an optical transport network*, is dedicated to analyze and assess whether or not the cognition proposal can be applied in networks, as a solution to achieve operational margin reduction leading to help telecom operators to save costs.

In Chapter 6, *Dynamic learning strategies for operation margin reduction*, a dynamic extension to the solution presented in the previous chapter is developed; the CBR cognitive technique and the details of the proposed active learning strategies are presented.

Finally, the main conclusions of this thesis and future lines of research are drawn up in Chapter 7.

Chapter 2

Design and configuration processes in long-haul optical transport networks

This chapter gives an overview of optical fiber transmission systems enabling new generation optical transport network deployment. To begin, a look at main devices and components for optical communications is firstly taken. Therein, a quick glance to WDM technology is thrown. Next, an optical link model is then proposed, accompanied by a further detail of the main parameters of the network elements involved in an optical link implementation. The focus is then put on the main basic procedures applied during design, deployment and commissioning stages of an optical transport network, with the aim of understanding their impact on the later maintenance and operation. Supported on the optical power budget tool, these network processes still present a set of challenges which are outlined in the next sections of this chapter and faced out throughout this thesis.

2.1 Optical network architectures

Optical Networks offer huge bandwidth and capacity (above Tbps), because the physical media used, the optical fiber, allows for low signal attenuation, low distortion and low material cost (without considering the deployment). Optical networks can be segmented based on the covered area criterion in Access Networks, Metropolitan Networks and National/International Networks.

As mentioned in the previous chapter, historically optical network evolution progressed from using optical fiber just as physical media to connect two point-to-point nodes, taking advantage of its physical properties, until resulting in photonic networks, with the creation of the optical paths or lightpaths transported over the optical fiber, with the corresponding evolution of the network nodes (particularly Reconfigurable Optical Add/Drop Multiplexers and Optical Cross Connect), allowing for an all-optical network with nationwide extension.

Access Networks cover the last-mile, from the Central Office (CO) of the area until home users. Metropolitan Networks (MAN) shall cover a city and the surrounding areas. National or International Networks (WAN) shall cover wide areas, countries and international connections. Depending on the type of optical network, technologies used to transport the optical signal may be different. For example, in the Access Networks ecosystem, GPON/XG-PON [15] [16] [17] standards are implemented in FTTx architectures (being FTTH, Fiber To The Home, or FTTCurb, Fiber To The Curb, the most widely extended). Therefore, the architecture of an optical network can be split into three main basic blocks, as show in Figure 2.1:

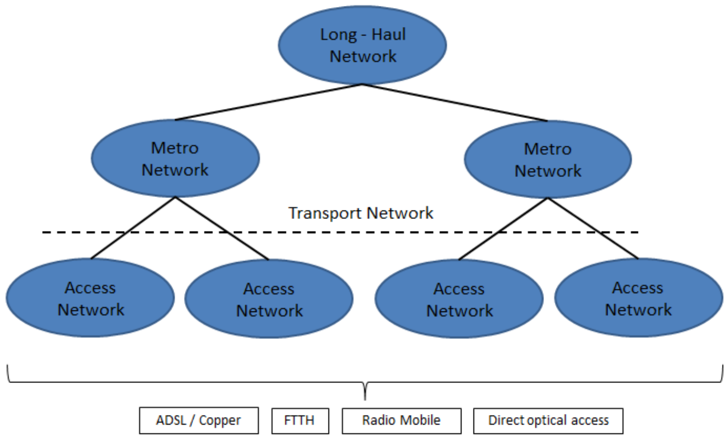

Figure 2.1. Optical network architecture

In this thesis, the focus is established on the long-haul optical transport networks. This segment of the network is characterized by high capacity optical fiber links between cities and major network elements. Typical distances between intermediate nodes can vary from 100 to 10.000 km. As indicated in the previous chapter a network based on the DWDM technology is assumed. Network topology depends on the network segment addressed, it can belong to mesh, star or ring categories. Services are transported over lightpaths or logical end-to-end optical connections between end nodes. Each lightpath is associated to a required Quality of Service to be guaranteed in order to ensure the communication. Thus, depending on the interconnection requirements, lightpaths can have different lengths and can be heterogeneous in terms of number or type of traversed nodes, so as the bandwidth needed per lightpath. Long-haul networks typically transport optical signals on the 1550 nm Band.

2.1.1 Wavelength division multiplexing systems

This technology is widely extended and implemented in optical transport networks, mainly in metro and WAN areas. It is one of the factors at the origin for the optical transmission systems deployment success.

Commercial WDM appeared around 1995 with the objective of multiplexing several traffic channels or client wavelengths over the same optical fiber to take advantage of its high capacity;

the number of kilometers of fibers already deployed in the field did also represent a driver. It was conceived to achieve transparent transport of multiple services and high capacity. More than simultaneous 160 channels with a capacity of 6,4 Tbps are possible.

WDM provides several important points that helped to its wide generalization: a huge transmission bandwidth, it is independent of the bit rate and the transported customer protocols, although IP it is the most commonly used, and signal remains in the optical domain; WDM also offers scalability, it allows for adding new channels on demand and enables a dynamic provisioning, being able to provide and implement new high bandwidth services in a relatively short time. WDM also offers lower cost and better scalability against legacy Synchronous Digital Hierarchy (SDH) structures for telecom operators. However, some weak points can be found as well: normally, at initial stages of this technology, signal had to be electrically converted at the end of the link and then, an important volume of transponders were needed. Moreover, new optical system components were necessary, such as multiplexers and demultiplexers.

Some standards were released: ITU-T Rec. G.692 [18], where the specification of multichannel optical interfaces was introduced, to achieve transversal compatibility between systems. This recommendation specifies other practical operational aspects, as the maximum number of channels (4/8/16/32/…), the type of signal to be transported (STM-64,…), span distances (long-haul, 80km, very long-haul, 120km and ultra-long-haul) and maximum span attenuation and fiber types (G.652/G.653/G.655).

Several flavors of WDM systems were proposed: Coarse Wavelength Division Multiplexing (CWDM, ITU-T Recommendation G.694.2 [19]) or low cost WDM systems, which use few optical channels (bands O to L), with a higher separation between contiguous channels, allowing the transport of a less volume of optical channels. Therefore, CDWM is adapted and commonly implemented in metropolitan networks. And Dense Wavelength Division Multiplexing (DWDM, ITU-T Recommendation. G.694.1 [20]), in the bands C and L, with a fixed grid (fixed spectrum) separation between channels (100 GHz and 50 GHz wavelength spacing) provides a higher number of simultaneous optical channels and it is usually implemented in national or international networks. In the recommendation ITU-T Recommendation. G.694.1 [20], the concept of flexible separation between channels or flexi-grid was introduced, a flexible allocation or separation of frequencies, allowing to use frequency slots of different bandwidths to optimize the requirements of the spectrum efficiency and capacity. This flexible concept of optical channel allocation on demand also enables to combine and mix bit rates and/or modulation formats for different individual or single channels in the same DWDM transmission system.

Finally, the ITU-T Recommendation G.696.1 [21] introduced bitrates of 100 Gbps, together with the number of spans and the span attenuation specifications (up to 11dB for short-haul, up to 22dB for long-haul and up to 33dB for very long-haul spans). Typically, current deployed systems offer 40/80/160 channels, bit rates of 40 Gbps, 100 Gbps or beyond and client interfaces for SDH, IP, GigaEthernet and the rest of the most commonly used protocols, accommodated over C, L and S transmission bands.

2.1.2 Optical link model

In this section a basic model of an optical transmission point-to-point link between two nodes is described, so as the main characteristics of the different network elements that can be part of it. A basic model of an optical end-to-end path can be characterized as follows:

- a transmitter followed by a Multiplexer,
- the fiber link and one or several in-line optical amplifiers; Dispersion Compensation Management modules (DCM) can also be part of the link,
- some intermediates nodes such as Reconfigurable Optical Add/Drop Multiplexers or Optical Cross Connects or OXC,
- a demultiplexer ending into a receiver.

In the optical path between two nodes, the link can be considered as composed of the concatenation of multiple amplified links.

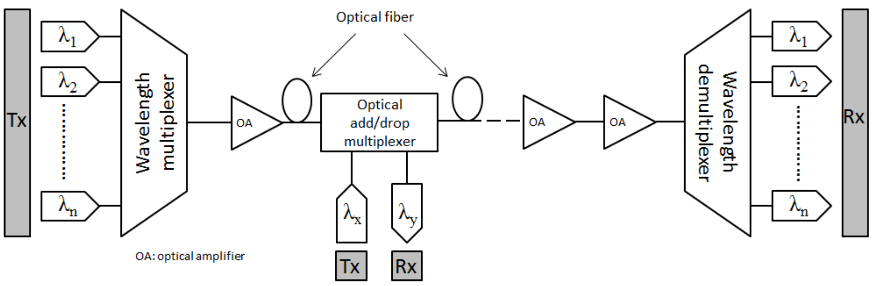

Figure 2.2. Optical link model

In this thesis, each lightpath has been modeled as a concatenation of links, which are in turn, a concatenation of several spans. Between both end nodes, there is a transparent optical signal transmission through several traversed intermediate nodes, without regeneration.

The following paragraphs present a brief description of the main network elements or devices that may have an impact on the optical power budget. Besides a basic explanation of the technology used to implement such nodes, the main parameters to be considered in the design phase of the network links and their typical values are indicated.

2.1.2.1 Transmitter

A single optical channel is characterized by a wavelength nominal value. The optical signal, once generated through an electro-optical signal conversion, it is modulated and transmitted. In current long-haul networks, the transmitter is based on laser technology. A laser has to provide stability in the emitted wavelength in terms on the spectral frequency, so as in the optical power launched on that wavelength. The transmitter parameters to be taken into consideration when designing the optical power budget of a link are usually specified by the provider. Some of them are: the transmitter center wavelength (nm) and the nominal values at both the beginning-of-life (BOL) and the end-of-life (EOL) of the device; the deviation raised from ageing is usually indicated in pm units; the modulated spectral width (nm units), normally indicated as the full width at -20 dB from the maximum value; the center wavelength spacing, expressed in GHz units; the transmitter Extinction Ratio, in dB units; the Relative Intensity Noise (RIN) in dB/Hz, the tolerable back reflection, in dB; the dispersion power penalty, in dB, and the transmitter optical output power, in dBm. Regarding the output power, it is usually quantified as the average power coupled into the single mode fiber of the link. Usually the working optical bands used for these transmitters are the band C (Conventional, 1530-1565 nm) and band L (Long, 1565-1625 nm).

With the aim of indicating some typical values, pluggable optical modules at transmission normally present, for example, for a link of 120 km and a transmission bit rate around 2.5 Gbps, a maximum launched power around +4 dBm, having at the receiver side (for example, an avalanche photodiode, APD, device) a sensitivity of -28 dBm, with a minimum receiver overload of -9 dBm [22]; for transmissions at 10 Gbps over links of 80 km a sensitivity (APD-XFP device) of -24 dBm and a minimum overload of -7 dBm may be found, or a sensitivity (PIN-XFP device) of -16 dBm (EOL value) and a minimum overload of 0 dBm; for devices using Pol-Mux BPSK and Pol-Mux DQPSK modulation formats, deployed optical pluggable modules normally present a maximum mean launched power of around 0 dBm and a minimum mean launched power of about -5 dBm, combined with a receiver sensitivity of -16 dBm and a minimum overload of 0 dBm (PIN device); whether Optical Duobinary (ODB) modulation is used in transmission, a maximum mean launched power of around 2 dBm and a minimum mean launched power of about -3 dBm, and a receiver sensitivity of -26 dBm with a minimum overload of -9 dBm (APD receiver) can be found. For Pol-Mux QPSK modulation, a maximum mean launched power of around 0 dBm and a minimum mean launched power of about -5 dBm, together with a receiver sensitivity of -16 dBm and a minimum overload of -0 dBm (PIN) can be found on field, for 80 km links. In case of considering 10 Gbps and 80 km links, a maximum mean launched power of around +4 dBm and a minimum mean launched power of about 0 dBm, and a receiver sensitivity of -24 dBm and a minimum overload of -7 dBm (APD device) can be deployed [22] [23] [24].

2.1.2.2 Advanced modulations formats for high spectral efficiency

In the previous paragraph, some transmission power values have been indicated, showing a dependency on the modulation used by the transmitter. One important aspect of both transmitter and receiver is the modulation format used for transmission; optical modulators and demodulator devices and different formats can be used to achieve high spectral efficiency. Several solutions are proposed by technology: from Intensity Modulation / Direct Detection (IM-DD) basic and initial schemes towards Phase Modulation / Differential Detection and Polarization Modulation / Multiplexing, combined with Coherent Detection. In the Modulation and Demodulations schemes several possibilities exist: Direct Modulation (of intensity, frequency or phase) which can be combined with intensity Direct Detection or Differential detection (of phase, frequency or polarization). Intensity Modulation or On-Off Keying (OOK) has been normally used to achieve until 10 Gbps rates. For bitrates above 10 Gbps, External Modulators (EML) are normally used, replacing the initial and simpler Direct Modulation

(DML) device [6], although they can also be used for bitrates below 10 Gbps [23], even if it is not very efficient. EML can modulate several features of light: intensity (EAM, Electro-absorption Modulators, using the Franz-Keldysh Effect [25], phase or polarization (ERM, Electro-Refraction Modulators, using the Pockels Effect, [25], so as both intensity and phase simultaneously (MZM or Mach-Zehnder Modulator flavors are used due to the versatility in the optical carrier processing) [6]. In fact Mach-Zehnder modulator has been further developed and used for high spectral efficiency and it is very used for most of the high efficiency modulations formats (DQPSK).

At reception, for high transmission rates, coherent detection technology is used in optical reception, against legacy Direct Detection initial solutions. In Direct Detection (DD), as the optical signal is directly detected by the photodiode without any processing, information on frequency and phase is lost, only amplitude (power) modulation can be used [6]. However, coherent detection techniques recover information from amplitude, frequency, phase and polarization; they are applied to allow very high transmission rates (40 Gbps and mainly 100 Gbps or beyond) while maintaining equivalent performance that the one showed by legacy 10 Gbps DD systems. Coherent detection normally uses a local oscillator (LO) at the receiver at the same frequency that the received signal to recover all the information. Among the devices using this type of reception technology, synchronous systems applying homodyne detection (same frequency) and heterodyne detection (different frequency) can be encountered on field. Normally, coherent technology presents higher tolerance to Chromatic Dispersion (CD) and Polarization Mode Dispersion (PMD) impairments, allowing to avoid the deployment of Dispersion Compensating Management devices (DCM) and consequently to enlarge the transmission spans without the need of applying dispersion compensation techniques which normally involve time processing costs. To be noted that coherent transmission systems can transmit both coherent and non-coherent signals; this allows to upgrade legacy networks equipped with DCM devices along the paths with coherent data channels. In a commercial network both types of wavelengths simultaneously transmitted can be encountered; these situations are normally originated due to a non-homogeneous upgrade of certain segments of the network. This fact may be one of the root causes at the origin of inconsistencies or misalignments between the designed optical power budget and behavior encountered on field.

Regarding the modulation itself, modulation phase formats (Phase-Shift Keying, PSK) are used for high bitrates transmission, as Binary PSK (BPSK), QPSK, DPSK, DQPSK (four states in the constellation phase space, with the information contained in the differential phase), Dual-Polarization QPSK (DP-QPSK with two polarization modes being added to the DQPSK format), Pol-Mux QPSK or Pol-Mux QAM formats, combining modulations in amplitude and phase (QAM). These modulations formats are normally integrated in the Photonic Lightwave Circuits (PLC); they can offer 40 Gbps, 100 Gbps and beyond, integrating Polarization Division Multiplexing (or Pol-Mux) Quadrature Phase-Shift Keying (PDM-QPSK) coherent technology in commercial products. Each modulation format presents either advantages and weak points, depending on the situation. For example, DPSK is quite robust against non-linear impairments and tolerant against CD and PMD effects. DQPSK can be used to transport 40 Gbps signals (40G) and it can be used to reduce non-linear effects related to the phase, such as self-phase modulation (SPM) and cross-phase modulation (XPM). In 100 Gbps wavelength channels (100G) chromatic dispersion, PMD and non-linear effects raise as important limitations for long-haul optical networks; coherent detection techniques may help to cope with them [24] [26]. Pol-MUX is based on QPSK modulation and exploits the orthogonal polarization feature of light to modulate separately the X and Y axis polarization modes with QPSK format. Pol-Mux QPSK is normally used in 100 Gbps systems, and Pol-Mux BPSK, only uses two phase states, allowing longer transmission distances; this modulation is used normally for 40 Gbps signals in long-haul networks [24] [26].

Then, among the modulation formats more commonly used for high spectral efficiency transmission can be considered DQPSK and Polarization Division Multiplexing variations. Typical formats found on field may be 20 Gbps DQPSK & 40 Gbps Pol-Mux DQPSK, 100 Gbps Pol-Mux QPSK and 40 Gbaud DQPSK/D8PSK transmission systems (where SPM and XPM non-linear impairments can be important and limiting the communication). 40G Pol-Mux BPSK and 100G Pol-Mux QPSK modulation types are applied in coherent transmission systems (for 40-wavelength systems) [24] [26]. In current transport networks an hybrid transmission of optical channels is commonly deployed, for example, a simultaneous transmission of 100G and 40G BSPK signals, 100G and 40G DQPSK signals, 40G BPSK and 40G DQPSK signals, 100G and 10G/40G ODB signals, 40G BPSK and 10G/40G ODB signals, as well as 40G BPSK and 10G/40G ODB signals. This hybrid transmission over the same fiber of simultaneous optical channels at different bitrates and using different modulation formats lead to impairments that must be appropriately compensated when designing the optical power budget for a lightpath.

2.1.2.3 Multiplexer and demultiplexer

The next type of network element in the model of an optical link is the multiplexer and demultiplexer (MUX/DEMUX) node. This network element is a passive device made with tunable filters. Several technologies can be used to implement such nodes [5]: Thin Film Filters (TFF), Fiber Bragg Gratings (FBG filters) and Array Waveguide Gratings (AWG). These optical filters have a wide tuning range to allow a selection of a great number of channels (wavelengths). AWG devices are commonly used as MUX/DEMUX nodes to combine and extract a high number of wavelengths channels spaced by few nanometers. In fact, the channel spacing of the wavelengths to be combined is an important design parameter; commercial devices with 50 GHz spacing can be normally deployed. They are based on a series on multipath Mach-Zehnder interferometers. These AWG components can also be used as switching devices to build Optical Add/Drop Multiplexer (OADM) and Optical Cross-Connect (OXC) nodes. Ideally, from a performance point of view, they have to introduce low insertion losses and low polarization dependent losses (PDL), so as to present a very accurate ability to tune wavelengths and to keep stability when it is done; low CD and low crosstalk can distinguish good quality devices on the field. Some of the typical parameters encountered in the commercial boards used are: in the MUX boards, insertion losses <= 6.5 dB, adjacent channel isolation around > 25 dB, PDL <= 0.5 dB, PMD < 0.5 ps. In DEMUX boards, insertion losses <= 8.0 dB (BOL value) or 8.5 dB (EOL value) [27], adjacent channel isolation around > 25 dB, attenuation ranges between 0-15 dB and PDL <= 0.5 dB [24] are usually found.

2.1.2.4 Optical amplifier

One of the main network elements in a link is the optical amplifier (OA). Several types of amplifiers can be found depending on their location on the network and objective: boosters (normally located at the beginning of the link, when optical signal is delivered to the fiber in the input), in-line amplifiers (all along the paths and between nodes) and pre-amplifiers (located at the end of the link, when optical signal is arriving at the reception node). The more common OAs used and deployed in commercial networks are those based on the fiber itself: they are known as EDFA (Erbium Dropped Fiber Amplifier) and Raman amplifier (amplification based on non-linear effects on fiber) [6]. In this thesis, focus is done on in-line amplifiers. Key elements in an optical amplifier are the bandwidth, the noise figure (NF) and the gain (G); also the bandwidth range and the number of simultaneous/maximum channels to be amplified. This type of devices amplifies optically the signal, although it does not compensate the dispersion and usually introduces noise. Semiconductor Optical Amplifiers (SOA) devices shall present diaphony problems; they are normally used as boosters [6]. Characteristic parameters and typical values presented by these type of SOAs may be an input power signal around 0 dBm and an output power signal of around 20 dBm. In case of being used as pre-amplifiers, they normally present a gain around 35 dB, with an input power of around -30 dBm and NF values around 3.5 - 8 dB, at the transmission and reception of the lightpaths. SOA amplifiers normally present less nominal gain than EDFA devices and a higher NF. From a technological point of view, EDFA and RAMAN amplifiers are based on a forward and back pump process. EDFA is usually used in the third window (C and L bands). The limiting aspect when designing and calculating the optical power budget regarding EDFA is the noise introduced (Amplifier Spontaneous Emission, ASE noise) by this type of amplifier, which degrades the OSNR at the receiver and then limits the maximum number of cascade EDFAs allowed to be installed along the fiber; EDFA is normally deployed in commercial networks because they present low diaphony between channels, although due to variations in the spectrum not all the channels can be equally amplified, and an equalizer functionality or device shall also be used in this case.

Regarding optical specifications [24] [26] [27] an EDFA OA device presents the following common parameters which have to be taken into account when designing the link: the operating wavelength range (normally, the third window, 1530-1565 nm), the nominal (and channel) gain (between 17-31 dB), the nominal input power range (between -32 to -6 dBm), the input power range per wavelength ([-32, -16] dBm for 40 channels systems), the nominal single wavelength input and output optical power (around -16 and +4 dBm, for 40 wavelengths systems), the noise figure (with maximum values around 7.5-5.5 dB), the flatness gain (0.5-2.0 dB), the maximum total output optical power (around +22 dB for in-line applications), the input power range, the Polarization Dependent Losses value (PDL, normally $\leq$ 0.5 dB), the Polarization Mode Dispersion value (PMD, around 0.5 ps) and the Polarization Dependent Gain (around 0.5 dB).

For its part, RAMAN uses the Stimulated Raman Scattering (SRS) effect to amplify the optical signal (by transferring optical power towards higher wavelength channels). This type of amplifier should present PDL impairments. Concerning optical amplifiers aspects and parameters to be considered in the design phase, they can be mainly found in ITU-T Recommendation G.662 [28].

One important aspect to be considered is how the channel gain is affected when wavelengths are added or dropped. An abnormal loss on the line can be raised due to factors as optical fiber ageing, optical connector ageing and other power changes. When this situation occurs, the optical signal-to-noise ratio (OSNR) of the system will be degraded and the quality of service and even the communication may be lost. Functionalities to adjust the optical output power of the amplified channels so as to ensure their flatness in terms of output power are implemented in commercial networks in order to avoid communication issues.

2.1.2.5 Optical fiber

Regarding the optical fiber itself as the physical transport media, the elements to be taken into account in the transmission characteristics are the attenuation losses along the fiber (modeled by the attenuation coefficient), the dispersion introduced, as chromatic dispersion, so as the PMD limit per channel. Values of these parameters must remain as low as possible in order to optimize the transmission. All of them shall depend on the type of fiber used. The attenuation coefficient models the maximum attenuation of light along the fiber and its value shows a dependency on the wavelength range; common characterization values found on commercial products are around 0.4 dB/Km @1310 nm, 0.21-0.25 dB/Km @1550 nm and 0.25 dB/Km @1625 nm for AllWave™ Lucent's Single-Mode and AllWave® Zero Water Peak OFS Fitel ITU-T G.652 optical fibers [23] [29] [30]; or 0.25 dB/km @1550 nm and 0.28 dB/Km @ 1620 nm, for TeraLight™ Fiber ITU-T G.655 [31]. The dispersion phenomenon means the broadening of the pulse of light when travelling along the fiber due to a difference in a group-velocity depending on the wavelength, known as the Group-Velocity Dispersion (GVD) parameter. The input pulse is composed of slightly different colors and the output pulse is broaden causing the overlapping with neighboring pulses, leading to errors at reception. This type of dispersion depends on the wavelength and it is called the Chromatic Dispersion (CD). Optical fiber can be modified to manage the chromatic dispersion effect; with this aim the Dispersion Shifted Fiber (DSF) (built to provide no dispersion at 1550 nm) and the Non-Zero Dispersion Shifted Fiber (NZ-DSF) (modified to provide zero dispersion in the limits of the Band-C) were developed. Regarding the optical fiber, several ITU-T recommendations exist, although the main ones are G.652 (monomode fiber), G.653 (monomode fiber with shifted dispersion) and G.655 (non-zero dispersion monomode fibers). Concerning their deployment on commercial networks, standard fiber G.652 presents high dispersion at 1550 nm, which is necessary to be compensated to achieve bitrates above 10 Gbps for single channels.

There is another type of dispersion effect that can be found on field, the PMD (Polarization Mode Dispersion). Modal dispersion means that two different polarizations travel at different speeds along the optical fiber due to random imperfections and asymmetries in it. Thus, this type of dispersion leads to random broadening the light pulses depending on the polarization, because elipticity or tension lead to birefringence (different refraction indexes on the horizontal or vertical modes, mainly in the LP01 mode). Then, PMD effect limits the rate at which data can be transmitted over a fiber. PMD is statistical in nature, average values are considered when characterizing an optical link. The maximum transmission distance decreases when transmission bit rate increases. That is, due to PMD, maximum length span without amplification at 40 Gbps is lower than that reached at 10 Gbps. In terms of optical power budget, a PMD penalty is normally introduced and typical values are < 1dB when specifying PMD values. It is measured in ps/√Km. ITU-T Recommendation G.663 [32] recommends to cope with the PMD effect; this impairment has to be compensated if bitrate is above 40 Gbps and the link length is above 600 km.

In order to manage dispersion some external elements can be introduced, which are called DCM (Dispersion Compensation Management) modules, such as Tunable FBG-Dispersion Compensator devices, which present low insertion losses (around 2 dB) and low polarization dependent losses (around 0.3-05 dB), so as electronic Chromatic Dispersion compensators. Dispersion can also be directly managed at transmission, for example by using Chirp Managed Lasers (CML) [33] and at reception, with electronic compensation techniques in the DSP, or in both sides by using modulation formats providing protection against dispersion. For example, DQPSK modulation scheme can be used for CD ad PMD compensation in 40 Gbps bitrates scenarios, improving CD and PMD robustness.

Other type of losses that can be found in optical links are the PDL (Polarization Dependent Losses). These losses are due to changes in the polarization of the optical signal. The transmitter laser light is polarized and random changes when travelling along the fiber can occur. This can cause fluctuations during the detection. This maximum optical power fluctuation is measured by the PDL.

2.1.2.6 Reconfigurable optical add/drop multiplexer

An important network element in transport optical networks is the Reconfigurable Optical Add/Drop Multiplexer (ROADM), which opened the way towards photonic switching. As indicated in precedent sections, this network node allows to insert or extract individual wavelength channels into or from the transport fiber without impacting the rest of the data channels. In an optical transport network, the ROADM node is the element in the edge of the network interfacing with the client routers (Ethernet, IP routers) for inserting and delivering client traffic. The end-to-end lightpaths normally start and end in this type of network node. Several technologies can be used to implement them, such as Thin-Film Filters (TFF) and tunable Fiber-Bragg Gratings (FBG), based on light reflection properties by reflecting particular wavelengths and by transmitting others, combined with other optics as optical circulators. Other solutions are 2D/3D MEMS mirrors (Micro-Electro-Mechanical Systems) which are used as MxN optical switches [6]. These devices are based on addressing the lightwave from an input fiber towards a mirror (reflector), which can be mechanically manipulated to readdress the lightwave towards another mirror and to the desired output fiber. MEMS devices parameters to be taken into account when designing the power budget are the insertion losses of both passed-through lightpaths and added/dropped lightpaths (values between 0.2 and 1.5 or 2.5 dB), PDL (around 0.3 dB), crosstalk (around -50 dB), wavelength dependency (0.5 dB) and input optical power (+20 dBm) [6]. MEMS devices flavors can be 2D and 3D, although they may also present a 4-Plane configuration, this last one allowing switching between input and drop channels, add and output channels and input and output channels. The 3D MEMS technology in optical switches allows for all-optical switching with low insertion losses (< 5 dB), low diaphony (above -50 dB) and low PDL. Other technology that can be used in Optical Add/Drop Multiplexer (OADM) nodes is the Array Waveguide Grating (AWG), which in turn can also be used as optical switching. Moreover, an OADM node can become a ROADM, which can be dynamically configured based, for example, on wavelength blocker technology and by using tunable transceivers. These wavelength blocker devices [6] present normally parameters and typical values as follows: channel spacing (50 GHz), low insertion losses (between a maximum of 4 and 5 dB), PMD (0.5 ps), PDL (0.3 dB), maximum optical power per channel (+17 dBm) and total optical power (+27 dBm) [27]. Wavelength routing is another application of the wavelength-blockers. ROADM nodes can be built as Wavelength Selective Switches (WSS-based) ROADMs, which are a combination of 1xN and Nx1WSS modules [6]. A WSS node can present the following performance parameters: wavelength range, channel spacing, channel insertion losses (6.2-8.0 dB), chromatic dispersion (-20/+20 ps/nm), maximum optical input power per channel (+14 dBm) and maximum total optical input power (+24 dBm) [27]. ROADM reconfigures wavelengths by adding, blocking or cross-connecting them. These network nodes, operated with an appropriate management protocol can dynamically and remotely adjust the fact of adding, dropping and passing-through wavelengths in 40-wavelengths systems. Terms as colored-colorless and directioned-directionless are commonly used in the industry, related to ROADM nodes. Colored ports mean that each port is able to add/drop only fixed wavelengths; if any wavelength channel has to be reconfigured, it is normally done manually. By the contrary, colorless ports mean that any wavelength can be added at a port and any wavelength can be dropped at a port of the board. Another characteristic is the Direction functionality, meaning that a wavelength can only be transmitted in one route; directionless functionality means that a wavelength channel can be transmitted in any direction. A ROADM node can present several degrees, representing the number of possible directions in which the traffic can be transmitted: one, two, three, four, five degrees and beyond can be found in commercial products. In the Fixed/Reconfigurable OADM nodes some signals are dropped at the network element and the other wavelength channels are either passed-through or multiplexed with the locally added new wavelengths and transmitted in the configured direction. For example, Figure 2.3 lays out a 4-degree ROADM:

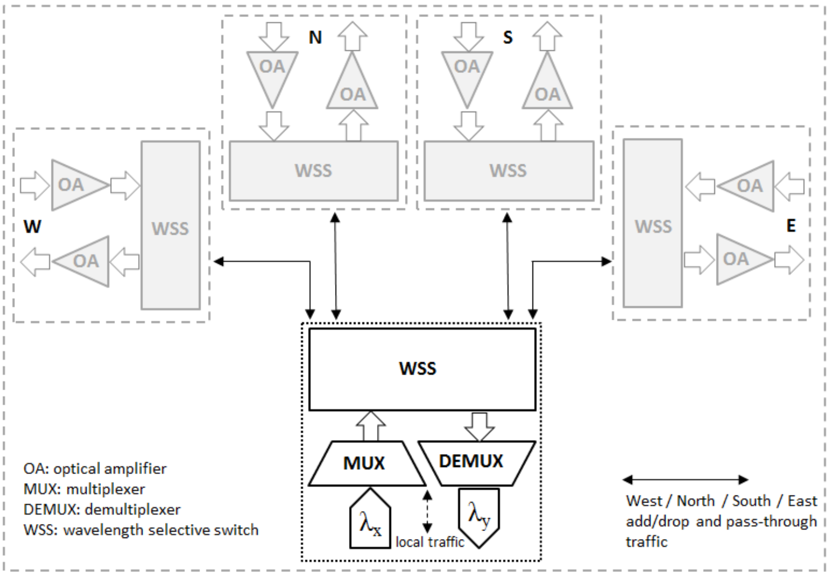

Figure 2.3. Simplified architecture of a 4-degree ROADM

When considering Fixed OADM network elements, the following parameters are to be taken into account: adjacent channel spacing (around 20 nm, depending on the multiplexing technology), drop channel insertion losses (<= 1.5 dB), adjacent channel isolation around (> 25dB), add channel insertion losses (<= 1.5 dB) and isolation (>= 13 dB) [24].

In the case of the ROADM nodes, the following parameters can be found in deployed cards: insertion losses (around 8 dB), port isolation (>= 25 dB), directivity (>= 35 dB), module switch time (<= 3 ms), PDL (<= 1.0 dB) and a dynamic attenuation range around 0-15 dB; parameters concerning the optical amplifier integrated in this node for adding channels are the nominal input power range ([-32,-9] dBm), the NF (<= 6dB), the nominal gain (for example 22dB), the gain flatness (normally around <= 2 dB), the maximum total output power (for example +13 dBm) and PDL (<= 0.5 dB); the optical amplifiers integrated in the ROADM for drop channels normally present a nominal input power range of [-32,+1.5] dBm, a NF around <= 6dB, a nominal gain for example of 19dB, a gain flatness <= 2 dB, a maximum total output power of +20.5 dBm and PDL <= 0.5 dB [24].

2.1.2.7 Optical cross-connect

Once the optical signal is being transported in the optical transport network, it is switched by means of OXC nodes. These network elements are also based in AWG technology. In optical channel switching several possibilities do exist: it can be addressed as fiber switching (all transported channels are switched), as wavelength channel switching (between different input and output ports) and as wavelength switching (with wavelength conversion being used). OXC nodes can be based on MEMS technology as well, and it may be usual to find hybrid OXC-OADM nodes, using WSS (Wavelength Selection Switches) tunable transceivers on commercial networks [6].

2.1.2.8 Receiver

Finally, receiver device demodulates the optical input signal and after an optical-electrical (O/E) conversion is delivered to the client side. The receiver is usually a photodiode device. As full-duplex transmission is used, single channels are transported over a single fiber and the same physical device is used for transmission and reception of the optical channel, which is called the transceiver. The most common deployed devices are the Small Form Factor Pluggable (SFP) transceiver modules, so as the more recent 10G Small Form Factor Pluggable (XFP) modules for bitrates above 10 Gbps and Centum Form Factor Pluggable (CFP) 40G/100G modules [34]. Parameters characterizing the receiver module are: the input wavelength, the receiver reflectance (expressed in dB), the dispersion noise penalty (dB), the range of the input optical power received and the input optical power receiver damage threshold (in dBm). One important parameter of the receiver is the minimum optical power receiving sensitivity for a specific BER to be guaranteed. SFP, XFP or CFP transceiver modules are devices to be plugged in the boards of node equipment. Today, tunable XFP or CFP devices are commonly deployed. Typical values of receiver parameters, depending on the reception device used, have been pointed out in the Transmitter section 2.1.2.1.

2.2. Non-Linear impairments

In optical transport networks, a high number of wavelength multiplexed channels travel simultaneously over the same physical medium and then a high optical power is present on the fiber. This high optical power involves the appearance of nonlinear effects, giving rise to optical power losses due to these non linearities; these negative effects have to be compensated in the optical power budget with the so called nonlinear power penalties. Normally, when input optical power is higher than +3dBm [35] nonlinear effect starts to appear and shall cause Self-Phase/Cross-Phase Modulation (SPM/XPM), Four Wave Mixing (FWM), Stimulated Brillouin Scattering (SBS) and Stimulated Raman Scattering (SRS) effects, among others. These non-linear effects become important when the Chromatic Dispersion on the fiber is reduced and they are particularly important in long-haul optical amplified and no regenerated transmission systems.

From a physical point of view, the first two types of nonlinear impairments (SPM/XPM and FWM) are due to the Kerr's effect: the refractive index of the fiber depends on the propagating signal power [36]. For their part, the SBS and SRS are due to the appearance of phonons caused by the scattering of photons to a lower energy level. The difference between both effects lies in that in SBS the created phonons are acoustical whereas in SRS they are of optical nature.

In the following paragraphs a brief description of the main effect to be considered in transport network is presented.

2.2.1 SPM (Self-Phase Modulation)

This interference is caused by a phase-shift in the optical pulse, due and proportional to its own intensity leading to a intersymbol interference and a degradation in the BER. It also depends on the fiber dispersion. For transmission rates above 10 Gbps, the SPM effect increases [35]. In [37], it is indicated for example that, for 40 Gbps bit rates and a maximum launch power of +2 dBm, the maximum distances are around 540 km (under the condition that all spans are dispersion compensated, except the last one).

2.2.2 XPM (Cross-Phase Modulation)

This nonlinear effect is equivalent to SPM, however the optical power causing this impairment is that of the others signals travelling simultaneously in the fiber [38]. Then, apart from the launched channel power, it also depends on the channel spacing used and the fiber dispersion [35]. By using dispersion compensating fiber this effect may be reduced.

2.2.3 FWM (Four-Wave Mixing)

FWM is an intermodulation distortion in optical networks: three wavelengths travelling together in nonlinear mediums they give raise to a fourth wavelength. FWM effect is also known as interchannel crosstalk, which reduces OSNR and increases the required BER [38]. As indicated above, FWM can be mitigated by using a flexible grid between channels or by using fibers presenting non-zero chromatic dispersion: ITU-T recommends the use of G.655 fiber to reduce this type of distortion. These methods can be used to reduce FWM interference although they do not completely eliminate them.

Among the different types of fiber that can be deployed in commercial networks, ITU-T G.653 fiber (zero-dispersion at 1550 nm) is the more impacted by FWM effect. A fixed separation between channels (fix grid) can worsen the problem. For the fiber types G.652 and G.655, ITU-T G.692 recommends a fix grid regarding channel spacing in G.694.1, for DWDM systems.

SPM, XPM and FWM non linearities limit the maximum transmission bitrate in the optical link. As indicated in a previous paragraph, DQPSK modulation format can be used to reduce some of the non-linear effects related with the phase such as the SPM, XPM and also the FWM. Besides, this modulation format presents higher tolerance against CD and PMD effects and it is used in long-haul transmission networks [24].

2.2.4 SRS (Stimulated Raman Scattering) and SBS (Stimulated Brillouin Scattering)

In SRS energy is transferred from 1550 nm signals to the 1660 nm signals, leading to cross-band interference; it is to be noted that this same phenomena is also used in the Raman amplification devices but in this case to take advantage of it and amplify the signal. In the transport optical networks, as multiple wavelengths are simultaneously multiplexed on the same link, the SRS optical power is transferred among them, involving degradation of the performance. In SBS the same effect appears leading to similar degradation on the performance, and cross-talk interference between channels may appear [36]. Therefore both SBS and SRS effects impact on the channel spacing and the number of channels used.

2.3 Design, deployment and commissioning processes

In general, when an optical network site is to be deployed and installed by a telecom operator, a common rule and practice followed by the network design teams is to over dimensioning the volume of boards and transceivers not only to support the primary paths but also to provide protection strategies. Moreover, once a lightpath is established to support client communications, the transmission power launched by the transceivers is also normally over dimensioned to ensure the proper quality of service between end nodes. However, of course, a telecom operator needs simultaneously to save both CAPEX and OPEX. Thus, regarding such over dimensioning practices, one of the factors to be tackled to reduce CAPEX may be the optical transmission power, by properly reviewing the design and commissioning processes. Actually, if the launched power may be diminished, the transceiver's lifetime can be prolonged [39][40][41][42][43], and therefore telecom operator could reduce their replacement rate all over the network. This way, the needs to purchase new transceivers is relaxed, in terms of both replacement parts and maintaining stock. The transceiver life can be extended because the laser life can be prolonged when decreasing the working time or optical power transmitted [40]. As a consequence, the CAPEX dedicated budget can be reduced.

2.3.1 Designing a long-haul optical transport network

During the design phase of a network, the map of the network is firstly drawn. This diagram depicts how sites and locations are connected as well as the type of sites, such as for example multi-degree (2 and beyond) ROADMs. The end nodes or terminal stations are also indicated, which are specified as level 1. It means for example that if a level 3 ROADM is deployed in a location, one of the directions is indicated as terminal, meaning that in this path there is insertion and extraction of client traffic (terminal station). In the network map the location of the in-line amplifiers along the inter sites links are indicated.

The envisioned protection paths are also depicted, so as the links that are owned by the operator and also the leased lines or third-party (alien) lambdas, if existing. The length of the link and the spans are also layout.

The second step is to list the available routes; in case of a national or international network it is not a list between each pair of nodes, because it could make difficult the overall view of the network design. Typically, the main routes are identified and listed; in fact, they traversed the nodes and this approach provides a clearer global view of the network while simultaneously all the nodes and links are finally considered in the design and parametrization. For the same route, the design is done for both clockwise and anticlockwise directions.

In terms of design documentation used for calculations, regarding fiber parameters, in each site the type of connectors is indicated (i.e., SC/APC, SC/UPC, FC-APC and others) so as the distance between intermediate sites multiplied by the fiber attenuation coefficient, normally considering transmission over the third window. For the connectors insertion losses, maximum nominal values are also applied, together with the PMD value depending on each type of connector.

Regarding lightpaths between end nodes, losses in the link between major sites and type of boards are indicated, specially amplifier boards; ageing and safety margins are included in the span losses. Regarding ROADMs, insertion losses in any direction (e.g., east-west, west-east, east-north, etc.…) are also indicated, which have not to be the same over the entire network.

All these parameters are included in the design documentation in order to calculate the optical power budget and the OSNR for the lightpaths to be established to support client traffic.

For each of them, the vendor or infrastructure provider of both ends has to be taken into account. Actually, telecom carriers normally build the transport network based on equipment from several providers, in order to save costs and at the same time to implement diversification policy in terms of risks, avoiding dependence of a single infrastructure provider. Thus, taking into account the required interoperability among devices from several providers, the design of the optical budget becomes then much more complex. In the optical power budget calculation, line equalization parameters or line design parameters are indicated. For example, let us consider the link between two sites (A and B); the side A transceiver parameters, such as number of channels, modulation format (10 Gbps, hereinafter referred to as 10G systems, 40G QPSK with 10G, 40G PDM BPSK, 100G PDM QPSK, 40G BPSK DCU free, 40G QPSK DCU free, 100G DCU free of different vendors) are specified, so as fiber type (SMF-28® [44], LEAF® [45], TrueWave® [46]) to which the transceiver is connected. Regarding the transmission type some parameters considered are the FEC limit, the baseline EOL, OSNR, the nonlinear penalties and PMD penalties, the crosstalk effect and whereas the transceiver applies coherent reception or not. Regarding fiber parameters, apart the attenuation coefficient, other parameters may also be used, such as the effective area of the connected fiber, dispersion on the connected fiber, dispersion slope, PMD and the maximum losses in span (22, 23, 24 dB…). For each type of board of each vendor, specified parameters may be mean and max PDL (in terms of dispersion), max and min gains, min and max Noise Figure and max transmission power for amplifiers boards, depending whereas it is an EDFA or RAMAN type.

2.3.2 Optical power budget tool

When designing the links of an optical transport network, the optical power budget is used to calculate the theoretical optical link losses. It is one of the most important design parameters. Basically, optical link losses are defined as the power reduction from the transmitter until the receiver when traversing the different elements along the transmission path: fiber spans, connectors, splices and passed-through network nodes. It can be measured as the loss of power experimented by the optical signal between the input and the output of a passive component. Among them, WDMs multiplexers, DCM modules and others can be encountered, which are typically characterized by means of their insertion losses. In order to compensate this effect some active elements such as optical amplifiers are introduced in the link.

The objective of the optical power budget is to guarantee that the optical power received is enough to ensure the communication along the transmission path with the quality of service required, respecting the operation parameters of transceivers both in reception (mainly sensitivity and overload) but also in transmission (maximum optical power launched, controlling the non-linear effects and range of operation transceivers).

In the design phase, the optical power budget is normally calculated as an accumulation of optical losses of each individual component and network elements along the lightpath. Starting from the transmission power, individual losses are progressively subtracted. If the final remained optical power is greater than the sensitivity of the receiver and lower than its overload threshold, the lightpath will ensure the end-to-end communication with the required QoS. The first phase when calculating the link power budget is to use infrastructure and devices provider specification values. Later, measurements performed on field during the commissioning phase will serve to adjust the power budget. In the design phase a worst-case approach is typically followed, although providers are used to indicate nominal and worst-case values. Figure 2.4 shows a typical diagram used by designers.

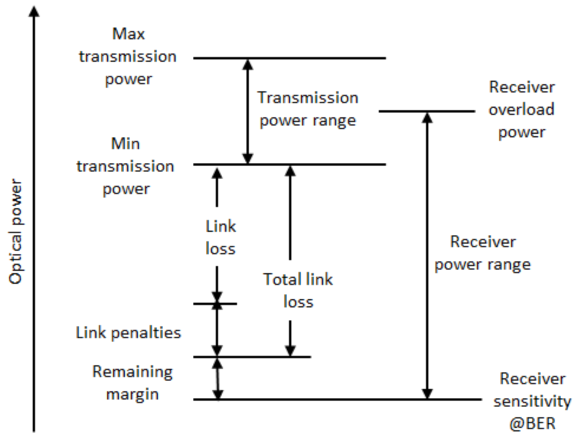

Figure 2.4. Relationship of the optical parameters in power budget

Penalties and margins are introduced as part of the individual items of the link losses. The obtained value is used as reference for beginning-of-life (BOL) of the operation in the network. Typical items included in the link losses are fiber losses, connectors losses, splices losses, multiplexer and demultiplexer losses, DCM losses (if any is deployed along the path), penalties losses (such as dispersion losses or penalties - CD, PMD and PDL and non-linear effects-) and the amplifier gain. Finally, a security margin is introduced to absorb unforeseen degradations and system ageing. The introduction of this last value incorporate the concept of end-of-life (EOL) of the transport network in the link budget. As power losses are dependent on the used wavelength, the optical power budget is calculated for each individual optical channel. In WDM networks is normally worked out for the first and the last optical channel to ensure that the whole range of wavelengths are guaranteed.

As depicted in Figure 2.4, the designed power budget shall provide several required values useful for network designers and deployment teams: the minimum transceiver budget, which is the difference between the minimum transmission power and the receiver sensitivity; the maximum measurable reception power, which is the maximum transmission power minus the link losses without penalties; and the remaining margin, which is the minimum transceiver budget minus the total link losses, including penalties. In the ITU-T recommendation G.957 [47] further detail concerning the relationship of the optical parameters in the power budget is given.

In the process of building an optical transport network several guidelines can be followed: the first step is the optical fiber link to be built by installing new fiber plant or by leasing dark fiber spans to commercial operators. In the second case, either specific wavelengths or the overall spectrum can be leased. If leased lines are part of the transport network, WDM equipment can be added to increase capacity, although it may be not always possible, depending on the dark fiber plant offered by the carrier, since dark fiber leasing infrastructure may not be WDM enabled. In case WDM systems are able to be installed, the WDM equipment and amplifiers can be deployed at appropriate locations of the dark fiber link following the network designer instructions. The main advantage of dark fiber is that any protocol and any data rate can be transported. In this phase it is important to consider the type of fiber of the link (G.652, G.655 or G.653). For long-haul networks, lower attenuation and dispersion losses are desired, and G.655 fiber is a common solution due to its lower dispersion coefficient value. Protection paths are also foreseen at this stage. Whereas leased dark fiber links have been selected for the primary paths, those protection paths can be part of other alternative solutions or carriers, and not necessarily belonging to the same one. In any case, protection paths mean additional network equipment in terms of boards or even cabinets, so as volume of transmission units equipped with transceivers, especially if protection paths have been implemented through an alternative solution distinct to the primary leasing carrier.

During exploitation of the network, if new fibers are deployed, their correct characterization regarding design parameters is important because it will help either to ensure that optical power budget is respected and to establish a reference value for the beginning of life milestone, allowing to detect degradation along time.

The next step in the design phase is to identify the total volume of required optical channels and transmission rates. Concerning the volume of optical channels needed it is important to take into account if client circuits can be multiplexed in time and aggregated into a larger one or if they have to be separated and then optically multiplexed. This point will also condition the selection of the appropriate network end nodes and their dimensioning in terms of required boards and available ports for transceivers.

When the links and network nodes have been selected and properly dimensioned, the next step in the design phase is to calculate the optical link power budget, so as the OSNR and dispersion budgets as well. Optical power budget is calculated for all the links; however, dispersion budget is calculated for links with transmission rates above 1 Gbps (CD dispersion) and above 10 Gbps (PMD dispersion) and OSNR budget is typically worked out for optical links with in-line optical amplifiers. Nonlinear effects are always introduced, although some operators do it only for WDM systems with more than 40 channels. Sometimes the provider of the network infrastructure may be selected after the power budget has been performed, in order to select the best solution in terms of boards dimensioning (hosted by network elements) determined by calculations, availability of required volume of transmission ports depending on the type of available boards, transceiver parameters, compatible types and values adapted to the designed optical power budget. Capacity for future network expansion is also important. Regarding the selection of the optical network provider, the transmission capacity is one of the main drivers when taking commercial decisions, because the objective of the telecom carrier is to accept and accommodate as much client traffic as possible in order to make grow the revenues, at the same time that CAPEX and OPEX needs have to be as low as possible, in order to minimize costs and increase the benefits. However, as indicated above, telecom carrier tends to over dimension the transmission capacity, in terms of available transmission and reception ports, at any site, in order to ensure the quality of the transmission and the client satisfaction to keep customers. This over dimensioning practice leads to increase the number of boards in the network elements, both at transmission and reception, in intermediate nodes (ROADMs, OXCs) and optical amplifiers, which finally leads to highly increase the volume of needed transceivers in the whole transport network.

In the ITU-T Recommendation Series G Supplement 39 [48] developing the “Optical system design and engineering considerations” the worst-case system design is detailed: it is applied in optical systems in client networks, such as OTN and it is characterized by applying optical parameters with maximum and minimum values at the end-of-life ([49], [50] and [51]). In [48] the power budget for multichannel WDM systems are also specified. In this worst-case approach the following optical parameters are considered and applied: maximum and minimum mean (single-channel) output power; maximum mean total output power (for multichannel applications); maximum and minimum attenuation; maximum and minimum chromatic dispersion; maximum differential group delay (DGD); maximum mean (channel) input power; maximum mean total input power (for multichannel applications); so as minimum receiver sensitivity and maximum optical path penalty. It is also indicated in this recommendation that whereas the optical link includes optical amplifiers, the last two parameters are replaced by the minimum receiver OSNR tolerance and maximum optical path OSNR penalty.

2.3.3 Commisioning phase of an optical transport network

Once the design phase is finished and the network sites are installed and deployed, the commissioning phase can start. The main objective of this phase is to measure, verify and adjust, if needed, the design phase parameter values.

From an operation point of view, in the commissioning phase several tools are typically utilized by the operational teams, regarding the optical power budget and the OSNR of the link. In order to ensure that the optical power link budget has been correctly calculated, the total link losses and the amplifier gain are measured and verified on field with tools such as optical power meters (OPMs). It helps operation teams to measure the received optical power, the receiver sensitivity and the receiver overload threshold at the reception port. The optical power can be measured both in the client side interface or in the optical network side (WDM) interface card. It is also able to measure the optical power of the multiplexed signals. The methodology followed when using this tool consists on launching an unmodulated optical signal at the specific wavelength for testing each individual single channel, with the optical meter test placed at reception. It is also common to perform measurements in both directions, as specified in the design phase when calculating clockwise and anticlockwise link losses. However, the optical power meter does not allow to measure the effect of penalties and nonlinear impairments. To these purposes, another tool is the Optical Spectrum Analyzer (OSA) which helps to measure the optical power but mainly the OSNR and the central wavelength for multiplexed signals. In case of WDM systems the optical power of a single channel inside the multiplexed signal is more accurately measured by means of the OSA than with the OPM. Other tools can be used depending on the type of client traffic: OTN, GigaEthernet or 10GigaEthernet analyzers for example.

During commissioning phase, the engineering design documentation is used as the base to verify and modify parameters if needed. Basic released documents are the network diagram, where each site is detailed: the cabinets diagram layout connection with the utilized boards; one of the sections of this diagram is generally the wavelengths or optical channels allocation scheme. In this documentation the parameters established during the design phase are followed: the transmission power, the reception power and the margins decided to ensure quality of service of lightpaths, established following an over dimensioning security policy.

The optical power commissioning procedures can be done remotely or directly on site. Basically the commissioning phase is divided in two steps: the optical power and the network commissioning procedures. The optical power procedures aim to individually verify the requirements at every network node (input, passed-through and output boards) following the flow of the optical signal when traversing the node. It is done for end-to-end nodes, in-line optical amplifiers, ROADMs and OXCs. Setting parameters of each utilized card are adjusted and fixed following the overall optical power budget calculated. The network commissioning procedures are supported by the previous right optical power commissioning and confirm and adjust the end-to-end lightpath commissioning along the transmission path so as other end-to-end procedures such as end-to-end power controlling and protection functionalities, verifying the right optical power, BER and OSNR at reception. The set of services offered to the client are commissioned in this second set of procedures.

Thus, the overall design and commissioning process of an optical transport network can be structured in several steps. The optical transport network has been designed: it includes the network diagram, sites location, cabinets and boards layout and connections and the wavelength allocation. The node equipment have been installed. The boards of each equipment in every network site have been configured. The cross-connections in the ROADMs and/or OXC nodes have been configured; the optical power commissioning procedures have been applied in every network element, following the on-site, remote or automatic processes. The optical paths have been set up in the system. The services have been configured. Each network element has been configured and the optical power has been commissioned at both node and end-to-end lightpath level (service commissioning). The protection paths have also been checked in terms of service commissioning. And finally the network commissioning is done.

Then, the overall network is commissioned. It is to be noted that the same or different wavelengths can be used along a lightpath. In case that several lambdas are used, the optical power budget is ensured during the commissioning phase. It has been guaranteed because commissioning procedures for each single-wavelength are verified in each link of the lightpath between sites, including the in-line optical amplifiers traversed. In the configuration of each node, two main steps are done: the configuration of the transmission and reception ports of each board and the performance monitoring parameters of the network element. When creating the optical paths through the nodes special attention is to be paid if the node is an ROADM or an OXC: the cross-connections are first configured in the node and the power commissioning is then to be done taking into account the possible combinations in terms of input and output power of the boards as function of the number of simultaneous multiplexed wavelengths.

When configuring boards, the attributes of the card are set (as the operating wavelength of the respective current port, power and advanced functions such as protection against fiber cuts). In typical configuration systems tools, fiber parameters (type and main attributes, such as length and attenuation and dispersion coefficients and the designed allowed losses) are also set. As indicated above, during the design phase the worst-case approach is followed. As a configuration principle, when introducing the design parameters in the system, the designed maximum losses of the fiber are introduced; if a dispersion compensation module exists in this segment of the span, the maximum insertion losses of this unit is also introduced. It leads to increase the transmission power of the laser of the transceiver module used in the downstream network node. When configuring the cross-connections, in individual ROADMs and/or OXCs, the routes among the boards are defined and set: the optical power of the optical cross-connection can be adjusted manually or automatically. In any case, what is adjusted is the range of the optical attenuator of the dynamic add/drop multiplexer board. When creating the optical paths, the end-to-end lightpath services are being configured. The final step consists on verifying the end-to-end optical power or OSNR of the lightpath. If any abnormal situation occurs, checking of boards of amplifiers or intermediate sites is done, so as fiber configuration and cross-connections or wavelengths used.

Some rules are to be respected during the design and commissioning phases. For example, the incident optical power, which depends on several factors as the type of modulation format used by the transceiver (10G or 40G DQPSK or 40G ODB or 100G PDM-QPSK), the number of transported wavelengths (10, 16, 40, 80…), the channel spacing (100, 50 GHz…) and mainly the type of fiber used; G.652 fiber presents in this sense less constrained requirements than a G.653 fiber or a G.655 fiber. If high gain optical amplifiers are used in the link the incident power needs to be increased by 2 or 3 dBs in the commissioning process. When mixed-rate transmission systems are implemented, i.e., transporting a combination of 10G, 40G and 100G wavelength channels, rules on minimum distance separation, depending on the type of adjacent channels must be respected and it also depends on the type of fiber. For example, for 10G and 40G optical channels, the spacing between these adjacent channels must be at least one channel for G.652 fibers and 400 GHz for G.655 fibers. Other typical rule regarding the single-wavelength optical power commissioning at both transmission and reception nodes is that, according to design engineering documentation, the single-wavelength input optical power have to be within the range of the nominal power +/- 2 dB at both transmit and receive ends. When the link has more than 20 spans, the noise on the short wavelengths increases and the difference between the optical power flatness and the OSNR flatness increases. Then, in long-haul systems, it is preferred to allocate short lambdas to transport channels below 40 Gbps.

One of the objectives of the commissioning phase is to ensure the flatness of both the optical transmission power of each single optical channel and the multiplexed optical signal. The OSNR flatness as well; this last will be guaranteed of the optical power flatness is respected. Due to this reason, if the emitted optical power may be decreased, it will contribute to maintain the quality of the service transported by the lightpath. In terms of ensuring the flatness some of the traversed network nodes are used to balance the optical power.

In the commissioning process the design documentation has to be collected and must comply with the design requirements in order to avoid nonconformance in terms of wavelength allocation for mixed-rate systems, dispersion compensation, allowed optical power losses and OSNR. The network elements and boards are then configured. The optical transmission power of the transmit end node must be flatten, then the optical power of each in-line amplifier must be commissioned and the optical power must be balanced along the path between each pair of network nodes identified and used as power balancers. The process shall be followed for single-wavelength channels and the multiplexed signal, with particular attention about this point in the in-line optical amplifiers.

When verifying the link, each span has to be checked in terms of insertion losses. In fact, the actual insertion losses shall be lower than those specified in the design phase, because maximum or high values are used in the calculation. When checking the dispersion, the values indicated in the design phase must be respected, for each DCM. When calculating the dispersion on the link, over compensation is normally applied. That is, if a DCM module can be used every 70 km, DCM modules are typically placed at 60 or 65 km, meaning that a greater number of these equipment are finally used along the path. This leads to increase the inherent insertion losses and thus the required transmission power in the transmit node.

Apart of the optical power budget, network designers and commissioning operational teams may calculate and verify two other types of design and control mechanisms: the OSNR budget and the Q-factor budget. OSNR is a figure of merit used in fiber link planning and it is mainly observed and measured at reception: the receiver has a minimum required OSNR for a specific BER and below this value, errors in communication may occur. OSNR is normally measured by the OSA tool, in [52] the methodology for measurement of OSNR and mathematical equation for DWDM networks are further detailed. Normally, OSNR calculations for each single-wavelength channel is performed, in terms of signal and noise power measurements. OSNR link budget is performed when optical amplifiers exist along the link, where the known ASE noise is the main source of the noise, motivating this calculation.

Normally in OSNR calculation budget and equations, the power penalties are not integrated. In this case design teams can use the Q-factor budget to cover this question. The Q-factor is a parameter allowing to measure the performance, as BER parameter does, and it may also be used in performance planning during the design phase. Conceptually it can be seen as an electrical signal to noise ratio measured at the receiver decision circuitry level. In fact, BER and Q-factor performance parameters are related: for example, for a BER equals to 10^{-9} a Q-factor of 6.0 is associated and for a BER of 10^{-15}, Q-factor yields 7.94. The Q-factor budget is also a way to control the impairments, both linear and nonlinear, on the optical link [53].

2.4 Operational network margins and reduction opportunities

Telecom operators tend to maximize commercial benefits. Among the strategies to achieve this objective they have to reconcile and balance their investments in enhancing network infrastructure (CAPEX), in order to be able to offer more and new services, and their operational costs (OPEX), including, for example, maintenance costs, reparation faults, energy consumption and others. An opportunity to lessen these costs is to reduce the operation margins applied in the optical power budgets and used in the exploitation of the optical transport network. These operation margins are calculated and established by network engineers during the design phase of the transport network. The definitive values are adjusted and set during the commissioning phase on field. They are designed to absorb the unforeseen link degradations including those due to ageing of the network. Traditional methodologies calculate the theoretical value of these operation margins by means of application tools in the design phase of a network, based on several hypothesis which are corroborated in the subsequent commissioning phase performed on the field. They are normally dimensioned considering the end-of-life (EOL) of the optical network components (e.g., fiber, connectors, nodes). This second phase will serve to consolidate the theoretical values and to adjust them based on the specific particularities found on the real network. Once the operation margin values are confirmed, network designers normally set their values as fixed. And these fixed values are applied in the exploitation of the network from the beginning.

This thesis explores the use of the cognitive science in order to improve the application of those margins. The line of work is to use flexible values during the operation of the network.

Moreover, to use flexible and low values applied at the beginning of the exploitation of the network, instead of fixed, permanent and conservative margins, since they are normally calculated by network designers by applying the worst-case hypothesis, and they are put in use from the first exploitation of the optical network. When it is said that the low and variable values are applied from the beginning of the exploitation it does not necessarily mean that they are applied merely in the implementation of the network, but also when new maintenance interventions are done, as it can be considered that the optical transport network is again in its “initial” stages. Then, the objective is to assess if these operation margins can be variable and adapt to the evolution of the network conditions by establishing low values in the first steps of the network lifetime and get increased when ageing and degradation impact on the optical network infrastructure, in order to guarantee the end-to-end quality of service of the traffic requests.

This thesis proposes to apply the cognitive science [54] [55] in order to achieve its objective. The cognitive process, as described in [55][56], consists on to be aware of the external environment, to reflect on the internal and external knowledge, to think based on this knowledge, to take a decision and to act or to plan, while learning constantly from the experience. As mentioned in precedent paragraphs, previous related works presents the application of the cognitive techniques in a real-time context [57] to help on the lightpath establishments. The objective of the present thesis is to reduce the operation margins, leading to a reduction of the OPEX of the telecom operator, basing the solution on cognitive science. Particularly, this thesis addresses the reduction of one of these operation margins, the System Margin, taking into account the long-term ageing process of the components of the optical network when setting the optical power margins during the establishment of the lightpaths. As such time scale is part of the outline, an offline application of the cognition technique is proposed and presented, assuming that such an approach can present certain advantages on the big data era. Specifically the proposed solution is based on an adaptation of the case-based reasoning (CBR) technique; it will directly provide a lower transmission power value than the initially pre-assigned one and this, based on earlier experiences, learning from them. The advantage of achieving lower provisioning times, additionally supported by the application of a lower value, against trial and error alternative strategies can be exploited for the telco operator. As indicated above, network carriers search for diminish their OPEX or operational costs. Technology has evolved and flexible transponders can be found in the market, together with higher order modulation formats. It allows for improving the capacity, although an important reduction in reach. To reduce margins in network can be an strategy to cope with this situation [54]. The System Margin is one of the operation margins applied in the network. During the design phase its value is estimated and it is introduced in the optical link power budget to cope with the unforeseen path degradations. During the commissioning phase it is adjusted and fixed. This permanent and constant value is then applied during the whole lifetime of the network, and it does not change in any network conditions in any situation. The cognition solution is applied to address this situation.

2.5 Related works

Reducing network margins is an issue that has already been raised and discussed. For example, in [54], an exposition and classification of the different network margins has been presented.

Authors suggest different strategies to cope with them and to reduce them. In particular, the introduction of bit rate variable transceivers to improve network reconfiguration and optimization is identified as one way to reduce system margins. In particular, authors discuss three types of network margins: unallocated margins, design margins and system margins. The first type of margin is a side effect of the network traffic demand heterogeneity in reach and capacity. That is, a single transponder is parametrized such that the maximum reach sometimes exceeds the transmission reach required, i.e., transponder offers more capacity than the requested one. The second type of margins are design margins is the results of the calculation tools of the transponder reach when designing from the worst-case design approach: lack of knowledge of the topology and error distributions in amplifiers NF and transponder back-to-back OSNR, among other considerations, addresses this approach. Finally, the third kind of margin is a safeguard of reliable network operation, allocated for impairments and line degradations. Regarding the unallocated margins, flexible transponders can offer reconfiguration during system life proving a partial solution to the situation. Regarding the third type, the system margins, authors highlight the idea of trading the transponder capacity against margin to adapt to time varying impairments for example, based on real time performance monitoring. However, the difficulties to remove fast time varying penalties are highlighted, because they are beyond any transponder reaction time.

In [58] the network margins categorization proposed in [54] by Augé is revisited. Pointurier highlights that in [54] author indicates that operator margins, a type of system margins, as it is required by the operators to guarantee the quality of the transmission no effort is made to minimize or leverage them. In [58] further explanation of those network margins and their characteristics is presented, so as more strategies and techniques to leverage on them with the aim to increase network capacity. Among these techniques, depending on the category of network margin to manage, the use of rate-flexible TRX and ROADM (essentially filters in them), online reconfiguration and an adapted control plane are presented as the more important ones against unallocated and system margins, so as design margins. It is mentioned the importance of the optical monitoring, although the practical difficulties of such system is also underlined. Overall, it is exposed that to properly address the network margin reduction requires a previous and rigorous network planning. Authors emphasizes that using those techniques and components in real networks is considered an enormous operational challenge.

In the same line as previous mentioned works to exploit the application of flexible transponders, in [59], authors discuss about the rate-adaptable optical transmission devices to reduce the transport networks cost to accommodate the growing capacity needs of telco operators. They consider in the assessment two main types of flexible transponders: those adjusting the transported bit rate (client data rate) and those adapting the symbol rate, while maintaining a fixed bit rate. Bit-rate adaptable optical transmitters, based on DSP technology, operates at a constant symbol rate and the net bit rate may be selected from a list; these transponders require that client side rates to be also adaptable. And they can operate in traditional fixed-bandwidth grids. The symbol-rate adaptable devices present a variable symbol rate while maintaining the net bit rate constant and the use of flex-grid ROADMs should be needed in this case. Among the conclusions depicted in this work, authors underline two: the application of the rate-adaptable transponders through the use of DSP technology in both the transmitter and the receiver, combined with a coherent detection in the last one, is a powerful mechanism to reduce costs in transport networks; and that bit-rate adaptable transponders expense will be lower than when using symbol-rate adaptable devices.

In [60] the effect of link margin on spectrum savings for high bit rate demands of multimedia applications is assessed. This work takes a point to point optical link as reference for the evaluation. Authors discuss about the benefits provided by using a flexible and adaptive network able to be adjusted to the incoming traffic requirements by means of flexible transceivers and network elements, i.e., the elastic optical networking paradigm. It is claimed that flex-grid technology alone by itself is not enough to achieve high spectrum efficiency, but combined with flexible transceivers and mainly the adaptability of the modulation format parameter is a key factor to reach these objectives. They introduce the concept of the Link Operational OSNR (LOOSNR) which incorporates the link margin, as an important parameter in link budget, to the required OSNR of the communication, by subtracting it from the estimated OSNR, as a security measure. They underline that the value of the link margin depends on the state of the conditions of the equipment of the link, evolving from perfect state until average or bad conditions. Different spectrum savings results with varying link margins are presented, together with the required LOOSNR. By using flex-grid compared to fixed grid, bandwidth is saved to admit new demands, then minimizing wasted bandwidth in the network. Significant efficiency in spectrum savings is achieved by using flex-grid and for low link margins.

In [57] the CBR technique is presented to estimate the Quality of Transmission (QoT) of a lightpath. Authors propose to compute the associated Q-factor before its establishment and then classify the lightpaths into high or low level quality categories, regarding their QoT. This operation is proposed to be executed on-line. As a follow-up of the previous work, in [61] an experimental setup of the quality of transmission estimator for lightpaths is presented in a basic testbed and configuration; authors demonstrate that case-based reasoning can be successfully employed to predict the QoT of optical channels. In [39], the use of cognitive techniques in the design of efficient virtual topologies in terms of throughput and energy consumption is presented.

In [62], authors expose the idea that application of techniques belonging to machine learning framework can provide benefits in optical communications. Particularly, they present Markov Chain Monte-Carlo combined with bayesian filtering and expectation-maximization algorithm to mitigate non-linearities, applied to estimate probabilistic parameters and compute the optimum decision boundaries for constellation impaired with non-linear phase noise. Cross-phase modulation (XPM) induced impairments can be tracked and compensated more easily.

In [63], even though it is a work dated on 2012, authors underline the importance of optical network for the *future* Internet requiring a huge capacity to the incoming ultra-high bandwidth demands, because it provides the physical infrastructure of the core backbone networks. As a key driver for the EU research, authors expose the concepts of flexible and cognitive optical networks. A cognitive architecture in order to materialize a flexible infrastructure is presented. This work demonstrate the benefits of implementing heterogeneous flexible networks based on three parameters: spectrum efficiency, cost and energy consumption; and it lets open several lines of investigation works in how to efficiently route traffic and how to allocate the spectrum and choose the appropriate transmission/switching technique, modulation format, bit rate and optical launch power among other parameters. It is highlighted that exploitation of cognitive techniques in optical communication is addressed on the CHRON (Cognitive Heterogeneous Reconfigurable Optical Network) European project which allocates intelligence to the optical layer [64] with the aim of using resources as efficiently as possible and then to minimize CAPEX and OPEX; this project translates cognition to three leverages: how to route new demands, how to assign efficiently available resources and how to ensure energy-efficient processes. As specified by CHRON the core element is the *cognitive decision system* complemented by a *network monitoring system* and a *control and management mechanisms*.

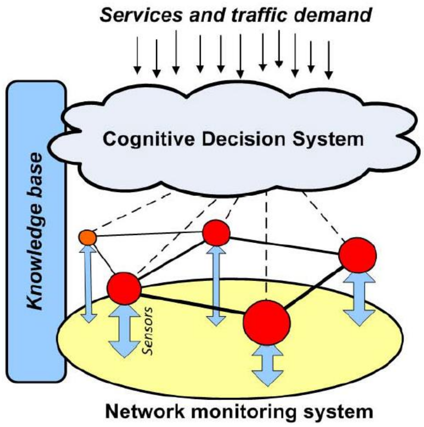

Figure 2.5. Main subsystems in CHRON approach (figure taken from [65])

In this work the architecture of CHRON approach is further explained and it links with the quality of transmission estimator for lightpaths presented in [57]; authors explain the advantages of using mixed line-rate and flexible networks materialized in spectrum allocation advantages, cost efficiency advantages (in terms of transponders and node equipment and number of dark channel slots) and energy efficiency advantages. The overall work is an exposition of the CHRON approach and the potential let open for research in terms of cognition.

2.6 Chapter summary

The first section of this chapter has provided an overview of long-haul optical transport networks. Such a review has paid special attention to optical link implementation. An end-to-end optical link model has been proposed, enumerating and describing the main network devices and components which are part of it. The optical path between any pair of end nodes shall be considered as a concatenation of multiple amplified links. Furthermore, for each one of the network elements involved in such an end-to-end optical link, the main parameters characterizing them and having an impact on the link implementation have been mentioned. Typical values indicated by network providers and found in commercial network have been pointed out. For transceiver devices, all the attention has been got to maximum and minimum output power launched into the optical fiber, paired with receiver sensitivity and minimum overload values. In this context, the most commonly deployed high-order modulation formats have been listed, such as 40G Pol-Mux BPSK and 100G Pol-Mux QPSK modulation types, leading to hybrid transmission networks, where signals of different and mixed rates are multiplexed over the same optical link. Among others, this issue impacts on link design considerations. Regarding multiplexer devices, typical insertion losses and adjacent channel isolation figure among the main parameters to be considered; for their part, ROADMs nodes parameters to take into account are insertion losses of both passed-through and added/dropped lightpaths, so as maximum input and output power, per wavelength and for all the channels. Optical amplifiers are elements widely deployed along the paths in commercial networks and they present a special importance on the lightpath transmission; among their parameters conditioning the optical power budget, the maximum input and output power values, for both single channel and multiplexed signals, gain and power flatness, can be highlighted. Moreover, non-linear impairments are effects to keep in mind when designing an optical link.

The second section of the chapter focus on the main design and commissioning procedures and general rules to be respected followed by a telecom carrier when creating, building and operating a long-haul optical transport network. The optical power budget is the main tool used for design and operational teams to implement the network. Following these calculations, a minimum power has to be ensured at reception in order to guarantee client services with the appropriate Quality of Service. This section has underlined that to achieve this end, a general practice followed by operators consists on over dimensioning the network resources, in terms of equipment, boards, transmission power and network margins used. The “worst-case” approach is normally applied in the design phase, as indicated in ITU-T Recommendation Series G Supplement 39. This way of addressing these procedures presents a challenge.

In the fourth section of the chapter, the line of research of this thesis has been further explained. The System margin is presented as one of the operation margins, which is established in design stages and applied during the exploitation of the network. The present thesis suggests that this operation margin can be variable and adapt to the evolution of the network conditions. Low values can be used at the beginning of the network, that can be increased to accommodate ageing and degradation effects along the time. This thesis proposes a solution based on cognitive science to achieve this aim.

Finally, the last section of the chapter has been devoted to review the related works in this context.

Chapter 3

Machine learning fundamentals and case-based reasoning

An overview of the main characteristics of machine learning is presented in this chapter. This application of artificial intelligence has been the basis for developing the cognitive proposal in this thesis. The chapter starts with a brief explanation of the main families and approaches in machine learning. Herein a further detail is given for the particular systems related to the learning methodology used to construct the proposal. Next, an introduction to basic human memory processes is provided. Some of these mechanisms have been used to support the developments of the proposed solution. Finally, an explanation of the particulars of case-based reasoning method is given, since this approach has been used to elaborate the suggested cognitive solution.

3.1 Basic concepts

Machine learning is a framework that aims to reproduce human learning in systems and processes. It deals with the study of methodologies, techniques and algorithms to implement a system which improves its performance for a specific task based on experience, and adapt automatically to situations without a previous and explicit programming of the system (Arthur Samuel, 1959) [66].

In the learning process and knowledge acquisition three key aspects can be considered: to increase the acquired knowledge, to perform the same tasks more accurately (or more efficiently) and to be able to perform new tasks. Machine learning can be applied to perform several tasks such as prediction, medical diagnosis, classification (for example, knowing profiles of customers to determine whether they will buy or not some specific products), grouping elements, characterization (having a set of elements presenting similar behavior, to determine why they resemble), improvement of efficiency (for example, optimize network routing), behavior understanding (with a direct application to marketing trends: which customers are interested in some specific products, which kind of adds might interest a specific taxonomy of persons), controlling (as robots substituting humans in recent intelligent car driving) and some other application in marketing, industry and health areas. Typically, in the context of tasks related to behavior understanding the unsupervised learning is often used; in contrast, in the framework of situation prediction, supervised learning techniques are applied; or reinforcement learning methods are used in controlling processes, for example. Other areas of Machine learning applications are speech recognition, information retrieval (to process huge volumes of information), gaming, computer vision to identify human behavior, robotic control, domotics to efficiently manage the energy consumption, banking (to support decisions whether authorizing a credit to a customer depending on his expected behavior and the recommended amount), space images cataloguing, pattern discovery, data mining linked to data warehouses (extracting knowledge, relationships or patterns among a huge volume of available data) and text mining.

Learning approaches and techniques can be divided into three types: inductive learning, deducing learning and hybrid learning methods. Inductive learning aims to infer a general rule or hypothesis from the information provided by a set of examples; they search for generalization, that is, to extract a general description for a concept; these methods are data intensive, namely, a lot of examples are usually needed. Deducing learning aims to explain and analyze only one single example of a concept from the available knowledge; these type of learning searches to particularize for a single example; thus they are necessarily knowledge intensive. Finally, hybrid methods can propose either a mix of the previous approaches (for example, combining deductive methods to extract information and then applying inductive methods to generalize) or using other techniques, for example, methods based on genetic algorithms or learning by analogy.

Before continuing, some definitions of the basic concepts manipulated by machine learning are listed as follows:

- An attribute is a variable modeling a characteristic when defining an element in a dataset.
- An instance, observation or register is a set of several attributes with their corresponding values.
- A class is a subset in which the whole set of instances shall be divided. Each class is disjoint with the others.
- A hypothesis or generalization is a description representing one subset of instances of a class, not representing the instances of the other classes. One of the main hypotheses sustaining the inductive learning establishes that if a hypothesis or generalization describes correctly the concept, according to a sufficiently high and significant volume of learning examples, this hypothesis will also describe the concept for future examples [67].
- A dataset, or knowledge, is composed of instances, registers or observations. Each observation can be defined and modeled as a pair of input variables and output variables, that is, the attributes. As indicated, these attributes are parameters describing the example; in the case of labeled data, the dataset can be defined as $D = \{\boldsymbol{x}, \boldsymbol{y}\}$, where the input variables or attributes are the set $\boldsymbol{x} = \{x_1, x_2, ..., x_n\}$ and the output variables are the set $\boldsymbol{y} = \{y_1, y_2, ..., y_n\}$.

inputs output

Weather	Temperature	Month	Distance	Selection
Rain	15°	April	4 km	To walk
Sun	28°	August	20 km	To walk
Snow	1°	December	7 km	To drive

instances

attribute

Figure 3.1. Basic methodology in machine learning

The attributes can be categorized depending on the nature of the characteristic to be modeled:

- Nominal: values are discrete, without integrating a relationship of order or distance among them; for example, colors or months of the year.
- Numerical: values with an existing relationship of order defined among them; they can take then discrete (age) or continuous (weight) values.
- Output variable: already named *label* or *class*. This variable can be binary (true/false) or discrete and numerical. In the latter case, it is a classification or regression problem.

This thesis focuses on inductive learning. In this approach, techniques can be divided into two main categories: supervised and unsupervised. Since learning can be addressed as a classification problem, the key difference between both categories is whether or not a dataset of observations correctly classified in the past is available.

Supervised learning, from the dataset of input examples (pairs of inputs and outputs) aims to find the rules that model the best relation between the input and the output (label of the observation and assigning the class or subset). This category tries to infer the relation, namely, a model, a mathematical function or some rules, existing between the input and the corresponding output [67]. As the input dataset observation contains information of the input parameters and the output values, during the learning process the system tries to learn from the input/output observations to establish the relation. When it finishes and the system is in the run phase, the generated model will be able to deduce the corresponding output, unknown, from the new incoming input observations.

The unsupervised learning techniques aim to find hidden structures, categories or relations underlying in an unlabeled dataset [66], that is, observations whose class is unknown. That is, in unsupervised learning, label of the input observations is not available. It tries to extract conclusions from an unlabeled dataset of input examples by observation of several of their variables. The challenge is to understand the behavior of the dataset, with few criteria being available for the validation of the proposed solutions. Thus, in this situation, there is no input and output variables: all the parameters modeling the registers are input parameters. All of unsupervised learning approaches are exploratory methods of data, to find relations among the input variables or to be able to propose groups or subsets; and depending on the applied method, different groups will be formed. Typical applications are found in medicine, image analysis and market prospection, as detailed in the following subsections.

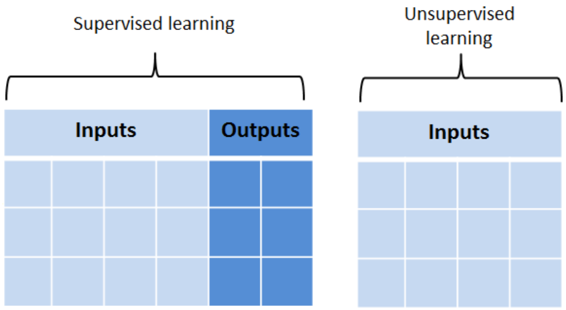

Figure 3.2. Supervised and unsupervised learning instances

Several techniques exist in both supervised and unsupervised learning families, some of them are depicted in Figure 3.3:

Unsupervised learning	Clustering	K-means, Expectation-Maximization
	Factor analysis	Principal component analysis
	Visualization	Self-organizing maps, multidimensional scaling
Supervised learning	Non-linear decision	Lazy learning, trees, feature selection, kernel learning
	Linear decision	Support vector machines, linear perceptron
	Probabilistic methods	Bayesian learning

Figure 3.3. Machine learning techniques

One of the issues to solve when implementing a specific learning method is the representation of the knowledge. Different learning methods choose different representation solutions. And they vary depending on, for example, if decision tree techniques are used, or neural networks or principal component analysis approaches are applied.

Machine learning is closely linked to the big data field, an area that manages huge volumes of information. The management of such information and the learning ability to extract useful information from this set it is known as data mining.

The cognitive proposal developed in this thesis is based on a supervised, nonlinear decision and lazy learning context. Thus, a more detailed explanation of these solutions is presented in the following sections. Moreover, a quick overview of the basics of some other main techniques is given.

3.2 Unsupervised Learning

Among the unsupervised learning, clustering, factor analysis and visualization can be highlighted [67]. Clustering consists on forming groups of elements, known as clusters, from an initial dataset, such that objects being part of the same group or cluster are similar to each other in any way, and they are less similar against objects of other clusters. Some of the applications of this technique can be found in astronomy (to identify and classify galaxies, to group sets of galaxies), in biology (taxonomy), in marketing (market segmenting), in data mining and in pattern recognition. Several methods to form the clusters can be followed. Among them, K-means and expectation-maximization (EM) can be underlined. Both are iterative and partitioning algorithms, where the number of groups is previously known. In K-means each instance is assigned to the closest cluster, in terms of its distance to the centroid of the cluster. Both the process of assignment of instances to clusters and the recalculation of the centroid of each one of the k clusters is iteratively executed. In K-means, an instance is solely assigned to a cluster; it does not consider the uncertainty about the belonging to more than one group. In this way, there is a single assignment. Whereas EM does consider that a single instance can belong to more than one category, it is a soft-clustering version. To do that, EM recognizes probabilities instead of distances to assign an observation to a cluster. As a consequence, every cluster or category is defined by a mean and a standard deviation.

Factor analysis consists on synthesizing and reducing the data dimensionality. It is composed of several methods to summarize the information contained in observable and measurable variables, trying to infer or identify the latent variables that are not directly observable, losing as less information as possible in the process. One of the main approaches in factor analysis is the principal component analysis (PCA) [67]. The aim of PCA is to reduce the initial dataset to a smaller set of *principal components*, which are a lineal combination of the original variables and independent among them. To do that, PCA uses the eigenvector and eigenvalues of a covariance matrix, producing the principal components. By selecting the highest eigenvectors and their eigenvalues, dimensionality of the initial input dataset is reduced, the core of the information is acquired, trying to capture as much of the original variance as possible. This reduction of the dimensionality, losing as less information as possible, and complexity of the input dataset has a clear drawback.

Visualization is a set of techniques used to graphically depict the input information to find and explore similarities and/or dissimilarity in the dataset. Visualization tries to answer the question about how to get low-dimensional views of high-dimensional data. Among the techniques, models based on neural networks can be highlighted, as self-organizing maps (SOMs) [68] and multidimensional scaling (MDS). The main drawback of these techniques is the interpretation of the dimensions and then the global understanding of the information.

3.3 Supervised Learning

The other main category in machine learning refers to the supervised learning techniques. In this kind of learning, correctly classified or labeled instances are available.

From the knowledge provided by a set of classes already available, the aim is to determine the rule or set or rules for assigning every new observation to the (correct) belonging class and then building a model performing well in the future. Past data is the basis and it is expected that the future will remember this past behavior in order to continue with this same inferred behavior. This is the main raison why supervised learning may be applied to make predict.

Mathematically, the available input dataset can be represented as $\{(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2),\ldots, (\boldsymbol{x}_n, y_n)\}$, where y represents the class or label, it can also be a n-tuple. The objective is to obtain the unknown target function allowing to explain the data behavior: $f : \boldsymbol{X} \rightarrow Y$. A set of hypothesis H is selected and a learning algorithm shall provide a function $h : \boldsymbol{X} \rightarrow Y$ modeling the target function, $h(\boldsymbol{x}) \approx f(\boldsymbol{x})$ [67]. In this model of a supervised learning classifier one important aspect has to be taken into account: the committed error when selecting an initial hypothesis over which the learning algorithm shall be applied and that shall approximate to the maximum $h(\boldsymbol{x}) \approx f(\boldsymbol{x})$.

As an example, it can be considered a certain set of climatologic conditions described by $\boldsymbol{X}$ that have ended in snowing, Y. Based on a set of input observations, the supervised learning model shall learn from them and to predict if it is going to snow by means of $h(\boldsymbol{x})$.

Moreover, there are several aspects to be considered in supervised learning: there may be noise in the input dataset and the number of induced rules depends inversely on the volume of input data; that is, if more data is available, less hypothesis are possible. Besides, in the inducted supervised learning the evaluation and the over-fitting are two important items. Evaluation consists on checking the proposed model. And the over-fitting means that the learned and proposed model is built only for a specific data and fit it quite well, that is, it is too adjusted to some part of the data and then the model losses the generalization principle.

A possible classification of supervised techniques is Linear Decision, Non-Linear Decision and Probabilistic Decision. In the next sections, they are briefly explained.

3.3.1 Linear decision supervised learning

Among linear decision techniques in supervised learning, two main methods can be underlined: perceptron learning and support vector machines (SVM). The linear perceptron is a linear classifier where each simple is labeled or classified upon its sign. It is a kind of neural network normally applied over continuous data, in a supervised model. But this method presents a problem: it works correctly in a separable problem, and poorly when it faces a non-linear separable input dataset. For example, in a bi-dimensional plane, the samples of the two categories are mixed among them and a separation line cannot be drawn in that 2D plane allowing to separate them, that is, to classified them.

SVM is a method to solve the problem of binary classification. The objective of SVM is to find a hyperplane that perfectly separates the d-dimensional input dataset into two classes. As indicated above, it may occur that the dataset is complex (or even impossible) to be linearly separable. It was formulated by Vladimir Vapnik et al. in 1979 [69].

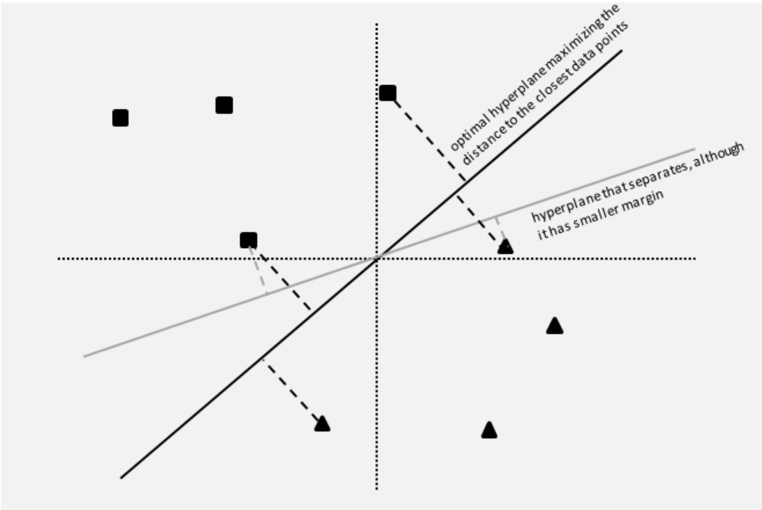

Figure 3.4. Two hyperplanes, one of them maximizes the margin

A hyperplane is a dividing object used in geometry: in one dimension space it is a point that divides a line, in a bi-dimensional space is a line dividing a plane, in a three dimension space is a plane dividing the space and so on for more than three dimension spaces.

SVM technique establishes that only some training examples, called support vectors, are needed to define the optimal hyperplane. However, it can occur that the data points set cannot be linearly separable by a hyperplane. In this case the “soft-margin” classifier concept is used, which allows some of the data points to be misclassified. Thus, the optimal hyperplane will be that one minimizing the misclassified samples. Intuitively, the support vector machines are defined by the “borderline” data points (training examples) in the decision function trying to be learnt. One advantage of SVM is that it is robust face to noisy elements.

3.3.2 Probabilistic decision

Bayesian reasoning provides some tools to manipulate probabilities in learning algorithms. Among the main features characterizing this type of algorithms can be mentioned that they incorporate probabilities about if a hypothesis is correct. Or to combine prior knowledge with observed data to determine the final probability that a hypothesis is correct. They use Bayes’s theorem which provides a method for calculating probabilities of hypothesis based on their prior probabilities, the probability of observing various data given a hypothesis and the observed data itself [66]. One of the more known algorithms is the naive Bayes learner, It simplifies the calculation of the probabilities for each hypothesis, assuming that data values are conditionally independent. It means that data don't interact internally, although this condition is unlikely in real world.

3.3.3 Nonlinear decision supervised learning

Among the nonlinear decision supervised techniques, several methodologies can be encountered. The cognitive proposal developed in this thesis is based on one of these approaches. Thus, instance-based learning methods are more detailed and an outline of others techniques, as trees, feature selection and kernel learning is given.

3.3.3.1 Trees

Decision trees are one of the basic nonlinear learning methods. The idea behind a decision tree is to recursively divide the input space into blocks and to assign the best model to each block or partition. The two more extended decision trees are regression trees and classification trees. The first one consists on continuously dividing by using parallel hyperplanes to the Cartesian axis and assigning constants to each piece or area. The objective is to minimize the number of nodes; to avoid the computational load the process is repeated iteratively, removing nodes until reaching a pre-fixed number of them.

The idea behind a classification tree is similar, although what this strategy tries to minimize is a measure of the error in the classification of the final leaves; entropy is often used in order to grow the tree, based on the principle of the information gain: the attribute allowing to better explain the decisions is selected continuously.

A common problem to decision trees is that more than one may be defined for the same input dataset. And they normally present a high variance: small changes in data become great changes in the hypothesis. They reveal as very appropriate to handle multi-class functions. It is advantageous to apply them when the instances of the problem can be represented by pairs attribute-value (for example, attribute Car and value Porsche), the target function has discrete output values and descriptions of the objects are disjunctive. The most known algorithms are ID3 and C4.5.

3.3.3.2 Feature selection

Feature selection is a learning field with the aim of reducing the dimension of the input data. In this way it has the same objective as the previously mentioned factor analysis unsupervised techniques. It may be thought that information removal might lead to loss of accuracy. This issue is the key point to be avoided in feature selection; reducing volume of information is required to diminish the risk of over-fitting, and also the needed capacity of storage. Over-fitting consists on excessively training the model to certain situations. If over-fitting occurs, the model will not be general enough but adapted to very specific conditions. Normally, a high number of attributes are available in each observation, although quite often irrelevant data are part of them. These data drive the model towards failures. Thus, even paradoxical, discarding information can help to better learning, because solely the relevant information is retained. The idea behind this approach is close to the human mind: if people must have memories of every second of their life and have to retain every acquired knowledge, experience, feelings and emotions, humans shall probably collapse. And human head should increase its size and processing time should increase accordingly.

It is the reason why human brain and mind try to store and process the relevant information, that contributes to solve the widest range of possible situations and then to learn. Thus, feature selection is a key technique in machine learning to reduce dimensionality of the available information and to extract the essential.

Regarding dimensionality reduction a drawback is evidently raised: discriminality property of the information may not be preserved.

3.3.3.3 Kernel learning

Sometimes the input dataset is not linearly separable. In this case, there are other methods to separate the information. One of them is to use polynomial curves or circles, although finding the optimal curve that fits the data may sometimes be difficult. The basic idea behind is to transform the input data, non-linearly separable, into a new feature space, usually of higher dimension, where an hyperplane exists in the new space allowing to separate the data, as illustrated in Figure 3.5:

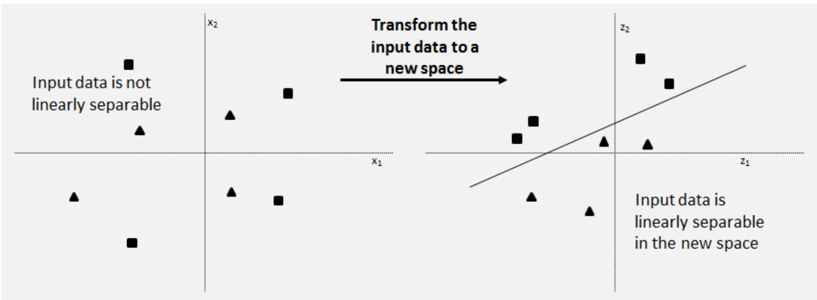

Figure 3.5. Data separated in another feature space

This strategy proposes the inverse approach about reducing dimensionality of the input dataset. It can be argued thinking on the function of a microscopy: if the information can be augmented in order to better appreciate the details, maybe data that seem initially inseparable can be finally separated.

The kernel concept was introduced by Aizerman et al. in 1964 [70] and applied in machine learning by Boser et al. in 1992 [71] giving rise to the support vector machine techniques. It can be considered a function whose arguments are functions and which returns a scalar. Moreover, a linear combination of kernel functions, each one focused on one of the training data points can be contemplated [72]. Kernels are used to manage symbolic objects.

Inside kernel learning, a related method can be encountered, known as radial basis functions (RBF). It is associated to instance-based learning, explained later.

RBF networks represent a bridge between instance-based learning and neural networks. As such, it is related to instance-based learning methods and sometimes it can be considered as one of them. It provides a global approximation to the target function, in terms of linear combination of many local kernel functions. The number of kernel functions to be considered is normally predetermined, a Gaussian function is commonly used. Each kernel function has an spatially localized influence regarding each input instance: the value provided by the kernel function is taken into account when the new instance falls into the region defined by the corresponding kernel function. That is, a kernel function is normally used to estimate the density zones of the input data. Upon Mitchell [66], the kernel function K is defined so that it decreases as the distance between the query point and the training example increases, being applied to determine the weight of every training example.

In this way, it is a kind of neural network where the radial basis function network can be viewed as a smooth linear combination of many local approximations to the target function. It is also closely related to distance-weighted regression. RBF is quite used in image classification.

3.3.3.4 Instance-based learning (lazy learning)

This machine learning branch waits for starting learning, and then for the generalization, until a new attempt arrives to the system. The classification cost is materialized only when the new test example comes. The key idea behind instance-based learning (IBL) simply consists on storing all training examples. Other learning methods search for building an explicit target function from available training examples, that is, they search for generalization. In instance-based learning this generalization is delayed until a new instance must be classified. And it will be proposed from training examples. When a new query arrives to the system, its relationship with the stored examples is evaluated and then a target function value is assigned. This delay in the processing is the differential factor of lazy learning techniques. This approach is used to obtain local solutions to the problem to be solved. That is, the target function is locally and differently approximated for each new incoming instance to be classified, instead of estimating it once for the entire instance space [66]. Then, several local approximations can exist. This approach easily adapts to changes in the problem domain. However, although the learning phase is quite fast, the release of a solution can be slow. Among the more common methodologies related to instance-based learning, k-nearest neighbor (k-NN), locally weighted regression (LWR) and case-based reasoning (CBR) can be found. When it is assumed that instances can be represented as points in an Euclidean space, nearest neighbors and locally weighted regression methods are used [66]. If more complex and symbolic representations of instances are manipulated, case-based reasoning methods are considered.

Following the mathematical modelling indicated above, a set of example input data is available $\boldsymbol{X} = \{\boldsymbol{x}_i\}$, where each sample is defined by a series of attributes $\boldsymbol{x}_\mathrm{i} = (x_1, x_2,\ldots, x_n)$, and the corresponding class or label, $\boldsymbol{Y}$, so as a target function that maps $\boldsymbol{X}$ onto $\boldsymbol{Y}$, f: $\boldsymbol{X} \rightarrow \boldsymbol{Y}$. The starting input dataset consist on a set of n-tuples {observation, target function value}, such that $D = \{(\boldsymbol{x}_1, f(\boldsymbol{x}_1), (\boldsymbol{x}_2, f(\boldsymbol{x}_2),\ldots, (\boldsymbol{x}_n, f(\boldsymbol{x}_n)\}$. A hypothesis function *h()* has to be found such that $h(\boldsymbol{x}) \approx f(\boldsymbol{x})$. The available classified dataset can be considered as training data. The task to be accomplished is to predict for every new incoming query, $\boldsymbol{x}_k$, the value $f(\boldsymbol{x}_k)$.

3.3.3.4.1 Nearest neighbors

This family of algorithms is the more basic and extended method of IBL, which assigns to the new incoming instance the label or output of the nearest member from the input dataset; the hypothesis consists in assuming that the output of the new member shall be the same of the closest neighbor. The training phase is essentially the storage of the available classified input dataset. They are considered when training data volume is huge, when each instance has less than 20 attributes [66] and when instances map to the n-dimensional space R^n. Although k-NN does not aim to provide a general hypothesis about the target function value, it exists a representation of the implicit general function. It is known as the Voronoi diagram. It depicts decision surfaces, each one surrounding a set of training examples. These polyhedra completely determine the classification of the new instances: each query point inside the corresponding polyhedron is classified as the training example generating that decision surface. And instances outside this polygon are nearer to some other training examples. Decision surfaces induced in the Voronoi diagram depend on the k value of the k-NN algorithms.

3.3.3.4.2 Locally weighted regression

It is a learning method that builds local approximations to the target function and it can be considered as a generalization of k-NN algorithm. First of all, regression means approximating a real-valued function. In previous section, it has been said that k nearest-neighbors method does not search for building an explicit general target function $f(\boldsymbol{x})$, it is limited to classify the new instance. That is, it forms an explicit local approximation to $f(\boldsymbol{x})$ for each new instance point $\boldsymbol{x} = \boldsymbol{x}_k$, over a local region surrounding this x_k. Locally weighted regression is a learning method that can be thought of as a generalization of k-NN method. The local approximation of $f(\boldsymbol{x})$ is based on training examples near to the query instance and the contribution of each one of these training examples to calculate the approximated $f'(\boldsymbol{x})$ is weighted by its distance to the new instance point. The obtained approximation fits the training examples in the neighborhood of the new instance. This target function approximation can be worked out by using a linear function, a quadratic function, a multilayer neural network or some other functional form [66]. What is a key characteristic of this IBL method is that a different local approximation of $f(\boldsymbol{x})$ will be calculated for each new instance. When locally approximating the target function, several choices to minimize error are possible. If using a linear function to construct the approximation of the target function, the classic gradient descent algorithm can be used to minimize the error for a given set of local training examples. Then, to minimize the squared error over only the k nearest neighbors is one option. Other possibility is to minimize the squared error but for the entire set *D* of training examples, while the error of each training instance is weighted by some decreasing function *K* of its distance to the query point, being *K* a kernel function; although this option is the most complete since every training instance collaborates to error calculation, it represents a high computational cost. Then an intermediate solution may consist in combining both options in a third choice: to minimize the squared error over only the k nearest neighbors and simultaneously to use the *K* function to weight the error of each one of the k neighbors [66].

Several advantages are presented by this kind of approach. It is to be highlighted that training is very fast, no information is lost and it is relatively easy to solve complex target functions. Among the main drawbacks, an important storage capacity is needed, it can be slow at query time and the importance of the irrelevant attributes can be mentioned. These techniques normally react poorly when managing them. It is called the curse of dimensionality: in high dimensional contexts, the number of features is too high compared to the volume of available samples, leading to a poor generalization of the classifier, besides multiplying the required storage capacity. These techniques are often used to disease diagnosis.

Finally, case-based reasoning is an instance-based learning method applied to more complex objects or input data. Compared to k-NN or LWR, case-based reasoning manipulates symbolic and heterogeneous logic structural descriptions of instances. This methodology shall be further developed and explained in section 3.5, as the basis of the cognition solution proposed in this thesis.

3.3.3.4.3 Lazy and eager methods

RBF is an eager algorithm. It is important to note that an eager learner generalizes before seeing the new instance, that is, it provides a single global approximation that covers the whole instance space and all future new instances. However a lazy learner may delay the decision of how to generalize until each new instance arrives. The difference between eager and lazy learning is related to the distinction between global and local approximations to the target function as indicated in [66]. RBF networks can be thought of a kind of intermediate solution, since although this method provides a global approximation, and it is an eager learner in this way, it is constructed as a combination of multiple local approximations or local kernel functions. Nevertheless, as an eager algorithm, it must provide the global approximation before observing the new instance, not when it arrives, as a lazy algorithm would do. Thus, the local approximations that they produce are not as targeted to the new incoming instance as those created by a lazy learner.

3.4 Human memory and learning processes

Cognition can be defined as the study of perception, memory, learning, categorization and reasoning. Cognitive processes can be defined and measured. Thus, the elements that are mainly involved in recognition and categorization can be analyzed and, in this way, they can help to discriminate individuals or classes.

Several descriptions of human memory have been developed and can be found in literature. The different types of memory are organized as short-term or working memory and long-term memory. Traditional classifications establish that, in rough outlines, long-term human memory can be divided into two systems: a declarative memory (also referred as explicit memory) and a non-declarative memory (implicit memory) [73]. The first one is responsible for retaining the semantic knowledge or elements which have been consciously learned (for example, the PIN code of a credit card or some French rivers). Implicit or unconscious memory contains the unconscious interconnections and skills, it allows for automatic execution of tasks [74]. One region of the human brain is the hippocampus which works as the central executive part of the conscious learning. What has been consciously learned can be forwarded to the implicit memory, such as movements coordination, swimming for example; once this learning has been automated, it does not require a conscious control. But humans do not always learn consciously. In [75] and [76] it is indicated that most of the learning processes are unconscious and that both explicit and implicit memories work separately. It was verified during the fifties decade with the patient H.M. Surgeons removed most of his hippocampus; later, they remarked that he was not able to retain any new information, that is, this patient could not store new data consciously. However, he could retain unconscious memories: if a person gave H.M. a painful handshake, although he perfectly forgot two seconds later this person, he had not want to receive any other handshake.

The multisystem model of human memory in [77] establishes that five types of memory exist: episodic, semantic, sensory, working and procedural. Episodic memory registers the events associated to a context (i.e., a particular Christmas dinner), enclosed in time and space, that is, associated to a concrete place and moment. Semantic memory encodes general knowledge of meanings, facts and concepts of the external world (what is the Mediterranean Sea and where it is). Sensory memory records what our senses are perceiving, but without any association to a context or meaning; that is, it notices shapes, tastes, sounds, smells or tactile impressions. These three types of memories form the long-term memory. Working memory stores information for a short period of time. This form of memory is working continuously in human daily life; it retains data and information just while they are needed to trigger actions, it is useful and required just for that same instant; for example, working memory allows to retain and process simultaneously that milk is on the fridge and that it is needed to get the brick from it in order to have breakfast now. It can be said that working memory is the operative memory. Finally, procedural memory stores how to do things, as the movements of the body or abilities, such as walking or driving a car. It concerns skill learning and preservation, it is the action memory. As responsible of retaining automated sequences and processes, daily life is developed completely normal thanks to this type of memory. Both working and procedural memories form the short-term memory.

Richard Atkinson and Richard Shiffrin developed in 1968 the Atkinson-Shiffrin or modal model [78], which established that memory is the concatenation of three stages, from sensory to short-term to long-term memory.

In 2001 Endel Tulving proposed that the sequential interaction of sensory, semantic and episodic memory, in this order, constitutes a chain that leads to the codification of memories [77][79]. The linking and connection of these three types of memory with their respective information registers the human memories. It is the long-term memory, that is, encoding and retaining of information during a long time period. Upon E. Tulving, the sequential intervention of sensorial (i.e., humans first perceive shapes, smells or sounds), semantic (humans identify that it is people coming home) and episodic (it is a cold night and family is coming home to celebrate Christmas) leads from the perception until the meaningful event, and thus to the encoding of that year Christmas dinner in memory. E. Tulving suggested that episodic memory is the determining type in human life [80].

This thesis proposes a cognitive solution applied in an optical transport network framework. One of the components of this solution is the memory of the system. The model of human memory as a sequence of three stages proposed by E. Tulving described above has been used and integrated in the cognitive proposal. Mainly, the view of the long-term representation episodic memory in the knowledge system is incorporated; as indicated, it is responsible for encoding the whole context of memories, enclosed in space and time and associated to specific situations. Network situations along the time have been registered following this approach.

However the model of the cognitive system memory has not been limited to this view. In [77], F. Eustache and B. Desgranges propose an integrated approach, where the intervention and interaction of the five types of memory constitute the model of human memory. The interaction of episodic with working memory collaborates in the construction of the procedural memory. These authors propose a review of the model of E. Tulving and they suggest existing inverse relations between episodic and semantic and sensorial, so as sometimes interactions between short-time and long-time memory, working integrated in a global model.

In the cognitive approach applied in this thesis, semantic memory has also been integrated, as it puts in context a lightpath parameter which is being stored, combined with episodic memory: what happened with this variable in a specific moment, that is, during a particular network situation. During learning, not only the value of a parameter is recorded, but it is integrated in a definite network situation and it is associated to the rest of the involved variables.

The cognitive proposal searches for the development of the knowledge, supported by episodic memories, and not just a simple storage of high volume of meaningless information. In [77], authors propose some complements and variations to the Tulving's model. For example, an inverse sequence from episodic to semantic and finally to sensorial memory. Some general knowledge (semantic) is formed based on the frequent repetition of the same episodic memory: it is a semantic transformation of episodic memories. For example, people start remembering their back to school of the fourth year, also the one of the next year and finally the concept of *back to school* is formed and encoded, without remembering later on a particular back to school (except if one of them made a strong impression).

It can be interpreted as a generalization and a way of learning, which also applies to the cognitive approach presented in this thesis: whereas in a particular network situation a specific operational security margin value is applied and it works, if any time that a similar network situation happens, the same margin value is set, finally it is generalized, and the process of learning occurs. On the other hand, if only episodic memories are recorded, with no relation or common points established among them, thus without no generalization, the sense of things would not perceived and acquired (*back to school* concept) and learning would not happen. In this case, humans would just retain a great volume of memories, but without knowing what to do with them. It is the reason why humans do not record every day of life as an episodic memory; however it is used for learning. In [77] authors also suggest that there is a direct relation between working and episodic memory. For example, the way of talking to a waiter in a drive-in auto (and it will be completely forgotten one year later) depends on past information (for example, either kindly or stressed in order to get be served more quickly) or precedent events in life. The fact itself of proposing case by case the application of a specific operational margin, in relation with precedent situations or memories, is a reflection of this suggestion of interaction between episodic and working memory.

Thus, the cognitive system memory model presented in this thesis is based on the Tulving's model. The contribution of authors in [77] is also integrated, specifically in the inverse sequential relation between episodic and semantic memory, so as in the pattern identification, which can be explained somehow upon that model as a relation between episodic and procedural memory.

Regarding the memory size in the cognitive proposal, which is an important point to be considered in terms of the knowledge storage capacity, it is to be noted that humans only retain a limited number of episodic memories. One of the advantages of incorporating big data, and be combined with machine learning, is the exponential increase of the memory capacity and information management. With respect to the comparison between human memory capacity storage against a hard disk, the last one can contain high volumes of information, but human brain works differently. Humans have distinct learning systems available, each one with a potentially endless capacity. That is, memory should not be compared to a rigid box, as a hard disk is, because it works as a network in continuous change, able to establish many connections almost at will [81].

Comparison mechanism takes part of retrieval of information from memory during learning processes and it intervenes in how human brain manages knowledge. The transformation of information stored in brain into a meaningful memory is developed with the collaboration of the hippocampus; this brain area is implicated in that process and allows for the comparison and connection of some memory elements with others already recorded. It has a great impact in the organization of memories [74]. In [82] it is indicated how hippocampus collaborates in the process of recording of information and evocation. Knowledge from different sensory systems converges in this area and it plays a core role in memorization. It is a kind of novelty detection [82] mechanism, which compares new information to existing data. If differences are revealed, hippocampus reacts and emits signals to other brain regions and, by means of a feedback process, storage of information is empowered and persistency of this content in memory is reinforced.

Comparison mechanism between new incoming and already recorded information in human memory has been also integrated in the cognitive proposal. This process will be part of the core of the solution and it will be actively and continuously used in the information management.

Picking up the thread of the novelty detection concept, it is a neurological mechanism describing how new information is detected and stored in memory. In [74] the author indicates that the trace left by a stimuli in memory is more strength when the analysis degree or use to which is subjected to is more frequent. More often information is used, more persistent it is in memory and then, more easily shall be evocated. This usability criteria is incorporated into the cognitive solution as well, by taking into account the frequency of use of past experiences. They are involved in the maintenance in the memory system of just certain memories. In the same line and inversely, forgetting has also a direct relationship with the processing of stimuli. In the cognitive proposal, stimuli is equivalent to new incoming traffic demands. Creation of synaptic connections is materialized with the use of new stimuli and it is reinforced with putting into practice what has been learned; but if it is not used, it finally disappears and episodes vanish from memory [74]. In [82], a test case is presented showing that sensory and learning capacity is increased when new information is presented to human brain. A higher chemical activity between hippocampus and other brain regions is contrasted. It seems that it is in the root cause of a greater memorization capacity. Thus, this dynamic system has also been integrated in the forgetting process of past experiences in the cognitive solution memory model, by given less importance to recorded memories which have been less often used in the learning process.

Another interesting answer is how long the positive effect on the novelty contributes to a greater sensory capacity. In their investigations, the Shaomin Li's dubliness [87] research group suggested that this effect become obvious not just at the stimuli time, but also may noticed later on. Tests with mice confirmed that their Long Term Potentiation (LTP) might be triggered in the near future. LTP mechanism is a lasting improvement in the communication between two neurons after a transfer of impulses through some contact areas. Long Term Potentiation is considered the main cellular learning and memorization mechanism and it is then related to the consolidation and storage in memory processes.

In other test described in [82], following the conclusions of Shaomin Li's research group, a group of persons was shown some photos. Then, some words to be classified by conceptual importance order. Next day, before learning task, a subset of those persons was submitted to new stimuli (experimental group) against the rest (control group) who was shown the same photos that the day before. And then, the same list of words was distributed among all of them. They were asked to remember as many related concepts as possible. That is, they were requested to remember and associate simultaneously. Results showed that the experimental group was able to remember more words that the control group. A conclusion to be proposed is that to perceive and store new information enhances memory performance. This fact is also integrated in the cognitive solution developed in this thesis when proposing a dynamic memory. That is, novelty can improve memorization and learning performance.

Human brain has to answer questions and make predictions based on signs or evidences, often uncertain, which do not constitute the global view, but just some fragments of the whole context. Furthermore, human memory is not an unitary block, but a set of interactions among several modules or types of memory which form an integral and complete unit of memory. The activity of the sensory memory reinforces the creation of episodic memories.

Learning process, although in its more basic form such as associative learning, requires of the participation of several brain structures. Learning and memorization is a distributed task.

3.5 Cased-based reasoning

The present thesis particularly focus on the lazy learning techniques, in the supervised learning, non-linear decision category. As indicated above, this machine learning branch waits for starting learning, and then for the generalization, until a new attempt arrives to the system. An advantage of this strategy is to solve several different problems simultaneously. Moreover, it can more easily manage changes in the problem domain. This characteristic may result very useful in the context of the work developed, when a new traffic request arrives to the optical network, whose state at that moment has to be considered.

Inside the Lazy Learning strategies, CBR has been selected, an advanced technique of IBL [66] [88], which is applicable to complex objects. CBR is able to handle more developed representations of the information under analysis, such as, images, documents, situations. It is a powerful tool used to map the new complex instances from the training examples to the target function. In this way, CBR is sometimes considered itself as a subfield of machine learning, since its proposed solutions are not limited to find a concrete solution to a problem, but they largely extent to wider contexts. For example, past experiences and complex cases representations have been used for modeling legal reasoning cases, heterogeneous scheduling situations, such as transportation planning problems, or new industrial pieces manufacturing, by reusing and adapting partial parts of the previously solved cases. However it can also be used for tasks such as to answer help-desk queries by simple matching of useful cases.

CBR is a memory-based problem solving by reusing past experiences. Case-based reasoning method has several features that makes it different from other machine learning solutions. First, instead of using general knowledge of the problem, CBR relies on specific knowledge of that problem, i.e., past experiences on that item. Second, it is an approach to incremental and sustained learning, because a new experience is retained each time a problem is solved, and thus it is available for future instances problems. In [88] CBR is defined as a method to solve a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation. In CBR a case means a problem situation.

It is based on an optimization of the nearest neighbor classifier, the k-NN algorithm. In its more basic version, given an input example, the nearest neighbor algorithm searches for the most similar observation previously stored and directly assigns its output as the solution to the new observation. Instead, the k-NN version searches for the k nearest neighbors. If the class or labels of the observations are discrete-valued, it returns the mode of the k neighbors; if the class takes real values, it returns the mean value. That is, one of the key ideas behind CBR is that, given a set of training data, D, when a new test instance arrives, k-NN finds the more similar matches. Moreover, k-NN tries to minimize the risk of errors due to examples close to the border or outliers. Given the training data set $D = \{(\boldsymbol{x}_1, f(\boldsymbol{x}_1)), (\boldsymbol{x}_2, f(\boldsymbol{x}_2)),\ldots, (\boldsymbol{x}_n, f(\boldsymbol{x}_n))$, and the new test input, $\boldsymbol{x}_k$, k-NN tries to predict $f(\boldsymbol{x}_k)$ as the function:

$$\boldsymbol{x}_{nn} = argmin_{\boldsymbol{x}\in D}\left(d(\boldsymbol{x}, \boldsymbol{x}_k)\right) \tag{3.1}$$

being $d()$ a distance function. Following a hypothesis such that $h(\boldsymbol{x}) \approx f(\boldsymbol{x})\ \forall \boldsymbol{x}$, the hypothesis of k-NN is $h(\boldsymbol{x}_k) = f(\boldsymbol{x}_{nn})$.

In this sense, several ways for distance calculation may be used, such as the Minkowski's metric, the Euclidean distance (which is a particular case of the Minkowski's metric), the Mahalanobis distance or the Pearson Correlation coefficient (correlation product and momento of two vectors of variables).

As the observation data $\boldsymbol{x}$, is composed of several variables or attributes and the units of each one of them cannot have the same order of magnitude, when using the distance function, to avoid problems is necessary to normalize previously the data:

$$\boldsymbol{x}'_k = \frac{x_k - \overline{x_k}}{\sigma_k} \tag{3.2}$$

where $\overline{x_k}$ is the mean of the k^th attributes and $\boldsymbol{\sigma_k}$ is standard deviation of the k^th attributes.

3.5.1 Brief history of cased-based reasoning

The first CBR system implemented was the CYRUS system developed by Janet Kolodner in 1983 at Yale University. Her work was based on the works of Roger Schank in 1982 about the role of earlier episodes or cases in problem solving. And it can be linked to the theories in philosophy and psychology around concept formation, problem solving and experimental learning of Wittgenstein in 1953, Tulving in 1972 and Smith in 1981 [88]. Since then, other systems were developed such as PERSUADER [89] and JULIA [90]. Other investigation groups released another set of models, such as the PROTOS system [91] based on concept learning for classification tasks. This system aims to integrate in a single representation structure both general knowledge in a domain and specific cases knowledge. This idea also leads to applications in law domain and legal judgements, materializing the GREBE system [92]. That combination of general domain knowledge and specific cases for problem solving was also addressed by A. Aamodt and colleagues in [93] producing the CREEK system, in the knowledge-intensive CBR model. E. Plaza and R. Lopez developed a system for medical diagnosis [94]. And M. Keane and his group worked on analogical reasoning in [95].

3.5.2 Types of case-based reasoning methods

CBR methods can be grouped into several characteristic types. A wide range of CBR methods have been developed in order to provide an answer to the different items involved in the process, such as organizing, indexing cases, retrieving and combining past solutions. The driving idea common to all of them is the same: identify the problem to be solved, find the past similar cases, reuse the suggested solution found at that time, evaluate it on the current problem and decide whether updating the system. CBR types differ on which part of the problem is focused, what type of problems drive the different methods and how it is implemented. Some of them are described in [88]: cases can be stored either as concrete situations or grouping a set of them leading to a kind of *generalized* case; the solution from a past case can be directly applied or adapted to the new case; cases can be recorded as separate knowledge units or distributed within the knowledge structure.

In this field some confusion when using CBR terminology may exist. In [88] an attempt to clarify this situation is proposed. For example, learning by analogy or analogy-based reasoning can be sometimes used as a synonym of case-based reasoning; even though use of past experiences is also used in solving by analogy, this approach focuses in analogies across domains, whereas CBR can be considered a type of intra-domain analogy. Analogy searches for applying past cases from a different domain and case-based reasoning focuses on single-domain cases. Cross-domain analogies were developed in [96]. The term case-based reasoning can itself be used as a generic denomination of this kind of learning methods and particularly as one of these particular approaches. This last one is characterized for assuming a complex and rich internal description of a case with subsequent impact on the general knowledge structure. The suggested solution can be modified and adapted to the new problem. Exemplar-based reasoning term refers to a view of the concept definition learning problem. This approach addresses problem solving as a classification task [97] [98]: to find the right class of the unclassified instance is the objective, where the set of classes form the set of possible solutions. Modification of a solution is not in the scope of this method. Another type is the instance-based reasoning method, which is a specialization of exemplar-based reasoning into a highly syntactic CBR-approach [88]. In this approach the representation of instances is normally simple, a feature vector, and it is characterized by using a large number of instances to form a concept definition. It is non-generalization approach to the concept learning problem addressed by classical, inductive machine learning methods [88]. Finally, memory-based reasoning approach addresses reasoning as the way of accessing and searching in a large memory of past cases, Organization of this large memory is mainly the focus of this type of CBR methods.

From now on, case-based reasoning or CBR will be used as a generic term in this thesis, if no more explicit explanation is indicated.

3.5.3 Case-based reasoning model process

CBR methodology is based on a four phases cycle: Retrieve, Reuse, Revise and Retain. The initial Retrieve phase consists on finding similar past problems, modeled as *cases*, composed of several attributes, which are stored in memory, that is, in a database called Knowledge Base (KB). The concept of similarity is a key point because it conditions the utility and reusability of such cases. Particularly, it is modeled and calculated as the distance between the query point and the similar past cases. Then, retrieval is usually based on the k-NN algorithm, considering k neighbors, on some CBR methods. A global similarity approach between the observations is typically considered: its means that the whole object is compared, not only specific features of them. In this case, some features or attributes can be more representative in the description of the object than others: a weight system can be applied to give more importance to more relevant variables. In [88], the Retrieve phase is subdivided in several sequential subtasks: matching (to return a set of cases sufficiently similar to the new case) and selection (to choose the best match among the set of similar past cases).

In the Retrieve phase, as is based on the searching on the memory of the system, an efficient indexing system should be implemented: literature suggest several solutions; for example using KD Trees [99] or even by applying clustering to the stored instances. In this context, representation of cases is an important point in this phase, so as in the Retain step, since the same issue is addressed: how to store a case in the KB. In [88] two case memory models are reviewed: the dynamic memory model of Schank [100] and Kolodner [101], used in the CYRUS system, and the category-exemplar model of Porter and Baress [102], used in the PROTOS system. In the first one, the case memory is a hierarchical structure, where specific cases sharing similar properties are organized under a more general structure, known as a generalized episode (GE). A GE is composed of norms (common features to all cases indexed under the same GE), indices (discriminating features between cases under the same GE) and cases. In this way the whole memory is a discrimination network: when the best matching of a new instance is searched for, the input case is pushed down the memory network structure, starting at the root node. The second memory model is a network structure composed of categories, features and cases. A case, also known as *exemplar*, is associated with a category. And different features are assigned different importance in describing a case's membership to a category [88]. Categories are inter-linked, also containing the linked features.

The second phase, Reuse, consists on proposing solutions to the current situation based on the retrieved cases, by reusing partial or completely their past solutions. Normally, two main strategies can be applied in this step: the more basic one is to copy the past solution to the new case. However it is not always possible to completely transfer the same solution to the new case. In this case, the second strategy consists on adapting the retrieved solution. In this way the differences between the new case and the retrieved cases are reflected. Here, the substitution of some parts of the retrieved solution is commonly the simplest form of adaptation. But a transformation is also an option, by altering the structure of the suggested solution.

The third step or Revise phase, consists on evaluating, verifying and correcting or repairing the proposed solution by the Reuse phase. To do this, several criteria can be used for revision, such as correctness of the solution, quality of the solution or user preferences.

Finally, the fourth phase, Retain, consists on storing the new case and its solution in the KB. It materializes the learning process. At this stage, what can be learned is the key issue. It will be used for future problem situations searching for a solution. When incorporating new cases to the existing knowledge, it may involve to retain only a part of the information contained in the new case. Forgetting cases for efficiency or because out of date reasons may represent a point to take into consideration in this phase. Some other important points to be considered are how to integrate the new case in the memory structure and how to index it for later retrieval. Regarding this last issue, further detail has been indicated above, in the Retrieval phase.

These four phases are depicted by the CBR cycle described by Aamodt and Plaza [88] in 1994 and illustrated in Figure 3.6:

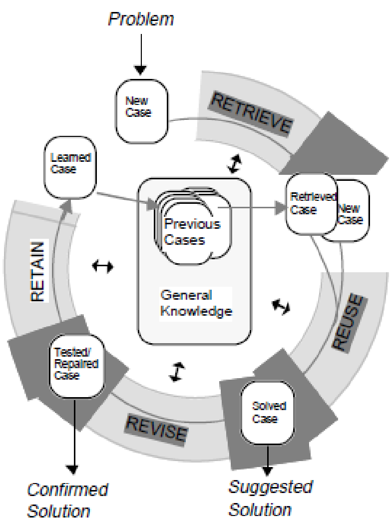

Figure 3.6. The CBR cycle (taken from [88])

Based on further descriptions indicated in above sections, CBR has been selected in the present thesis due to several reasons. It is important to be noted that, the cognitive solution proposed is *based* on CBR. It means that a combination of parts and aspects of the different methods explained in precedent paragraphs has been considered, and not a single particular approach has been followed. First of all, it is applicable to build structural and complex descriptions of objects, for example to describe and adapt to an evolving optical network. Also, CBR techniques provide local approximations to the target function: this characteristic shall be exploited in the framework of this work because the best solution in a particular moment in the optical network is desired to be obtained, and not a general solution to the problem. CBR is based on the previous experience to solve new situations: similar problems have similar solutions and situations often repeat. Other hypotheses behind CBR are that situations often repeat. Moreover, as indicated in subsection 3.3 for supervised approaches, decisions are based on past experience, expecting that similar situations will have to be faced in the future, thus the same behavior will be reproduced. This technique approaches to the human thinking and reasoning: a new problem is tried to be solved by finding similar past experiences stored in the memory and reusing them by adapting and applying total or partially the previous solution to the new situation. CBR has a relatively fast training phase, as a lazy learning algorithm, and can learn complex functions in a relatively simple way (i.e., a solution can be quickly proposed and the domain under analysis does not need to be fully understood) and does not lose information. CBR methodology applies correctly for classification and diagnosis problems and for prediction tasks, for configuration and decision support. This fits our needs regarding the behavior to be predicted in an optical network. Additionally, it is a technique that requires less maintenance effort compared to alternative cognition techniques and can adapt to changes in the environment. Its main drawback, however, is the storage capacity or memory needed to store past experiences; CBR can also be revealed as low to solve specific problems because learning is done when a new query arrives. In view of this, our proposal is to perform learning offline and not in a real-time context as previous works using CBR proposed [57]. Other disadvantages are that best cases are not always selected and applied and memory can contain irrelevant information. However the advantage of CBR is that it can adapt to changes in the environment and this is the characteristic more relevant in our work context: the evolution along time of a real optical transport network. And to integrate this evolution in the knowledge structure may represent an advantage.

Thus, in the next chapters, a cognitive approach based on CBR is proposed and developed, to be applied in a national optical transport network.

3.6 Chapter summary

The main features of machine learning framework have been illustrated in this chapter. Main unsupervised and supervised learning approaches have been briefly indicated. Supervised learning is characterized for having available the output of the classified instances of the input dataset. Herein, instance-based learning methods have been further explained. Lazy learning is defined as waiting for starting learning until a new instance arrives to the system. This approach delays the decision of the generalization. Thus, it can be adapted to the context of transport optical network situation addressed. A further detail is provided for case-based reasoning, since this method is used as the basis to develop the cognitive solution in this thesis. Moreover, a basic review of human learning and memory processes has been presented. Aspects of some of these procedures, such as the long-term episodic memory and its inter-relations to other modules or parts of memory, have been used to elaborate the cognitive proposal. They have been put in context in order to complete the solution. In this regard, it is worth mentioning that case-based reasoning is the framework wherein the developments that compose this thesis have been realized.

Chapter 4

Cognitive science applied to reduce optical network operational margins and work scenario

This chapter presents the approach followed to optimize the System Margin. To this end, the network model employed is described in the first section and the optical power balance equation to model the end-to-end path is introduced. Furthermore an explanation of the involved parameters is provided. Subsequent sections detail the proposed strategy applied to reduce the operational System Margin. In particular, the adaptation of the case-based reasoning methodology to construct the cognitive solution is presented. To achieve this, several novel schemes have been introduced in the reuse phase of the CBR cycle. Moreover, the indicators used to monitor the performance of the proposed solution have been presented. Finally, a software-defined network architecture is suggested.

4.1 Network model

The objective of this thesis is to reduce operational margins in optical transport networks; in particular, the aim is to reduce the System Margin, by optimizing the optical link power budget in the end-to-end paths. This target is intended to be achieved by applying a CBR-based cognitive solution which will propose a new launched power value, in some cases allowing the operator to use lower values than previously designed.

The network scenario used is a national long-haul optical network composed of 9 nodes, as depicted in Figure 4.1. In order to develop and verify the cognitive solution, four representative lightpaths have been selected. It has been considered that among all of them they gather and cover all the spectrum of the heterogeneity of the optical transport network in terms of total length, number of links and number of nodes elements passed through. Each end-to-end path is composed of several optical links, spans, intermediate ROADM/WSS nodes and optical amplifiers. Several parameters have been taken into consideration in order to characterize each path, that is: length, number of in-line amplifiers, number of simultaneous wavelengths allocated in each one of the links and minimal spectral distance among them, non-linear impairments and the net link losses, which are modeled by the accumulated losses in the fiber, the connectors and the splices. The traffic request flowing over each lightpath has also been modeled by means of the following attributes: the requested throughout, the quality of service represented by the required BER and the required sensitivity at the receiver for each incoming traffic request. The System Margin set for each request in the lightpath and the necessary transmission optical power assigned are also contained in the description of the lightpath. All of these attributes model the lightpath and they conform the CBR case. Thus, a CBR case is a vector containing all these attributes; each one of these n-tuples, modeling and representing a concrete network situation, is stored in the Knowledge Base.

One of the mentioned attributes is the System Margin, which is the security margin introduced in the optical power budget to manage the unforeseen degrading effects. In the design phase of an optical transport network the value of this parameter is established taking into account the end of life of the components. It is configured as a fixed and conservative value; it is adjusted during the commissioning phase of the network, then applied in the further operation and exploitation. In this thesis, the aim is to optimize this operational margin. The approach is to not apply that conservative value from the beginning of the exploitation of the transport network, but a lower and flexible value, more adapted to the current network conditions. The cognitive CBR technique proposes a more optimized value, while guaranteeing the required transmission quality over the lightpath [103]. This proposed value is obtained taking into account the state and ageing of the different components of the network.

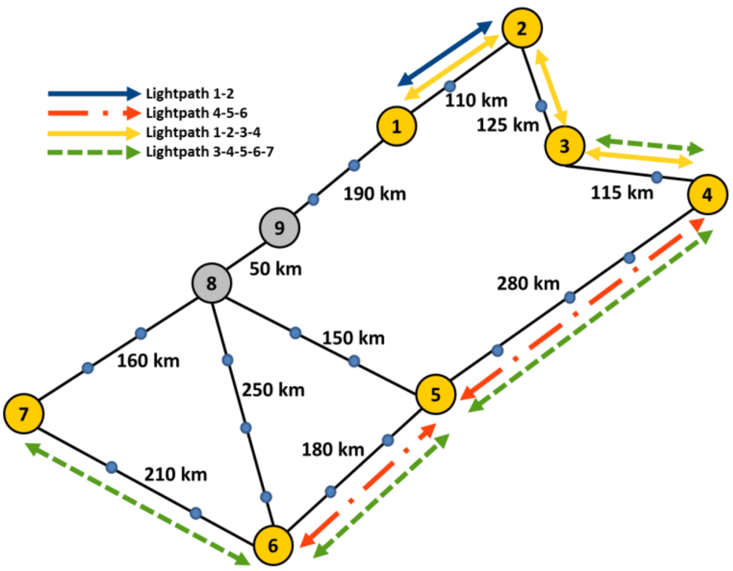

Figure 4.1. Network topology used

One of the first and key phases in the implementation of an optical transport network is the commissioning of the optical power: when building a new optical transport network, the design of the optical power budget is firstly done. After the design phase, commissioning on field is executed. This task is usually executed twice along the lifetime of the network: at the very beginning, when the optical network does not transport any service yet; and when new services are deployed. At this last time, the optical power budget commissioning phase shall be normally done sometimes by previously stopping the other services, then causing temporary interruption. However, it can be also done by reengineering the network deviating the traffic towards other possible paths. The cognition-based approach proposed in this thesis is based on searching for precedent similar situations and then to directly propose a transmission optical power, avoiding this way to interrupt running services.

The commissioning phase is comprised of several steps that can be followed in sequence: setting the fiber type, configuring, measuring and adjusting the multiplexer and demultiplexer parameters, the optical amplifier (OA) parameters and the ROADM parameters of the intermediate nodes, evaluating the network scenarios and, finally, commissioning the optical power. In an optical transport network, a single network node is part of several routes, it is an intermediate passed through network element shared by several lightpaths. Thus, some of the points to be evaluated during commissioning are the input and the output optical power on these nodes regarding the mix of simultaneous wavelengths flowing through them; this assessment shall be done for every lightpath. At the end of the commissioning phase, and for every path, the operational team shall have evaluated and registered the optical power received and the corresponding BER. Other typical parameters evaluated during the commissioning, having an impact on the performance of the network are: the number of network nodes passed through along the path, their boards (volume of ports and port types), the number of wavelengths going through the OA boards in each network node, the single wavelength input and output optical power through the crossed network nodes (for this parameter nominal values are normally considered, which are set with the minimum nominal gain value of the different OA boards), the OSNR or BER evolution along the nodes through the path, the multiplexed wavelength optical power, the nominal gain and the attenuation in every network element, the link losses (considering the fiber, splices and connectors attenuation in each link of the path, so as the total end-to-end losses between end-to-end nodes), the CD and PMD compensations, the crosstalk and the reception indicators, materialized in the received optical power and the BER or OSNR or Q parameter values.

The optical transport network has been modeled and managed as a mesh of end-to-end point-to-point optical links. That is, the end-to-end paths across the network are composed of several optical links and spans with intermediate ROADM/WSS nodes being considered as pass-through optical amplifiers. The following basic power balance equation has been applied to model the end-to-end path as a point-to-point link between two end nodes:

$$Ptx \geq Srx + CL + NLI + M \tag{4.1}$$

This equation integrates and considers the affecting optical parameters when building a network and having an impact during the transmission. In more details, Srx is the sensitivity of the optical receiver, that is, the minimal optical power to be received in order to correctly detect the signals. It has been established based on the Quantum Limit of the receiver [38] [104] and adapted to the typical values used by a commercial network operator, trying at the same time to be agnostic with respect to the infrastructure provider. The sensitivity has been calculated for the specific required BER for every new incoming client request. The range of allowed values varies between -24 dBm and -12.5 dBm.

When travelling along the network the launched optical power is affected by the attenuation losses, the dispersion and the physical nonlinear impairments. These effects are introduced in the equation (4.1) as follows:

- CL parameter models the channel net losses, including fiber, connectors and splices. Its value will increase as time passes due to components degradation/ageing. In this thesis, the attenuation range has been established to be between 12 dB and 24 dB.
- NLI parameter encompasses the non-linear impairments and the power penalties, based on the affecting parameters in the DWDM long-haul amplified and non-regenerated systems. As indicated in chapter 2, the nonlinear effects become dominant when the chromatic dispersion in the fiber is reduced. Even though some techniques can be applied to cope specifically with some of these impairments, a long-haul optical network is a complex and heterogeneous ecosystem where the mix of products and materials makes difficult to maintain and to control all the optical nonlinear impairments. For example, some spans in some links may have been built with G.653 fiber and then FWM effects might appear. Even though operational teams try to maintain as homogeneous as possible the network implementation, it is not rare if some spans are composed of several types of fibers (G.652, G.655 and G.653) and maybe fibers can have been replaced in different moments, making not homogeneous the several spans of the same link and globally the links of a lightpath. Among the nonlinear impairments, the phenomena more likely to be present and affecting a commercial DWDM network have been selected, such as Stimulated Raman Scattering, Stimulated Brillouin Scattering, Self-phase Modulation, Cross-phase Modulation, Four-wave Mixing, Polarization Dependent Loss, Polarization Mode Dispersion, Crosstalk and Power Varying. In the literature, different criteria and typical value ranges for them can be found [36] [38] [47] [50] [60] [104] [105]. In this thesis the allowed NLI range considered varies from 0.02 dB throughout 5 dB. Furthermore, if the path transports traffic requests above 40 Gb/s, an additional 1.5 dB penalty has been added due to power penalties depending on the number of spans and crossed high-power amplifiers passed-through; the Hybrid Transmission Penalties (around 1.2 dB) and the crossed ROADM have been also included in the above indicated range.
- M parameter represents the System Margin, also known by the operation teams as Security Margin or Operator Margin. This value can vary considerably both in the literature and in an optical commercial network: between 5 dB and 10 dB including power penalties [104], between 3-6 dB [36], between 3-4.8 dB [105], between 4 and 6 dB, including Power Penalties [38] and between 0 and 9 dB [60]. The considered range in this thesis will fluctuate between 1 dB and 4 dB to incorporate the unforeseen degradations and the aging effects.

Finally, regarding the transmission power launched by the Optical Transmission Units boards, a grid of discrete allowed values typically used in commercial networks, between [7.5, -2.5] dBm, with a step of 0.5 dBm, has been set.

As indicated in the beginning of this section, four different paths between end network nodes have been selected for the analysis of the cognitive solution. It has been considered that they represent and comprehend sufficiently the heterogeneity of the whole optical transport network in terms of the number of links (they are paths composed of one to four links), the network nodes and the total length (physical lengths of 110, 350, 460, 785 Km, respectively, with variable span lengths in the links and with the in-line amplifiers not being installed following a constant length).

4.2 Proposed approach

Regarding the equation (4.1) CL and NLI parameters are random variables. Their value is unknown beforehand; thus, they bring some uncertainty. To quickly measure, compute and report their exact value in real network scenarios could be a hard and very complex task, not always possible, and a complex and costly monitoring system would be required. These uncertain values of the ageing of the passed through components for the lightpath and the existing non-linear impairments over the path have been integrated in the CL and NLI parameters. The CBR cognitive proposal considers these parameters as part of the calculation when evaluating performance. In this way, CBR learns from the precedent data how the ageing is affecting on the performance of the transmission; and as it is integrated in the calculation it is not necessary to know accurately these random values. In this way CBR-based cognitive solution proposes a successful transmission power and simultaneously overcomes the inherent complexity. This is the advantage of CBR: to learn from the experience, that is, from the precedent similar situations, and to reduce the System Margin initially assigned to each lightpath by proposing a new and lower launched power.

The Knowledge Base (KB) is a database storing precedent successful lightpaths (LP). As a first approach in this thesis, it is suggested and assumed that the KB is initially populated offline (before network operations start) with successful test lightpaths establishments performed by the telecom operator. Moreover, this KB can be renewed offline by realizing appropriate measurements with new test LPs by the operational teams every certain time window, for example, every month or every year.

The telecom operator has launched test LPs at different moments and has performed real measurements. Thus, these successful LPs together with the real measurements of their attributes are stored in the KB as part of the process of the generation of the initial KB. Then, the initial KB is generated based on an offline learning strategy. CBR will use the successful stored LPs in the KB to propose a solution to the new incoming LPs requests. It is important to be noted that the KB does not store active LPs. By the contrary, the KB only collects and stores precedent successful cases corresponding to different historical moments: each stored case or lightpath responds to certain traffic requests, modeled with BER, throughput and wavelength parameters, established in certain network conditions, modeled by the CL and the NLI parameters. Specifically, mainly the CL gives information on the net losses and integrates itself the ageing effect, and the NLI informs about the non-linear impairments present due to the corresponding reasons. The KB would be renewed in a time scale adequate to incorporate the evolution of ageing effects. Although it does not necessarily mean that the new candidate cases to be integrated in the KB will involve higher ageing effects. That is, the KB is not a chronological list of ordered lightpaths establishments or CBR cases whose System Margin is higher and higher, because of the ageing of the network is more important as time passes. They represent a collection of past network heterogeneous situations at different moments of the optical transport network lifetime.

This is explained because the operational maintenance teams do not act over the whole network simultaneously: maintenance can be applied on certain links and network nodes, and then the whole network does not becomes older homogeneously. As a consequence, a same LP can have some links or network nodes which have been maintained at different moments; this heterogeneous evolution generate different network conditions along the time. In this way several network situations can be happened for a same LP in terms of ageing and non-linear impairments at different times along the life of the optical network. The KB collects all these heterogeneous situations and CBR exploits this information to adapt to the network context and propose a lower transmission power value for the new LPs.

As explained above, the KB only stores past successful lightpath experiences; then the KB cases contain both the launched power applied and the M value selected, lower than the pre-assigned one during the design and commissioning phases (which should be M = 4 dB, as indicated above), guaranteeing the successful establishment of the lightpath, assuring the quality of service required on certain channel conditions.

To generate the numerical results of this thesis, the optical power budget Equation 1 has been applied, setting a successful transmission power value and applying a System Margin lower than 4 dBs. The CL and NLI parameters values have been randomly generated among the ranges indicated in Table 4.1, as if they would have been real measurements. For every KB case, random values of the attributes have been generated and applying several conditions:

1) Ageing probably implies more impact in longer lightpaths, because more components are involved in terms of links, spans and network nodes.

2) Non-linear impairments are probably more important if more simultaneous lightpaths are active and sharing the links; then, under these conditions, NLI value is probably higher.

3) Non-linear impairments are probably higher when lambdas of simultaneous connections sharing the same link are closer; this impact is probably more important when network load is higher.

4) When ageing impact is higher, the System Margin applied is probably higher.

In Table 4.1 the ranges of the attributes for generating the KB cases are indicated:

Name	Minimum value	Maximum value
Receiver sensitivity (Srx)	-24 dBm	-12.5 dBm
Channel net losses (CL)	12 dB	24 dB
Non-linear impairments and power penalties (NLI)	0.02 dB	5 dB (6 dB, if request > 40 Gb/s
System Margin or Operator Margin (M)	1 dB	4 dB
Bit error rate (BER)	10^{-15}	10^{-9}
Throughput	1 Gb/s	100 Gb/s
Number of simultaneous lambdas	1	40
Transmission power (Ptx)	-2.5 dBm	7.5 dBm

Table 4.1. Parameters of the model to describe the scenario

The initial KB has been offline populated with the aim of collecting as much heterogeneity as possible in terms of different network situations; in the second part of this thesis, when the dynamic KB is explored, for the simulation it has been preferred to mark a clearer trend on the value of the attributes of the cases modeling the conditions found by the lightpaths in the network; thus, the CL and NLI parameters of the CBR cases populating the initial KB have been generated following a uniform distribution. And in the second part of the thesis, related to the dynamic KB, those parameters have been generated upon a Gaussian distribution for the new incoming requests, as indicated in recommendations [47], [106], [107] and [108].

When a new incoming lightpath request, with its particular required quality of service, arrives to the network its transmission power value is calculated taking into account the pre-assigned M parameter value, which is 4 dBs. CBR is applied during the operation of the network at this stage: the precedent network similar situations are searched in the Knowledge Base and the transmission power value used is revisited, leading in most of the requests to set a new optimized System Margin value, reducing the initial one, predetermined during the design phase.

This reduction of the M value allows the network operator to get savings in the transmission power and this shall extend the life of the transceiver, then reducing the maintenance costs of the telco carrier. OPEX are the recurring negative benefits or costs related to the network usage, such as energy consumption, network maintenance and fault reparations costs, as well as the underuse of the network devices arising from an undesirably short effective life [39]. In [41] it is also indicated that cost savings should be achieved by not stressing hardware components, e.g., allowing lower launch power leading to a power consumption reduction.

For the analysis and assessment realized in this thesis, 10^4 new incoming requests have been generated and the cognitive CBR based solution has been applied to obtain a new transmission power. In order to monitor the performance of the solution, three indicators have been established: two of them are related to the successful rate of applying the cognition methodology and the third one to control the savings. “CBR%” provides the success rate of the cognitive solution when applying it to a new incoming request, that is, if the CBR based proposal is able to provide a transmission power value that guarantees the quality of service required. The second indicator “FitCases %” denotes the percentage of the new proposed values by CBR leading to a reduction in the launched power, namely, suggesting a transmission power equal or lower than the pre-assigned power calculated with the initial M = 4 dB value. This second indicator is introduced because in some situations CBR may propose a transmission power value valid for the lightpath establishment but higher than the preassigned one, hence inappropriate. Sometimes it can be observed that “FitCases%” increases but the proposed transmission power remains in the same range as the one for new case; that is, even though the proposed solution is correct, no direct advantages for the operational optimization can be taken, since no power savings are obtained; only when the proposed launched power is in a lower grid range effective savings are obtained and it is useful for operational purposes: the difference between both transmission power values, the initial one and the proposed by CBR is implicitly subtracted to the initial System Margin applied and this reduction is the savings obtained in the operation margins. Finally, the mean savings obtained by applying the new launched power are measured with the “Ptx Mean Savings %” indicator.

Ageing may evolve along the time and its impacts can become more important. In these situations, the needed System Margin may have to be increased. One possible preventive strategy may be to establish an upper threshold on the receiver side, in terms of OSNR, BER or received power, in order to decide if triggering the increase of this System Margin. These network situations have been modeled in the KB as part of the cases presenting higher CL attribute value.

When these situations arrive the System Margin increase is translated into a transmission power increasing of the corresponding lightpath which will probably cause non-linear impairment higher values. This negative effect will affect both the connection itself and the other connections sharing the link, which in turn will need to increase their System Margin and then their transmission power. Certain automatic mechanisms shall be implemented in the network to control this increase of the launched power in order to guarantee that the optical power flatness remains inside the ranges decided in the design and commissioning phases, below a given Power Unbalanced Threshold (for example, 1.5 dBs).

The trade-off between increasing the transmission power to cope with noise effects in the path and limiting the power to not shoot up and to control the non-linear impairments has to be taken into account as defined by equation (4.1). The potential loop related to the launched power in the fiber and the NLI is upper-limited by the maximum allowed transmission power value in equation (4.1), which is a design rule valid for all the network; it is to be noted that this value depends on the deployed technology and it has been set to +7.5 dBm in this thesis. The possible launched power varies between a minimum and a maximum value and the NLI is also limited by a maximum value, integrated in equation (4.1). When the transmission power increases, then the NLI increases and the minimum launched power to satisfy equation (4.1) will in turn increase, until reaching the highest transmission power allowed value, which cannot be exceed. The network designers have been established these values during the design phase, so as the System Margin (+4 dB) supposing that the set value will be able to absorb the maximum non-linear impairments and ageing effect in the network. Thus, applying this value will lead to the successful establishment of the incoming lightpaths. The value of the optical path parameters worked out and consolidated during the design and commissioning phases are set to guarantee the quality of service of the different traffic requests and define the limits of the satisfactory operation on the network and commercial networks are dimensioned following these sets of values. If they are not respected it may lead to lightpaths establishments no assuring the required bit error rate and having negative impacts not only on themselves but also on the simultaneous connections sharing the links of the path. In case that the required transmission power exceeds the limits and it is needed a higher value than the maximum allowed one, applying re-routing policies to this lightpath through a protection path could be a solution; in any case, this connection will not be established over that path. The maximum NLI value taken into account for the maximum allowed transmission power is set to NLImax = 5 dB (or NLImax= 6.5 dBs for requests above 40 Gbps).

As indicated above, commercial networks implement security mechanisms to monitor and control that the Output Power Upper Threshold is not exceed. In case it could be reached, alarms are generated that allow the exploitation teams to take the appropriate measurements to avoid this situation and ensuring the stability of the optical signal.

4.3 Cognitive CBR based approach

The cognitive solution proposed in this thesis is based on the CBR technique. As indicated in chapter 3, CBR is a four-cycle process. Our new methodologic proposal is supported by this machine learning technique. It is explained in detail in the following paragraphs.

The Retrieve phase has the objective of finding the most similar neighbors. In our solution, the neighbors represent the network situations and the solution proposed in terms of System Margin applied (lower than 4 dB) and consequent transmission power launched, at that time, for that lightpath and in those network conditions context. The retrieval function in CBR is normally supported by the supervised learning algorithm nearest neighbor (NN), which searches for the most similar neighbor to the new incoming request. A variant of this algorithm is introduced by considering not only the most similar neighbor, but the k more similar neighbors, enlarging the scope of the search. The resultant k-NN algorithm is then applied. Its advantage is to minimize the risk of selecting spurious examples, as it will be observed in the obtained results in the chapter 5 in some situations. In our approach, this process is applied and adapted to the optical transport network: for any new incoming traffic request (testing instance), modeled as a CBR case with the initial System Margin predetermined (4 dB) and the corresponding transmission power assigned, the k more similar network situations, also modeled as CBR cases, are looked for in the KB and returned as a list. Here, a key point in the process comes to play: how similarity degree is considered. To do that, similarity is calculated as the distance between the testing instance and each neighbor. Usually, in the literature, the Euclidean distance is applied to work out this value. In our work, this typical scope has also been enlarged and the Minkowski's metric formulation has been considered (equation 4.3), which introduces the r parameter in the distance calculation. Thus, the pair [k,r] of CBR parameters are considered in the analysis: the number of neighbors or past network situations, modeled by the k parameter of the k-NN algorithm, and the scope of the distance calculation, modeled by the r parameter. The range considered for each parameter in the analysis has been k = [1-10] and r = [1-3]. Typically, k-NN algorithm returns the mode (most often occurring value) for discrete output variables and the mean for continuous output variables.

The Reuse phase is the second step in the cycle. It takes the output of the Retrieve phase, that is, the list of the k more similar neighbors extracted from the KB, and it combines their respective outputs to produce a new one. Thus, the transmission power applied in the situation modeled in each neighbor is combined to propose a new launched power value. The way the respective output power values of the neighbors are integrated depends on the algorithms used, also called schemes. In the literature, the most commonly schemes applied are the mean and the distance-weighted [66]. Additionally, four other schemes are developed and presented in this thesis. Thus, the aforementioned k-NN function output cases are combined according to six proposed schemes:

- *MEAN*: mean voting scheme.
- *DISTANCE-WEIGHT* (DW): a dynamic weight scheme depending on the distance of each neighbor to the instance.
- *MIN*: new proposal where the minimum value among the candidate neighbors is selected.
- *FIXED-WEIGHT* (FW): new proposal using a fixed weight scheme, according to the number of neighbors considered, with weights distributed in a decreasingly linear way
- *DISTANCE-WEIGHT INVERSE* (DWI): new proposal where a dynamic weight scheme depending on the distance of each neighbor to the instance and giving slightly more weighted to farther ones, is applied.
- *MINTOMEAN*: new proposal where a value between the minimum power and the mean power of the neighbors is proposed.

Each CBR case is a vector of the attributes explained in the previous paragraphs. This n-tuple describes the observation, whose output is the transmission power applied in the corresponding network situation which allowed to successfully establish the lightpath:

$$(x_1, x_2, x_3, \dots x_n) \tag{4.2}$$

The Minkowski's metric is used to quantify the distance between two cases or instances as follows:

$$d(case\ x, case\ y) = \sqrt[r]{\sum_{i=1}^{n} |x_i - y_i|^r} \tag{4.3}$$

Then, the degrees of similarity is calculated taking into account the network conditions of the end-to-end path and the traffic request. Figure 4.2 illustrates this process:

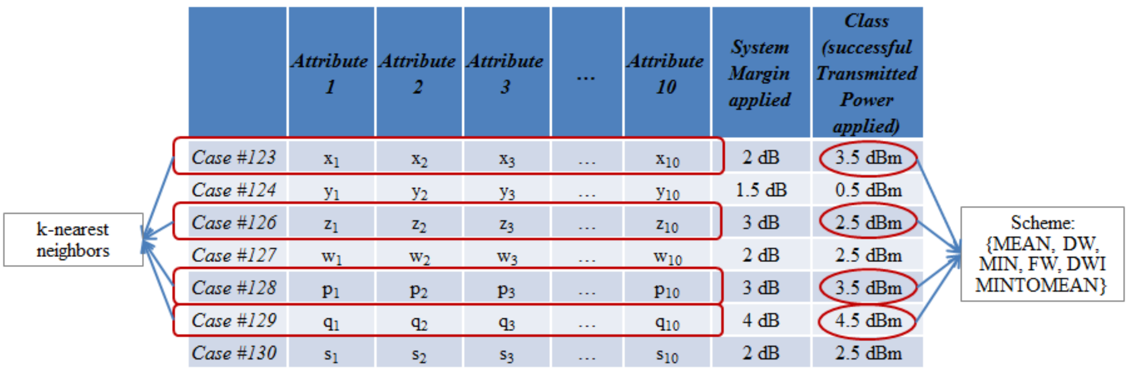

Figure 4.2. Example of the proposed CBR process.

In the depicted example, the chosen k value is set to 4. It means that the Retrieve phase selects the 4 nearest neighbors from the KB by applying r=3, for example to evaluate the distance respect to the new incoming instance. Next, the Reuse phase extracts the transmission power of each of these four past successful experiences and it applies one of the six proposed schemes to combine them. Each scheme will produce a specific new transmission power. Table 4.2 indicates the values that each one of them would propose:

	MEAN scheme	MIN scheme	FW scheme	DW scheme	DWI scheme	MINTOMEAN scheme
Proposed Transmission Power	3.5 dBm	2.5 dBm	3.8 dBm	4.1 dBm	3.9 dBm	3.0 dBm

Table 4.2. CBR transmission power proposed

To avoid an incorrect similarity computation, the margin itself is excluded. It would prevent to select the most similar neighbors.

In the first part of this thesis, presented in chapter 5, the KB is static: LPs stored in the memory are not replaced by newer ones. In chapter 6 the KB is considered as dynamic, meaning that an online replacement of the LPs takes place. In this case, it is to be noted that the new successful lightpath establishments modeled as a CBR case and to be integrated in the KB does not have necessarily a higher transmission value, as ageing and preventive maintenance may not be done homogeneously over all the links of the LP, but only in one or some of them. As the KB is not a chronological ordered list of network situations, several strategies to renew the KB can be implemented regarding the transmission power of the new cases incorporated. This correspond to the coherent objective of the KB, the storage of as many heterogeneous network situations as possible, in order to learn from past experiences. This is the reason why the initial KB is populated following an offline generation strategy. CBR is applied to manage the uncertainty in real network life.

The Revise phase performs the comparison between the new transmission power value proposed by CBR and the predetermined one. If the new launched power satisfies the quality of service required by the new lightpath, "CBR%" monitoring the power budget will increase, so as "FitCases%" monitoring the operational improvement if existing and then power savings will be obtained, quantified by the "Ptx Mean Savings %" indicator. If the proposed value by CBR is not enough to guarantee the quality of service, "CBR%" simply will not increase, because the new LP could be blocked, and the predetermined transmission power value, and the associated System Margin, will be applied, leading to no savings obtained for that LP. A threshold of "CBR%" = 95% has been fixed to determine if the cognition solution accomplish the objective.

The verification of the proposed solution in the Revise phase is done by a direct confirmation at the receiver in our assumption. An unmodulated signal is sent with the new proposed transmission power value and it is monitored at reception in order to detect if it guarantees the required quality of service and the power losses along the path have been balanced. If the new launched power would be not enough, the receiver could send a command to the transmitter in order to increase the launched power value by *Ptx_default* - *Ptx_CBR* dBs. In the section 4.5 a basic SDN based architecture is suggested. Following this strategy, if our cognition methodology does not success when proposing a new lower power value, the transmission power will be increased, simply by using the initial predetermined value guaranteeing the transmission of the service.

An alternative solution to our cognition approach could consist on trying with all allowed discrete launched power values until identifying the one that could enhance the initial assignment. This continuous and sequential search for the optimized value could be done in increasing order or by dichotomy-based searching techniques. It might start attempting very low transmission values and increasing them in discrete steps for example, until an eventual setting up of the incoming lightpath is succeed. However, our CBR-based technique directly proposes one transmission power value to be applied, reducing the time needed to select a new power for the lightpath to be established.

The Retain phase is the final step in the CBR cycle. In this phase the instance may be integrated in the Knowledge Base if the policy allows it. The learning capacity of the system is enhanced. The resulting instance, modelling the lightpath, with the new System Margin and transmission power values should be incorporated to the memory structure as a new case. In the Retain phase several policies can be applied. One of them is to not include new cases, independently of the success in the new and lower power value. In this case the system becomes a non-learning classifier, which can still be used to propose a cognitive solution for new incoming lightpaths and optimized the operational security margin but not enhancing the learning capabilities. This policy has been applied in the first part of our work, presented in the chapter 5. Moving further, other strategies could be possible: one of them may consist on incorporating to the KB any new successfully established LP. However, this policy would increase the KB size and then the CBR computation time. One solution to this point would consist on setting a threshold which would set the maximum potential LPs to be added to the memory, limiting in this way the maximum acceptable computation time. Other policy could consist on adding only those new lightpaths involving a significant enhancement or difference with respect to those ones already stored in the KB, thus avoiding the storage of redundant information. Alternatively, other possible policy would be to store not the correct revisited lightpaths but the incorrect ones: that is, those lightpaths for which our CBR solution have proposed an inappropriate launched power value for the required service in certain network conditions. It would represent a strategy to learn from errors. The second part of this thesis raises the dynamic update of the KB by applying an strategy that will populate the KB with the successfully CBR revisited lightpaths. The results are presented in chapter 6.

4.4 SDN-based architecture proposal

A SDN-controlled optical network architecture is proposed as the framework to implement the cognitive system (Figure 4.3). The CBR Module is hosted by the SDN Controller. The cognition solution will provide a new launched power which shall be monitored to decide if it guarantees the quality of service along the path. This will be measured at the receiver node and the system shall be informed about the result of the process, in order to maintain or to modify the transmission power. As indicated above, all this process will be done by means of a probe unmodulated signal. Thus, the SDN Controller shall interact with the network nodes through the

Southbound Interface (SBI) [109] in order to manage the optical transceivers and set the transmission power. This communication can be structured following a basic three steps handshake:

1) The SDN Controller configures the transmitter to emit the proposed candidate launched power calculated by the cognitive solution.
2) The SDN Controller collects the monitored optical power received at the end node.
3) Based on the information received, the SDN Controller decides to maintain the lower transmission power value or, by the contrary, to apply the initial pre-assigned value; in this unsuccessful case, the SDN Controller would indicate the transceiver to transmit such pre-determined power, by calculating the difference *PtxDefault – PtxCBR*.

The OpenFlow (OF) protocol is selected for implementing the communication process, even though there are other alternatives. In the OF protocol version 1.4.0 [110] extensions to manage optical transport networks are released. In fact, with respect to the previous versions, some features to enable control and status monitoring of optical devices have been introduced. The OF protocol v1.4.0 specification includes a set of structures, definitions and enumerations used for OF protocol messages. The following switch configuration messages exchanged between the SDN Controller and each Network Element (NE) represent a possibility to implement the protocol communication and specifically to set the optical power to be transmitted by the transceiver: OFPT_FEATURES_REQUEST (message sent by the Controller to query the NE) and the answer by the NE by means of OFPT_FEATURES_REPLY. Another possibility would be supported in the sending of the OFPT_GET_CONFIG_REQUEST to query the NE for its configuration, whose answer shall be sent by the OFPT_GET_CONFIG_REPLY. Other alternative might be to use the message OFPT_SET_CONFIG to set the NE configuration and the impacted parameters values; also the couple of messages OFPT_MULTIPART_REQUEST and OFPT_MULTIPART_REPLY could be used in case of Multipart process is invoked.

It can also be found in the OFP v1.4.0, as part of the Port Description Structures, the Port Description Properties list structure, describing the configuration and state of the optical port. It might be also applied and exploited for implementing the CBR-based technique. By means of available OF parameters or a combination of them, the SDN Controller might request, control and be informed about the properties of the NE's optical ports implicated in the lightpath establishment. For example, the OFPOPF_RX_TUNE (indicating that the port receive function can be tuned), the OFPOPF_TX_TUNE (indicating that the port transmit function can be tuned) and mainly the OFPOPF_TX_PWR indicating to the SDN Controller that the transmit power is configurable and can be set. To do that, the SDN Controller would query and set the configuration parameters in the corresponding OpenFlow-enabled NE by means of the OFPT_GET_CONFIG_REQUEST and OFPT_SET_CONFIG pair of messages mentioned above. The first option would be completed with the REPLY sent back from the receiver; if the second option would be used, no REPLY answer from the NE is expected by the SDN Controller.

The SDN Controller can also modify parameters of the optical port of the NE with the OFPT_PORT_MOD message: in the OFPPMPT_OPTICAL property, the field "tx_pwr" related to power is contained; it could be used by the Controller to set the launched power to be applied. And this, in both cases, firstly with the CBR-based power value and, if failed, with the predetermined power value using the pre-assigned System Margin.

In order to report the Controller about the reception power, the OFPPSPT_OPTICAL property, as part of the OFPMP_PORT_STATS multipart request type, might be used. It can be applied for collecting statistics of the port and the “rx_pwr” field could be the attribute used, indicating the current reception power. The CBR module would be able to decide if the lower launched power proposed would be appropriate. The flags field contained in this message might be used to inform about the validity of the statistics reported values: for example, the OFPOSF_RX_PWR flag would indicate if the “rx_pwr” value in the OFPPSPT_OPTICAL received structure can be considered as valid and then useful for taking decisions or not. The same flag OFPOSF_TX_PWR is proposed for the transmission power value.

Thus, the SDN Controller can be based on the application of the above messages and fields to set the transmission power and to control the received power in the CBR-based cognitive solution. It is assumed that SDN-enabled transceivers are used in our optical network architecture proposal. Furthermore, some extensions to OpenFlow in order to support OTN optical transport can also be found in [111].

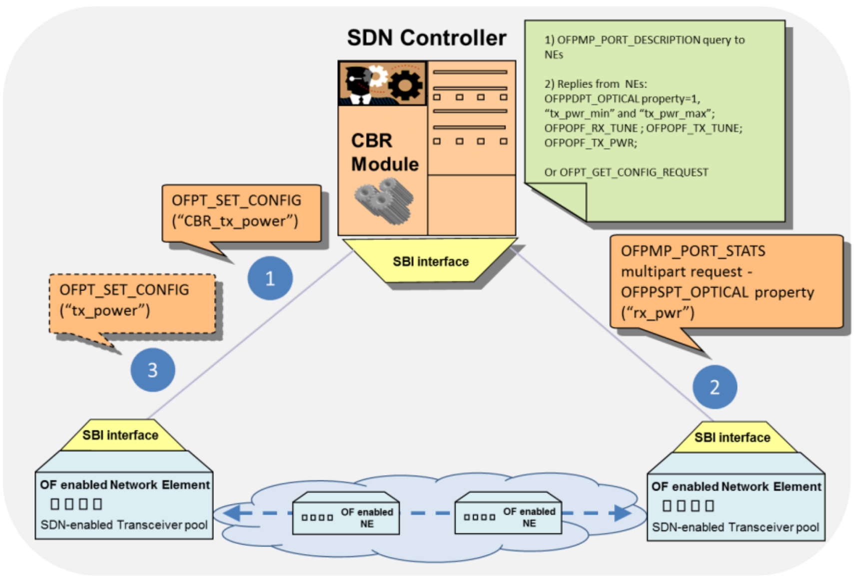

Figure 4.3. SDN based proposed architecture exchange mechanism using OpenFlow possibilities

4.5 Chapter summary

This chapter has introduced the proposed approach to optimize the operational System Margin in optical transport networks by optimizing the optical link power budget in the end-to-end paths. To start with, the network scenario and the optical power balance equation used have been detailed in the first section. Therein, the main parameters involved have been described. Later on, the cognitive solution based on case-based reasoning methodology has been presented. It intends to achieve the objective by proposing a new launched power value, allowing the telecom operator, in some cases, to use lower values than previously designed. To accomplish this task several novel schemes have been introduced in the CBR cycle. Besides, the followed indicators to monitor the performance of the solution have been described. To conclude the chapter, in the framework of software-defined networks, an architecture proposal has been advanced. In the following chapters, the analysis of the obtained results obtained by applying the CBR-based cognitive approach are presented.

Chapter 5

Cognitive approach evaluation to reduce the system margin over an optical transport network

This chapter reports the evaluation of the CBR-based approach to reduce the operation margins, following the strategy explained in chapter 4. First, the selection of the knowledge base of the system is addressed. To do this, several sizes are considered and the assessment has been done for all the proposed schemes. Moreover, the analysis has been extended to the four selected lightpaths and other mean network loads. Next, the selection of the best [k,r] pair of CBR parameters is addressed. In particular, a lightpath has been identified and the analysis has been done in this context. Once again, all the schemes and mean loads have been involved in the evaluation. Thus, a first recommendation is proposed. Moreover, a similar analysis is realized for the other three lightpaths. Based on the obtained results for the first lightpath, for sake of conciseness, three schemes and two network loads have been retained to continue the evaluation. Finally, a global view for the four representative lightpaths based on the final CBR recommended configuration is presented. The contributions of this chapter are summarized in the last section. Throughout this chapter, a static KB is assumed.

5.1 Selection of the Knowledge Base size

The first step in the evaluation is to set the proper size of the KB. To this aim, a typical end-to-end path in the network, i.e., LP1234, has been selected, so as common configuration and network load conditions, establishing then the mean network load to 50% and the CBR parameters [k,r] = [3,2]. Three possible KB sizes have been considered: 500, 1000 and 1500 cases respectively. Moreover, two criteria have been considered for the analysis: the success rate when proposing an optimized transmission power and the corresponding mean savings achieved. The cognition success rate has been evaluated in its turn by means of two indicators: “CBR%” and “FitCases %”. The first one indicates the success rate when proposing a new transmission power and the second one, “FitCases%”, controls if the proposed power is not higher than that already initially assigned. In that case, the new launched power, even if it is correct, it would worsen the initial assignment, and then it does not provide a real advantage. It has been decided to show the "CBR%" indicator because it reveals that our cognitive methodology based on the adaptation of CBR technique is able to provide a solution and fits with our aim. Regarding the mean savings provided, the "Ptx Mean Savings %" parameter is used.

Figures 5.1, 5.2 and 5.3 depict some results.

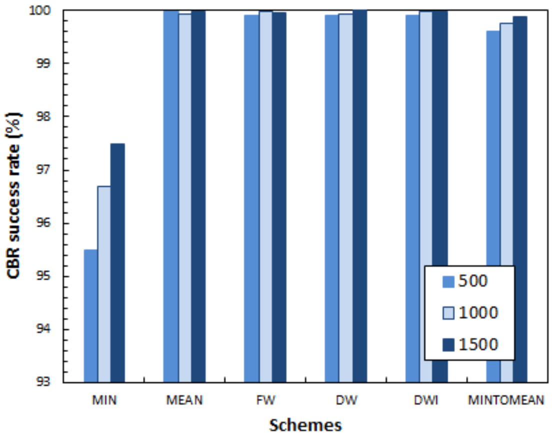

Figure 5.1. Evolution of CBR% for different KB sizes, with network load 50% and path 1234, for [k,r]=[3,2]

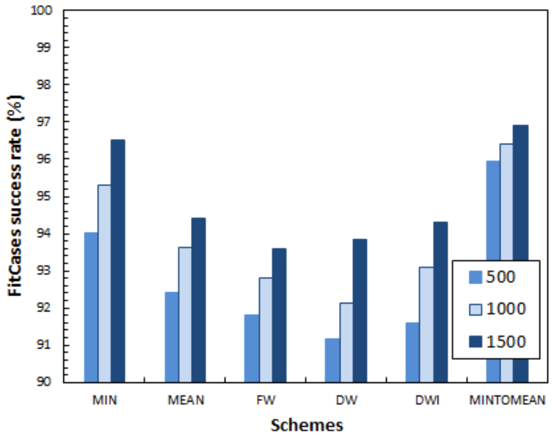

Figure 5.2. Evolution of FitCases% different KB sizes, with network load 50% and path 1234, for [k,r]=[3,2]

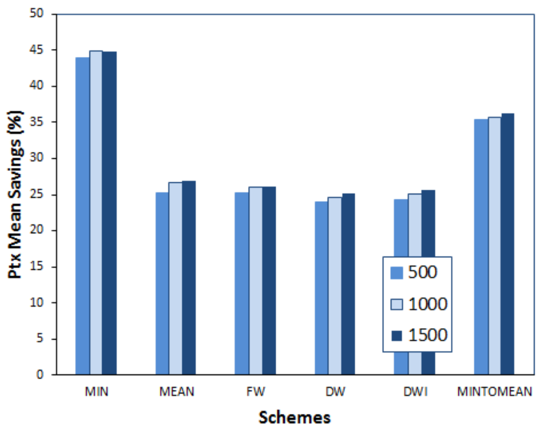

Figure 5.3. Evolution of Ptx Mean Savings% for different KB sizes, with network load 50% and path 1234, for [k,r]=[3,2]

As a first conclusion, it can be noted that the proposed cognition approach based on CBR is able to provide a proper solution; in fact, CBR success rate is above 95% for any of the considered KB sizes and reaching almost 100% for MEAN, FW, DW, DWI and MINTOMEAN schemes. For all the schemes, the higher the KB size is, the better are the results for the three criteria: CBR success rate, FitCases success rate and power mean savings. The advantage of our CBR proposal is to provide power savings while guaranteeing simultaneously the CBR success rate (both CBR% and FitCases%). A KB size of 1500 cases seems to provide the best results; however if we just consider the CBR% indicator, results with KB sizes between 1000 and 1500 are very similar. Moving forward in the analysis, of particular interest is the FitCases% indicator. It provides the success rate of CBR when providing a new transmission power that is equal or lower than the pre-assigned one; in these cases, the CBR-based approach is able to provide power savings and reduce the System Margin. It can be noted in Figure 5.2 that the best results are provided by KB size 1500 for all the schemes with noticeable differences against KB 1000 and 500 cases.

Regarding the power savings in Figure 5.3, results are quite similar for all the sizes, being only very slightly higher for the case of 1500 entries.

As a conclusion, if decision is based only on the achieved power savings, a KB size set to 500 cases could be good enough, because there are no noticeable differences with the cases with 1000 and 1500 entries. Nevertheless, the FitCases% value has to be good enough to be applied in commercial networks. Therefore, the case with 500 entries has to be discarded, because only 94% is achieved for the MIN scheme, while the other KB sizes guarantee higher values. The same happens for the rest of the schemes, except for the MINTOMEAN scheme which assures 96% for KB500. Focusing on Figure 5.3, the best results are clearly provided by the MIN scheme, even above the MINTOMEAN scheme which could be also a good solution, providing the second better results. Thus, as a first approximation, the MIN scheme is selected in order to provide the higher savings, while simultaneously assuring a FitCases% value above 95% in KB1000 and KB1500.

Then, if MIN scheme is selected, the best KB size to be used is 1500 cases, if combined with the CBR success rate; in fact, KB500 provides 95,49% of CBR% and 94,02% of FitCases%, with 43,98% of Ptx Mean Savings%. KB1000 provides CBR% 96,68% and FitCases% 95,29%, with 44,83% of Ptx Mean Savings%. And KB1500 provides 97,48% of CBR% with 96,51% of FitCases% with 44,87% of savings.

Taking into account these results and considering simultaneously the CBR success rate when proposing savings, KB1000 might also be a correct solution, because FitCases% is above 95%. However, it is convenient not to forget that presented results are the average of statistical results and then KB1500 seems to guarantee a higher CBR success rate for the best performing scheme MIN. Thus, KB size set to 1500 cases is the most appropriate size to be selected.

To generalize such conclusion when selecting the KB size, different lightpaths (LPs) and different network loads have been analyzed. Although not depicted, with regards to other LPs, in the equivalent conditions (same mean network load, 50%, and same [k,r] = [3,2] pair), the obtained results are quite similar. In particular, both CBR success rates are good enough and the mean savings are significant (above 35% for the MIN scheme, and for the LP showing less performance, LP456). MIN scheme is again the scheme providing the best results in terms of savings while guaranteeing a correct success rate. For the other LPs considered, that is, LP12, LP456 and LP34567, results for FitCases% above 95% are achieved by both KB1000 and KB1500, being slightly better for KB1500 (around 96%) against KB1000 (around 95%).

On the other hand, regarding the same LP1234 but considering other mean network loads, results for the different KB sizes are also very similar, although again for the MIN scheme and the maximum load KB1500 a better FitCases% is achieved, higher than 95%; KB1000 provides a lower FitCases%, slightly below to 95% and KB500 provides around 92% for the maximum load and 93% for a 70% mean load. That is, KB1500 is the only size that guarantees results above 95% for any load and any LP. Even though KB size 1000 cases provides correct results for MIN scheme and [k,r] = [3,2], as it will be reported in the next sections for other configurations and policies, results for KB1000 get poorer and degradate the performance, not assuring the quality to be guaranteed. Thus, on the basis of the performed analysis, it was decided to set the KB size to 1500 cases.

To provide more details, we analyzed if the length and the number of links have any impact in the FitCases success rate and the mean savings provided. The same CBR parameters values [k,r] = [3,2] are applied for the representative considered LPs.

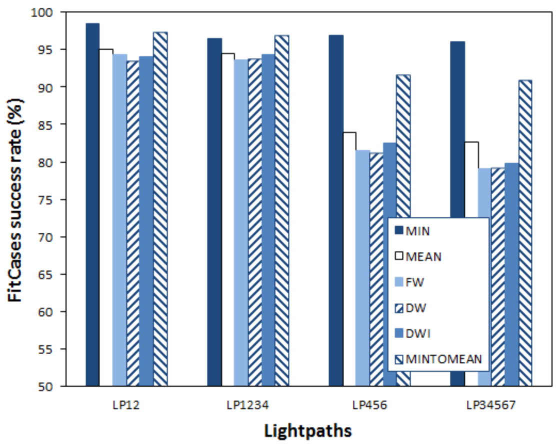

Figure 5.4. Evolution of FitCases% for all the LPs and different schemes

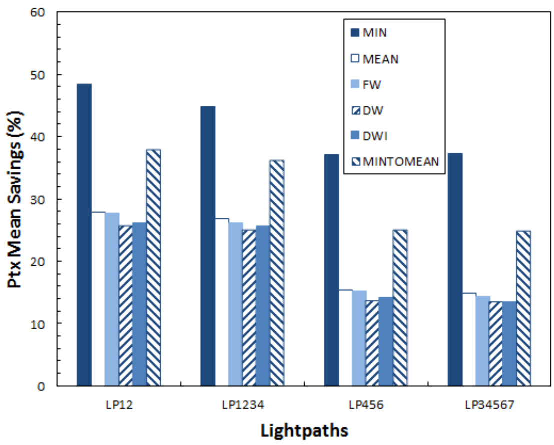

Figure 5.5. Evolution of Ptx Mean Savings% for all the LPs and different schemes

As an example, in both Figures 5.4 and 5.5, it can be noted that both the FitCases% success rate and the mean power savings reached decrease when the LP is longer and this behavior happens for all the schemes proposed; that is, the distance plays a role in the success of CBR to propose a new transmission power and the mean power savings reached. In particular, if we look at the MIN scheme behavior, for the shortest LP, i.e., LP12, FitCases% is 98,53% and the power savings achieved reaches 48,37%, which means almost the half of the initial assigned power. However, for the longest path, i.e., LP34567, still for MIN scheme, FitCases% downs to 96,09% and mean savings proposed are 37,28%, much reduced compared to the LP12 case. This happens not only for the MIN scheme; in fact, if we look at the other more performant scheme, MINTOMEAN, the precedent behavior is repeated: results in LP12 are 97,38% for FitCases% and 37,98% in savings and a decrease to 90,89% is obtained in LP34567 for FitCases% with 24,92% of savings, a quarter of the initial power can be saved. For the rest of the schemes results show the same behavior.

Our CBR-based approach provides better performance for short LPs compared to longer LP. It is worth to be noted, however, that even for the long LP it also achieves significant power savings. In principle, the longer a LP is, more spans, links and node equipment (ROADMS, optical amplifiers and passive component) are passed though. More launched power is needed to guarantee the required quality of service and then, less savings can be achieved. Additionally, more heterogeneous network situations can be found along the long LPs, regarding maintenance, status of the network at some parts or segments or geographic areas. This makes our CBR methodology to have more difficulties to propose a new and somehow optimized launched power.

5.2 Selection of CBR [k,r] parameters

The objective of this section is to analyze the best combination of [k,r] CBR parameters in order to get the best mean power savings while simultaneously assuring a correct success rate when proposing a new launched power. In a first phase, we have selected the LP1234 to perform the analysis [103], because this LP can be considered as representative enough in terms of length and number of links, network nodes passed through and then having a potential impact in the cognitive proposal performance, because more variables can come into play. In this first approximation to the analysis, a nominal mean load of 50% has been considered. We start the analysis by considering the MIN scheme.

The range of the [k,r] parameters considered is k=[1-10] and r=[1-3]. The *k* parameter controls the number of neighbors, meaning those which represent the closest (and previous) network situations to the current incoming LP requirement in terms of network state, considered for the calculation of the new transmission power. The *r* parameter controls the option for considering the distance or degree of similarity between the selected neighbors in the KB and the incoming request.

The following figures 5.6, 5.7 and 5.8 show the obtained results.

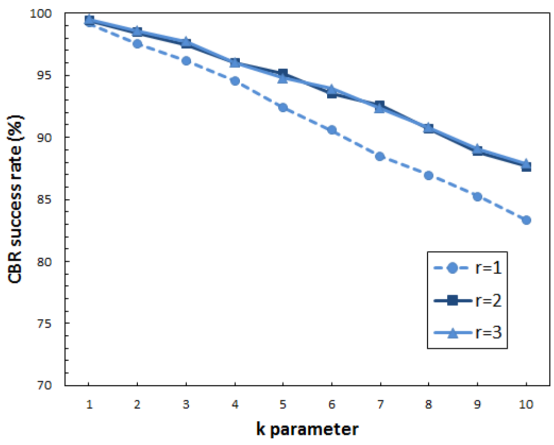

Figure 5.6. Evolution of CBR% as function of [k,r], for LP1234, scheme MIN and network load 50%

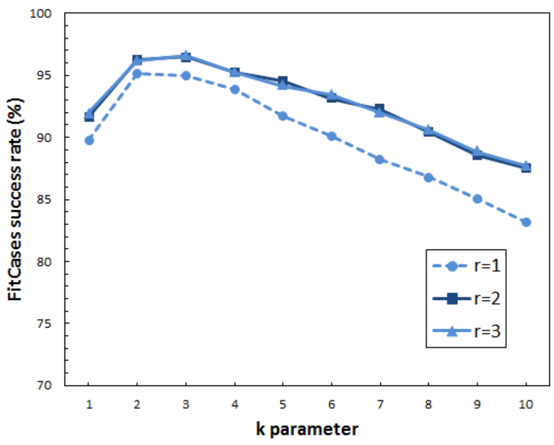

Figure 5.7. Evolution of FitCases% as function of [k,r], for LP1234, scheme MIN and network load 50%

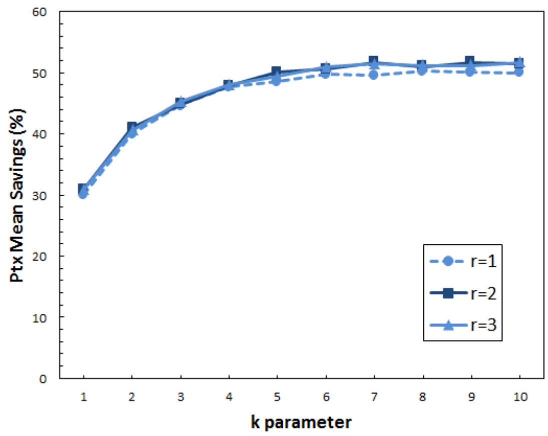

Figure 5.8. Evolution of Ptx Mean Savings% as function of [k,r], for LP1234, scheme MIN and network load 50%

From the figures above, it can be observed that results for r=1 are poorer than for r=2 or r=3, in terms of the CBR% and FitCases% success rates. For mean savings there is no such differences but as our objective is also to guarantee the maximum CBR success rate, this r=1 value has to be discarded among the valid values. This behavior is similar for the other schemes, being more noticeable for the FitCases% indicator, as it will be show later.

Regarding the behaviour with respect to the *k* parameter, it can be observed that, for LP1234, scheme MIN and a mean network load of 50%, the success of the cognitive technique decreases as *k* increases. In the case of the FitCases% indicator, the results for k=1 are poorer respect to k=2. And from k=2, it can be observed that the success rate decreases with *k*. It is the only scheme presenting this particular behavior between k=1 and k=2 values. It can be explained due to the scheme used when proposing a new optimized power. The MIN scheme selects the minimal transmission power among the more similar previous network situations. If *k* is set to 1, the transmission power used in the more similar precedent network situation is selected and applied, and results revealed that this value may be not applicable to obtain a direct advantage; the success rate obtained if it is applied to the new incoming request is about 92%. However, if an additional network situation is considered, that is, two neighbors are used, k=2, then the algorithm can select a minimum launched power more adapted to provide commercial advantage and the success rate is increased up to 96,17%. The decrease of the cognitive technique as *k* increases can be explained because when *k* parameter increases, we are considering more candidate similar neighbors, that is to say, more precedent similar network situations for the calculation of the new launched power. However, the results obtained show that it does not necessarily mean that the farthest neighbors used for the calculation, that is, from k=7 or k=8, really represent similar network situations. In literature of the CBR classic methodology, the number of neighbors to be considered is typically 5 or 6 [66], which is aligned with the obtained results.

Regarding the mean power savings provided, it can be noticed from Figure 5.8 that savings increases as *k* increases. The slope of the observed continuous incremental ramp starts to decrease from k=5 or k=6, reaching savings around 50% for both r=2 and r=3; from these *k* values, the slope does not show a remarkable increase and the best value is obtained for k=10, 51,68% (r=3). With our cognitive proposal we want to provide launched power savings but guaranteeing simultaneously a confident and correct success rate when proposing the new value. Thus, when selecting the [k,r] parameters to be applied, both criteria have to be taken into account and a trade-off shall to be considered. In this case, we can observe that even though the best power savings are reached with k=10 (51,68% for r=3), and k=9 (51,65% for r=2), the respective success rate (FitCases%) are somehow low, below 90%, and may not to be appropriate for a commercial network. They are 87,70% (r=3) and 88,59% (r=2) respectively. However, if we decide to select a lower *k* parameter value, in the range k=[2-5], the success rates are correct (around 96%-94%) and the achieved mean savings results also advantageous, around 40%-50%. Regarding the Figures 5.6, 5.7 and 5.8, it can also be noted that differences in mean power savings obtained when using r=2 or r=3 value are not remarkable. For example, for *k* parameter value set to 5, savings attained 50,09% (r=2) and 49,45% (r=3), with respective success rates of 94,56% (r=2) and 94,15% (r=3). If *k* value is set to 4, mean savings for r=2 are 48% (with 95,25% of success rate) and 48,11% for r=3 (with 95,24% of success rate). In view of these results, both *r* values might be applied. The same trend is observed for the other mean network load for this LP: for 30% the best [k,r] combination regarding mean savings is k=5 and r=3, with 51,31% and a success rate of 95,21% and again results for r=2 are slightly lower. For both 70% and 100% load, the best [k,r] combination regarding the same criteria is again k=4 and r=3, being results for r=2 very slightly lower and correct. However there does not exist a best [k,r] combination common and valid for all the paths and all network loads. If we decided to establish 95% as a threshold for success rate, we could then select k=4 for LP1234 combined with the best performant scheme MIN, in a 40 wavelengths network. A parameter value k=5 might also be used, as mean savings are a bit higher than for k=4, whether a slightly lower success rate is obtained, slightly below 95%, reaching the lowest value for a mean load of 100% (around 93,73% of success rate for r=3); it is also true that a 100% of mean network load is rarely found in commercial networks.

That is, in the case of a nominal LP1234, regarding length, number of links and volume of network nodes, for a nominal load and the scheme MIN, the best combination of CBR parameters may be k = [4-5] and r = [2-3], depending on FitCases% degree success rate. The combination [k,r] = [4,3] can be a potential selection. The above analysis has been done for the MIN scheme. To generalize the conclusions, the results for the other schemes are also presented. In particular, results are indicated for the three indicators, CBR success rate (CBR%), FitCases success rate (FitCases%) and transmission power mean savings provided (Ptx Mean Savings%) for LP1234 and a nominal load of 50%. For the sake of clarity, these results are grouped and presented by each scheme.

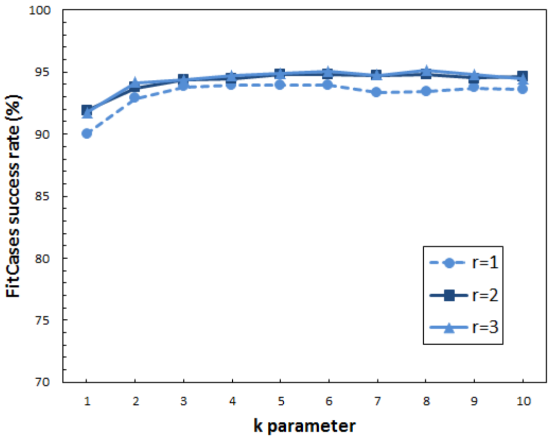

Figure 5.9. Evolution of FitCases% as function of [k,r], for LP1234, scheme MEAN and network load 50%

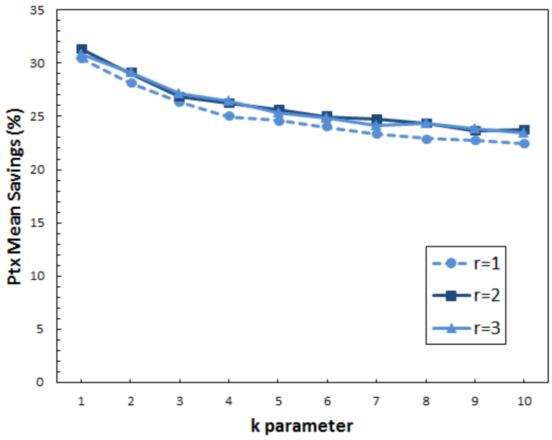

Figure 5.10. Evolution of Ptx Mean Savings% as function of [k,r], for LP1234, scheme MEAN and load 50%

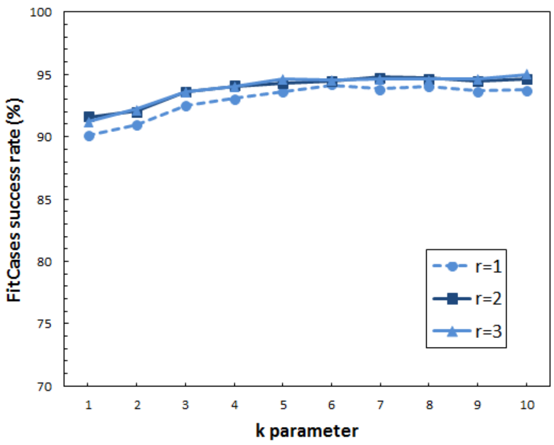

Figure 5.11. Evolution of FitCases% as function of [k,r], for LP1234, scheme FW and network load 50%

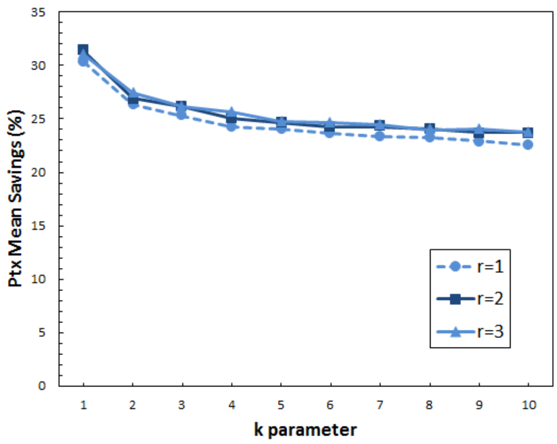

Figure 5.12. Evolution of Ptx Mean Savings% as function of [k,r], for LP1234, scheme FW and load 50%

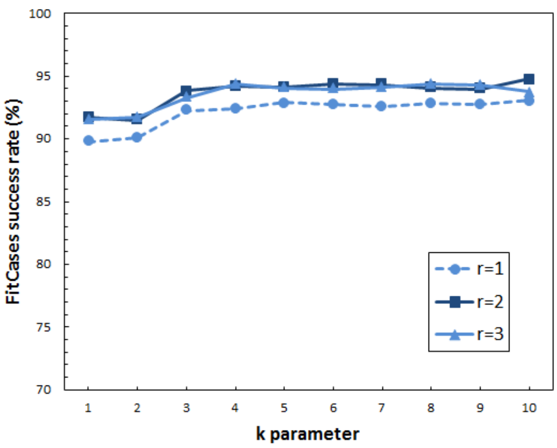

Figure 5.13. Evolution of FitCases% as function of [k,r], for scheme DW

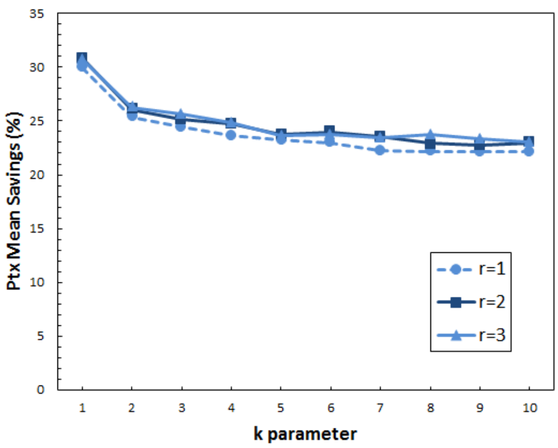

Figure 5.14. Evolution of Ptx Mean Savings% as function of [k,r], for DW

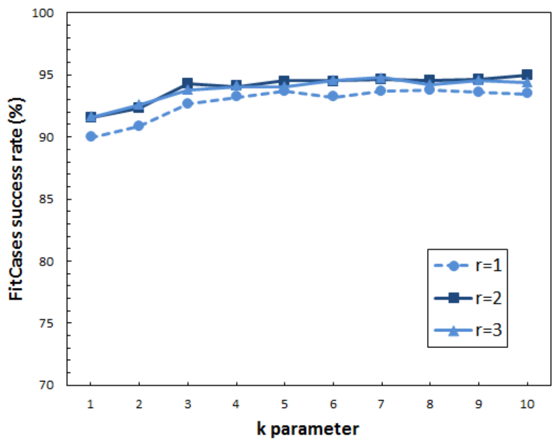

Figure 5.15. Evolution of FitCases% as function of [k,r], for LP1234, scheme DWI and network load 50%

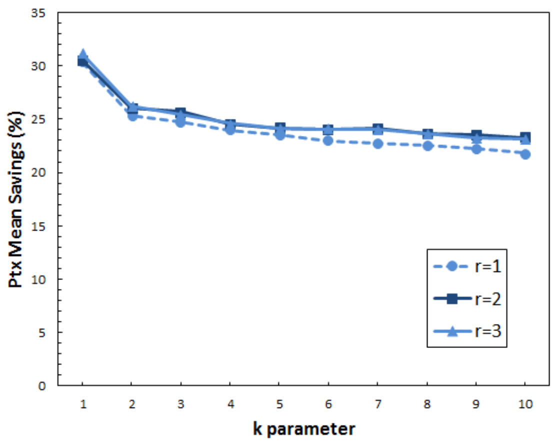

Figure 5.16. Evolution of Ptx Mean Savings% as function of [k,r], for LP1234, scheme DWI and load 50%

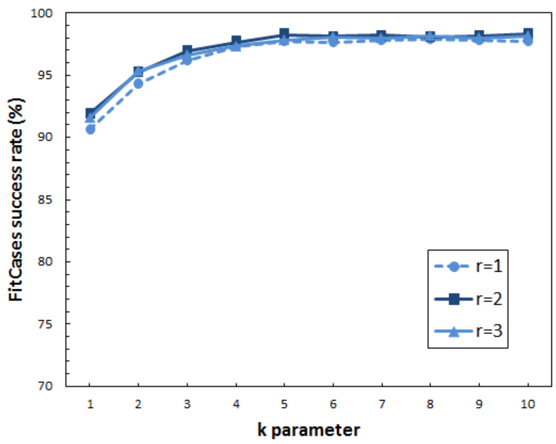

Figure 5.17. Evolution of FitCases% as function of [k,r], for LP1234, scheme MINTOMEAN and load 50%

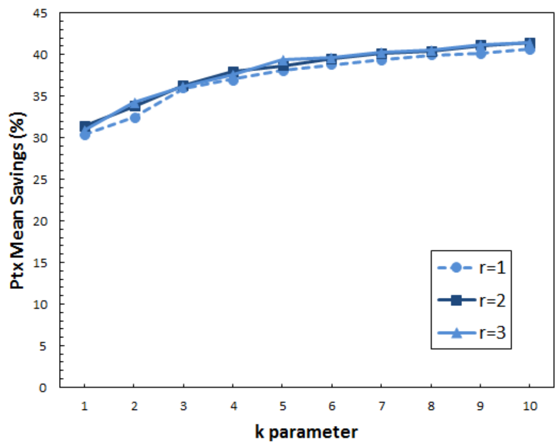

Figure 5.18. Evolution of Ptx Mean Savings% as function of [k,r], for LP1234, scheme MINTOMEAN 50%

From the Figures 5.9 through 5.18, the first point to be noted is that results for r=1 are poorer, as it has been also noted for MIN scheme. Then, in terms of CBR% and FitCases% this value can be discarded. Thus, from now on, the analysis continues considering only r=2 and r=3 values.

Although not depicted for sake of conciseness, it can be noted that for the values r=2 or r=3, CBR% success rate reaches almost 100% for these five schemes from k=2 value, with a quite stable behavior, revealing our cognitive proposal as a proper solution to provide suitable transmission power values for new incoming requests. The FitCases% shows an improvement of the success rate when k increases, with the particularity that this increases tends to be stabilized from k = 4 for most of those schemes. The first values of k=[1-3] show an important increase, from an initial starting point around 92% of success rate. From k=4, this success rate reaches around 94,5%. Among these five schemes, MEAN and MINTOMEAN provides the best results, particularly MINTOMEAN. These two schemes provide values close to or above

95%: the MEAN scheme provides this value for k=6 and r=3 (95,04%), although 94,83% is reached for k=5 and r=2. The MINTOMEAN scheme is the one showing best performance: the success rate exceeds 95% from k=2 (95,2% and this for both r=2 and r=3) and remains in 98% from k=5 and r=2. This scheme seems to provide better results in average for FitCases success rate than the MIN scheme, particularly for higher *k* values; however, for low *k* values, for example k=[2-4], results provide for MIN scheme are better or similar to those offered by MINTOMEAN; for example MIN scheme provides 96,17%, 96,55% and 95,24% for k=[2-4] and r=3, while MINTOMEAN scheme reaches 95,28%, 96,57% and 97,56% for the same *k* range and *r* value. However, it is important not to forget that performance of both schemes in terms of mean power savings offered are to be taken into account, because these savings are the advantage of using our cognitive approach, that is, reduce margins. For the three remaining schemes, the Figures 5.9 through 5.18 resuming FitCases% success rate indicate that FW, DW and DWI also provide acceptable results although they are the ones showing less performance. Among these three schemes it is FW the one which reaches 95,01% (k=10 and r=3), whereas DWI offers 94,94% in k=10 and r=2. For these three schemes, FW shows better performance (94,4% for k=5 and r=3) followed by DWI (94,51% for k=5 and r=2), being DW the scheme presenting a poorer behaviour, around 94%, although it does not necessarily mean that they are bad results. It is to be noted that FW improves the performance over the distance-weighted approach found in literature [66]. The continuous increasing improvement in terms of mean savings of the five schemes, except MIN, indicates that these schemes needs a higher volume of neighbors or precedent network situations to provide better results; this fact is somehow less efficient when compared to MIN, which seems to need less neighbors to reach better results. It has been indicated above that, in the case of MIN scheme, as it selects the minimum transmission power among the selected previous network situations, the higher is the number of them taken into account, the less is the accuracy provided by these situations, this scheme selects only one value. However for the rest of the schemes, the trend is inverse: the higher is the number of similar precedent network situations considered, the higher accuracy is obtained, because all the five schemes take into account several values for working out and proposing a new launched power. That is, more values are introduced in the calculation and the final proposed power is somehow averaged and smoothed out. The MEAN scheme presents very correct FitCases success rate results, but it is MINTOMEAN which provides the best behavior when *k* value increases. This fact confirms that the combination of both MIN and MEAN schemes properties results in a successful solution. The other three algorithms, FW, DW and DWI concedes and distribute different importance to the precedent situations: for FW and DWI results are slightly better, DWI follows an equivalent distribution of importance among the neighbors. Due to the nature of these schemes, it is reasonable that they need more volume of neighbors to be more accurate.

Then, for FitCases%, as observed for the MIN scheme, a good enough success rate value can be achieved if we focus in in the range k=[3-6] and this value is selected, except for FW which show better performance starting in k=4; thus, it confirms that the range k=[3-6] provides good results and can be applied in commercial networks.

Once we have confirmed that our cognitive CBR-based approach can be applied to reduce the System Margin, the next step in the assessment is to evaluate the mean savings provided for the remaining five schemes. The obtained results are presented in the Figures 5.9 through 5.18 above showing the corresponding launched power mean savings.

Several conclusions can be drawn. The first one is that MINTOMEAN provides the higher savings among the five algorithms, although it does not reaches the best mean savings provided by the MIN scheme. The best results for this KPI shown by MINTOMEAN are reached for k=10, providing 41,49% (for r=2) and 41,38% (for r=3). However, MIN scheme exceeds these results from k=3, presenting for k=4, 47,93% (r=2) and 48,11% (r=3) and reaching 50,09% for k=5 (r=2). Thus, MIN scheme is the scheme showing best performance in mean savings, while assuring a correct FitCases success rate. The best value in terms of mean savings provided by MIN scheme are 51,67% (k=7 and r=2) and 51,68% (k=10 and r=3) and this indicator remains around 51% from k=7, showing the same continuous increase when *k* increases. This behavior as function of *k* is similar as the one showed by MINTOMEAN, although in general, the savings offered are 10% lower than the same *k* value when it is compared with MIN scheme. For both schemes, it is observed that when more previous network situations are considered to propose a new launched power, more savings are reached. A trade-off between these two schemes is to be done by the telecom operator. In view of the obtained savings and the success rate achieved in the indicated range of *k* value, it is the MIN scheme which provides the best performance and it is the suitable candidate to be applied in operational networks.

5.3 Cognitive solution applied for LP1234 - other network mean loads

Until this point analysis for LP1234 has been done for a nominal network load of 50%. In this section, results for other mean loads are presented and analyzed. Based on the obtained results in the precedent sections, the first phase is to considered the outperforming MIN scheme; results for r=1 are also shown for sake of completeness, even if this value has been already discarded in the precedent section.

The assessment is done for complementary mean network loads of 30%, 70% and 100%. For sake of conciseness, only the results for load of 30% are depicted, for the three KPIs.

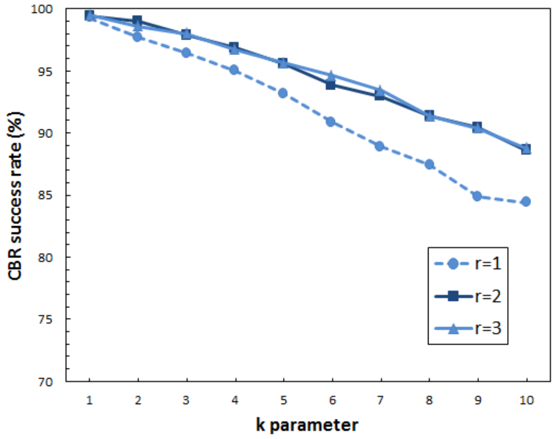

Figure 5.19. Evolution of CBR% as function of [k,r], for LP1234, scheme MIN and network load 30%

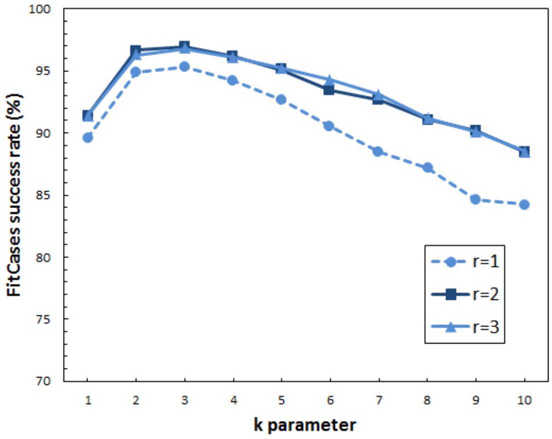

Figure 5.20. Evolution of FitCases% as function of [k,r], for LP1234, scheme MIN and network load 30%

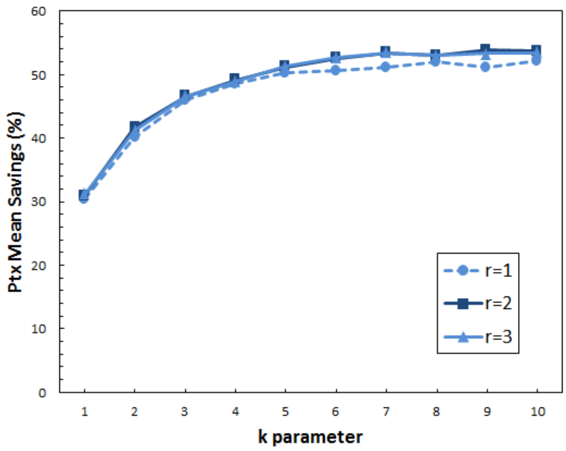

Figure 5.21. Evolution of Ptx Mean Savings as function of [k,r], for LP1234, scheme MIN and load 30%

From Figures 19 through 21, it can be noted that the MIN scheme behavior is similar for any network load. In terms of success rate when applying cognition solution CBR% success rate and FitCases% shows the same trend: these KPIs decrease as *k* increases, except the transition from k=1 to k=2 where an increase occurs for FitCases%. Similarly, savings achieved increase when *k* increases, as observed when mean load is 50%. But if the behavior is similar for any load, the interesting point to be noted is that results regarding success rate for both KPIs are slightly lower when network load is higher, and this trend is more marked for mean savings achieved. Thus, our cognition approach is more efficient when network load is lower. This trend follows the expected results for the MIN algorithm: when applying the established configuration during the design and commissioning phases, the initially launched power is fixed and remains fixed independently of any network situation. For low network loads it is not maybe necessary to transmit the same power than for higher network loads to guarantee the required quality of service of the lightpath at reception; then, there is more potential network situations where to reduce the System Margin. The MIN scheme proposes such lower transmission power values, the room where to achieve savings is wider and thus, this scheme finally provides higher savings for lower loads. When network load gets increased, more transmission power is necessary to assure the quality of service and the rooms to manage savings decrease. Then, the MIN scheme continues to provide lower values than the initial pre-assigned one but, as the limits of the room to reduce are lower even if applying a minimal power, the potential achievable savings decrease.

5.4 Cognitive solution applied for LP1234 - best performance [k,r] pair for the other schemes

In the above sections, the couple [k,r] = [4,3] has been proposed as the best combination of CBR parameters for LP1234 for the MIN scheme, and globally valid for any network load. This pair provides the best mean savings, while guaranteeing correct success rates. The analysis has been done using the outperforming MIN scheme. In order to avoid any bias in the evaluation, the best combination for the other schemes is assessed, for the same LP1234, setting for the comparison the mean nominal load in 50%. In section 5.3, results show that behavior regarding the application of the cognitive solution is equivalent in terms of savings and success rate for any network load.

Thus, in the following tables the [k,r] combination offering the highest mean savings and the corresponding success rates for all the proposed schemes are presented. The Table 5.1 indicates the [k,r] combination maximizing the mean savings for each scheme, independently of the success rate reached when proposing the new launched power value:

	Maximizing Mean Savings		
	best [k,r]	Ptx savings (%)	FitCases%
MIN	[10,3]	51,68%	87,70%
MEAN	[1,2]	31,29%	91,90%
FW	[1,2]	31,37%	91,57%
DW	[1,2]	30,85%	91,72%
DWI	[1,3]	31,15%	91,58%
MINTOMEAN	[10,2]	41,39%	98,28%

Table 5.1. Best [k,r] couple maximizing savings, for LP1234 and load 50%

As illustrated in Table 5.1, the MIN scheme provides the highest savings, more than +10% over the second best performing proposal, the MINTOMEAN scheme. However, for the corresponding [k,r] couple, the success rate is poor, 87,7% and moreover it is obtained with a high *k* value (k=10), which is not very efficient; it is not to forget that the 10^{th} nearest neighbor it does not necessarily mean that it models a very similar network conditions to establish the LP for the new incoming request. Regarding MINTOMEAN, it might be selected as the best performing scheme. It could be a potential solution, for some telecom carriers: to give up 10% in power savings, but assuring a really high success rate when doing the proposition (98,28%).

Nevertheless, in that case, it can be confirmed that if another [k,r] combination proposing slightly lower mean savings is selected for the MIN scheme, success rate increases reaching 95% and the corresponding savings does not decrease significantly. It is shown in the Tables 5.2 and 5.3. It can also be noted in Table 5.1 that the MEAN, FW, DW and DWI schemes provide maximum savings values around 30%-31%, while presenting success rates around 92%. But in any case, they does not exceed the maximum savings provided by MIN. Ranking the results, again the MEAN and our novel FW scheme provides higher results than DWI and the proposed DW scheme in [66].

	Alternative 1: Maximizing Mean Savings and success rate around 95%		
	best [k,r] (95%)	Ptx savings (%)	FitCases%
MIN	[4,3]	48,11%	95,24%
MEAN	[6,3]	24,85%	95,04%
FW	[10,3]	23,78%	95,01%
DW	[10,2]	22,98%	94,77%
DWI	[10,2]	23,29%	94,94%
MINTOMEAN	[10,2]	41,39%	98,28%

Table 5.2. Alternative 1 for [k,r] pair maximizing savings, for LP1234 and load 50%

	Alternative 2: Maximizing Mean Savings and success rate around 95%		
	best [k,r] (95%)	Ptx savings (%)	FitCases%
MIN	[5,2]	50,09%	94,56%
MEAN	[4,3]	26,41%	94,70%
FW	[7,2]	24,28%	94,77%
DW	[6,2]	23,97%	94,39%
DWI	[5,2]	24,16%	94,51%
MINTOMEAN	[10,2]	41,39%	98,28%

Table 5.3. Alternative 2 for [k,r] pair maximizing savings, for LP1234 and load 50%

Results are confirmed as shown in Tables 5.2 and 5.3. With respect to Table 5.1, in Table 5.2, the best [k,r] combination for each scheme maximizing the mean savings, while simultaneously assuring a success rate above 95%, is indicated. The MIN scheme is again the one providing the highest savings and guaranteeing a correct success rate, around 48%, more than +6% over the MINTOMEAN scheme showing the highest FitCases%. To be noted that none alternative is presented in Table 5.2 for MINTOMEAN because if success rate is reduced, mean savings are even lower and no advantage is obtained, as seen in the corresponding Figures in section 5.3. The other schemes see their success rate get increased around or above 95% and mean savings are reduced down to around 23%-24% (-7%.).

In Table 5.3 a second alternative to select the [k,r] pair to be applied is indicated. The difference against the Table 5.2 is that success rates have slightly decreased, below but very closed to 95%, with the advantage of increasing the gain in savings +2% for MIN scheme (so as for MEAN) or + 1% for FW, DW and DWI schemes. It can be also a selection to be applied in commercial networks. The final decision is to be taken by the network carrier, without forgetting that the presented achievements are statistical results and values very closed to 95% can be rounded and considered as completely appropriate, they can fluctuate around this threshold value.

Thus, based on the presented results, it is confirmed that the MIN scheme is the best solution to achieve savings and to be selected when applying CBR cognitive approach in production networks. Regarding the [k,r] combination to be chosen, several criteria can then be followed by the telecom operator, depending on if the operational teams prefer to maximize savings and guaranteeing success rates. As indicated, there is not an optimal and unique “best” solution, common to any load and LPs, although the range k = [3-5] and r=3 provides the best trade-off and [k,r] = [4,3] it is our preferred selection.

In the next sections, the analysis for the other three considered representative lightpaths is presented. For each one of them, the evaluation of the six schemes and the four mean network load values has been realized. Nevertheless, the obtained results for LP1234 confirm that MIN, MINTOMEAN and MEAN are the schemes showing the best performance. Furthermore, it has been observed that the behavior of both FitCases% success rate and mean savings indicators is quite similar for any network load and it does not have a significant impact on the conclusions. Moreover, it is rare to find loads as 70% or 100% in commercial networks. Thus, for sake of conciseness, it has been decided to present the results for the three remaining lightpaths considering the best three schemes (MIN, MINTOMEAN and MEAN) and two mean loads (30% and 50%). Additionally, only the achieved performance on transmission power mean savings is illustrated.

5.5 Cognition solution applied for LP34567

In this section the analysis of the longest lightpath is realized. The analysis is first done considering a mean network load of 50%. Both the CBR% and the FitCases% indicators are used to control the success rate of the cognitive proposal applied to the longest path; and the achievements in the mean savings are presented.

Firstly, in general it can affirmed that evolution of CBR% success rate and FitCases% as function of *k* value shows a quite similar behavior that the one observed for LP1234. Both indicators increase when *k* increases for all the schemes, except for the MIN algorithm, which show the inverse trend, as for LP1234. And the *r* parameter value set to 1 provides the lower performance.

Regarding the MIN algorithm both the CBR success rate and the applicable cases success rate decrease when the number of neighbors considered increases. Moreover, some important items are raised when compared to LP1234. The most important one is that higher performance values are reached in the longest path, with more volume of node equipment and composed of more links, LP34567. For example, if [k,r] combination is set to [5,2], MIN scheme provides 98,26% and 97,14% in LP34567 respectively for both success rate indicators, whereas it presents 95,12% and 94,56% in LP1234. It is also observed that for r=2 and r=3 values, both indicators are always above 95% of success rate in LP34567, when it is not the case in LP1234. Finally, FitCases% decreasing slope is smoother in LP34567 than in LP1234. In terms of success rate, MIN scheme shows then better performance in LP34567.

Regarding the MEAN scheme the same trend in evolution with respect to *k* is shown. However, for LP34567 lower performance values are reached in FitCases success rate. It provides values in the range 80-84% from k=3 in the LP34567. When applied to LP1234, a range between 93-95% from k=3 is found. Thus, in the contrary that for MIN scheme, MEAN shows poorer performance in a longest path and having more links. The same behavior is observed for the other schemes, although the results are not reported for lack of space.

The MINTOMEAN scheme shows also lower performance when applied to LP34567 than in LP1234, influenced by the fact of introducing the mean values of the neighbors in the calculation of the proposed transmission power. For example, if [k,r] combination is set to [5,2], this scheme provides 94,47% for FitCases% in LP34567 and 98,25% when applied to LP1234.

That is, for the longest path and having more links, the behavior of our CBR approach is quiet similar than for LP1234, although MIN scheme is more performant in LP34567 and presents lower success rate values for the other algorithms. This is the behavior respect to the FitCases success rate. Now it will be analyzed the evolution of mean savings in this LP34567; the obtained results for all the schemes are presented in Figures 5.22 to 5.24.

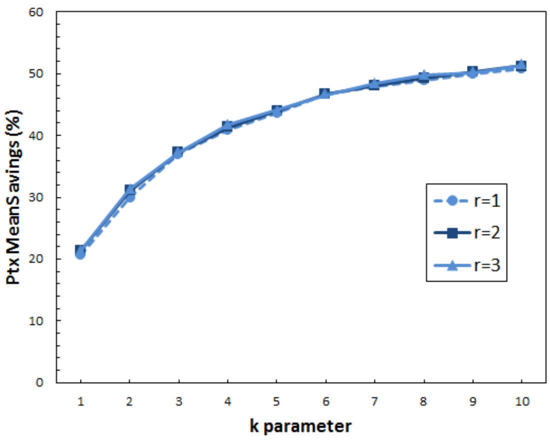

Figure 5.22. Evolution of Ptx Mean Savings% as function of [k,r], for LP34567, scheme MIN and network load 50%

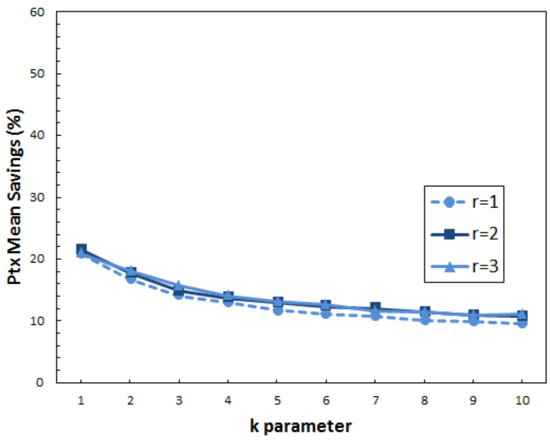

Figure 5.23. Evolution of Ptx Mean Savings% as function of [k,r], for LP34567, scheme MEAN and network load 50%

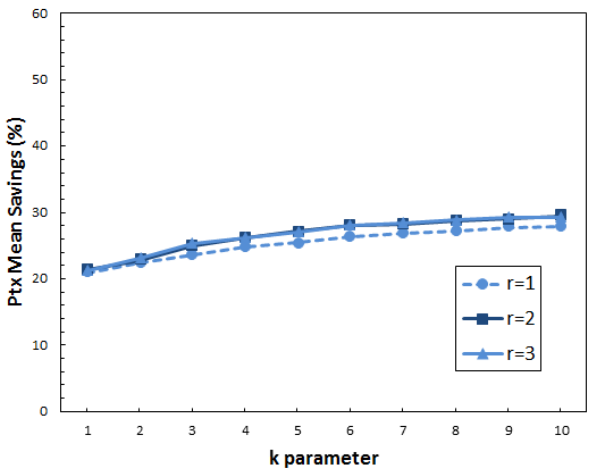

Figure 5.24. Evolution of Ptx Mean Savings% as function of [k,r], for LP34567, scheme MINTOMEAN and network load 50%

It can be observed that the evolution of the transmission power mean savings depending on the number of neighbors considered is the same than for LP1234. For both MIN and MINTOMEAN algorithms, higher savings are achieved when *k* increases; this increase is more remarkable for MIN scheme. The explanation for this behavior is the same than for LP1234, that is, the more the neighbors are introduced in the calculation, the more chances to recover a correct and simultaneously lower launched power exist. The mean savings for MEAN get decreased when *k* increases.

One important issue to be remarked is that mean savings provided by cognitive proposal in LP34567 are lower than when applied to LP1234. For example, MIN scheme starts from 20% (k=1) and exceeds 50% from k=9 for LP34567; however when applied to LP1234 it starts from 30% (k=1), and exceeds 50% of savings from k=5 (and r=2). The MEAN scheme varies between 21% and 10% in LP34567, providing in average around 12-13%; and it evolves between 30% and 23% in LP1234, proving in average around 24%-25% of savings. Finally the MINTOMEAN algorithm also provides lower savings in LP34567, around 25-30%, compared to 35-40% offered in LP1234.

Thus, for a longest path and having more links (and then more network elements are passed through) savings provided are lower. This can be explained because more launched power is needed to guarantee the quality of service of the lightpath and the potential margin to reduce the System Margin is lower in order to assure a correct received power at reception, because more power is needed to travel along a longest path. And this is observed for any scheme. Furthermore, as indicated when analyzing the success rate, cognitive proposal applied in LP34567 also provides lower success rate values, except for MIN scheme.

It can be inferred the conclusion that cognitive proposal applied to longest and link-composed paths show less performance. However, the MIN scheme presents a particular behavior: mean savings are effectively lower for LP34567 but FitCases success rate is in general higher than for a shorter path LP1234, mainly for *k* values above 3. It means that the more neighbors are used, the more performant this scheme is in longer paths. It can also be observed that for LP34567 the MIN scheme is the one providing more performance, over the other algorithms. Any value above k=3 (for both r=2 and r=3) can be selected for being applied in commercial networks. A slightly decrease of the FitCases% success rate can be observed from k=6, although this indicator is above 95% from k=3. As mean savings increase with *k* value, a combination [k,r] = [10,2] could be selected to provide the highest savings, but if a *k* value in the range k=[3-6] was selected it may be an appropriate option, providing for example 46,67% of savings with FitCases% value reaching 97,18% of success rate for k=[6,2]. When compared to the also very good performing scheme MINTOMEAN, this one provides 27,96% of savings and a 94,83% of FitCases success rate. Thus, even though savings are lower than for a shorter path, the MIN scheme is again the best scheme to be applied in long lightpaths.

The above assessment is done for a nominal load of 50%. The Figure 5.25 presents the behavior of mean savings indicator for a mean load of 30% and the outperforming MIN scheme:

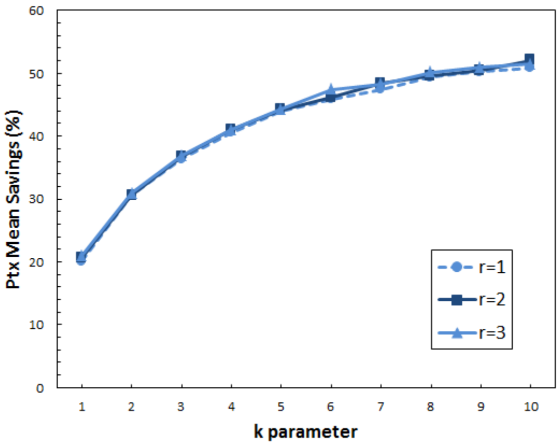

Figure 5.25. Evolution of Ptx Mean Savings% as function of [k,r], for LP34567, scheme MIN and load 30%

From this Figure 5.25 it can be observed that no noticeable differences are raised with network load changes for LP34567. For a mean load of 30% and [k,r] = [6,2], FitCases% is 97,57% and it reaches 46,22% for mean savings. As mentioned, this very slight decreasing is not affecting the performance of the cognitive solution. The trend in the evolution of the three indicators with *k* value is the same for any network load, as seen in LP1234.

In the previous section it has been showed that the MIN scheme is the one presenting the best performance, as for LP1234. In the Table 5.4 the best [k,r] combination maximizing the mean savings for the three considered schemes is presented, for a nominal mean load of 50%.

	Maximizing Mean Savings		
	best [k,r]	Ptx savings (%)	FitCases%
MIN	[10,3]	51,39%	95,90%
MEAN	[1,2]	21,48%	79,60%
MINTOMEAN	[10,2]	29,48%	96,67%

Table 5.4. Best [k,r] pair maximizing savings, for LP34567 and load 50%

In this case, for LP34567, the [k,r] combination providing the highest mean savings also guarantees a FitCases success rate above 95%, for MIN and MINTOMEAN schemes. For the MEAN proposal, the FitCases success rate does not exceeds 85% even for k=10; then, in its case, other [k,r] alternatives do not offer any advantage.

Thus, for LP34567, the results of cognitive approach are advantageous and MIN is the outperforming scheme. When applied to this longest LP, any *k* value above 3 can be used, taking into account that the higher the *k* value is, the higher mean savings are obtained. However, in order to do not apply a high *k* value, by selecting this parameter value in a range [3,6] may provide mean savings between 35% and 45%, respect to the initial pre-assigned transmission power value.

5.6 Cognition solution applied for LP12

In this section, analysis of cognitive proposal over the shortest considered path, LP12 and with only one link is done.

The evolution of both success rate indicators is similar to LP1234 and LP34567 for each corresponding scheme. Although not depicted, for all the schemes, except MIN, the success rate reached when applying the CBR-based approach (CBR%) is closed to100%. It does not guarantee that the new transmission power proposal provides an advantage over the initial pre-assigned one, since this value can be higher than the initial one. This is controlled by the FitCases% indicator. Regarding the MIN scheme, the same decreasing behavior as *k* value increases is evidenced, as shown for LP34567 and LP1234. And, as obtained for LP34567, higher values than for LP1234 are achieved. For MINTOMEAN scheme, the evolution is always increasing with *k*, although in a less noticeable way. And for MEAN this indicator increases with *k* and from k=8 it starts decreasing. That is, each scheme follows a respectively evolution similar to previous analyzed lightpaths. However the most remarkable point to be noted is that higher values are obtained for LP12 than for LP1234 and LP34567, and this for any of the three schemes. For example for MEAN, FitCases% achieves 93-94% in average (depending on *k* value), whereas this same scheme achieves around 80-84% in average for LP34567; for LP1234 slightly lower values are also present, also around 93-94%, although the difference is not noticeable and it does not impact the process. For MINTOMEAN scheme results are also higher, in general for any *k* value: around 98% in average for LP12, whereas it presents around 97% for LP1234 and 93% for LP34567. Finally the MIN scheme present also higher values, 97% in average for LP12.

Once the success rate indicators have been presented, the mean power savings results obtained for the shortest LP12 are shown in the Figures 5.26 to 5.28:

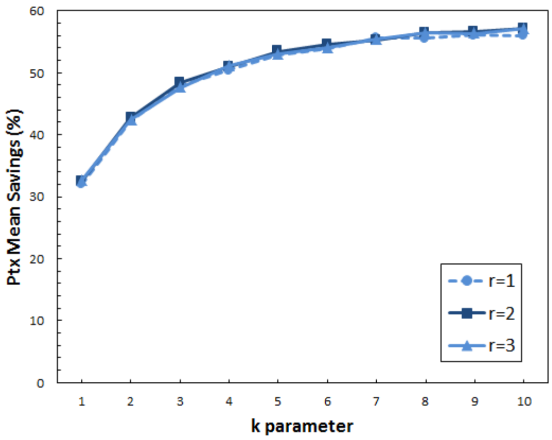

Figure 5.26. Evolution of Ptx Mean Savings as function of [k,r], for LP12, scheme MIN and network load 50%

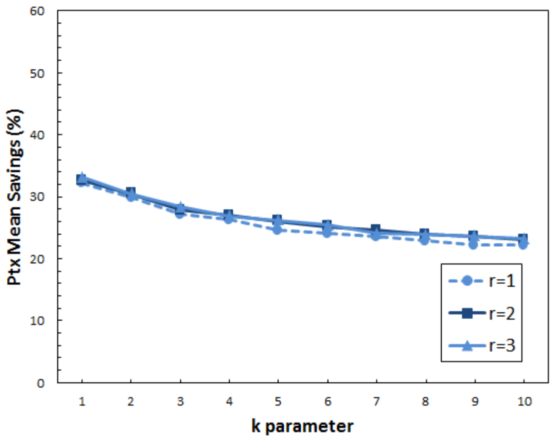

Figure 5.27. Evolution of Ptx Mean Savings as function of [k,r], for LP12, scheme MEAN and network load 50%

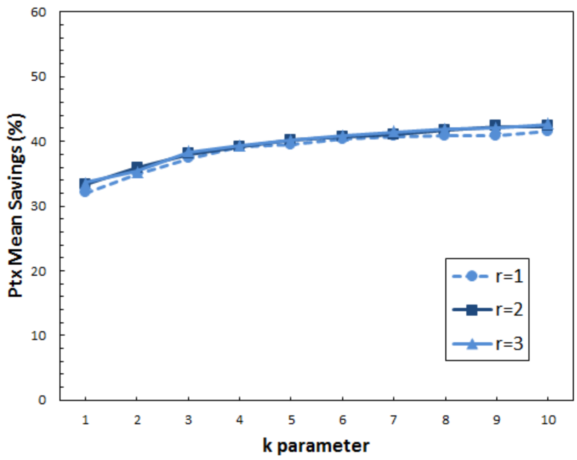

Figure 5.28. Evolution of Ptx Mean Savings as function of [k,r], for LP12, scheme MINTOMEAN and network load 50%

The same evolution than for previous analyzed paths is obtained: mean savings increase as the number of neighbors are considered for MIN and MINTOMEAN schemes, reaching respectively the highest savings for the analyzed lightpaths. In the case of MIN, it provides real high results, 51,07% from k=3 and until 57,11% for k=10. In the case of MINTOMEAN, results are also improved when compared to LP1234 and LP34567, offering above 40% from k=5, around +13% from k=5 with respect to the longest lightpath. It can be explained because in the case of short lightpaths and a small number of passed through nodes, the preassigned and fixed transmission power established during design phase is normally quite conservative regarding the System Margin applied and a great potential of reduction does exist. It is confirmed by the MIN scheme, and also, in lesser extent, for MINTOMEAN. That is, the cognitive approach shows better performance for shorter lightpaths and when less network nodes are passed through. In terms of achieved mean savings and guaranteed success rate, higher values are provided for both indicators. In the case of LP12, the MIN scheme is also revealed as the best option to be applied to provide savings, because it offers really high savings and guarantees very good success rates. In this case, the range k=[4-7] could be used, achieved mean savings are above 50% (from k=7 value, improvement is less appreciable) and FitCases success rates attain 95%, with the peak of values in the range k=[3-6].

Regarding the results depending on the mean network load, the figure 5.29 shows the behaviour for the MIN scheme when 30% of load is observed in the network:

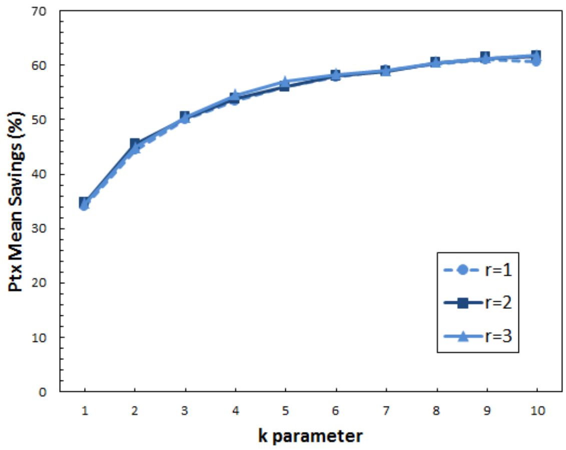

Figure 5.29. Evolution of Ptx Mean Savings% as function of [k,r], for LP12, scheme MIN and load 30%

In Figure 5.29 it is revealed that load in the network can impact the achievements of the application of the MIN algorithm, although the effect is not affecting the overall performance. Both FitCases success rates and mean power savings generally decrease when network load increases, as for LP34567 and LP1234. Anyway, considering a nominal network load, MIN scheme has also been revealed for LP12 as the scheme showing the best performance.

In terms of comparison for the other schemes and as it has been done for previous analyzed lightpaths, the Table 5.5 shows the best [k,r] combination for the three remaining schemes:

	Maximizing Mean Savings		
	best [k,r]	Ptx savings (%)	FitCases%
MIN	[10,3]	57,11%	94,04%
MEAN	[1,3]	33,14%	93,79%
MINTOMEAN	[10,3]	42,65%	98,85%

Table 5.5. Best [k,r] pair maximizing savings, for LP12 and load 50%

Table 5.5 shows that MIN scheme is the one showing the best performance in terms of mean savings, with a FitCases success rate of 94,04%. It provides +15% over the MINTOMEAN scheme, although this last one provides a success rate above 95%. If the network operator would want a higher FitCases success rate, another [k,r] alternative is presented in Table 5.6. In this option, the MIN scheme provides 96% of success rate and offers 56,49% of mean savings, which may represent a better solution for the network carrier. It is to be noted in Table 5.6 that by selecting this last [k,r] combination, MIN scheme still provides higher savings than the MINTOMEAN algorithm.

	Alternative 1: Maximizing Mean Savings		
	best [k,r] (95%)	Ptx savings (%)	FitCases%
MIN	[8,2]	56,49%	96,00%
MEAN	[4,2]	26,97%	95,04%
MINTOMEAN	[10,2]	42,65%	98,85%

Table 5.6. Alternative 1 for [k,r] couple maximizing savings, for LP1234 and load 50%

5.7 Cognition solution applied for LP546

In this section the analysis of the LP456 is presented. As LP1234, it can be considered an intermediate path in terms of number of network nodes and length. It has been selected for the evaluation since it is longer than LP1234 but composed of a smaller number of links.

For this intermediate lightpath a similar evolution of success rate, for both the CBR% and FitCases% indicators, is observed with respect to LP1234 and the other two analyzed LPs. Regarding the number of considered neighbors, success rate increases with *k* value for all the schemes, except for MIN scheme. In case of the FitCases%, MIN and MINTOMEAN schemes confirm that very high rates can be reached when taking advantage of the proposed new power applied in commercial networks. For the MEAN scheme, even though the evolution get increased with *k*, provided values are around 85% - 82%, depending on the *k* value.

The evolution in terms of mean savings, in a network situation with a mean load of 50%, is presented in the Figures 5.30 to 5.32, with the same behavior as for the precedent paths:

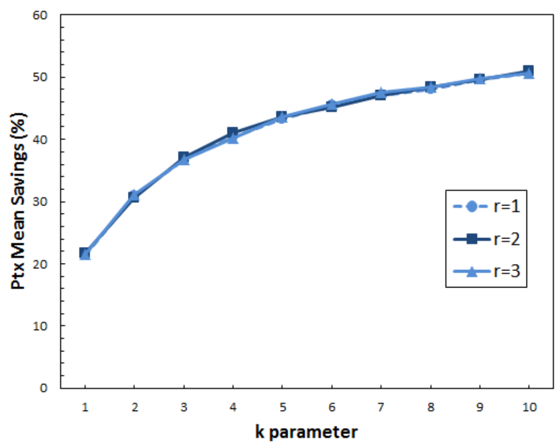

Figure 5.30. Evolution of Ptx Mean Savings as function of [k,r], for LP456, scheme MIN and network load 50%

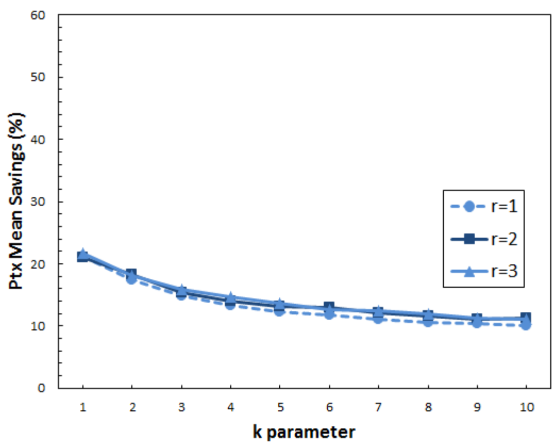

Figure 5.31. Evolution of Ptx Mean Savings as function of [k,r], for LP456, scheme MEAN and network load 50%

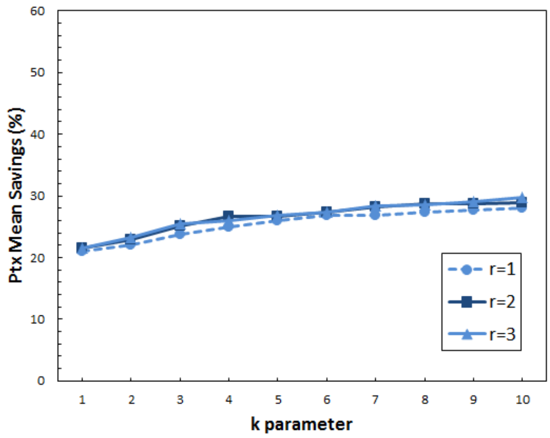

Figure 5.32. Evolution of Ptx Mean Savings as function of [k,r], for LP456, scheme MINTOMEAN and network load 50%

Mean savings reached are higher for MIN and MINTOMEAN schemes when the number of neighbors involved in the calculation increases, showing the MIN scheme better performance in general and for any *k* value. In fact MINTOMEAN normally provides savings around 25%-30%, until k=10, whereas MIN scheme provides 30% of savings already from k=2 and it continuously increases, moving in values from 30% until 50% for k=10. For MEAN scheme, savings decrease with the *k* value. As MIN assures FitCases% above 95% from k=3, this scheme is again the best selection to be applied also for this LP456.

Mean savings achieved on transmission power for a mean network load of 30% and the MIN scheme are presented in the Figure 5.33:

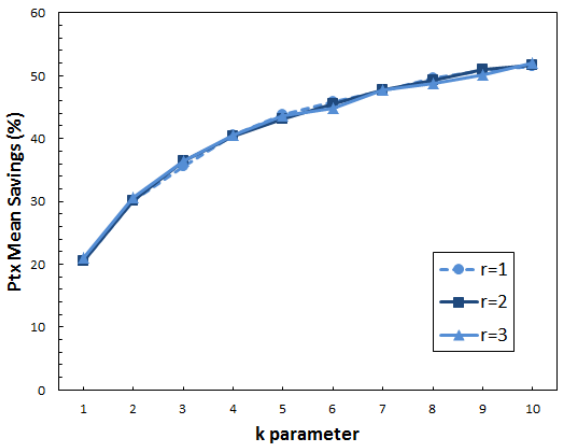

Figure 5.33. Evolution of Ptx Mean Savings as function of [k,r], for LP456, scheme MIN and load 30%

No noticeable differences are presented in terms of this KPI and its evolution. It is noticed that for lower loads, even if it is not depicted, success rates are higher, so as mean savings reached. In the case of 30%, it can be seen that above 50% from k=5 value.

As for the precedent lightpaths, the Table 5.7 presents the results for the [k,r] combination providing the best achievements for each one of the analyzed schemes:

	Maximizing Mean Savings		
	best [k,r]	Ptx savings (%)	FitCases%
MIN	[10,2]	50,92%	96,19%
MEAN	[1,3]	21,67%	82,10%
MINTOMEAN	[10,3]	29,68%	96,80%

Table 5.7. Best [k,r] pair maximizing savings, for LP456 and load 50%

As verified for the other lightpaths, MIN is definitively confirmed as the algorithm providing the highest mean savings, more than 50% and guaranteeing 96% of FitCases success rate. The second best option is to apply the MINTOMEAN scheme, although it provides around 30% of savings, almost -20% below the MIN option; FitCases success rate of that algorithm is also very high, around 97%. For the MEAN scheme, savings are around 21%, but the offered FitCases success rate is a bit low, around 82% in general, for being applied in a production network. Thus, MIN scheme is again the recommended selection also for this LP.

5.8 Global performance of the selected CBR-based solution

In the precedent sub-sections the analysis of CBR-based proposal has been done for the four considered representative lightpaths, in the application of all the proposed schemes and in different mean network load situations. In this section the selection of the more appropriate CBR parameters solution is proposed as recommendation for telecom operators.

Let us start for the LP1234. It can be noted from Figures 5.6, 5.7 and 5.8, for nominal load of 50%, that the success rate follows an increasing trend with the number of neighbors. Then, a value k=10 might be used. However, the FitCases% indicators recommends to select a *k* value in the margin 3 through 5, in order to get a success rate for exploitable operational cases around 95%. In section 5.4, a combination [k,r] = [4,3] was identified as a correct solution.

In that precedent section 5.4, MIN scheme has been proposed as the best solution for LP1234. By starting the analysis for a nominal load of 50% a first solution could be [k,r] = [4,2] which offers 47,9% of savings and 95,25%. However, when network load increases success rate slightly decreases. Even though a potential 100% of load is quite rare to be found in commercial networks, a success rate around 94% would be achieved in that case. Even if it may be considered as good enough, by selecting [k,r] = [4,3] both the savings (48,11%) and the success rate, (95,24%) are improved. For *k* value set to 5, mean savings increase compared to k=4 (for example, we get 48,36% for k=5 and 46,81% for k=4, r=2, for a mean load of 70%), although success rates decrease, below 95% for all the mean loads, except 30%. Nevertheless, if *r* value is set to 3, success rate for all the loads is above 95%. Upon these cases, the recommendation as the best combination for LP1234 offering a trade-off between mean savings achieved and guaranteed success rates for all the mean network loads is [k,r] = [4,3].

In Figures 5.34 and 5.35, results for this [k,r] selection are shown. For sake of completeness, the obtained results for all the schemes and mean network loads are illustrated:

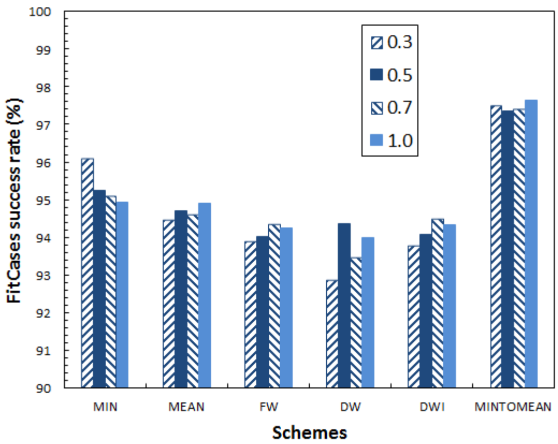

Figure 5.34. FitCases success rate for LP1234 and [k,r]=[4,3]

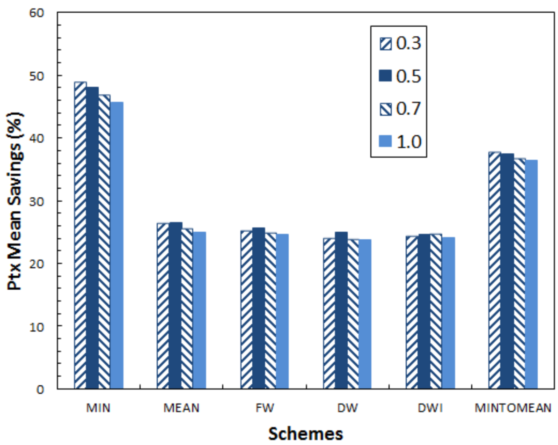

Figure 5.35. Mean transmission power savings achieved in LP1234 and [k,r]=[4,3]

Several of the points commented in the precedent sections are observed in these figures. Firstly, the MIN scheme provides the maximum savings over the other five ones and this, for all the mean network loads. For a nominal load of 50%, MIN achieves 48,11% of savings while guaranteeing 95,24% of success rate. When network load is low, savings reached 49% and a success rate of 96,1%. Even though MINTOMEAN provides clear higher success rates, above 97%, the mean savings provided, which is the main objective of the cognition proposal, are -10% down respecting MIN scheme. As noted, telecom operators could prefer to apply this scheme, although our recommendation is to maximize the mean power savings, which finally leads to reduce the operational System Margin. Regarding savings, it is confirmed that they decrease when network load increase. The other schemes present a lower performance respect to MIN and MINTOMEAN, but it does not necessarily mean than their performance is bad. It is true that success rate are lower, but values around 94% are provided, especially for MEAN and the new proposed FW and DWI schemes, while maintaining very correct mean savings, around 23% or 24%, which represent really important power savings for an operator if working in stationary mode along the time. However, these reduction achievements are more important for the other two schemes. The algorithm showing worse performance, but not necessarily bad, is the DW scheme, found in literature. For success rate, it decreases when load increases for the MIN scheme, although the other five schemes follow the inverse trend, success rate increase in general when network load increase.

Thus, for LP1234, the [k,r] = [4,3] CBR combination is confirmed as our best recommendation.

In the next paragraph the same exercise is done for the shortest lightpath, LP12. Although success rates results are not depicted for this one link lightpath, success rate is above 95% in practically all the range of *k* values, although the higher values are obtained when applying k in a range [2-5]; if looking at the mean savings, in Figure 5.26, situation is quite similar: savings increase with *k* value and high values are already reached in the range k = [3-8], although from k=6 the slope of the increasing curb is reduced. Searching a trade-off solution combining these both indicators, it is proposed a [k,r] combination set to [4,3], although [5,2] might be a correct selection. Only for some comparison reasons, in case that [k,r] = [5,2], all the mean savings are above 50%, for the MIN scheme and for any load. If the operator selects [k,r] = [4,3], savings for 70% and 100% of load are slightly below 50% (49,6% and 48,49%). Nevertheless, the success rates reached for MIN algorithm for [k,r] = [4,3] are slightly higher, above 98% for any load, than the ones offered by [k,r] = [5,2]. Then, as indicated, the decision has not to be necessarily unique, both solutions could be applied. In order to maintain the same selection than for LP1234, the recommendation is to apply [k,r] = [4,3] CBR combination for LP12. In this case, Figures 5.36 and 5.37 present the overall results achieved for the shortest and mono-link lightpath LP12 for this selected [k,r] pair:

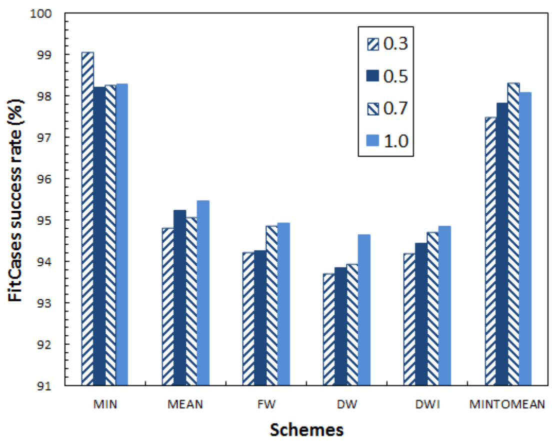

Figure 5.36. FitCases success rate for LP12 and [k,r]=[4,3]

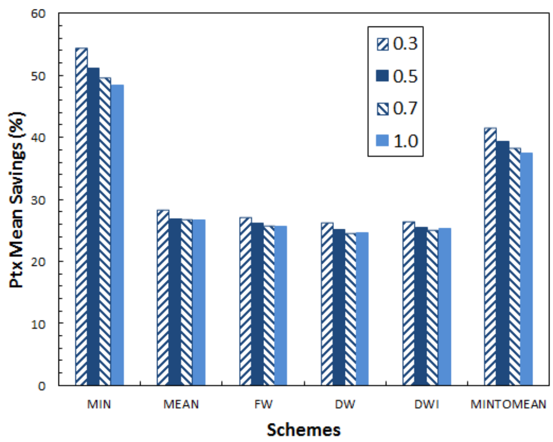

Figure 5.37. Mean transmission power savings achieved in LP12 and [k,r]=[4,3]

As for LP1234, MIN scheme is confirmed as the best solution to be applied over the rest of the proposed schemes, and this, regarding both KPIs. This algorithm improves the results of the second best performing option, MINTOMEAN, and this also for both indicators, which represents a difference with respect to the LP1234 (MINTOMEAN scheme provides in this path higher success rates for any load). MEAN, FW and DWI also improve the performance of the DW algorithm. For a nominal load of 50%, MIN scheme provides to the operator mean savings of 51,07% over the initial launched power pre-assigned, while guaranteeing simultaneously an operational success rate of 98,20%. Mean savings and success rate results jump up to 54,5% and 99,01% in the case of a mean load of 30%, showing the advantage of applying our cognition solution for reducing the System Margin.

Regarding the longest path, composed of more links, LP34567, the analysis shows that the best *k* margin to apply in order to get correct success rates varies around [3,7] in order to assure values above 95% . Due to the increasing nature of the mean savings, values from k=4 are appropriate to get values above 40%. The discussion in this LP is similar to that of LP12. A good solution to be applied may be [k,r] = [5,2] or [k,r] = [5,3] and [k,r] = [4,3], no remarkable differences are raised when comparing theses three selections. Success rates for all of them are above 96% for any load (MIN scheme). Regarding mean savings, a more noticeable improvement is show for k=5 (and both r=2 and r=3), around 44%, compared to 41% provided by k=4. Then, for LP34567, the recommendation is to apply [k,r] = [5,2] (no differences are shown in *r* parameter). The following figures show results for [k,r] = [5,2].

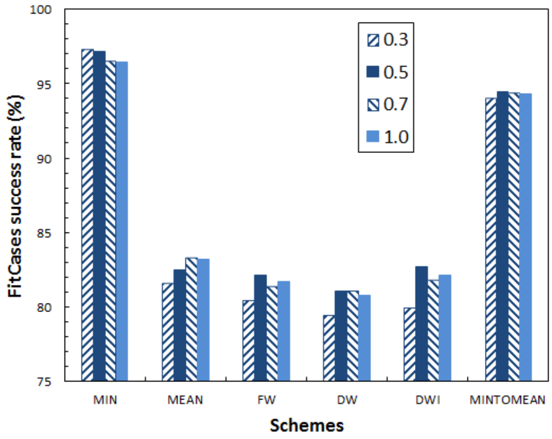

Figure 5.38. FitCases success rate for LP34567 and [k,r]=[5,2]

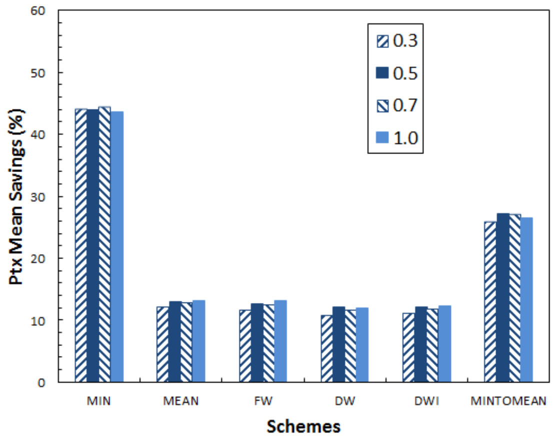

Figure 5.39. Mean transmission power savings achieved in LP34567 and [k,r]=[5,2]

Cognitive solution applied in LP3467 for MIN scheme and a mean load of 50% provides 43,9% of savings and 97,14% of success rate.

In terms of homogeneity regarding the application of the same [k,r] combination, the achievements obtained when selecting [k,r] = [4,3] are presented in Figures 5.40 and 5.41:

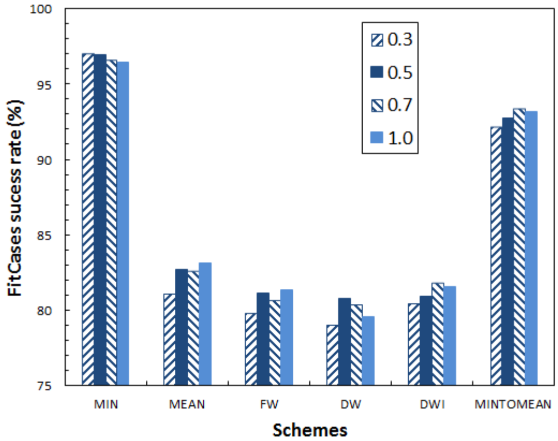

Figure 5.40. FitCases success rate for LP34567 and [k,r]=[4,3]

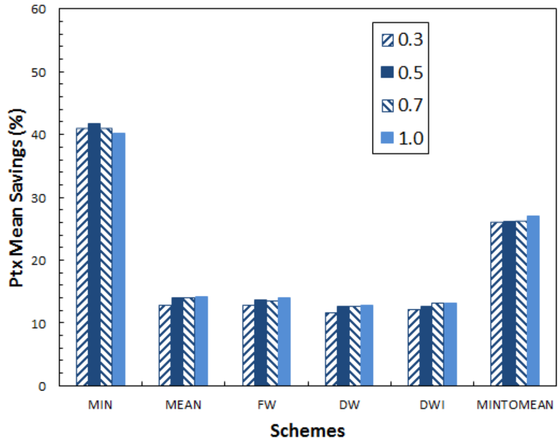

Figure 5.41. Mean transmission power savings achieved in LP34567 and [k,r]=[4,3]

In this case, CBR-based proposal achieves 41,73% of mean savings and 96,97% of success rate. Thus, this [k,r] = [4,3] combination can also be selected for the network operator for longest paths when a great number of links are passed though.

Finally, the last path considered is the LP456, which is, as LP1234, an intermediate LP in terms of length and number of links. It is composed of two links, but the total length is 700 km, that is, it is formed by long links. Looking at Figures 5.30 and 5.33, it can be seen that several [k,r] combinations can be selected to obtain high savings. For example, [k,r] = [5,3] presents convincing results for MIN scheme, around 43% for a mean load of 50% and 50,52% for a nominal load of 30%, with 97% of success rate in both cases. If [k,r] = [5,2] is selected, the same results are obtained: 43% and 50,46% for network loads of 50% and 30% respectively. Both situations are supported by success rates of 97,70% and 97,88%. As done for LP12 and LP34567, in order to select the same [k,r] CBR parameters as for LP1234, the [k,r] = [4,3] value is also analyzed; this option provides 40,1% of mean savings with a 97,3% of success rate for a mean load of 50%; and 48,49% and 98,29% as achievements for both KPIs in the case of less loaded networks, 30%. That is, the difference in mean power savings between k=4 and k=5 is around +2%. Our recommendation in this case is to select the [4,3] CBR pair, following a simplicity and homogeneity criterion for the telecom operator. Then, if [k,r] = [4,3], results for LP456 are presented in the following tables:

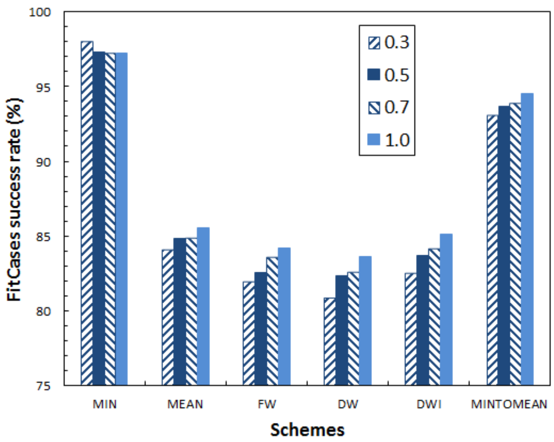

Figure 5.42. FitCases success rate for LP456 and [k,r]=[4,3]

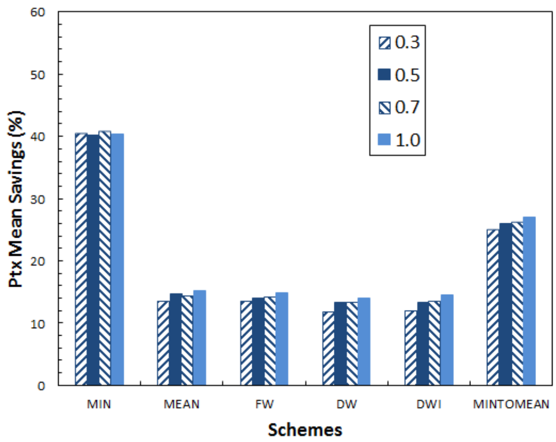

Figure 5.43. Mean transmission power savings achieved in LP456 and [k,r]=[4,3]

The same conclusions as for previous paths can be confirmed: MIN is the scheme presenting the higher performance in mean savings and success rate. The second best option is the MINTOMEAN scheme offering 26% of mean savings and 93,66% of success rate for a nominal load of 50%. MIN is the only scheme providing more than 40% of savings while guaranteeing 95% for any load. For this LP a particular high performance, common to all the schemes is obtained for relatively low loaded networks. When load is 30%, a peak of mean savings accompanied with the corresponding success rate is reached. For example, MINTOMEAN scheme offers 37% of savings and 98% of load compared to around 26% of mean savings and 93% of success rates for the other loads. MEAN scheme reaches 26% and 95% for the considered KPI, for 30% of load, against 14% and 84% of KPI values for the rest of loads. For the rest of the schemes is similar, FW and DWI provides best results and it is DW the scheme slightly providing the lowest performance.

At the starting point of this chapter, in section 5.1, the [k,r] = [3,2] pair has been selected as one of the variables used to select of the KB size. Even though this [k,r] combination shows a good performance, the final recommended CBR parameters are [k,r] = [4,3]. Although not reported in the thesis, there is no significant variations in the results, if this combination would have been chosen in the selection of the knowledge base.

5.9 Chapter summary

This chapter has studied and evaluated the performance of the CBR-based cognitive approach in an optical transport network. To this end, section 1 has been devoted to the selection of the knowledge base size. Three possible options have been considered. The assessment has been realized for one lightpath and all the proposed schemes. Moreover, the analysis has been widen to the other considered lightpaths and other network mean loads. A final set of 1500 entries is decided, providing appropriate results in terms of both mean savings and success rates.

Next, the selection of the best [k,r] pair of CBR parameters has been addressed. For the evaluation, the three indicators (CBR%, FitCases% and Ptx Mean Savings%) have been used in order to monitor simultaneously the transmission power mean savings and the success rates. In particular, the analysis has been firstly done for the LP1234. The evolution and behaviour of the three KPIs with *k* and *r* parameters have been presented. The assessment has been extended taking into account all the schemes and network loads. Several conclusions are obtained from this analysis: first, the [k,r] = [4,3] pair is recommended to maximize mean savings while guaranteeing good success rate. Second, the MIN scheme is the outperforming option to achieve the best performance. In order to avoid any bias, the evaluation has been completed presenting the best [k,r] pair maximizing mean savings for the other schemes. The obtained results confirm this conclusion. The cognitive approach achieves 48% in transmission power mean savings and a FitCases success rate of 95%. Finally, it has been observed that network load has not a significant impact of the performance of the CBR-based approach, although slightly better results are reached for low network load.

In sections 6, 7 and 8, a similar evaluation has been done for the other representative lightpaths. Based on the obtained results for LP1234, only the three schemes showing the best performance (MIN, MINTOMEAN and MEAN) and two mean loads (30% and 50%) have been selected to continue the analysis. Similar behaviour and results in terms of launched power mean savings and achieved FitCases success rate are obtained. They confirm that MIN is the scheme showing the best performance. An important conclusion reached from these sections is that there is not a *best* [k,r] pair *common* to all lightpaths, although by selecting the *k* parameter value in the intermediate range [3-5] provides the best results. The recommendation [k,r] = [4,3] highlighted in section 3 is confirmed as the best common CBR combination to be applied in the four lightpaths.

Finally, in section 9, the overall view for this [k,r] pair is presented for all the analyzed lightpaths.

In this chapter, the knowledge base of the system is static. The obtained results may be improved by implementing a dynamic memory. This approach is further developed and evaluated in chapter 6.

Chapter 6

Dynamic learning strategies for operation margin reduction

In this chapter, the online renewal of the KB is addressed. In chapter 5, the KB was populated offline with test lightpaths launched by the telecom operator, allowing to record real measurements of the lightpath attributes contained in the CBR cases. It was also proposed to renew this initial KB with new offline measurements performed by the operator every certain time window. In this chapter, another approach is analyzed: the update of the KB by applying dynamic learning algorithms.

This chapter proposes several algorithms to dynamically renew the KB. To start with, the potential limitations of static learning are mentioned and subsequently, dynamic learning to improve the cognitive approach is presented. Therein, a description of the dynamic strategy and the corresponding algorithms have been detailed. Moreover, the methodology followed for the analysis is explained. Next, dynamic learning algorithms are evaluated in sections 2, 3 and 4, providing a further detail for the shortest and the longest lightpaths. Later on, an overall overview of the dynamic algorithm providing the best performance is presented, In particular, the gain in savings with respect to static strategy is illustrated. Finally, based on the results outlined in previous sections, the best trade-off considering the global performance of the best dynamic algorithm for the four end-to-end representative lightpaths is given.

6.1 Dynamic learning approach

In this chapter, once the offline learning policy has been explored, a dynamic approach is addressed [112]. In chapter 5, the whole cognitive analysis has been done assuming a static memory of the system, that is a static KB [103]. It was offline populated before the exploitation of the network and our CBR-based methodology has been acted upon this assumption, with no new information dynamically incorporated to the KB. But memory in humans is a complex and dynamic system. In order to emulate these underlying mechanisms, dynamic and active learning strategies and algorithms are proposed and evaluated. The aim is to dynamically renew the KB with new elements and knowledge in order to take into account new arising network situations. This new elements, modeled as CBR cases, are integrated in the memory of the system. And this new information is supposed to provide a higher value to the network operator to take more accurate decisions and obtain further benefits. Additionally, since an optical transport network is maintained over time, some of the CBR cases recorded in the KB may become obsolete. To overcome these potential limitations of the static learning and to improve the effectiveness of the system, the dynamic learning approach is developed. Thus, applying dynamic learning processes to renew online the KB may improve the performance of our cognitive solution.

The Retain phase of the CBR cycle is the appropriate step dedicated to this purpose. In the first part of the analysis, presented in chapter 5, when the static KB has been considered, this phase has been simply bypassed. Learning occurred when new situations raise; that is, by learning from previous knowledge, a new launched power value is proposed and tested by the system. But no advantage is taken from the potential new information. In this chapter, this new information shall be integrated in the cognitive system. When a new incoming lightpath is established by using the optimized transmission power value provided by CBR, this new generated information will be stored in the KB. In the Retain phase it is decided if and how to store this new information. To do this, several strategies and active learning algorithms are proposed. The main strategy decided among several possibilities is to integrate in the KB only such *correct* cases, that is, those new lightpaths whose optimized transmission power proposed by CBR is correct (a lower value than the initial pre-assigned one, while guaranteeing the quality of service required). The implicit System Margin is then reduced and this information is updated in the KB. Another taken decision in the dynamic approach is to keep constant the size of the KB. It means that the active learning algorithms will identify and remove existing KB entries, so as to be replaced by new ones, more adapted to the current network conditions or situations. By introducing new CBR cases in the KB more current network conditions are incorporated to the memory of the system and knowledge and learning capacity is thus strengthened.

To this end, the following active learning strategies have been applied in the renewal of the KB. Each one of them focuses on some specific attributes or variables of the network situation, modeled as CBR cases, to evaluate and take decisions:

1) *Usefulness, launched Power Deviation and Age of the KB case* (UPODA): this algorithm is based on the information provided by three attributes of the CBR case:
    a. Its usefulness: it means how many times this CBR case has been selected among the candidate nearest neighbors of the new incoming request in order to be used to calculate the new transmission power.
    b. The deviation between the launched power indicated for this case and the mean launched power of the KB (average of the transmission power of all the CBR cases contained in the KB)
    c. The age of the case: total time elapsed from its introduction in the KB

This algorithm combines these attributes of the cases stored in the KB in order to select those ones to be removed from the KB. More particularly, this algorithm only considers firstly the number of times that the case has been selected to participate in CBR decisions (its usefulness). An additional criteria is introduced to take into account two indicators: the evolution of the global mean transmission power of the KB respect to the initial one (when no new cases had been integrated yet) and the volume of the wrong CBR proposals, that is, the number of times that CBR proposes an incorrect launched power. This algorithm monitors continuously the evolution of both indicators. And this additional criteria comes into play when two respective thresholds are exceeded: 30% for the deviation respect to the initial total KB mean power and 2% for the error CBR proposals. Thus, this algorithm proposes that less used cases, presenting a higher distance to the KB average transmission power and being the older ones in the KB are progressively removed from the KB, which is populated with new cases or network situations.

2) *Usefulness, launched Power Case and Age of the KB case* (UPOCA): this algorithm uses the same CBR case attributes that UPODA, but applied and combined in a different way. It uses a linear combination of these three attributes of each KB case to decide if the case is to be removed from the KB. The meaning of the usefulness and the age properties is the same as explained for UPODA. However this algorithm only takes into account the transmission power of the case, not its deviation from the mean total KB power. The cases having been less used, showing a lower transmission power and being the older ones are progressively selected to be removed from the KB. Two main differences respect to UPODA: the first one is that in UPOCA, the three attributes are considered from the beginning in order to flag the case as potential case to be removed; the second difference is that a linear weighted combination of the three attributes is used.

3) *Net Losses Heterogeneity* (NELHET): this algorithm takes into account the net losses (CL) attribute value of every KB case and its deviation from the global KB CL average value. Cases presenting less distance respect to the global KB CL mean value are removed, favoring an heterogeneity of the range of the net losses values (network situations) in the KB.

4) *Non-Linear Impairments Heterogeneity* (NLIHET): this algorithm takes into account two attributes:
   a. The Non-Linear Impairments (NLI) attribute value of the KB case (that is, the information about the non-linear impairments found in the network situation modeled by the case).
   b. The age of the case.

This algorithm calculates the deviation of the NLI value for every KB case with respect to the average KB NLI value (average of the NLI attribute value of all KB cases). Cases presenting less distance to the KB NLI average value and the older ones are progressively removed from the KB. In this way, the heterogeneity of network situations regarding the non-linear impairments is reinforced.

5) *Net Losses Homogeneity* (NELHOM): this algorithm is similar to NELHET. The same net losses (CL) attribute of every KB case is considered, so as its deviation from the global KB CL average value. It removes from the KB the cases presenting a higher distance to the global KB CL mean value. In this way an homogeneity of the range of the net losses network situations is searched to be maintained in the KB.

6.1.1 Methodology approach

The objective of the analysis in this chapter is to identify if an improvement of the performance of the cognitive proposal is achieved if the KB is dynamically renewed; that is, if an increase on the mean savings is reached by renewing the memory of the system.

The size of the initial KB is maintained and only the CBR correct cases are incorporated to the KB. It will be then assessed whether the efficiency in the transmitted optical power is increased when applying dynamic learning algorithms to update the KB vs. a static memory, which also yields significant savings in the launched power when applying our CBR proposal, developed in chapter 5.

The following methodology is applied in the analysis: the maximum mean savings achieved by CBR when a static KB is used are set as reference. The pair [k,r] of CBR parameters used are also registered. Then, the different dynamic learning algorithms are applied to renew the KB and the maximum mean savings proposed by CBR for each renewal strategy are observed, so as the [k,r] pair employed. Both maximum savings values are then compared in order to register which policy can offer more advantages. By introducing the [k,r] pair used in the analysis, a global and more complete performance of the each strategy can be assessed. As a consequence, the telecom carrier shall be able to decide which policy to apply. Our CBR-based cognitive solution was found in previous chapter to propose a more optimized application of the operational System Margin. In this chapter, it will be investigated if renewing the KB can achieve higher mean power savings.

In the following sections are presented the results for:

1) Mean savings proposed by CBR for all the learning strategies; when using a static memory (called NONE policy, because no renewal of the CBR cases exists) and when dynamically renewing the KB (for the different dynamic learning algorithms UPODA, UPOCA, NLIHET, NELHET and NELHOM), for the whole ranges of k=[1-10] and r=[1-3] parameter values. At this stage, only a comparison of the maximum values is done, without evaluating the global performance of each strategy, in terms of the [k,r] values used to obtain those maximum savings. This exercise is done for each one of the four representative lightpaths selected.

2) The equivalent results are presented, but introducing an additional condition in order to select the maximum savings achievable: a FitCases% success value around 95% must be guaranteed.

Upon the results obtained in chapter 5, the MIN scheme is selected, as it is probed to be the algorithm presenting the best performance; and a mean network load of 50% has been considered. For the whole analysis, the same initial KB composed of around 1500 CBR cases is used as the starting point for the application of any strategy. Moreover, 10^4 new incoming observations are generated following the same range of attributes values indicated in Table 4.1. With the aim of preserving coherence when comparing the performance of the different static and dynamic learning strategies, the same set of 10^4 new incoming requests is used each time. As highlighted in chapter 4, the random generation of CL and NLI attribute values of the new incoming requests has followed a Gaussian distribution.

6.2 Results for LP12

The results for the shortest path are presented in this section. The evaluation has been done based on two performance indicators: the FitCases% and the Ptx Mean Savings%. The first exercise done is the selection of the *r* parameter (addressing the calculation of the distance or degree of similarity between the new incoming request and the precedent network situations or neighbors). This analysis has been done in chapter 5 in a static learning scenario; it is realized in dynamic scenario to confirm results and avoid any bias. Thus, the exercise is done for the range k=[1-10], as shown for NONE (static KB) and UPODA learning strategies in Figures 6.1 and 6.2, respectively.

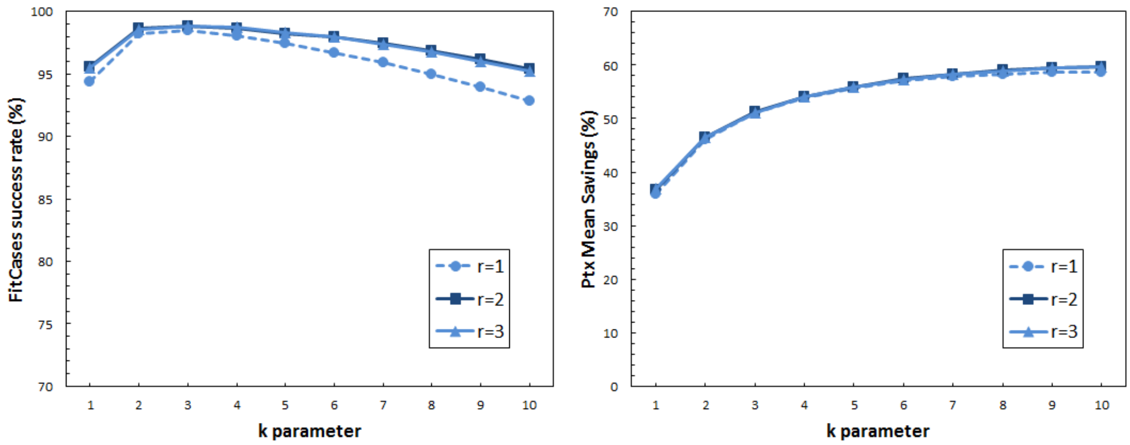

Figure 6.1. FitCases success rate and mean transmission power savings for NONE strategy

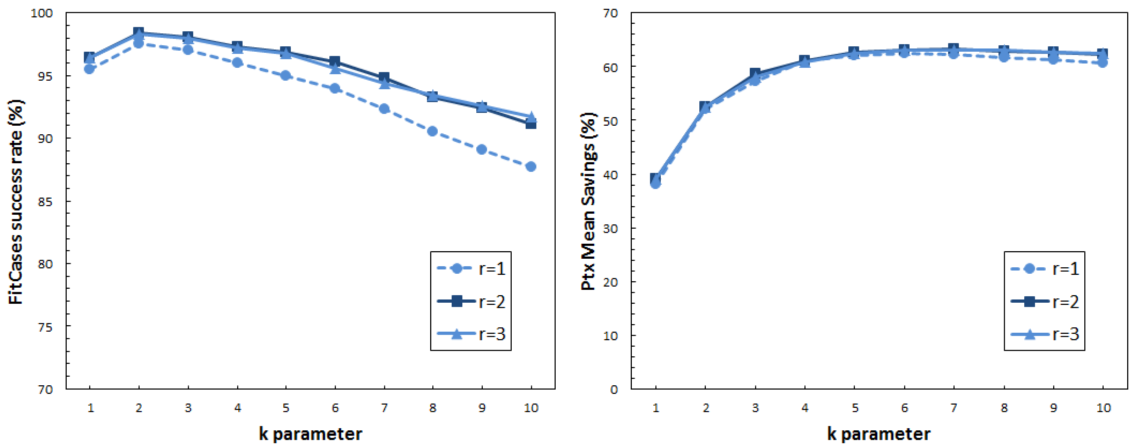

Figure 6.2. FitCases success rate and mean transmission power savings for UPODA strategy

Several points can be noted from the figures above. The first one is that r=1 can directly be removed from the analysis, as its performance is the poorest in terms of case-based reasoning success rate. Regarding the mean savings achieved, no remarkable differences are seen, but when observing the success rate of the application of the cognitive solution, it can be excluded, for both static and dynamic learning strategies. Moreover, no significant differences are observed when setting r=2 or r=3 both in terms of mean savings and FitCases success rate. Hence, based on the results presented in chapter 5, the value r=3 is selected for the analysis. The results of the other learning algorithms are similar for the different *r* values, thus not shown for the sake of clarity. Then the analysis with respect to the policy renewal of the KB are presented in Figure 6.3 for LP12, for k=[1,10] and r =3.

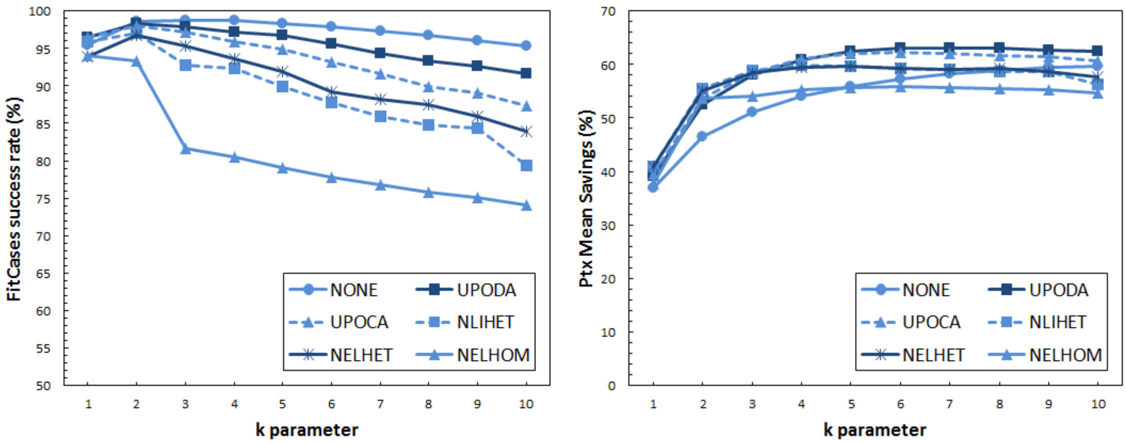

Figure 6.3. Evolution of FitCases success rate and mean transmission power savings for LP12, k=[1,10] (r=3) and all the learning strategies

Several important points can be derived from Figures 6.1, 6.2 and 6.3. Regarding mean savings on transmission power, it can be observed that they increase when k increases. That is, when more neighbors are considered in the proposal of the new launched power to be used, the obtained savings are higher. And this behavior is observed for all learning strategies, both static and dynamic. It is also important to be noted that the increase on savings is more important for lower *k* values, until k= 5 or k=6, and seems to stabilize from k=7 onward, except for the NONE strategy, which shows a continuous increase until k=10. The most remarkable point to be noted is that, despite the continuous increase of savings when NONE is applied, the maximum value reached does not exceed that one achieved by the dynamic UPODA or UPOCA algorithms. Particularly, maximum savings reached by NONE are 59,67% and those achieved by UPODA and UPOCA are 63,11% and 62,31%, respectively. Moreover these maximum values are reached by using lower *k* values in dynamic algorithms (k=7 and k=6 for UPODA and UPOCA), whereas static strategy reaches it with k=10. Although regarding Figures 6.2 and 6.3, by using *k* values in the range [2,5] provides very high savings and it could be considered enough for the telecom operator.

As indicated in previous chapter, using low *k* values, rather than higher ones is preferable because two reasons; the main one is related to the guaranteed FitCases success rate. It can be observed in Figure 6.11 that FitCases success rate decreases when the number of *k* closest neighbors increases. For UPODA, rates above 95% are obtained until k=6, and for UPOCA strategy until k=4. Therefore, a trade-off between maximum savings and guaranteed FitCases success rate exists when selecting the *k* value.

The objective of the work is to maximize the mean savings reached, but always assuring a correct cognitive success rate when applying the solution in a real network. Then, it can be derived that when taking *k* values in the range k=[2-5], the lower the *k* value the higher the guarantees of success when proposing a lower launched value. In this regard, UPODA provides the highest savings with the lowest *k* values, thus becoming the strategy offering the best performance for the operator. As indicated, UPODA provides the maximum savings, i.e., 63,11% with k=7 (+3,44% than NONE) and guarantees a 94,39% success rate. If an operator wants to guarantee a higher rate, k=6, k=5 or k=4 can be used offering 63,02% savings (+3,36%) with 95,60% success rate, 62,39% (+2,72%) with 96,73% or 60,97% (+1,31%) with 97,23%, respectively. In turn, UPODA provides its maximum savings with k=6, namely, 62,31% (+2,64%) with 93,21% success rate. If using this algorithm, an operator could apply k=5 obtaining 62,09% (+2,43% versus NONE) or k=4 obtaining 60,98% (+1,30%) and guaranteeing 94,89% and 95,86% respectively. Once again, in terms of maximum potential achievable savings, dynamic algorithms that renew the contents of the KB provide higher values than the static strategy. If considering lower *k* values, savings obtained are still higher that the maximum ones provided by NONE, and guarantee higher CBR success rates. Among the dynamic algorithms, UPODA provides the best performance among them. For sake of clarity, both indicators are depicted in the following Figure 6.4, only for NONE and UPODA algorithms.

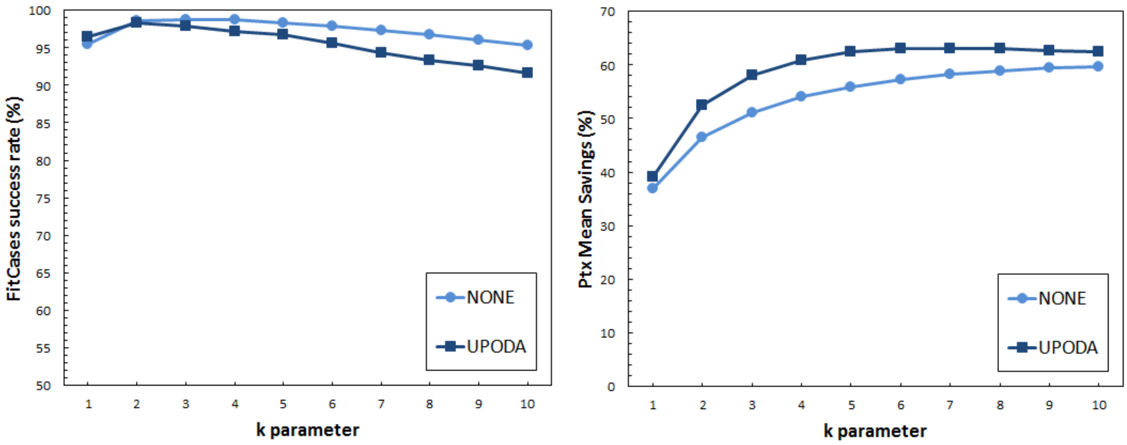

Figure 6.4. Evolution of FitCases success rate and mean transmission power savings for LP12, k=[1,10] (r=3) for NONE and UPODA learning strategies

The evolution of the mean savings and the FitCases success rate indicators for dynamic algorithms, particularly UPODA and also when compared to the static strategy can be explained as a direct consequence of the dynamics of both learning approaches, combined simultaneously with the MIN scheme, selected due to its higher performance. When applying NONE, by considering more similar neighbors (i.e., higher k value), it is more likely to find a lower transmission value than the pre-assigned one. Hence, the mean savings obtained increase with k. However, low transmission power values may not be enough to guarantee the quality of lightpaths upon reception, so the success rate decreases. This evolution was explained in chapter 5.

When applying a dynamic learning approach, two factors come into play: thanks to these strategies, new network situations presenting a lower and successful optimized transmission power value are dynamically incorporated to the renewed KB. Then, more candidate neighbors with low transmission powers than with the NONE strategy are available. Simultaneously, the

KB *is* dynamically and continuously renewed along the time. Thus, when more neighbors are selected, whose launched power values are continuously decreasing due to the KB updating dynamics, the achieved gain will tend to slightly decrease with k; and at the same time, gain differences compared to NONE will also be lower when *k* increases, because the static strategy does not update and then it does not optimize the KB.

This behavior can be remarked in the high range of *k* values: a higher number of neighbors leads to lower launched power values leading to lower success rates when proposing them. And at this point, it is important to note that when CBR selects the number of similar neighbors for the calculation, for high *k* values it does not necessarily mean that all of them are appropriate. That is, in terms of similarity, the closer neighbor can be similar, although the 10^{th} closer one may be not. This fact contributes to the success rate reduction and explains the risk of high *k* values, as confirmed with the FitCases success rate for UPODA and for the whole dynamic algorithms in Figure 6.3.

The other dynamic algorithms, namely, NLIHET, NELHET and NELHOM show the same behavior: savings increase but FitCases success rate decreases with *k*. Among them, NELHET is the algorithm presenting a slightly better global performance regarding the FitCases success rate: it achieves around 59% until k=8 and NLIHET reaches it until k=7, even if the differences are not remarkable. It is the FitCases indicator which shows slight higher values, for example NELHET providing 58,45% savings with k=3 and guaranteeing 95,30% success rate, whereas NLINET offers 58,82% savings and 92,71% success rate for the same number of similar neighbors (k=3). Then, for this LP12, this algorithm which only considers the non-linear impairments to renew the KB show very good results in savings although case-based reasoning application success rates are poorer when compared to NONE. Finally, NELHOM algorithm provides the poorest performance in terms of success rate. It has to be noted that, in average for any *k* value, this algorithm achieves 53,36% savings, which is not a poor result. However the average success rate guaranteed of 80,33% can be too aggressive for an operator to apply it in an operational network. Basically, when compared to other dynamic algorithms and also the static NONE strategy, it can be discarded.

When applying the additional condition indicated in the section 6.1 of this chapter, that is, making the comparison of learning strategies guaranteeing around 95% of FitCases success rate, the obtained results are similar, as shown in Table 6.1.

Learning algorithm	Best Ptx Mean Savings (%) (success rate >= 95%)	Corresponding Success Rate (%)	Gain Ptx (%)	[k, r=3]
NONE (static)	**59,67**	95,27		[10,3]
UPODA	**63,02**	**95,60**	**+3,35**	**[6,3]**
UPOCA	60,98	95,86	+1,31	[4,3]
NLIHET	55,53	97,11	-4,14	[2,3]
NELHET	58,45	95,3	-1,22	[3,3]
NELHOM	37,75	93,99	-21,92	[1,3]

Table 6.1. Best results for the different learning strategies, LP12, FitCases success rate around 95%

It can be seen that UPODA continues achieving the higher maximum savings, better NONE and guaranteeing a specific success rate strictly above 95% and, besides, using a lower k=6 value. UPOCA presents a similar behavior in terms of savings and success rate, although results are slightly worse, and NLIHET and NELHET might be also options to be considered, although they do not improve the maximum savings provided by NONE. It is important to highlight again at this point that the performance comparison between dynamic and static strategies are being done in terms of the *maximum* mean savings achievable. If the global performance is considered, that is, the mean savings (not necessarily the maximum ones) encompassed with the success rate achieved and also the *k* value used, the performance of the UPODA algorithm respect to NONE, but also that of NLIHET and NELHET, in the lower *k* values is even better. This global point of view will be analyzed in section 6.6.

Regarding the dynamics of UPODA, when using k=3, over the 10.000 incoming requests, the cognitive solution took error decisions on 340 of them and the percentage of remaining initial cases at the end of the process was 28,97%. In case of k=4, the volume of error decisions raised to 555 and the percentage of remaining initial cases kept on the resultant KB was 30,7%.

Thus, it can be concluded that for the shortest LP12, the UPODA dynamic approach renewing the memory of the system shows the best performance.

6.3 Results for LP34567

In this section the behavior of dynamic learning approach applied to the longest path has been analyzed. Figure 6.5 shows the mean savings and FitCases success rate evolution with respect to *k* and r=3, for all learning strategies, both dynamic and static.

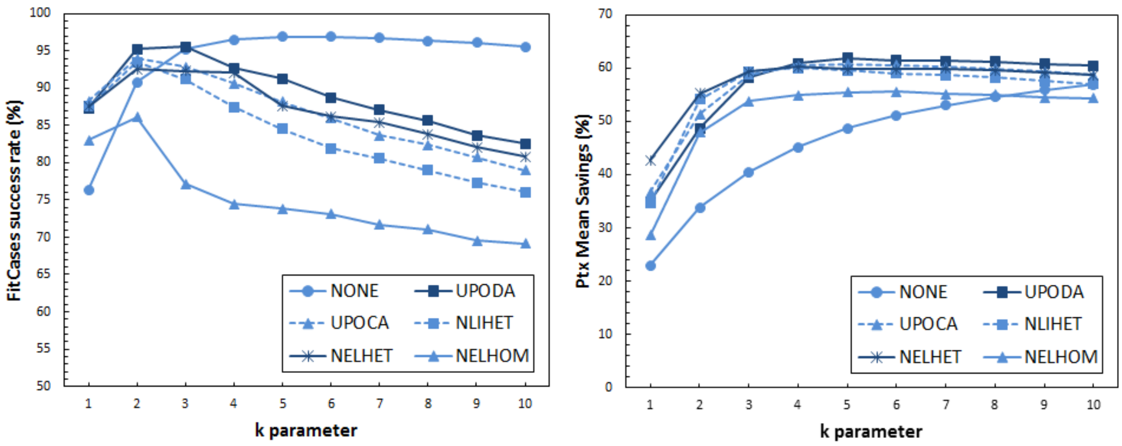

Figure 6.5. Evolution of success rate and mean transmission power savings for LP34567, k=[1,10] (r=3) and all the learning strategies

It can be noted in Figure 6.5 that globally both KPIs follow an equivalent trend as the one shown for LP12. Dynamic algorithms achieve mean savings that increase with *k* value until reaching k=5 or k=6, and then savings start to slightly decrease. Conversely, NONE shows a continuous increase with the value of *k*. However, the maximum mean savings proposed by NONE do not exceed those achieved by dynamic learning algorithms, except NELHOM from k=9 on. Considering the success rate, differences between dynamic and static learning approaches are more remarkable for this longer LP34567 than for the shortest LP12. It can be observed that to obtain success rates around 95%, the range k=[2-4] shall be selected. The common trend for both strategies is the success rate to decrease with *k*; this behavior has been further explained in the previous section.

In terms of mean savings, NONE provides its best bet with k=10, reaching 56,95% with a success rate of 95,6%. The dynamic UPODA algorithm seems to achieve the maximum savings, 61,89% (+5%) with a 91,28% success rate for k=5. If the operator can guarantee a higher success rate, k=4 can be used, obtaining 61% of savings (+4%) with around 93% success rate, or even 58% (+1%) with 95,27% success rate, but using k=3, implying also an improvement in the calculation burden. UPODA shows the best performance, as happened for LP12. Figure 6.6 shows the results only for UPODA and NONE approaches.

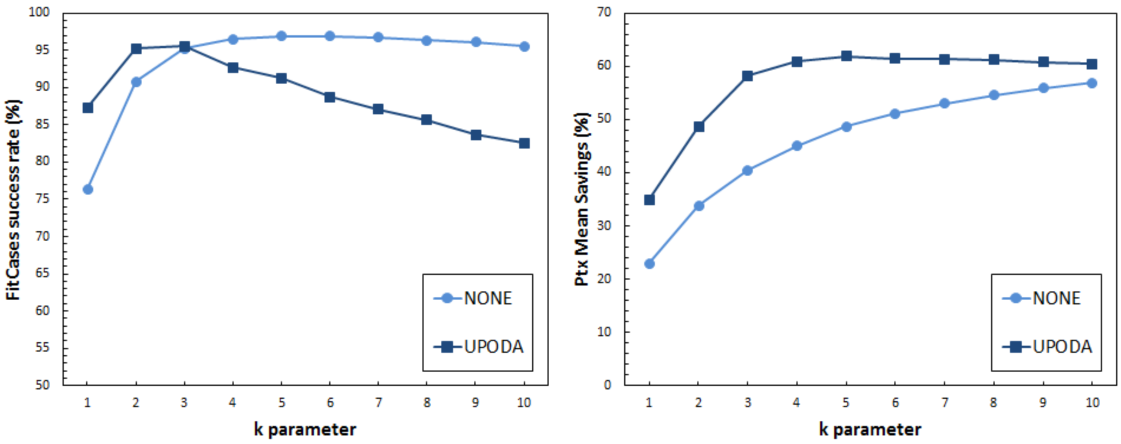

Figure 6.6. Evolution of success rate and mean transmission power savings for LP34567, k=[1,10] (r=3) for NONE and UPODA learning strategies

Regarding the rest of dynamic algorithms, a similar behavior is shown. UPOCA shows good performance results, although slightly worse than those of UPODA. This option offers to the telecom carrier a maximum savings of 60,77% with a success rate of 88,21% (k=5). This rate may be improved until 93,26% with k=2, achieving 51,42% of savings. That algorithm, in case of the longest LP34567 does not really offer an advantage to the operator when compared to NONE. For NLIHET and NELHET options, an equivalent situation is found. Mean savings are clearly higher than for NONE, although success rate values do not offer clear solutions to be applied in commercial networks, around 86% and 89% in average, respectively, in the range k=[2-7]. Finally it shall be the operator's decision to apply these options. NELHOM, as for LP12, achieves higher savings than NONE until k=8, but success rates are not appropriate to be applied in an operational network, around 76% of average in the range k=[2-7].

Two items can be pointed out about results on LP34567. With respect to the shortest LP12, in general, slightly higher mean savings are achieved for shorter lightpaths, given a specific *k* value; this trend is more pronounced in case of NONE. For example, NONE achieves 55,95% in LP12 (k=5) and 48,64% in LP34567 (k=5). For the same k=4 value, UPODA gives 62,39% in LP12 and 61,89% in LP34567. For UPOCA it is 62,09% in LP12 and 60,77% in LP34567; and around 59% for NLIHET and NLINET for both LPs. It is analyzing the obtained success rate when differences are more important. Clearly higher values are obtained for LP12 that decrease for LP34567. For example, for k=5 value, NONE provides 98,33% (LP12) and 96,9% (LP34567); UPODA provides 96,73% (LP12) and it downs to 91,28% (LP34567); UPOCA offers 94,89% (LP12) and 88,21% (LP34567); NLIHET around 90% (LP12) and around 85% (LP34567); and finally around 92% (LP12) and 88% (LP34567) for NELHET algorithm.

Thus, above these results, when the cognitive dynamic approach is applied to renew the knowledge base of the system, the shortest the path (and the lower the number of links it has), the higher the achieved FitCases success rate, with respect to the number of neighbors taken into consideration for the new transmission power. Mean savings present the same trend, although differences are less remarkable than those obtained for success rates.

The longest path LP34567 presents more complexity for CBR to estimate and propose an optimized and lower transmission power value. This path is the longest one and it is composed of more intermediate network nodes and thus more parameters to be controlled and estimated. As indicated before, the application of dynamic learning, specifically UPODA, still works better than the initial static approach, specifically for the lower *k* range values, k=[2-5]. Even for the highest k=10 value, the static approach offers mean savings around 57% and a success rate of 95,6%. UPODA offers a similar success rate, 95,5% and mean savings of 58,28% (+1,33%) and thus using a quite lower *k* value (k=3).

In terms of percentage of initial cases that remain in the KB at the end of the renewal process, it was 26,46% for k=3. And 28,78% for k=4.

As a conclusion, also for the longest LP34567, dynamic learning approach, and UPODA algorithm in particular, provides quite interesting higher mean savings, leading to a higher System Margin reduction, with respect to the initial static KB strategy. In this longest and having more links path, success rate are more impacted by the application of dynamic approach, but correct and appropriate rate values are obtained when applying low *k* values.

As depicted for LP12, the Table 6.2 presents the cognitive results when a success rate around 95% is chosen by the operator:

Learning algorithm	Best Ptx Mean Savings (%) (success rate >= 95%)	Corresponding Success Rate (%)	Gain Ptx (%)	[k, r=3]
NONE (static)	**56,95**	95,6		[10,3]
UPODA	**58,28**	**95,53**	**+1,33**	**[3,3]**
UPOCA	51,42	93,96	-5,53	[2,3]
NLIHET	54,13	93,51	-2,82	[2,3]
NELHET	55,27	92,52	-1,68	[2,3]
NELHOM	47,94	86,11	-9,01	[2,3]

Table 6.2. Best results for the different learning strategies, LP34567, success rate around 95%

Even when applying UPODA, dynamic learning can achieve slight better results than NONE as in LP12.

6.4 Results for LP456 and LP1234

In this section, results for LP456 and LP1234 are presented. As for precedent analyzed LPs, the behaviour encountered for LP456 and LP1234 is globally similar for both Ptx Mean Savings%

and FitCases% indicators. Mean savings results indicate the same evolution with respect to the *k* value, and also when comparing the static and dynamic strategies. UPODA improves NONE for intermediate *k* values in terms of mean savings with a controlled success rate. Moreover, UPODA continues to provide the best performance among the dynamic learning strategies.

Summarizing the obtained results, for LP456 UPODA provides 62,86% (+7,17%) with k=7 against 55,69% achieved by NONE with k=10. UPODA attains 90,5% success rate in this case. If a higher rate is to be guaranteed, k=5 provides 62,12% (+6,43%) of savings with 93,59% success rate. If the rate has to be around 95%, then by applying k=4 value, success rate is 95,52% and mean savings achieved are 60,66% (around +5%). That is, for LP456, when the path is long and does not have a large number of links, to apply dynamic learning to renew the KB can represent an advantage to the telecom carrier. UPODA solution can achieve higher savings than the maximum ones offered by NONE, with lower *k* values.

For LP1234 path, one difference is to be noted with respect to the precedent paths: from k=9 on, NONE provides higher mean savings than dynamic learning. However, the corresponding savings obtained for these high *k* values do not surpass the savings reached with dynamic algorithms with lower *k* values. Thus, UPODA provides a gain of +1,48%, with k=5, against the best savings reached with static approach, with k=10 (53,83%); the corresponding success rate is around 92% (against 91% provided by NONE). Anyhow, if the telecom operator would want to apply NONE, by using UPODA it shall obtain similar mean savings (53,60%) and a higher 95,79% success rate with a much lower k value (k=3).

For the rest of the dynamic algorithms, a similar behaviour as for LP12 and LP34567 is found. For LP456, UPOCA offers 62,11% with k=6, while NLINET and NELHET attain 60,31% and 60,64%, both of them with k=5. In turn, for LP1234, UPOCA provides a mean savings value equivalent to the maximum one offered by NONE, by applying k=3 and obtaining 53,89% savings and 95,0% success rate. In the case of NLINET, with k=5, it achieves 53,66% savings with 87,1% success rate. HELHET provides 53,34% savings with k=4 and 91,64% success rate. For both LP456 and LP1234, NELHOM algorithm shows the poorest performance and it can definitively discarded for application in commercial networks.

Moreover, the continuous decrease of success rate with *k* can also be appreciated. For these LPs, the preferable *k* range to get appropriate success rate values extends between k=2 and k=5.

Considering the initial cases kept in the KB at the end of the renewal process, it was 26,6% for k=3, 30,15% for k=4 and 31,72% for k=5, for LP456. For LP1234, the percentage of absorption of new cases or new network situations was 71,03%, that is, 28,97% of the initial cases remained in the KB.

For sake of illustration, only the mean savings and success rate for UPODA and NONE strategies are depicted, in Figures 6.7 and 6.8.

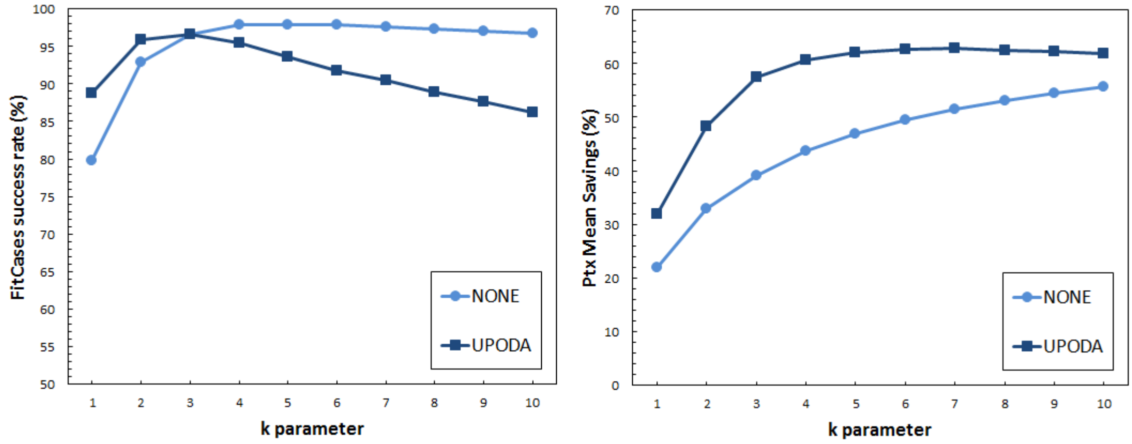

Figure 6.7. Evolution of success rate and mean transmission power savings for LP456, k=[1,10] (r=3) for NONE and UPODA learning strategies

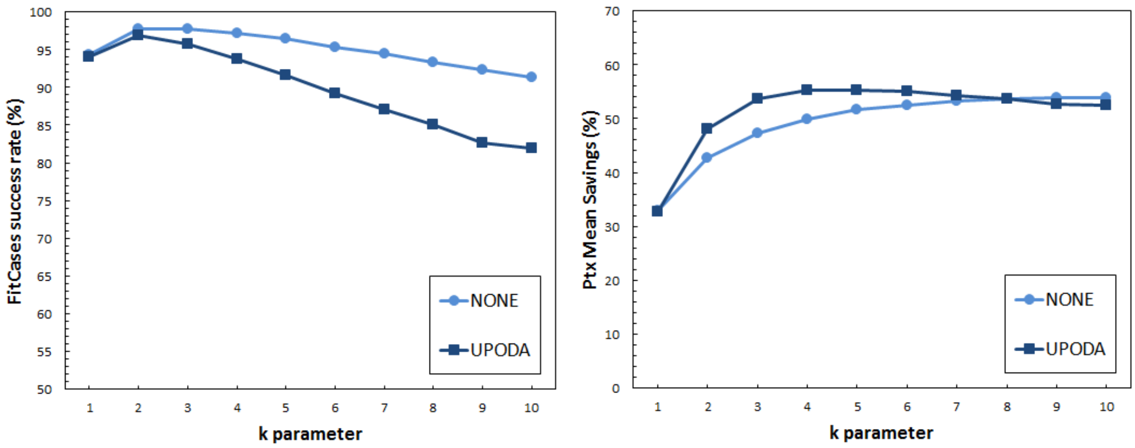

Figure 6.8. Evolution of success rate and mean transmission power savings for LP1234, k=[1,10] (r=3) for NONE and UPODA learning strategies

When introducing the additional condition in order to obtain success rates around 95%, the benchmark among the different learning strategies is similar as for precedent shorter and longer paths, as shown in Tables 6.3 and 6.4:

Learning algorithm	Best Ptx Mean Savings (%) (success rate >= 95%)	Corresponding Success Rate (%)	Gain Ptx (%)	[k, r=3]
NONE (static)	**55,69**	96,74		[10,3]
UPODA	**60,66**	**95,52**	**+4,97**	**[4,3]**
UPOCA	57,43	95,11	+1,74	[3,3]
NLIHET	54,97	94,1	-0,72	[2,3]
NELHET	54,64	92,97	-1,05	[2,3]
NELHOM	30,93	86,16	-24,76	[1,3]

Table 6.3. Best results for the different learning strategies, LP456, success rate around 95%

Learning algorithm	Best Ptx Mean Savings (%) (success rate >= 95%)	Corresponding Success Rate (%)	Gain Ptx (%)	[k, r=3]
NONE (static)	**52,53**	95,35		[6,3]
UPODA	**53,6**	**95,79**	**+1,07**	**[3,3]**
UPOCA	53,89	95	+1,36	[3,3]
NLIHET	49,37	96,11	-3,16	[2,3]
NELHET	49,08	95,79	-3,45	[2,3]
NELHOM	31,37	92,11	-21,16	[1,3]

Table 6.4. Best results for the different learning strategies, LP1234, success rate around 95%

That is, UPODA guarantees a higher savings than static policy on one side and the other dynamic proposal on the other side.

Thus, as UPODA is confirmed as the algorithm showing the best performance, in the following section, a further analysis of this approach is presented.

6.5 Overall performance of UPODA dynamic learning algorithm

The analysis of the application of dynamic learning approaches has been elaborated in previous sections, focusing on the maximum reachable mean savings. It has been verified that most of the active learning algorithms offer higher benefits than the static (i.e., NONE) strategy.

Furthermore, the best performance trade-off between mean savings and success rate can be achieved by applying dynamic learning approaches and not using necessarily the *k* value that maximizes power savings, but a lower one that guarantees almost the same results. And this is one of the main advantages provided by dynamic learning.

In this section, an analysis is presented considering that only dynamic learning is applied along the operation of the network. And the outcome is compared to that achieved if static strategy NONE had been applied. UPODA has risen as the outperforming algorithm; it has been then selected to be applied in commercial network for this exercise. The following Figure 6.9 depicts the gain in transmission power mean savings achieved by UPODA with respect to NONE:

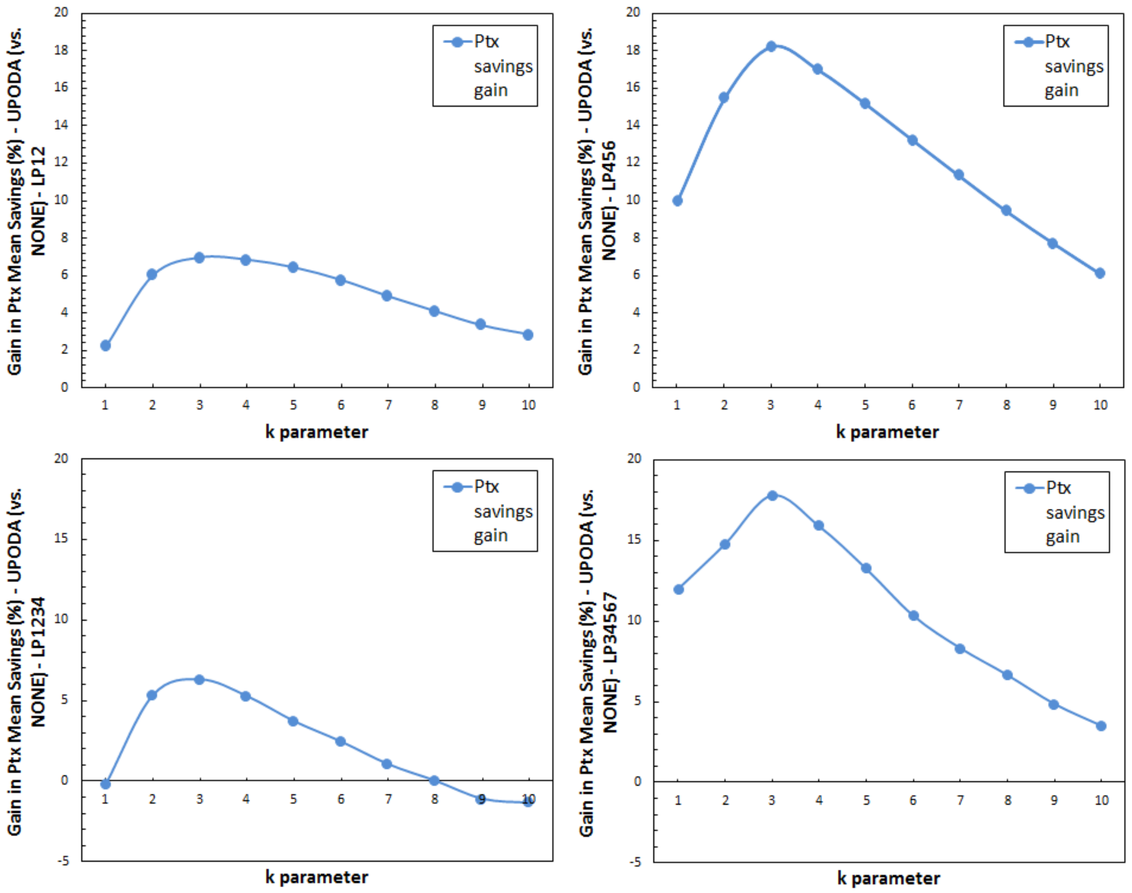

Figure 6.9. Transmission power mean savings gain provided by UPODA algorithm against NONE strategy as a function of k (r=3) for the LP12, LP34567, LP456 and LP1234 end-to-end paths

It can be observed in Figure 6.9 that the application of UPODA enables the telecom operator to obtain higher mean launched power savings than using a static approach of the KB. And this by using lower *k* values, which represents an advantage in terms of calculation load and reducing errors risk, confirmed by the higher success rate. For the shortest lightpath LP12, savings obtained can be + 7% for k=3 and +6,9% for k=4 vs. NONE. It is also the case for LP34567, which presents more complexity due to the number of links and network elements along the path; UPODA achieves an important higher gain, +18% for k=3. If k=4 is applied by the operator, then the gain reaches +16%. When observing LP456, which is also a long path, gain goes to +18% for k=3 and +17% for k=4. Applied over LP1234, UPODA also provides a gain of +6,32% for k=3 and +5,27% for k=4. As explained in section 6.4, regarding LP1234 it can be observed in Figure 6.8 that until k=8 dynamic learning provides better savings, but from k=9 on NONE provides higher gain. However, for this number of neighbors considered in the CBR calculation, NONE offers 53,80% mean savings with a success rate of 92,32%, whereas UPODA is able to provide similar mean savings, 53,60% with a success rate of 95,75% and this, by using a k=3 value. Thus, in this situation, the static approach does not represent any advantage, and the telecom operator could discard the application of NONE and select UPODA as the best option.

The advantage of using UPODA is highlighted in Table 6.5, which shows the success rate values corresponding to the high gains presented in Figure 6.9, obtained for the lowest *k* values for both NONE and UPODA and for the four considered lightpaths. It can be observed that by applying during the operation of the network the highlighted *k* value, the success rate offered by UPODA is similar to the one provided by NONE. The added-value proposed by UPODA is indicated below in the table: the improvement in gain when compared to NONE and the higher savings reached.

FitCases success rate (%)								
	LP12		LP456		LP1234		LP34567	
k parameter	NONE	UPODA	NONE	UPODA	NONE	UPODA	NONE	UPODA
1	95,52	96,45	79,78	88,72	94,33	94,10	76,41	87,30
2	98,61	98,30	92,89	95,92	97,80	96,92	90,85	95,27
3	**98,81**	**97,95**	**96,63**	**96,57**	**97,69**	**95,79**	**95,24**	**95,53**
4	98,73	97,23	97,90	95,52	97,20	93,75	96,48	92,69
5	98,33	96,73	97,97	93,59	96,45	91,68	96,90	91,28
Gain (%)	k=3	+7%	k=3	+18,3%	k=3	+6,32%	k=3	+17,8%
Ptx Savings (%)		58,08%		57,43%		53,6%		58,28%

Table 6.5. Success rate for highest gains provided by UPODA algorithm against NONE for the four end-to-end paths and added value of UPODA

Finally, it can be considered the overall performance of dynamic learning considering jointly and globally the transmission power mean savings, the pertinent success rate when using UPODA and the *k* value applied. Taken into consideration all these aspects, the best trade-off performance solution to be applied in a commercial network to reduce the operational System Margin is proposed in the following table:

	Best Trade-off UPODA			
	LP12	LP456	LP1234	LP34567
Ptx Savings (%)	60,97%	60,66%	53,6%	58,28%
k value (r=3)	4	4	3	3
FitCases success rate (%)	97,23%	95,52%	95,79%	95,53%
Gain (%)	+6,9%	+17%	+6,32%	+17,8%

Table 6.6. Best Trade-off considering global performance of dynamic learning UPODA for the four end-to-end representative lightpaths

According to the results, a common *k* value for all the paths cannot be defined. Selecting it in the range k=[3-5] leads the operator towards the best performance.

Regarding the results indicated in Table 6.6 and the recommendations presented in chapter 5, when applying static learning is applied, it can be remarked that the recommended [k,r] combination for LP1234 in a dynamic learning context is [3,3]. In chapter 5, the [k,r] = [4,3] pair was outlined as that one showing the best performance. It attained 48,11% of savings and 95,24% of success rate. Thus, UPODA improves the performance on mean savings by +5,49%, with a controlled success rate. A similar behaviour is observed for LP34567. In this lightpath, 41,73% mean savings were obtained by applying [k,r] = [4,3] pair with static learning, and 43,9% savings with [k,r] = [5,2]. In both cases, UPODA improves the performance with respect to NONE strategy, +16,55% and +14,38% respectively.

6.6 Chapter summary

This chapter has studied the performance of a dynamic learning approach to improve the CBR-based cognitive solution by the online renewal of the KB. To this end, section 1 has been devoted to the description of this strategy. Limitations of static learning have been indicated and thus, dynamic approach has been proposed to enhance the cognition system. Next, several novel dynamic learning algorithms have been outlined. The common driving idea behind all of them is to store in the KB only the new successfully established lightpaths, that is, those whose new launched power value proposed by CBR is correct and guaranteeing the quality of service of the request. The other common aspect on the strategy is to maintain the size of the initial KB. Thus, the dynamic algorithms address different forgetting strategies.

Sections 2, 3 and 4 have presented the evaluation of the dynamic algorithms for the four considered representative lightpaths. Besides, the assessment has been realized with respect to the achieved results offered by the static learning approach. In this context, two criteria have been used in the benchmark of the performance. First, in terms of maximum savings attainable by both learning strategies. Second, by applying a [k,r] pair that offers the best trade-off performance with regards to mean savings and success rate, and not necessarily providing the maximum values. In both cases, results demonstrate that UPODA rise as the dynamic algorithm achieving the best performance among all of them. And specially, UPODA improves the static learning results. For sake of generalization, UPODA improves the results offered by NONE for intermediate *k* values and with controlled success rates. This algorithm reaches gains respect to the static approach, raising up to +7% for the shortest LP12 or +18% for the longest LP34567.

Finally, a best trade-off recommendation [k,r] pair considering the global performance of UPODA for the four end-to-end representative lightpaths is given. As highlighted in chapter 5 for static learning, there is not a common best *k* value to all lightpaths when dynamic learning is applied.

Chapter 7

Conclusions and future work

Telecom market environment is increasingly competitive with small product offer differentiation. Network infrastructures have to accommodate a growing volume of traffic demands, pushed by ultra-high definition experiences and the emerging 5G-based services. Network operators have to maximize commercial benefits as a trade-off between investments on the network infrastructure and the operational costs. Thus, a continuous maximization of efficiency, while guarantying the quality of the provided services, remains a main objective for any telecom operator. An opportunity to accomplish this aim is to reduce the operation margins applied in the optical links power budgets. Typically, these margins are configured during the design and commissioning phases and are used throughout the exploitation of the optical transport network without any change. They take into account, among other constraints, unforeseen link degradations, due to ageing of the network infrastructure. They normally have a conservative fixed value, taking into account the end-of-life of the optical network components. However, in the recent years, the introduction of machine learning techniques has appeared as a promising solution to manage massive data traffic demands and help to take more efficient decisions. Optical transport networks is an appropriate scenario to put this artificial intelligence application into practice. In particular, the over-dimensioning is a traditional and common practice used by operational network teams in design processes. On this basis, the present thesis identifies and addresses margin optimization in optical networks from the cognition perspective. In particular, this thesis addresses the reduction of one of these operation margins, the System Margin, taking into account the long-term ageing process of the components when setting the optical power margins during the establishment of lightpaths.

Inside machine learning the case-based reasoning methodology is selected to support the development of our cognitive approach, since it fits with the heterogeneity and complexity of the network situations encountered in optical transport networks. Furthermore, case-based reasoning method leverages on past experiences to learn.

The cognitive approach based on CBR technique is proposed to be applied in commercial optical transport networks with the aim of reducing the operational System Margin. It proposes a new lower launched power guaranteeing the quality of service of the new incoming lightpath. To this aim, it relies on the transmission power applied in similar previous network situations, modeled as CBR cases, and representing several networks conditions and context at different past moments. All this knowledge is stored in the memory of the system, the knowledge base, which is one of the main components of the cognitive solution. Based on past experiences, the system can learn from those different past network and successful situations to adapt and to propose solutions to the new incoming situations to be solved, and simultaneously, reducing operational margins. To be noted that the knowledge base used only stores successful past situations, that is, those network situations, modeled as CBR cases, containing the transmission power applied that assured the right establishment of the lightpath and its required quality of service.

Several novel schemes are presented in order to propose the new launched power. The CBR parameters k and r model, respectively, the number of past network similar situations used in one side and the type of similarity metric to be applied to the new incoming lightpath in the other side.

In a first approach in this thesis, the KB is initially populated offline with test lightpaths launched by the telecom operator, allowing to record real measurements of the lightpath attributes contained in the CBR cases. Although this initial KB can be renewed with new offline measurements performed by the operator every certain time window, the KB is static. That is, lightpaths stored in the memory are not replaced by newer ones. Thus, no new information is dynamically incorporated to the KB.

In this static learning context, the scheme showing the best performance is the MIN scheme, and this, for the four representative lightpaths considered and for any mean network load. It achieves the highest mean savings, and it is, while guaranteeing correct success rates, completely applicable in production networks. Normally it has been observed that no remarkable differences can be noted when applying this solution in different network load situations, although higher performances are normally provided in lower mean load situations. In some cases, other scheme, MINTOMEAN, can show better performance in success rate reached, but MIN scheme offers the highest mean savings, with appropriate success rates. One of the reached conclusions is that there is not a unique and common best [k,r] CBR parameter combination, valid for all lightpaths in all network situations. However, the margin of k values providing the best trade-off for any lightpath is recommended to be selected in the range k=[3-5]. Particularly the [k,r] pair set to [4,3] is the recommendation proposed in this analysis, although the final decision is let to the telecom carrier, depending on whether the operator want to achieve the highest savings or to apply a more conservative policy which guarantees higher success rates. The obtained results show that the cognitive approach achieves 48% in transmission power mean savings and a FitCases success rate of 95%, depending on the path.

The performance of the cognitive solution is improved by means of a dynamic learning approach. It can be stated that renewing the KB of the system by the application of a dynamic learning strategy enables the operator to improve savings in launched power, while maintaining pertinent success rates, when compared to the static approach which maintains the memory of the system fixed. The KB is considered as dynamic, meaning that an online replacement of the recorded lightpaths takes place, by applying dynamic learning algorithms. Five novel active learning algorithms are presented. The common driving idea behind all of them is to store in the KB only the new successfully established lightpaths, that is, those whose new launched power value proposed by CBR is correct and guarantees the quality of service of the request. The initial size of the KB is maintained during the learning process. It means that the dynamic learning algorithms identify and remove existing KB entries, which are replaced by new ones, more adapted to the current network conditions or situations. Thus, knowledge and learning capacity is strengthened. To reach this conclusion, assessment is realized from two points of view: first, only taken into consideration the maximum mean savings values achieved by each strategy, static or dynamic, no matter of the k value used; second, evaluating the global performance in views of the mean savings reached simultaneously combined with the ensured success rate and the k value used. In both cases, dynamic learning offers the best performance allowing the telecom operator to improve the operational margin reduction. As obtained for the static learning approach it is confirmed that the best performance of the cognitive approach is achieved by using k intermediate values, in the range [3-5], while maintaining controlled the success rates. Moreover, in terms of the [k,r] pair combination, the same conclusion as for static strategy is reached: there is not a best [k,r] pair valid and common for all the paths. Among the five proposals assessed, UPODA algorithm is that one providing the best operational solution, improving the obtained results when compared to a static approach. The high performance of UPODA suggests that the attributes on which it leverages, as well as the reference taken and their combination seem to be the ones having greater influence. Thus, the previous usefulness, the transmission power used and the age on the KB rise as the most impacting factors. Decisions are taken considering the deviation of each CBR case, with respect to the overall mean transmission power of the network situations stored in the KB and not only the absolute transmission power case. That is, the average mean launched power of the cases integrated in the KB is constantly monitored and controlled in order to ensure an appropriate value, avoiding biased average values. Moreover, a control mechanism is implemented by the algorithm, monitoring the volume of error decisions taken based on the actual KB mean power value. UPOCA strategy is based on the same attributes, usefulness, transmission power value and time stored in the KB, although this algorithm integrates them differently. No checking mechanism with respect to the KB mean power value is implemented and the absolute launched power value is considered. As shown, UPOCA presents a good performance, although below UPODA. The other three algorithms present correct performance, but they confirm that only using net losses or non-linear impairments information present in the path combined with the age of the KB cases does not lead to the best performance. The best trade-off recommendation [k,r] pair considering the global performance of UPODA for the four end-to-end representative lightpaths is given. This algorithm achieves gains raising up to +7% or +18% with respect to the static approach, depending on the path.

In conclusion, the cognitive approach based on case-based reasoning technique is a proofed methodology that can be useful to be applied in commercial optical transport networks with the aim of reducing the operational System Margin.

This thesis opens several future research lines. The contributions presented in chapter 6 concerning dynamic learning strategy could be extended by studying variations of the KB size. Moreover, other renewal KB strategies could be analyzed, such as those based on storing incorrect information on the system. It would mean to incorporate in the KB the lightpaths whose CBR proposed new transmission power would have led to an unsuccessful establishment (and then, the initial power was respected and applied). Learn from errors is a powerful mechanism. Moreover, a complete architecture specification of the centralized SDN controller running CBR and able to control network nodes during the lightpath establishment and their quality assessment (CBR revise phase) would also be a key milestone toward the deployment of the thesis proposals in production scenarios.

Appendix A

Publication List

A.1 Publications in Journals

1. **L. D. N. Calleja**, S. Spadaro, J. Perelló G. Junyent, "Cognitive science applied to reduce network operation margins", Photonic Network Communications, December 2017, Volume 34, Issue 3, pp. 432–444, https://doi.org/10.1007/s11107-017-0717-9.

2. **D. Notivol**, S. Spadaro, J. Perelló, G. Junyent, "Applying Cognitive Dynamic Learning Strategies for Margins Reduction in Operational Optical Networks", Journal of Network and Systems Management (submitted).

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