

Optimization Problems in WDM Optical Transport Networks with Scheduled Lightpath Demands

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À Diana.
À mes parents.

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Foreword

This thesis presents my research work developed from October 1999 to September 2003 as part of my Ph.D. in Telecommunication at ENST Paris. My advisor was Professor Maurice Gagnaire. I was member of a research team on optical networks led by Professor Gagnaire. The team is part of the group "Access and Mobility in Networks" of the Computer Science and Networks Department at ENST Paris.

This work was part of a partnership research project between ENST Paris and a research group of the Network Architecture Systems Unit (formerly, Photonic Networks Unit) of Alcatel R & I in Marcoussis, France, led by Mr. Amaury Jourdan. The project aims at defining efficient resource allocation methods in optical transport networks with multiple switching granularities. The methods must provide quantitative information to support decisions about the design of optical networking equipment architectures.

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Abstract

Wavelength division multiplexing optical transport networks are expected to provide the capacity required to satisfy the growing volume of telecommunications traffic in a cost-effective way. These networks, based on standards and implementation agreements currently under development by the ITU-T, the IETF and the OIF, are likely to be deployed during the next 5 or 6 years.

New optimization problems arise in connection with these networks for several reasons. Firstly, the cost of optical networking equipment is not still well known due mainly to the early stage of development of the relevant technologies. In fact, the cost of the network strongly depends on the technologies used to implement it. Secondly, the uncertainty of traffic demands, due to the competition in the telecommunications market and to the massive adoption of new data applications, render difficult the accurate dimensioning of networks. Finally, the early stage of development of optical technology results in new functional constraints that must be taken into account during the design and dimensioning of the network.

In this thesis we investigate optimization problems arising in the engineering of an optical transport network. Network engineering concerns the configuration of existing network resources in order to satisfy expected traffic demands. Unlike network planning and traffic engineering, network engineering problems are relevant at time scales ranging from hours to weeks.

At these time scales, the dynamic evolution of the traffic load is an important factor that must be taken into account in the configuration of the network. Moreover, the periodic nature of the traffic load observed (for instance, on a weekly basis) in operational transport networks suggest that the traffic may be modeled deterministically. We propose a dynamic deterministic traffic model called Scheduled Lightpath Demands (SLDs). An SLD is a connection demand represented by a tuple $(s, d, n, \alpha, \omega)$ where s and d are the source and destination nodes of the demand, n is the number of requested connections and α, ω are the set-up and tear-down dates of the requested connections. The model captures the time and space distribution of a set of connection demands and, being deterministic, eases the use of combinatorial optimization

techniques to solve network optimization problems.

We first describe the use of WDM technology in transport networks and present the problems addressed in the domain of network optimization (Chapters 2 and 3). We then introduce the SLD traffic model and explain its application in network engineering problems and equipment architecture design problems (Chapter 4). We then investigate three network optimization problems involving the SLD traffic model.

We first address the Routing and Wavelength Assignment (RWA) for SLDs problem in a wavelength-switching network (Chapter 5). The routing subproblem and the wavelength assignment subproblem are addressed separately. The former is formalized as a time/space combinatorial optimization problem with two possible objective functions, which leads to two versions of the subproblem. We propose a Branch & Bound (B&B) algorithm that computes optimal solutions and a Tabu Search (TS) meta-heuristic algorithm that computes approximate solutions to instances of this subproblem. The wavelength assignment problem is formulated as a graph vertex coloring problem. We use a greedy algorithm proposed in the literature to find approximate solutions.

We then investigate the problem of Diverse Routing and Spare Capacity Assignment (DRSCA) for SLDs in a wavelength-switching network (Chapter 6). The problem consists of defining a pair of span-disjoint paths for each SLD so that the working and spare capacity required to satisfy the demands is minimal. The required capacity may be reduced by sharing resources among connections. We propose a channel reuse technique to reduce the required working capacity and a backup-multiplexing technique to reduce the spare capacity required for protection. The problem is formulated as a time/space combinatorial optimization problem. We propose a Simulated Annealing (SA) meta-heuristic algorithm to compute approximate solutions.

Finally, we investigate the problem of Routing and Grooming of SLDs (SRG) in a multi-granularity switching network (Chapter 7). We consider a network whose nodes have a switch that integrates a wavelength cross-connect (WXC) and a waveband cross-connect (BXC). A waveband is an association of several wavelengths. The problem is formulated as a time/space combinatorial optimization problem whose objective is to minimize the cost of the network. The cost of the network is equal to the sum of the nodes' costs and the cost of a node is a function of the number of ports in its switch. We propose a TS meta-heuristic algorithm to compute approximate solutions to instances of this problem. We determine the conditions under which a network based on multi-granularity switches is more economical than a wavelength-switching network.

We make an extensive use of meta-heuristic algorithms since they provide approximate solutions of good quality in reasonable computing time to large instances of the

investigated optimization problems, which are otherwise computationally intractable. Furthermore, meta-heuristic algorithms ease the introduction of complex constraints found in real-world optimization problems.

Résumé

Les réseaux optiques à multiplexage en longueur d'onde (réseaux WDM) offrent la possibilité de satisfaire économiquement la demande croissante de services de télécommunications. Ces réseaux, basés sur des normes en cours de développement à l'UIT-T, l'IETF et l'OIF, seront très probablement déployés dans les 5 ou 6 années à venir.

De nouveaux problèmes d'optimisation apparaissent en relation avec ces réseaux pour plusieurs raisons. En premier lieu, les coûts des équipements optiques sont encore mal connus en raison du caractère récent des technolologies utilisées pour ces réseaux. Deuxièmement, l'incertitude de la demande, liée notamment à la concurrence dans le marché des télécommunications et à l'adoption massive de nouvelles applications informatiques, rendent difficile le dimensionnement des réseaux. Enfin, les nouvelles technologies optiques conduisent à de nouvelles contraintes fonctionnelles qui doivent être prises en compte dans la conception et le dimensionnement du réseau.

Nous étudions les problèmes d'optimisation liés à l'ingénierie d'un réseau de transport optique. L'ingénierie de réseaux concerne la configuration des ressources réseau existantes pour satisfaire des demandes de trafic connues. À la difference de la planification des réseaux et de l'ingénierie de trafic, les problèmes d'ingénierie de réseaux sont pertinents à des échelles de temps allant de l'heure à la semaine. À cette échelle de temps, l'évolution dynamique de la charge de trafic représente un élément important qui doit être pris en compte dans la configuration du réseau. Par ailleurs, la périodicité de l'évolution de la charge de trafic observée dans des réseaux de transport opérationnels (sur 1 semaine par exemple) suggère que le trafic peut être modélisé de façon déterministe.

Nous proposons un modèle de trafic dynamique déterministe appelé *Scheduled Lightpath Demand* (SLDs). Une SLD est une demande de connexion representée par un quintuplet $(s, d, n, \alpha, \omega)$ où s et d représentent les nœuds source et destination de la demande, n représente le nombre de connexions requises et α et ω les dates d'établissement (set-up) et de fin (tear-down) des connexions demandées. Le modèle

décrit la distribution spatiale et temporelle d'un ensemble de connexions et, par son caractère déterministe, facilite l'utilisation de techniques d'optimisation combinatoire pour la résolution de problèmes d'optimisation réseau.

Nous décrivons d'abord l'utilisation des technologies WDM dans les réseaux de transport et présentons les problèmes typiquement étudiés dans le domain de l'optimisation réseaux (Chapitres 2 et 3). Nous présentons ensuite le modèle de trafic SLD et son application dans des problèmes d'ingénierie de trafic et de conception d'architecture d'equipements (Chapitre 4). Enfin, nous étudions trois problèmes d'optimisation réseau impliquant ce modèle de trafic.

Dans le Chapitre 5 nous étudions le problème du routage et de l'affectation de longueurs d'onde (RWA) pour des SLDs dans un réseau à commutation de longueurs d'onde. Les sous-problèmes du routage et de l'affectation sont traités séparément. Le sous-problème du routage est formulé sous forme d'un problème d'optimisation combinatoire avec deux fonctions objectif possibles. Nous proposons une méthode par séparation et évaluation (*Branch & Bound* ou B&B, en anglais) et un algorithme méta-heuristique de type Recherche Tabou (RT) pour le calcul de solutions exactes et approchées, respectivement. Le problème d'affectation de longueurs d'onde est formulé sous forme d'un problème de coloration de sommets d'un graphe. Nous utilisons un algorithme glouton existant pour trouver des solutions approchées.

Dans le Chapitre 6 nous étudions le problème du routage avec protection pour des SLDs dans un réseau à commutation de longueurs d'onde. Le problème consiste à déterminer pour chaque demande un couple de chemins disjoints de telle sorte que le nombre de canaux primaires et de protection soit minimal. Nous proposons une technique de partage de la capacité de réserve pour réduire le nombre de canaux dédiés à la protection. Le problème est formulé sous forme d'un problème d'optimisation combinatoire. Nous proposons un algorithme méta-heuristique parallèle de type Recuit Simulé (RS) pour calculer des solutions approchées.

Finalement, nous étudions dans le Chapitre 7 le problème du routage et de l'agrégation des SLDs (RAS) dans un réseau avec deux niveaux de granularité de commutation. Nous considérons un réseau dont les nœuds disposent d'un commutateur de longueurs d'onde et d'un commutateur de bandes. Le problème est formulé sous forme d'un problème d'optimisation combinatoire. Nous proposons un algorithme méta-heuristique parallèle de type RT pour le calcul de solutions approchées. Nous définissons les conditions sous lesquelles un réseau avec deux niveax de granularité de commutation est plus économique qu'un réseau à commutation de longueurs d'onde.

Nous faisons appel aux techniques méta-heuristiques en raison de leurs avantages pratiques, notamment, la possibilité de calculer des solutions de bonne qualité dans

un temps de calcul raisonable vis-à-vis des instances considerées. De plus, les méta-heuristiques permettent d'intégrer facilement des contraintes opérationelles variées (*e.g.*, des modularités d'équipements, des contraintes de capacité d'équipement, etc.).

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Part I.

General introduction

1. Introduction

Standards for Wavelength Division Multiplexing (WDM) optical transport networks are currently under development at the ITU-T and the IETF. These networks are to be deployed in the next years in order to satisfy the growing telecommunications traffic demands generated mainly by the massive adoption of data applications.

Network optimization provides the means to design, dimension and operate these networks in a cost-effective way. Cost-efficiency is a critical goal of network operators because it enables the sustainable development of their business. However, the currently available network optimization methods are ill-suited to the characteristics of optical transport networks for several reasons. First, the immaturity of key enabling optical technologies lead to functional constraints that must be taken into account in the design, dimensioning and operation of these networks. Second, the relatively recent presence of optical networking equipment in the market results in a lack of knowledge of the costs of this equipment. Finally, the massive adoption of data applications and the competition in the telecommunications market make the traffic demands difficult to understand.

In recent years, many research efforts addressing network planning and traffic engineering problems in optical transport networks have been carried out. Network planning concerns the definition in the long term of the network infrastructure and traffic engineering concerns the assignment in real time of resources to random traffic demands so that target traffic performance metrics are achieved. Little attention has been paid however to optimization problems arising in engineering of the network, that is, to problems concerning the day-to-day, weekly or even monthly operation of the network. In these problems, the aim is to efficiently configure available network resources and assign them to expected traffic demands. At this time scales (days, weeks), the dynamic evolution of the traffic load is an important factor that must be taken into account in the configuration of the network. Moreover, the periodicity of the traffic load evolution observed in operational transport networks suggest that the traffic may be modeled deterministically. We propose a dynamic deterministic model to represent traffic observed at these time scales and investigate problems involving

this traffic model.

Network engineering is particularly useful in situations where the investments in network infrastructure upgrades cannot be carried out at the time they were planned and the network must be efficiently configured in order to satisfy the expected traffic demands with less resources than what was originally envisaged. These situations are likely to arise in periods of economical difficulties faced by operators.

1.1. Contributions of this thesis

We introduce an original approach to network optimization based on a deterministic traffic model called Scheduled Lightpath Demands. The model captures the time and space distribution of traffic demands in a network. Being deterministic, the SLD traffic model eases the formalization of network optimization problems as combinatorial optimization problems and the use of well known combinatorial optimization techniques to solve these problems. The specific contributions of this thesis are the following:

- the Scheduled Lightpath Demands (SLDs) traffic model (Chapter 4);
- the formalization as time/space combinatorial optimization problems of the following network optimization problems:
  - Routing and Wavelength Assignment (RWA) for SLDs in a wavelength-switching network (Chapter 5),
  - Diverse Routing and Spare Capacity Assignment (DRSCA) for SLDs in a wavelength-switching network (Chapter 6) and,
  - Routing and Grooming of SLDs (SRG) in a multi-granularity switching network (Chapter 7);
- the design of Branch & Bound, greedy and meta-heuristic algorithms to find solutions to these problems.

The proposed models and algorithms have potential applications for both network operators and equipment manufacturers. They may be used by the former as part of their dimensioning and engineering tools and by the latter for the design of flexible architectures of networking equipment. Moreover, the models and algorithms are, to some extent, technology independent in the sense that they may be used in other connection oriented networks such as SDH/SONET, ATM and MPLS.

1.2. Structure of the document

This thesis is structured in two main parts. The first part is a general introduction that describes the technological context and the network optimization concepts required to understand the contributions of the thesis. In particular, Chapter 2 describes the multiplexing, transmission and switching technology currently considered for the realization of optical transport networks and the standardization work leading to the development of standard-based optical networks. Chapter 3 presents a framework to classify network optimization problems in general and outlines the problems specific to the optimization of optical transport networks.

The second part contains the contributions of the thesis. In Chapter 4 we introduce the Scheduled Lightpath Demands (SLDs) traffic model, explain its differences with respect to other traffic models and discuss its application in network engineering problems. In Chapter 5 we investigate two versions of the Routing and Wavelength Assignment for SLDs problem in a wavelength-switching network. A mathematical formalization of the two versions and both exact and approximate solution algorithms are presented. In Chapter 6 we investigate the problem of defining diverse routes and assigning spare capacity to SLDs in a wavelength-switching network. We formalize two versions of the problem and describe the problem-specific elements of a Simulated Annealing meta-heuristic algorithm that computes approximate solutions. In Chapter 7 we investigate the problem of routing and grooming SLDs in a multi-granularity switching network (switching both wavelengths and bands). In this chapter we assess the advantages of introducing the band-switching granularity by comparing the cost of instantiating a same set of SLDs on a wavelength-switching network and on a multi-granularity switching network. Instantiating SLDs in a wavelength-switching network leads to a routing problem similar to the one presented in Chapter 5. We formalize both the routing and grooming problem in a multi-granularity switching network and the routing problem in a wavelength-switching problem. We describe the problem-specific elements of a TS meta-heuristic algorithm that computes approximate solutions to instances of these problems. Chapter 8 presents the conclusions of the thesis.

2. Wavelength division multiplexing in telecommunications

Wavelength Division Multiplexing (WDM) is the most used multiplexing technology in optical networks today. This chapter presents an introduction to the different multiplexing modes and the use of WDM in transmission and switching systems of optical networks. The chapter also presents the standardization efforts of three organizations aimed at defining open standards for optical networking.

2.1. Multiplexing

One important function in a telecommunications network is the simultaneous transmission of multiple signals on a shared medium. The simultaneous transmission is achieved by *multiplexing* the signals. The most common forms of multiplexing are Time Division Multiplexing (TDM), Frequency Division Multiplexing (FDM) and Code Division Multiplexing (CDM).

In TDM, the transmission capacity of a communications channel is logically divided into time frames of equal duration. Each time frame is further divided into a set of n time slots. A subchannel with a capacity equal to $1/n$ of the channel capacity is obtained by using the same slot in successive frames.

In FDM, several signals are combined into a composite signal by modulating each signal onto a specific carrier frequency chosen so that the spectra of each modulated signal do not overlap. In this way, the transmission bandwidth (the frequency band suitable for transmission on the medium) is divided up into a number of frequency bands, each of which accommodates a signal.

Unlike TDM and FDM, where signals make exclusive use of either a time slot or a frequency band, in CDM the signals overlap both in time and in frequency. Each individual signal is assigned a unique carrier signal called Pseudo-random Noise Spreading Sequence (PNSS). Modulating the individual signal onto the PNSS has as effect in the frequency domain the spread of the signal over the PNSS frequency band.

The PNSSs assigned to different individual signals must be orthogonal functions. The recovery of an individual signal is achieved by multiplying the composite signal (sum of several individual signals) by the individual signal's PNSS and integrating the output over the individual signal's period. The term *noise* in PNSS refers to the fact that the other individual signals are considered as noise.

Though TDM and CDM have been investigated for use in optical networks (*i.e.*, networks using light for the transmission of signals), only WDM, which is basically FDM, has been adopted as the multiplexing mode of choice for real-world optical networks.

2.2. Transmission

Optical fibers are the most commonly used transmission media used for optical communications. An optical fiber is made primarily of silica (SiO_2). The fiber consists of a cylindrical core, surrounded by a cladding with a different refractive index than the core[1]. In optical fibers where the core radius is large (about 50 to 85 μm), light can propagate in multiple possible trajectories or modes. These fibers are called multi-mode. When the core radius is small, light propagates in a single fundamental mode. These fibers are called single-mode or mono-mode and are the most used in modern long-haul optical communications.

The propagation of light in an optical fiber is subject to a number of impairments. Loss of power, or *attenuation*, due to material absorption, scattering or bending, is one of them. Attenuation, α, is defined as the ratio of optical output power P_{out} to the optical input power P_{in} of a fiber of length L and is usually expressed in decibels per kilometer (dB/km), where the logarithm of the power ratio is used:

$$\alpha = -\frac{10}{L} \log_{10} \left(\frac{P_{out}}{P_{in}} \right). \tag{2.1}$$

Figure 2.1 shows the attenuation in standard single mode fiber (SSMF, see below) as a function of wavelength. There are three main wavelength bands used for communications in this fiber: around 800 nm, 1300 nm and 1500 nm. The attenuation at these three bands is about 2.5 , 0.4 and 0.25 dB/km, respectively. The attenuation peaks separating these bands are primarily due to the presence of residual impurities inherent to the manufacturing process, in particular, water ions (OH^-). New optical fiber manufacturing processes have virtually eliminated the "water absorption peak" at the 1400 nm wavelength, enabling transmission in the 1285 to 1625 nm band. Fibers without this peak are called Zero Water Peak Fibers (ZWPF).

[1]The refractive index of a material is the ratio of the speed of light in vacuum to the speed of light in that material.

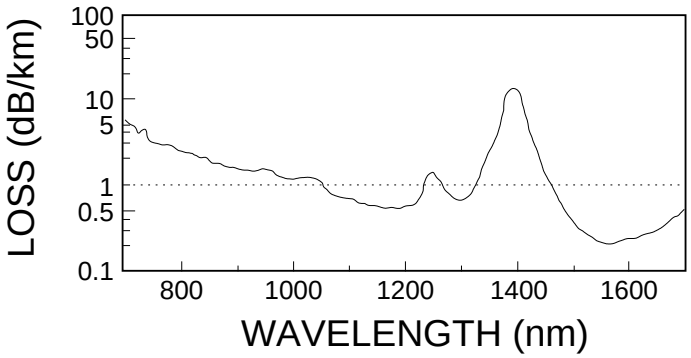


Figure 2.1.: Attenuation as a function of wavelength in standard single mode fiber (G.652).

Another transmission impairment is the *dispersion—(*, wherein components of a signal propagate at different speeds in a fiber[2]. As a consequence, the signal's components arrive at different times at the receiver. The main forms of dispersion are modal, polarization-mode and chromatic dispersion. Modal dispersion occurs only in multi-mode fibers, where the different modes of a signal propagate at different speeds (because the trajectory of each mode is different). A single mode optical fiber actually carries two polarization modes, which are indistinguishable in an ideal fiber because of the cylindrical symmetry of the core. However, real fibers deviate from cylindrical symmetry to a more elliptical shape because of manufacturing processes and/or mechanical stresses applied to the fiber. This accidental loss of symmetry results in two distinct polarization modes, each with different propagation speed [11]. Polarization Mode Dispersion (PMD) occurs because the two polarization modes arrive at different times at the receiver. PMD is usually expressed in ps/km$^{1/2}$. Chromatic dispersion is the consequence of two contributing factors. The first one, known as material dispersion, occurs because the refractive index of silica is a function of the spectral components of the signal. The second factor, called waveguide dispersion, occurs because part of the signal's power propagates on the core and part in the cladding, which have different refractive indices. Chromatic dispersion is usually expressed in ps/nm-km.

As the bit rate and/or the signal's optical power increase, other forms of impairments called *non-linear effects* arise in the transmission of signals. Indeed, as long as the optical power is small, the fiber can be considered as a linear medium, *i.e.*, its loss and refractive index are independent of the signal's power. However, with high power, non-linear effects arise because both the loss and the index are actually dependent

[2]By components we refer to either the signal's modes, polarizations or spectral components.

on the signal's power. These non-linear effects are the stimulated Brillouin scattering (SBS), stimulated Raman scattering (SRS), four-wave mixing (FWM), self-phase modulation (SPM) and cross-phase modulation (CPM).

Several types of single mode fibers have been developed over the years to improve their transmission capacity in the presence of impairments. The International Telecommunications Union - Standardization Sector (ITU-T) has issued a series of recommendations that define the properties of three single mode fibers. There are various differences among the three types, but the main parameter distinguishing them is the chromatic dispersion. Table 2.1 shows the characteristic parameters of the standard single mode fiber (SSMF, G.652)[3], the dispersion-shifted fiber (DSF, G.653) and the non-zero dispersion fiber (NZDSF, G.655) recommended by the ITU-T.

SSMF is a fiber designed to provide zero chromatic dispersion at 1310 nm to support the early long-haul transmission systems operating at this wavelength. The DSF was introduced later to provide zero dispersion in the 1550 nm wavelength range when transmission systems began using this band. However, as more wavelengths are introduced in transmission systems and the optical power in the systems becomes higher, *non-linear effects* arise that seriously penalize performance. The effects can be reduced if a limited chromatic dispersion exists in the fiber. This resulted in the development of NZDSF.

Table 2.1.: ITU-T single mode fibers' parameters.

Fiber type	Optimized region (nm)	Attenuation (dB/km)	λ_0[a] (nm)	Dispersion (D) (ps/nm-km)
SSMF (G.652)	1310	<0.44	1312±0.002	17[b]
DSF (G.653)	1550	0.35	1550±50	3.5[c]
NZDSF (G.655)	1530-1565	0.35		max/min=6/0.1[d] max/min=10/1[e]

[a] Zero-dispersion central wavelength.

[b] Typical chromatic dispersion at 1550 nm.

[c] Maximal chromatic dispersion in the region 1550±25 nm.

[d] G.692 optical interfaces with 200 GHz minimum channel spacing.

[e] G.692 optical interfaces with 100 GHz minimum channel spacing.

It is worth to note that virtually every fiber commercially available today outperforms the ITU-T recommended values. Moreover, vendors adopt design solutions

[3]The ITU-T recently issued Recommendation G.652.C that defines the characteristics of SSM Zero Water Peak Fibers (ZWPF).

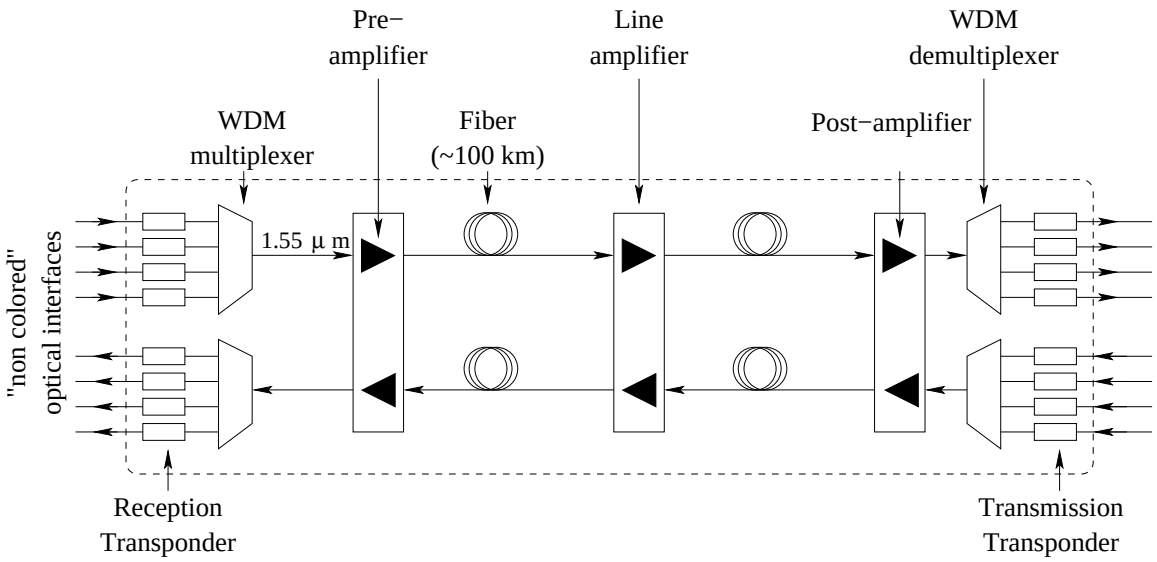


Figure 2.2.: Typical configuration of a WDM transmission system.

to overcome the effects of impairments and to optimize the behavior of the fibers for specific applications. In particular, recently developed fibers are designed to overcome the effects of PMD and non-linear effects, which become critical in transmission systems operating at high bit rates (*e.g.*, OC-192 interfaces at 10 Gbps and OC-768 interfaces at 40 Gbps probably available in the future). However, the problem remains of how to design transmission systems using old optical fibers (installed from the mid 1980's to the mid 1990's), since at time of deployment, these fibers did not have to meet any requirement concerning PMD and non-linear effects.

2.2.1. WDM transmission systems

Wavelength Division Multiplexing has been used for a long time as a cost-effective mean to increase the capacity of submarine and long-haul point-to-point transmission systems. Impairments like attenuation, dispersion and non-linear effects , limit the rate that can be received on a channel at acceptable Bit Error Rate (BER)[4] levels over long distances[5]. Thus, a manner to increase the capacity of these systems is to wavelength-multiplex multiple channels in the system. Figure 2.2 shows a typical configuration of a WDM transmission system.

The system uses *transponders* to adapt the signal for transmission on the system. In particular, transponders modulate individual signals onto distinct wave-

[4]We limit our discussion to digital optical networks.

[5]The transmission is generally said error-free when the BER is less than 10^{-13} after correction using a Forward Error Correction (FEC) code [87].

lengths around the 1550 nm wavelength. A transponder is a device integrating a receiver (Rx), an electronic regenerator and a transmitter (Tx). Besides the regeneration function, a transponder can implement the adaptation of signal characteristics such as wavelength, optical power, modulation format (*e.g.*, OOK , RZ , NRZ, etc.) and transmission format (*e.g.*, addition of a FEC code), etc. After adaptation, the wavelengths are multiplexed to form a composite signal which is amplified before being propagated through the fiber. The signal is amplified several times on the line (roughly, every 100 km). At the receiver's side, the signal is pre-amplified and demultiplexed in order to recover the individual signals. Transponders are used to adapt these signals for processing by a network element.

The devices most commonly used today for amplification are the Erbium-doped Fiber Amplifier (EDFA) and the Raman amplifier. Amplifiers represent an economically and functionally interesting alternative to transponder-based regenerators. Indeed, amplifiers are advantageous because they are capable of simultaneously amplifying many wavelengths without any opto-electronic and electro-optical (OEO) conversion, which is expensive due to the high cost of transponders. Furthermore, amplification with these devices is *transparent*, in the sense that the amplification is independent of the signal's bit rate and modulation format. However, the gain bandwidth of amplifiers (S-band: 1460-1530 nm, C-band 1530-1565 nm, and L-band: 1565-1625 nm) is relatively narrow with respect to the low-attenuation band of fibers. This imposes a limit on the number of channels that can be wavelength-multiplexed in the system (a minimum spacing must exist between channels).

Table 2.2, after [87], shows the characteristics of five experimental WDM submarine transmission systems. Capacity and Distance refer to the total transmission capacity and the length of the system, respectively. The optical spectral efficiency is defined as the ratio of the channel bit rate to the channel spacing. The column Amplification indicates the type of amplifiers and the amplification band. The last column indicates the power margin of the system. This margin is necessary to compensate for time varying system performance impairments, manufacturing impairments , allowance for repair and aging.

There is a number of techniques used in WDM submarine systems to increase their transmission. Among these are the Forward Error Correction (FEC) codes with concatenated coding, dispersion management, increased optical amplified bandwidth and new modulation formats used to increase the spectral efficiency.

Table 2.2.: Capacity of experimental WDM submarine transmission systems.

Author	Capacity (Tbit/s)	Distance (km)	Spectral efficiency	Amplification	Margin (dB)
Alcatel	1.05	6638	27%	EDFAs(32nm)	2.8
	1.12	6300	40%	EDFAs(23nm)	2.8
	1.80	6500	40%	EDFAs(36nm)	2.4
Fujitsu	1.04	10127	20%	hybrid C+L(43nm)	2.3
TyCom	1.01	9000	30%	EDFAs(28nm)	3.2

2.3. Switching

2.3.1. Opaque and transparent switching

In the SDH and SONET based optical transport networks deployed today, WDM is used primarily in point-to-point transmission systems. In switching equipment such as Add Drop Multiplexers (ADM) and Digital Cross-Connects (DXC) , the information is processed electronically. Significant research efforts are being carried out to introduce optically-performed networking functions in switching equipment, typically called Optical ADMs (OADM) and Optical Cross-Connects (OXC). The ultimate goal of this trend is the realization of transparent or *all-optical networks* wherein signals are processed optically from end to end, that is, without any opto-electronic (O/E) or electro-optical (E/O) conversion at intermediate switching equipment. The motivation for all-optical networks is twofold. On one hand, eliminating O/E and E/O conversions significantly reduces the cost of the network, since the cost of transponders used to implement these conversions represents today between 50% and 75% of the network cost. On the other hand, transparency to signal characteristics, in particular, modulation and transmission formats, would render these networks more versatile in the sense that signals with different characteristics could be transported using the same infrastructure. Furthermore, all-optical networks would evolve more easily than current transport networks towards higher bit rate signals because of their transparency. Despite these advantages, all-optical networks are far from becoming a reality basically because the technologies used to perform key networking functions in the optical domain are currently under development. In fact, given the current state of the art of technology, transparency introduces more problems than solutions. In the short and mid term, transparency is likely to be introduced in a limited way in the network as a mean to reduce costs. Thus, the challenge today for network equipment manufacturers is to design equipment combining both optically and electronically performed networking functions resulting in the best possible cost

performance ratio for network operators [6].

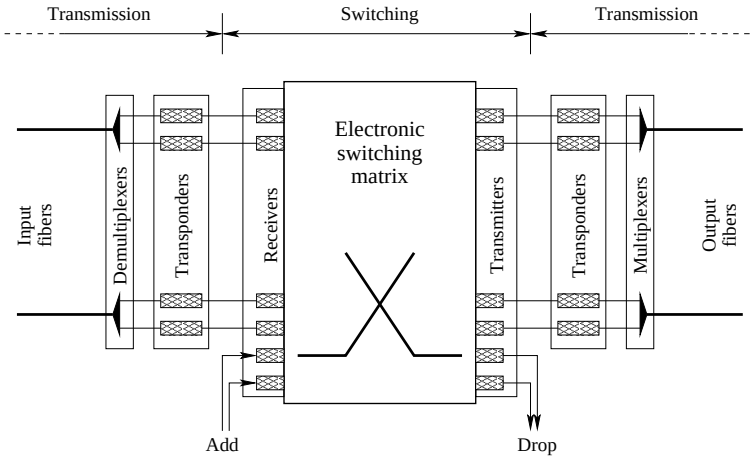
Figure 2.3 shows three possible OXC architectures with different degrees of transparency. Architecture 2.3(a) (opaque) consists of receivers and transmitters (for O/E and E/O conversion) and an electronic switching matrix. The matrix is opaque to the signal's characteristics, that is, it switches the specific bit rate and format of the signal. Though the technology required to implement this type of architecture is mature and available today, the OXC has several disadvantages: it is expensive (receivers and transmitters' cost) and it is not adaptable to changes in the signal's characteristics. Architecture 2.3(b) consists of transponders connected to the input/output ports of an optical switching matrix. The transponders in the OXC are indispensable in this type of architecture, particularly in the case of optical matrices with significant loss of optical power, which will be the case in the short and probably the mid term. On the other hand, the transparency of the matrix allows the switching function to be decorrelated from the signal's characteristics, which renders the architecture more adaptable to changes of these characteristics. Architecture 2.3(c) consists of an optical switching matrix whose input/output ports are directly connected to the transponders of the transmission system. Eliminating the transponders from the OXC has a significant impact on the cost of the equipment. However, the performance of switching matrices, in particular in terms of optical power loss, must improve in order to make this type architecture feasible. In a strictly all-optical network, even the transponders of the transmission system would be eliminated.

2.3.2. Optical packet, burst and circuit switching

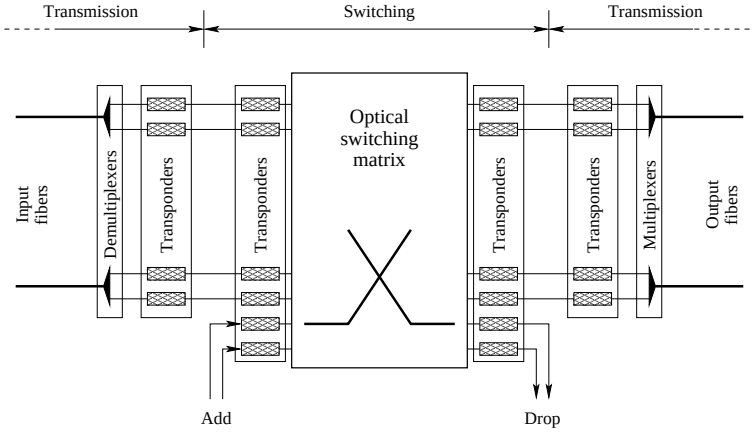
Switch architectures for optical packet-switching, optical burst-switching (OBS) and optical circuit-switching have been investigated in recent years. The main difference among these switching modes stems basically from the required switching speeds for each mode.

In packet-switching, a data stream is broken up into *packets* of small size before being transmitted. Routing information is added to the overhead of each packet so that intermediate switches between the source and destination nodes of the data stream are able to determine the output port for any packet arriving at an input port.

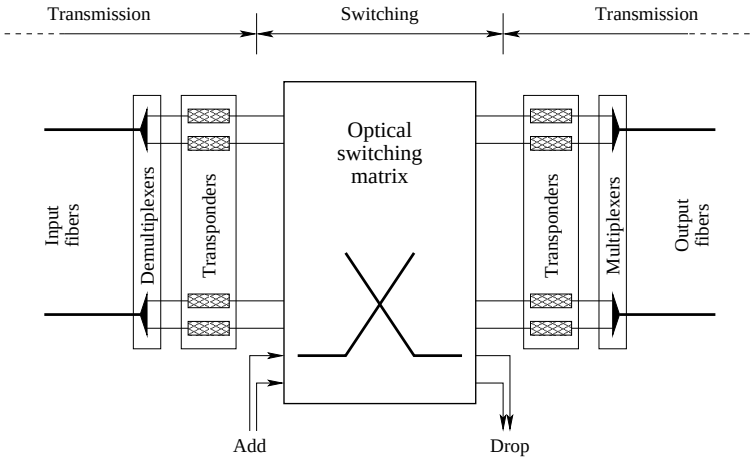
[6] A French national research project on this topic called RHYTME, involving France Telecom, Alcatel, ENST Paris and other partners, will begin in the last trimester of 2003. The aim of the project is to determine the feasibility and the economical advantage of introducing partial or total transparency in the network. As part of the project's methodology, physical layer performance parameters will be introduced in the design, dimensioning and engineering of the considered networks.



(a) Opaque OXC.



(b) Transparent-core OXC.



(c) Transparent OXC.

Figure 2.3.: OXC architectures with different degrees of transparency.

Packet-switching makes sense when two conditions hold simultaneously: a) there are significant changes in the network traffic load at time intervals of the same order of magnitude as the packets' transmission time, and b) transmission resources are more expensive than switching resources.

In a circuit-switching network, information is transmitted between any two nodes using *connections* (*e.g.*, lightpaths in WDM networks, LSPs in MPLS networks, VCs in ATM networks, etc.). A connection has a life-cycle of three phases: set-up, operation and tear-down. In the set-up phase, the connection is instantiated by assigning resources on the links and switches traversed by the connection (time slots in TDM links, frequency bands in FDM or WDM links and input/output ports in switches). In the operation phase, the information is transmitted using the reserved resources. The resources remain reserved for the connection even if no information is transmitted. Finally, in the tear-down phase, the resources are released. Connections can be either permanent or non-permanent.

It must be noted that both, packets and connections, are logical entities used to transmit information between two points of the network. The difference between them is defined by the relationship between the transmission time T_t of the entity and the propagation time T_p between the two points of the network (T_p is constant). For a packet, the transmission time is shorter than the propagation time, *i.e.*, $T_t < T_p$, whereas for a connection, the transmission time is much greater than the propagation time, *i.e.*, $T_t \gg T_p$. In general, the smaller T_t, the better the network resource utilization is, but the higher the reconfigurability speed of switches must be. The reconfigurability speed is limited by the technology used to implement the switch.

There are two main aspects that render the implementation of optical packet switches particularly difficult. On one hand, at very high bit rates, a very high switching matrix reconfiguration time (in the order of nanoseconds) is necessary, which is hardly achievable with current optical switching technologies. On the other hand, no technology is known today to implement an optical Random Access Memory (RAM), necessary to resolve contention of packets at output ports. Though several optical packet-switching network prototypes have been developed [8, 30, 45, 73, 85], this type of networks are unlikely to be deployed in the short and mid term due, in particular, to technological limitations. Moreover, optical packet switching must be competitive in terms of cost and performance with respect to networks based on electronic packet switches (*e.g.*, electronic IP routers) that will exist at the time the technology will be mature enough to be deployed in operational networks.

Optical Burst Switching [90, 86] is basically a form of packet switching proposed to circumvent the implementation obstacles of optical packet switching. The idea is to aggregate packets going from the same source to the same destination into *bursts* of

large size using electronic buffers in the source node's switch. Because of the bursts' large size, their transmission time T_t is typically longer than for packets. Before a burst is transmitted, a control packet is sent and electronically processed by all the intermediate switches that will be traversed by the burst. The information in the packet is used by each of these switches to reserve an input and output port and to configure its switching matrix. The control packet may be acknowledged [86] or not [90]. An offset time is left between the transmission of the control packet and the actual transmission of the burst to allow the intermediate switches to be configured. After the offset time, the burst is transmitted; each intermediate switch remains in the required configuration state only during the time the burst pass through the switch. By using bursts with long T_t, the reconfiguration time of switching matrices can be longer than in the case of optical packet switching. Furthermore, no packet contention at output ports exists because of the resource reservation mechanism implemented with the control packet (when acknowledgement is used). Despite these advantages with respect to optical packet switching, OBS remains mainly a subject of academic study because this switching mode rises additional technological challenges. In particular, the fact that the offset time decreases each time that the control packet traverses an intermediate node makes the detection of the burst's boundaries difficult.

Optical circuit-switching is the switching mode that will most likely be implemented in optical transport networks in the near future.

2.4. Standardization of optical transport networks

Three main organizations work on the development of open standards for optical transport networks. The ITU-T has issued Recommendations G.872, G.709 and G.8080/Y.1304 that define the reference architecture of an Optical Transport Network (OTN), the interfaces to the OTN and the reference architecture of the OTN control plane. The Internet Engineering Task Force (IETF) works on the standardization of a set of protocols for the control plane of transport networks (not only optical networks). The set of protocols is collectively known as Generalized Multi-Protocol Label Switching (GMPLS). The Optical Internetworking Forum (OIF) produces implementation agreements for a User to Network Interface (UNI) and a Node to Node Interface (NNI) of optical networks. The following subsections describe in more detail the work of these organizations.

2.4.1. The ITU-T OTN and ASON/ASTN standards

The ITU-T defines an OTN as a connection oriented network composed of a set of Optical Network Elements (ONE) connected by optical fiber links, able to provide functionality of transport, multiplexing, routing, management, supervision and survivability of optical channels carrying client signals. The OTN has a layered structure comprising optical channel (OCh), optical multiplex section (OMS) and optical transmission section (OTS) layer networks[7].

During the standardization of the OTN, it was realized that, because of limitations of the current optical technology, the only techniques presently available to meet the management requirements defined for the OCh layer network in G.872 are digital techniques. Thus, it was decided that a digital framed signal with digital overhead would be used to implement the OCh layer network. This resulted in the introduction of digital framed signals for 3 bit rates: 2.5, 10 and 40 Gbps, referred to as signals of order k=1, k=2 and k=3, respectively. A signal of order k is defined by 3 units that correspond to 3 layer networks above the OCh layer network:

OPUk - OCh Payload Unit of order k. The OPUk includes the payload and an overhead. The payload contains the mapped client information and the overhead includes the information required to support the mapping.

ODUk - OCh Data Unit of order k. The ODUk includes overhead for path performance monitoring (PM), Tandem Connection Monitoring (TCM) and protection control communication channels (APS,PCC).

OTUk - OCh Transport Unit of order k. The OTUk includes a FEC code and overhead for management and performance monitoring. The FEC is based on the Reed Solomon coding defined in Recommendation G.975 [52].

Figure 2.4 shows the layered structure of the OTN. The OPUk, ODUk and OTUk units use associated overhead whereas the OCh, OMS and OTS use non-associated overhead. The non-associated overhead forms an OTM Overhead Signal (OOS) borne by an Optical Supervisory Channel (OSC). Optical channels (OCh) are modulated onto Optical Channel Carriers (OCC), which are multiplexed to form an OMS of order n (OMSn). The order n is the number of OCCs in the OMS. An Optical Transport Module of order n (OTMn) is an association of a OMSn and an OSC. An OTM0 is an special case of an OTM with no OSC and single-OCC OMS called OMS0. The OTM0 is used at the interface between the OTN and a client equipment. An OTM0

[7]The complete ITU-T terminology for functional description of transport networks is found in Recommendation G.805 [48].

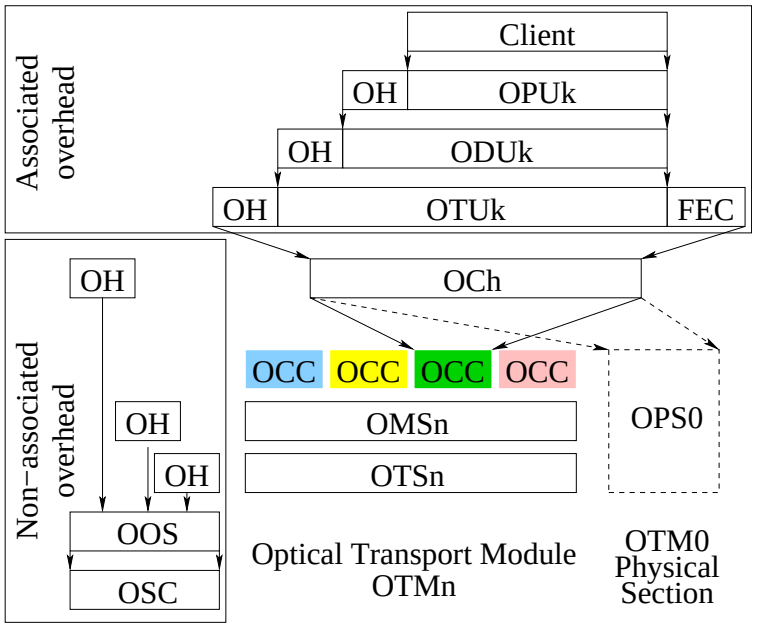


Figure 2.4.: Layered structure of the OTN.

Physical Section (OPS0) consists of a OMS0 and a single OTS called OTS0. The details of the OTN layered structure are described in Recommendation G.709 [49].

Figure 2.5 shows an example of OTSn, OMSn, OCh, OTUk, ODUk and OPUk trails in a OTN. In ITU-T terminology, a trail is an architectural component capable of transferring information between two endpoints of a same layer network. The integrity of the information transfer is monitored. When the trail is capable of transferring information only on one direction, it is called an "unidirectional" trail. Note that OMSn trails terminate at ONEs (*e.g.*, OADM or OXC).

In this thesis we adopt the terminology presented in Table 2.3 to refer to ITU-T architectural components. The terminology is widely adopted in the literature about optical networking. To illustrate the difference between a WDM channel and a wavelength, suppose a network in which WDM channels $(\lambda_{1550nm}, 1, 2)$, $(\lambda_{1580nm}, 1, 2)$, $(\lambda_{1550nm}, 2, 3)$ and $(\lambda_{1580nm}, 2, 3)$ are required. In this case, 4 WDM channels and 2 wavelengths are required.

The OTN is expected to support different forms of dynamically controlled connections by means of a control plane. A control plane is a set of communicating entities responsible for the set up, release, supervision and maintenance of connections; the control plane is supported by a signaling network [50]. The functions that

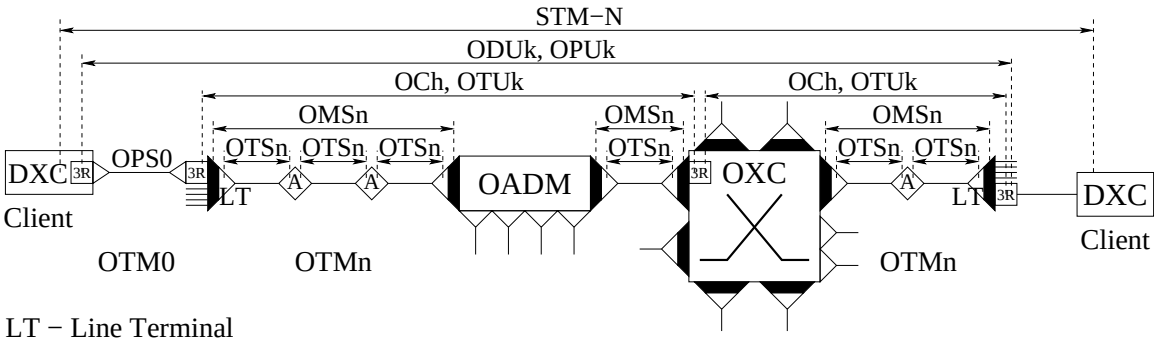


Figure 2.5.: Example of OTN trails.

Table 2.3.: Terminology used to refer to ITU-T OTN architectural components.

Term	Description
lightpath	An OCh capable of transferring information in one direction.
link	The part of an OMSn trail transferring information in one direction.
span	An OMSn trail or, equivalently, a pair of links in opposite direction.
WDM channel	A particular OCC on a *link*, characterized by a tuple (λ, s, d), where λ is the wavelength of the OCC and s and d are the source and destination ONEs of the link. For example, the tuple $(\lambda_{1550nm}, 2, 3)$ represents the WDM channel using wavelength λ_{1550nm} between ONEs 2 and 3.
Wavelength	A particular carrier frequency available in the network.

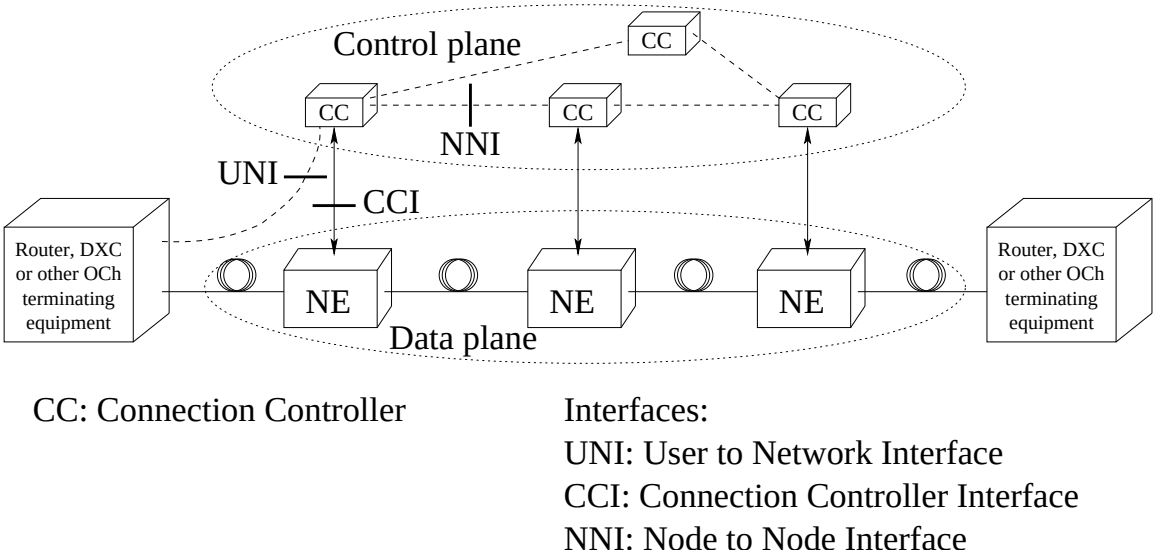


Figure 2.6.: Architecture of an ASTN as defined by the ITU-T.

must be implemented in a control plane include signalling, routing, connection admission control, and naming/addressing. A signalling interface is a logical relationship between entities of the control plane defined by the particular flow of information between these entities. The information flowing through a signalling interface may include equipment's names and addresses, reachability, topology, authentication and admission control information, connection services messages, etc.

In the ITU-T terminology, an OTN implementing a control plane for the dynamic control of connections is known as an Automatically Switched Optical Network (ASON). In general, a transport network implementing a control plane is known as an Automatically Switched Transport Network (ASTN). The ITU-T defined in Recommendation G.807 [50] the functionality required in the control plane of an ASTN and the architecture of the ASON in Recommendation G.8080/Y.1304 [51]. It must be noted that both recommendations are reference standards and not implementation standards (like Recommendation G.709 [49]).

Figure 2.6 illustrates the architecture of a ASTN as defined by the ITU-T. The control plane is formed by Connection Controllers associated to Network Elements and interconnected by a signalling network. Network equipment of the client network (*e.g.*, IP, ATM or SDH/SONET) communicates with the Connection Controllers through a UNI.

2.4.2. The IETF GMPLS protocols

The IETF works on the standardization of a suite of protocols called Generalized Multi-Protocol Label Switching (GMPLS) [25] for the control plane of transport networks. Originally, MPLS was developed basically as an encapsulation technique used in the data plane to simplify the forwarding function of IP packets in routers. MPLS evolved later into a network architecture integrating the encapsulation technique with control plane functions for Traffic Engineering (TE) of IP networks. The idea behind GMPLS is to generalize the MPLS control plane so that it can be used as a control plane for other networks, in particular SDH/SONET networks and optical networks.

Though there have been some efforts to align the GMPLS control plane standards to the ITU-T ASTN reference model, it is not sure that this alignment will be achieved. Indeed, the divergent cultures and working methods of the two standardization bodies, as well as the commercial interests of the participating members, often complicate the cooperation work.

2.4.3. The OIF

The Optical Internetworking Forum (OIF) is an industry forum whose objective is to accelerate the uptake of optical networking by producing implementation agreements on different aspects of control-plane-enabled transport networks. So far, the main output of the OIF is a User to Network Interface (UNI), version 1.0, for the exchange of signalling information between client network equipment (*e.g.*, IP routers, SDH/SONET DXCs, etc.) and switching elements of an optical network. The UNI allows connections to be established by client network equipment on the optical network. The signalling messages of the UNI are based on protocols defined in GMPLS. The OIF currently works on version 2.0 of the UNI and on the definition of a Node to Node Interface (NNI).

The OIF serves as an interface between the ITU-T work on reference architectures and the IETF work on protocols. It is a forum where representatives of both organizations interact and necessary compromises are reached to achieve working implementations of optical networks.

3. Network optimization

Designing and operating telecommunications networks in an economically efficient way are activities of strategic importance for carriers. The ultimate goal of these activities is to offer high quality services to customers while keeping infrastructure and operation costs low. This tradeoff is critical for a sustainable development of the carrier's business.

The problems arising from the design and operation of networks are commonly addressed as *network optimization* problems. The formalization and the resolution of these problems appeals to modeling approaches and algorithms derived from disciplines like graph theory, Operations Research (OR) or queueing theory. In this section we present an introduction to network optimization. We provide a framework to describe in a structured manner the problems and methods considered in this field. The framework is necessary to clearly define the contribution of this thesis.

Though we focus on telecommunications, it is worth to note that network optimization also concerns problems arising from other domains such as transportation systems.

3.1. Classification of problems

Network optimization problems are so diverse that it is difficult to classify them parsimoniously using a single criterion. We propose two criteria in order to provide a comprehensive and structured view of this research field. A first criterion, based on time scale horizon, allows network optimization problems to be classified according to the range of time units (microseconds, seconds, days, months, etc.) in which these problems are relevant. A second classification is based on the network's functions and structural aspects involved in the problem, *e.g.*, routing, aggregation, location of functions, etc.

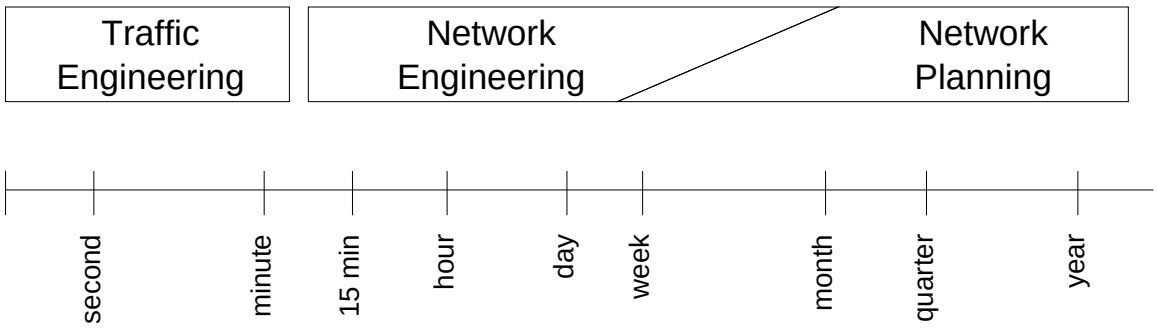


Figure 3.1.: Time scale domain of Traffic Engineering, Network Engineering and Network Planning.

3.1.1. Time horizon classification

Network optimization problems may be classified according to the range of time units wherein they are relevant. Figure 3.1 shows three types of problems and their time units of relevance.

Traffic Engineering (TE) consists of allocating existing network resources to traffic demands in order to meet specified traffic performance objectives. The traffic demands are usually assumed to be *random*. As a consequence, the network resources must be assigned to the demands as these arrive. Furthermore, the network configuration is assumed to remain unchanged during the operation of the network, that is, no links are added to or deleted from the network and the capacity remains constant on the links and the switching equipment.

Traffic Engineering has been largely investigated in packet-switching networks like ATM and the Internet, particularly in connection with the provisioning of communication services with assured Quality of Service (QoS). In a packet-switching network, the QoS objectives of a particular communication service can be defined in terms of target values of performance metrics such as transit delay, packet loss probability and jitter.

Network Engineering (NwE) concerns problems of efficient allocation of existing network resources to *expected* traffic demands. NwE differs from TE in that the traffic demands are usually known for a given period of time (typically ranging from hours to weeks) and the resources are already installed in the network but must be set up (to define a network configuration) and assigned to the demands. Given that there are many possible network configurations and resource assignments, the goal is to find a network configuration and resource assignment that makes an efficient use of resources. The meaning of the term "efficiency" depends on the particular problem under consideration. For example, given a model defining the cost for each resource

in the network, "efficiency" can be interpreted as the cost-effective use of resources. NwE problems are commonly formulated as optimization problems.

Network Planning (NwP) concerns the definition and the dimensioning of network aspects which are characterized by a long lifetime and large investments for their deployment [28]. Network Planning is a long term process aimed at defining the schedule of investment and deployment of network equipment. The traffic demands are usually static and correspond to long term forecasts of the traffic load. Network Planning problems are commonly formulated as optimization problems.

3.1.2. Functional classification

Network optimization problems can be classified according to functional and structural criteria into three groups: location, synthesis and resource allocation problems[1].

Location problems concern the identification of places where certain network functions must be installed. The general objective in these problems is to concentrate large amounts of traffic in specific nodes of the network in order to take advantage of economies of scale of high speed and/or added-value network equipment. An equilibrium must be found between the cost of installing this equipment and the cost of accessing it. Examples of these problems are the location of multicast or hosting servers in an IP network or the location of concentrators in a telephone network.

Network synthesis problems concern the definition of a network topology in terms of links and the dimensioning of these links in order to satisfy the traffic demand. These problems arise when either a new network must be designed from scratch, strategic network development plans must be defined or the equilibrium between the order of magnitude of the traffic volume and the order of magnitude of equipment capacity is broken (*e.g.*, sharp growth of traffic demand or evolution of equipment speed from Gbit/s to Tbit/s). These problems frequently include multiple constraints derived from network management policies, protection/restoration mechanisms, transit delay, path length, etc.

Resource allocation problems concern the assignment of existing network resources to traffic demands. These problems arise either as subproblems of network synthesis problems or during the operation of the network (*e.g.*, to manage resources and traffic when mismatches exist between planned and presently required resources or to allocate resources to traffic in case of network perturbations). Resource allocation and routing are related problems since both concern the flow of traffic through the resources of the network. Quality parameters such as transit delay or packet loss ratio in packet-switched networks or blocking probability in circuit-switched networks are

[1] Classification proposed in [66].

commonly expressed as constraints of the problem.

3.2. Optimization problems in WDM networks

One of the expectations from optical networks is that they will provide large bandwidth at a very low price. Under these conditions, the problem of optimizing transport networks should not exist anymore. The bandwidth indeed, has increased significantly thanks to the introduction of optical networks, but the cost of equipment remains high. Consequently, the problem of optimizing these networks remains an important one.

From a network optimization perspective, there are two main problems introduced by optical networks. First, the equilibrium between the order of magnitude of the equipment capacity and the order of magnitude of the traffic demands, which is well understood by operators for present networks, has been broken. Indeed, the rate of optical connections becomes too large with respect to the rate of individual demands. Thus, the tradeoff between taking advantage of the economies of scale of large capacity equipment and the cost of aggregating traffic into this equipment must be characterized and understood in order to minimize the total cost of the network. The second problem is that, even if the new equipment provides large capacity, the optical technology is relatively immature with respect to electronics. This leads to new functional constraints that must be considered in the design, dimensioning and engineering of optical networks. For example, the high cost and/or the limited performance of wavelength converters impose constrains on the continuity of the wavelength(s) assigned to optical connections. Additionally, the amplification and regeneration functions that must be introduced in order to meet stringent power budgets have a significant impact on the cost of the network. Moreover, network optimization problems become more difficult to tackle due to the constant evolution of network equipment offered by manufacturers.

Part II.

Network optimization problems with Scheduled Lightpath Demands

4. Scheduled Lightpath Demands

Network operators use long term forecasts of traffic demands to dimension transport networks and to develop investment plans for network infrastructure. Forecasts are usually based on measurements of current traffic and traffic growth models.

In recent years, the uncertainty of demands has made the accurate long term forecasting of traffic a particularly difficult problem. The uncertainty is due to factors such as the massive adoption of data applications and the development of competition in the telecommunications market. Indeed, the requirements in terms of bit rate of some data applications are not well understood and the competition makes it easy for clients of communication services to change of provider (which changes the traffic demand of the providers). An unexpected growth of the traffic demand may lead to the exhaustion of network resources and the consequent inability to provide communication services. The network may be over-dimensioned in order to eliminate this risk. However, over-dimensioning implies an increased investment on network infrastructure, which may be extremely onerous or even unaffordable for network operators. To avoid resource exhaustion one may have recourse to network engineering tools (§ 3.1.1) to efficiently assign existing network resources to traffic demands.

Paradoxically, the day-to-day traffic is fairly predictable because of its periodic nature. Figure 4.1 shows the traffic on the New York - Washington link of the Abilene backbone network [1] from 4/03/03 to 4/10/03. The periodicity of traffic is explained by human activity: office hours and evening hours are peak periods for communication services. The volume of traffic decreases during the night, when only computing processes such as the backup of large databases communicate, usually without human participation. The pattern repeats on a day to day basis with minor changes on weekends and special days like holidays.

The predictability of the day-to-day traffic demands suggests that they can be modeled deterministically. We propose a deterministic traffic model called Scheduled Lightpath Demands (SLDs) that deterministically captures the time and space distribution of traffic demands in a network. An SLD is represented by a tuple $(s, d, n, \alpha, \omega)$ where s and d are the source and destination nodes of the demand, n is the number

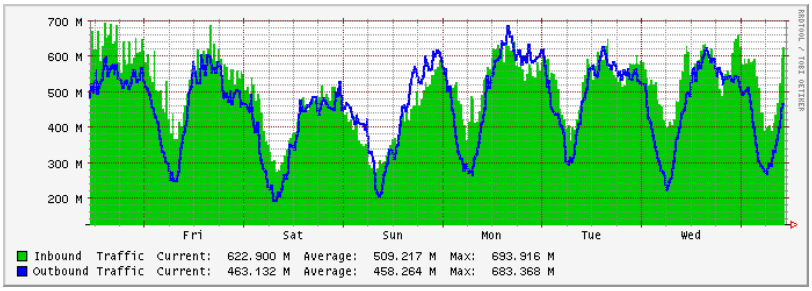


Figure 4.1.: Traffic on the New York - Washington link of the Abilene backbone network in a typical week.

Table 4.1.: A set of 3 SLDs.

SLD	s	d	n	α	ω
δ_1	2	8	2	08:00	14:40
δ_2	3	7	3	11:00	13:00
δ_3	1	6	2	17:00	19:30

of requested lightpaths and α, ω are the set-up and tear-down dates of the demand. Figure 4.1 shows an example of 3 SLDs.

4.1. The SLD traffic model and other traffic models

The model used to represent the traffic on a network depends on the problem being addressed. In network planning problems (§ 3.1.1), long term traffic forecasts are represented by traffic matrices $\Lambda = (\lambda^{sd})_{1 \leq s,d \leq N}$, where N is the number of nodes in the network and λ^{sd} is the expected volume of traffic between source node s and destination node d. A traffic matrix is a deterministic static representation of the expected spatial distribution of traffic in a network at some time in the future. Network optimization problems are commonly formulated as mathematical programming problems using Multi-Commodity Flow (MCF) models [2]. In this context, the traffic matrix Λ is called a multi-commodity flow requirement and each element λ^{sd} represents a commodity.

As one moves from long term to short term network optimization problems, the dynamics and the randomness of traffic become important factors that must be taken into account. In traffic engineering problems, the traffic is usually characterized by stochastic processes that capture these factors. A *stochastic process* is defined as a family of random variables $\{X_t : t \in T\}$ where each random variable X_t is indexed by parameter $t \in T$, which is usually called a time parameter if $T \subseteq \mathbb{R}_+$. The

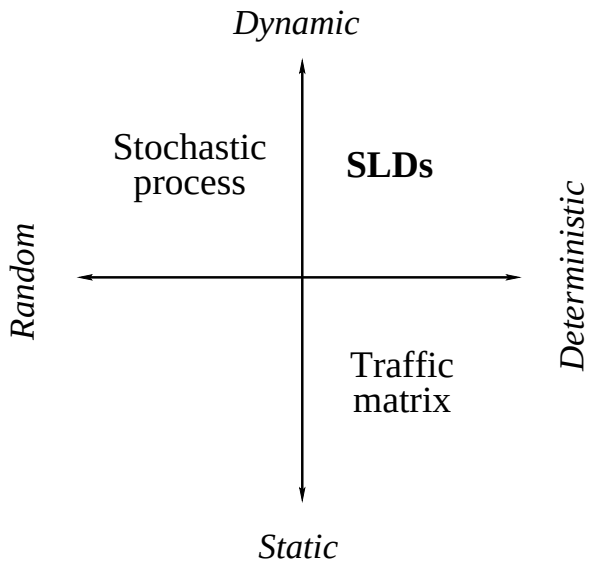


Figure 4.2.: Classification of traffic models.

set of all possible values of X_t (for each $t \in T$) is known as the state space S of the stochastic process [10]. They are used to characterize traffic in the performance evaluation of traffic engineering algorithms. Stochastic processes are also used in network planning problems [4]. For example, queueing systems (which are based on stochastic processes) are used in the dimensioning of telephonic networks, where the objective is to design the network to meet target objectives for the blocking probability.

As indicated in Subsection 3.1.1, network engineering problems are mid term problems relevant at time units ranging from hours to weeks. In this time horizon, the dynamic dimension is still important but the randomness of traffic disappears in favor of more predictable patterns as we can notice in Figure 4.1. The SLD traffic model proposed in this thesis is both *dynamic* and *deterministic* in that it deterministically captures the time and space distribution of traffic demands in a network. Figure 4.2 shows a two-criteria classification of traffic models and situates the SLD traffic model with respect to the traffic models based on traffic matrices and stochastic processes.

An alternative to the SLD traffic model consists of defining a set of n non-simultaneous traffic matrices $\Lambda_1, \Lambda_2, \ldots, \Lambda_n$. The model, known in the literature as multi-hour traffic matrices (MHTM) or non-simultaneous multi-commodity flow requirements (NSMCF), has been used to model traffic in problems of network design under reliability constraints or time varying traffic [36, 37, 69, 71, 70, 83, 67, 65] and most recently in virtual topology reconfiguration problems [41, 79, 33]. The SLD and MHTM models are equivalent in that a set of SLDs may be represented by the

MHTM model[1]. However, as will be seen in the next chapters, the SLD model allows a more flexible modeling of individual lightpaths' properties (*e.g.*, route, wavelength, etc.) than the MHTM model.

4.2. Applications of the SLD traffic model

The SLD traffic model has both the advantage of taking into account the time and space distribution of traffic demands and, being deterministic, the advantage of easing the use of combinatorial optimization techniques. The next chapters describe the use of the SLD model for three network engineering problems: routing and wavelength assignment in a wavelength-switching network, diverse routing and spare capacity assignment in a wavelength-switching network and routing and grooming in a multi-granularity switching network.

Besides the modeling of observed traffic (as in Figure 4.1), SLDs may be used to characterize the traffic generated by innovative services such as scheduled connection services. A client company may replace the leased lines that it uses today to interconnect its sites by scheduled connections that are active only during the time the company really needs the interconnection service (*e.g.*, office hours and the night for the backup of large databases). The advantage for the client company is that it reduces its expenses because it pays for the interconnection service only during the time it is really needed. For the network operator, the knowledge of scheduled demands reduces the uncertainty of traffic, which is essential for the accurate dimensioning of the network and, ultimately, for the reduction of network infrastructure cost.

Another application of the SLD traffic model is the design of network equipment architectures. For example, the algorithm for routing and grooming of SLDs presented in Chapter 7 may be used to determine, by means of comparisons, the conditions (*e.g.*, time and space distribution of traffic demands, switch cost function parameters, etc.) under which a network using multi-granularity switches integrating a wavelength cross-connect and a waveband cross-connect is more economical than a network using only wavelength cross-connects.

[1] In a MHTM representation of a set of SLDs, there are as many matrices Λ_i as different set-up and tear-down dates.

5. Routing and wavelength assignment for SLDs in a wavelength-switching network

Routing is a network problem that concerns the computation of paths[1] for traffic demands. Routing may be regarded as an optimization problem whose objective function is either performance-oriented, cost-oriented or a combination of both. An example of a performance-oriented objective function is the network congestion (the amount of traffic traversing the most loaded link of the network). Congestion has incidence on the blocking probability in circuit-switched networks and on the average packet delay and average packet loss in packet-switched networks. Thus, minimizing congestion is an important objective in networks because of its incidence on network performance metrics. As indicated later in this chapter, minimizing congestion may be also important for reasons related to technological constraints. An example of a cost-oriented objective function commonly used in network planning problems is the sum of links' costs. The cost of a link is modeled as a function of the amount of traffic traversing it, for example, a concave nondecreasing function $\phi(x) = x^c, c < 1$, where x is the amount of traffic. The concavity of the function corresponds to the so-called economy of scales phenomenon, which results in a decreasing marginal link cost as the amount of traffic increases [26].

In a WDM optical transport network, a lightpath is instantiated by assigning source and destination ports at the termination nodes of the lightpath and WDM channels (see Table 2.3) on the traversed links. If the network is all-optical (see § 2.3.1), the absence of transponders at intermediate nodes constraints the WDM channels assigned to the lightpath to have the same characteristic wavelength unless devices for optical wavelength conversion are available in the nodes[2]. This constraint

[1] In graph theory, a *path* is a walk with no repeated vertices. A *walk* is an alternating sequence of vertices and edges (or arcs), with each edge being incident to the vertices immediately preceding and succeeding it in the sequence.

[2] Optical wavelength conversion devices are currently in a early stage of development. As a con-

is referred in the literature as the wavelength continuity constraint. Two factors make the assignment of WDM channels to lightpaths a complex problem: on one hand, the number of WDM channels in the links, and hence the number of wavelengths in an optical network, is typically assumed to be small (usually 16 or 32); on the other hand, the number of different wavelengths required to instantiate a set of lightpaths is likely to be greater with the wavelength continuity constraint than without it.

Routing and wavelength assignment are often addressed in the literature as a single problem mainly because of the assumed limited number of wavelengths and the incidence of the lightpaths' routing on the number of wavelengths required to instantiate them. However, when this problem is formulated as a combinatorial optimization problem, the solution space of realistic-size instances is extremely large. Consequently, these instances are computationally intractable. Another approach consists of addressing routing and wavelength assignment as separate problems. A potential disadvantage of this approach is the loss of perception of the global problem when solving a particular problem. An information exchange mechanism may be optionally introduced to take into account wavelength assignment information into the routing problem formulation and *vice versa*.

In this chapter we investigate the problems of Routing and Wavelength Assignment (RWA) for SLDs. We address the problems separately without any information exchange mechanism. Our objective is to assess the number of required wavelengths under stringent conditions (*i.e.*, routing and wavelength assignment problems addressed separately, no information exchange mechanism and wavelength continuity constraint holding) in order to define a form of "worst-case" requirement of wavelengths and compare this number with the typically assumed number of wavelengths in optical networks. However, as indicated in Subsection 2.3.1, strictly all-optical networks are unlikely to exists –at least in the mid term– so wavelength conversion will probably exist due to the (partial) opacity of optical networks.

The next section presents a description of the RWA for SLDs problem. Two versions of the routing problem are introduced: one whose objective is to minimize the number of required WDM channels and another whose objective is to minimize the congestion. Section 5.2 presents previous work found in the literature about the RWA problem in general. Section 5.3 describes the mathematical formalization of the routing and wavelength assignment problems as combinatorial optimization problems. The section also presents a metric used to characterize the time correlation among SLDs. In Section 5.4 we propose algorithms to compute solutions to instances of the routing and wavelength assignment problems. Section 5.5 shows the experimental

sequence, their performance is relatively poor (with respect to electronic wavelength conversion devices). They are unlikely to be used in carriers' transport networks, at least in the mid term.

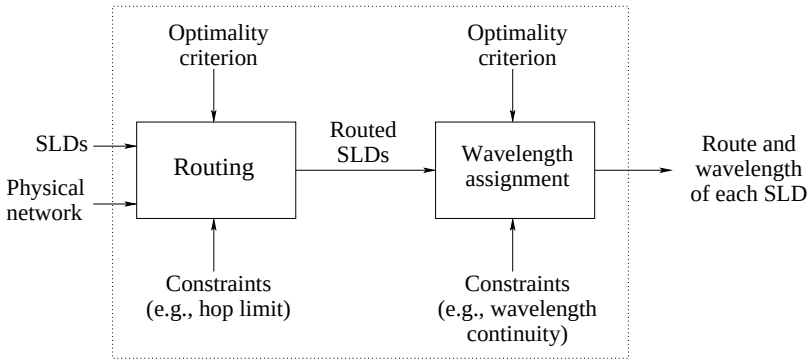


Figure 5.1.: Schematic representation of the RWA of SLDs problem.

evaluation of the proposed algorithms and Section 5.6 presents concluding remarks and propositions for future work.

5.1. Description of the problem

In informal terms, the RWA for SLDs problem is the following: given a network and a set of SLDs, find the routing in the network for the SLDs which meets an optimality criterion. Then, for this routing solution, find the assignment of wavelengths[3] to lightpaths that minimizes the number of required wavelengths, while satisfying the wavelength continuity constraint. Different optimality criteria may be considered in the routing problem, for instance, the minimization of the number of WDM channels or the minimization of the congestion (the number of lightpaths in the most loaded link). Minimization of the number of WDM channels is particularly important in opaque WDM networks where two transponders or a pair Tx/Rx is required for each channel (transponders and Tx/Rx often represent the dominant cost of the network). On the other hand, congestion minimization is important when the number of wavelengths in the network is limited since the congestion is a lower bound on the number of required wavelengths. We consider both versions of the routing problem. We denote the WDM channel minimization version of the problem by R_{ch} and the congestion minimization version by R_{cg}. Figure 5.1 represents schematically the problem under consideration.

The time disjointness (if any) among demands is taken into account to minimize either the number of required WDM channels or the congestion. This point is illustrated by Figure 5.2. The figure shows two possible routing solutions for the three SLDs of Table 4.1. In Solution 1 (left side), $2 \times 4 = 8$ WDM channels are required for SLD δ_1 (the number of channels is equal to the size of the SLD, n, multiplied by

[3]the terms *link*, *WDM channel* and *wavelength* are defined in Table 2.3.

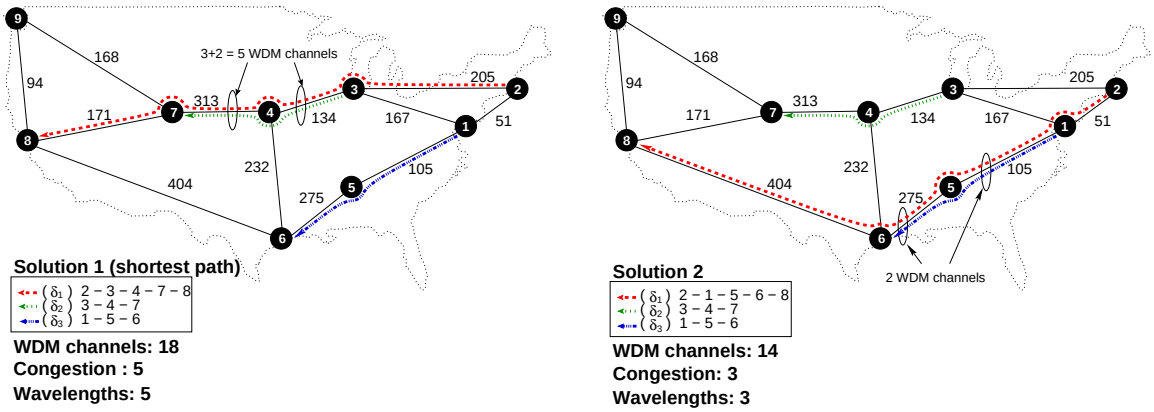


Figure 5.2.: Two possible routing solutions for the 3 SLDs of Table 4.1.

the number of traversed links), $3 \times 2 = 6$ for SLD δ_2 and $2 \times 2 = 4$ for SLD δ_3, which totals 18 WDM channels. The congestion and the number of required wavelengths is five. In Solution 2 (right side) only 14 WDM channels are required because the WDM channels on links 1-5 and 5-6 used from 08:00 to 14:00 by the lightpaths of SLD δ_1 are reused by the lightpaths of SLD δ_3 from 17:00 to 19:30. The congestion and the number of required wavelengths is 3 in this case.

In the RWA for SLDs problem under consideration we assume that:

1. the network has an arbitrary connex topology;

2. there is only one optical fiber per link;

3. the number of WDM channels on a link is unlimited and that

4. there is no wavelength conversion functionality in the switches of the network nodes, therefore, the wavelength continuity constraint holds.

Assumptions 2, 3 and 4 are simplifications that we define in order to ease the mathematical formalization of the problem. In particular, assumption 2 allows the wavelength assignment problem to be formulated as a graph vertex coloring problem (explained in Subsection 5.3.2), which is a largely investigated problem in graph theory. Moreover, to instantiate a given set of lightpaths, a network with only one fiber per link will require at least the same number of wavelengths than a network with multiple fibers per link. Thus, the assumption is in line with our objective of defining a worst-case requirement of wavelengths.

5.2. Related work

Routing and Wavelength Assignment in optical transport networks has been extensively investigated in connection with planning and traffic engineering problems in these networks. RWA problems are often classified in the literature according to the nature of the considered traffic demands, namely, whether they are static or dynamic [91][4]. Static demands correspond to traffic forecasts and dynamic demands to connections arriving randomly to the network. RWA problems assuming dynamic (random) demands are in fact traffic engineering problems, since it is typically assumed that the transmission and switching capacity is fixed (*e.g.*, [80]). On the other hand, RWA problems assuming static demands are further classified into traffic engineering and network planning problems. The objective in the former is to optimize some network performance metric (*e.g.*, minimize connection blocking probability) [82], whereas in the latter the objective is to minimize the amount of network resources or, more generally, the network cost [5, 3].

Routing and Wavelength Assignment of lightpaths and the problems of defining a logical topology of lightpaths and routing electronic traffic on this topology are investigated together in some papers [6, 78].

Routing with dynamic deterministic traffic has been investigated in the context of network synthesis problems with non-simultaneous single- or multi-commodity flow requirements. In practice, these problems arise in the design of networks with survivability constraints and in multi-hour wide-area network planning [70]. The traffic is modeled by a finite set of single-commodity or multi-commodity flow requirements (see Section 4.1). The cost of the links is a function of the amount of traffic routed through them. The objective is to satisfy each flow requirement (*i.e.*, route it through the network) independently of the others so that the network cost is minimized. Solution approaches based on generalized linear programming (*i.e.*, constraint generation) [37, 69, 71], generalized upper bounding [83], Lagrangean relaxation [67] and surrogated duality methods coupled with a Tabu Search meta-heuristic [65] have been proposed. The network synthesis problem with non-simultaneous single-commodity flow requirements assuming a linear link cost function and integer link capacities is equivalent to the particular case of the SLD routing problem where all the SLDs are non-simultaneous. The general SLD routing problem is equivalent to the network synthesis problem with non-simultaneous multi-commodity flow requirements assuming a linear link cost function and integer link capacities [65]. In this case, a

[4]There is a widespread misconception of static and dynamic traffic. In fact, it is often implicitly assumed that deterministic traffic and static traffic refer to the same thing and that dynamic traffic is necessarily stochastic. However, the SLD traffic model is both deterministic and dynamic (see Figure 4.2).

different multi-commodity flow requirement exists each time there is a change in the traffic demands, that is, each time a SLD is either set-up or torn-down. Solving the SLD routing problem as a network synthesis problem with non-simultaneous multi-commodity flow requirements is impractical because of the potentially large number of different multi-commodity flow requirements.

5.3. Mathematical model

We use a modeling approach based on *ad hoc* formulations rather than on the mathematical programming formulations, in particular Integer Linear Programming (ILP) formulations, commonly used to formalize this type of network optimization problems.

The ILP formulations ease the comprehension of formalized problems since they are familiar to operations research and network optimization scientists. Furthermore, the availability of public domain and commercial LP and ILP solvers like lp_solve, IBM's OSL and ILOG's CPLEX make it possible to compute solutions to those problems without the burden of designing and implementing a solution algorithm from scratch.

However, ILP problems are NP-complete [58], which in practical terms implies that only problem instances with a limited number of variables can be solved in reasonable computing time. We used ILP and Mixed ILP (MILP) formulations in [77, 78, 64] to describe topological design and routing problems in WDM networks. We concluded in that work that the approach has limited practical application since we only were able to compute solutions for networks with up to 14 nodes in around 60 hours. Moreover, the linearity in ILP and MILP formulations limits the modeling possibilities. This is an important handicap when dealing with complex technology-specific problem constraints.

Besides their modeling flexibility, the proposed *ad hoc* formulations allow for the cost function and other elements of the combinatorial optimization model (*e.g.*, vector ρ, explained below) to be directly integrated in the description of the algorithms used to solve the problems.

Subsections 5.3.1 and 5.3.2 below describe the formulation of the routing and the wavelength assignment problems as combinatorial optimization problems. In Subsection 5.3.3 we provide a formula to characterize the time correlation of a set of SLDs.

5.3.1. Routing

We first present the notations used in the model of the routing problem.

$G = (V, E, w)$
is an arc-weighted symmetrical directed graph with vertex set $V = \{v_1, v_2, \ldots, v_N\}$, arc set $E = \{e_1, e_2, \ldots, e_L\}$ and weight function $w : E \to \mathbb{R}_+$. The graph represents a physical telecommunications network. The set V corresponds to the network nodes, the set E to the links interconnecting the nodes (see terminology of Table 2.3) and the function w to the physical length or cost of the links (*e.g.*, set by the network operator).

$N = |V|$, $L = |E|$
are, respectively, the number of nodes and links in the network.

$\Delta = \{\delta_1, \delta_2, \ldots, \delta_M\}$
is the set of M SLDs, where:

$\delta_i = (s_i,\ d_i,\ n_i,\ \alpha_i,\ \omega_i)$
is a tuple representing the SLD number i; $s_i, d_i \in V$ are the source and destination nodes of the demand, n_i is the number of requested lightpaths, and α_i and ω_i are the set-up and tear-down dates of the demand, respectively.

(G, Δ)
is a pair representing an instance of the routing problem.

$P_{k,i}$, $1 \leq k \leq K$, $1 \leq i \leq M$
represents the k^{th} path in G from s_i to d_i. For the purposes of this work, we compute the K physically shortest paths for each demand using the algorithm defined in [27]. However, the paths might be defined according to any other criterion. Moreover, the paths do not need to be necessarily neither link disjoint nor node disjoint. For example, in Figure 5.2 the physically shortest path for SLD δ_1 corresponds to the first alternate path $P_{1,1}$ and the second shortest path to the second alternate path $P_{2,1}$.

$\pi_{\rho,\Delta} = (P_{\rho_1,1}\ \ P_{\rho_2,2}\ \ \ldots\ \ P_{\rho_M,M})$, $\rho \in \{1, \ldots, K\}^M$
is called an *admissible routing solution* for Δ. ρ is an M-dimensional vector whose elements can take values in $[\![1, K]\!]$. The element ρ_i indicates the path (among the K) selected for the SLD δ_i. All the lightpaths of an SLD are routed through the same

path (*i.e.*, no bifurcated routing is used). An admissible routing solution is fully characterized by ρ.

$\Pi_\Delta = \left\{\pi_{\rho,\Delta}, \rho \in \{1,\ldots,K\}^M\right\}$
is the set of admissible routing solutions for Δ. There are $|\Pi_\Delta| = K^M$ admissible routing solutions in the set (assuming that the K paths exist for each SLD; otherwise, $|\Pi_\Delta| < K^M$).

$C_{ch} : \Pi_\Delta \to \mathbb{N}, \quad C_{cg} : \Pi_\Delta \to \mathbb{N}$
are the cost functions that compute, respectively, the number of WDM channels and the congestion in an admissible routing solution $\pi_{\rho,\Delta}$. In such a solution, a path is defined for each SLD $\delta \in \Delta$. Each lightpath of an SLD requires one WDM channel on every link traversed by its defined path. The same WDM channel can be used by several lightpaths, provided that they occur at different times. To formalize functions $C_{ch} : \Pi_\Delta \to \mathbb{N}$ and $C_{cg} : \Pi_\Delta \to \mathbb{N}$ we define the following additional notations.

$\theta = (\theta_{ij})$
is a $\{0,1\}^{M\times M}$ upper triangular matrix; θ_{ij}, $i \leq j$, indicates whether the SLDs δ_i and δ_j overlap in time ($\theta_{ij} = 1$) or not ($\theta_{ij} = 0$). By definition $\theta_{ii} = 1$, $1 \leq i \leq M$, and $\theta_{ij} = 0$ for $i > j$. This matrix expresses the temporal relationship between the SLDs.

$\beta = (\beta_{ij}) = diag(n_i)$
is a diagonal matrix where $\beta_{ii} = n_i, \ \ 1 \leq i \leq M$, *i.e.*, β_{ii} is the number of lightpaths required by the SLD δ_i.

$\gamma^{\pi_{\rho,\Delta}} = (\gamma_{ij}^{\pi_{\rho,\Delta}})$
is a $\{0,1\}^{L\times M}$ arc-path incidence matrix; $\gamma_{ij}^{\pi_{\rho,\Delta}}$ indicates whether arc $e_i \in E$ is part of path $P_{\rho_j,j}$ in solution $\pi_{\rho,\Delta}$ ($\gamma_{ij}^{\pi_{\rho,\Delta}} = 1$) or not ($\gamma_{ij}^{\pi_{\rho,\Delta}} = 0$). For the sake of simplicity, we note γ instead of $\gamma^{\pi_{\rho,\Delta}}$. This matrix describes the physical routing of the SLDs for a given ρ.

$\eta = \theta \cdot \beta \cdot \gamma^T = (\eta_{ij})$
is a $\mathbb{N}^{M\times L}$ matrix; η_{ij} indicates the number of time-overlapping lightpaths on link e_j between SLD δ_i and SLDs δ_k, $\forall\, k > i$.

Thus, the C_{ch} cost function is defined by:

$$C_{ch}(\pi_{\rho,\Delta}) = \sum_{j=1}^{L} \max_{1 \leq i \leq M} \eta_{ij}, \tag{5.1}$$

and the C_{cg} function is defined by:

$$C_{cg}(\pi_{\rho,\Delta}) = \max_{1 \leq j \leq N} \max_{1 \leq i \leq M} \eta_{ij}. \tag{5.2}$$

Let us consider the example of Figure 5.2 to illustrate the definition of the cost functions. The ρ vector for Solution 1 is (1 1 1), *i.e.*, the shortest path is used for each demand. Matrices θ and β are:

$$\theta = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \qquad \beta = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 2 \end{pmatrix}$$

The arc-path incidence matrix for ρ is[5]:

$$\gamma = \begin{array}{c} \\ e_{23} \\ e_{34} \\ e_{15} \\ e_{56} \\ e_{47} \\ e_{78} \end{array} \begin{array}{c} \begin{array}{ccc} P_{1,1} & P_{1,2} & P_{1,3} \end{array} \\ \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} \end{array}$$

The corresponding η matrix is[5]:

$$\eta = \theta \cdot \beta \cdot \gamma^T = \begin{array}{c} \\ \delta_1 \\ \delta_2 \\ \delta_3 \end{array} \begin{array}{c} \begin{array}{cccccc} e_{23} & e_{34} & e_{15} & e_{56} & e_{47} & e_{78} \end{array} \\ \begin{pmatrix} 2 & 5 & 0 & 0 & 5 & 2 \\ 0 & 3 & 0 & 0 & 3 & 0 \\ 0 & 0 & 2 & 2 & 0 & 0 \end{pmatrix} \end{array}$$

Finally, the costs of this solution with C_{ch} and C_{cg} are:

$$C_{ch}(\pi_{\rho,\Delta}) = \sum_{j=1}^{L} \max_{1 \leq i \leq M} \eta_{ij} = 2 + 5 + 2 + 2 + 5 + 2 = 18,$$

and

[5]Only the arcs used by at least one SLD in the solution are represented in this matrix.

$$C_{cg}(\pi_{\rho,\Delta}) = \max_{1\leq j\leq N} \max_{1\leq i\leq M} \eta_{ij} = 5.$$

The R_{ch} version of the routing problem is formulated as the following combinatorial optimization problem:

$$\textbf{Minimize:} \quad C_{ch}(\pi_{\rho,\Delta}), \tag{5.3}$$

subject to:

$$\pi_{\rho,\Delta} \in \Pi_{\Delta}, \tag{5.4}$$

that is, we search an admissible routing solution $\pi_{\rho,\Delta}$ that minimizes the number of required WDM channels for the set of demands Δ. Due to constraint (5.4), the path for an SLD δ_i has to be selected among the K paths $P_{k,i}$ precomputed for this demand. A practical advantage of using precomputed paths is that their properties (*e.g.*, geographical length, number of hops, etc.) can be under direct engineering and jurisdictional control.

The R_{cg} version of the routing problem is formulated as:

$$\textbf{Minimize:} \quad C_{cg}(\pi_{\rho,\Delta}), \tag{5.5}$$

subject to:

$$\pi_{\rho,\Delta} \in \Pi_{\Delta}, \tag{5.6}$$

that is, we search an admissible routing solution that minimizes the congestion.

5.3.2. Wavelength assignment

The solution to the routing problem is an admissible routing solution $\pi_{\rho,\Delta}$ that defines a route on the physical network for each SLD in Δ. This solution constitutes an instance of the WA problem.

The solution to the WA problem defines the wavelength assigned to each lightpath of the SLDs in Δ for the chosen $\pi_{\rho,\Delta}$ so that the number of used wavelengths is minimal and *i*) each lightpath uses the same wavelength on all the links spanned by its route (wavelength continuity constraint), and *ii*) any two time-simultaneous lightpaths whose routes have at least one link in common use different wavelengths.

The WA problem in networks with one optical fiber per link assuming the wavelength continuity constraint and the static traffic model (Section 4.1) reduces to a well known graph vertex coloring problem (described in Appendix B) [91]. We generalize this model for the WA problem using the SLD traffic model. The following notations are used:

$\psi = \gamma^T \cdot \gamma = (\psi_{ij})$
is an $\mathbb{N}^{M \times M}$ matrix; ψ_{ij} is the number of arcs on routing solution $\pi_{\rho,\Delta}$ where SLD δ_i overlaps with SLD δ_j (remember that γ is a simplified notation for $\gamma^{\pi_{\rho,\Delta}}$).

μ_i
is the set of lightpaths belonging to the SLD δ_i; μ_i^j, $1 \leq j \leq n_i$, denotes the j^{th} lightpath of SLD δ_i.

$G_c = (V_c, E_c)$
is an undirected graph where $V_c = \cup_{i=1}^{M} \{\mu_i\}$ and $E_c = \{(\mu_p^i, \mu_q^j) \mid \mu_p^i \neq \mu_q^j, \psi_{pq} > 0, \theta_{pq} = 1\}$. This graph is called the conflict graph associated to the considered WA problem instance.

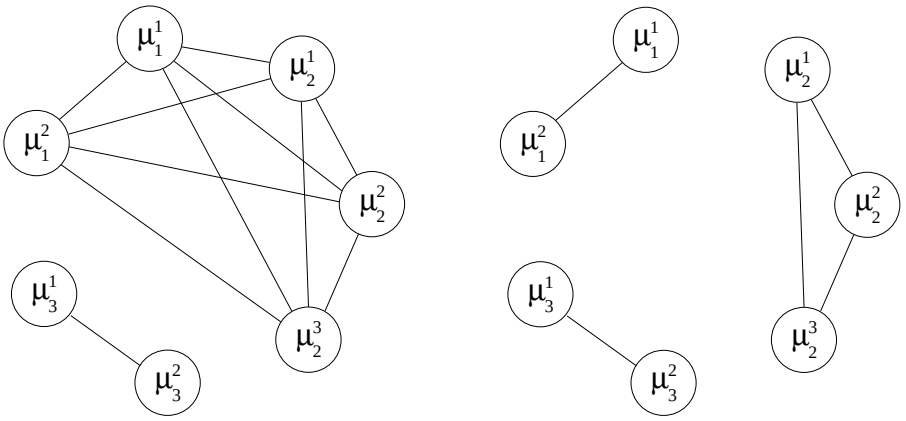
Once the graph vertex coloring problem is solved, the color associated to each vertex in G_c represents the wavelength to be assigned to the lightpath represented by this vertex.

Figure 5.3 shows the conflict graphs G_c associated to Solutions 1 and 2 of Figure 5.2. Note that in the latter there are no edges between vertices μ_1^1, μ_1^2 (lightpaths of SLD δ_1) and vertices μ_3^1, μ_3^2 (lightpaths of SLD δ_3) because the respective SLDs are time-disjoint even if they share links.

5.3.3. Characterization of problem instances

The time correlation among the SLDs in Δ has a significant incidence on the cost of a solution of an instance of the RWA problem under consideration. In fact, a set of SLDs with significant time disjointness should ease the reuse of WDM channels and, as a consequence, lead to a small number of required WDM channels or a small congestion. We characterize the sets Δ according to the time correlation among demands. In order to define this correlation, let

$$\varepsilon = (\bigcup_{i=1}^{M} \{\alpha_i\}) \cup (\bigcup_{i=1}^{M} \{\omega_i\}) \tag{5.7}$$



(a) Graph G_c associated to Solution 1.

(b) Graph G_c associated to Solution 2.

Figure 5.3.: Conflict graphs G_c associated to Solutions 1 and 2 of Figure 5.2.

be an ordered set of $T = |\varepsilon|$ values $\varepsilon_1 < \varepsilon_2 < \ldots < \varepsilon_T$ (of course, $T \leq 2M$ since some α_i and some ω_i might be the same) and

$$B_q = \{j \in \{1, \ldots, M\} \mid [\varepsilon_q, \varepsilon_{q+1}] \subseteq [\alpha_j, \omega_j]\},\ 1 \leq q \leq T-1, \tag{5.8}$$

be the set of SLD indexes j such that the SLD is active at least over time period $[\varepsilon_q, \varepsilon_{q+1}]$. Thus, the time correlation of a SLD set is given by the formula:

$$\tau(\Delta) = \frac{\displaystyle\sum_{q=1}^{T-1} \sum_{j \in B_q : |B_q| > 1} n_j(\varepsilon_{q+1} - \varepsilon_q)}{\displaystyle\sum_{i=1}^{M} n_i \cdot (\omega_i - \alpha_i)}. \tag{5.9}$$

Note that only index sets with cardinality $|B_q| > 1$ must be considered in the numerator's sum, since they correspond to time overlapping of at least 2 SLDs. A value $0 \leq \tau(\Delta) \leq 1$ close to 0 means weak time correlation and a value close to 1, strong time correlation.

We compute the time correlation of the 3 SLDs of Table 4.1 to illustrate the use of formula (5.9). The set ε is defined as $\varepsilon = \{480, 660, 780, 1120, 1360, 1170\}$ (time expressed as minutes since midnight). The sets $B_q, 1 \leq q \leq T-1, T = 6$, are:

$$B_1 = \{1\}, B_2 = \{1, 2\}, B_3 = \{1\}, B_4 = \emptyset, B_5 = \{3\}$$

and the time correlation is:

$$\tau(\Delta) = \frac{2 \cdot 120 + 3 \cdot 120}{2 \cdot 360 + 3 \cdot 120 + 2 \cdot 150} \approx 0.43478.$$

Note that only the elements of set B_2 are considered in the sum of the numerator.

5.4. Algorithms

In this section we propose algorithms to find solutions to the routing and the wavelength assignment problems formulated in Section 5.3.

5.4.1. Routing

Branch and Bound

We first describe a branch and bound (B&B) algorithm that computes optimal solutions[6] to instances of the R_{ch} or the R_{cg} version of the routing problem stated in Section 5.3.1. We only describe the B&B algorithm that solves R_{ch}. The B&B algorithm that solves R_{cg} is obtained by replacing B_{ch} and C_{ch} (see below) by B_{cg} and C_{cg}, respectively.

The solution of a problem with a B&B algorithm can be described as a search through a dynamically built enumeration tree. As its name suggests, an enumeration tree is a structure used to enumerate all the feasible solutions of the problem. The root node of the tree corresponds to the whole solution space, the remaining nodes are solution sub-spaces and the leaves are feasible solutions to the problem. The aim of the algorithm is to find a feasible solution (*i.e.*, a leaf) for which the cost is minimal[7] without *explicitly* enumerating all the solutions. A description of B&B principles can be found in [19].

In order to explain the way we adapted B&B to our problem, we first define some terms. Recall that an admissible routing solution $\pi_{\rho,\Delta}$ can be fully characterized by the vector $\rho \in \{1,\ldots,K\}^M$. Indeed, the value ρ_i $(1 \leq i \leq M, 1 \leq \rho_i \leq K)$ indicates that the i^{th} SLD is routed through the ${\rho_i}^{\text{th}}$ path between nodes s_i and d_i. Hereafter we refer to a vector ρ as a solution. Furthermore, we define an *m-solution-subspace* ρ^m, or simply an *m-subspace*, as a subspace of solutions wherein only the paths for the first m, $(m < M)$ SLDs are defined, whereas the paths of the remaining $\delta_i, m < i \leq M$ SLDs are undefined. The following example illustrates this definition. Consider a set $\Delta = \{\delta_1, \delta_2, \delta_3\}$ of $M = 3$ SLDs and $K = 2$ possible routes for each demand. The vectors (1, 1, 1), (1, 1, 2), (1, 2, 1), (1, 2, 2), ..., (2, 2, 2) represent the set Π_Δ of admissible routing solutions $\pi_{\rho,\Delta}$ for Δ. Vectors $(1, *, *)$ and $(2, *, *)$ are 1-subspaces, since only the path of the first SLD is defined (undefined paths are indicated with an asterisk). Solutions (1, 1, 1), (1, 1, 2), (1, 2, 1) and (1, 2, 2)

[6] Solutions that satisfy the optimality condition (5.3) or (5.5) of R_{ch} and R_{cg}, respectively.
[7] Maximization problems can be solved with B&B algorithms with small changes.

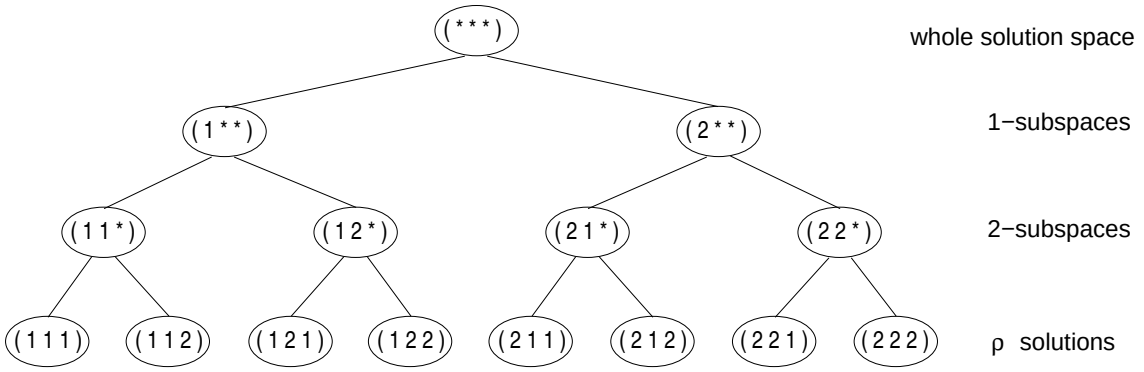


Figure 5.4.: Enumeration tree of solutions to a problem with $M = 3$ and $K = 2$. Nodes correspond to m-subspaces and leaves to solutions ρ.

belong to the $(1, *, *)$ 1-subspace. We denote this type of relationship by $\rho \in \rho^m$. We can build an *enumeration tree* of all the solutions to the routing subproblem in the following manner: the root node corresponds to the 0-subspace (*i.e.*, the whole solution space). Child nodes are derived from the root node, each child corresponding to one of the K 1-subspaces. K child nodes are in turn derived from each 1-subspace. This second level is the enumeration of all the possible 2-subspaces. Subsequent levels of child nodes are derived until the ρ solutions are enumerated (*i.e.*, we have reached the leaves of the tree). We refer to the derivation of a node as a *branching* operation. Figure 5.4 illustrates the enumeration tree for the above example. The root node corresponds to the 0-subspace $(*, *, *)$. The level 1 and level 2 nodes are the enumeration of the 1-subspaces and the 2-subspaces, respectively. Finally, the leaves of the tree correspond to the ρ solutions.

Let $\Pi_{m,\Delta}$ be the set of m-subspaces (the nodes of the m^{th} level in the enumeration tree). We define $B_{ch} : \Pi_{m,\Delta} \rightarrow \mathbb{N}$ as a *lower bound function* that determines the total number of WDM channels (as in the C_{ch} function) required by the m SLDs for which the routing is defined in a $\rho^m \in \Pi_{m,\Delta}$ m-subspace. The function is a lower bound for the number of channels required by the solutions belonging to an m-subspace, *i.e.*, $C_{ch}(\pi_{\rho,\Delta}) \geq B_{ch}(\pi_{\rho^m,\Delta}),\ \forall \rho \in \rho^m$. Furthermore, this lower bound increases as a function of m, *i.e.*, $B_{ch}(\pi_{\rho^j,\Delta}) \geq B_{ch}(\pi_{\rho^i,\Delta})$ for $j > i$ and $\rho^j \in \rho^i$.

An initial solution must be provided[8]. This solution is considered at the beginning of the algorithm as the current best or *incumbent solution* ρ^*.

The dynamically developed tree contains at the beginning the root node, which is assigned to an initially empty pool of live nodes. In each *iteration* of the B&B

[8]The $k = 1$ alternate path for all the SLDs is a candidate solution. However, as indicated later, the use of meta-heuristics to obtain an initial solution may be a better alternative for the problem under consideration.

algorithm, a node is selected from the pool using a selection strategy. Branching is then performed on the selected node to create its K children. In the case that the created nodes are leaves of the tree (*i.e.*, admissible routing solutions), their cost are compared to $C_{ch}(\pi_{\rho^*,\Delta})$, *i.e.*, to the cost of the incumbent solution. If the cost of a created solution is smaller than $C_{ch}(\pi_{\rho^*,\Delta})$, this created solution becomes ρ^*. Otherwise, if the nodes created by the branching are not leaves, the B_{ch} function is used to compute the bound associated to each of these nodes. The nodes with a bound $B_{ch}(\pi_{\rho^m,\Delta}) < C_{ch}(\pi_{\rho^*,\Delta})$ are stored in the pool of live nodes. Conversely, the nodes with a bound $B_{ch}(\pi_{\rho^m,\Delta}) \geq C_{ch}(\pi_{\rho^*,\Delta})$ are discarded since, at this point, we know that all the solutions derived from these nodes (subspaces) have a cost higher than or equal to $C_{ch}(\pi_{\rho^*,\Delta})$. The operation of discarding a node is referred to as fathoming or *bounding*. The algorithm ends when the pool of live nodes is empty. The final solution is the current value of ρ^*.

By bounding a node, the associated solution subspace is eliminated from the search. It is thus important to bound nodes as close as possible to the root node since, as such, large portions of the complete solution space are not explored. Two factors with direct incidence on the bounding efficiency are the selection of a good initial solution and the strategy used to select nodes from the pool of live nodes. A good initial solution can be obtained, for instance, with the Tabu Search meta-heuristic algorithm described below. For the selection of nodes from the pool of live nodes, several strategies such as best first search (BeFS), breadth first search (BFS) or depth first search (DFS) exist [19, 20].

The time complexity of the B&B algorithm is $O(K^M)$. Indeed, if no bounding is performed at all, the whole set of admissible routing solutions Π_Δ must be explicitly explored. This exponential complexity precludes the use of the algorithm when solving problem instances with a large number of demands.

Tabu Search

In order to solve problem instances of large size, we need to resort to heuristic or meta-heuristic algorithms. These algorithms allow approximate solutions to be found in reasonable computing time since only a fraction of the solution space is explored. Heuristic algorithms are in general computationally simpler than meta-heuristics, however, meta-heuristics compute solutions of better quality (*i.e.*, solutions whose cost is closer to the optimal one). There is in fact a trade-off between the computationally complexity of the algorithm and the quality of the computed solution.

We propose a Tabu Search (TS) meta-heuristic algorithm to find approximate solutions to the R_{ch} and R_{cg} versions of the routing problem. As for the B&B algorithm, we only describe the TS algorithm that solves R_{ch}. The TS algorithm that solves

R_{cg} is obtained by replacing C_{ch} by C_{cg}. A description of a generic TS algorithm is presented in Appendix A.

Remember from Subsection 5.3.1 that an admissible routing solution $\pi_{\rho,\Delta}$ is fully characterized by the vector ρ. The three problem-specific functions (see Section A.2) required to implement the TS algorithm for the R_{ch} problem are the following. The initial solution is created by a function that defines a vector ρ whose components are all equal to 1. The cost function is defined by function (5.1). Finally, the function used to generate a neighbor solution $\pi_{\rho',\Delta}$ from a current solution $\pi_{\rho,\Delta}$ is defined by the following algorithm:

1. Generate a pseudo-random number i, uniformly distributed in the interval $[1, M]$.

2. Generate a pseudo-random number j, uniformly distributed among the elements of the set $\{1, \ldots, K\} \backslash \{\rho_i\}$, such that the replacement of ρ_i by j is not present in the tabu list.

3. Generate a new vector ρ' by replacing ρ_i by j in ρ.

The algorithm creates a new solution from a current one $\pi_{\rho,\Delta}$ by randomly selecting a demand from Δ and randomly modifying the selected route for this demand. For example, a solution whose ρ vector is (2, $\boxed{1}$, 1, 3) can be "perturbed" according to this procedure and leads to the solution (2, $\boxed{3}$, 1, 3).

This algorithm is used to create a random sample of the current solution's neighborhood. As explained in Section A.2, computing a *random sample* of the neighborhood is an alternative to compute the complete neighborhood aimed at reducing the computational burden of evaluating the cost of the solutions in the *complete* neighborhood.

5.4.2. Wavelength Assignment

In order to solve the graph vertex coloring problem on the conflict graph G_c, we used the greedy algorithm described in [57], which computes approximate solutions. We selected this algorithm because of its ability to compute solutions of good quality in a relatively short computing time (according to the authors' empirical comparison with other algorithms).

5.4.3. An (alternative) sequential RWA algorithm

The algorithms proposed in this section are based on a combinatorial optimization approach wherein all the demands are simultaneously considered, so that the time

disjointness among them is globally exploited. An alternative to solve the same RWA problem is to use a sequential algorithm that computes the routing and wavelength assignment sequentially, that is, demand by demand. In a sequential algorithm, the path and wavelength(s) assigned to a particular demand depend on the state of the network at the moment the routing and wavelength assignment decision is taken. Moreover, a sequential algorithm is myopic in the sense that what may seem a good decision for a given demand may have a negative impact on the global cost. However, sequential algorithms are in general computationally simpler than combinatorial optimization based algorithms. We present a simple sequential RWA algorithm called sRWA that we use in Section 5.5 as a reference to evaluate the performance of the algorithms of Subsections 5.4.1 and 5.4.2.

The sRWA algorithm works in two phases. In the first one, the SLDs in Δ are sorted by descending order of weights $w_i = n_i \cdot h_{*,i}$, where n_i is the number of lightpaths of SLD δ_i and $h_{*,i}$ is the number of hops in the longest path $P_{*,i}$ (in terms of hops) for this SLD. The reason for processing the SLDs with the longest path and the largest number of lightpaths first is explained in [17]. Intuitively, demands with long paths and large size are harder to establish than demands with short paths and small size because more unallocated wavelengths must be found on more links. In the second phase, the path and the wavelength(s) are computed for each demand, one by one, according to the order defined in the first step. We use fixed-alternate routing and First Fit (FF) wavelength assignment [91]. In fixed-alternate routing, k alternate paths are computed in advance for each source/destination pair in the network (in the sRWA algorithm proposed here, the paths are not necessarily link-disjoint). When a demand from s to d is processed, the k paths between s and d are ranked according to the value computed by the FF algorithm for each path (see below) and the path with the lowest value is selected. If more than one path have the same lowest value, the physically shortest path is selected. In FF wavelength assignment, the WDM channels in a link are sorted by ascending order of characteristic wavelength (*e.g.*, $\lambda_{1550.0nm} < \lambda_{1550.1nm} < \lambda_{1550.2nm} \ldots$). When searching for an available WDM channel in the links a path, a lower-numbered WDM channel is considered before a higher-numbered one. A WDM channel is available in a path if it has not been previously assigned to a lightpath that is time-overlapping with the lightpath currently being processed.

5.5. Experimental results

In this section we experimentally evaluate the algorithms proposed in the previous sections. We use the following acronyms to refer to these algorithms:

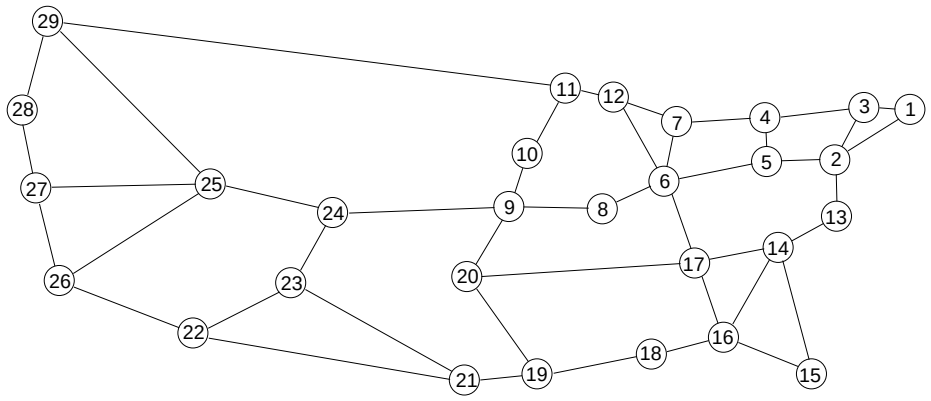


Figure 5.5.: Graph G representing the physical network.

B&B$_{ch}$. The B&B routing algorithm for WDM channel minimization (§ 5.4.1),

TS$_{ch}$. The TS routing algorithm for WDM channel minimization (§ 5.4.1),

TS$_{cg}$. The TS routing algorithm for congestion minimization (§ 5.4.1),

GGC. The greedy vertex coloring algorithm (§ 5.4.2) and

sRWA. The alternative sequential RWA algorithm (§ 5.4.3).

We implemented the B&B algorithm using a library of parallel search algorithms called ZRAM [68]. The use of the library allowed individual problem instances to be solved on a cluster of 40 Sun Ultra-SPARC 5 computers with 128 MB of RAM each, running the Solaris 5.8 operating system. The library was particularly useful when dealing with problem instances with more than 10^{18} potential solutions ($M = 30$, $K = 4$).

The TS algorithm was implemented in C. We used the pseudo-random number generator (PRNG) proposed in [56] to implement the neighbor-generating procedure. For the GGC algorithm, we used an implementation in C provided by the authors. The sRWA algorithm was implemented in Perl. These three programs were executed on a Sun Fire 280R computer with 1 GB of RAM running the Solaris 5.8 operating system.

Figure 5.5 shows a graph G representing the physical network used in the problem instances (G, Δ) considered in this section. The network corresponds to a hypothetical US backbone network of 29 nodes and 44 spans. A weight, representing the physical length, is associated to each edge of the graph (weights not shown in the figure).

We considered two classes of sets Δ: a class S_w of sets Δ with weak time correlation, $\tau(\Delta) \approx 0.01$, and a class S_s of sets Δ with strong time correlation, $\tau(\Delta) \approx 0.8$.

Table 5.1.: Quality loss for different values of K.

Class	Quality loss (%) (Avg | Max | Std Dev)								
	$K = 2$			$K = 3$			$K = 4$		
S_w	0.70	3.98	0.98	0.59	8.14	1.61	1.13	12.88	2.02
S_s	0.52	4.90	1.02	0.35	6.58	1.04	0.56	10.08	1.55

The source and destination nodes, the number of lightpaths and set-up and tear-down dates of the SLDs were drawn from random uniform distributions in the intervals $[\![1, 29]\!]$, $[\![1, 10]\!]$ and $[1, 1440]$, respectively (1440 is the number of minutes in a day). The set-up and tear-down dates of the SLDs in a set Δ were constrained to satisfy the target time correlation of the class the set Δ belongs to.

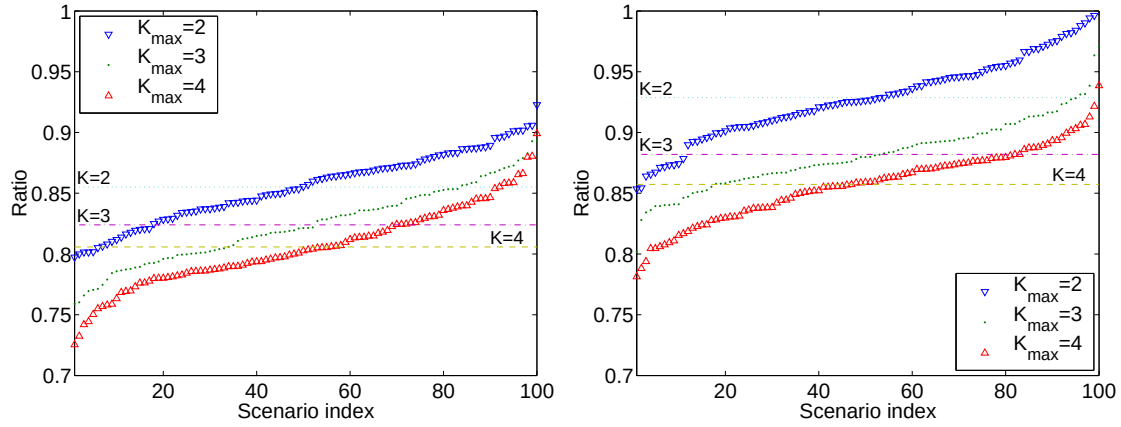
5.5.1. Quality of (approximate) TS routing solutions

Since the approximate solutions computed with TS are not guaranteed to be optimal, we first need to assess the quality of these approximate solutions with respect to the optimal solutions computed with B&B. We use the B&B$_{ch}$ and TS$_{ch}$ algorithms for this comparison (WDM channel minimization). For a given problem instance (G, Δ), we want to know the quality loss $\frac{C_{ch}(\pi_{\rho_{TS},\Delta}) - C_{ch}(\pi_{\rho_{BB},\Delta})}{C_{ch}(\pi_{\rho_{BB},\Delta})} \cdot 100$, of the cost $C_{ch}(\pi_{\rho_{TS},\Delta})$ computed with TS$_{ch}$ with respect to the cost $C_{ch}(\pi_{\rho_{BB},\Delta})$ computed with B&B$_{ch}$.

We generated 60 sets Δ of each class (S_w and S_s) with $M = 30$ SLDs each. For the TS$_{ch}$ algorithm we used the following parameters' values: 3000 iterations, a neighborhood of 200 solutions and a tabu list of 400 elements. The parameters' values were defined empirically. Additionally, we implemented a diversification function (see Section A.2) to avoid being trapped in local minima. The function modifies the current solution by applying multiple times the neighbor generating function to the same solution if no cost improvement has been obtained after a large number of iterations. The search effort is thus shifted from one region of the solution space to another. Table 5.1 shows the average, maximum and standard deviation, over the 60 sets Δ, of the quality loss for each class using these parameters. Quality loss increases with K because the size of the solution space grows while the number of iterations of TS$_{ch}$ remains constant, which means than a smaller fraction of the solution space is explored. Note however that the average quality loss is small even if the maximum quality loss becomes as high as 12.88%. These results show that the cost of solutions computed by TS is close to the optimal one, at least when the comparison is possible.

Table 5.2.: Comparison of the average number of WDM channels (routing metric) computed with sRWA and TS_{ch}.

Class	sRWA	TS_{ch}			Gain of TS_{ch} *vs.* sRWA		
		$K = 2$	$K = 3$	$K = 4$	$K = 2$	$K = 3$	$K = 4$
S_w	606.34	518.11	497.51	485.93	14.55 %	17.94 %	19.85 %
S_s	678.17	628.53	597.98	581.63	7.31 %	11.82 %	14.23 %



(a) Weak time correlation (S_w). (b) Strong time correlation (S_s).

Figure 5.6.: Ratio of the number of WDM channels computed by TS_{ch} to the number of WDM channels computed by sRWA (small values are better).

5.5.2. Gain with respect to sequential algorithm

We want to asses the gain obtained with the combinatorial optimization based algorithms when compared to sRWA. We generated 100 sets Δ of each class (S_w and S_s) with $M = 500$ SLDs each. We first evaluate the gain in terms of WDM channels (routing metric) obtained by TS_{ch} with respect to sRWA. We considered $k = 10$ paths for the sRWA algorithm.

Table 5.2 shows the average number of WDM channels computed by sRWA and TS_{ch} using different values of K for classes S_w (weak time correlation) and S_s (strong time correlation). The table also shows the gain of TS_{ch} with respect to sRWA. The gain increases with K (regardless the class) because the size of the solution space increases with K. As a consequence, TS_{ch} has a larger solution space to explore. Finally, the gain is higher for class S_w than for class S_s because the greater potential of channel reuse in S_w is better exploited by TS_{ch} than by sRWA.

Figure 5.6 shows the ratio of the number of WDM channels computed by TS_{ch}

Table 5.3.: Comparison of the average number of wavelengths (wavelength assignment metric) computed with sRWA and TS_{cg}/GGC.

Class	sRWA	TS_{cg}/GGC			Gain of TS_{cg}/GGC *vs.* sRWA		
		$K=2$	$K=3$	$K=4$	$K=2$	$K=3$	$K=4$
S_w	12.52	9.49	9.49	9.41	24.20 %	24.20 %	24.84 %
S_s	16.08	11.65	11.16	11.23	27.54 %	30.59 %	30.16 %

($K = 2, 3, 4$) to the number of WDM channels computed by sRWA for the 100 sets Δ of each class. Clearly, the smaller the ratio value, the greater the gain. The ratio value is smaller for sets Δ of class S_w than for than for sets Δ of class S_s, which is consistent with the results of Table 5.2.

We now evaluate the gain in terms of wavelengths (wavelength assignment metric) obtained with the combination of algorithms TS_{cg}/GGC with respect to sRWA. Note that we use TS_{cg} instead of TS_{ch} because the former aims at minimizing the congestion, which sets a lower bound on the number of required wavelengths.

Table 5.3 shows for each class the average number of wavelengths computed by sRWA, and by GGC on the routing solutions obtained with TS_{cg} using different values of K. The average number of wavelengths is smaller in the weak time correlation class S_w (regardless the algorithm). Indeed, the greater time disjointness of SLDs in the S_w class allows for a better "time reuse" of wavelengths. Note however that the gain in this class is smaller than in S_s. A point worth noting is that in all cases we require on average less than 16.08 wavelengths to satisfy $M = 500$ SLDs, that is, the number of required wavelengths is significantly smaller than the number of demands even under the stringent conditions considered in this chapter (*i.e.*, routing and wavelength assignment problems addressed separately, no information exchange mechanism and wavelength continuity constraint holding). Moreover, the required number of wavelengths is compatible with the number of wavelengths typically assumed in WDM optical transport networks (16 or 32).

The combined execution time of TS_{cg} and GGC was of 6480 seconds in average (200 problem instances). The execution time of sRWA was of 20 seconds on average. The gain, both in WDM channels and wavelengths, makes the execution time increase worthwhile, in particular, in opaque networks, where the WDM channels are very expensive because of the required transponders. It must be said that the algorithms are not expected to be run in a real-time environment (as would be the case for sRWA) but as batch processes at time intervals of several hours (remember that the SLDs correspond to planned demands).

5.6. Conclusions

In this chapter we investigated the problem of routing and wavelength assignment for SLDs in a wavelength-switching network. Routing and wavelength assignment were addressed as separate problems and formulated as combinatorial optimization problems. A Branch & Bound and a Tabu Search algorithm were proposed to compute exact and approximate solutions, respectively, to instances of the routing problem. For the wavelength assignment problem, an existing greedy graph vertex coloring algorithm was used. For comparisons purposes, we proposed an alternative sequential RWA algorithm for SLDs based on alternate fixed routing and first fit wavelength assignment.

We evaluated the quality of approximate solutions computed by the Tabu Search algorithms with respect to the optimal solutions computed with Branch & Bound when the comparison is possible. Although the maximum quality loss was of 12.88%, the worst average quality loss was as low as 1.13%. We also evaluated the gain provided by the Tabu Search algorithms with respect to the sequential RWA algorithm. The gain is greater in sets Δ with weak time correlation than in sets Δ with strong time correlation—) because there is more time disjointness among SLDs that can be exploited by the algorithm. Regarding the wavelength assignment problem, the number of required wavelengths was in general relatively small with respect to the number of SLDs and compatible with the number of wavelengths typically assumed in WDM optical transport networks. The greater computing time of the proposed combinatorial optimization algorithms is worthwhile given the provided gain and the high cost of transponders (in the case of opaque networks).

In order to make the problem more realistic, simplification assumptions 2, 3 and 4 cited in Section 5.1 could be eliminated by introducing additional constraints in the problems' formulations. In particular, a capacitated version of the problem could be investigated by introducing link capacity constraints. A capacitated version is more realistic in a network engineering context, where it is typically assumed that equipment is already installed. Moreover, in a capacitated version, the optimality criterion would be the minimization of the blocking probability (or the maximization of throughput), instead of the minimization of WDM channels or congestion considered here.

6. Diverse routing and spare capacity assignment for SLDs in a wavelength-switching network

6.1. Introduction

Survivability is a critical aspect of transport networks because of the inherent vulnerability of wire-based transmission systems and because of the increasing reliance of society on telecommunications services. Network survivability mechanisms may be classified into two main categories: restoration and protection. The former includes methods that compute backup paths and allocate spare resources *a posteriori* for working traffic affected by a network failure. These methods are potentially efficient in terms of network resource utilization since spare resources are allocated only in case of a network failure. However, it is usually difficult to guarantee *bounded* restoration times with them. On the other hand, protection mechanisms compute backup paths and allocate spare resources *a priori*, which is essential for rapid reconfiguration and, ultimately, to assure bounded restoration times. Protection is in general suitable for transport networks, where this type of guarantees is mandatory.

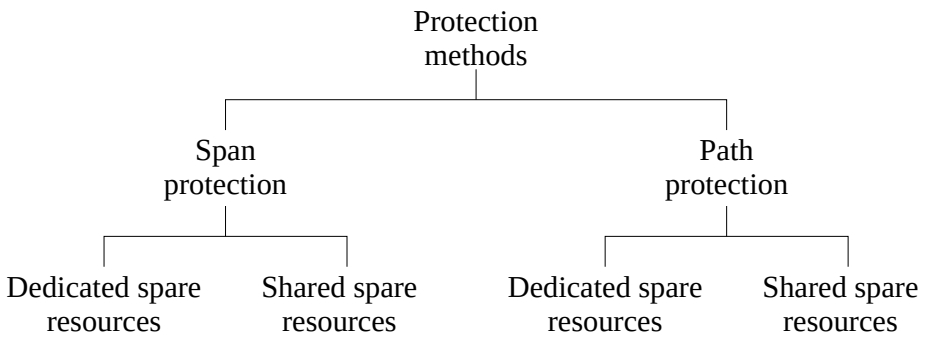


Figure 6.1.: Classification of protection methods.

Figure 6.1 shows the different types of protection methods. Span protection methods provide a replacement to a failing span[1] by allocating resources on a path connecting the endpoints of this span. Path protection methods provide replacements to connections (instead of spans) affected by a failure by allocating resources on paths defined between the endpoints of the affected connections. Spare resources can be either dedicated to the protection of a span or connection, or shared among multiple spans or connections. Dedicated spare resource protection methods are computationally simpler than shared protection, but less efficient in terms of resource utilization, which depends on the extent to which spare resources can be shared. In this chapter we investigate the problem of defining span-disjoint working and protection paths for SLDs and assigning shared spare resources using path protection. The resources assigned to connections are WDM channels (defined in Table 2.3).

The next section describes the channel reuse and the backup-multiplexing techniques used to share WDM channels and two versions of the SLD Diverse Routing and Spare Capacity Assignment problem (SLD DRSCA): SLD DRSCA without backup-multiplexing (SLD DRSCA$_{\mathrm{A}}$) and SLD DRSCA with backup-multiplexing (SLD DRSCA$_{\mathrm{B}}$). Section 6.3 presents previous work found in the literature about the DRSCA problem in general. Section 6.4 describes the mathematical formalization of both versions as combinatorial optimization problems. Section 6.5 describes the problem-specific functions needed to implement a Simulated Annealing (SA) metaheuristic algorithm that computes approximate solutions to the problem. Section 6.6 presents the experimental evaluation of the proposed algorithm and Section 6.7 concluding remarks on this work as well as propositions for future work.

6.2. Description of the problem

In informal terms, the SLD DRSCA problem is the following: given a network and a set of SLDs, define for each SLD a pair of span-disjoint paths to be used as working and protection paths, such that the number of WDM channels (both working and spare) required to instantiate the SLDs is minimized. The number of WDM channels is minimized by sharing them among multiple lightpaths using the channel reuse and backup-multiplexing techniques described below. Figure 6.2 represents schematically the problem under consideration. Note that the problem of assigning wavelengths to lightpaths is *not* considered. Thus, in a solution to an instance of the problem, we know that a WDM channel is shared among certain lightpaths, but we do not know the characteristic wavelength of this WDM channel.

A first technique that may be used to reduce the number of working WDM chan-

[1]The term span is defined in Table 2.3.

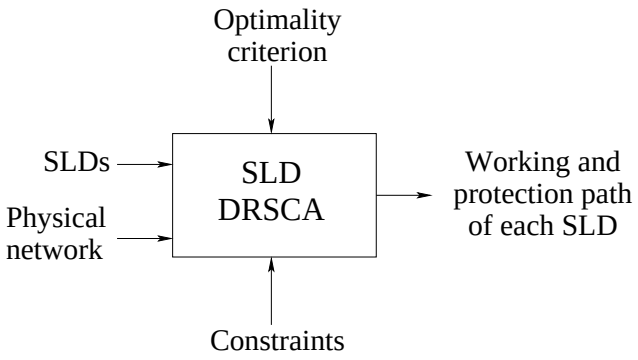


Figure 6.2.: Schematic representation of the SLD DRSCA problem.

nels consists of assigning a same WDM channel to as many lightpaths as possible, provided that these lightpaths are not simultaneous in time. The technique, called *channel reuse*, is illustrated in the example of Figure 5.2. The figure shows how two different sets of working paths for the three SLDs of Table 4.1 lead to different amounts of required working WDM channels depending on whether channel reuse is exploited or not.

Channel reuse may be also used to reduce the number of spare WDM channels required for restoration in case of failure. However, a more resource-efficient technique called *backup-multiplexing* can be used for spare WDM channels. In this technique, a same spare WDM channel may serve to protect multiple lightpaths provided that two conditions do *not* hold simultaneously: the involved lightpaths are simultaneous in time and their working paths have at least one span in common. The point is illustrated in Figure 6.3: spare WDM channels can be shared for protection using backup-multiplexing in cases 1, 2 and 3; with mere channel reuse, the channels may be shared only in cases 1 and 3. Backup-multiplexing is basically a form of channel reuse but, as we will see in Section 6.6, it is more resource-efficient than mere channel reuse. Backup-multiplexing is inspired on an idea originally described in [54]. Figure 6.4 shows the number of spare WDM channels required in the links of a network for two combinations of working paths when channel reuse and backup-multiplexing are used. Depending on whether backup-multiplexing is used or not for spare WDM channels, we have two versions of the SLD DRSCA problem: SLD DRSCA_B and SLD DRSCA_A, respectively. Note that a channel may serve either as a working channel or as a spare channel, but not as both.

In the SLD DRSCA problems under consideration we assume that the network has an arbitrary connex topology and that the number of WDM channels on a link is unlimited (this assumption eases the design of the algorithms proposed in Section 6.5). Additionally, we assume that full wavelength conversion exists in all the network

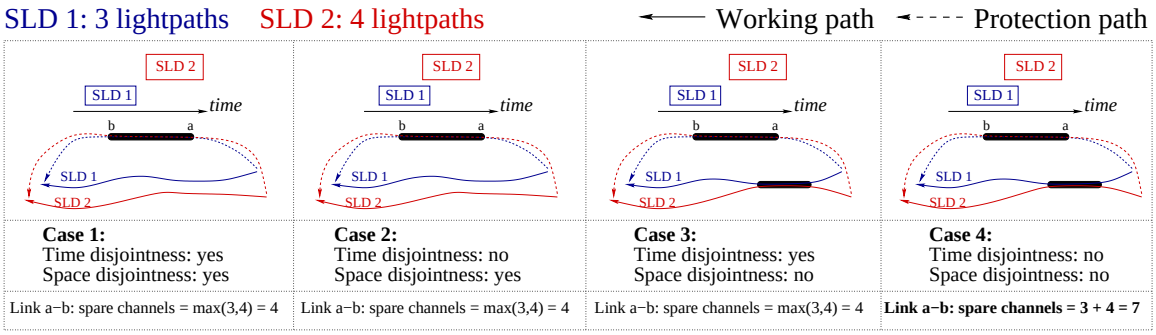


Figure 6.3.: The four cases of time and space disjointness between demands. Backup-multiplexing is possible in cases 1, 2 and 3. Mere channel reuse is possible only in cases 1 and 3.

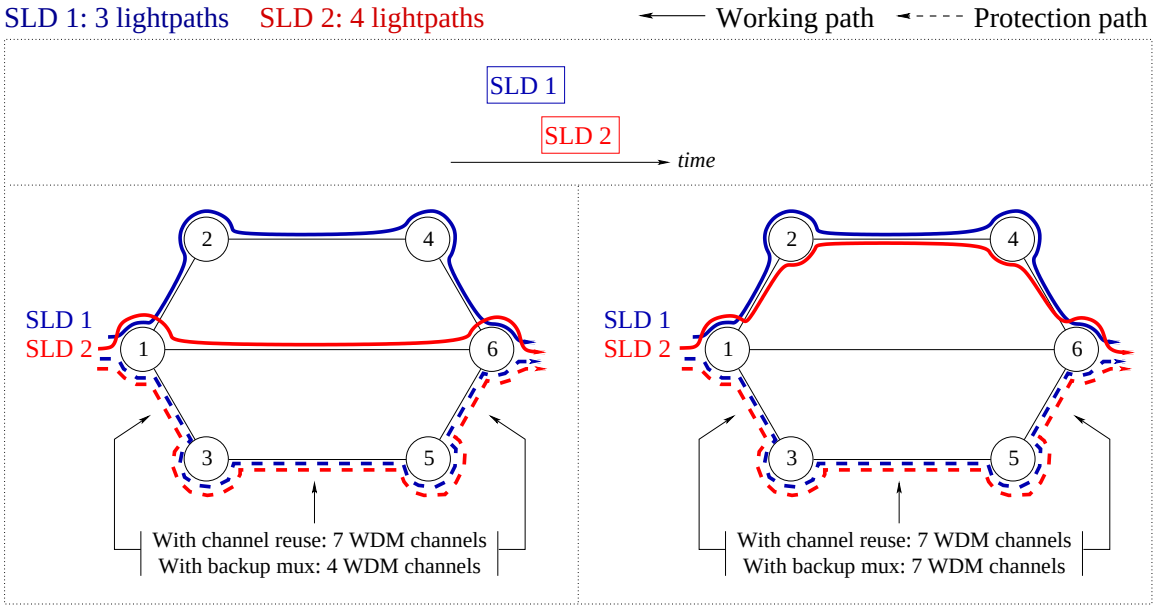


Figure 6.4.: Example of mere channel reuse and backup-multiplexing of spare WDM channels.

nodes so that in a given link, any available WDM channel (whatever its characteristic wavelength) can be assigned to a lightpath routed through this link. With this simplification assumption we avoid addressing the wavelength assignment problem.

6.3. Related work

The SLD DRSCA problem belongs to the general class of Routing and Spare Capacity Assignment (RSCA) problems in connection-oriented networks. Span- and path-protection RSCA methods have been developed for SDH/SONET, ATM [39, 54, 74, 89] and WDM networks [29, 81, 72, 12, 92] in the context of network planning problems. Specific aspects such as the effect of equipment capacity modularity [23] and network topology [38] on the spare capacity assignment, hybrid mesh-ring networks [40] and comparisons with spare capacity assignment methods in a client IP network [84] have been investigated.

The problem of dimensioning the "reserve" network for static traffic, that is, dimensioning the spare capacity on the links, has been formulated as a network synthesis problem with non-simultaneous single- or multi-commodity flow requirements (described in Section 5.2) [70, 65]. If span-protection is used, each span failure may be seen as a new single-commodity flow requirement with a value equal to the total flow originally routed on the span. If path-protection is used, each demand affected by a span failure is rerouted from its origin to its destination, resulting in a multi-commodity flow requirement. Thus, the network synthesis problem with non-simultaneous single- or multi-commodity flow requirements has been used to represent either the multi-hour wide-area network planning problem or the "reserve" network dimensioning problem but not both problems together.

6.4. Mathematical model

We first present the notations used to formally define the SLD DRSCA_A and SLD DRSCA_B problems as combinatorial optimization problems.

$G = (V, E, w)$
is an arc-weighted symmetrical directed graph with vertex set $V = \{v_1, v_2, \ldots, v_N\}$, arc set $E = \{e_1, e_2, \ldots, e_L\}$ and weight function $w : E \to \mathbb{R}_+$. The graph represents a physical telecommunications network. The set V corresponds to the network nodes, the set of arcs E to the links interconnecting the nodes (see terminology of Table 2.3) and the function w to the physical length or to the cost of the spans (*e.g.*, defined by the network operator).

$U = \{(e, e') \mid e, e' \in E, s(e) = d(e'), d(e) = s(e')\}$
is the set of spans in the network. A span is represented by a pair of arcs $e, e' \in E$ such that the source of one of the arcs is the destination of the other and *vice versa*.

$N = |V|$, $L = |E|, S = |U| = L/2$
are, respectively, the number of vertices, arcs and spans in G. Note that there are exactly $L/2$ spans in U because the graph is symmetrical.

$\Delta = \{\delta_1, \delta_2, \ldots, \delta_M\}$
is the set of M SLDs, where:

$\delta_i = (s_i,\ d_i,\ n_i,\ \alpha_i,\ \omega_i)$
is a tuple representing the SLD number i; $s_i, d_i \in V$ are the source and destination nodes of the demand, n_i is the number of requested lightpaths, and α_i and ω_i are the set-up and tear-down dates of the demand, respectively.

(G, Δ)
is a pair representing an instance of the SLD DRSCA problem.

$P = \{(x_0, x_1), (x_1, x_2), \ldots, (x_{z-1}, x_z)\}$
is an ordered set of z arcs representing a *path* from x_0 to x_z. The $(x_{i-1}, x_i) \in E$ arcs of P are all distinct (the paths are loop-free).

$P_{k,i}$, $1 \leq k \leq K$, $1 \leq i \leq M$
represents the k^{th} alternate *working path* in G from s_i to d_i. For the purposes of this work, we compute the K physically shortest paths for each demand using the algorithm defined in [27]. However, the paths might be defined according to any other criterion.

$P'_{k,i}$, $1 \leq k \leq K$, $1 \leq i \leq M$
represents the k^{th} alternate *backup path* in G from s_i to d_i. The pair $(P_{k,i}, P'_{k,i})$ represents the k^{th} couple of arc-disjoint paths between s_i and d_i. Two paths P_{k_a,i_a} and P'_{k_b,i_b} must be arc-disjoint only if $(k_a, i_a) = (k_b, i_b)$. In this work, $P'_{k,i}$ is the k^{th} path computed with the algorithm defined in [27] on the graph $G' = (V, E')$, where $E' = E \backslash P_{k,i}$.

$\pi^a_{\rho,\Delta} = (P_{\rho_1,1}\ P_{\rho_2,2}\ \ldots\ P_{\rho_M,M})$, $\rho \in \{1,\ldots,K\}^M$
is called an *admissible routing solution* for Δ. ρ is an M-dimensional vector whose elements can take values in $[\![1,K]\!]$. All the lightpaths of an SLD are routed through the same path (*i.e.*, no bifurcated routing is used). An admissible routing solution is fully characterized by ρ.

$\pi^b_{\rho,\Delta} = (P'_{\rho_1,1}\ P'_{\rho_2,2}\ \ldots\ P'_{\rho_M,M})$, $\rho \in \{1,\ldots,K\}^M$
is called the *backup solution* associated to $\pi^a_{\rho,\Delta}$. An admissible routing solution has only one associated backup solution.

$\Pi_\Delta = \left\{(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta}), \rho \in \{1,\ldots,K\}^M\right\}$
is the set of solution pairs $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$ for Δ. There are $|\Pi_\Delta| = K^M$ solution pairs in the set (assuming that the K couples of arc-disjoint paths exist for each SLD; otherwise, $|\Pi_\Delta| < K^M$). Hereafter we use the generic term *solution* to refer to either an admissible routing solution $\pi^a_{\rho,\Delta}$ or a backup solution $\pi^b_{\rho,\Delta}$. We denote this solution by $\pi_{\rho,\Delta}$.

$C : \Pi_\Delta \to \mathbb{N}$
is the cost function that computes the number of required WDM channels for a given solution $\pi_{\rho,\Delta}$. If $\pi_{\rho,\Delta}$ represents an admissible routing solution, C computes the number of required working WDM channels. If $\pi_{\rho,\Delta}$ represents a backup solution, C computes the number of required spare WDM channels when backup-multiplexing is *not* used. To formalize the function C, we define the following additional notations:

$\theta = (\theta_{ij})$
is a $\{0,1\}^{M\times M}$ upper triangular matrix; θ_{ij}, $i \leq j$, indicates whether the SLDs δ_i and δ_j overlap in time ($\theta_{ij} = 1$) or not ($\theta_{ij} = 0$). By definition $\theta_{ii} = 1$, $1 \leq i \leq M$, and $\theta_{ij} = 0$ for $i > j$. This matrix expresses the temporal relationship between the SLDs.

$\beta = (\beta_{ij}) = diag(n_i)$
is a diagonal matrix where $\beta_{ii} = n_i$, $1 \leq i \leq M$, *i.e.*, β_{ii} is the number of lightpaths required by the SLD δ_i.

$\gamma^{\pi_{\rho,\Delta}} = (\gamma_{ij}^{\pi_{\rho,\Delta}})$
is a $\{0,1\}^{L\times M}$ arc-path incidence matrix; $\gamma_{ij}^{\pi_{\rho,\Delta}}$ indicates whether arc $i \in E$ is part of path $P_{\rho_j,j}$ in solution $\pi_{\rho,\Delta}$ ($\gamma_{ij}^{\pi_{\rho,\Delta}} = 1$) or not ($\gamma_{ij}^{\pi_{\rho,\Delta}} = 0$). For the sake of simplicity, we note γ instead of $\gamma^{\pi_{\rho,\Delta}}$. This matrix describes the physical routing of the SLDs for a given solution $\pi_{\rho,\Delta}$.

$\eta = \theta \cdot \beta \cdot \gamma^T = (\eta_{ij})$
is a $\mathbb{N}^{M \times L}$ matrix; η_{ij} indicates the number of time-overlapping lightpaths on arc e_j between SLD δ_i and SLDs δ_k, $\forall\, k > i$ for a given solution $\pi_{\rho,\Delta}$.

Thus, the cost function C is defined as:

$$C(\pi_{\rho,\Delta}) = \sum_{j=1}^{L} \max_{1 \le i \le M} \eta_{ij}. \tag{6.1}$$

6.4.1. The SLD DRSCA$_{\mathsf{A}}$ problem

When backup-multiplexing is not allowed, we can use function C to compute both the number of working WDM channels in an admissible solution $\pi^a_{\rho,\Delta}$ and the number of spare WDM channels in its associated backup solution $\pi^b_{\rho,\Delta}$. Thus, the cost of a given solution pair $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$ is:

$$C(\pi^a_{\rho,\Delta}) + C(\pi^b_{\rho,\Delta}). \tag{6.2}$$

The SLD DRSCA$_{\mathrm{A}}$ problem is formally defined by the following combinatorial optimization problem:

$$\textbf{Minimize:} \quad C(\pi^a_{\rho,\Delta}) + C(\pi^b_{\rho,\Delta}), \tag{6.3}$$

subject to:

$$(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta}) \in \Pi_\Delta, \tag{6.4}$$

that is, we search a solution pair $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$ in Π_Δ that minimizes the number of required working and spare WDM channels for the set of demands Δ. As in the problem of Chapter 5, due to constraint (6.4), the working/backup couple of paths for a demand δ_i has to be selected among the K couples of paths $(P_{k,i}, P'_{k,i})$ precomputed for this demand. A practical advantage of using precomputed paths is that their properties (*e.g.*, geographical length, number of hops, etc.) can be under direct engineering and jurisdictional control.

6.4.2. The SLD DRSCA$_{\mathsf{B}}$ problem

We need to define additional notations to describe the SLD DRSCA$_{\mathrm{B}}$ problem.

$B : \Pi_\Delta \to \mathbb{N}$
is the cost function that computes the number of spare WDM channels required for backup solution $\pi^b_{\rho,\Delta}$ when backup-multiplexing is used. The following notations are necessary to describe this function:

$\Delta_e^{\pi^b_{\rho,\Delta}} = \{\delta_i \mid e \in P'_{\rho_i,i}\}$
is the subset of SLDs, $\Delta_e^{\pi^b_{\rho,\Delta}} \subseteq \Delta$, whose backup path contains the arc $e \in E$ in backup solution $\pi^b_{\rho,\Delta}$. For the sake of simplicity, we note Δ_e instead of $\Delta_e^{\pi^b_{\rho,\Delta}}$.

$\Gamma^{\pi^a_{\rho,\Delta}} = (\Gamma_{ij}^{\pi^a_{\rho,\Delta}})$
is a $\{0,1\}^{S\times M}$ span-path incidence matrix similar to $\gamma^{\pi_{\rho,\Delta}}$. $\Gamma_{ij}^{\pi^a_{\rho,\Delta}}$ indicates whether at least one of the arcs of span $i \in U$ is part of path $P_{\rho_j,j}$ ($\Gamma_{ij}^{\pi^a_{\rho,\Delta}} = 1$) or not ($\Gamma_{ij}^{\pi^a_{\rho,\Delta}} = 0$) in admissible routing solution $\pi^a_{\rho,\Delta}$. As for γ, we note Γ instead of $\Gamma^{\pi^a_{\rho,\Delta}}$.

$\phi = \Gamma^T \cdot \Gamma = (\phi_{ij})$
is an $\mathbb{N}^{M\times M}$ matrix; ϕ_{ij} is the number of spans in admissible routing solution $\pi^a_{\rho,\Delta}$ where SLD δ_i overlaps with SLD δ_j.

$G_e = (\Delta_e, E_e)$
is a *conflict graph* associated to arc $e \in E$ for solution pair $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$. Each vertex of G_e represents an SLD in Δ_e. The edge set is defined as $E_e = \{(\delta_i, \delta_j) \mid \delta_i, \delta_j \in \Delta_e, \theta_{ij} = 1, \phi_{ij} > 0\}$, that is, there is an edge between two vertices if the respective SLDs overlap in time ($\theta_{ij} = 1$) and the working paths of these SLDs in solution $\pi^a_{\rho,\Delta}$ have at least one common span ($\phi_{ij} > 0$). For example, the graph G_e for arc $e = (1, 3)$ of the network on the left-side of Figure 6.4 is defined by the set $\Delta_e = \{\delta_1, \delta_2\}$ and the set $E_e = \emptyset$. The set E_e is empty because the working paths of the respective SLDs do not share spans. The graph G_e for the same arc on the network of the right-side is defined by the same set Δ_e and by the edge set $E_e = \{(\delta_1, \delta_2)\}$. The idea of using a conflict graph that integrates the time correlation among demands as part of the "conflict" between demands was initially used in Chapter 5 to solve the Wavelength Assignment problem.

$\mathcal{A}$
is a deterministic algorithm that finds a *proper coloring* for G_e. A proper coloring of a graph $G = (V, E)$ is a partition of V such that any two vertices of a same class are not connected by an edge. For the purposes of this work, we use a polynomial-time

sequential algorithm called Largest-First First-Fit (LFFF)[2]. The algorithm computes a proper coloring with a number of colors $\chi'(G)$ that approximates the chromatic number[3] $\chi(G)$: $\chi'(G) \geq \chi(G)$. Finding a proper coloring with exactly $\chi(G)$ colors in an NP-complete problem.

$\Delta_{e,i}, \quad 1 \leq i \leq \chi'(G_e)$
is the subset $\Delta_{e,i} \subseteq \Delta_e$ of SLDs whose vertices in G_e have been colored with color i using $\mathcal{A}$.

The cost function B is defined as:

$$B((\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})) = \sum_{e \in E} \kappa(G_e), \tag{6.5}$$

where,

$$\kappa(G_e) = \sum_{i=1}^{\chi'(G_e)} \max_{\delta_j \in \Delta_{e,i}} n_j \tag{6.6}$$

is the cost of G_e when colored with $\mathcal{A}$. In fact, $\kappa(G_e)$ corresponds to the number of spare channels required on arc e for a given backup solution $\pi^b_{\rho,\Delta}$ when backup-multiplexing is used.

The cost of a given solution pair $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$ when backup-multiplexing is used is given by:

$$C(\pi^a_{\rho,\Delta}) + B((\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})). \tag{6.7}$$

Thus, the SLD DRSCA$_{\mathrm{B}}$ problem is formally defined by the following combinatorial optimization problem:

$$\textbf{Minimize:} \quad C(\pi^a_{\rho,\Delta}) + B((\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})), \tag{6.8}$$

subject to:

$$(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta}) \in \Pi_\Delta. \tag{6.9}$$

Ideally, we would like $\mathcal{A}$ to minimize $\kappa(G_e)$. On the other hand, the LFFF algorithm aims at minimizing $\chi'(G_e)$. Though these two objectives are not necessarily equivalent, we selected the LFFF algorithm because of practical reasons. The

[2]The choice of this algorithm is justified at the end of this subsection
[3]See Appendix B.

Simulated Annealing (SA) algorithm described in the next section evaluates tens of thousands of different solution pairs $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$. When solving the SLD DRSCA$_\mathrm{B}$ problem, a conflict graph G_e must be built and colored for each arc $e \in E$ of a backup solution $\pi^b_{\rho,\Delta}$. Consequently, algorithm $\mathcal{A}$ must have a low time complexity (which is the case of LFFF) in order to the SA algorithm to be usable on problem instances of large size.

6.5. Simulated Annealing algorithm

A possibility to solve the SLD DRSCA$_\mathrm{A}$ and SLD DRSCA$_\mathrm{B}$ problems is to use a Branch & Bound (B&B) algorithm similar to the one proposed in Chapter 5 to solve the SLD routing problem. However, the exponential time complexity of the algorithm renders it inapplicable when tackling problem instances of large size. Another possibility consists of using a meta-heuristic algorithm, such as TS. In this section we propose a Simulated Annealing (SA) [55] algorithm to find approximate solutions to the SLD DRSCA$_\mathrm{A}$ and SLD DRSCA$_\mathrm{B}$ problems. The generic form of the algorithm is described in Appendix A. We call SA DRSCA$_\mathrm{A}$ and SA DRSCA$_\mathrm{B}$ the versions of the SA algorithm that solve the SLD DRSCA$_\mathrm{A}$ and SLD DRSCA$_\mathrm{B}$ problems, respectively. We choose SA instead of TS for three reasons. Firstly, TS is computationally more expensive than SA because the exploration of a neighborhood (or even a part of a neighborhood) at each iteration. Secondly, the SLD DRSCA problem under consideration is computationally more complex than the RWA for SLDs problem of Chapter 5. This is particularly true for the SLD DRSCA$_\mathrm{B}$ problem. Finally, we had the opportunity of using parSA [59], a parallel implementation of SA. The parallelization provides a computing capacity that increases (sub)linearly with the number of used computers. This is an important practical consideration.

Remember from Section 6.4 that a solution pair $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$ is fully characterized by a vector ρ. The three problem-specific functions (see Section A.1) required to implement the SA algorithm are similar to those used to implement the TS algorithm of Chapter 5. The initial solution is created by a function that defines a vector ρ whose components are all equal to 1. The cost functions for SA DRSCA$_\mathrm{A}$ and SA DRSCA$_\mathrm{B}$ are defined by (6.2) and (6.7), respectively. Finally, the function used to generate a neighbor $(\pi^a_{\rho',\Delta}, \pi^b_{\rho',\Delta})$ from a current solution pair $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$ is defined by the following algorithm:

1. Generate a pseudo-random number i, uniformly distributed in the interval $[1, M]$.

2. Generate a pseudo-random number j, uniformly distributed among the elements

of the set $\{1, \ldots, K\} \backslash \{\rho_i\}$.

3. Generate a new vector ρ' by replacing ρ_i by j in ρ.

An SA algorithm iteratively explores the solution space until a stop condition is satisfied. ParSA provides a set of control parameters to implement various stop conditions. For example, stopping after a given number of iterations or temperature steps without significant cost improvement or stopping after a given CPU-time budget is exhausted. We denote the former condition by IWIS (Iterations Without Improvement Stop) and the latter by ETBS (Exhausted Time Budget Stop).

6.5.1. Time complexity

The only difference between SA DRSCA$_{\mathrm{A}}$ and SA DRSCA$_{\mathrm{B}}$ is the cost function. Therefore, if we want to compare the time complexity of both algorithms we only need to focus on the complexity of the functions implementing (6.2) and (6.7). Let us call these functions $\mathcal{C}_a$ and $\mathcal{C}_b$, respectively.

To compute the cost of a solution pair $(\pi^a_{\rho,\Delta}, \pi^b_{\rho,\Delta})$, function $\mathcal{C}_a$ adds the number of working and spare WDM channels on the arcs $e \in E$, $L = |E|$. To compute the number of working WDM channels on an arc $e \in E$, the set-up and tear down dates of the $O(M)$ SLDs passing through e must be first sorted in $O(M \log_2(M))$ time and then, the $O(M)$ time intervals (between two subsequent sorted dates) must be sequentially traversed in order to find the interval where the number of lightpaths is maximal. Thus, the number of working WDM channels on an arc is computed in $O(M \log_2(M) + M)$. The number of spare WDM channels is also computed in $O(M \log_2(M) + M)$. Since there are L arcs in G, the time complexity of function $\mathcal{C}_a$ is $O(LM(\log_2(M) + 1))$.

In $\mathcal{C}_b$, the number of working WDM channels on an arc is also computed in $O(M \log_2(M) + M)$. To compute the number of spare WDM channels, the conflict graph G_e must be built in $O(M^2)$ and colored with the LFFF algorithm. LFFF sorts the vertices in $O(M \log_2(M))$ and colors them in $O(M^2)$. Thus, the number of spare WDM channels on an arc is computed in $O(M^2 + M \log_2(M) + M^2)$ and the number of spare WDM channels in the whole network in $O(LM(\log_2(M) + M))$. The complexity of $\mathcal{C}_b$ is greater because a conflict graph must be built and colored for each arc.

6.6. Experimental evaluation

The purpose of the experimental evaluation is to compare algorithms SA DRSCA$_{\mathrm{A}}$ and SA DRSCA$_{\mathrm{B}}$ in order to characterize the trade-off between the gain provided by

backup-multiplexing with respect to mere channel reuse for spare WDM channels, and the computational cost of this technique.

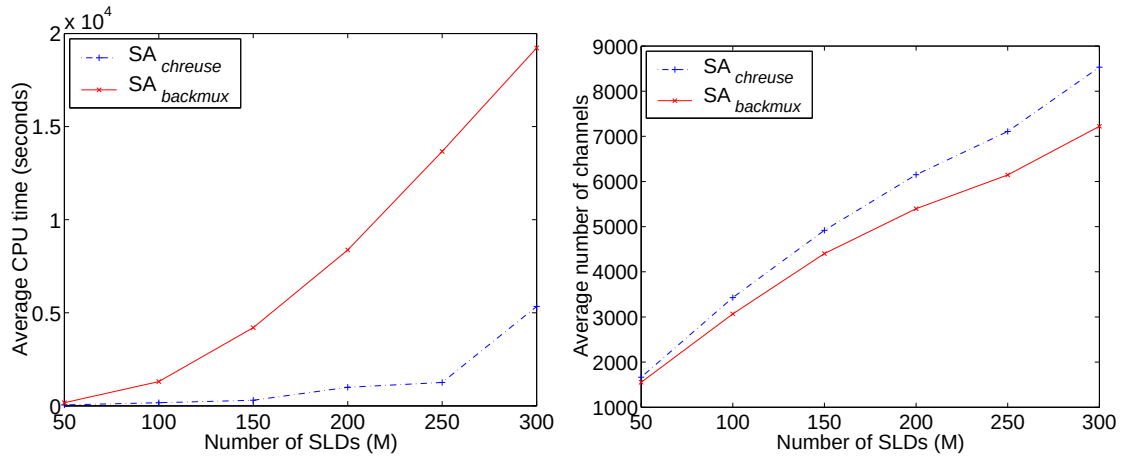
We first describe the parameters common to all the experiments. Figure 5.5 shows the graph G used for all the problem instances (G, Δ) investigated in this section. It is the same graph used for the experiments of Sections 5.5.1 and 5.5.2. For the sets Δ, the source and destination nodes, the number of lightpaths and the set-up and tear-down dates of the SLDs were drawn from random uniform distributions in the intervals $[\![1, 29]\!]$, $[\![1, 10]\!]$ and $[1, 1440]$, respectively (1440 is the number of minutes in a day). The set-up and tear-down dates were constrained to satisfy a target time correlation[4] value $\tau(\Delta)$. We used the sequential implementation on Linux (kernel v2.4.18) and the parallel implementation on Solaris 5.8 of the ParSA library (v2.2). The former was executed on a PC with an AMD 266 MHz processor and 128 MB of RAM and the latter on a cluster of 10 Sun Ultra-SPARC 5 computers with 128 MB of RAM each. The sequential implementation was used in experiments involving the measurement of execution time (see below). To avoid interference from uncontrollable resource-consuming processes, the PC executing this implementation was configured as a single-user system and was disconnected from the network.

A first way to characterize the trade-off between gain and computational cost of backup-multiplexing is to execute algorithms SA DRSCA_A and SA DRSCA_B on a same problem instance using an IWIS condition, that is, running the algorithms until no significant cost improvement is obtained. With this condition, SA DRSCA_B should compute a solution with a cost (number of WDM channels) lower than SA DRSCA_A, but should take a longer time to complete. For this experiment, we used the sequential implementation of the ParSA library with a minimum acceptance ratio[5] of 20%, a frozen limit of 5 and a geometric temperature schedule $T_i = a \cdot T_{i-1}$ with constant $a = 0.9$. We averaged the CPU time and the cost over 5 runs on sets Δ with an increasing number M of SLDs and a time correlation of $\tau(\Delta) \approx 0.99$. Figure 6.5 shows the average CPU time and the average number of WDM channels computed by SA DRSCA_A and SA DRSCA_B for sets Δ with different number M of SLDs using an IWIS condition. The difference of CPU-time growth rate between the two algorithms reflects their respective difference of time complexity. On the other hand, the difference in number of channels grows less abruptly because it depends on the gain provided by backup-multiplexing with respect to mere channel reuse of spare WDM channels, as used in SA DRSCA_A.

A typical characteristic of SA (and other local descent meta-heuristic algorithms) is that most of the improvements in cost occur during the first iterations of the

[4]The time correlation metric is defined in Subsection 5.3.3.

[5]See the ParSA library documentation [59] for the explanation of these parameters.



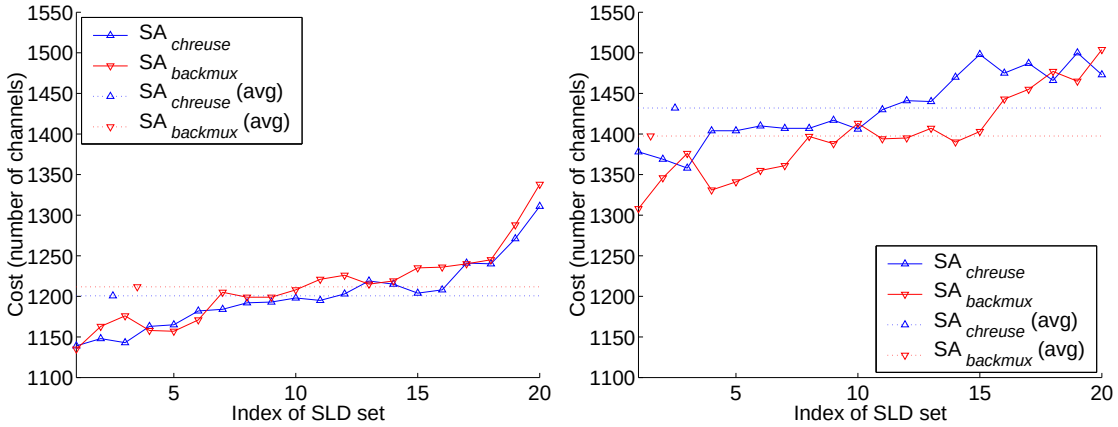
(a) Average CPU time.

(b) Average number of WDM channels.

Figure 6.5.: Average CPU time and number of WDM channels computed by SA DRSCA$_{\mathrm{A}}$ and SA DRSCA$_{\mathrm{B}}$ for different values of M with an IWIS condition.

algorithm and improvements after this initial phase are relatively seldom. This sort of Pareto's law suggests that the algorithm may be stopped after a small number of iterations and still compute a solution whose cost is not far from the cost of the best solution that the algorithm can potentially find. Based on this idea, we carried out an experiment to compare the cost of solutions computed with SA DRSCA$_{\mathrm{A}}$ and SA DRSCA$_{\mathrm{B}}$ using an ETBS condition, that is, running the algorithms with a limited CPU-time budget. We generated 40 sets Δ of $M = 150$ SLDs, 20 of them with a time correlation of $\tau(\Delta) \approx 0.1$ and the other 20 with $\tau(\Delta) \approx 0.9$. We fixed the CPU-time budget to 600 seconds (in the previous experiment, the average CPU-time for the problem instance with $M = 150$ was of 301.44s for SA DRSCA$_{\mathrm{A}}$ and of 4197.85s for SA DRSCA$_{\mathrm{B}}$).

Figure 6.6 shows the number of WDM channels computed by SA DRSCA$_{\mathrm{A}}$ and SA DRSCA$_{\mathrm{B}}$ for each set Δ and the average number of WDM channels (dotted lines in the figure) for $\tau(\Delta) \approx 0.1$ and $\tau(\Delta) \approx 0.9$. The number of WDM channels is in general smaller for sets Δ with weak time correlation (around 1200 for $\tau(\Delta) \approx 0.1$) than for sets Δ with strong time correlation (around 1400 for $\tau(\Delta) \approx 0.9$). Indeed, the greater time disjointness of the former allows a more efficient use of resources by means of channel reuse. For $\tau(\Delta) \approx 0.1$, the average number of WDM channels computed with SA DRSCA$_{\mathrm{A}}$ and by SA DRSCA$_{\mathrm{B}}$ are almost the same because, for a same CPU-time budget, SA DRSCA$_{\mathrm{A}}$ explores more solutions than SA DRSCA$_{\mathrm{B}}$ and thus, has more opportunities to improve the solutions cost. SA DRSCA$_{\mathrm{B}}$ compensates this disad-



(a) $\tau(\Delta) = 0.1$ (b) $\tau(\Delta) = 0.9$

Figure 6.6.: Number of WDM channels computed by SA DRSCA$_{\mathrm{A}}$ and SA DRSCA$_{\mathrm{B}}$ in 600 seconds on sets Δ of $M = 150$ SLDs with weak and strong time correlation.

vantage with the gain provided by backup-multiplexing. For $\tau(\Delta) \approx 0.9$, the average number of WDM channels computed with SA DRSCA$_{\mathrm{B}}$ is smaller than the corresponding value of SA DRSCA$_{\mathrm{A}}$ because the gain provided by backup-multiplexing becomes more significant under limited time disjointness conditions.

6.7. Conclusions

In this chapter we investigated the problem of diverse routing and spare capacity assignment for SLDs in a wavelength-switching network. The versions of the problem with and without backup-multiplexing were described. The problem was formulated as a combinatorial optimization problem and an Simulated Annealing meta-heuristic algorithm was proposed to find approximate solutions. The results show that the gain in cost of SA DRSCA$_{\mathrm{B}}$ with respect to SA DRSCA$_{\mathrm{A}}$ increases with the number of SLDs but the growth rate of this gain is lower than the CPU-time gap growth rate. For a limited CPU-time budget and a weak time correlation among demands, the performance of both algorithms is almost the same. However, as the time correlation increases, the possibility of reusing WDM channels decreases and backup-multiplexing for spare WDM channels becomes more advantageous despite its computational cost. This means that, with weak time correlation, using SA DRSCA$_{\mathrm{A}}$ – which is computationally simpler than SA DRSCA$_{\mathrm{B}}$ – is enough to compute solutions whose cost is close to the cost of solutions computed with SA DRSCA$_{\mathrm{B}}$.

An aspect that must be further investigated is the ratio of spare to working capacity and the incidence of the time correlation $\tau(\Delta)$ and the precomputed paths $(P_{k,i}, P'_{k,i})$ on this ratio. This ratio is a metric useful to compare the proposed algorithms to alternative approaches.

Another aspect that must be further investigated is the definition of a search-efficient combination of algorithm's parameters so that the algorithms can find a solution of lowest possible cost (hopefully the optimal one) using a limited CPU-time budget. A first step to achieve this goal is to understand the structural properties of the solution space of a problem instance. The solution space can be dominated, for example, by plateaus of near equal-cost solutions or by a multitude of attractor basins. Moreover, some properties can be either particular to a class of instances or general to all the instances of a problem. In the case of the SLD DRSCA problem considered in this chapter, we need to investigate the incidence of both the time correlation and the precomputed paths of an instance (G, Δ) on the structure of the instance's solution space.

7. Routing and grooming of SLDs in a multi-granularity switching network

Introducing multiple switching granularities in a transport network basically aims at solving a scalability problem and at reducing network costs. An appropriate aggregation of low order connections into high order connections can *reduce the number of connections* to be handled in the network, simplifying thus the control/management of the network and reducing the network cost (since less ports are required). Moreover, using a high order switching granularity technology with a *cost-per-bit* lower than the cost-per-bit of the low order switching granularity technology may further reduce the network cost.

In this chapter we investigate the advantages of a multi-granularity switching network with respect to a single-granularity switching network taking into account the time and space distribution of traffic demands. More precisely, we asses the gain in network cost provided by a wavelength/band switching network (multi-granularity) with respect to a wavelength-switching network (single-granularity) and define the conditions under which the former is more economical than the latter. These conditions include the time and space distribution of traffic demands, the topology of the physical network and the parameters of the functions defining the cost of switches. We use the SLD model to represent the traffic demands.

To assess the network cost gain and determine the conditions of economical attractiveness of multi-granularity networks, we solve the problem of instantiating a set of SLDs in both a wavelength/band switching network and a wavelength-switching network. In a wavelength/band switching network, instantiation of SLDs leads to a SLD Routing and Grooming problem (SRG). In a wavelength-switching network, the problem reduces to a SLD Routing problem (SR), similar to the one investigated in Chapter 5.

The next section describes the SRG and SR problems as well as the architecture of switches used in wavelength/band and wavelength-switching networks. Section 7.2 summarizes previous work on this subject found in the literature. Section 7.3

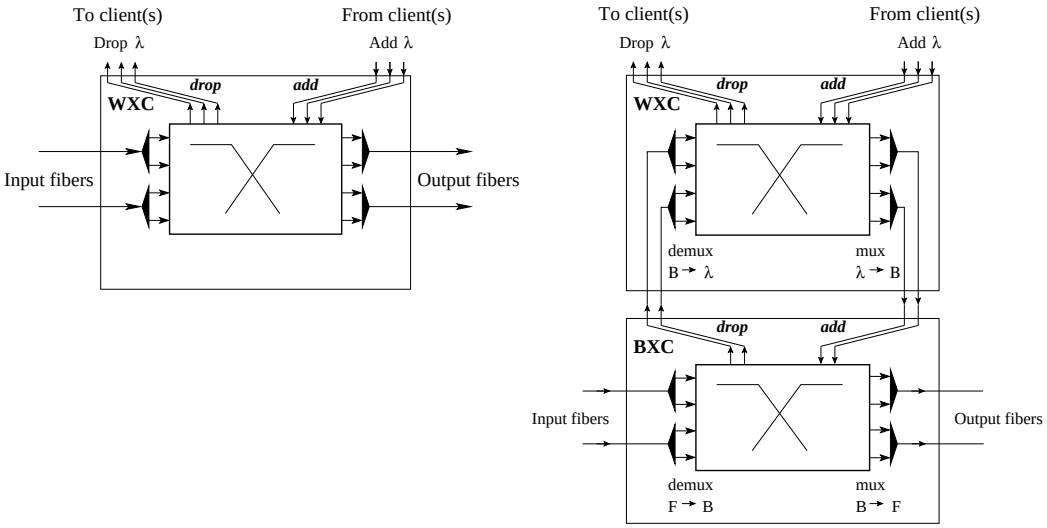
describes the mathematical formalization of both problems as combinatorial optimization problems. Section 7.4 presents an example to illustrate the notations of Section 7.3. In Section 7.5 we propose a Tabu Search meta-heuristic algorithm to compute approximate solutions to instances of both the SRG and SR problems. Section 7.6 describes a method to determine the envelop of switch cost parameters for which a multi-granularity is more economical than a single-granularity network. In Section 7.7 we experimentally evaluate the TS algorithm and show an application of the method of Section 7.6. Finally, Section 7.8 presents concluding remarks on this work and propositions for future work.

7.1. Description of the problem

In this section we describe the SLD Routing (SR) and the SLD Routing and Grooming (SRG) problems that we need to solve to assess the cost gain and to determine the conditions of economical attractiveness of multi-granularity networks. These problems arise in the instantiation of SLDs in wavelength and wavelength/band switching networks, respectively.

Figure 7.1(a) shows the architecture of the wavelength cross-connects (WXC) considered for the nodes of wavelength-switching networks. WXCs add, drop and switch lightpaths (wavelength-switching connections). We assume that WXCs have a full wavelength conversion functionality. This assumption is realistic in opaque networks, where wavelength conversion can be performed by the transponders. Furthermore, we assume that a WXC is symmetrical in the sense that the number of input ports is equal to the number of output ports and the number of add ports is equal to the number of drop ports. Virtually all existing transport network switches, optical or not, are symmetrical. Figure 7.1(b) shows the architecture of wavelength/band cross-connects (WXC/BXC) considered for the nodes of wavelength/band switching networks. These cross-connects additionally add, drop and switch *band-switching connections*. The connections at the output (input) ports of the WXC are multiplexed (demultiplexed) into (from) bands which are directly added to (dropped from) the BXC. Thus, the WXCs are not directly connected among them but through band-switching connections between BXCs. This means that lightpaths are instantiated over a logical topology of band-switching connections (or band layer network). Band-switching connections cannot be directly added to or dropped from the BXC. BXCs are also assumed to be symmetrical. The number of WXC input/output ports is a multiple of the band size.

Figure 7.2 shows how two lightpaths may be instantiated over a logical topology formed by two band-switching connections, one between nodes 1 and 3 and another



(a) WXC (b) WXC/BXC

Figure 7.1.: Switch architectures.

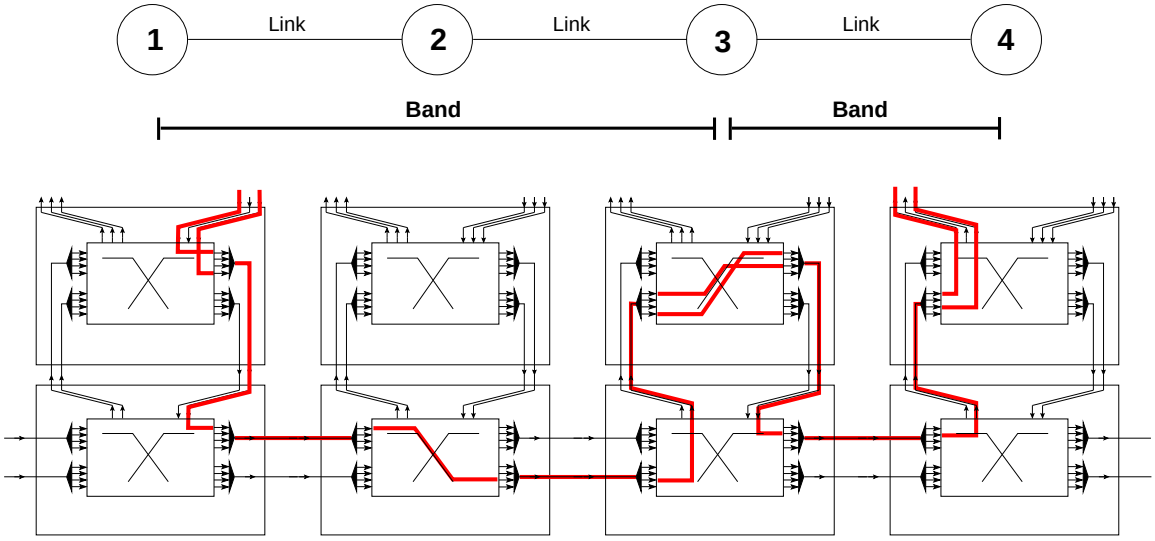


Figure 7.2.: A possible configuration of WXC/BXCs used to set up two lightpaths.

between nodes 3 and 4. The lightpaths are added to the WXC of node 1 using the WXC add ports. They are then multiplexed into a band, which is added to the BXC of the same node using one BXC add port. The resulting band is multiplexed into a fiber. In node 2, the band is demultiplexed from the incoming fiber, switched to an output port and multiplexed into a fiber. In node 3, the band is demultiplexed from the incoming fiber and dropped using one BXC drop port. This band is demultiplexed in order to get the two lightpaths which are then switched from the input to the output ports of the node. The lightpaths are multiplexed again into a band and added to the BXC of the node. The band is multiplexed into a fiber. In node 4 the band is demultiplexed from the incoming fiber and dropped. The two lightpaths are demultiplexed from the band and dropped using the WXC drop ports of the node.

In Chapter 5 we formulated the problem of instantiating SLDs in a wavelength-switching network *without* wavelength conversion as a routing and wavelength assignment (RWA) problem. The absence of wavelength conversion results in the wavelength continuity constraint, which makes the wavelength assignment problem difficult. In the SR problem of this chapter, the assumption of full wavelength conversion in the WXCs simplifies the wavelength assignment problem so that we can focus exclusively on the routing problem. Moreover, the objective function of the SR problem is different from those of Chapter 5. Our goal is to minimize the cost of the network, which is equal to the sum of the switches' costs (the cost of transmission systems is ignored). The cost of a switch is modeled as a function of its number of ports, for example with function $f(x) = a + bx^c$, where x is the number of ports and a, b, c are parameters. The number of ports of a switch is derived from the routing of SLDs in the network.

Band-switching introduces an intermediate layer network between the physical network and the SLDs. A logical topology of band-switching connections must be defined and mapped on the physical network. An SLD is instantiated by defining a path on the logical topology and assigning band-switching connections on each arc of the path to the SLD's lightpaths. In this context, grooming refers to the aggregation (and disaggregation) of lightpaths into band-switching connections of the logical topology. Thus, the SRG problem under consideration consists of defining a logical topology of band-switching connections, routing these connections on the physical network, routing the SLDs on the logical topology and assigning resources of the logical topology to the SLDs. The problem is schematically illustrated in Figure 7.3. An instance of the problem is defined by a set of SLDs and the topology of a physical network. Like in the SR problem, the switch cost function is used to compute the cost of a switch as a function of its number of ports. The network functional model defines the architecture of the switches (Figure 7.1(b)). The model

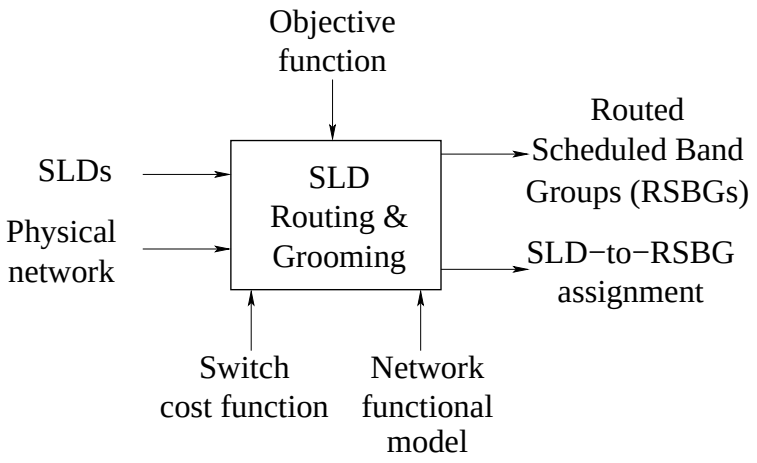


Figure 7.3.: Schematic representation of the SLD routing and grooming problem.

defines, among other things, the size of the bands (the number of lightpaths that can be groomed into a band-switching connection). The objective function defines the optimality criterion to be satisfied, for example, minimization of the network cost. The solution to the problem consists of a set of Routed Scheduled Band Groups (RSBGs) and of an assignment of SLDs to RSBGs. An RSBG is similar to an SLD in that it is defined by a tuple $(s, d, n, \alpha, \omega, P)$ where s and d are the source and destination BXCs of the RSBG, n is the number of band-switching connections in the group, α and ω are the set-up and tear-down dates of the RSBG and P is the route in the physical network. The set-up date α (tear-down date ω) of a RSBG is the earliest set-up (latest tear-down) date of any of the SLDs assigned to this RSBG.

7.2. Related work

The problem of grooming (or grouping) connections in a network with multiple switching granularities has been investigated since the 1970's in the context of telephonic networks [76, 24, 60] and in the context of SDH/SONET networks with network elements implementing several switching granularities of the Synchronous Digital Hierarchy [47, 46] since their deployment in the 1980's. More recently, the problem of grooming connections has been investigated in SDH/WDM ring networks [16]. Most of these works focus in reducing the number of required SDH ADMs or, more generally, the network cost [34].

In optical mesh networks, grooming must be addressed together with the routing problem since multiple possible paths exist between the end points of connections. The problem of instantiating static SDH/SONET connections in a WDM mesh network has been only recently investigated. In [94], multi-commodity flow models are

used to formulate as a single ILP problem the related problems of defining a logical topology of lightpaths, routing SDH/SONET connections over this topology, routing the lightpaths on the physical network and assigning wavelength to the lightpaths. Given a limited amount of network resources, the objective in the problem is to maximize the number of satisfied connections or, if connections provide different revenue, maximize the network revenue. Since ILP problems are NP-complete, the authors resort to heuristic algorithms to compute approximate solutions. In [93], SDH/SONET connections are instantiated over a SDH/WDM network using an original approach based on the definition of an auxiliary graph that represents the multi-granularity network. The connections are instantiated by computing shortest paths on this graph. Different grooming policies may be implemented using this representation by changing the weights of the auxiliary graph's edges. The demands are processed sequentially, which makes the approach suitable for traffic engineering problems considering dynamic random traffic.

7.3. Mathematical model

In this section we present the notations used to formally define the SR and SRG problems as combinatorial optimization problems. We first present the notations common to both problems.

7.3.1. Common notations

$G = (V, E, w)$
is an arc-weighted symmetrical directed graph with vertex set $V = \{v_1, v_2, \ldots, v_N\}$, arc set $E = \{e_1, e_2, \ldots, e_F\}$, and arc weight function $w : E \rightarrow \mathbb{R}_+$. The graph represents a physical telecommunications network. The set V corresponds to the nodes of the network and the set of arcs E to the links interconnecting the nodes (see terminology of Table 2.3). Function w corresponds to the physical length or to the cost of the links (*e.g.*, defined by the network operator).

$N = |V|$, $F = |E|$, K, L, B
are, respectively, the number of nodes and arcs in the network, the maximum number of possible alternate paths for each demand, the maximum number of possible layouts (see § 7.3.3) for each path and the size of a band-switching connection in number of lightpaths (all the band-switching connections in the network have the same size).

$P = (x_0, x_1, \ldots, x_z)$

describes a *path* in G and is composed of arcs $(x_0, x_1), (x_1, x_2), \ldots, (x_{z-1}, x_z)$ where the $(x_{i-1}, x_i) \in E$ are all distinct. The path has z arcs (hops).

$\Delta = \{\delta_1, \delta_2, \ldots, \delta_M\}$
is the set of M Scheduled Lightpath Demands (SLDs), where:

$\delta_i = (s_i,\ d_i,\ n_i,\ \alpha_i,\ \omega_i)$
is a tuple representing SLD i; $s_i, d_i \in V$ are the source and destination nodes of the demand, n_i is the number of requested lightpaths, and α_i and ω_i are the set-up and tear-down dates of the demand.

(G, Δ)
is a pair representing an instance of the SR or the SRG problem.

$P_{i,k} = (x_0^{i,k}, x_1^{i,k}, \ldots, x_{z_{i,k}}^{i,k})$, $1 \leq i \leq M$, $1 \leq k \leq K$
is the k^{th} alternate path for SLD i from $x_0^{i,k} = s_i$ to $x_{z_{i,k}}^{i,k} = d_i$. The path has $z_{i,k}$ hops. For the purposes of this chapter, we compute the K physically shortest paths on G for each demand using the algorithm defined in [27]. However, the paths might be defined according to any other criterion (*e.g.*, shortest paths in terms of hops).

$C_{SR} : \Pi_\Delta^{SR} \to \mathbb{R}_+, \quad C_{SRG} : \Pi_\Delta \to \mathbb{R}_+$
are functions that compute, respectively, the cost of an admissible SR solution $\pi_{\rho,\Delta}$ (see § 7.3.2) and the cost of an admissible SRG solution $\pi_{\rho,\nu,\Delta}$ (see § 7.3.3). In order to formalize these functions we define the following additional notations.

$\theta = (\theta_{ij})$
is a $\{0,1\}^{M \times M}$ upper triangular matrix; θ_{ij}, $i \leq j$, indicates whether the SLDs δ_i and δ_j overlap in time ($\theta_{ij} = 1$) or not ($\theta_{ij} = 0$). By definition $\theta_{ii} = 1$, $1 \leq i \leq M$, and $\theta_{ij} = 0$ for $i > j$. This matrix expresses the temporal relationship between the SLDs.

$\beta = (\beta_{ij}) = diag(n_i)$
is a diagonal matrix wherein $\beta_{ii} = n_i$, $1 \leq i \leq M$, *i.e.*, β_{ii} is the number of lightpaths required by the SLD δ_i.

$\mathcal{I} = (\mathcal{I}_{ij})$
is a $\{0,1\}^{N \times F}$ matrix; $\mathcal{I}_{ij}$ indicates whether vertex v_i is the termination vertex of arc e_j ($\mathcal{I}_{ij} = 1$) or not ($\mathcal{I}_{ij} = 0$).

$\mathcal{O} = (\mathcal{O}_{ij})$
is a $\{0,1\}^{N \times F}$ matrix; $\mathcal{O}_{ij}$ indicates whether vertex v_i is the source vertex of arc e_j ($\mathcal{O}_{ij} = 1$) or not ($\mathcal{O}_{ij} = 0$).

$\mathcal{T} = (t_{ij})$
is a $\{0,1\}^{M \times N}$ matrix; t_{ij} indicates whether vertex v_j is the source node of SLD i ($t_{ij} = 1$) or not ($t_{ij} = 0$).

$\mathcal{U} = (u_{ij})$
is a $\{0,1\}^{M \times N}$ matrix; u_{ij} indicates whether vertex v_j is the destination node of SLD i ($u_{ij} = 1$) or not ($u_{ij} = 0$).

$\mathcal{D} = \theta \cdot \beta \cdot \mathcal{T} = (\mathcal{D}_{ij})_{1 \leq i \leq M, 1 \leq j \leq N}$, $\mathcal{D}_j^* = \max_{1 \leq i \leq M}\{\mathcal{D}_{ij}\}$
$\mathcal{D}^*$ is an N-dimensional vector; $\mathcal{D}_j^*$ indicates the maximum number of simultaneously active lightpaths originating at node v_i.

$\mathcal{E} = \theta \cdot \beta \cdot \mathcal{U} = (\mathcal{E}_{ij})_{1 \leq i \leq M, 1 \leq j \leq N}$, $\mathcal{E}_j^* = \max_{1 \leq i \leq M}\{\mathcal{E}_{ij}\}$
$\mathcal{E}^*$ is an N-dimensional vector; $\mathcal{E}_j^*$ indicates the maximum number of simultaneously active lightpaths terminating at node v_i.

$\psi : \mathbb{N} \rightarrow \mathbb{R}_+$
is the function that determines the cost of a switch (either a WXC or a BXC) as a function of its number of ports. In this work, we consider the function

$$\psi(x) = a + bx^c \quad a, b \in \mathbb{R}_+, c \in [1, 2[. \tag{7.1}$$

The function captures various technology-specific factors with incidence on the cost of a switch. Parameter a represents the fixed cost of installing the switch. Parameter b represents the cost of a port. Finally, parameter c reflects the impact on the cost of the increasing implementation complexity of switching matrices with a large number of ports. The parameter is limited to take values smaller than 2 because, for greater values, it is in general more economical to stack multiple small switches than building a large one when a significant number of ports is required.

7.3.2. The SR problem

The notations specific to the SR problem are the following:

$\pi_{\rho,\Delta} = (P_{1,\rho_1}, P_{2,\rho_2}, \ldots, P_{M,\rho_M})$, $\rho \in \{1, \ldots, K\}^M$
is called an *admissible SR solution* for Δ. ρ is an M-dimensional vector whose elements can take values in $[\![1, K]\!]$. $\pi_{\rho,\Delta}$ is fully characterized by ρ. An admissible SR solution $\pi_{\rho,\Delta}$ defines a path $P_{i,k}$ for each SLD.

$\Pi_\Delta^{SR} = \left\{\pi_{\rho,\Delta}, \rho \in \{1, \ldots, K\}^M\right\}$
is the set of all admissible SR solutions for Δ. There are $|\Pi_\Delta^{SR}| = K^M$ admissible SR solutions in the set (assuming that K distinct paths are available for each SLD; otherwise, $|\Pi_\Delta^{SR}| < K^M$).

$\gamma^{\pi_{\rho,\Delta}} = (\gamma_{ij}^{\pi_{\rho,\Delta}})$
is a $\{0,1\}^{F \times M}$ arc-path incidence matrix; $\gamma_{ij}^{\pi_{\rho,\Delta}}$ indicates whether arc $e_i \in E$ is part of path $P_{\rho_j,j}$ in admissible SR solution $\pi_{\rho,\Delta}$ ($\gamma_{ij}^{\pi_{\rho,\Delta}} = 1$) or not ($\gamma_{ij}^{\pi_{\rho,\Delta}} = 0$). For the sake of simplicity, we note γ instead of $\gamma^{\pi_{\rho,\Delta}}$. This matrix describes the physical routing of the SLDs for a given admissible SR solution $\pi_{\rho,\Delta}$.

$\vartheta = \theta \cdot \beta \cdot \gamma^T = (\vartheta_{ij})$
is a $\mathbb{N}^{M \times L}$ matrix; ϑ_{ij} indicates the number of time-overlapping lightpaths on link e_j between SLD δ_i and SLDs δ_k, $\forall\, k > i$.

$\vartheta^* = (\vartheta_j^*)_{1 \le j \le F}$, $\vartheta_j^* = \left\lceil \frac{1}{B} \max_{1 \le i \le M} \vartheta_{ij} \right\rceil$
is an F-dimensional vector[1]; ϑ_j^* indicates the maximum number of simultaneously active lightpaths on arc e_j.

$\mathcal{X} = \mathcal{I} \cdot \vartheta^*$
is an N-dimensional vector; $\mathcal{X}_i$ indicates the number of input ports required in the WXC of node v_i to implement admissible SR solution $\pi_{\rho,\Delta}$.

$\mathcal{Y} = \mathcal{O} \cdot \vartheta^*$
is an N-dimensional vector; $\mathcal{Y}_i$ indicates the number of output ports required in the WXC of node v_i to implement admissible SR solution $\pi_{\rho,\Delta}$.

$\mathcal{Z} \in \mathbb{R}_+^N, \quad \mathcal{Z}_i = \psi_{WXC}(\max(\mathcal{D}_i^*, \mathcal{E}_i^*) + \max(\mathcal{X}_i, \mathcal{Y}_i))$
is an N-dimensional vector; $\mathcal{Z}_i$ indicates the cost of the WXC at node v_i for admissible SR solution $\pi_{\rho,\Delta}$. The max function represents the symmetry of input/output and add/drop ports of the WXC (see Section 7.1).

[1] $\lceil x \rceil$ is the smallest integer greater than or equal to x.

The cost function $C_{SR} : \Pi_{\Delta}^{SR} \rightarrow \mathbb{R}_+$ is defined as:

$$C_{SR}(\pi_{\rho,\Delta}) = \sum_{i=1}^{N} \mathcal{Z}_i. \tag{7.2}$$

The optimization problem to solve is:

$$\textbf{Minimize:} \quad C_{SR}(\pi_{\rho,\Delta}), \tag{7.3}$$

subject to:

$$\pi_{\rho,\Delta} \in \Pi_{\Delta}, \tag{7.4}$$

that is, we search an admissible SR solution $\pi_{\rho,\Delta}$ of minimal cost.

7.3.3. The SRG problem

The notations specific to the SRG problem are the following:

$\lambda = \{\lambda^n\}_{1 \leq n \leq I}$
is a partition of the set of arcs describing path P. We call λ a *layout* and an element λ^n of this partition a *subpath*. For example, a layout of path $(x_0, x_1, x_2, x_3, x_4)$ is $\lambda = \{(x_0, x_1, x_2), (x_2, x_3, x_4)\}$. This layout has subpaths $\lambda^1 = (x_0, x_1, x_2)$ and $\lambda^2 = (x_2, x_3, x_4)$. Another layout is $\{(x_0, x_1), (x_1, x_2, x_3, x_4)\}$. The number of subpaths in a layout is denoted by I. The elements of a subpath must be contiguous arcs of P.

$\Lambda_{i,k} = \{\lambda_{i,k,j}\}$, $1 \leq i \leq M$, $1 \leq k \leq K$, $1 \leq j \leq L$
is the set of layouts available for path $P_{i,k}$; $\lambda_{i,k,j}$ is the j^{th} layout of the path. We assume that there are L different layouts defined for a path. In this work we assume that the layouts are computed with the algorithm described in Appendix C using parameters $MinVertex = 3$ and $MaxVertex = \infty$.

$\pi_{\rho,\nu,\Delta} = ((P_{1,\rho_1}, \lambda_{1,\rho_1,\nu_1}), (P_{2,\rho_2}, \lambda_{2,\rho_2,\nu_2}), \ldots, (P_{M,\rho_M}, \lambda_{M,\rho_M,\nu_M}))$,
$\rho \in \{1, \ldots, K\}^M$, $\nu \in \{1, \ldots, L\}^M$
is called an *admissible SRG solution* for Δ. ρ and ν are M-dimensional vectors whose elements can take values in $[\![1, K]\!]$ and $[\![1, L]\!]$, respectively. $\pi_{\rho,\nu,\Delta}$ is fully characterized by the pair (ρ, ν). An admissible SRG solution $\pi_{\rho,\nu,\Delta}$ defines for each SLD, a path $P_{i,k}$ and a layout $\lambda_{i,k,j}$ of this path. A subpath λ^n can be part of several layouts defined in $\pi_{\rho,\nu,\Delta}$. We call the association of λ^n to the subset $\Delta' \subseteq \Delta$ of SLDs whose

layouts in $\pi_{\rho,\nu,\Delta}$ share λ^n, a Routed Scheduled Band Group (RSBG). Thus, besides a path and a layout for each SLD, an admissible SRG solution $\pi_{\rho,\nu,\Delta}$ also defines a set of RSBGs.

$\Pi_\Delta = \left\{\pi_{\rho,\nu,\Delta}, \rho \in \{1,\ldots,K\}^M, \nu \in \{1,\ldots,L\}^M\right\}$
is the set of all admissible SRG solutions for Δ. Its cardinality is $|\Pi_\Delta| = (KL)^M$ (assuming that K paths and L layouts are available for each path; otherwise, $|\Pi_\Delta| < (KL)^M$). The set represents the solution space of an SRG problem instance (G, Δ).

$\mathcal{S}_{\rho,\nu,\Delta} = \bigcup_{i=1}^{M} \lambda_{i,\rho_i,\nu_i}$
is the set of all subpaths used in the admissible SRG solution $\pi_{\rho,\nu,\Delta}$. The cardinality of the set is denoted $S = |\mathcal{S}_{\rho,\nu,\Delta}|$. For the sake of simplicity, we note $\mathcal{S}$ instead of $\mathcal{S}_{\rho,\nu,\Delta}$.

$\mathcal{A} = (a_{ij})$
is a $\{0,1\}^{M\times S}$ matrix; a_{ij} indicates whether SLD i uses subpath $\mathcal{S}_j$ (a_{ij}=1) or not ($a_{ij} = 0$) in admissible SRG solution $\pi_{\rho,\nu,\Delta}$.

$\mathcal{B} = (b_{ij})$
is a $\{0,1\}^{F\times S}$ arc-subpath incidence matrix; b_{ij} indicates whether arc e_i is part of subpath $\mathcal{S}_j$ ($b_{ij} = 1$) or not ($b_{ij} = 0$).

$\eta = \theta \cdot \beta \cdot \mathcal{A} \cdot \mathcal{B}^T = (\eta_{ij})$
is a $\mathbb{N}^{M\times F}$ matrix; η_{ij} indicates the number of time-overlapping lightpaths on link e_j between SLD i and SLDs k, $k > 1$.

$\eta^* = (\eta^*_j)_{1\le j\le F}$, $\eta^*_j = \left\lceil \frac{1}{B} \max_{1\le i\le M} \eta_{ij} \right\rceil$
is an F-dimensional vector; η^*_j indicates the number of bands required on arc e_j for the maximum number of simultaneously active lightpaths on the arc.

$\mathcal{IN} = \mathcal{I} \cdot \eta^*$
is an N-dimensional vector; $\mathcal{IN}_i$ indicates the number of input ports required in the BXC of node v_i to implement admissible SRG solution $\pi_{\rho,\nu,\Delta}$.

$\mathcal{OUT} = \mathcal{O} \cdot \eta^*$
is an N-dimensional vector; $\mathcal{OUT}_i$ indicates the number of output ports required in the BXC of node v_i to implement admissible SRG solution $\pi_{\rho,\nu,\Delta}$.

$\mathcal{G} = (g_{ij})$
is a $\{0,1\}^{N\times S}$ matrix; g_{ij} indicates whether vertex v_i is the source of subpath $\mathcal{S}_j$ ($g_{ij} = 1$) or not ($g_{ij} = 0$).

$\mathcal{H} = (h_{ij})$
is a $\{0,1\}^{N\times S}$ matrix; h_{ij} indicates whether vertex v_i is the termination of subpath $\mathcal{S}_j$ ($h_{ij} = 1$) or not ($h_{ij} = 0$).

$\mathcal{J} = \theta \cdot \beta \cdot \mathcal{A} \cdot \mathcal{G}^T = (\mathcal{J}_{ij})_{1\le i\le M, 1\le j\le N}, \quad J_j^* = \left\lceil \frac{1}{B} \max_{1\le i\le M} \mathcal{J}_{ij} \right\rceil$
$\mathcal{J}^*$ is an N-dimensional vector; $\mathcal{J}_j^*$ is the number of bands added at the BXC of node v_j.

$\mathcal{K} = \theta \cdot \beta \cdot \mathcal{A} \cdot \mathcal{H}^T = (\mathcal{K}_{ij})_{1\le i\le M, 1\le j\le N}, \quad \mathcal{K}_j^* = \left\lceil \frac{1}{B} \max_{1\le i\le M} \mathcal{K}_{ij} \right\rceil$
$\mathcal{K}^*$ is an N-dimensional vector; $\mathcal{K}_j^*$ is the number of bands dropped at the BXC of node v_j.

$\mathcal{Q} \in \mathbb{R}_+^N, \quad \mathcal{Q}_i = \psi_{BXC}(\max(\mathcal{IN}_i, \mathcal{OUT}_i) + \max(\mathcal{J}_i^*, \mathcal{K}_i^*))$
is an N-dimensional vector; $\mathcal{Q}_i$ indicates the cost of the BXC required at node v_i to implement admissible SRG solution $\pi_{\rho,\nu,\Delta}$. The max function represents the symmetry of input/output and add/drop ports of the BXC (see Section 7.1).

$\mathcal{R} \in \mathbb{R}_+^N, \quad \mathcal{R}_i = \psi_{WXC}(\max(\mathcal{D}_i^*, \mathcal{E}_i^*) + B\max(\mathcal{J}_i^*, \mathcal{K}_i^*))$
is an N-dimensional vector; $\mathcal{R}_i$ indicates the cost of the WXC required at node v_i to implement admissible SRG solution $\pi_{\rho,\nu,\Delta}$. Note that the number of input/output ports, $B\max(\mathcal{J}_i^*, \mathcal{K}_i^*)$, is a multiple of the band size B. The parameters defining the function ψ_{WXC} may be different from those defining the function ψ_{BXC}.

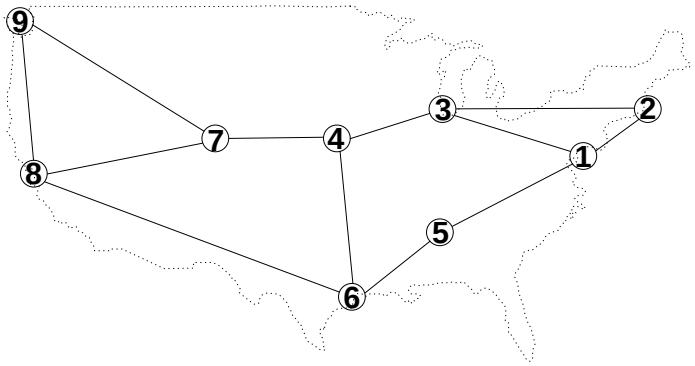
The cost function $C_{SRG} : \Pi_\Delta \to \mathbb{R}_+$ is defined as:

$$C_{SRG}(\pi_{\rho,\nu,\Delta}) = \sum_{i=1}^{N} (\mathcal{Q}_i + \mathcal{R}_i). \tag{7.5}$$

The optimization problem to solve is:

$$\textbf{Minimize:} \quad C_{SRG}(\pi_{\rho,\nu,\Delta}), \tag{7.6}$$

$$\textbf{subject to:}$$



(a) Graph G representing a physical network.

SLD	s	d	n	α	ω
δ_1	2	8	8	08:00	14:00
δ_2	1	9	10	11:00	13:00

(b) Set Δ of $M = 2$ SLDs.

Figure 7.4.: An instance (G, Δ) of the SRG problem.

$$\pi_{\rho,\nu,\Delta} \in \Pi_\Delta, \tag{7.7}$$

that is, we search an admissible SRG solution $\pi_{\rho,\nu\Delta}$ of minimal cost.

7.4. A numerical example

In this section we present an example to illustrate how the mathematical model of the previous section is used to represent an instance of the SRG problem and an admissible solution for this instance. The example also illustrates how the cost of the solution is computed.

We study the problem instance of Figure 7.4 which defines a set Δ of $M = 2$ SLDs and a graph G representing the considered physical network. Additionally, we choose the paths and layouts defined in Table 7.1 ($K = 2$ and $L = 3$) and define a band size of $B = 4$. For the sake of simplicity, we choose functions $\psi_{WXC}(x) = x$ and $\psi_{BXC}(x) = x$ to represent the cost of switches, *i.e.*, we choose $a = 0$, $b = 1$ and $c = 1$ in Equation (7.1). Figure 7.5 illustrates the admissible SRG solution $\pi_{\rho,\nu,\Delta}$ with vectors $\rho = (1, 1)$ and $\nu = (3, 3)$ for the instance of Figure 7.4. Path $P_{1,1}$ and layout $\lambda_{1,1,3}$ are selected for SLD δ_1 and path $P_{2,1}$ and layout $\lambda_{2,1,3}$ are selected for SLD δ_2. The figure also shows the set of Routed Scheduled Band Groups (RSBGs) defined by the solution.

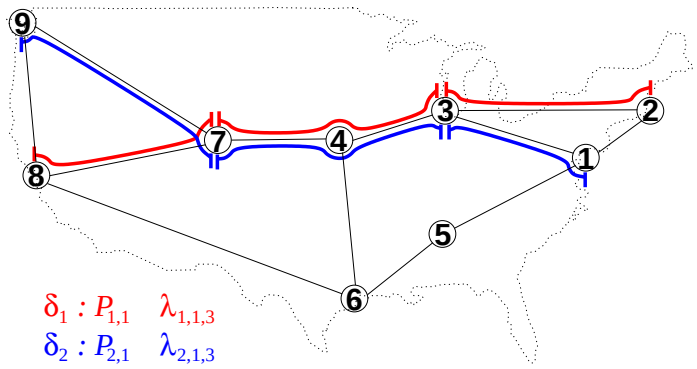
The following matrices are used to compute the cost of the chosen admissible SRG solution:

$$\theta = \begin{array}{c} \\ \delta_1 \\ \delta_2 \end{array} \begin{array}{c} \begin{array}{cc} \delta_1 & \delta_2 \end{array} \\ \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \end{array} \qquad \beta = \begin{array}{c} \\ \delta_1 \\ \delta_2 \end{array} \begin{array}{c} \begin{array}{cc} \delta_1 & \delta_2 \end{array} \\ \begin{pmatrix} 8 & 0 \\ 0 & 10 \end{pmatrix} \end{array}$$

$$\mathcal{S}_{\rho,\nu,\Delta} = \{(1, 3), (2, 3), (3, 4, 7), (7, 8), (7, 9)\}$$

Table 7.1.: Chosen paths and layouts for the instance of Figure 7.4.

SLD	Path ($P_{i,k}$)	Layout ($\lambda_{i,k,j}$)
δ_1	$P_{1,1} = (2,3,4,7,8)$	$\lambda_{1,1,1} = \{(2,3,4,7,8)\}$
		$\lambda_{1,1,2} = \{(2,3,4)\ (4,7,8)\}$
		$\lambda_{1,1,3} = \{(2,3)\ (3,4,7)\ (7,8)\}$
	$P_{1,2} = (2,1,5,6,8)$	$\lambda_{1,2,1} = \{(2,1,5,6,8)\}$
		$\lambda_{1,2,2} = \{(2,1,5)\ (5,6,8)\}$
		$\lambda_{1,2,3} = \{(2,1)\ (1,5,6)\ (6,8)\}$
δ_2	$P_{2,1} = (1,3,4,7,9)$	$\lambda_{2,1,1} = \{(1,3,4,7,9)\}$
		$\lambda_{2,1,2} = \{(1,3,4)\ (4,7,9)\}$
		$\lambda_{2,1,3} = \{(1,3)\ (3,4,7)\ (7,9)\}$
	$P_{2,2} = (1,5,6,8,9)$	$\lambda_{2,2,1} = \{(1,5,6,8,9)\}$
		$\lambda_{2,2,2} = \{(1,5,6)\ (6,8,9)\}$
		$\lambda_{2,2,3} = \{(1,5)\ (5,6,8)\ (8,9)\}$



(a) Paths and layouts.

Subpath (λ^n)	$\Delta' \subseteq \Delta$
$(1,3)$	$\{\delta_2\}$
$(2,3)$	$\{\delta_1\}$
$(3,4,7)$	$\{\delta_1, \delta_2\}$
$(7,8)$	$\{\delta_1\}$
$(7,9)$	$\{\delta_2\}$

(b) Routed Scheduled Band Groups (RSBGs).

Figure 7.5.: An admissible SRG solution $\pi_{\rho,\nu,\Delta}$ to the instance of Figure 7.4.

$$\mathcal{A} = \begin{array}{c} \\ \delta_1 \\ \delta_1 \end{array} \begin{array}{c} \begin{array}{ccccc} \mathcal{S}_1 & \mathcal{S}_2 & \mathcal{S}_3 & \mathcal{S}_4 & \mathcal{S}_5 \end{array} \\ \begin{pmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \end{pmatrix} \end{array} \qquad \mathcal{B} = \begin{array}{c} \\ e_{13} \\ e_{23} \\ e_{34} \\ e_{47} \\ e_{78} \\ e_{79} \end{array} \begin{array}{c} \begin{array}{ccccc} \mathcal{S}_1 & \mathcal{S}_2 & \mathcal{S}_3 & \mathcal{S}_4 & \mathcal{S}_5 \end{array} \\ \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

$$\eta = \theta \cdot \beta \cdot \mathcal{A} \cdot \mathcal{B}^T = \begin{pmatrix} 10 & 8 & 18 & 18 & 8 & 10 \\ 10 & 0 & 10 & 10 & 0 & 10 \end{pmatrix} \qquad \eta^* = \begin{pmatrix} 3 \\ 2 \\ 5 \\ 5 \\ 2 \\ 3 \end{pmatrix}$$

$$\mathcal{I} = \begin{array}{c} \\ v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \\ v_7 \\ v_8 \\ v_9 \end{array} \begin{array}{c} \begin{array}{cccccc} e_{13} & e_{23} & e_{34} & e_{47} & e_{78} & e_{79} \end{array} \\ \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array} \qquad \mathcal{O} = \begin{array}{c} \\ v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \\ v_7 \\ v_8 \\ v_9 \end{array} \begin{array}{c} \begin{array}{cccccc} e_{13} & e_{23} & e_{34} & e_{47} & e_{78} & e_{79} \end{array} \\ \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array}$$

$$\mathcal{IN} = \mathcal{I} \cdot \eta^* = (0,\, 0,\, 5,\, 5,\, 0,\, 0,\, 5,\, 2,\, 3)$$
$$\mathcal{OUT} = \mathcal{O} \cdot \eta^* = (3,\, 2,\, 5,\, 5,\, 0,\, 0,\, 5,\, 0,\, 0)$$

$$\mathcal{G} = \begin{array}{c} \\ v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \\ v_7 \\ v_8 \\ v_9 \end{array} \begin{array}{c} \begin{array}{ccccc} \mathcal{S}_1 & \mathcal{S}_2 & \mathcal{S}_3 & \mathcal{S}_4 & \mathcal{S}_5 \end{array} \\ \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \qquad \mathcal{H} = \begin{array}{c} \\ v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \\ v_7 \\ v_8 \\ v_9 \end{array} \begin{array}{c} \begin{array}{ccccc} \mathcal{S}_1 & \mathcal{S}_2 & \mathcal{S}_3 & \mathcal{S}_4 & \mathcal{S}_5 \end{array} \\ \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

$$\mathcal{T} = \begin{array}{c} \\ \delta_1 \\ \delta_1 \end{array} \begin{array}{c} \begin{array}{ccccccccc} v_1 & v_2 & v_3 & v_4 & v_5 & v_6 & v_7 & v_8 & v_9 \end{array} \\ \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array}$$

$$\mathcal{U} = \begin{array}{c} \\ \delta_1 \\ \delta_1 \end{array} \begin{array}{c} \begin{array}{ccccccccc} v_1 & v_2 & v_3 & v_4 & v_5 & v_6 & v_7 & v_8 & v_9 \end{array} \\ \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

$$\mathcal{D} = \theta \cdot \beta \cdot \mathcal{T} = \begin{pmatrix} 10 & 8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$$\mathcal{D}^* = \begin{pmatrix} 10 & 8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$$\mathcal{E} = \theta \cdot \beta \cdot \mathcal{U} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 8 & 10 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 \end{pmatrix}$$

$$\mathcal{E}^* = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 8 & 10 \end{pmatrix}$$

$$\mathcal{J} = \theta \cdot \beta \cdot \mathcal{A} \cdot \mathcal{G}^T = \begin{pmatrix} 10 & 8 & 18 & 0 & 0 & 0 & 18 & 0 & 0 \\ 10 & 0 & 10 & 0 & 0 & 0 & 10 & 0 & 0 \end{pmatrix}$$

$$\mathcal{J}^* = \begin{pmatrix} 3 & 2 & 5 & 0 & 0 & 0 & 5 & 0 & 0 \end{pmatrix}$$

$$\mathcal{K} = \theta \cdot \beta \cdot \mathcal{A} \cdot \mathcal{H}^T = \begin{pmatrix} 0 & 0 & 18 & 0 & 0 & 0 & 18 & 8 & 10 \\ 0 & 0 & 10 & 0 & 0 & 0 & 10 & 0 & 10 \end{pmatrix}$$

$$\mathcal{K}^* = \begin{pmatrix} 0 & 0 & 5 & 0 & 0 & 0 & 5 & 2 & 3 \end{pmatrix}$$

$$\mathcal{Q} = \begin{pmatrix} 6 & 4 & 10 & 5 & 0 & 0 & 10 & 4 & 6 \end{pmatrix}$$

$$\mathcal{R} = \begin{pmatrix} 22 & 16 & 20 & 0 & 0 & 0 & 20 & 16 & 22 \end{pmatrix}$$

The cost of the admissible SRG solution $\pi_{\rho,\nu,\Delta}$ according to (7.5) is:

$$C_{SRG}(\pi_{\rho,\nu,\Delta}) = 28 + 20 + 30 + 5 + 0 + 0 + 30 + 20 + 28 = 161.$$

7.5. Tabu Search algorithm

We propose a TS meta-heuristic algorithm to compute approximate solutions to instances of the SR and SRG problems. As explained in Section A.2, the TS algorithm is computationally expensive since the complete set of solutions in the neighborhood of the current solution must be evaluated at each iteration. In the TS algorithm proposed for the routing problem of Chapter 5 we circumvented this problem by computing a random sample of the actual neighborhood of a solution. In this section

Table 7.2.: Vectors ρ and ν of the solutions in the neighborhood $N(\pi^{ini}_{\rho,\nu,\Delta})$ of $\pi^{ini}_{\rho,\nu,\Delta}$ for the problem instance of Section 7.4.

neighbor	ρ	ν
1	$(1,1)$	$(1,2)$
2	$(1,1)$	$(1,3)$
3	$(1,1)$	$(2,1)$
4	$(1,1)$	$(3,1)$
5	$(1,2)$	$(1,1)$
6	$(1,1)$	$(1,1)$

we propose a different approach based on the parallelization of the neighborhood evaluation. The approach is described in Subsection 7.5.1.

We only describe the TS algorithm that solves the SRG problem. The TS algorithm that solves the SR problem is obtained by replacing function C_{SRG} by C_{SR} and considering only neighbors of ρ in the *GenerateNhood*() function (explained below).

Remember from Subsection 7.3.3 than an admissible SRG solution $\pi_{\rho,\nu,\Delta}$ is fully characterized by the pair of vectors (ρ,ν). The three problem-specific functions (see Section A.2) required to implement the TS algorithm are the following. The initial solution, that we denote by $\pi^{ini}_{\rho,\nu,\Delta}$, is created by a function that defines vectors ρ and ν whose elements are all equal to 1. In this work, $\pi^{ini}_{\rho,\nu,\Delta}$ defines for each SLD $\delta_i \in \Delta$ the shortest path $P_{i,1}$ and the layout $\lambda_{i,1,1}$ consisting of the complete path $P_{i,1}$ (see definition of $\pi_{\rho,\nu,\Delta}$ in § 7.3.3 and Appendix C). The cost function is defined by function (7.5). Finally, the function $GenerateNhood(\pi^{c}_{\rho,\nu,\Delta}, T)$ generates the neighborhood N_c of a current solution $\pi^{c}_{\rho,\nu,\Delta}$. The neighborhood is the subset $N_c \subseteq \Pi_\Delta$ of solutions that are obtained by making a *single* change to a value of either ρ or ν. Table 7.2 shows vectors ρ and ν of solutions in the neighborhood of $\pi^{ini}_{\rho,\nu,\Delta}$ for the problem instance of Section 7.4. In TS, the neighborhood N_c excludes the solutions obtained by changes (typically called moves) contained in the tabu list T.

As for the TS algorithm of Chapter 5, we implemented a diversification function to avoid being trapped in local minima. The function is invoked after a large number of iterations (defined by an algorithm's control parameter) without cost improvement. In order to shift the search effort to a region of the solution space different from the one surrounding the current solution, the function uses a pseudo-random number generator (PRNG) to assign pseudo-random numbers in the intervals $[1,K]$ and $[1,L]$ to the elements of vectors ρ and ν, respectively. The current iteration number is used as the seed of the PRNG. In this way, the TS algorithm is deterministic in that any two executions of the algorithm (with the same control parameters, of course) result

in the same final solution $\pi^{ts}_{\rho,\nu,\Delta}$.

7.5.1. Parallelization of the algorithm

Parallelizing the TS algorithm provides a means to explore the solution space of a problem in a more efficient way than a sequential TS algorithm. By distributing the task of exploring the solution space over multiple processors, a parallel TS algorithm can explore in a same amount of elapsed time a larger fraction of the solution space than a sequential TS.

Numerous strategies for the parallelization of TS have been proposed in the literature. They can be classified according to the control cardinality, the type of control and communication and the search differentiation [21]. We parallelized our TS algorithm according to a simple master-slave approach where the master keeps the global information and synchronizes the work of p slave processes.

In the initialization of the algorithm, all the processes (master and slaves) set the current solution $\pi^{c}_{\rho,\nu,\Delta} \leftarrow \pi^{ini}_{\rho,\nu,\Delta}$ and initialize the tabu list T. At each iteration, each slave defines the *complete* list of neighbor solutions of $\pi^{c}_{\rho,\nu,\Delta}$. The list is divided into p sublists and each slave evaluates the cost of the solutions in one of these sublists. The particular sublist evaluated by a slave is defined by its (unique) process ID. Then, the master process collects the best solution computed by each slave from its list, sets as the new current solution the best solution in the complete neighborhood and broadcast this solution to the slaves so that all the processes keep the same current solution $\pi^{c}_{\rho,\nu,\Delta}$ at the beginning of the next iteration.

The master process controls the diversification function. After a large number of iterations without cost improvement, it sends an instruction to the slaves to (pseudo)randomly generate a new solution. All the slaves compute exactly the same solution since they use the current iteration number as the seed of the PRNG that sets the values of the new solution's ρ and ν vectors.

7.6. Economical attractiveness of multi-granularity

In order to evaluate the economical attractiveness of the multi-granularity architecture, we must compute for a same problem instance (G, Δ) the solutions $\pi_{\rho,\Delta}$ and $\pi_{\rho,\nu,\Delta}$ to the SR and SRG problems, respectively. We can thus determine the cost gain $C_{SR}(\pi_{\rho,\Delta}) - C_{SRG}(\pi_{\rho,\nu,\Delta})$ provided by the introduction of the band-switching functionality. The cost gain depends on:

1. the problem instance (G, Δ),

2. the band size B,

3. the algorithm used to compute a solution and

4. the parameters of the switch cost function.

In Section 7.3 we modeled the cost of a switch (either a WXC or a BXC) as a function $\psi(t) = a+bt^c$ of the number of ports t. Thus, the cost of a WXC, a BXC, and a WXC/BXC are defined by functions $\psi_{WXC}(t) = a_w + b_w t^{c_w}$, $\psi_{BXC}(t) = a_b + b_b t^{c_b}$ and $\psi_{WB}(x_w, x_b) = \psi_{WXC}(x_w) + \psi_{BXC}(x_b)$, respectively. Independent variables x_w and x_b represent the number of ports in a WXC and a BXC.

For a given problem instance (G, Δ), a band size B and a solution algorithm, we propose a method to define the combinations of parameters $a_w, b_w, c_w, a_b, b_b, c_b$ for which a multi-granularity network is more economical than a single-granularity network. If the problem instance, the band size and a deterministic algorithm are given, the number of ports on each switch, and hence the cost of the network, only depends on the parameters' values. Note that in a single granularity network only parameters a_w, b_w, c_w are relevant.

Let $p = (a_w, b_w, c_w, a_b, b_b, c_b) \in \mathbb{R}^6_+$ be a vector representing a combination of switch cost function parameters and $q = (\Delta, G, B, \mathcal{A})$ be a tuple representing an association of a problem instance, a band size B and a solution algorithm $\mathcal{A}$. We denote by $C^{p,q}_{SR}(\pi_{\rho,\Delta})$ the cost of a solution $\pi_{\rho,\Delta}$ to the SR problem and by $C^{p,q}_{SRG}(\pi_{\rho,\nu,\Delta})$ the cost of a solution $\pi_{\rho,\nu,\Delta}$ to the SRG problem for the same tuple q and vector p.

Let $P_q = \{p, C^{p,q}_{SRG}(\pi_{\rho,\nu,\Delta}) < C^{p,q}_{SR}(\pi_{\rho,\Delta})\}$ be the set of vectors for which the cost of the solution to the SRG problem is smaller than the cost of the solution to the SR problem for the same tuple q. Note that the algorithm $\mathcal{A}$ must be deterministic so that multiple executions of $\mathcal{A}$ using the same tuple q and vector p lead to the same pair of costs $C^{p,q}_{SRG}(\pi_{\rho,\nu,\Delta})$ and $C^{p,q}_{SR}(\pi_{\rho,\Delta})$.

The idea of the method proposed in this section is to sample a fraction of the 6-dimensional space P_q in order to find a subset $P'_q \subset P_q$ and then compute the convex hull[2] $conv(P'_q)$ enveloping the points in P'_q. Thus, $conv(P'_q)$ envelopes (hopefully all) the combinations $(a_w, b_w, c_w, a_b, b_b, c_b)$ for which the multi-granularity network is more economical than the single-granularity network. The convex hull $conv(P'_q)$ must be interpreted as an *approximate representation* of the set of combinations $(a_w, b_w, c_w, a_b, b_b, c_b)$ of economical interest, since both, points *not* satisfying the $C^{p,q}_{SRG}(\pi_{\rho,\nu,\Delta}) < C^{p,q}_{SR}(\pi_{\rho,\Delta})$ condition may fall inside $conv(P'_q)$ and points satisfying the condition may be outside the convex hull.

The method consists of the following steps:

[2]The convex hull of a set of points is the smallest convex set that contains these points.

1. Define for each parameter, a set V of values to evaluate. For example, for parameter b_w, define the set $V_{b_w} = \{1, 2, 4, 8, 16, 32\}$.

2. Build subset P'_q by finding the vectors $p \in \{V_{a_w} \times V_{b_w} \times V_{c_w} \times V_{a_b} \times V_{b_b} \times V_{c_b}\}$ for which condition $C^{p,q}_{SRG}(\pi_{\rho,\nu,\Delta}) < C^{p,q}_{SR}(\pi_{\rho,\Delta})$ holds.

3. Compute $conv(P'_q)$.

Finding a convex hull is an elementary problem in computational geometry. There are many algorithms that solve this problem. The suitability of a particular algorithm depends on factors like the number of dimensions and the number of points in the convex hull. Quickhull [7] is a good choice for general dimensions (in particular from 2 to about 8 dimensions) with a large number of points.

The proposed method may be useful in the design of a WXC/BXC switch architecture. Convex hulls can be computed for several tuples q corresponding to different reference scenarii. Thus, the designer may find quickly the set of such scenarii for which the vector p corresponding to a particular, technology-specific, combination of parameters is contained within the convex hull. In other words, the scenarii for which that particular architecture is economically advantageous with respect to a WXC-based network.

7.7. Experimental results

The objective of this section is to assess the advantages of introducing the band switching granularity in the network and to determine the conditions under which this switching granularity provides a gain in terms of network cost.

We first describe the parameters common to all the experiments. Figure 7.6 shows the network used for all the problem instances (G, Δ) investigated in this section. The graph represents the 14 node US National Science Foundation backbone network considered in numerous research papers. We choose a 14 node network instead of the 29 node network of chapters 5 and 6 because, for a coarse switching granularity layer network (the band-switching layer network) to be cost-efficient, there must be a small number of links and nodes so that the traffic of the client layer network(s) can be aggregated and economies of scale can be exploited. That is why, in general, service networks (*e.g.*, IP, ATM) are in general greater than their server networks (*e.g.*, SDH/SONET) in terms of nodes and links.

We generated 10 sets Δ of $M = 700$ SLDs each with weak time correlation[3] ($\tau(\Delta) \approx 0.1$) and 10 sets Δ of $M = 700$ SLDs each with strong time correlation

[3]The time correlation metric is defined in Subsection 5.3.3.

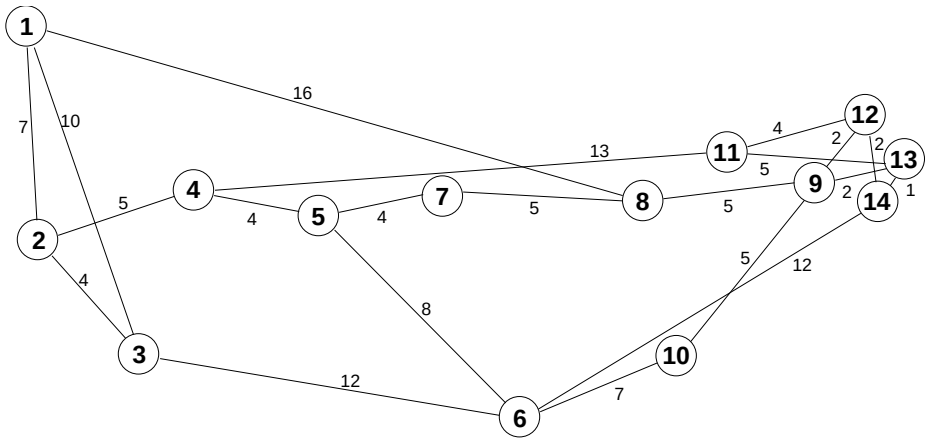


Figure 7.6.: Network used in the experiments of this section.

($\tau(\Delta) \approx 0.9$). The source and destination nodes, the number of lightpaths and the set-up and tear-down dates of the SLDs were drawn randomly from the ranges $[\![1, 14]\!]$, $[\![1, 10]\!]$ and $[1, 1440]$, according to an uniform distribution (1440 is the number of minutes in a day). The set-up and tear-down dates of the SLDs in a set Δ were constrained to satisfy the time correlation of the set. We executed the parallel TS on a cluster of 35 Sun Ultra-SPARC 5 computers with 128 MB of RAM each. We set the number of iterations to 200 and the size of the tabu list to 100 elements.

7.7.1. Port and cost gain due to the band switching granularity

We first evaluate the gain in terms of WXC input/output ports due to the introduction of the band switching granularity. The number of WXC input/output ports may be reduced by using band-switching connections to bear SLDs between no physically adjacent nodes. In this way, WXCs between the end points of band-switching connections are bypassed by the SLDs. This leads to a reduction on the number of WXC input/output ports. Introduction of the band switching granularity means, however, that BXC ports are added to the network. Therefore, gaining WXC input/output ports by introducing the band switching granularity makes economical sense as long as the cost of BXC ports – and the cost of the band-switching layer in general – is proportionally lower that the cost of WXC ports.

We consider for each problem instance (G, Δ) the initial solutions $\pi^{ini}_{\rho,\Delta}$ and $\pi^{ini}_{\rho,\nu,\Delta}$ to the SR and SRG problems, respectively. Solution $\pi^{ini}_{\rho,\Delta}$ defines the first alternate path $P_{i,1}$ for each SLD $\delta_i \in \Delta$ and solution $\pi^{ini}_{\rho,\nu,\Delta}$ additionally defines layout $L_{i,1,1}$ for this path.

Table 7.3 shows, for each network node, the average number of ports in solution $\pi^{ini}_{\rho,\Delta}$ (WXC network), and solution $\pi^{ini}_{\rho,\nu,\Delta}$ (WXC/BXC network) with band sizes $B = 4$

Table 7.3.: Average number of ports in WXCs and BXCs for sets Δ with strong time correlation $\tau(\Delta) \approx 0.9$.

No. Node		WXC network		WXC/BXC network							
				$B = 4$				$B = 8$			
	$\overline{W}_{ad}$	$\overline{W}_{io}$	$\frac{\overline{W}_{ad}}{\overline{W}_{io}}$	$\overline{W}_{io}$	$\frac{\overline{W}_{ad}}{\overline{W}_{io}}$	$\overline{B}_{ad}$	$\overline{B}_{io}$	$\overline{W}_{io}$	$\frac{\overline{W}_{ad}}{\overline{W}_{io}}$	$\overline{B}_{ad}$	$\overline{B}_{io}$
1	300.9	300.9	**1.00**	321.6	**0.94**	80.4	80.4	352.0	**0.85**	44.0	44.0
2	297.1	686.5	**0.43**	316.0	**0.94**	79.0	183.4	344.0	**0.86**	43.0	99.5
3	290.2	424.1	**0.68**	308.8	**0.94**	77.2	113.0	331.2	**0.88**	41.4	60.9
4	297.7	966.8	**0.31**	316.8	**0.94**	79.2	258.4	345.6	**0.86**	43.2	140.8
5	292.5	809.4	**0.36**	312.8	**0.94**	78.2	216.7	337.6	**0.87**	42.2	118.3
6	299.0	621.7	**0.48**	319.6	**0.94**	79.9	165.4	347.2	**0.86**	43.4	90.0
7	284.8	733.3	**0.39**	303.2	**0.94**	75.8	196.0	330.4	**0.86**	41.3	106.7
8	287.6	969.9	**0.30**	309.2	**0.93**	77.3	260.1	334.4	**0.86**	41.8	141.6
9	303.7	1196.9	**0.25**	322.0	**0.94**	80.5	320.2	347.2	**0.87**	43.4	173.2
10	325.1	461.8	**0.70**	346.8	**0.94**	86.7	123.2	373.6	**0.87**	46.7	66.3
11	313.7	583.6	**0.54**	332.0	**0.94**	83.0	155.3	359.2	**0.87**	44.9	84.6
12	294.9	561.0	**0.53**	310.4	**0.95**	77.6	148.8	337.6	**0.87**	42.2	80.6
13	304.2	632.6	**0.48**	322.4	**0.94**	80.6	169.3	348.8	**0.87**	43.6	91.8
14	286.3	509.5	**0.56**	305.2	**0.94**	76.3	135.4	329.6	**0.87**	41.2	73.4
Avg			**0.50**		**0.94**				**0.87**		

and $B = 8$. The average values were computed over the 10 problem instances (G, Δ) whose set Δ has a strong time correlation, $\tau(\Delta) \approx 0.9$. $\overline{W}_{ad}$ and $\overline{W}_{io}$ are the average number of add/drop and input/output ports in a WXC, respectively. In the same way, $\overline{B}_{ad}$ and $\overline{B}_{io}$ are the average number of add/drop and input/output ports in a BXC, respectively. Since $\overline{W}_{ad}$ is the same for a the set of problem instances regardless the solution and type of network (WXC or WXC/BXC), the difference of the ratio $\overline{W}_{ad}/\overline{W}_{io}$ between the WXC-based network and the WXC/BXC-based network is a measure of the gain in terms of WXC input/output ports introduced by the band switching granularity: the more the ratio increases when passing from a WXC-based to a WXC/BXC-based network, the greater the gain. In fact, a high ratio in WXC/BXC networks means that many lightpaths bypass the WXCs in the nodes between the lightpaths' end points.

Table 7.3 shows that the ratio increases by introducing the band switching granularity layer. Moreover, the increment is greater for $B = 4$ than for $B = 8$. Note first that in a WXC/BXC-based network $\overline{W}_{io} \approx B \cdot \overline{B}_{ad}$ since the input/output ports of the WXC are directly connected to the add/drop ports of the BXC. Furthermore, the number of lightpaths for the considered SLDs was drawn randomly in the integer

Table 7.4.: Average number of ports in WXCs and BXCs for sets Δ with weak time correlation $\tau(\Delta) \approx 0.1$.

No. Node		WXC network		WXC/BXC network							
				$B = 4$				$B = 8$			
	$\overline{W}_{ad}$	$\overline{W}_{io}$	$\frac{\overline{W}_{ad}}{\overline{W}_{io}}$	$\overline{W}_{io}$	$\frac{\overline{W}_{ad}}{\overline{W}_{io}}$	$\overline{B}_{ad}$	$\overline{B}_{io}$	$\overline{W}_{io}$	$\frac{\overline{W}_{ad}}{\overline{W}_{io}}$	$\overline{B}_{ad}$	$\overline{B}_{io}$
1	66.8	90.6	**0.74**	176.4	**0.38**	44.1	44.1	204.8	**0.33**	25.6	25.6
2	76.3	171.9	**0.44**	175.6	**0.43**	43.9	106.6	201.6	**0.38**	25.2	61.9
3	70.3	107.8	**0.65**	179.6	**0.39**	44.9	62.6	212.0	**0.33**	26.5	36.8
4	74.8	230.4	**0.32**	177.2	**0.42**	44.3	151.1	208.8	**0.36**	26.1	88.7
5	72.4	192.8	**0.38**	180.4	**0.40**	45.1	122.7	212.8	**0.34**	26.6	72.3
6	76.7	170.6	**0.45**	173.2	**0.44**	43.3	91.2	204.8	**0.37**	25.6	53.9
7	67.8	154.3	**0.44**	174.8	**0.39**	43.7	108.5	204.0	**0.33**	25.5	63.6
8	66.1	213.1	**0.31**	173.2	**0.38**	43.3	147.9	202.4	**0.33**	25.3	87.1
9	69.0	265.2	**0.26**	168.8	**0.41**	42.2	177.3	195.2	**0.35**	24.4	104.0
10	72.6	107.3	**0.68**	178.4	**0.41**	44.6	63.9	208.0	**0.35**	26.0	37.4
11	72.8	150.7	**0.48**	176.0	**0.41**	44.0	85.0	204.8	**0.36**	25.6	49.5
12	71.5	148.4	**0.48**	170.0	**0.42**	42.5	82.6	197.6	**0.36**	24.7	48.0
13	65.7	152.9	**0.43**	168.4	**0.39**	42.1	89.8	202.4	**0.32**	25.3	53.0
14	73.7	144.9	**0.51**	177.2	**0.42**	44.3	76.6	207.2	**0.36**	25.9	44.9
Avg			**0.47**		**0.41**				**0.35**		

range $[\![1, 10]\!]$ according to a uniform distribution. Thus, a single SLD will require either 4, 8 or 12 WXC input/output ports in the source and destination nodes if the band size is $B = 4$ and either 8 or 16 ports if $B = 8$. Clearly, the gain in terms of WXC input/output ports improves as the band size closely matches the size of the demands since, in this way, the number of WXC input/output ports that must be implemented but actually not used by traffic, is reduced.

Table 7.4 shows the average number of ports for the 10 problem instances (G, Δ) whose set Δ has a weak time correlation, $\tau(\Delta) \approx 0.1$. While the average ratio $\overline{W}_{ad}/\overline{W}_{io}$ for the WXC-based network remains roughly the same as for the strong time correlation sets, the average ratio decreases significantly for the WXC/BXC-based networks, which means that the introduction of the band switching granularity leads to a greater number of required WXC input/output ports. Note that the average number of WXC add/drop ports ($\overline{W}_{ad}$) is smaller than for the strong time correlation sets since it corresponds to the average number of maximum *simultaneous* lightpaths being added or dropped at a node, which decreases with the time correlation. If all the $\overline{W}_{ad}$ average maximum simultaneous lightpaths added at a node would have the same destination node, the number of BXC add/drop ports at the source node

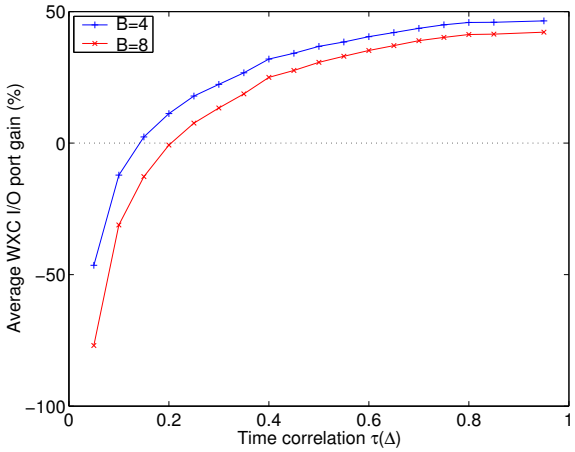


Figure 7.7.: Average WXC I/O port gain as a function of time correlation $\tau(\Delta)$.

would be $\overline{B}_{ad} \approx \lceil \overline{W}_{ad}/B \rceil$. However, the lightpaths added at a node have up to $N-1$ different destinations. Since we are considering the initial solution $\pi^{ini}_{\rho,\nu,\Delta}$, having up to $N-1$ destinations means that there are band-switching connections towards each of those destinations. The number of band-switching connections towards a destination is $\lceil \overline{W}_{ad}/(B(N-1)) \rceil \leq n \leq \lceil \overline{W}_{ad}/B \rceil$. The value of n actually depends on the average number of maximum simultaneous lightpaths toward *that* destination and is typically greater than $\lceil \overline{W}_{ad}/(B(N-1)) \rceil$. As a consequence, $\overline{B}_{ad} > \lceil \overline{W}_{ad}/B \rceil$ and $\overline{W}_{io} \approx B \cdot \overline{B}_{ad} > \overline{W}_{ad}$.

Since the time correlation $\tau(\Delta)$ has a significant incidence on the WXC input/output port gain, we carried out an experiment to characterize this gain as a function of $\tau(\Delta)$. We generated 19 groups of sets Δ. Each group consists of 10 sets Δ with approximately the same time correlation. The gain in terms of WXC input/output ports for a given network node $1 \leq i \leq N$ is $100 \cdot (W^{io}_{sg}(\pi^{ini}_{\rho,\Delta}, i) - W^{io}_{mg}(\pi^{ini}_{\rho,\nu,\Delta}, i))/W^{io}_{sg}(\pi^{ini}_{\rho,\Delta}, i)$, where $W^{io}_{sg}(\pi^{ini}_{\rho,\Delta}, i)$ is the number of WXC input/output ports required in node i to implement solution $\pi^{ini}_{\rho,\Delta}$ (WXC network) and $W^{io}_{mg}(\pi^{ini}_{\rho,\nu,\Delta}, i)$ is the number of WXC input/output ports required in node i to implement solution $\pi^{ini}_{\rho,\nu,\Delta}$ (WXC/BXC network).

Figure 7.7 shows the average WXC input/output port gain as a function of $\tau(\Delta)$ for band sizes $B = 4$ and $B = 8$. The average for a given $\tau(\Delta)$ is computed over the N network nodes for each of the 10 sets Δ with the same $\tau(\Delta)$, that is, we compute the average over $10 \cdot N$ values. The average gain is greater for $B = 4$ than for $B = 8$ because, as explained before, a band size $B = 4$ provides a "fine" band granularity that closely matches the size of the demands. This reduces the number of WXC input/output ports that must be implemented-but-not-used when introducing the band switching layer. With weak time correlation, the volume of maximum *con-*

current traffic in the network is not enough to fully utilize the minimum amount of WXC input/output ports required by the introduction of the band switching layer. This explains the negative port gain. The gain becomes positive at $\tau(\Delta) \approx 0.15$ for $B = 4$ and at $\tau(\Delta) \approx 0.2$ for $B = 8$. The difference between the gain with $B = 4$ and $B = 8$ decreases as $\tau(\Delta)$ increases because the *proportion* of implemented-but-not-used WXC input/output ports is in general greater for $B = 8$ than for $B = 4$. As the volume of maximum concurrent traffic grows (by increasing the time correlation), more WXC input/output ports – that with weak time correlation would be "implemented-but-not-used" – become used for $B = 8$ than for $B = 4$. The slope of the two curves decrease as $\tau(\Delta)$ increases (*i.e.*, the gain stabilizes) because, with a high volume of maximum concurrent traffic, the gain obtained by SLDs bypassing intermediate WXCs is masked by the high number of WXC input/output ports required at endpoints to connect the WXC to the BXC.

We now evaluate the gain in terms of network cost of the solutions $\pi^{ts}_{\rho,\Delta}$ and $\pi^{ts}_{\rho,\nu,\Delta}$ computed by TS with respect to the cost of initial solutions $\pi^{ini}_{\rho,\Delta}$ and $\pi^{ini}_{\rho,\nu,\Delta}$. We also evaluate the gain in cost provided by the WXC/BXC-based network with respect to the WXC-based network for both the initial solution and the TS computed solution. We consider different combinations of switch cost function[4] parameters $a_w, b_w, c_w, a_b, b_b, c_b$. We set parameters a_w and a_b to 0 since they represent a fixed cost component. Parameters b_w and b_b are defined to evaluate the cost gain for ratios $\frac{b_w}{b_b} = 2$, $\frac{b_w}{b_b} = 3$ and $\frac{b_w}{b_b} = 5$, that is, to evaluate the cost gain when a WXC port is 2, 3 and 5 times more expensive than a BXC port. Finally, parameter c_b is defined to take values 1 and 1.3 in order to reflect the fact that a band-switching matrix may be technologically more complex to implement than a wavelength-switching matrix, in particular, if the former is transparent (*i.e.*, all optical) or partially transparent. The band size is $B = 4$.

In Table 7.5, $\overline{C}_{SR}(\pi^{ini}_{\rho,\Delta})$ refers to the average cost (over the 10 strong time correlation sets) of the initial solution to the SR problem and $\overline{C}_{SRG}(\pi^{ini}_{\rho,\nu,\Delta})$ to the average cost of the initial solution to the SRG problem. Similarly, $\overline{C}_{SR}(\pi^{ts}_{\rho,\Delta})$ refers to the average cost of the solution to the SR problem computed by TS and $\overline{C}_{SRG}(\pi^{ts}_{\rho,\nu,\Delta})$ refers to the average cost of the solution to the SRG problem computed by TS. A cost gain is equal to 1 minus the value of a particular ratio, hence, the smaller the ratio, the greater the gain.

The two combinations of parameters b_w and b_b giving the same value $\frac{b_w}{b_b}$ (*e.g.*, $\frac{2}{1} = \frac{4}{2}$) lead to the same average cost ratio since these combinations represent the same cost relationship between a WXC port and a BXC port. TS provides a greater

[4]The cost of a WXC, a BXC and a WXC/BXC are defined by functions $\psi_{WXC}(t) = a_w + b_w t^{c_w}$, $\psi_{BXC}(t) = a_b + b_b t^{c_b}$ and $\psi_{WB}(x_w, x_b) = \psi_{WXC}(x_w) + \psi_{WXC}(x_b)$, respectively.

Table 7.5.: Ratios of average costs for different values of the switch cost function parameters on sets Δ with strong time correlation $\tau(\Delta) \approx 0.9$.

Function parameters						Average cost ratio			
a_w	b_w	c_w	a_b	b_b	c_b	$\frac{\overline{C}_{SR}(\pi^{ts}_{\rho,\Delta})}{\overline{C}_{SR}(\pi^{ini}_{\rho,\Delta})}$	$\frac{\overline{C}_{SRG}(\pi^{ts}_{\rho,\nu,\Delta})}{\overline{C}_{SRG}(\pi^{ini}_{\rho,\nu,\Delta})}$	$\frac{\overline{C}_{SRG}(\pi^{ini}_{\rho,\nu,\Delta})}{\overline{C}_{SR}(\pi^{ini}_{\rho,\Delta})}$	$\frac{\overline{C}_{SRG}(\pi^{ts}_{\rho,\nu,\Delta})}{\overline{C}_{SR}(\pi^{ts}_{\rho,\Delta})}$
0	2	1	0	1	1	0.946	0.992	0.766	0.803
0	4	1	0	2	1	0.946	0.992	0.766	0.803
0	3	1	0	1	1	0.946	0.994	0.721	0.758
0	6	1	0	2	1	0.946	0.994	0.721	0.758
0	5	1	0	1	1	0.946	0.995	0.686	0.721
0	10	1	0	2	1	0.946	0.995	0.686	0.721
0	2	1	0	1	1.3	0.946	0.966	1.348	1.376
0	4	1	0	2	1.3	0.946	0.966	1.348	1.376
0	3	1	0	1	1.3	0.946	0.972	1.110	1.140
0	6	1	0	2	1.3	0.946	0.972	1.110	1.140
0	5	1	0	1	1.3	0.946	0.980	0.919	0.951
0	10	1	0	2	1.3	0.946	0.980	0.919	0.951

cost gain (with respect to the initial solution) when solving the SR problem than when solving the SRG problem for several reasons. Firstly, the number of solutions evaluated by TS is the same for both problems (same number of iterations executed in both cases), while the size of the solution space is greater for SRG than for SR, that is, $(KL)^M > K^M$. Thus, the fraction of the solution space explored by TS is smaller in the case of the SRG problem. Secondly, in the SRG problem, the initial solution is already a good solution from a cost point of view since the lightpaths are routed through direct band-switching connections between the source and destination nodes of the lightpaths and not through a path of band-switching connections. By using direct connections, no BXC add/drop ports (and their corresponding WXC input/output ports) are required in the transit nodes.

Regarding the ratio $\overline{C}_{SRG}(\pi^{ini}_{\rho,\nu,\Delta})/\overline{C}_{SR}(\pi^{ini}_{\rho,\Delta})$, the gain due to the introduction of the band-switching granularity increases as the wavelength-switching becomes more expensive, *i.e.*, as the ratio $\frac{b_w}{b_b}$ increases. Note however that there is a negative gain for $\frac{b_w}{b_b} = 2$ and $\frac{b_w}{b_b} = 3$ with $c_b = 1.3$ since, under these conditions, the band-switching is relatively more expensive because of parameter c_b. The ratio $\overline{C}_{SRG}(\pi^{ts}_{\rho,\nu,\Delta})/\overline{C}_{SR}(\pi^{ts}_{\rho,\Delta})$ (TS solutions) is in general greater than the ratio $\overline{C}_{SRG}(\pi^{ini}_{\rho,\nu,\Delta})/\overline{C}_{SR}(\pi^{ini}_{\rho,\Delta})$ because, as explained above, the cost gain provided by TS with respect to the initial solution is greater for the SR problem than for the SRG problem. Note however that the difference between $\overline{C}_{SRG}(\pi^{ini}_{\rho,\nu,\Delta})/\overline{C}_{SR}(\pi^{ini}_{\rho,\Delta})$ and $\overline{C}_{SRG}(\pi^{ts}_{\rho,\nu,\Delta})/\overline{C}_{SR}(\pi^{ts}_{\rho,\Delta})$ remains roughly

Table 7.6.: Average cost ratios for different values of the switch cost function parameters on sets Δ with weak time correlation $\tau(\Delta) \approx 0.1$.

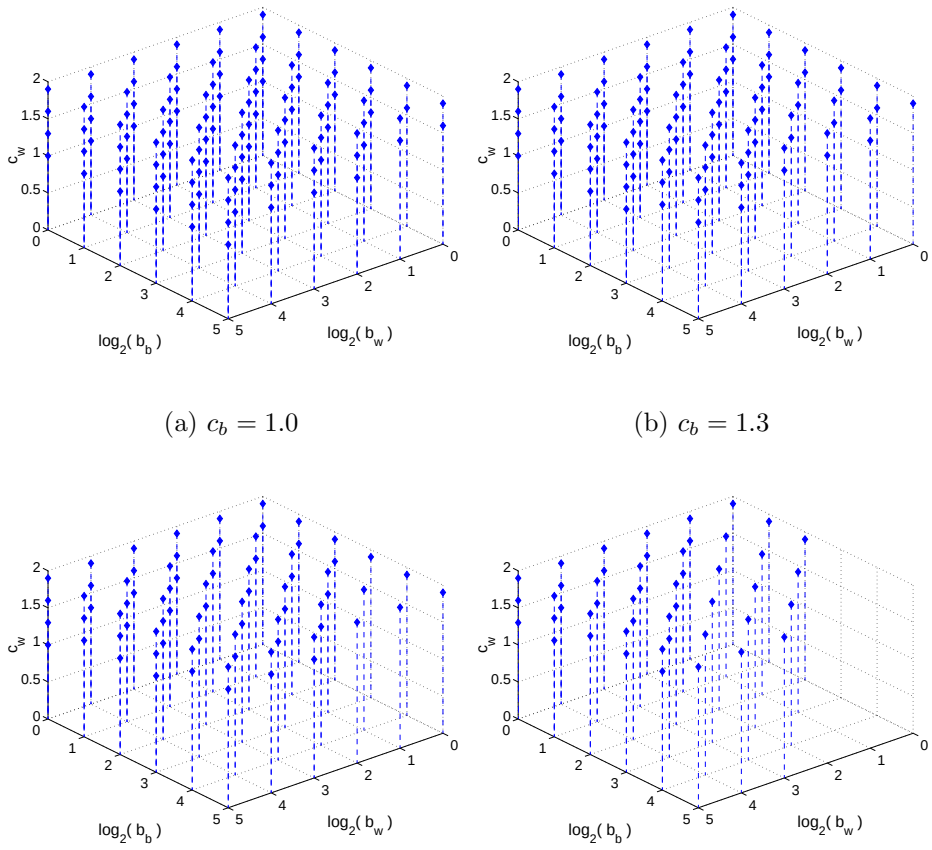
Function parameters						Average cost ratio			
a_w	b_w	c_w	a_b	b_b	c_b	$\frac{\overline{C}_{SR}(\pi^{ts}_{\rho,\Delta})}{\overline{C}_{SR}(\pi^{ini}_{\rho,\Delta})}$	$\frac{\overline{C}_{SRG}(\pi^{ts}_{\rho,\nu,\Delta})}{\overline{C}_{SRG}(\pi^{ini}_{\rho,\nu,\Delta})}$	$\frac{\overline{C}_{SRG}(\pi^{ini}_{\rho,\nu,\Delta})}{\overline{C}_{SR}(\pi^{ini}_{\rho,\Delta})}$	$\frac{\overline{C}_{SRG}(\pi^{ts}_{\rho,\nu,\Delta})}{\overline{C}_{SR}(\pi^{ts}_{\rho,\Delta})}$
0	2	1	0	1	1	0.891	0.955	1.353	1.450
0	4	1	0	2	1	0.891	0.955	1.353	1.450
0	3	1	0	1	1	0.891	0.959	1.250	1.345
0	6	1	0	2	1	0.891	0.959	1.250	1.345
0	5	1	0	1	1	0.891	0.962	1.168	1.261
0	10	1	0	2	1	0.891	0.962	1.168	1.261
0	2	1	0	1	1.3	0.891	0.923	2.427	2.512
0	4	1	0	2	1.3	0.891	0.923	2.427	2.512
0	3	1	0	1	1.3	0.891	0.931	1.967	2.054
0	6	1	0	2	1.3	0.891	0.931	1.967	2.054
0	5	1	0	1	1.3	0.891	0.940	1.598	1.686
0	10	1	0	2	1.3	0.891	0.940	1.598	1.686

constant for a same combination of parameters. Based on this last observation, we use the initial solutions instead of the TS computed solutions in the experiments of Subsection 7.7.2.

Table 7.6 shows the ratios for the sets Δ with weak time correlation. Though the cost gain provided by TS with respect to the initial solution is in general greater than for the strong time correlation sets, the average gain due to the introduction of the band-switching granularity is negative for both the initial solution and the TS computed solution. As shown in Table 7.4, for weak time correlation traffic, the introduction of the band-switching layer network results in a lower $\overline{W}_{ad}/\overline{W}_{io}$ ratio, *i.e.*, the introduction of the band-switching layer network increases the number of WXC input/output ports. As a consequence, for a same weak time correlation problem instance, the cost of a WXC/BXC-based network is higher than the cost of a WXC-based network, whatever the combination of parameters.

7.7.2. Economical attractiveness of multi-granularity

We apply the method proposed in Subsection 7.6 to the sets Δ with strong time correlation. We first define the elements of tuple $q = (\Delta, G, B, \mathcal{A})$. The set Δ is each of the ten sets with strong time correlation and G is the graph of Figure 7.6. The band size is set to $B = 4$ and $\mathcal{A}$ is the algorithm that computes the initial solutions



(a) $c_b = 1.0$ (b) $c_b = 1.3$

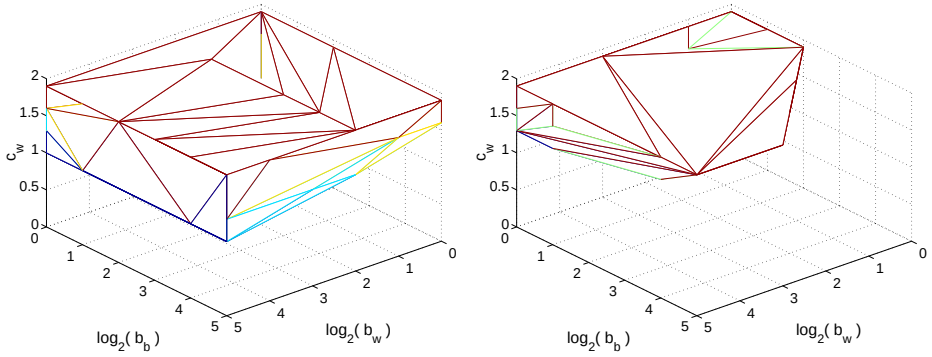
(c) $c_b = 1.6$ (d) $c_b = 1.9$

Figure 7.8.: Set P'_q of parameter combinations $p = (a_w, b_w, c_w, a_b, b_b, c_b)$ for which $C^{p,q}_{SRG}(\pi_{\rho,\nu,\Delta}) < C^{p,q}_{SR}(\pi_{\rho,\Delta})$.

to the SR and the SRG problem, that is, solutions $\pi^{ini}_{\rho,\Delta}$ or $\pi^{ini}_{\rho,\nu,\Delta}$. In this subsection, the costs $C^{p,q}_{SR}(\pi_{\rho,\Delta})$ and $C^{p,q}_{SRG}(\pi_{\rho,\nu,\Delta})$ are actually the average costs over the ten sets Δ. For the switch cost function parameters, we consider the following possible values: $V_{a_w} = V_{a_b} = \{0\}$, $V_{b_w} = V_{b_b} = \{1, 2, 4, 8, 16, 32\}$ and $V_{c_w} = V_{c_b} = \{1, 1.3, 1.6, 1.9\}$.

Since it is difficult to visually represent spaces of more than 3 dimensions, we had to adapt the results of method in order to illustrate sets P'_q and convex hulls in 3D. Figure 7.8 shows the set P'_q for combinations of parameters a_w, b_w, c_w, a_b, b_b. Each subfigure presents a subset of points for a given value of parameter c_b. The number of points in the subfigures decreases as parameters b_b and c_b take greater values because, by increasing b_b and c_b, the band-switching layer network becomes more expensive.

Figure 7.9 shows the convex hull of the points in Subfigures 7.8(a) and 7.8(d) computed with Quickhull [7].



(a) $c_b = 1.0$ (b) $c_b = 1.9$

Figure 7.9.: Convex hull of parameter combinations for $c_b = 1.0$ and $c_b = 1.9$.

7.8. Conclusions

In this chapter we investigated the economical advantage of a multi-granularity switching network with respect to a wavelength-switching network taking into account the time and space distribution of demands. Our objective was to provide a framework to determine the conditions under which a multi-granularity network is more economical than a wavelength-switching network.

We formulated the problems of instantiating a set of SLDs in both a wavelength-switching network and a wavelength/band switching network. These problems led to a SLD routing problem (SR) and a SLD routing and grooming problem (SRG). Both problems were formulated as combinatorial optimization problems and a parallelized TS algorithm was proposed to find approximate solutions. We also proposed a method to define the combinations of switch cost function parameters for which a multi-granularity switching network is more economical than a wavelength-switching network for a given network and set of traffic demands.

For traffic demands with strong time correlation, the introduction of the band-switching granularity led to a gain in terms of WXC ports due to the bypassed traffic in the band-switching layer network. Moreover, the gain was greater when the band size closely matched the size of the demands. Conversely, when traffic demands had weak time correlation, the introduction of the band-switching granularity led to a greater number of WXC ports and network cost. In terms of network cost, the gain provided by the introduction of the band-switching granularity depends not only on the time correlation between demands but also on the cost difference between the wavelength-switching and the band-switching layer networks, which is defined by the switch cost function parameters.

The main conclusion drawn from this study is that the incidence of the time distribution of traffic demands on the economical advantage of a multi-granularity network is as significant as the cost difference between the two layer networks. Hence, it is very important for an equipment manufacturer using the proposed framework to consider, as far as possible, all the reference traffic load distributions that are likely to exist in the network for which the equipment is being designed.

Though the models and the algorithm of this chapter were developed in the context of a wavelength/band switching network, it is worth to note that the proposed framework is generic and may be successfully applied in the engineering of other connection-oriented multi-granularity networks. Examples of such networks are MPLS over SDH/SONET, SDH/SONET over OTN (G.709) or even Low Order over High Order (LO/HO) SDH/SONET connection networks (*e.g.*, VC-3 over VC-4).

Some aspects that must be further investigated are the relationship between the computed paths/layouts and the time correlation as well as the incidence of this relationship on the cost gain provided by the TS algorithm.

8. Conclusions of the Thesis

We investigated optimization problems arising in the engineering of WDM optical transport networks. Network engineering concerns the efficient configuration and assignment of resources to traffic demands in the day-to-day operation of the network. In network engineering problems, the dynamic change of the traffic load is an important factor that must be taken into account in the optimization of the network. Moreover, the periodicity of this change observed in operational transport networks suggests that the change may be modeled deterministically. The fundamental contribution of this thesis is a dynamic deterministic traffic model called Scheduled Lightpath Demands (SLDs) that captures the time and space distribution of traffic demands.

We investigated problems related to the provisioning SLDs in both wavelength-switching (single-granularity) and wavelength/band switching (multi-granularity) networks. Our goal with respect to the modeling of these problems was to be both realistic and mathematically rigorous, two objectives that are often difficult to conciliate. Regarding the resolution of the problems, we focused on the use meta-heuristic algorithms because of their practical advantages, namely: their flexibility, which allows complicate constraints found in real-world problems to be integrated, and the possibility of processing problem instances of large size in reasonable computing time. Our approach was different from the typically adopted approach to network optimization based on mathematical programming formulations and algorithms (mainly, linear programming).

In Chapter 5 (RWA for SLDs in a wavelength-switching network), the cost of the approximate solutions computed by the TS meta-heuristic were close to the optimal ones computed by the B&B algorithm (in average, around 1% above) in the cases where comparison was possible. The TS algorithm provides a greater gain in terms of WDM channels than the alternative sequential sRWA algorithm on sets of SLDs with weak time correlation because in this class of sets, the greater potential for channel reuse is better exploited by the meta-heuristic. Finally, the number of wavelengths required for a set of SLDs was around one order of magnitude smaller than the number

of requested lightpaths because of the temporal and spatial reuse of wavelengths.

In Chapter 6, (Diverse Routing and Spare Capacity Assignment for SLDs in a wavelength-switching network), we evaluated the trade-off between the resource-efficiency of backup-multiplexing and its computational cost with respect to mere channel reuse. The gain in terms of WDM channels provided by backup-multiplexing increases as a function of the number of SLDs, but the growth rate of this gain is smaller than the growth rate of the additional CPU-time required by the algorithm that computes the backup-multiplexing solution. The backup-multiplexing algorithm outperforms the channel reuse algorithm on sets of SLDs with strong time correlation because, in this class of sets, the reduction of the number of spare WDM channels is mainly due to the physical disjointness of the primary paths (and not to the time disjointness of demands), which is exploited by the backup-multiplexing algorithm only. However, with weak time correlation, the channel reuse algorithm computes solutions whose cost is very close to the cost of solutions computed with the backup-multiplexing algorithm.

In Chapter 7 (Routing and grooming of SLDs in a multi-granularity switching network), we show that two conditions must be satisfied in order to make the multi-granularity network under consideration economically attractive: on one hand, the time correlation among SLDs must be strong enough (a minimum of $\tau(\Delta) \approx 0.15$ is required) in order to avoid under-utilized band-switching connections (and the corresponding BXC add/drop ports and WXC input/output ports). On the other hand, the cost per transported bit must be lower in the band-switching layer network than in the wavelength-switching layer network. Additionally, the band size must match as close as possible the size of the demands.

In this Thesis we focused on the development of a flexible framework for the modeling of network engineering problems and on the suitable coupling of the resulting models with standard forms of known meta-heuristics (SA and TS). Further work is needed to identify the "best" meta-heuristic for a given problem. By "best" we mean the meta-heuristic that computes the best cost gain per unit of computing time. For this, we need to characterize the relationship between the precomputed paths (and layouts in Chapter 7) and the structural properties of the solution space on one hand, and to to identify the most suitable algorithmic components of meta-heuristics to search these spaces on the other hand. Recent trends in the development of meta-heuristics should be considered, for example, methods for exploiting better the information that becomes available during search and creating better starting points, more powerful neighborhood operators, refined parallel search strategies and hybridization.

The proposed models and algorithms must be adapted in order to be used in real-

world network engineering problems. For example, the selection of precomputed paths based on the paths' physical length must be replaced by a selection criterion that takes into account physical layer performance parameters, such as the Optical Signal to Noise Ratio (OSNR)[1], and the incidence of the selected paths on the potential for network resources' reuse.

A venue of future research concerns the integration of the proposed network engineering algorithms with traffic engineering algorithms in order to develop network operation systems usable by network operators.

The information provided in Chapters 5, 6 and 7 about the incidence of the time correlation among SLDs on the network cost may be used by network operators offering scheduled connection services (Section 4.2) to define fare policies. The policies would be used to persuade customers to shift part of their traffic demands to time windows that increase the potential of resource reuse for the operator.

The proposed models and algorithms have interesting potential applications to other networking technologies. For example, the contributions of Chapter 7 may be adapted to address the problem of provisioning connections in networks using integrated nodes. Integrated nodes are a combination of a WXC and a SDH/SONET cross-connect or IP/MPLS LSR. Many equipment manufacturers and operators are interested in integrated nodes because they are expected both to simplify the control and management of the network and and to reduce interfacing costs. The standardization of GMPLS at the IETF shall result in a control plane protocols for networks with this type of nodes.

[1] A French national research project on this topic called RHYTME, involving France Telecom, Alcatel, ENST Paris and other partners, will begin in the last trimester of 2003. The aim of the project is to determine the feasibility and the economical advantage of introducing partial or total transparency in the network. As part of the project's methodology, physical layer performance parameters will be introduced in the design, dimensioning and engineering of the considered networks.

Part III.

Appendices

A. Meta-heuristic algorithms

The theory of complexity developed in the 1970's [32] made clear that finding computationally simple algorithms to solve difficult combinatorial optimization problems (*e.g.*, NP-hard problems) is unrealistic. Unfortunately, these problems frequently arise in real-life applications, so, heuristic algorithms that find approximate solutions to them had to be developed. One of the most popular heuristics is the so called Local Search (LS) or Local Descent (LD) which can be summarized as a search algorithm that, starting from an initial feasible solution, iteratively improves it by making small changes to the solution until no improvements are possible. The major disadvantage of LS is that nothing precludes the obtained solution from being a local optimum. In fact, the closeness of the obtained solution to a global optimal solution is strongly dependent upon the initial solution and the particular sequence of changes made. As a consequence, the quality of solutions is often mediocre.

The publication in 1983 of a paper describing a new heuristic called Simulated Annealing [55] introduced a new approach to solve combinatorial optimization problems. Simulated Annealing is a generic heuristic algorithm based on an analogy from statistical mechanics that can be interpreted as a controlled random walk on the solution space of a problem instance. The algorithm motivated the interest of the research community on this approach and resulted in the proposition of many other similar algorithms such as Tabu Search [35] and Ant Colony Optimization [22]. Together with other methods like Genetic Algorithms [44], they were later referred to as *meta-heuristics*. The generic nature of meta-heuristic changed the approach to solve combinatorial optimization problems: instead of developing specialized heuristics from scratch for a particular problem or class of problems, the challenge is now to adapt a meta-heuristic to the problem, which requires much less work.

Though in most of the cases there are no mathematical proofs of the convergence of meta-heuristics to a global optimum, these algorithms are widely used in practice since, when the comparison is possible, it has been observed that they find solutions of good quality, that is, solutions whose cost is "close" to the optimal one. Furthermore, because meta-heuristics explore only a fraction of the solution space, they allow

problem instances of realistic size to be solved in reasonable computation time. Meta-heuristics provide a flexible framework that allows complicate constraints found in real-world problems to be integrated into the algorithms.

A.1. Simulated Annealing

Simulated Annealing (SA) is a stochastic iterative search strategy used to solve combinatorial optimization problems. In SA, modifications to a current solution leading to a greater solution cost can be probabilistically accepted. SA is based on an analogy to the physical annealing process used to find low energy states of solids [55]. In a combinatorial optimization context, a solution corresponds to a state of the physical system and the solution cost to the energy of the system. At each iteration, the current solution is randomly modified to generate a neighbor solution. If the new solution provides a improvement in cost, it is automatically accepted and becomes the new current solution. Otherwise, the new solution is accepted according to the Metropolis criterion, which states that the probability of acceptance is related to the difference of cost between the two solutions and a parameter called "temperature". A non-improving solution is more likely to be accepted if the temperature is high and the cost difference is low. The temperature parameter is progressively lowered, according to some predefined cooling schedule, and a certain number of iterations are performed at each temperature level. When the temperature is sufficiently low, only cost improving solutions are accepted and SA stops in a local optimum. As opposed to most meta-heuristics, SA asymptotically converges to a global optimum. Finite-time implementations, however, do not provide such a guarantee. An SA algorithm has the following generic form[1]:

SimulatedAnnealing(s_i **)**

```
/* Initialize current solution with initial solution */
```
$s_c \leftarrow s_i$

$T \leftarrow WarmingUp()$

repeat

  repeat

```
    /* Get a neighbor solution of s_c */
```
    $s^* \leftarrow GenerateNeighbor(s_c)$

```
    /* Compute the cost difference */
```
    $\Delta C \leftarrow C(s^*) - C(s_c)$

[1] We consider a minimization algorithm.

```
      if ΔC < 0 or Accept(ΔC, T)
        /* Accept neighbor solution as current */
        s_c ← s*
    until Equilibrium()
    T ← DecrementT()
  until Frozen()
  return s_c
end.
```

In order to implement a SA algorithm, three problem-specific functions must be defined:

- a function to generate an initial solution s_i,
- a function C to compute the cost of a given solution and
- a function to generate a neighbor solution from a given current solution s_c (the $GenerateNeighbor()$ function).

A.2. Tabu Search

Tabu Search (TS) is a deterministic iterative local search strategy used to solve combinatorial optimization problems. The principles of TS were originally proposed by Glover [35]. In an initialization phase, TS selects as the current solution an initial feasible solution. At each iteration, the best solution in the neighborhood of the current solution is selected as the new current solution, even if it leads to an increase in solution cost. As opposed to a pure LS heuristic, TS will thus escape from local minima. A short-term memory, known as the tabu list, stores recently visited solutions (or attributes of recently visited solutions) to avoid short-term cycling. Typically, the search stops after a fixed number of iterations or a maximum number of consecutive iterations without improvement of the incumbent (best known) solution cost. A TS algorithm has the following generic form[2]:

```
TabuSearch( s_i )
  /* Initialize current & incumbent solution with initial solution */
  s_c ← s* ← s_i
  /* Initialize tabu list */
```

[2]We consider a minimization algorithm.

```
  InitializeTabuList( T )
  for i from 1 to nIters do
    /* Generate neighborhood */
    N_{s_c} ← GenerateNhood( s_c, T )
    /* Pick best neighborhood solution */
    s_b ← PickBest( N_{s_c} )
    /* Compare cost */
    if C( s_b ) < C( s* ) then
      /* Update incumbent solution */
      s* ← s_b
    endif
    /* Make solution tabu */
    InsertInList( T, s_b )
    /* Update current solution */
    s_c ← s_b
  endfor
  return s*
end.
```

Starting from this simple canonical form, a number of developments and refinements have been proposed over the years. These include the introduction of diversification and intensification mechanisms, reactive mechanisms to dynamically adjust the search parameters (in particular, the size of the tabu list), randomization, etc.

Diversification and intensification mechanisms provide a means to balance a wide but shallow exploration of the solution space with a more focused and intense exploration of certain regions. Intensification is in general not necessary in TS since, in fact, it is a natural trend of the algorithm in its canonical form. Conversely, ensuring search diversification is a critical point that must be considered in order to explore interesting regions of the solution space that could remain unexplored otherwise.

In TS, the cost of each element in the neighborhood of the current solution must be evaluated. This can prove to be very expensive from a computational standpoint. An alternative consists of considering only a random sample of the neighborhood, reducing thus the computational burden. Another advantage of this alternative is that the added randomness may act as an anti-cycling mechanism.

As for SA, three problem-specific functions must be defined in order to implement a TS algorithm:

- a function to generate an initial solution s_i,
- a function C to compute the cost of a given solution and

- a function to generate a neighbor solution from a given current solution s_c (this function is used inside the *GenerateNhood*() function of TS).

B. The graph vertex coloring problem

The graph vertex coloring problem is a combinatorial optimization problem that belongs to the general class of assignment problems. Graph coloring deals with the fundamental problem of partitioning a set of objects into classes, according to certain rules. Applications of graph coloring to engineering and science problems include time table and scheduling [75, 88], frequency assignment [31], register allocation [13, 14, 18], etc.

We present a formal description of this problem. A k-coloring of an undirected graph $G = (V, E)$ is a function $c_k : V \rightarrow \{1, 2, \ldots, k\}$ such that $c_k(v_i) \neq c_k(v_j), \forall\ (v_i, v_j) \in E$. The minimal value of k for which a k-coloring exists is called the chromatic number of G, denoted $\chi(G)$. The graph vertex coloring problem consists of finding a $\chi(G)$-coloring of G.

There is a vast literature about graph vertex coloring algorithms. A technique commonly used for approximate coloring is called successive augmentation. In this technique a partial coloring is found on a small number of vertices and this is extended vertex by vertex until the entire graph is colored [9, 63, 42]. Simulated annealing [15, 53] and Tabu Search [43] meta-heuristic algorithms have proposed for approximate graph vertex coloring. Optimal graph vertex coloring is commonly based on implicit enumeration methods [61, 62].

We formalize the wavelength assignment problem of Chapter 5 and the spare capacity assignment problem of Chapter 6 as graph coloring problems.

C. Algorithm to compute the set of layouts of a path

In this appendix we propose an algorithm that recursively computes a set of layouts of a path. The algorithm is used in Subsection 7.3.3 to compute the set of layouts $\Lambda_{i,k}$ of a path $P_{i,k}$ in the SRG problem. The algorithm is the following:

BuildLayoutSet($P, MinVertex, MaxVertex, \Lambda$ **)**
  `/* Initialize the` $Prefix$ `layout */`
  $Prefix \leftarrow \emptyset$
  `/* Recursively compute the layouts */`
  RecursiveLayouts($Prefix, P, MinVertex, MaxVertex, \Lambda$ **)**
end.

The algorithm takes as input a path P and parameters $MinVertex$ and $MaxVertex$ that indicate, respectively, the minimum and maximum number of vertices that must exist in the subpaths of the computed layouts. The output is the set of layouts Λ. The algorithm initializes a layout called $Prefix$ that is used in the recursive computation of layouts. This recursive computation is performed by the following function:

RecursiveLayouts($Prefix, p, min, max, \Lambda$ **)**
  `/*` $z_p + 1$ `is the number of vertices in` p `*/`
  if $z_p + 1 \leq max$ **then**
    $\Lambda \leftarrow \Lambda \cup \{prefix \cup \{p\}\}$
  endif
  for i **from** $z_p - min + 1$ **to** $min - 1$ **step** -1 **do**
    $v_1 \leftarrow (x_0, \ldots, x_i)$
    $v_2 \leftarrow (x_i, \ldots, x_{z_p})$
    if $i < max$ **then**

$Prefix \leftarrow Prefix \cup \{v_1\}$
RecursiveLayouts($Prefix, v_2, min, max, \Lambda$ **)**
$Prefix \leftarrow Prefix \backslash \{v_1\}$
endif
endfor
end.

In **RecursiveLayouts()**, $z_p + 1$ is the number of vertices of input path p. Note that a layout consisting of the complete path P is added to Λ even if P has less than $MinVertex$ vertices. For a path $P_{i,k}$, this layout is denoted by $\lambda_{i,j,1}$. Moreover, the algorithm may compute less than L layouts for some combinations of P and parameters $MinVertex$ and $MaxVertex$.

To illustrate the algorithm, let us consider the following parameters: $P = \{1, 2, 3, 4, 5, 6\}$, $MinVertex = 3$ and $MaxVertex = \infty$. The computed set of layouts is: $\Lambda = \{\{(1, 2, 3, 4, 5, 6)\}, \{(1, 2, 3, 4)(4, 5, 6)\}, \{(1, 2, 3)(3, 4, 5, 6)\}\}$.

Some implementation details are not presented in the algorithms above, for example, the decision logic used to stop the algorithm after computing the first L layouts.

D. List of publications

- J. Kuri, N. Puech, M. Gagnaire, E. Dotaro and R. Douville, "Routing and Wavelength Assignment of Scheduled Lightpath Demands," in *IEEE JSAC Optical Communications and Networking Series*, vol. 21, No. 8, October 2003.

- J. Kuri and M. Gagnaire, "Routing and Grooming of Scheduled Lightpath Demands in a Multigranularity Optical Transport Network," Technical Report ENST/ALCATEL 03-02, ENST Paris, Department of Computer Science and Networks / Alcatel R&I, Paris, May 2003.

- N. Puech, J. Kuri, and M. Gagnaire, "Topological Design and Lightpath Routing in WDM Mesh Networks: A Combined Approach," in *Photonic Network Communications*, vol. 4, No. 3/4, pp. 443–456, July 2002.

- J. Kuri, N. Puech and M. Gagnaire, "Diverse Routing of Scheduled Lightpath Demands in an Optical Transport Network," in *Procs. of DRCN 2003*, (Banff, Canada), IEEE Communications Society, October 2003.

- J. Kuri, N. Puech, M. Gagnaire and E. Dotaro, "Routing and Wavelength Assignment of Scheduled Lightpath Demands in a WDM Optical Transport Network," in *Procs. of ICOCN 2002*, (Singapore), pp. 270–273, IEEE Communications Society, November 2002.

- J. Kuri, N. Puech, M. Gagnaire and E. Dotaro, "Routing Foreseeable Lightpath Demands Using a Tabu Search Meta-heuristic," in *Procs. of GLOBECOM 2002*, (Taipei, Taiwan), IEEE Communications Society, November 2002.

- J. Kuri, N. Puech and M. Gagnaire, "Resolution of a WDM network design problem using a decomposition approach and a size reduction method," in *Procs. of ECUMN 2002*, (Colmar, France), pp. 187–194, IEEE Communications Society, April 2002.

Bibliography

[1] Abilene Backbone Network. Advanced Networking for Research and Education. `http://abilene.internet2.edu/`.

[2] R. Ahuja, T. Magnanti, and J. Orlin. *Network flows: theory, algorithms, and applications*. Prentice Hall, Upper Saddle River, NJ, 1992.

[3] M. Alanyali and E. Ayanoglu. Provisioning Algorithms for WDM Optical Networks. *IEEE/ACM Transactions on Networking*, 7(5):767–778, 1999.

[4] M. Ammar, S. Cheung, C. Scoglio, I. Chlamtac, A. Faragó, and T. Zhang. Virtual path network design. In J. Roberts, U. Mocci, and J. Virtamo, editors, *Broadband Network Teletraffic. Final report of action COST 242*, pages 271–299. Springer-Verlag, Berlin Heidelberg, 1996.

[5] D. Banerjee and B. Mukherjee. A Practical Approach for Routing and Wavelength Assignment in Large Wavelength-Routed Optical Networks. *IEEE Journal on Selected Areas in Communications*, 14(5):903–908, 1996.

[6] D. Banerjee and B. Mukherjee. Wavelength-Routed Optical Networks: Linear Formulation, Resource Budgeting Tradeoffs, and a Reconfiguration Study. *IEEE/ACM Transactions on Networking*, 8(5):598–607, 2000.

[7] C. B. Barber, D. P. Dobkin, and H. T. Huhdanpaa. The Quickhull algorithm for convex hulls. *ACM Transactions on Mathematical Software*, 22(4):469–483, 1996.

[8] J. Benoit. ATMOS: ATM Optical Switching, project summary. Technical Report R2039, RACE, January 1997.

[9] B. Berger and J. Rompel. A better permance guarantee for approximate graph coloring. *Algorithmica*, 5:459–466, 1990.

[10] G. Bolch, S. Greiner, H. de Meer, and K. Trivedi. *Queueing Networks and Markov Chains. Modeling and Performance Evaluation with Computer Science Applications*. Wiley Interscience, New York, 1998.

[11] K. A. Simone Brown. Characterization of optical fibres for high speed communication systems. Master's thesis, The University of New Brunswick, New Brunswick, Canada, August 2001.

[12] B. Van Caenegem, W. Van Parys, F. De Turck, and P. Demeester. Dimensioning of survivable WDM networks. *IEEE Journal of Selected Areas in Communications*, 16(7):1146–1157, 1998.

[13] G. Chaitin. Register allocation and spilling via graph coloring. In *Proceedings of the ACM SIGPLAN 82 Symposium on Compiler Construction*, pages 98–105, New York, NY, 1982. ACM.

[14] G. Chaitin, M. Auslander, A. Chandra, J. Cocke, M. Hopkins, and P. Markstein. Register allocation via coloring. *Coputer Languages*, 6:47–57, 1981.

[15] M. Chams, A. Hertz, and D. De Werra. Some experiments with simulated annealing for coloring graphs. *European Journal of Operations Research*, 32:260–266, 1987.

[16] A. Chiu and E. Modiano. Traffic Grooming Algorithms for Reducing Electronic Multiplexing Costs in WDM Ring Networks. *IEEE Journal of Lightwave Technology*, 18(1):2–12, 2000.

[17] I. Chlamtac, A. Ganz, and G. Karmi. Lightpath Communications: An Approach to High Bandwith Optical WAN's. *IEEE Transactions on Communications*, 40(7):1171–1182, 1992.

[18] F. Chow and J. Hennessy. The priority-based coloring approach to register allocation. *ACM Transactions on Programming Languages and Systems*, 12(4):501–536, 1990.

[19] J. Clausen. *Branch and Bound Algorithms - Principles and Examples*. Department of Computer Science, University of Copenhagen. Available at `http://www.imm.dtu.dk/~jha/`.

[20] J. Clausen and M. Perregaard. On the Best Search Strategy in Parallel Branch-and-Bound - Best-First-Search vs. Lazy Depth-First-Search. *Proceedings of POC96*, 1996.

[21] T. Crainic, M. Toulouse, and M. Gendreau. Toward a Taxonomy of Parallel Tabu Search Heuristics. *INFORMS Journal on Computing*, 9(1):61–72, 1995. Available at http://citeseer.nj.nec.com/crainic95towards.html.

[22] M. Dorigo and G. Di Caro. The Ant Colony Optimization Meta-Heuristic. In D. Corne, M. Dorigo, and F. Glover, editors, *New Ideas in Optimization*, pages 11–32. McGraw-Hill, 1999.

[23] J. Doucette and W. Grover. Influence of modularity and economy-of-scale effects on design of mesh-restorable DWDM networks. *IEEE Journal on Selected Areas in Communications, Special Issue on Protocols and Architectures for Next Generation Optical WDM Networks*, 18(10):1912–1923, 2000.

[24] R. Doverspike. Multiplex bundler algorithms for network planning system. In *Proceedings of the 3rd International Network Planning Symposium (Networks '86)*, pages 29–32, Innisbrook, Florida, June 1986.

[25] Eric Mannie (Editor). Generalized Multi-Protocol Label Switching (GMPLS) Architecture. IETF ccamp group, March 2002. Work in progress.

[26] L. W. Ellis. La loi des volumes économiques appliquée aux télécommunications. *Revue des Télécomunications*, 1(50):4–20, 1975.

[27] D. Eppstein. Finding the k shortest paths. *SIAM Journal of Computing*, 28(2):652–673, 1998.

[28] Eurescom. Planning of Optical Network. Deliverable 3, Main Report P709, Eurescom, 2000.

[29] P. F. Fonseca. Pan-European multi-wavelength transport networks: network design, architecture, survivability and SDH networking. In *Proceedings of the First International Workshop on Design of Reliable Communications Networks*, Brugge, Belgium, May 1998.

[30] P. Gambini, M. Renaud, C. Guillemot, F. Callegati, I. Andonovic, B. Bostica, D. Chiaroni, G. Corazza, S. L. Danielsen, P. Gravey, P. B. Hansen, M. Henry, C. Janz, A. Kloch, R. Krahenbuhl, C. Raffaelli, M. Schilling, A. Talneau, and Zucchelli. Transparent Optical Packet Switching: Network Architecture and Demostrators in the KEOPS Project. *IEEE Journal on Selected Areas in Communications*, 16(7):1245–1259, September 1998.

[31] A. Gamst. Some lower bounds for a class of frequency assignment problems. *IEEE Transactions of Vehicular Technology*, 35(1):8–14, 1986.

[32] M. Garey and D. Johnson. *Computers and intractability: a guide to the theory of NP-completeness*. Mathematical Science. Freeman W. H., New York, 1979.

[33] A. Gencata and B. Mukherjee. Virtual-topology adaptation for WDM mesh networks under dynamic traffic. In *Proceedings of IEEE INFOCOM 2002*, pages 48–56, New York, NY, June 2002. IEEE Communications Society.

[34] O. Gertel, R. Ramaswami, and G. Sasaki. Cost-Effective Traffic Grooming in WDM Rings. *IEEE/ACM Transactions on Networking*, 8(5):618–630, 2000.

[35] F. Glover and M. Laguna. *Tabu Search*. Kluwer Academic Publishers, Boston, MA, 1997.

[36] R. Gomory and T. Hu. Multi-Terminal Network Flows. *SIAM Journal of Applied Mathematics*, 9:551–570, 1961.

[37] R. Gomory and T. Hu. Synthesis of a Communication Network. *SIAM Journal of Applied Mathematics*, 12:348–369, 1964.

[38] W. Grover and J. Doucette. Topological Design of Survivable Mesh-Based Transport Networks. *Annals of Operations Research*, 106:79–125, 2001.

[39] W. Grover, R. Iraschko, and Y. Zheng. Comparative methods and issues in design of mesh-restorable STM and ATM networks. In B. Sanso and P. Soriano, editors, *Telecommunication Network Planning*, chapter 10, pages 169–200. Kluwer Academic Publishers, 1999.

[40] W. Grover and R. Martens. Optimized design of ring-mesh hybrid networks. In *Proceedings of IEEE/VDE International Workshop on Design of Reliable Communications Networks*, pages 291–297, Munich, Germany, April 2000.

[41] B. Gurucharan and G. Mohan. A Two-Stage Approach for Virtual Topology Reconfiguration Using Path-Add Heuristics. *Optical Networks Magazine*, 2(3):58–71, May - June 2001.

[42] M. Halldórsson. A still better performance guarantee for approximate graph coloring. Technical Report 91-35, DIMACS, Brunswick, NJ, 1990.

[43] A. Hertz and D. De Werra. Using tabu search techniques for graph coloring. *Computing*, 39:345–351, 1987.

[44] J. Holland. *Adaptation in Natural and Artificial Systems*. MIT Press, Reading, MA, 1975.

[45] D. K. Hunter, M. H. Nizam, M. C. Chia, I. Andonovicand, K. M. Guild, A. Tzanakaki, M. J. O'Mahony, J. D. Bainbridge, M. F. C. Stephens, R. V. Penty, and I. H. White. WASPNET: a wavelength switched packet network. *IEEE Communications Magazine*, 37(3):120–129, March 1999.

[46] ITU-T. Recommendation G.707, Network Node Interface for the Synchronous Digital Hierarchy (SDH), October 2000.

[47] ITU-T. Recommendation G.803, Architecture of transport networks based on the Synchronous Digital Hierarchy (SDH), March 2000.

[48] ITU-T. Recommendation G.805, Generic functional architecture of transport networks, March 2000.

[49] ITU-T. Recommendation G.709, Interfaces for the Optical Transport Network, February 2001.

[50] ITU-T. Recommendation G.807, Requirements for automatic switched transport networks (ASTN), July 2001.

[51] ITU-T. Recommendation G.8080/Y.1304, Architecture for the automatically switched optical transport network, November 2001.

[52] ITU-T. Recommendation G.975, Forward error correction for submarine systems, January 2001.

[53] D. Johnson, C. Aragon, L. McGeoch, and C. Schevon. Optimization by simulated annealing: An experimental evaluation; part ii, graph coloring and number partitioning. *Operations Research*, 39(3):378–406, 1991.

[54] R. Kawamura, K. Sato, and I. Tokizawa. Self-healing ATM networks based on virtual path concept. *IEEE Journal of Selected Areas in Communications*, 12(1):120–127, 1994.

[55] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi. Optimization by simulated annealing. *Science*, 220:671–680, 1983.

[56] S. Kirkpatrick and E. Stoll. A Very Fast Shift-Register Sequence Random Number Generator. *Journal of Computational Physics*, 40, 1981.

[57] D. Kirovski and M. Potkonjak. Efficient Coloring of a Large Spectrum of Graphs. In *Proceedings of the 35th Conference on Design Automation*, San Francisco, CA, June 1998.

[58] P. Klein and N. Young. *Approximation algorithms for NP-hard optimization problems*. CRC Press, 1999.

[59] G. Kliewer and P. Unruh. Parallele Simulated Annealing Bibliothek: Entwicklung und Einsatz in der Flugplanoptimierung. Master's thesis, University of Paderborn, Paderborn, Germany, February 1998.

[60] P. Kopp. On solving the grouping problem in the planning of telecommunications networks. In Luis Lada, editor, *Proceedings of the 4th International Network Planning Symposium*, Palma de Mallorca, Spain, September 1989. Elsevier Science Publisher.

[61] M. Kubale and B. Jackowski. A generalized implicit enumeration algorithm for graph coloring. *Communications of the ACM*, 28:412–418, 1985.

[62] M. Kubale and E. Kusz. Computational experience with implicit enumeration algorithms for graph coloring. In M. Nagl and J. Perl, editors, *Proceedings of the WG'83 International Workshop on Graph Theoretic Concepts in Computer Science*, pages 167–176, Linz, Germany, 1983. Trauner Verlag.

[63] L. Kucera. The greedy coloring is a bad probabilistic algorithm. *Journal of Algorithms*, 12:674–684, 1991.

[64] J. Kuri, N. Puech, and M. Gagnaire. Resolution of a WDM network design problem using a decomposition approach and a size reduction method. In *Proceedings of ECUMN 2002*, pages 187–194. IEEE Communications Society, April 2002.

[65] M. Labbé, R. Séguin, P. Soriano, and C. Wynants. Network Synthesis with Non-Simultaneous Multicommodity Flow Requirements: Bounds and Heuristics. Technical Report 99/26, S. M. G., Université Libre de Bruxelles, 1999.

[66] B. Liau and B. Decocq. Réseaux optiques du futur : optimisation des réseaux. *Conférences France Télécom Recherche – Mémento*, 1(19):57–81, June 2002.

[67] A. Lisser, R. Sarkissian, and J. Vial. Survivability in Transmission Telecommunications Networks. Technical Report NT/PAA/ATR/ORI4230, Centre National d'Études des Télécommunications, Issy-les-Moulineaux, France, 1995.

[68] A. Marzetta. *ZRAM: A Library of Parallel Search Algorithms and Its Use in Enumeration and Combinatorial Optimization*. PhD thesis, Swiss Federal Institute of Technology, Zurich, Switzerland, 1998.

[69] M. Minoux. Optimum Synthesis of a Network with Nonsimultaneous Multicommodity Flow Requirements. *Annals of Discrete Mathematics*, 11:269–277, 1981.

[70] M. Minoux. Network Synthesis and Optimum Network Design Problems: Models, Solution Methods and Applications. *Networks*, 19:313–360, 1989.

[71] M. Minoux and J. Serrault. Synthèse optimale d'un réseau de télécommunication avec contraintes de sécurité. *Annales des Télécommunications*, 36:211–230, 1981.

[72] Y. Miyao and H. Saito. Optimal design and evaluation of survivable WDM transport networks. *IEEE Journal on Selected Areas in Communications*, 16(7):1190–1198, 1998.

[73] B. B. Mortensen and M. S. Berger. Optical Packet Switched Demostrator. In *Proceedings of COIN+PS 2002*, pages 27–29, Cheju, Korea, July 2002.

[74] K. Murakami and H. Kim. Joint optimization of capacity and flow assignment for self-healing ATM networks. In *Proceedings of IEEE ICC*, pages 216–220, Seattle, WA, June 1995.

[75] R. Opsut and F. Roberts. On the fleet maintenance, mobile radio frequency, task assignment and traffic phasing problems. In G. Chartrand, Y. Alavi, D. Goldsmith, L. Lesniak-Foster, and D. Lick, editors, *The Theory and Applications of Graphs*, pages 479–492. John Wiley & Sons, New York, NY, 1981.

[76] M. Peyrade. La constitution optimale des groupes de niveau supérieur dans le réseau national. formulation du problème et heuristique de resolution. *Annales des Télécommunications*, 32, 1977.

[77] N. Puech, J. Kuri, and M. Gagnaire. Models for the Logical Topology Design Problem. In *Proceedings of the 2nd IFIP-TC6 Networking Conference*. Springer-Verlag, May 2002.

[78] N. Puech, J. Kuri, and M. Gagnaire. Topological Design and Lightpath Routing in WDM Mesh Networks: A Combined Approach. *Photonic Network Communications*, 4(3/4):443–456, July 2002.

[79] B. Ramamurthy and A. Ramakrishnan. Virtual topology reconfiguration of wavelength routed optical WDM networks. In *Proceedings of IEEE GLOBECOM 2000*, pages 1269–1275, San Francisco, CA, November 2000. IEEE Communications Society.

[80] R. Ramamurthy and B. Mukherjee. Fixed-Alternate Routing and Wavelength Conversion in Wavelength-Routed Optical Networks. *IEEE/ACM Transactions on Networking*, 10(3):351–367, 2002.

[81] S. Ramamurthy and B. Mukherjee. Survivable WDM mesh networks, Part I - Protection. In *Proceedings of INFOCOM*, pages 744–751, New York, NY, March 1999.

[82] R. Ramaswami and K. Sivarajan. Routing and Wavelength Assignment in All-Optical Networks. *IEEE/ACM Transactions on Networking*, 3(5):489–500, October 1995.

[83] P. Rioux, B. Smith, and K. Thulasiraman. A Simplex Solution to the Minimum Cost Nonsimultaneous Multi-Commodity Flow Problem. Technical Report CRT-966, Center for Research on Transportation, Université de Montréal, 1994.

[84] L. Sahasrabuddhe, S. Ramamurthy, and B. Mukherjee. Fault management in IP-over-WDM networks: WDM protection versus IP restoration. *IEEE Journal on Selected Areas in Communications*, 20(1):21–33, 2002.

[85] E. Siren. Optical Packet Switching. Master's thesis, Helsinki University of Technology. Department of Electrical and Communications Engineering, Espoo, Finland, March 2002.

[86] J. S. Turner. Terabit Burst Switching. *Journal of High Speed Networks*, 8(1), 1999.

[87] G. Vareille. Multi-terabit per second transoceanic systems. In *Proceedings of ECOC 2002*, Copenhagen, Denmark, September 2002.

[88] D. De Werra. An introduction to timetabling. *European Journal of Operations Research*, 19:151–162, 1985.

[89] Y. Xiong and L.G. Mason. Restoration strategies and spare capacity requirements in self-healing ATM networks. *IEEE/ACM Transactions on Networking*, 7(1):98–110, 1999.

[90] M. Yoo, M. Jeong, and C. Qiao. A high-speed protocol for bursty traffic in optical networks. *SPIE Proceedings*, 3230:79–90, November 1997.

[91] H. Zang, J. Jue, and B. Mukherjee. A Review of Routing and Wavelength Assignment Approaches for Wavelength-Routed Optical WDM Networks. *Optical Networks Magazine*, 1(1):47–60, 2000.

[92] H. Zang, C. Ou, and B. Mukherjee. Path-protection routing and wavelength assignment (RWA) in WDM mesh networks under duct-layer constraints. *IEEE/ACM Transactions on Networking*, 11(2):248–258, 2003.

[93] H. Zhu, H. Zang, K. Zhu, and B. Mukherjee. A Novel Generic Graph Model for Traffic Grooming in Heterogeneous WDM Mesh Networks. *IEEE/ACM Transactions on Networking*, 11(2):285–299, April 2003.

[94] K. Zhu and B. Mukherjee. Traffic grooming in WDM mesh networks. *IEEE Journal on Selected Areas in Communications*, 20(1):122–133, January 2002.

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WXC ..... viii, 72–99, 102, 103

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ZWPF 8, 10

Glossary

A

ADM Add Drop Multiplexer 13

APS Automatic Protection Switching coordination channel 18

ASON Automatically Switched Optical Network 21

ASTN Automatically Switched Transport Network 21

ATM Asynchronous Transfer Mode 4

B

B&B Branch & Bound viii

BER Bit Error Rate 11

BXC Waveband Cross-Connect viii

C

CDM Code Division Multiplexing 7

CPM Cross-Phase Modulation 10

D

DRSCA Diverse Routing and Spare Capacity Assignment viii

DSF Dispersion-Shifted Fiber 10

DXC Digital Cross-Connect 13

E

E/O Electro-optical conversion 13

EDFA Erbium-doped Fiber Amplifier 12

ETBS Exhausted Time Budget Stop 66

F

FDM Frequency Division Multiplexing 7

FEC Forward Error Correction 11

FWM Four-Wave Mixing 10

G

G.652 See SSMF 10

G.653 See DSF 10

G.655 See NZDSF 10

GMPLS Generalized Multi-Protocol Label Switching 17

I

IETF Internet Engineering Task Force 17

ILP Integer Linear Programming 38

IP Internet Protocol 16

ITU-T International Telecommunications Union. Standardization Sector 10

IWIS Iterations Without Improvement Stop 66

L

LD Local Descent 107

LFFF Largest-First First-Fit algorithm 64

LS Local Search 107

LSP Label Switched Path 16

LSR Label Switching Router 103

M

MCF Multi-Commodity Flow 30

MHTM Multi-Hour Traffic Matrices 31

MPLS Multi-Protocol Label Switching 4

N

NNI Node to Node Interface or Network to Network Interface 17

NRZ Non Return to Zero 12

NSMCF Non-Simultaneous Multi-Commodity Flow 31

NwE Network Engineering 24

NwP Network Planning 25

NZDSF Non-Zero Dispersion Fiber 10

O

O/E Opto-electronic conversion 13

OADM Optical Add Drop Multiplexer 13

OBS Optical Burst Switching 14

OCC Optical Channel Carrier 18

OCh Optical Channel 18

ODUk OCh Data Unit of order k 18

OEO Opto-electronic and electro-optical conversion 12

OIF Optical Internetworking Forum 17

OMS Optical Multiplexing Section 18

OMSn Optical Multiplexing Section of order n 18

ONE Optical Network Element 18

OOK On-Off Keying 12

OOS OTM Overhead Signal 18

OPUk OCH Payload Unit of order k 18

OSC Optical Supervisory Channel 18

OSL IBM's Optimization Solutions and Library 38

OSNR Optical Signal to Noise Ratio 103

OTMn Optical Transport Module of order n 18

OTN Optical Transport Network 17

OTS Optical Transmission Section 18

OTUk OCh Transport Unit of order k 18

OXC Optical Cross-Connect 13

P

PCC Protection Communication Control channel 18

PM Path Performance Monitoring 18

PMD Polarization Mode Dispersion 9

PNSS Pseudo-random Noise Spreading Sequence 7

PRNG Pseudo-Random Number Generator 50

Q

QoS Quality of Service 24

R

RAM Random Access Memory 16

RSBG Routed Scheduled Band Group 75

RWA Routing and Wavelength Assignment viii

Rx Receiver 12

RZ Return to Zero 12

S

SBS Stimulated Brillouin Scattering 10

SDH Synchronous Digital Hierarchy 4

SLD Scheduled Lightpath Demand 29

SONET Synchronous Optical Network 4

SPM Self-Phase Modulation 10

SR SLD Routing problem 71

SRG SLD Routing and Grooming problem viii

SRS Stimulated Raman Scattering 10

SSMF Standard Single Mode Fiber 10

T

TCM Tandem Connection Monitoring 18

TDM Time Division Multiplexing 7

TE Traffic Engineering 22

TS Tabu Search viii

Tx Transmitter 12

U

UNI User to Network Interface 17

V

VC ATM Virtual Circuit 16

VC-3 SDH Virtual Container Level 3 100

W

WDM Wavelength Division Multiplexing 7

WXC Wavelength Cross-Connect viii

Z

ZWPF Zero Water Peak Fiber 8

Vita

Josué Kuri was born in Mexico City on August 29th 1974. He received a B. Sc. degree in Computer Science with Honors from Monterrey Institute of Technology (ITESM) in 1996. From 1996 to 1998 he worked as a software engineer for InfoSel SA, Monterrey, Mexico, where he developed software for a real-time financial information system. In 1999 he received a M. Sc. degree in Telecommunications from École Supérieure d'Electricité (Supélec), Rennes, France. His thesis work concerned the design and development of parallel algorithms for a high performance intrusion detection engine. In 2003 he received the Ph.D. in Telecommunications with Honors from École Nationale Supérieure des Télécommunications (ENST), Paris, France. His professional interests include the design, engineering and standardization of telecommunications networks.