# Off-line Configuration of a MPLS over WDM Network under Time-Varying Offered Traffic

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Abstract—Coupling MPLS Traffic Engineering on top of a wavelength-routed WDM layer offers great flexibility to operators to allocate traffic demands in their networks. In this paper we consider the problem of off-line joint configuration at both packet and optical layers. We consider time-variant offered traffic, and assume that the operator has knowledge of the traffic dynamics as a set of traffic matrices at different instants. A novel Mixed Integer Linear Programming (MILP) formulation is proposed, which takes in input this set of traffic matrices, and provide an optimal static configuration capable of accomodating the time-varying traffic. We provide a resolution strategy based on heuristics, and give numerical results for some sample cases. The proposed method is compared with a simple alternative approach for obtaining a single static solution, to show that our method utilizes much less resources. The solution under the proposed formulation is also compared with the set of solutions obtained by running distinct optimization problems at different instants, showing that the increase of resource is minimal. Hence our approach can provide a static configuration with about the same resources of a fully adaptable dynamical configuration.

#### I. INTRODUCTION

Network operators are committed today to face a continous increase in the amount of IP traffic. Coupling MPLS Traffic Engineering on top of a wavelength-routed WDM layer is a promising scenario for future networks. The ability to configure explicit routes at the packet level (Label Switched Paths, or LSPs) as well as at the optical level (wavelength path) gives the provider a high flexibility in the mapping of the offered traffic demands onto the available physical topology. In general, given the expected offered traffic matrix and the available physical topology and capacity constraints, the network operator looks for a *network configuration solution* that is optimal according to some criteria.

The configuration of a MPLS over WDM network involves the establishment of wavelength paths at the optical level and of LSPs at the packet level. A network *configuration solution* is defined by jointly selecting:

i) the logical topology (i.e. the set of wavelength paths to be established),

*ii)* the mapping logical topology  $\rightarrow$  physical topology (i.e. the routing of wavelength paths onto the physical links),

*iii)* the mapping traffic  $\rightarrow$  logical topology (i.e. the routing of LSPs onto wavelength paths).

Similarly to [1] [2] [3] we consider an optical network with full wavelength conversion capabilities, i.e. wavelength continuity constraints are not considered. This permits to model a physical link (a fiber or a bundle of fibers) simply as a bundle of wavelengths.

The traffic entering a network is intrinsically variable in time. Remarkably not only the absolute value of offered traffic changes in time but also its spatial distribution, especially in large wide area networks spanning different time zones. As for example discussed in [4] the offered traffic typically presents pseudo-periodic behavior over different time scales, e.g. daily over different hours, weekly over different days, etc. In this paper we focus on the daily variation over different hours, but the same approach can be applied to cope with variations at higher time scales. Because of such pseudoperiodic behavior, based on past measurements the operator can somehow predict the offered traffic matrices sampled at some characteristic instants (e.g. at morning, at noon, at evening). It is reasonable to exploit such a knowledge in the off-line process of selection of the network configuration solution. The operator can use a single network configuration solution (static configuration) or a set of network configuration solutions changing over time (dynamic configuration). The advantages of the static configuration are evident (less signaling overhead, no transitories during rearrangements) but likely come at the cost of a higher resource usage (e.g. more wavelength paths). We will show that with a priori knowledge (or better *prediction*) of the traffic matrices at the characteristic instants a static solution can be found with only minimal increase of resource usage.

This paper provides a novel Mixed Integer Linear Programming (MILP) formulation which takes in input a set of different traffic matrices, representative of a time-varying offered traffic, and provides a configuration solution which minimizes the amount of used resources, both at the packet and optical layer. Our method (called JCET throughout the paper) is compared with a reference simple method (called UCMT) for obtaining a static configuration solution. The UCMT is based on the maximum amount of traffic between each node pair over the characteristic instants.

Our results on a medium-size network show that JCET method can provide optimal static configuration with much less resources than UCMT, and with just a minor increment in the resource usage with respect to the dynamic method (called ICET). On the basis of such results, we conclude that the prediction of the traffic behavior in time can be exploited in the off-line configuration phase to avoid the need for periodical reconfigurations.

The proposed MILP formulation descends from the class of general multicommodity flows problem with integer routing variables, which are recognized to be NP-complete. It can be solved directly with the typical branch-and-bound [13, p. 602] procedure for networks of small-medium size ( $\sim 6$ nodes, with fully meshed traffic matrices). In order to attack network of larger size in reasonable time, we resort to *spacereduction heuristic* and *decomposition heuristic* to support the optimization procedure.

The rest of the paper is organized as follows: in section II we discuss how this work relates to previous studies, then in section III the MILP formulation for the proposed JCET method is given. The complete optimization procedure along with details of the supporting heuristics are discussed in section IV. Numerical results are presented in section V for some sample cases, in order to compare the performances of methods JCET, ICET and UCMT. Finally, conclusions and directions for further study are given in section VI.

#### II. Relation to Previous Works

The problem of reconfiguration due to changes in the offered traffic was studied in [1] and [2]. In both works the authors consider the case that at a certain time a starting configuration is active and provide methods to obtain a new configuration solution based on the updated traffic matrix, with a minimal amount of rearrangements at the optical layer (i.e. reuse the established arcs), while rearrangements at the packet level (i.e. LSP re-routing) are not minimized. In this paper we consider a different problem: in our approach the operator knows in advance the dynamics in time of the offered traffic, for example on the basis of past measurements, and wants to pre-compute an optimal static configuration solution able to accomodate such time-varying traffic. The solution is static both at the optical and at the packet level, i.e. no re-routing of LSPs nor wavelength path is allowed. Such a problem needs a new formulation, able to take in input multiple traffic matrices rather than just one. This is the first original contribution of this paper. Our formulation follows the multicommodity flows structure that was already adopted in several previous works (e.g. [1] [3] [5] [6]). A further novelty of this paper is that our MILP formulation considers a more complex cost function, which explicitly allows for explicit control over the balancing between opticallevel and packet-level resources. As a final remark, note that [1] and [2] give results only for the case of bifurcated LSPs, by relaxing some integrality constraints. Such results are of scarce applicability in practice, as current routing protocols do not support multipath routing (see also discussion in section III-C). A value of our work is that it provides results for the case of non-bifurcated LSPs. Results for the nonbifurcated routing were also obtained in [7], where in order to attack the complexity of the problem they used a decomposition heuristic with stochastic algorithms. In this paper we propose a novel approach which combines a deterministic space reduction heuristic with a decomposition heuristic in order to support the resolution process.

# III. Off-line Network Configuration Under Time-Varying Offered Traffic

In a MPLS over WDM network an operator should choose a network configuration solution which is able to support the expected offered traffic matrix, having assigned a certain topology and various capacity constraints of different kinds (e.g. on the number of wavelengths on each link, on the switching capacity of the nodes, on their processing capacity etc.). In this choice the operator tries to optimize some objective function, or *cost*. Typically the operator will try to use as few resources as possible, first of all becuse the more spare resources are available the more likely an unpredicted increase of traffic and / or modification in its spacial distribution can be accomodated without rearranging established paths.

The traffic which is offered to the network is inherently a two dimensional stochastic process  $T(\tau)$ , whose generic component  $t_{ii}(\tau)$  represents the amount of traffic originated by node i and directed to node j at time  $\tau$ . We consider the case that the network operator is able to predict on the basis of past measurements the quantities  $t_{ii}(\tau)$  for a discrete set of characteristic instants  $\tau = 1..\Theta$ , representative for example of different hours in a day (morning, noon, evening). The offered traffic matrices  $T(\tau)$  can vary sensibly in time, as they depend on the users behavior and habits at macroscopic level. Let us also assume that the operator is provided with some tool that, given the available network topology and resources (i.e. capacity bounds) and a single offered traffic matrix as the input, provides as the output an optimal configuration solution, according to some objective function to be minimized (e.g based on the formulation in [1]). Two possibilities exist for the operator to use this tool for the configuration of its network in case of time-varying traffic:

• Independent Configuration with Exact Traffic (ICET): run the optimization independently for each instant  $\tau = 1..\Theta$ , each time with the relevant traffic matrix  $T(\tau)$  as the input.

• Unique Configuration with Maximal Traffic (UCMT): run the optimization only once, taking the maximal traffic matrix  $T^{max}$  as the input. The elements of  $T^{max}$  represent the maximum value of exchanged traffic between two nodes over the whole set of characteristic instants, i.e.  $t_{ii}^{max} = max_{\tau} \{t_{ii}(\tau)\}.$ 

Both the methods have advantages and drawbacks. Method ICET will be more efficient in terms of allocated resources (e.g. number of used wavelength, number of activated wavelength paths, etc.) than method UCMT. On the other hand, the advantage of UCMT is that it provides a single configuration solution suitable for the whole set of characteristic instants, while ICET will in general provide different solutions for different instants, thus requiring reconfiguration capabilities in the network. The increase in the allocation of resources of UCMT with respect to ICET can be dramatic, and in some cases UCMT could even lead to unfeasibility if the available resources are scarce (further considerations will be made at the end of section V).

In this paper we propose a novel approach which aims at providing a single configuration solution, as method UCMT does, but more effective in terms of resource utilization. This method, called **Joint Configuration with Exact Traffic** (**JCET**), is based on the MILP formulation given in section III which explicitly takes in input the whole set of traffic matrices  $T(\tau)$  for  $\tau = 1..\Theta$ , rather than the single maximal matrix  $T^{max}$ . By considering the exact succession of traffic matrices, method JCET can gain in efficiency with respect to UCMT, exploiting the sharing of bandwidth between increasing and decreasing flows. In facts from instant  $\tau$  to  $\tau + 1$  certain traffic flows will increase while other will decrease in size: if such flows are coupled on a same path section, the increase in bandwidth of the ones will be partially compensated by a decrease of the others, so that the additional capacity reserved to absorb the traffic variation can be minimized.

### A. The Network Model

Let us first introduce the notation and the terminology used throughout the paper. The relevant network elements are:

•  $v_i$  is the generic node (vertex) in the physical topology. Each node can be a Label Switch Router (LSR, with label switching capability at the packet layer), an Optical Cross-Connect (OXC, with wavelength switching at the optical layer) or a Generalized Label Switch Router (GLSR, with switching capabilities at both layers).

•  $V^{LSR}$  and  $V^{OXC}$  denote the sets of nodes that can switch at the packet level and at the optical level respectively. Note that such sets are not disjoint, as a GLSR node belongs to both.

•  $l_j$  is the generic directed link in the physical topology, with an associated capacity expressed in terms of the (integer) number  $W_i^L$  of available wavelengths. As full wavelength conversion is assumed at any OXC (that is no wavelength continuity constraint is considered) a link in the physical topology, that in practice corresponds to a fiber or a bundle of fibers, can be simply modeled as a bundle of wavelengths. •  $a_m$  is the generic unidirectional wavelength-switched circuit defined as an ordered vector of crossed physical links  $a_m = \langle l_1, l_2, ... l_{d_m} \rangle$ . All intermediate nodes along the path of  $a_m$  must be wavelength-switching capable, i.e. OXC or GLSR, while the endpoint nodes must be packet-switching capable, i.e. LSR or GLSR.  $a_m$  represents the generic directed arc between two nodes in the logical topology, with a fixed capacity denoted by B. Note that we use the terms *link* and *arc* to refer to the edges of the physical and logical topology respectively.

•  $A_{v_i}^I, A_{v_i}^O, A_{v_i}^X$  denote respectively the sets of *incoming*, *outgoing* and *optically switched* arcs at node  $v_i$ .

•  $A_{l_i}^L$  denotes the set of arcs traversing link  $l_j$ .

•  $d_m$  denotes the physical length of arc  $a_m$ , i.e. the number of physical links it traverses.

•  $f^k(\tau)(\tau = 1..\Theta)$  represents the size (in Mb/s) of the generic k-th traffic demand (also called a *commodity*) at instant  $\tau$ . It represents an indivisible traffic flow that must be routed on a single Label Switched Path (LSP) from its source node to its destination node. LSPs and commodities are 1:1 associated. Each LSP represents the concatenation

of one or more crossed arcs over the logical topology.

•  $S^k$ ,  $D^k$  denote respectively the source and destination nodes of commodity k. Note that more than one commodity can be present between the same pair of source / destination nodes (this is useful for example in supporting independent VPNs).

•  $r_m^k$  is a binary variable telling whether or not the LSP for commodity k is routed over arc  $a_m$ .

•  $u_m$  is a binary variable telling whether arc  $a_m$  is "used" or not, that is if there is *at least* one commodity routed over it. In our problem we have to face a two layer configuration: the commodities (or better their associated LSPs) must be routed over arcs, and the arcs must be routed over the physical links. In other words, a two layer matching must be found: i) between the traffic matrix and the logical topology at the upper layer and ii) between the logical topology and the physical topology at the lower layer. Similarly to [6], in our approach we assume that for the given physical topology (nodes, links) the sets of all possible candidate arcs from node s to d, hereafter denoted by  $\mathcal{A}_{s,d}$ , is pre-computed. Eventually, some space-reduction heuristic can be applied at this early step (see discussion in section IV) to cut-away from  $\mathcal{A}_{s,d}$  those arcs which are less likely to be selected in the optimal solution, in order to reduce the problem size and then the resolution time. The MILP formulation takes the sets  $\mathcal{A}_{s,d}$  as the input of the optimization problem, and returns in output: i) the set of arcs that must be effectively established in the logical topology and ii) for each commodity kthe set of established arcs included in its path.

# B. Choice of cost function

The choice of the objective function to be optimized is a critical aspect of the problem formulation. Differently from [1] we chose to minimize a cost function which explicitly accounts for the resource usage both at the optical and at the packet level. The cost of resource usage should not be regarded as a direct monetary cost, but rather as a penalty associated to the fact that the resources currently allocated to active LSPs and circuits will be no more available for future (unpredicted) incoming traffic demands, unless rearranging the already established LSPs and circuits. In our formulation the cost function aims at limiting the overall resources usage by associating a *cost* to the following elements:

- amount of packet processing at each LSR  $(C_i^{ptr})$ .
- number of optically switched wavelengths at each OXC  $(C_i^{swl})$ .
- number of outgoing arcs from each LSR  $(C_i^{oua})$ .
- This choice was driven by the following considerations:

- A large part of the network monetary cost is concentrated in the switching equipment (OXC, LSR).

- By minimizing the amount of packet processing at the LSRs, we minimize the global average queuing delay (as was done in [1]).

- By jointly minimizing the number of optically switched wavelengths in the OXCs and the number of outgoing arcs, we also minimize the number of used wavelengths and the length of the wavelength paths. - By minimizing the number of outgoing arcs, we minimize the number of required LSR interfaces.

The cost associated to the first two components  $(C_i^{ptr}$  and  $C_i^{swl})$  is in the form of a 2-piece-linear convex function, as shown in Fig. 1. If the amount of used resources at a certain node exceeds a given limit (e.g. in our experiments we arbitrarely set it to 0.8 of the available resources), the marginal cost of using futher resources at that node increases sharply. The penalty associated to the exceeding of such limit should drive the optimal solution away from the full consumption of the available switching capabilities of the nodes. In facts due to above mentioned monetary cost of the switching capacity of the nodes to prevent the need for future equipment upgrading.

The cost associated to the number of outgoing arcs from the generic LSR is assumed linear: the minimization of such cost over the full set of LSR nodes equivalent to minimizing the total number of arcs in the logical topology.

Of course other choices are possible for the definition of the cost function. Further cost components could be added, or more articulated n-piece-linear cost functions could be used. However, adding more cost components will inevitably increase the complexity of the problem along with the resolution time. Moreover, from the operator point of view, as each cost component appears in a linear combination with the others, adding more cost components would require a bigger effort in evaluating the relative cost coefficients.

## C. MILP formulation

We first provide the MILP formulation for the case of an optical network with unidirectional circuits, then in section III-D we extend our model to consider the case of bidirectional circuits, which is currently the most common case in practice.

Minimize:

$$c = \sum_{v_i \in V^{LSR}} C_i^{ptr} + \sum_{v_i \in V^{OXC}} C_i^{swl} + \sum_{v_i \in V^{LSR}} C_i^{oua}$$

Subject to:

$$\sum_{\substack{n \in A_{v_i}^0}} r_m^k = 1 \quad \sum_{\substack{m \in A_{v_i}^I}} r_m^k = 0 \quad \forall k, v_i = S^k$$
(1a)

$$\sum_{n \in A_{v_i}^0} r_m^k = 0 \quad \sum_{m \in A_{v_i}^I} r_m^k = 1 \quad \forall k, v_i = D^k \tag{1b}$$

$$\sum_{m \in A_{v_i}^O} r_m^k - \sum_{m \in A_{v_i}^I} r_m^k = 0 \quad \forall k, \forall v_i \neq S^k, D^k$$
(1c)

$$u_m \ge r_m^k \quad \forall k, m \tag{2}$$

$$w_i^X = \sum_{m \in A_{v_i}^X} u_m \quad \forall i : v_i \in V^{OXC}$$
(3)

$$w_i^I = \sum_{m \in A_{v_i}^I} u_m \quad \forall i : v_i \in V^{LSR}$$
(4a)

$$w_i^O = \sum_{m \in A_{v_i}^O} u_m \quad \forall i : v_i \in V^{LSR}$$
(4b)

$$w_j^L = \sum_{m \in A_{l_j}^L} u_m \quad \forall j \tag{5}$$

$$b_m(\tau) = \sum_k f^k(\tau) \cdot r_m^k \quad \forall m, \tau = 1..\Theta$$
(6)

$$g_{i}\left(\tau\right) = \sum_{m \in A_{v_{i}}^{I}} b_{m}\left(\tau\right) \quad \forall i : v_{i} \in V^{LSR}, \tau = 1..\Theta \qquad (7)$$

$$b_m(\tau) \le \beta \cdot B \quad \forall m, \tau = 1..\Theta$$
 (8a)

$$g_i(\tau) \le G_i \quad \forall i : v_i \in V^{LSR}, \tau = 1..\Theta$$
 (8b)

$$w_i^X \le W_i \quad \forall i : v_i \in V^{OXC} \tag{9a}$$

$$w_i^I \le W_i^I \quad \forall i : v_i \in V^{LSR} \tag{9b}$$

$$w_i^O \le W_i^O \quad \forall i : v_i \in V^{LSR} \tag{9c}$$

$$w_j^L \le W_j^L \quad \forall j \tag{9d}$$

$$\begin{cases} C_i^{ptr}\left(\tau\right) \ge \alpha_{1,1}^{ptr} \cdot \frac{g_i(\tau)}{G_i} + \alpha_{1,2}^{ptr} \\ C_i^{ptr}\left(\tau\right) \ge \alpha_{2,1}^{ptr} \cdot \frac{g_i(\tau)}{G_i} + \alpha_{2,2}^{ptr} & \forall v_i \in V^{LSR} \end{cases}$$
(10)

$$C_{i}^{ptr} = \frac{1}{\Theta} \cdot \sum_{\tau=1..\Theta} C_{i}^{ptr}(\tau)$$
(11)

$$\begin{cases} C_i^{swl} \ge \alpha_{1,1}^{swl} \cdot \frac{w_i^X}{W_i} + \alpha_{1,2}^{swl} \\ C_i^{swl} \ge \alpha_{2,1}^{swl} \cdot \frac{w_i^X}{W_i} + \alpha_{2,2}^{swl} & \forall v_i \in V^{OXC} \end{cases}$$
(12)

$$C_i^{oua} = \sum_{m \in A_{v}^0} u_m \quad \forall i : v_i \in V^{LSR} \tag{13}$$

$$r_k^m \in \{0, 1\}, \quad 0 \le u_m \le 1$$
  
 $C_i^{ptr} \ge 0, \quad C_i^{swl} \ge 0$  (14)

Constraints 1 are network flows constraints for the active path of each traffic commodities. In particular 1a and 1b refer to the commodity source and destination nodes respectively, while 1c to the remaining intermediate nodes. Constraint 2 forces the generic support variable  $u_m \in [0, 1]$  to assume unitary value if at least one commodity is routed over arc  $a_m$ , thus accounting for the actual usage of the arc (see Appendix A for more detailed discussion). Constraint 3 defines the number of optically switched wavelengths at the generic *i*-th OXC node  $(w_i^X)$ . Constraints 4 define the number of transmitting  $(w_i^O)$  and receiving  $(w_i^I)$  arc terminations at the generic *i*-th LSR node, i.e. the number of required transmitting and receiving interfaces at the LSR. Constraint 5 defines the number of active wavelengths on the generic *j*-th link  $(w_j^I)$ . Constraint 6 defines the amount of

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consumed bandwidth  $b_m(\tau)$  on the generic *m*-th arc at time  $\tau$ . Similarly, constraint 7 defines the amount of packet traffic  $q_i(\tau)$  injected into the generic *i*-th LSR node. Constraints 8 and 9 are capacity bounds, i.e. limits to the amount of different resources: B is the wavelength transmission capacity  $(B=2.5 \text{ Gbps in our simulations}), \beta$  is the maximum allowed load factor for each wavelength path (we assume  $\beta=1$ ),  $G_i$ represents the maximum amount of packet traffic that can be injected into LSR node  $v_i$  (for sake of simplicity we ignored the traffic generated by  $v_i$  itself),  $W_i$  is the maximum number of switchable wavelengths at the i-th OXC (i.e. the size of the OXC),  $W_i^O$  and  $W_i^I$  are the number of available transmitting / receiving interfaces at *i*-th LSR router,  $W_i^L$ is the number of available wavelengths on j-th link. Constraints 10 jointly express the utilization cost associated to the packet processing / switching capability of the LSRs at time  $\tau$ , while 11 defines its average in time - which appears in the cost function to be minimized. Similarly 12 represents the utilization cost for the optical switch fabric of the OXC. Note that this last cost term is not time dependent, as the logical topology configuration is static. Both such cost components were assumed convex 2-piece-wise linear as discussed in section III-B, and the values of the coefficients  $\alpha_{i,j}^{\cdot}$ , i, j = 1, 2 were chosen in such a way to build the cost functions depicted in Fig. 1. Constraints 13 defines the number  $C_i^{oua}$  of outgoing arcs from the *i*-th LSR. Finally, bounds 14 define the allowed ranges for the problem variables.

In particular, note that the integrality constraint on variables  $r_m^k$  - which induces an integral value of the continous variables  $u_m$  in the final solution, as discussed in Appendix A - represents the *single path* constraint on the commodity routing, also referred to as *non-bifurcated routing*. A relaxed version of the problem can be derived by relaxing the integrality constraint on the  $r_m^k$ , thus allowing for solutions where a commodity can be routed over multiple paths (also referred to as *bifurcated* routing). In this case however the  $u_m$  must be explicitly restricted to take boolean values, thus the problem still remains of MILP type. In this case, as the number of the variables  $u_m$  is sizeably smaller than the  $r_m^k$ , the problem is likely faster to be solved. Anyway the relaxed solution is not applicable in current real networks, as to date multipath routing is not commonly supported.

The above MILP formulation is used in the JCET method with multiple input traffic matrices, i.e. when  $\Theta \geq 2$ . Nevertheless, it can be also used in the ICET and in the UCMT methods, both taking a single traffic matrix in input, by simply considering a set of characteristic instantants of cardinality 1, i.e.  $\Theta = 1$ .

#### D. Bidirectional circuits

In the above formulation we assumed that optical circuits (or wavelength paths) are unidirectional, i.e. it is possible to establish an arc  $a_{m^+} = \langle l_1, l_2, ..., l_{d-1}, l_d \rangle$  independently from its opposite arc  $a_{m^-} = \langle l_d, l_{d-1}, ..., l_2, l_1 \rangle$ , where indices  $m^+$  and  $m^-$  denote a pair of opposite arcs. In case we want to consider the case that only bidirectional circuits are allowed, we must constrain arcs  $a_{m^+}$  and  $a_{m^-}$  to be either both established or both not, i.e. insert the further con-

straints  $u_{m^+} = u_{m^-}$ . In our implementation the arc numbering is such that for each integer n arc  $a_{2n}$  is opposite to arc  $a_{2n+1}$ . With this numbering rule, the bidirectional circuit constraints can be written as:

$$u_{2n} = u_{2n+1} \quad n = 0, 1, \dots \tag{15}$$

#### IV. RESOLUTION STRATEGY

The above MILP formulation belongs to the class of multi commodities flow problems with integer constraints, which are recognized to be NP-complete. The direct resolution of this problem can not be achieved in reasonable time for networks of more than few nodes. In order to attack networks with sizes of practical interest, we developed a resolution process based on heuristics. In particular we jointly use a spacereduction heuristic and a decomposition heuristic. With the space-reduction heuristic a number of LSPs and arcs that are less likely to be selected in the optimal solution are cutted away from the search space. With the decomposition heuristic the overall resolution process goes through the iterative resolution of smaller subproblems. A subproblem is an instantiation of the complete problem in which only a subset of the variables are let free, while the remaining ones are fixed to some value. Each subproblem is then resolved using the classical branch-and-bound resolution technique [13, p. 602] by means of a generic linear optimization tool.

In the following of this section we describe the heuristic algorithms we used. In order to check the consistency of such algorithms we run the optimization on a small netwok (6) LSRs nodes, full meshed traffic), for which the exact optimal solution could be found, and verified that the obtained cost function value is within 3% of the real optimum. We are aware that from the experiment with a small network no general conclusions can be outdrawn about the goodness of the suboptimal solution for larger networks. For large networks in facts, where the real optimum can not be found, the goodness of the heuristic algorithm can be assessed by comparison with lower bounds obtained with some relaxation, typically integrality relaxation. But in the formulation given above the full relaxation of the integrality constraints (see discussion at the end of section III-C), by allowing for non-integer values of the support variables  $u_m$  in the final solution, simply destroys the two-layers nature of the routing problem, thus leading to lower bounds that are useless. Alternatively, in order to assess the goodness of the heuristic algorithm, one has to resort to a comparative analysis with different heuristics present in the literature. As the fine-tuning of such heuristics and their detailed evaluation are not the primary scope of this paper, this analysis was left to future works. In facts in the framework of this paper the heuristic algorithm presented above only have the instrumental role, that is to provide a common resolution framework and to obtain configuration solutions for the three methods presented above (namely ICET, UCMT, JCET), in order to perform a comparative analysis of such methods, rather than of the resolution heuristics themselves.

#### A. Space-reduction heuristic

An initial space-reduction heuristic (hereafter called SRH) is run to reduce the number of integer routing variables  $r_m^k$ . For each commodity k, only a subset of arcs  $\mathcal{A}_k$  out of the complete arc space are selected as possible candidates to support its path. To build the set  $\mathcal{A}_k$ , we first determine all the possible paths in the physical topology between the source  $S^k$  and the destination  $D^k$ . We then eliminate all the paths whose physical length (i.e. the number of crossed links) exceeds a maximum allowed value  $L_{max}(k)$ , and then select a number  $N_{max}(k)$  of shortest paths among the remaining ones. The value of maximum allowed physical path length  $L_{max}(k)$  was varied depending on the value of the shortest physical path length from  $S^k$  to  $D^k$ , denoted by  $L_{sp}(k)$  (values are given in table I). For simplicity we fixed  $N_{max}(k)$  to a unique value for all node pairs. The set of physical paths built so far defines a reduced directed graph from  $S^k$  to  $D^k$ . Finally, we include in  $\mathcal{A}_k$  all and only those arcs whose physical path is included in such reduced graph.

Similar heuristics are found in literature to reduce the problem size. Typically in several papers (e.g. [1]) a constraint to the end-to-end latency is imposed. As latency is proportional to the physical path length, this results in the elimination of a number of possible long paths.

The number of integer routing variables  $r_m^k$  can be taken as a rough measure of the problem size (note that the number of flow conservation constraints also depend on it). Let Nbe the number of LSR nodes and  $\gamma$  the average node degree on the logical topology (number of arcs attacched at a given node), assuming a full meshed traffic matrix between LSR (i.e. N(N-1) commodities), the number of routing variables is in the order of  $\gamma N^3$ . By considering only a subset of candidate arcs for each commodity in the SRH, this value can be reduced to  $\zeta N^2$ , being  $\zeta$  the average number of candidate arcs for each commodity, whose value depends on the value of the SRH parameters as well as on the topology.

#### B. Decomposition heuristic

For large networks the number of integer routing variables  $r_m^k$ , even after the SRH procedure, is still too large to obtain a solution in acceptable time. We then turn to a decomposition heuristic (hereafter called DEH), solving a succession of subproblems where only the routing variables for a subset of commodities of cardinality X (block size) are optimized at each iteration. Note that when the block size X equals the total number of demands  $N_f = card \{f^k(\tau)\}$  the full optimization process is run at once, i.e. no reduction is applied. The value of parameter X is critical. It is expected that when X increases, the quality of the sub-optimal solution improves, but the resolution time increases.

At the beginning of the DEH algorithm, the set of commodities are ordered with respect to the average size  $\overline{f_k} = \frac{1}{\Theta} \cdot \sum_{\tau} f^k(\tau)$ , in descending order, and all the routing variables  $r_m^k$  for each k, m are set to 0. In the initial phase of DEH algorithm, the commodities are allocated in the network in blocks of size X, from the bigger down to the smaller ones. At each iteration, the values of the  $r_m^k$  for the previ-



Fig. 1. Cost functions associated to the node switching resources, at the packet and at the optical layer. The slope increases by a factor of 10 after the limit  $G_i^*$   $[W_i^*]$ . In the experiments was set  $G_i^* = 0.8 \cdot G_i$   $[W_i^* = 0.8 \cdot W_i]$ .

ously allocated commodities are kept fixed. At the end of this initial phase (total of  $\lceil N_f/X \rceil$  iterations), all the commodities have been allocated in a sub-optimal solution. The next phase attempts at eliminating the *swl-critical* and the *ptr-critical* nodes. A ptr-critical [swl-critical] node is a LSR [OXC] node for which the amount of processed packet traffic [switched wavelengths] at some time instant is close to saturate the associated node capacity. In the final phase, the algorithm tries to reduce the total number of established arcs, particularly the less loaded ones. A detailed algorithmic description of DEH is given in Appendix B.

All the DEH phases are actually composed of several iterations: at each iteration a reduced MILP subproblem is optimized with a classical branch-and-bound procedure. We used CPLEX [11] as the solver tool, while the global optimization process was implemented in AMPL language [12]. We set the solver parameters to stop the optimization of each sub-problem within 0.5% of the optimality, or within a maximum time limit of 3 hours. In our experiments the maximum time limit was only reached in very few cases, and only in the very first iterations of the initial phase. In all the other steps, the solution of subproblems were relatively fast (see section V for more details).

### V. NUMERICAL RESULTS

We tested our formulation on the network depicted in Fig. 2, 15 nodes and 28 links, the same used in [9] [10]. All the nodes are GLSR, thus capable of both packet and wavelength switching. A full mesh of traffic demands between twelve nodes was considered (total of 132 commodities). Central nodes 5, 6, 9 do not generate traffic: they are only used for wavelength switching and traffic grooming at the packet level. The setting for the various parameters was as follows:  $B=2.5 \text{ Gb/s}, \beta = 1, G_i=16 \text{ Gb/s}, W_i=40, \frac{\alpha_{1,1}^{ptr}}{G_i} = \frac{3}{B}, \alpha_{2,1}^{ptr} = 10 \cdot \alpha_{1,1}^{ptr}, \frac{\alpha_{1,1}^{swl}}{W_i} = 1, \alpha_{2,1}^{swl} = 10 \cdot \alpha_{1,1}^{swl}, \alpha_{1,2}^{ptr} = \alpha_{1,2}^{swl} = 0, \alpha_{2,2}^{ptr} = \alpha_{2,2}^{swl} = -7.2, W_j^L = 20, W_i^I = W_i^O = 12.$ 

The set of traffic demands was originated randomly according to the following simple process, aimed at representing a *macro-traffic*process (i.e. the average amount of traffic exchanged between two nodes at a large time-scale, e.g. tens of minutes) where the geographical distribution of traffic intensities varies in time. The set of network nodes was divided into two disjoint geographical subsets, West (W) and East (E) as shown in Fig. 2. Two classes of commodities were defined, Hot and Cold: the bandwdith demand was picked randomly in the range  $[0, \frac{B}{3}]$  for the Cold commodities, and in  $\left[\frac{B}{3}, \frac{2B}{3}\right]$  for the Hot ones, where B = 2.5 Gb/s is the arc capacity. The generic traffic demand between nodes s and d at time  $\tau$  was assigned with probability  $\pi_{i,j}(\tau)$  and  $1 - \pi_{i,j}(\tau)$ respectively to the Hot and Cold class, being  $i, j \in \{W, E\}$ the geographical subsets of s and d respectively. The parameters  $\pi_{i,i}(\tau)$ , i.e. the average fraction of Hot commodities for subset i to j, was varied in time in order to modulate the spacial distribution of the macro-traffic intensity. We assumed that the offered macro-traffic process is periodic on a daily basis, and that the traffic dynamics within a day are captured by the traffic matrices at three characteristic instants  $\tau_1, \tau_2, \tau_3$  (respectively: morning, noon, evening). For each characteristic instant  $\tau$  we generated an offered traffic matrix according to the process described above, using a different grid of values for parameters  $\pi_{i,i}(\tau)$  for each specific instant. Two different grids were used, representing two different traffic scenarios: in the first one, called INTRA-HOT (Fig. 3-top), the most of the traffic is exchanged between nodes within the same region, i.e. the higher values of  $\pi_{i,j}(\tau)$ are found for E-E and W-W. In the second scenario, called INTER-HOT (Fig. 3-bottom), the most of the traffic is exchanged between nodes in different regions, i.e. the higher values of  $\pi_{i,i}(\tau)$  are found for E-W and W-E.

We remark that such traffic processes are just a simple attempt to model traffic dynamics in a wide area network, as no synthetic model for the time-space distribution of macrotraffic with a recognized matching with the actual behavior of real networks was found in the literature.

Fig. 4 shows the results for five different set of traffic matrices generated with the INTRA-HOT traffic process described above. For each experiment, the amount of used resources in the configuration solution obtained with the different methods is depicted, expressed in terms of the cost function value <sup>1</sup>. It can be noted that method UCMT uses almost the double of the resources compared to ICET, while method JCET uses only about 10% more resources than ICET. The numerical results show that JCET tends to use more arcs than ICET (e.g. 87 vs. 62 for the first experiment) but with a smaller utilization. For the first experiment, the distributions of the instantaneous arc load as obtained with ICET and JCET are compared in Fig. 5: on average, ICET uses 73% of the capacity of the established arcs, while JCET only 56%. This was an expected result: in facts JCET needs more spare arc capacity to absorb the traffic fluctuations, given that the commodities routes are static. On the other hand, the lower utilization efficiency of the optical circuits is compensated by the fact that no circuit rearrangements nor LSP rerouting are needed with the static configuration solution provided by JCET.

The resolution time for JCET problems (1000-18000 seconds) was about one order of magnitude longer than for the ICET and UCMT ones (100-400 seconds). This was expected: in facts the JCET problems are more complex as constraints 6-8 and 10 are repeated for each characteristic instant. From that it should be noted that the size of the problem (number of variables and constraints) depends on the number of considered characteristic instants.

We also repeated the experiments (with the same traffic matrices) imposing the bidirectional circuit constraint introduced in section III-D. The results shows that such additional constraint had no major impact on the amount of used resources, which were always very close to that obtained with unidirectional circuits.

In summary, in all the considered scenarios, method JCET provides a static configuration with only a minor overhead with respect to the dynamic (ICET) case, with a considerable gain with respect to UCMT. It is important to investigate the conditions under which these results hold true, more precisely:

**Q.I.** Which are the network / traffic conditions under which the relative gap in resources usage between UCMT and ICET (call it  $\Delta C_I$ ) is *large* ?

**Q.II.** If  $\Delta C_I$  is *large*, which are the network / traffic conditions under which the gap in resources usage between JCET and ICET (call it  $\Delta C_{II}$ ) is *small*?

The answer to the above questions defines the operational region where method JCET is effective (i.e.  $\Delta C_I$  large and  $\Delta C_{II}$  small). The results for the previous experiments show that the considered scenario falls definitely inside such a region, but from an engineering point of view we are interested in assessing its boundaries.

As regards Q.I, an indication of the gap between the UCMT and ICET can be assessed as follows. The amount of resources required to allocate a traffic matrix T roughly increases with the norm  $||T||_1 = \sum_{i,j} t_{ij}(\tau)$ . Thus we have that the gap  $\Delta C_I$  roughly increases with the difference  $||T^{max}||_1 - \max_{\tau} \{||T(\tau)||_1\}$ , being  $T^{max}$  the maximal traffic matrix defined in section III. This gap is null for example when the traffic matrices  $T(\tau)$  differ only for a scale factor. On the other hand, when there are significant shifts of traffic between the  $T(\tau)$ , the  $\Delta C_I$  gap can be considerable (this was the case of our previous experiments, where such difference was about 140-80=60 Gb/s).

Answering to Q.II is far more complicated. To this scope, we run further experiments in order to assess the impact on  $\Delta C_{II}$  of different time-space traffic distribution: we repeated the above experiments using the INTER-HOT traffic generation process in place of INTRA-HOT. Our expectation was that with INTER-HOT the gap  $\Delta C_{II}$  would have increased, as in this case the traffic completely inverts its spacial trends (from  $E \rightarrow W$  at time  $\tau_1$  to  $W \rightarrow E$  at time  $\tau_3$ ), rather than just shifting the main activity area (from E at time  $\tau_1$  to W at time  $\tau_3$ ) as in the INTRA-HOT case. Fig. 6 shows the results for 5 different experiments with traffic matrices generated with the INTER-HOT process. The comparison with fig. 4 shows that the results are quite similar to the INTRA-HOT case, i.e. we are still in the region where the static configuration provided by JCET method is efficient, and use almost the same resources as the dynamic configuration obtained with ICET. We have also considered the impact of the network topology on  $\Delta C_{II}$ . The available

<sup>&</sup>lt;sup>1</sup>Note that both UCMT and JCET produce a single (static) configuration solution, while ICET produces a set of configuration solutions over the set of characteristic instants, each one with an associated cost value. For ICET the average value of the cost function over the different configuration solutions is depicted in the figures.

$\mathbf{L_{sp}}(\mathbf{k})$	1	2	3	4	$\geq 5$
$\mathbf{L}_{\mathbf{max}}(\mathbf{k})$	3	5	6	7	$\infty$
$N_{max}(k)$	5	5	5	5	5

TABLE I PARAMETERS SETTING FOR SRH HEURISTIC.



Fig. 2. Test-topology

results on a different topology - we used the NSF network found in [1] [3] - are not significatively different from those previously presented, and were not included here for sake of space.

#### VI. CONCLUSION AND FUTURE WORKS

In this paper we faced the problem of off-line configuration of a MPLS over WDM network in case of time-variant offered traffic, assuming that the traffic behavior is known in advance in terms of a discrete set of traffic matrices. We proposed a novel MILP formulation to handle this case, along with a resolution strategy that integrates space-reduction and decomposition heuristics in order to find a sub-optimal solution in reasonable time. Our method (JCET) exploits the a priori knowledge of the traffic behavior to provide a single static configuration - at both packet and optical layers - able to accomodate the traffic in its variability. We provided numerical results to assess the performances of JCET, and showed that in the considered network scenarios it can achieve almost the same performances (in terms of resource usage) of a fully adaptable dynamic configuration. From a practical point of view, given a real network topology and predicted variable traffic demands, JCET can be used to assess the opportunity of introducing periodical reconfiguration into the network under study. In facts, by comparing

	τ <sub>1</sub>	τ <sub>2</sub>	τ3
	E <sub>d</sub> W <sub>d</sub>	E <sub>d</sub> W <sub>d</sub>	E <sub>d</sub> W <sub>d</sub>
INTRA-HOT	E <sub>s</sub> 0.6 0.1 W <sub>s</sub> 0.2 0.1	E <sub>s</sub> 0.3         0.2           W <sub>s</sub> 0.2         0.3	$\begin{array}{c c} {\sf E}_{\rm s} & 0.1 & 0.2 \\ {\sf W}_{\rm s} & 0.1 & 0.6 \end{array}$
INTER-HOT		$\begin{array}{c c} E_{d} & W_{d} \\ E_{s} & 0.2 & 0.3 \\ W_{s} & 0.3 & 0.2 \end{array}$	$     \begin{array}{ccc}       E_{d} & W_{d} \\       E_{s} & 0.1 & 0.1 \\       W_{s} & 0.6 & 0.2 \\     \end{array} $

Fig. 3. Values of  $\pi_{i,j}(\tau)$   $(i, j \in \{E, W\})$  for INTRA-HOT (top) and INTER-HOT (bottom) traffic processes.



Fig. 4. Resource usage obtained with the three methods for INTRAHOT traffic  $({\rm X}=44)$ 



Fig. 5. Distribution of arc load for experiment n. 1 with ICET (mean: 0.73, no. of arcs: 64) and JCET (mean: 0.6, no. of arcs: 75)

the resource usage of the static configuration obtained with JCET with those obtained with the ICET method (which implicitely assume fully dynamical configuration), one can evaluate the potential gain achievable by periodical reconfigurations.

Further work could be devoted to analyze the performances of the JCET method with more realistic macro-traffic models and larger topologies, in the effort to evaluate to what extent the preliminary knowledge (or prediction) of future traffic demands can be exploited to avoid the need for frequent network reconfigurations.

## Appendices

# A. Handling of max terms

In the MILP formulation given in section III-C the variables  $u_m$  converge to the value  $max_k \{r_m^k\}$  in the optimal solution, by effect of constraint 2 and the fact that the  $u_m$  appear in the cost function to be minimized. Typically such an artifice is used whenever a non-linear term in the form  $+max_i \{x_i\}$  is needed in a cost function to be minimized. The introduction of the support variable y in place of the term  $+max_i \{x_i\}$ , along with the support constraints  $y \ge x_i \ (\forall i)$ , preserves the linearity of the formulation. As the support variable y compares in the cost function to be minimized, its value in the optimal solution will be the smallest possible one. On the other hand, the above constraint



Fig. 6. Resource usage obtained with the three methods for INTER-HOT traffic (X = 44)

will preseve the value of y from descending below the values of the  $x_i$ , therefore in the optimal solution the value of the support variable y will equal  $+max_i \{x_i\}$ . As an important remark, note that support variable y does not need to be explicitely restricted to be binary, nor even integer: it suffices to let y continuous and bounded in the range  $0 \le y \le 1$ .

#### B. Decomposition Heuristic Agorithm

Details of the decomposition heuristic (DEH) algorithm presented in section IV are given here. At the generic iteration n, three disjoint subsets of commodities can be individuated:

•  $F^{CUR}(n)$  the set of commodities currently under optimization: the  $r_m^k$  for such commodities are the variables of the sub-problem. Note that  $card\left(F^{CUR}(n)\right) \leq X, \forall n$ .

•  $F^{PAS}(n)$  the set of commodities which have been already allocated in previous blocks. The  $r_m^k$  for such commodities are kept fixed to their last value in the current sub-problem. •  $F^{FUT}(n)$  the set of commodities which have not yet allocated at all. The network flow constraints for such commodifies are canceled in the current sub-problem.

At each iteration, the new set  $F^{CUR}(n)$  must be picked, and the other sets updated as follows:

$$F^{PAS}(n) = F^{PAS}(n-1) \cup F^{CUR}(n-1)$$
$$F^{FUT}(n) = F^{FUT}(n-1) \setminus F^{CUR}(n)$$

Such subsets are used in the DEH algorithm, which is composed of 4 phases, each one embedding different iterations: • Phase 1 - Initial Allocation. Allocate the commodities in blocks of size X, in descending size order, until all the commodities have been allocated. At each iteration n, let  $F^{CUR}(n)$  take the X biggest commodities in  $F^{FUT}(n-1)$ . At the end of this phase,  $F^{FUT}(n)$  reduces to the null set. • Phase 2 - Elimination of swl-critical nodes. Identify the set of swl-critical nodes. An OXC node is swl-critical if the number of switched wavelength exceeds the limit  $W_i^*$ , i.e. the knee of the convex 2-piece-linear cost function depicted in fig. 1. Pick all the arcs which have one of such nodes as an intermediate node. Order them in increasing average load order, i.e.  $\overline{h_m} = \frac{1}{\Theta} \cdot \sum_{\tau} h_m(\tau)$ . Select a number of least loaded arcs such that the number of commodities routed over them is not greater than X. Let  $F^{CUR}(n)$  be constituted by

all the commodities which are routed over such arcs in the current solution. Hopefully, for some arcs all the commodities on it will find an alternative route, so that the arc can be released. At the end of each iteration, if there are no swlcritical nodes or if the new objective function is within 1%from the previous one, continue to Phase 3, otherwise repeat Phase 2.

• Phase 3 - Elimination of ptr-critical nodes. Identify the set of ptr-critical nodes. A LSR node is ptr-critical if the amount of processed packet traffic at some time instat exceeds  $G_i^*$ . Let  $F^{CUR}(n)$  be constituted by all the commodities which are routed over such nodes in the current solution. Hopefully, some commodity among them will find an alternative route on a less loaded node. At the end of each iteration, if there are no ptr-critical nodes or if the new objective function is within 1% from the previous one, continue to Phase 4, otherwise repeat Phase 3.

• Phase 4 - Reduction of number of arcs. From the set of used arc in the current solution, select a number of least loaded arcs such that the number of commodities routed over them is not greater than X. Let  $F^{CUR}(n)$  be constituted by all the commodities which are routed over such arcs in the current solution. At the end of each iteration, if the new objective function is within 1% from the previous one or if the iteration counter has reached a maximum value (10 in our case), continue to Phase 4, otherwise stop.

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