A computation method for scenario studies in WDM network planning

James Yiming Zhang
School of Information Technology and Engineering, University of Ottawa, Ottawa, Canada

Jing Wu
Communications Research Centre (CRC) Canada, Ottawa, Canada

Gregor v. Bochmann
School of Information Technology and Engineering, University of Ottawa, Ottawa, Canada, and

Michel Savoie
Communications Research Centre (CRC) Canada, Ottawa, Canada

Abstract

Purpose – The purpose of this paper is to present the benefits of using the Lagrangian relaxation (LR) and subgradient methods in scenario studies for wavelength division multiplexing (WDM) network planning. The problem of WDM network planning for a given set of lightpath demands in a mesh topology network is to select lightpath routes and then allocate wavelength channels to the lightpaths. In WDM network planning, a scenario study is to find out the network performance under different lightpath demands and/or different network resource configurations.

Design/methodology/approach – A scenario study must solve a series of related static WDM network planning problems. Each static WDM network planning problem is an optimization problem, and may be formulated as an integer linear programming problem, which can be solved by the proposed Lagrangian relaxation and subgradient methods. This paper uses the Lagrange multipliers that are obtained from previous scenarios as initial Lagrange multiplier values for other related scenarios.

Findings – This approach dramatically reduces the computation time for related scenarios. For small to medium variations of scenarios, the method reduces the computation time by several folds. The proposed method is the first method that effectively considers the relations between related scenarios, and uses such relations to improve the computation efficiency of scenario studies in WDM network planning.

Practical implications – The method improves the efficiency of a scenario study in WDM network planning. By using it, many "what-if" type of scenario study questions can be answered quickly.

Originality/value – Unlike other existing methods that treat each scenario individually, this method effectively uses the information of the relation between different scenarios to improve the overall computation efficiency.

Keywords Wavelengths, Network analysis, Resource allocation, Communication technologies, Telecommunication network routing

Paper type Research paper

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I. Introduction

The wavelength routed wavelength division multiplexing (WDM) technology is the core of broadband networks. It provides huge bandwidth capacity with great network control and management flexibility (Zheng and Mouftah, 2004; Mukherjee, 2006; Ramaswami and Sivarajan, 1998). In wavelength routed WDM networks, each optical fibre carries multiple wavelength channels. Each wavelength channel in the same fibre uses a distinct wavelength. A WDM switch connects wavelength channels from its incoming fibres to its outgoing fibres. The switching configuration of a WDM switch can be changed through network control or management systems, which means that a lightpath coming into a WDM switch can be switched to a selected outgoing fibre. A lightpath consists of a chain of wavelength channels from a source node to a destination node.

For a given set of static lightpath demands, the WDM network planning problem is a combinatorial optimization problem, which requires a significant amount of computation to obtain the optimal or a near-optimal solution (Zang *et al.*, 2000; Dutta and Rouskas, 2000). First of all, because different lightpath demands compete for a common pool of network resources, the resource allocation problem must be solved for the whole set of lightpath demands, but not individually. When the number of lightpath demands and network size grow, the computation becomes very difficult. Second, for each lightpath demand, it is required to select a route through a mesh topology network and then select wavelength channels along the route. In general, the above two problems are dependent, and need to be solved together to obtain the optimal solution. These two problems compose the routing and wavelength assignment (RWA) problem.

In WDM network planning, a scenario study is to find out the network performance under different lightpath demands and/or different network resource configurations. A scenario consists of a given set of lightpath demands and a predefined network resource configuration. A scenario study must solve a series of related static WDM network planning problems. For example, lightpath demands are varied to investigate the impact of inaccurate traffic predication, traffic increase or decrease on the network performance. For this purpose, different network resource configurations are investigated to study the improvement of the network performance with incremental network resource investment or the re-organization of existing network resources. Although various computation methods for a single case WDM network planning were proposed in the literature (Jaumard *et al.*, 2007; Antonakopoulos and Zhang, 2007; Banerjee and Mukherjee, 2000; Tornatore *et al.*, 2002; Ozdaglar and Bersekas, 2003; Saad and Luo, 2004), most of them are inefficient for scenario studies. They treat each scenario individually, and do not use the relation between scenarios (Zang *et al.*, 2000; Krishnaswamy and Sivarajan, 2001; Wang *et al.*, 2005).

In this paper, we present the benefits of using the Lagrangian relaxation (LR) and subgradient methods in scenario studies for WDM network planning. The LR-based method has shown its advantages in computing a near-optimal solution for a single case WDM network planning problem (Zhang *et al.*, 2004, 2008; Lee *et al.*, 2004; Luh *et al.*, 1990; Lucena, 2006; Saad and Luo, 2004; Guan *et al.*, 2007). We use the Lagrange multipliers that are obtained from previous scenarios as initial Lagrange multiplier values for other related scenarios. In this manner, our approach dramatically reduces the computation time for related scenarios. For small to medium variations of scenarios, our method reduces the computation time by several folds. Our proposed method is the first method that effectively considers the relations between related scenarios, and uses such relations to improve the computation efficiency of scenario studies in WDM network planning.

This paper is organized as follows. In Section 2, we present a model and assumptions for a wavelength routed WDM network. In Section 3, we provide an integer linear programming formulation of the static RWA problem. In Section 4, we explain how the LR and subgradient methods are used to solve a single case WDM network planning problem, followed by a proposal of using the Lagrange multipliers that are obtained from previous scenarios to improve the efficiency of scenario study. In Section 5, we present two examples of scenario studies and compare the computation time savings. We conclude this paper in Section 6.

II. Network model and assumptions

Our network model consists of N nodes interconnected by E links. Each WDM switch is considered as a node in the network model. The set $\mathcal{V}$ represents all the nodes in the network. Each link has a pair of fibres, one for each direction. Each fibre has W non-interfering wavelength channels. The link between nodes i and j is denoted by e_{ij}. The cth wavelength channel on e_{ij} is denoted by w_{ijc} ($0 < c \leq W$). The set $\mathcal{E}$ represents all the links in the network.

We use general mesh network topologies. They are not restricted to any particular pattern. Different nodes may connect to different numbers of other nodes.

We allow wavelength conversion at switches. The number of wavelength converters at different switches varies, and could be zero. Wavelength converters are installed in a share-per-node manner, which means any input or output port may use a wavelength converter, if one is available. If a switch has an available wavelength converter, a lightpath travelling through the switch may use the wavelength converter to change the wavelength; otherwise, a lightpath travelling through the switch must use the wavelength channels with the same wavelength on both its input and output fibres.

In this paper, we use static lightpath demands for WDM network planning purpose. That means lightpath demands all arrive before the planning is conducted, and are all known in advance for the planning. If a lightpath demand is accepted, resources will be allocated to it for constructing a lightpath. A lightpath permanently uses the allocated resources. The set $\mathcal{L}$ represents all lightpath demands. Our model allows more than one lightpath being set up between a given node pair. The symbol s_{sdn} denotes the nth lightpath demand between the source-destination node pair (s,d).

We assume all resource costs are known. The total cost of the resources that are consumed by a lightpath is the summation of all the system modules and sub-systems that the lightpath travels through. Since each lightpath uses exactly one transmitter at its source and one receiver at its destination, for simplicity we do not count the costs of transmitters and receivers. For illustration purpose, we only count the resource costs of wavelength channels and converters.

We assume service charges for all lightpath demands are known. At the planning stage, we assume the service charge for a lightpath demand is irrelevant to its consumption of resources. A network operator uses the service charge of a lightpath demand to determine whether accepting the demand is profitable.

III. An integer linear programming formulation of the static RWA problem

We adopt a penalty-based objective function as in Zhang *et al.* (2008), wherein the rejection of demands and the use of network resources are penalized. Since a certain amount of potential revenue is lost when a request is rejected, the rejection penalty equals the amount of its potential revenue. On the other hand, when a request is accepted, its resource consumption is added as a penalty term in the objective function. The resource consumption penalty is the cost of resources used by the lightpath provisioned for the demand.

Our design objective is to minimize the function J, i.e. $\min_{A,\Delta,\Phi}(J)$, where:

$$J = \sum_{s_{sdn} \in \mathcal{L}} [(1 - \alpha_{sdn})P_{sdn} + \alpha_{sdn}C_{sdn}] \tag{1}$$

For each demand s_{sdn}, either the penalty of rejecting it (P_{sdn}), or the penalty of using resources (C_{sdn}) to set up a lightpath is added to the objective function (J), depending on s_{sdn}'s admission status α_{sdn}. The value of α_{sdn} is zero, if s_{sdn} is rejected and α_{sdn} is one, if s_{sdn} is admitted. Essentially, our design objective is to maximize the overall profit, which is measured by the excess of revenue of providing services to demands over the network resource cost. We will identify and accept profitable demands, while reject non-profitable demands. After the optimization results for one scenario are computed, the unused resources can be re-arranged or reduced to generate a new scenario. By studying a sequence of scenarios, a proper configuration is obtained for a given set of demands. Note that the design objective in the network planning is different from that in the dynamic operation of an existing network. The latter one is to maximize the utilization of existing resources to accommodate more demands. In the latter case, the penalty of using resources is generally not considered, since the resources are deployed already.

In addition to the design variables α_{sdn} ($\forall s_{sdn} \in \mathcal{L}$), we introduce the design variables δ_{ijc}^{sdn} ($\forall s_{sdn} \in \mathcal{L}$, $\forall e_{ij} \in \mathcal{E}$, $0 < c \leq W$), representing the use of w_{ijc} by s_{sdn} and the design variables ϕ_i^{sdn} ($\forall s_{sdn} \in \mathcal{L}$, $\forall i \in \mathcal{V}$), representing the use of a wavelength converter at node i by s_{sdn}. If w_{ijc} is used by s_{sdn}, δ_{ijc}^{sdn} equals one; otherwise, δ_{ijc}^{sdn} equals zero. If a wavelength converter is used by s_{sdn}, ϕ_i^{sdn} equals one; otherwise, ϕ_i^{sdn} equals zero. We use vector A to denote the acceptance status of all demands, vector Δ to denote their wavelength assignment and Φ to denote their use of wavelength converters. We use V to denote all the design variables (A,Δ,Φ). For an individual lightpath demand s_{sdn}, we use Δ_{sdn} to denote its wavelength assignment and Φ_{sdn} to denote its use of wavelength converters. Now we may define the cost of resources C_{sdn} as the cost of using wavelength channels and converters:

$$C_{sdn} = \sum_{e_{ij} \in \mathcal{E}} \sum_{0<c \leq W} d_{ij}\delta_{ijc}^{sdn} + \sum_{i \in \mathcal{V}} o_i \phi_i^{sdn}, \quad \forall s_{sdn} \in \mathcal{L}, \tag{2}$$

where:

d_{ij} – the cost of using w_{ijc}.

o_i – the cost of using a wavelength converter at node i.

The above static RWA problem must conform to the following constraints:

- Lightpath continuity constraints: if a demand is admitted, the lightpath assigned to it has to be continuous along a path between the source-destination pair. Since the assigned lightpath terminates at the two end nodes, we have:

$$\sum_{j \in \mathcal{V}} \sum_{0<c \leq W} \delta_{ijc}^{sdn} - \sum_{j \in \mathcal{V}} \sum_{0<c \leq W} \delta_{jic}^{sdn} = \begin{cases} \alpha_{sdn} & \text{if } i = s \\ -\alpha_{sdn} & \text{if } i = d \\ 0 & \text{otherwise} \end{cases}, \quad \forall s_{sdn} \in \mathcal{L} \tag{3}$$

- Wavelength channel exclusive usage constraints:

$$\sum_{s_{sdn} \in \mathcal{L}} \delta_{ijc}^{sdn} \leq 1, \quad \forall e_{ij} \in \mathcal{E}, \ 0 < c \leq W \tag{4}$$

  These constraints mean that each wavelength channel can only be used by one lightpath.

- Transmitter, receiver and wavelength converter capacity constraints:

$$\sum_{d \in \mathcal{V}} \sum_{0<n \leq N_{sd}} \alpha_{sdn} \leq T_s, \quad \forall s \in \mathcal{V} \tag{5}$$

$$\sum_{s \in \mathcal{V}} \sum_{0<n \leq N_{sd}} \alpha_{sdn} \leq R_d, \quad \forall d \in \mathcal{V} \tag{6}$$

$$\sum_{s_{sdn} \in \mathcal{L}} \phi_i^{sdn} \leq F_i, \quad \forall i \in \mathcal{V} \tag{7}$$

  The number of lightpaths originating from or terminating at a node must be no more than the number of transmitters or receivers at the node. We assume that all transmitters and receivers operate at any wavelength. The number of transmitters at source node s is denoted by T_s. The number of receivers at destination node d is denoted by R_d. The symbol N_{sd} is the number of lightpath demands between (s,d). The number of used converters at a node must be no more than the number of installed converters at the node. The number of wavelength converters at node i is denoted by F_i.

- Wavelength conversion constraints:

$$\phi_j^{sdn} = \begin{cases} 1 & \text{if } \exists m, k \in \mathcal{V} \text{ and } b \neq a, \delta_{mja}^{sdn} = \delta_{jkb}^{sdn} = 1 \\ 0 & \text{otherwise} \end{cases}, \quad \forall j \in \mathcal{V} \tag{8}$$

  A wavelength converter at an intermediate node j is used only when different wavelengths are assigned to s_{sdn} for the incoming and outgoing signals at this node.

IV. Computation method

A. Solve the static RWA problem by the LR and subgradient methods

We use the LR and subgradient methods to solve the static RWA problem. By using the LR framework, a dual problem (DP) can be derived from the primal problem $\min_{V}(J)$. A heuristic algorithm is used to obtain a feasible solution to the primal problem from the solution to the Lagrangian DP. The achieved value of the Lagrangian DP is a bound of the objective function in the primal problem. The key of solving the Lagrangian DP is its decomposition into independent sub-problems, whose optimal solutions can be easily obtained. Once the optimal solutions to the sub-problems are computed, we use the subgradient method to solve the Lagrangian DP iteratively. The overall algorithm is shown in Figure 1. When the algorithm converges, the optimized Lagrange multipliers are obtained. In addition to the built-in nature of attempting to respect the relaxed constraints in solving the Lagrangian DP, the heuristic algorithm forces the violated constraints to be respected.

The Lagrangian DP is derived by relaxing the constraints that represent resource limitations. Lagrange multipliers ξ_{ijc}, π_s, θ_d and λ_i are introduced in association with the wavelength channel exclusive usage constraints in equation (4), transmitter, receiver and wavelength converter capacity constraints in equations (5)-(7), respectively. We use ξ, π, θ and λ to denote the vectors of Lagrange multipliers (ξ_{ijc}), (π_s), (θ_d) and (λ_i), respectively. We use M to denote all the Lagrange multipliers $(\xi, \pi, \theta, \lambda)$. The Lagrangian function L is defined as:

$$\begin{aligned} L(V,M) = {} & J(V) + \sum_{e_{ij}\in\mathcal{E}}\sum_{0<c\leq W}\xi_{ijc}\left(\sum_{s_{sdn}\in\mathcal{L}}\delta_{ijc}^{sdn}-1\right) + \sum_{s\in\mathcal{V}}\pi_s\left(\sum_{d\in\mathcal{V}}\sum_{0<n\leq N_{sd}}\alpha_{sdn}-T_s\right) \\ & + \sum_{d\in\mathcal{V}}\theta_d\left(\sum_{s\in\mathcal{V}}\sum_{0<n\leq N_{sd}}\alpha_{sdn}-R_d\right) + \sum_{i\in\mathcal{V}}\lambda_i\left(\sum_{s_{sdn}\in\mathcal{L}}\phi_i^{sdn}-F_i\right) \end{aligned} \tag{9}$$

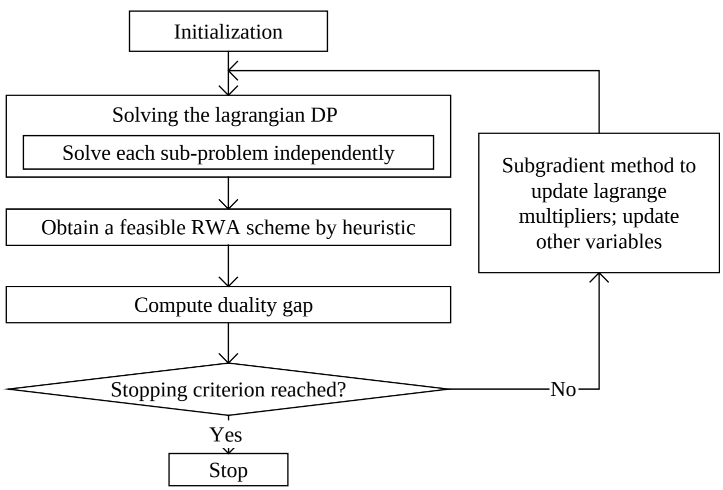

Figure 1.
Schematic depiction of the overall algorithm

We define the dual function $q(M)$ as the infimum of $L(V,M)$:

$$q(M) = \min_{V}[L(V, M)] \tag{10}$$

The Lagrangian DP is $\max_{M \geq 0}[q(M)]$, subject to the constraints in equations (3) and (8). We use q^* to denote Lagrangian DP's optimal value. The corresponding optimal Lagrange multiplier values are denoted by $M^* = (\xi^*, \pi^*, \theta^*, \lambda^*)$. The optimal value of the Lagrangian DP is a lower bound to the primal problem (Bertsekas, 1999):

$$q^*(M^*) = \min_{V}[L(V, M^*)] \leq \min_{V}[J(V)] \tag{11}$$

Two important facts lead to our decomposition of the Lagrangian DP. The first fact is the relations $\delta_{ijc}^{sdn} = \alpha_{sdn}\delta_{ijc}^{sdn}$ and $\phi_i^{sdn} = \alpha_{sdn}\phi_i^{sdn}$. After removing the terms that are independent of the decision variables, the dual function becomes equation (12). Refer to Zhang *et al.* (2004, 2008) for the mathematical details. The second fact is that the resource allocation to each lightpath is independent, because the resource usage constraints in equations (4)-(7) are relaxed. The complex competition among lightpaths for shared resources does not need to be considered when we allocate resources to individual lightpaths. So, the dual function is composed of the summation of all lightpath-level sub-problems, i.e.:

$$q(M) = \sum_{s_{sdn} \in \mathcal{L}} \mathrm{SP}_{sdn},$$

where SP_{sdn} denotes the sub-problem that corresponds to s_{sdn}. The lightpath independence dramatically reduces the huge global problem space into partitioned pieces of sub-problem space, where the optimal solutions to the decomposed sub-problems can be computed using well-established existing algorithms. The global optimal solution to DP is efficiently searched by the subgradient-based iterations:

$$\begin{aligned} q(M) = \min_{V}\Bigg\{ \sum_{s_{sdn} \in \mathcal{L}} \Bigg[(1 - \alpha_{sdn})P_{sdn} + \alpha_{sdn} \Bigg(\sum_{e_{ij} \in \mathcal{E}} \sum_{0 < c \leq W} \delta_{ijc}^{sdn}(\xi_{ijc} + d_{ij}) \\ + \sum_{i \in \mathcal{V}} \phi_i^{sdn}(\lambda_i + o_i) + \pi_s + \theta_d \Bigg) \Bigg] \Bigg\} \end{aligned} \tag{12}$$

The optimal solution to SP_{sdn} is computed by equation (13). SP_{sdn} corresponds to s_{sdn}'s acceptance or rejection, and the associated RWA problem if it is accepted:

$$\begin{aligned} \mathrm{SP}_{sdn}(\alpha_{sdn}, \Delta_{sdn}, \Phi_{sdn}) = \min_{\alpha_{sdn}} \Bigg[(1 - \alpha_{sdn})P_{sdn} + \alpha_{sdn} \min_{\Delta_{sdn}, \Phi_{sdn}} \Bigg(\sum_{e_{ij} \in \mathcal{E}} \sum_{0 < c \leq W} \delta_{ijc}^{sdn}(\xi_{ijc} + d_{ij}) \\ + \sum_{i \in \mathcal{V}} \phi_i^{sdn}(\lambda_i + o_i) + \pi_s + \theta_d \Bigg) \Bigg] \end{aligned} \tag{13}$$

We solve SP_{sdn} in equation (13) in two steps: lightpath routing, and decision of acceptance or rejection. The first step is to solve the lightpath routing problem:

$$D_{sdn} = \min_{\Delta_{sdn}, \Phi_{sdn}} \left\{ \sum_{e_{ij} \in \mathcal{E}} \sum_{0<c\leq W} \delta_{ijc}^{sdn}(\xi_{ijc} + d_{ij}) + \sum_{i \in \mathcal{V}} \phi_i^{sdn}(\lambda_i + o_i) \right\}, \tag{14}$$

subject to the constraints in equations (3) and (8) for s_{sdn}. We assign an auxiliary cost $(\xi_{ijc} + d_{ij})$ to w_{ijc}, and an auxiliary cost $(\lambda_i + o_i)$ to a wavelength converter in node i. The optimal solution is computed by using the modified minimum cost semi-lightpath algorithm in Zhang *et al.* (2004).

The second step is to solve the decision problem:

$$\min_{\alpha_{sdn}} [(1 - \alpha_{sdn})P_{sdn} + \alpha_{sdn}(D_{sdn} + \pi_s + \theta_d)] \tag{15}$$

If P_{sdn} is greater than $(D_{sdn} + \pi_s + \theta_d)$, then reject s_{sdn}. On the contrary, if P_{sdn} is smaller, then accept s_{sdn} (i.e. $\alpha_{sdn} = 1$). A tie is broken arbitrarily.

B. Convergence acceleration in a scenario study by reusing Lagrange multipliers

An important feature of using the LR and subgradient methods to solve the static RWA problem is that the Lagrange multipliers of two similar scenarios are similar too. The Lagrange multipliers preserve the "neighbourhood property". When a new scenario is in the neighbourhood of a previous one, the previous Lagrange multipliers produce a good estimate for the new scenario. This property enables reusing Lagrange multipliers to save computation time in scenario studies. To study a new scenario, instead of solving a new optimization process starting from zero Lagrange multipliers, the Lagrange multipliers obtained from the previous scenarios can be reused as initialization points in searching for the optimized Lagrange multipliers. Such approach reduces the time to reach the convergence of the algorithm in a scenario study.

The neighbourhood property is better preserved in the dual space than in the primal space. For two similar scenarios, their solutions in the dual space, i.e. their optimized Lagrange multipliers, are close to each other. But, their solutions in the primal space, i.e. the demand acceptance and the RWA schemes for the accepted demands, may be distant from each other. This property makes our method for a scenario study more efficient than initializing the search of a new solution to a similar scenario in the neighbourhood of the solution to the previous scenario. Therefore, our method is more suitable for a scenario study than the methods that direct search in the primal space, such as the Tabu search method (Wang *et al.*, 2005).

The neighbourhood property of our method is mainly attributed to two factors: solely relaxing carefully selected constraints to generate the DP, and the robustness of the subgradient-based iterations. We only relax the constraints that represent resource limitations, i.e. the wavelength channel exclusive usage constraints in equation (4), transmitter, receiver and wavelength converter capacity constraints in equations (5)-(7), respectively. The constraints that govern the RWA of individual lightpaths are all strictly respected. The potential conflict of using the same resources by multiple lightpaths is solved by the subgradient-based iterations, which has robust convergence, i.e. the fluctuation of individual parameters does not affect the general trend of the subgradient.

V. Examples

In the first example, we study a series of scenarios where the lightpath demands change in a fixed network resource configuration and network topology. We use the Pan-European network with 28 nodes and 61 links (shown in Figure 2). The parameters used in the example are $P_{ij0} = 1{,}000.0$ for all lightpath demands, $d_{ij} = 5.0$ for all links, $F_i = \infty$, $T_i = R_i = 18$, $o_i = 0$, $t_i = r_i = 0$ for all nodes and $W = 16$. We run the heuristic algorithm once every five iterations to obtain a feasible solution. The lightpath demands for the two scenarios are shown in Tables I and II. The second scenario is a minor variation of the first one. The variations of the lightpath demands from the first scenario to the second one are highlighted by italics numbers in Table II.

We compare the number of iterations required for the convergence of the optimization process. When studying the second scenario, we use two different schemes in initializing the Lagrange multipliers:

(1) *Scheme-A* (*Zero Init*). Initializing all the Lagrange multipliers to zeros.

(2) *Scheme-B* (*Good Init*). Initializing the Lagrange multipliers to the obtained optimized Lagrange multipliers from the first scenario.

A dramatic difference on the convergence time is observed between the two initialization schemes (shown in Figure 3). In Scheme-B, the computation almost reached the optimal values after 40 iterations. In contrast, in Scheme-A, the optimization process does not converge to a similar duality gap until after 400 iterations.

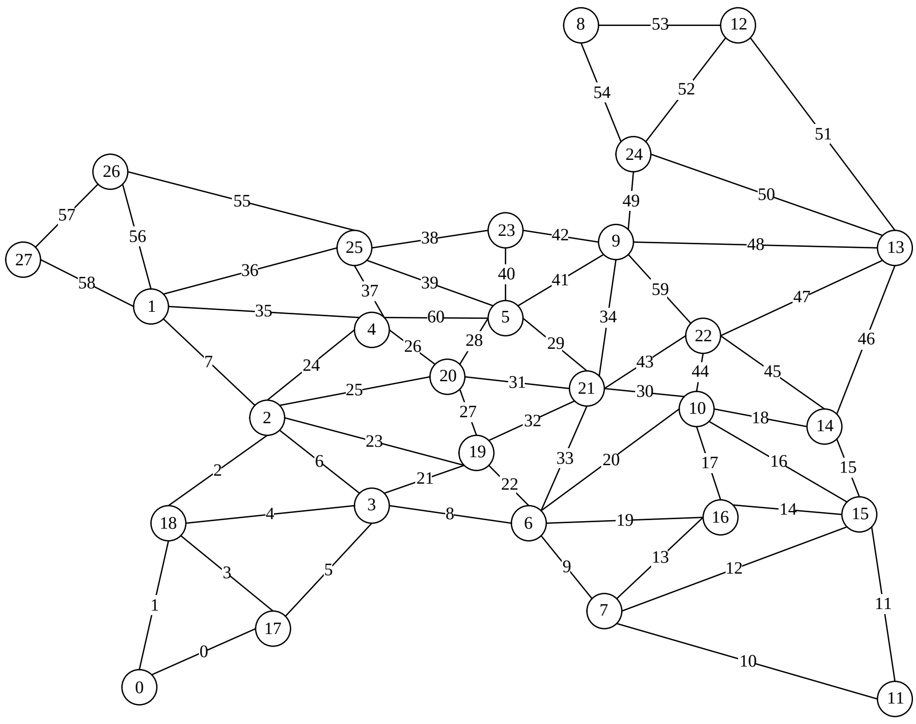

Figure 2.
Pan-European network with 28 nodes and 61 links

0	2	2	2	2	1	2	1	0	0	1	1	0	0	0	0	0	0	0	2	1	1	0	0	0	0	0	0
2	0	2	1	1	2	0	0	0	1	2	0	0	0	0	0	1	2	2	1	1	0	0	0	0	2	0	2
2	2	0	1	2	2	1	0	0	0	1	1	0	0	0	0	1	2	2	2	2	1	0	0	2	0	1	1
2	1	2	0	1	0	2	2	0	1	1	1	0	0	0	1	2	2	1	2	1	1	1	0	1	1	0	0
2	2	2	1	0	2	1	0	1	2	1	0	1	0	0	0	1	0	0	2	2	2	0	2	0	2	0	1
0	2	1	0	2	0	0	2	2	1	2	0	1	1	2	1	0	0	1	0	0	2	1	0	2	0	2	2
2	1	1	0	1	2	0	0	0	0	1	1	0	0	2	0	0	2	2	0	0	0	0	0	0	1	0	2
1	2	1	2	0	0	0	0	0	2	0	0	0	0	0	2	0	1	2	2	0	2	0	0	2	1	1	1
0	0	0	0	0	2	0	1	0	2	1	0	2	2	1	1	0	0	0	1	1	2	2	2	0	1	2	2
0	0	1	0	2	2	1	0	2	0	0	0	2	2	1	0	1	0	1	0	1	2	2	1	0	0	2	2
0	1	0	1	0	1	0	0	1	2	0	2	1	1	2	1	0	0	0	0	2	1	1	1	0	2	0	0
0	1	0	0	0	1	2	1	0	1	1	0	0	0	1	0	2	0	0	1	0	0	0	2	0	1	0	2
0	0	0	1	0	2	1	0	0	2	1	0	0	2	2	1	1	0	0	1	1	2	2	2	1	2	0	0
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2	1	1	0	2	0	1	0	1	0	0	1	1	0	0	2	1	2	2	0	0	1	0	2	0	0	2	0
0	0	0	1	1	0	1	0	2	0	2	0	0	1	1	1	1	1	1	0	0	0	2	0	2	0	0	2
0	2	1	0	0	2	0	2	2	0	2	0	2	2	2	0	2	0	0	1	0	1	0	2	0	2	0	1
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0	0	0	1	1	0	1	0	0	2	2	0	0	2	2	0	1	0	0	0	1	2	2	2	0	0	0	0
1	2	0	0	2	2	0	0	1	1	0	1	1	0	1	1	1	1	1	0	1	0	0	2	2	0	1	0
1	2	2	1	1	0	2	0	0	0	1	0	0	2	1	0	1	1	2	1	1	1	1	0	1	2	0	2
1	2	2	0	0	2	1	2	0	0	0	1	0	0	0	1	0	1	1	2	0	0	1	2	0	1	0	0

Table I.
Initial lightpath demands in the first network planning session

Our extensive simulation results show that the neighbourhood property is very robust. We simulated variations of lightpath demands by 1, 5, 10 and 30 per cent. Our simulation results show that even in the scenarios with relatively large variations of lightpath demands, the previously obtained Lagrange multipliers are still a good estimate for a new scenario, leading to a quick convergence. Another observation is that initializing Lagrange multipliers to zero is generally better than initializing them randomly. Thus, for the first scenario in a series, it is a wise choice to initialize them to all zero.

In a second example, we study a series of scenarios where the network resource configuration changes in a fixed network topology with fixed lightpath demands. We use the network topology shown in Figure 2 and the lightpath demands shown in Table I. In the original network resource configuration (Case 1), the number of wavelength channels on each link is 16. The achieved design objective is 119,788, with a lower bound of 115,906. We study three other scenarios. In Case 2, we add two wavelength channels to the six most critical links identified in Case 1, i.e. links 2, 4, 5, 49, 50 and 51. The Lagrange multipliers for the wavelength channels on these links are significantly larger than for those on other links. The achieved design objective is 114,859, with a lower bound of 111,814. So, adding new resources at critical locations improves the design objective. In Case 3, we add two wavelength channels to six randomly selected non-critical links, e.g. 10, 17, 28, 33, 47 and 57. The achieved design objective is 119,780, with a lower bound of 115,923. In Case 4, instead of adding

0	2	2	2	2	1	2	1	0	0	1	1	0	0	0	0	0	0	0	2	*2*	1	0	0	0	0	0	0
2	0	2	1	*2*	2	0	0	0	1	2	0	0	0	0	0	1	2	2	1	1	0	0	0	0	2	0	2
2	2	0	1	2	2	1	0	0	0	1	1	0	0	0	0	1	2	2	2	2	1	0	0	2	0	1	1
2	1	2	0	1	0	2	2	0	1	*2*	1	0	0	0	1	2	2	1	2	1	1	1	0	1	1	0	0
2	2	2	1	0	2	1	0	1	2	1	0	1	0	0	0	1	0	0	2	2	2	0	2	0	2	0	1
0	2	1	0	2	0	0	2	2	1	2	0	1	1	2	*2*	0	0	1	0	0	2	1	0	2	0	2	2
2	1	1	0	1	2	0	0	0	0	1	1	0	0	2	0	0	2	2	0	0	0	0	0	0	1	0	*1*
1	*1*	1	2	0	0	0	0	0	2	0	0	0	0	0	2	0	1	2	2	0	2	0	0	2	1	1	1
0	0	0	0	0	2	0	*0*	0	2	1	0	2	2	1	1	0	0	0	1	1	2	2	2	0	1	2	2
0	0	1	0	2	2	1	0	2	0	0	0	2	2	1	0	1	0	1	0	1	2	2	1	0	0	2	2
0	1	0	1	0	1	0	0	1	2	0	2	1	1	2	1	0	0	0	0	2	1	1	1	0	2	0	0
0	1	0	0	0	1	2	1	0	1	1	0	0	0	1	0	2	0	0	1	0	0	0	2	0	1	0	2
0	0	0	1	0	2	1	0	0	2	1	0	0	2	2	1	1	0	0	*0*	1	2	2	2	1	2	0	0
0	0	0	1	0	0	0	2	2	0	0	0	2	0	0	1	0	0	0	0	0	1	2	2	2	1	0	0
0	0	0	0	0	0	1	2	1	1	0	1	2	1	0	0	1	0	0	1	1	2	2	0	2	0	1	0
0	0	1	1	1	0	0	2	1	0	0	0	1	1	*2*	0	0	0	0	0	0	2	0	1	1	1	0	0
1	0	0	1	1	1	0	1	0	2	1	2	0	0	2	1	0	0	0	2	0	1	1	0	1	0	0	2
0	2	2	2	2	1	2	1	0	*0*	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	1	0	0
0	1	2	2	1	0	2	1	0	0	0	0	0	0	0	0	1	2	0	2	2	2	0	0	0	1	0	1
2	1	2	1	2	2	0	0	0	2	0	2	0	0	0	1	0	*2*	1	0	2	1	0	0	2	0	2	0
2	1	1	0	2	0	1	0	1	0	0	1	1	0	0	2	1	2	2	0	0	1	0	2	0	0	2	0
0	0	0	1	1	0	1	0	2	0	2	0	*1*	1	2	1	1	1	1	0	0	0	2	0	2	0	0	2
0	2	1	0	0	2	0	2	2	0	2	0	2	2	1	0	2	0	0	1	0	1	0	2	0	2	0	1
0	2	1	0	0	1	0	2	2	1	0	0	2	0	0	2	2	0	0	0	2	0	0	0	2	*0*	1	0
0	0	0	1	1	0	1	0	0	2	2	0	0	2	2	0	1	0	0	0	1	2	2	2	0	0	0	0
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1	2	2	1	1	0	2	0	0	0	1	0	0	2	1	0	1	1	2	1	1	1	*0*	0	1	2	0	2
1	2	2	0	0	2	1	2	0	0	0	1	0	0	0	1	0	1	1	2	0	0	1	2	0	1	0	0

Table II.
Changed lightpath demands for the second scenario

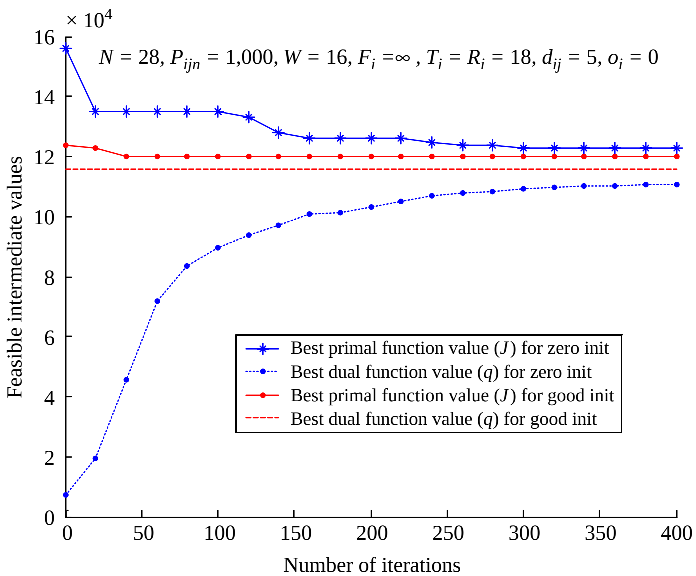

Figure 3.
Convergence time comparison between different initialization schemes of Lagrange multipliers

resources, we reallocate two wavelength channels from each of the six non-critical links to the six most critical links, i.e. from links 2, 4, 5, 49, 50 and 51 to links 10, 17, 28, 33, 47 and 57. The achieved design objective is 114,857, with a lower bound of 111,836. The comparisons of convergence time between different initialization schemes for Cases 2-4 are shown in Figures 4-6. The convergences of the three scenarios with good initialization are fairly quick.

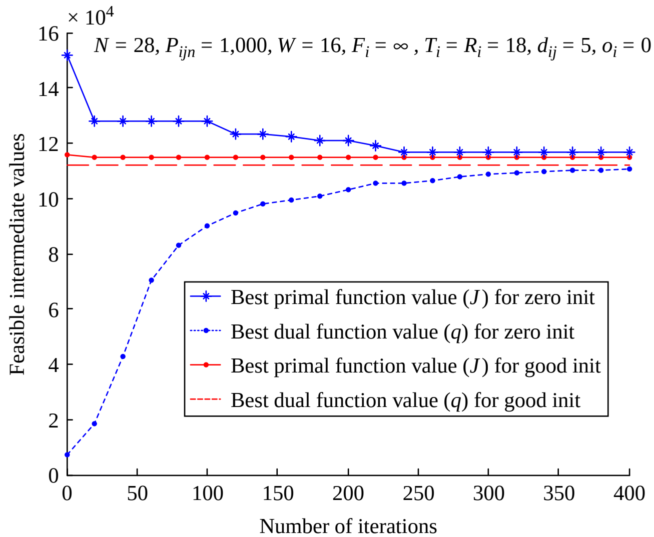

Figure 4. Convergence time comparison between different schemes of Lagrange multiplier initialization for Case 2

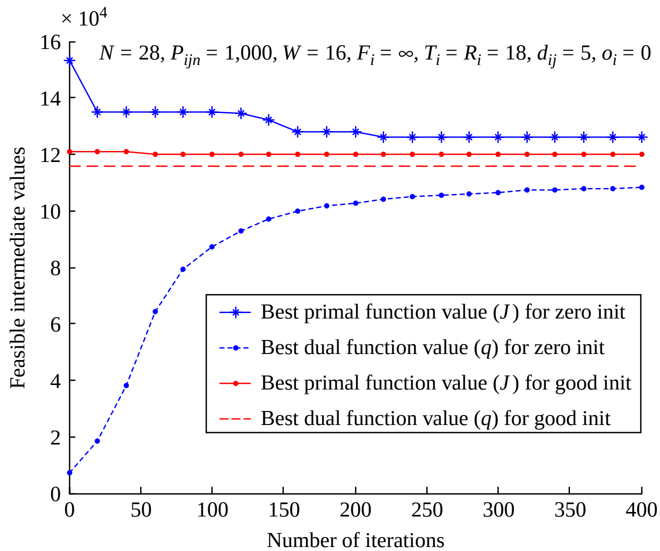

Figure 5. Convergence time comparison between different schemes of Lagrange multiplier initialization for Case 3

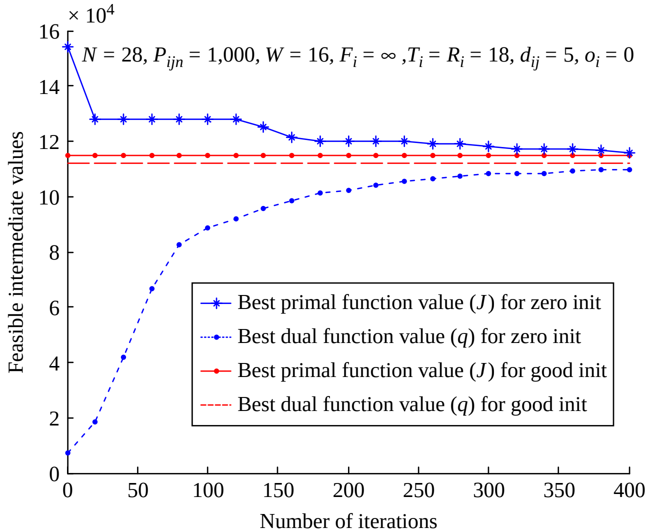

Figure 6.
Convergence time comparison between different schemes of Lagrange multiplier initialization for Case 4

VI. Conclusions

We proposed to use the LR and subgradient methods to solve the scenario study problems in static WDM network planning. The optimized Lagrange multipliers that are obtained from previous scenarios are used as initialization points for related scenarios. In this way, the computation time for new scenarios is significantly reduced. Our simulations show that when lightpath demands varies or network resource configuration changes, by reusing previous Lagrange multipliers, the computation time may be reduced by several folds. The superior computation time, together with the good features of the LR and subgradient methods, such as being able to provide a performance bound to evaluate the quality of the near-optimal solutions, make our approach attractive in the practical "what-if" types of scenario studies in WDM network planning.

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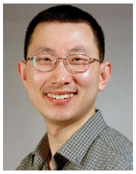
About the authors

James Yiming Zhang obtained a PhD degree in Electrical Engineering from University of Ottawa, Ontario, Canada. He received both his BS and MS degrees in Electronic Science from Zhejiang University, China. He is currently working as a post-doctoral fellow at School of Information Technology and Engineering in University of Ottawa. His research interests include optimization algorithms for the communication networks and the manufacturing processes, object detection, recognition and tracking in images, machine learning, high-speed digital hardware design and biometrics.



Jing Wu obtained a BSc degree in information science and technology in 1992, and a PhD degree in systems engineering in 1997, both from Xi'an Jiao Tong University, China. He is now a Research Scientist at the Communications Research Centre Canada (CRC) (Ottawa, Canada), an Agency of Industry Canada. In the past, he worked at Beijing University of Posts and Telecommunications (Beijing, China) as a faculty member, Queen's University (Kingston, Canada) as a postdoctoral fellow and Nortel Networks Corporate (Ottawa, Canada) as a System Design Engineer. Currently, he is also appointed as an Adjunct Professor at the University of Ottawa, School of Information Technology and Engineering. He has contributed over 70 conference and journal papers. He holds three patents on internet congestion control, and one patent on control plane failure recovery. His research interests include control and management of optical networks, protocols and algorithms in networking, optical network performance evaluation and optimization. He is a Co-chair of the sub-committee on "network architecture, management and applications" of the Asia Communications and Photonics Exhibit and Conference (ACP), which will take place 2-6 November 2009, in Shanghai, China. He is a member of the technical program committees for many international conferences such as IEEE ICC, IEEE GLOBECOM. He is a Senior Member of IEEE. Jing Wu is the corresponding author and can be contacted at: jing.wu@crc.gc.ca

Gregor v. Bochmann is a Professor at the School of Information Technology and Engineering at the University of Ottawa since January 1998, after 25 years at the University of Montreal. He is a fellow of the IEEE and ACM and a member of the Royal Society of Canada. He did research on programming languages, compiler design, communication protocols and software engineering and published many papers in these areas. He was also actively involved in the standardization of formal description techniques for communication protocols and services in the 1980s. He had many research projects in collaboration with industry and, from 1989 to 1997, held the Hewlett-Packard – NSERC – CITI Industrial Research Chair on communication protocols at the University of Montreal. His present work is the area of software engineering for distributed systems, peer-to-peer systems, quality of service and security management for distributed multimedia applications and control procedures for optical networks.

Michel Savoie is the Research Program Manager for the Broadband Applications and Optical Networks group of the Broadband Network Technologies Research Branch at the CRC, an Agency of Industry Canada. He maintains expertise in broadband systems and related technologies such as: user controlled lightpaths (UCLP), Infrastructure as a service (IaaS), Green ICT, Application Oriented Networking, advanced IP, ATM and WDM-based Optical Networks in order to provide advice on important national initiatives and to demonstrate the application of CRC technologies in a real operational environment. He has managed two UCLP projects funded under CANARIE's directed research program and was involved with EUCALYPTUS: A Service-oriented Participatory Design Studio project funded under the CANARIE Intelligent Infrastructure Program (CIIP). He is also involved with PHOSPHORUS: A Lambda User Controlled Infrastructure for European Research integrated project funded by the European Commission under the IST 6th Framework; the Health Services Virtual Organization project under CANARIE's Network-Enabled Plaftorms program; and the High Performance Digital Media Network (HPDMnet) research initiative. CRC and its partners are currently engaged in the further development of the Argia/UCLP and the IaaS Framework software. He holds a BSc and MSc in Electrical Engineering from the University of New Brunswick.