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Applying MOEAs to solve the static Routing and Wavelength Assignment problem in optical WDM networks ☆

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ABSTRACT

Wavelength-Division Multiplexing (WDM) in optical networks has revolutionized the Telecommunication field. This technology is able to exploit the enormous bandwidth capability of this kind of networks, allowing communication between end users via all-optical WDM channels (lightpath). Given a set of demands, the problem of setting up lightpaths by routing and assigning a wavelength to each connection is known as Routing and Wavelength Assignment (RWA) problem. There are two types of connection demands: static (demands are given in advance) and dynamic (demands are given in real-time). In this paper we present two different Multiobjective Evolutionary Algorithms (MOEA) with the aim of solving the static RWA problem. The first one is a population-based algorithm, the Differential Evolution (DE), but incorporating the Pareto Tournament concept (DEPT). The second one is a multiobjective version of the Variable Neighborhood Search (VNS), MO-VNS. In order to prove the goodness of our metaheuristics, we have compared them with the standard Fast Non-Dominated Sorting Genetic Algorithm (NSGA-II), typical heuristics in the Telecommunication field, and different varieties of Multiobjective Ant Colony Optimization Algorithms. On the whole, we conclude that our approaches have obtained very promising results.

1. Introduction

Nowadays the optical networks are designed with the Wavelength Division Multiplexing (WDM) technology. This technique is able to exploit the huge bandwidth capability of optical networks. There are emerging communication applications that have high-bandwidth requirements. The aim of this technology is to divide the enormous transmission bandwidth of an optical fiber (about 50 Tbps) into multiple communication channels (about 10 Gbps) compatible with the processing speed of the electronic devices. These channels are also known as lightpaths.

WDM uses wavelength routing to remedy the lack of wavelength reuse (Mokhtar and Azizoğlu, 1998). A wavelength router (Fig. 1) is an optical switch that is capable of routing a signal based on its input port and its wavelength. Furthermore, this kind of router may have the capability of changing the wavelength of the signal.

A problem comes up when it is necessary to interconnect a set of connection requests, this problem is called Routing and Wavelength Assignment problem (RWA problem). There are two different varieties of the RWA problem, depending on the demands: static-RWA and dynamic-RWA. With static connections, the entire set of requests is known in advance, so the problem is to set up all lightpaths trying to minimize the use of network resources. We will focus on static-RWA problem because at present time it is the most used one.

As an example of static-RWA problem, in WANs (Wide Area Networks) this problem appears because they are oriented to precontracted services (Hamad and Kamal, 2002). The static-RWA problem is an NP-complete problem, therefore it is very common to use heuristic techniques to solve it (Saha and Sengupta, 2005; Mukherjee et al., 1996).

To tackle the static-RWA problem, we have decided to use two different Multiobjective Evolutionary Algorithms (MOEAs). In general, there are two types of evolutionary algorithms: population-based and trajectory-based. In this paper we have chosen one of the each type.

As population-based algorithm, we have developed the Differential Evolution (DE) algorithm (Storn and Price, 1997), that basically adds the weighted difference between two population vectors to a third vector. We have added the concept of Pareto Tournament (DEPT) to solve this multiobjective problem.

As trajectory-based algorithm, we have implemented the Variable Neighborhood Search (VNS) (Hansen and Mladenovic, 2001).

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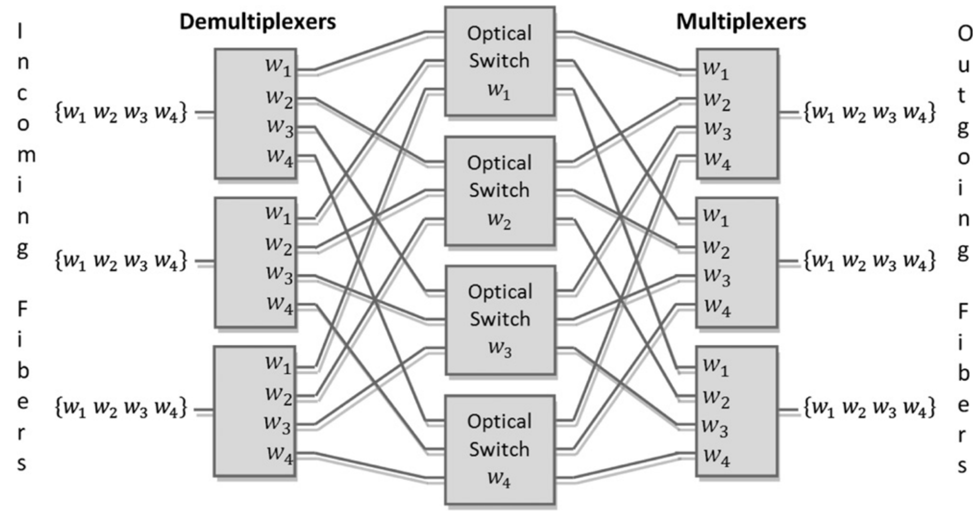

Fig. 1. A wavelength router with nodal degree three and four wavelengths.

This algorithm tries to escape from local optima trap by changing the neighborhood structure. We have modified this algorithm to adapt it to a multiobjective context too, we will refer to it as MO-VNS.

We have carried out several experiments to adjust both algorithms by using two real-world topologies: NSF network (USA) and NTT network (Japan); and six sets of source-destination pairs for each topology, a total of twelve instances.

In order to demonstrate the goodness of our proposals, we have compared them with the standard Fast Non-Dominated Genetic Algorithm (NSGA-II) (Deb et al., 2000), one of the most known standard algorithms nowadays. We have also made a comparison with other approaches published in the literature. First of all, we have compared our MOEAs with typical heuristics in the Telecommunication field. In the second comparison we have compared them with different varieties of Multiobjective Ant Colony Optimization algorithms.

The rest of this paper is organized as follows: Section 2 introduces the related work. Section 3 describes the RWA problem in a formal way. In Section 4 we explain in detail the DEPT and the MO-VNS algorithms, and also the NSGA-II. The experiments to adjust the MOEAs are presented in Section 5, as well as a comparison among them. The comparisons with other approaches published in the literature are left for Section 6. Finally, in Section 7 we present conclusions and future work.

2. Related work

The first authors in considering the problem of routing connections in a reconfigurable optical network using Wavelength Division Multiplexing were Ramaswami and Sivarajan (1995). They solved the static-RWA problem by using mixed-integer linear programming. In order to tackle the optimization problem, they suggest dividing it into two subproblems: *Routing*, and *Wavelength Assignment*—solving each one separately. Both subproblems have been tackled in the literature, a comprehensive review of various proposed algorithms can be found in Zang and Jue (2000).

On one hand, we can find diverse algorithms for dealing with the *routing* subproblem in the literature. The *Fixed Routing* (Li and Somani, 1999) heuristics calculate a single permanent route for each demand and determine routes using a least cost algorithm. In Chan and Yum (1994) and Masayuki et al. (1997) a modification of *Fixed Routing* heuristics is proposed, the main difference is that this new method (*Fixed-alternate Routing*) stores more than one fixed route. In Ramamurthy and Mukherjee (2002), the authors propose the *Adaptive routing* heuristics, which offer a trade-off between quality of network information and overhead. Finally, Varela and Sinclair (1999) suggest the use of *Ant Colony Optimization* (ACO) for solving the routing subproblem.

On the other hand, numerous articles are devoted to solve the *wavelength assignment* subproblem. In Chlamtac et al. (1989), Birman and Kershenbaum (1995), and Jeong and Ayanoglu (1996) we find classical heuristics for solving this subproblem: *Random*, *First-Fit*, *Least-Used*, *Most-Used*, *Min-Product*, and *Least Loaded*. A *MAX-SUM* heuristics is proposed in Barry and Subramaniam (1997) for solving this telecommunication subproblem. Other algorithms, such as *Relative Capacity Loss*, *Wavelength Reservation*, and *Protecting Threshold* are proposed in Karasan and Ayanoglu (1998), Subramaniam and Barry (1997), and Zhang and Qiao (1998).

Randhawa and Sohal (2010) propose two new heuristics for solving the static RWA problem: *Maximum Empty Channel Routing* (SRW3) and *Combined Path Algorithm* (SRW4).

Due to the complexity of the RWA problem (NP-hard), many authors propose the use of metaheuristics instead of traditional methods for solving this problem. The *Tabu Search* algorithm is applied in Morley and Grover (2001), Grosso et al. (2001), Yan et al. (2001), and Charbonneau and Vokkarane (2010) for tackling the RWA problem. Other authors solve this optical optimization problem by using *Simulated Annealing* (Mukherjee et al., 1996; Rodriguez-Dagnino et al., 1999); as well as *Genetic Algorithm* (Inkret et al., 1998; Ali et al., 1999; Shiann-Tsong et al., 2001; Zong and Ramamurthy, 2001; Saha and Sengupta, 2005; Banerjee et al., 2004). A comparative study between *Simulated Annealing* and *Genetic Algorithm* is presented by Thompson and Bilbro (2000).

Markovic et al. (2012) present a Bee Colony Optimization (BCO) approach for solving the lightpath scheduling problem, which implies solving the RWA problem. For solving the RWA problem, the authors use *Fixed-alternate routing* and *First-fit* wavelength assignment heuristics.

As we can see, all mentioned heuristics and metaheuristics consider the RWA problem as a monoobjective optimization problem, solving the routing subproblem and the wavelength assignment subproblem separately. However, the RWA problem has been tackled as a Multiobjective Optimization problem, solving both subproblems jointly. In this way, using Multiobjective Optimization, we are looking for a solution for which each