

# Wavelength Converter Allocation in Optical Networks: An Evolutionary Multi-Objective Optimization Approach

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**Abstract**—The huge bandwidth of optical fibres is exploited through wavelength division multiplexing technology, which introduces new complexities in the routing problem. In this context, the wavelength converter allocation problem has become a key factor to minimize blocking. The wavelength converter allocation problem has been treated as a mono-objective problem minimizing the number of wavelength converters or minimizing blocking; however, both criteria are in conflict with each other. Therefore, the wavelength converter allocation problem is studied here in a pure multi-objective optimization context for more appropriate decision making. This work proposes a multi-objective optimization approach based on an evolutionary algorithm which simultaneously minimizes blocking and the number of wavelength converters. Extensive simulations on three real optical networks show promising results in the sense that our algorithm generates the trade-off curve between blocking and the number of converters needed, and outperforms a recently proposed approach.

**Keywords**—Optical Network; Wavelength Converter; Evolutionary Algorithm; Multi-Objective Optimization;

## I. INTRODUCTION

Wavelength division multiplexing (WDM) is a mature technology that has solved the electronic bottleneck problem [1]. In this context, WDM networks provide a larger bandwidth at the expense of a higher technological complexity. WDM networks have several critical issues such as the *routing and wavelength assignment* (RWA) problem and the *WDM network design* problem, areas of active research [2]-[1]. The RWA approach aims to calculate the optimal *lightpath*, which is conformed by optical fibres and assigned wavelengths. The main objective of a WDM network design is to minimize request blocking with the minimum investment and management costs [1].

Typically, a WDM network imposes the use of just one wavelength in the whole lightpath. This is known as the *wavelength continuity constraint* problem, which is the main issue that causes the blocking problem [3], [1]; this is, the incapability of assigning a lightpath to a request. To overcome the blocking generated by this constraint it is necessary to add *wavelength converters* into optical routers. A wavelength converter is a device that changes a wavelength ( $\lambda$ ) into another wavelength ( $\lambda'$ ). Deciding how many and

where to locate these wavelength converters is a particular design problem known as the *wavelength converter allocation* (WCA) problem, which is NP-hard when dealing with irregular network topologies [4]. The WCA problem has been treated as a mono-objective optimization problem. More specifically, there are two approaches reported in the literature: (a) *minimize the number of wavelength converters* subject to a given blocking probability bound [2], and (b) *minimize the blocking probability* subject to a given number of wavelength converters [5]. Other works [6], [5] have detected the existence of conflict between the minimization of the blocking probability and the minimization of the number of wavelength converters; i.e., in order to get solutions with minimal blocking probability it is necessary to locate a large number of wavelength converters. This conflict implies that the WCA problem should be treated in a multi-objective context. Therefore, this work proposes to deal with it as a *multi-objective optimization problem* (MOP) to be solved with a *multi-objective evolutionary algorithm* (MOEA) [7]. This algorithm simultaneously minimizes *blocking* and the *number of wavelength converters*. This study considers a dynamic traffic scenario. In this context, a decision will be carried out within a set of promising trade-off solutions.

This work is organized as follows: Section II states the problem. In Section III, major works related to the state-of-the-art are discussed. The proposed evolutionary approach is presented in Section IV. Experimental results are given in Section V. Finally, conclusions and ideas for future work are exposed in Section VI.

## II. PROBLEM STATEMENT

Several architectures with conversion capability have been proposed [4]. A scheme of shared converters has been considered in this work. Shared schemes are efficient because they have converters that can be used by all input channels. In particular, this paper considers a node architecture where converters are shared by all input channels. This architecture, shown in Figure 1, is known as *Share-per-node wavelength converter router* (SNWCR) [8]. It is composed of  $F$  input ports and  $F$  output ports,  $F$  de-multiplexers and  $F$  multiplexers,  $m$  wavelength converters and one optical switch.

When using a set of wavelengths  $\Lambda$ , the optical switch is made of  $(F \times |\Lambda| + m)$  input and output ports, where  $|\cdot|$  indicates cardinality of a set.

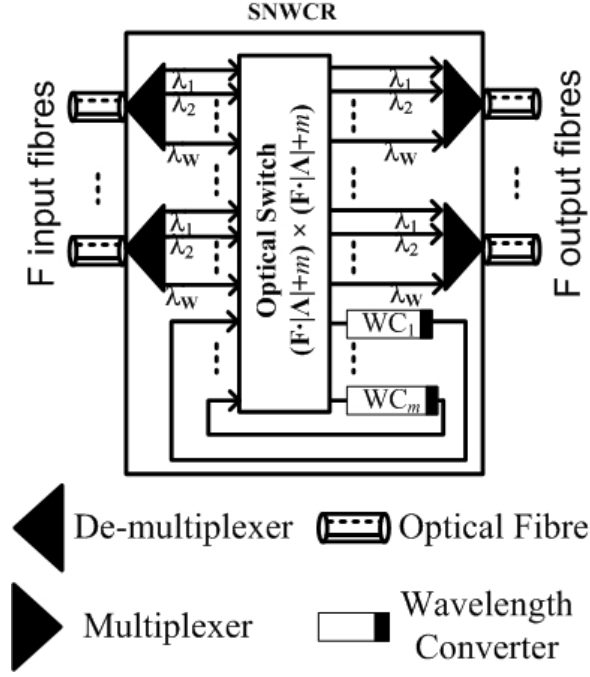


Figure 1. Wavelength converter router.

At the same time, this work considers a complete-range of wavelength conversion because of its low blocking characteristic [1]. In a complete-range wavelength conversion, each wavelength  $\lambda \in \Lambda$  can be changed into any other wavelength  $\lambda' \in \Lambda$ .

For the sake of completeness, the next nomenclature and basic symbols used in this article, are defined:

- $G$  Direct graph representing a network topology.
- $V$  Set of nodes in  $G$ .
- $L$  Set of links in  $G$ .
- $v \in V$  Optical node.
- $(v, w) \in L$  Direct link, where  $v, w \in V$ .
- $D_v$  Degree of node  $v \in V$ . This is equal to number of optical fibres in a node  $v \in V$ .
- $s, d \in V$  Source and destination nodes of a request.
- $t_o, t_f$  Star time and finishing time of a request.
- $k_v$  Maximum number of wavelength converters endured by node  $v \in V$ .
- $k_{max}$  Maximum value in the set  $\{k_1, k_2, \dots, k_{|V|}\}$ ;  $k_{max} = \max_{v \in V} \{k_v\}$ .
- $x_v$  Number of wavelength converters at node  $v \in V$ .
- $x$  A solution to the WCA problem;  $x = [x_1, x_2, \dots, x_{|V|}]$ .
- $c$  Unicast request;  $c = (s, d, t_o, t_f)$ .

- $C$  Set of unicast requests generated by simulation of a given traffic pattern;  $C = \{c_1, c_2, \dots, c_{|C|}\}$ .
- $\Psi$  Set of dynamic traffic patterns;  $\Psi = \{C_1, C_2, \dots, C_{|\Psi|}\}$ .
- $B_c^x$  Variable indicating blocking; if request  $c$  was blocked in a simulation of solution  $x$ , then  $B_c^x = 1$ , otherwise  $B_c^x = 0$ .
- $\Omega$  Utilization Matrix of size  $(|V| \times (k_{max} + 1))$ , in which the  $(v, j)$ -th entry denotes the percentage of time that  $j$  wavelength converters are being utilized simultaneously at node  $v \in V$ , where  $j \in K = \{0, 1, \dots, k_{max}\}$ .
- $Y_{x_v}^i$  Binary Variable; if  $i \leq x_v$ , then  $Y_{x_v}^i = 1$ , otherwise  $Y_{x_v}^i = 0$ .

#### A. Standard Problem Formulation

A recent work [5] proposed to solving the WCA problem as a mono-objective optimization problem under an indirect-simulation approach. Statistical information from the simulation stage is consolidated in  $\Omega$ . Given a topology  $G$ , the utilization matrix  $\Omega$ , and a fixed number of wavelength converters ( $NWC$ ), a differential evolution algorithm computes a solution  $x$  that approximately maximizes the *sum of total utilization*  $\Theta$  in the optimization stage according to:

$$\text{Maximize } \Theta(x) = \sum_{v \in V} \sum_{j \in K} \Omega_{v,j} \cdot Y_{x_v}^j \quad (1)$$

subject to:

$$x_v \leq k_v = |\Lambda| \times D_v \quad \forall v \in V \quad (2)$$

$$\sum_{v \in V} x_v \leq NWC \quad (3)$$

Numerical experiments show that minimizing (1) ensures the minimization of the blocking probability.

#### B. Multi-objective Formulation

This work proposes to solve the WCA problem as a multi-objective optimization problem under a direct-simulation approach. Given a topology  $G$ , a RWA algorithm and a set of dynamic traffic patterns  $\Psi$ , the goal is to calculate a solution  $x$  that simultaneously minimizes the *Number of Wavelength Converters*  $f_1(x)$  and the *Number of blocked requests*  $f_2(x)$ :

$$\text{Minimize } y = f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \end{bmatrix} \quad (4)$$

where

$$f_1(x) = \sum_{v \in V} x_v \quad (5)$$

$$f_2(x) = \sum_{c \in C} \sum_{C \in \Psi} B_c^x \quad (6)$$

subject to restriction given by equation (2), which assures that wavelength converters installed at a node  $v$  do not go beyond a maximum number  $k_v$ , imposed by the degree of a node.

### III. RELATED WORK

Recently, some works have proposed WCA approaches that adapt to any RWA algorithm [9], [5], [4]. They use direct or indirect traffic simulations as a fundamental tool. A *direct-simulation* approach evaluates each solution applying a RWA algorithm under a dynamic traffic pattern [9]. An *indirect-simulation* approach, on the other hand, solves problems in two stages: *simulation stage* and *optimization stage* [5], [4]. Given a traffic pattern and all available resources in a WDM network, simulation stage is carried out to obtain statistical information about the amount of time wavelength converters are used at each node. With the previous information, an indirect-simulation approach begins the optimization stage.

Algorithms based on indirect-simulations are simpler and faster than those based on direct-simulations, but they depend on statistical information [5]. However, a direct-simulation gives full information about the performance of the proposed solution [9]. Other works reported *heuristic* approaches, which allocate a great quantity of wavelength converters at random [8], [10]. Their objective was mainly to analyze the advantage of using wavelength conversion in WDM networks [5].

Roy and Naskar [5] recently proposed an indirect-simulation approach based on a *differential evolution algorithm* (DEA) [11] as the optimizer, and the use of a *utilization matrix* ( $\Omega$ ) as the storage of statistical information. They considered a fixed number of wavelength converters to be allocated in a SNWCR architecture (Figure 1). Essentially,  $\Omega$  is obtained from the simulation stage and it represents the overall usage of wavelength converters, for the considered traffic pattern [4]. Their work is an improvement over the one of Xiao and Leung [4], which was the first to propose an indirect-simulation approach using a heuristic as the optimizer. In the optimization stage, the DEA's main objective is to find how many wavelength converters should be allocated at each node in such a way that the sum of the total utilization ( $\Theta$ ) is maximized. A solution with high  $\Theta$  should give low blocking probability according to reports in [4] and [5].

*Proposed Approach.* This work has adopted the direct simulation approach considering its high ability to work with several RWA algorithms. An evolutionary algorithm will be implemented under this approach, in a similar way to what has been done in [9] but, this time, in a pure multi-objective context.

### IV. EVOLUTIONARY ALGORITHM

We propose to use the *Strength Pareto Evolutionary Algorithm* (SPEA) [12] to solve the WCA problem. SPEA is

a second generation multi-objective evolutionary algorithm (MOEA), successfully used to solve several engineering problems [7]. SPEA is based on three populations: the current population (PA) which is replaced by individuals from the evolutionary population (PX), and an external population (PE) that keeps the best individuals calculated during the evolutionary cycles.

In this multi-objective optimization context, the best individuals (or solutions) are known as non-dominated. Let us consider individuals  $x$  and  $x'$ . It is said that  $x$  dominates  $x'$  ( $x \succ x'$ ) if every objective function of  $x$  is better than or equal to the same objective function of  $x'$ , and  $x$  is strictly better than  $x'$  in at least one objective [7]. Pareto Set (PS) is a set of non-dominated solutions considering the whole solution space and its evaluation in the objective space is called Pareto Front (PF) [7]; i.e.  $PF = f(PS)$ . At the end of the evolutionary process it is desirable that  $PE = PS$ . The chromosome representation used in this work and the evolutionary operators are explained below.

*Chromosome.* Each individual is represented by a chromosome  $x$ , which is composed of  $|V|$  genes. Each gene  $x_v$ , represents the amount of wavelength converters to be installed at node  $v \in V$  ( $x_v \in \{0, 1, \dots, k_v\}$ ). It should be noticed that every solution  $x$  should satisfy restriction (2).

*Evaluation.* The number of wavelength converters represented by  $f_1(x)$  is the sum of the  $x_v$  values given by the genes, as shown in equation (5). Given a RWA algorithm, a topology  $G$  and a set of dynamic traffic patterns  $\Psi$ , the blocking number of each individual  $x$  is assessed by applying the direct-simulation approach. The implemented simulation is given in Algorithm 1, of Section V.

*Adjustment.* After assessing the blocking number, the unused wavelength converters are removed. For example, let us assume that  $x_v = 4$  and the simulation registered only 3 simultaneous wavelength conversions at node  $v \in V$ . Then, the value of  $x_v$  is adjusted to  $x_v = 3$ . This last process is a local optimization process that has the objective of accelerating convergence.

*Fitness.* Each individual receives a quality value or fitness which is calculated according to the Strength Pareto approach proposed in [12]. The fitness of one chromosome is calculated on the base of its number of wavelength converters  $f_1(x)$  and blocking number  $f_2(x)$ . Basically, each individual  $x \in PE$  receives a value of *strength* proportionally to the number of individuals it dominates. The fitness of each individual in PE is equal to its strength. Each individual  $x' \notin PE$  gets fitness inversely proportional to the sum of the individuals strengths that belong to the PE and dominate it [12].

*Selection.* We have adopted a binary tournament approach given its simplicity and robustness [7].

*Crossover.* Considering the structure of the chromosome, the one-point crossover operator was considered in this study. The probability  $p_c$  of applying crossover was selected

according to [7].

*Mutation.* The mutation operator was implemented in two stages. First, an individual is randomly selected with a probability  $p_m$ . Then, each gene is modified with a probability  $p_g$ .

## V. EXPERIMENTAL RESULTS

This section presents the traffic model we use, the assumptions imposed on the problem in question and the experimental results of the comparison between the proposed SPEA approach and the DEA algorithms. The tests were executed on an Intel Pentium IV, 3.2 GHz and 1GB of RAM personal computer. The SPEA and DEA algorithms were implemented in Java 1.6 under Windows XP.

### A. Traffic Models and Simulation Algorithm

A dynamic traffic pattern  $C \in \Psi$  is composed of  $\Gamma$  time slots and  $|C|$  requests.  $\Gamma$  is selected according to a maximum simulation time (MST) and an estimated request arrival period of time (PT). This is,  $\Gamma$  can be estimated as  $\Gamma = \text{MST}/\text{PT}$ . The direct-simulation algorithm is carried out according to Algorithm 1. Given a dynamic traffic pattern  $C$ , a topology  $G$ , a RWA algorithm and a solution  $x$ , Algorithm 1 calculates the blocking number  $f_2(x)$  of solution  $x$ , according to equation (6).

Direct-Simulation[ $\Psi, G, \text{RWA}, x$ ]

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1:  $f_2(x)=0$ 
2: for all  $C \in \Psi \wedge t \in \{1, 2, \dots, \Gamma_C\}$  do
3:   for all  $c \in C$  do
4:     if  $t = c(t_f)$  then
5:       free  $\text{lightpath}_c$  resources in  $G$ 
6:     for all  $c \in C$  do
7:       if  $t = c(t_o)$  then
8:         compute a  $\text{lightpath}_c$  with RWA
9:       if  $\text{lightpath}_c = \text{Blocked}$  then
10:         $f_2(x)=f_2(x)+1$ 
11:       else
12:        reserve  $\text{lightpath}_c$  resources in  $G$ 
13: return  $f_2(x)$ 

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Algorithm 1: Pseudo-code for a Direct-Simulation.

### B. Assumptions

In the study that follows we assume that:

- The bandwidth of every request is equal to the bandwidth of a wavelength, i.e. each request uses one lightpath.
- The number of optical fibres at each link is one.
- All optical fibres have 10 wavelengths ( $|\Lambda|=10$ ).
- For a given topology  $G$ , we consider the maximum supported load capacity as  $LM = |V| \cdot \chi \cdot |\Lambda|$ , where  $\chi$  is the average number of links of the nodes.

- The Shortest Path (SP) routing and First-Fit (FF) wavelength assignment algorithms [1] were used to build the utilization matrix  $\Omega$  for our simulations as proposed in [5].
- The Shortest Path Aware (SPA) routing and First-Fit (FF) wavelength assignment algorithms [1] were used to evaluate the solutions using the direct simulation approach.
- For simplicity, the set of dynamic traffic patterns  $\Psi$  consists of a single set  $C$ , i.e.  $\Psi = \{C\}$ .

### C. Outline of the experiment

The experimental tests have as main objective a fair comparison between SPEA and DEA approaches in the WCA problem. Note that, SPEA is a multi-objective approach while DEA is a mono-objective approach. DEA takes as input the number of wavelength converters (NWC) to be allocated. To achieve a fair comparison DEA is executed for each value of NWC for which a Pareto solutions was calculated using SPEA. This way, DEA can get a set of trade-off solutions similar to the one found with SPEA. Given a topology  $G$  and a RWA algorithm, the details of our experimental tests are given below:

1. *Dynamic Scenario.* The set of dynamic traffic patterns  $\Psi$  is generated with  $\Gamma = 1000$ , an uniform distribution was considered for simplicity.

2. *Statistical use.* Utilization matrix  $\Omega$  is calculated applying a simulation considering a set of dynamic traffic  $\Psi$ , a topology  $G$ , a RWA algorithm, and all available resources of  $G$  in the network.

3. *SPEA executions.* SPEA is executed 10 times obtaining 10 approximate Pareto Fronts. The union of all these 10 Pareto Fronts is calculated. Then, dominated solutions are deleted to get a good Pareto Front approximation  $PF_{spea}^*$ .

4. *DEA executions.* After finishing the executions of the SPEA algorithm, DEA executions begin. A set of trade-off solutions is obtained using the following steps: (a) DEA is run 10 times for each NWC found with SPEA, obtaining a set of solutions  $PF_{dea}$ . (b) The blocking number  $f_2(x)$  of solutions  $x \in PF_{dea}$  is calculated applying direct simulation (Algorithm 1) and the dominated solutions are deleted from  $PF_{dea}$  to obtain a good Pareto Front approximation  $PF_{dea}^*$ .

5. A consolidated set of the best solutions  $PF_{best}$  for the considered problem is obtained calculating the union of  $PF_{dea}^*$  and  $PF_{spea}^*$ . Then, non dominated solutions are deleted to get  $PF_{best}$ .

6. Let  $a \in \{SPEA, DEA\}$  be the algorithm, so the quality of a Pareto Front  $PF_a^*$  is calculated using three quality metrics given by vector  $M = [M_1, M_2, M_3]$  [7], where:

(a)  $M_1$  is known as *Overall Non-dominated Vector Generation Ratio* to the best Pareto Front  $PF_{best}$ :

$$M_1(a) = \frac{|PF_a^* \cap PF_{best}|}{|PF_{best}|} \quad (7)$$

Values of  $M_1(a)$  close to 1.0 indicates that many solutions from  $PF_a^*$  belong to  $PF_{best}$ .

(b)  $M_2$  is also known as *Generational Distance*, which reports how far, on average,  $PF_a^*$  is from  $PF_{best}$ :

$$M_2(a) = \frac{(\sum_{y \in PF_a^*} \min \{d_{y,y'}^2 | y' \in PF_{best}\})^{\frac{1}{2}}}{|PF_a^*|} \quad (8)$$

where  $d_{y,y'}$  indicates the Euclidean distance between solutions  $y = f_1(x)$  and  $y' = f_1(x')$ . When  $PF_a^*$  is close to  $PF_{best}$ ,  $M_2(a)$  gets low values.

(c)  $M_3$  represents the *Accuracy* to the best Pareto Front  $PF_{best}$ , it is mathematically defined as:

$$M_3(a) = \sum_{y \in PF_a^*} \sum_{y' \in PF_{best}} AC_{y,y'} / |PF_a^*| \quad (9)$$

where  $AC_{y,y'} = 1$  if  $y = y'$ , otherwise  $AC_{y,y'} = 0$ . If all solutions of  $PF_a^*$  belong to  $PF_{best}$  then the accuracy of  $PF_a^*$  is one.

#### D. Results and Discussion

The experimental tests which are presented below were performed on three network topologies [1]: a) National Science Foundation (NSF) composed of 14 nodes and 42 links, b) Network France (NF) with 43 nodes and 142 links and c) Nippon Telephone and Telegraph (NTT), with 55 nodes and 144 links. The evolutionary parameters are empirically set to:  $p_c = 1$ ,  $p_m = 0.3$ ,  $p_g = 0.4$  and 100 individuals conform each population, i.e.  $|PA| = |PX| = 100$ . The stopping criterion applied to DEA was 1000 iterations. On the other hand, two stopping criteria are considered for SPEA: a) 100 consecutive iterations without changes in the external population (PE) or b) a maximum of 1000 iterations.

The steps summarized in Section V-C were applied to each topology under the following traffic scenarios: low load  $|C|_{low} = 30\%LM$ , half load  $|C|_{half} = 60\%LM$ , high load  $|C|_{high} = 90\%LM$  and saturation load  $|C|_{sat} = 100\%LM$ . The experimental results for saturation traffic are presented in Figure 2. Other tests are omitted because of space constraints.

A summary of all experimental results considering vector performance metrics  $M$  are given in Table I. In almost all scenarios it can be noticed that  $PF_{best} \cong PF_{spea}^*$ , this is the reason why the best Pareto Front  $PF_{best}$  was not included in Figure 2. All experimental results report that  $PF_{spea}^*$  is better than  $PF_{dea}^*$ .

Figure 2 and Table I show that SPEA has contributed with better solutions than DEA in all experimental tests. Using the concepts of dominance Pareto, the quality metrics indicated that  $M_{spea} > M_{dea}$  in all scenarios. However, it is important to highlight that some good solutions calculated by DEA were not discovered by SPEA on the NSF topology, as shown in Table I. Note that, the NSF topology is smaller than

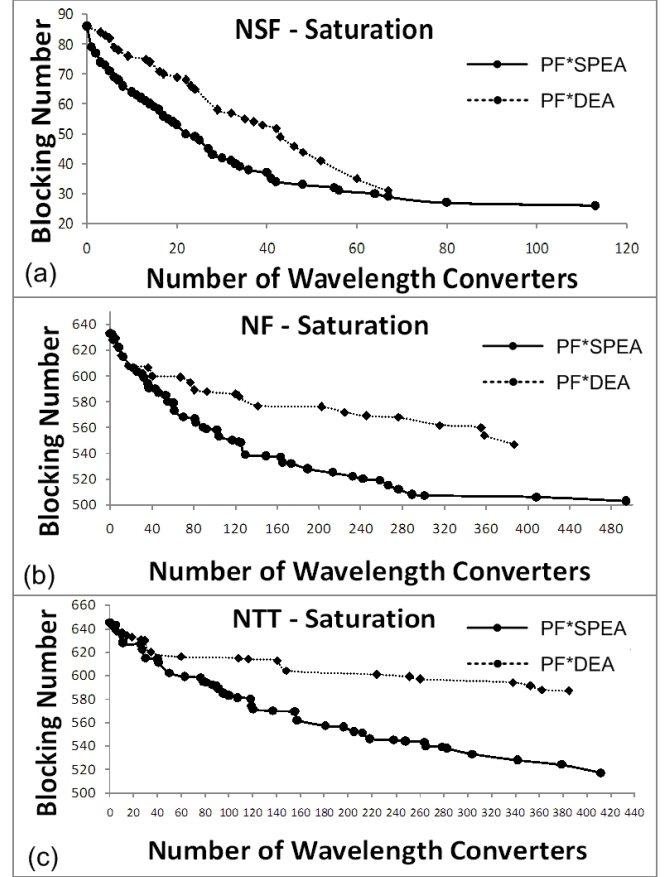


Figure 2. Non dominated Pareto Fronts of (a) NSF, (b) NF and (c) NTT Network to saturation traffic.

the NF and NTT topologies. This suggests that DEA generates good solutions for low complexity topologies. In this context, we can say that statistical information calculated by simulation is a good approach for low complexity topologies. For high complexity topologies (as NF and NTT), SPEA performance better although it spent more computation time than DEA.

Finally, Table II presents a better appraisal on the experimental results, a consolidated time in seconds spend per solution (s/sol) (see column TRT/TSA), where  $TRT$  represents the full running time of an experimental test, and  $TSA$  is the total number of trade-off solutions calculated by an algorithm in all scenarios, while  $TSA_{best}$  is the total number of non dominated solutions (best set) obtained by an algorithm. We can observe that, SPEA running time was longer than the one of DEA. SPEA spent 10% more time than DEA because of the evaluations based on a direct-simulation approach. However, considering all solutions of  $PF_a^*$ , the worn-out time for solutions is 40% less for SPEA than for DEA. On the other hand, the solutions contributed to the best Pareto Fronts by SPEA improve a great deal the

Table I  
EXPERIMENTAL RESULTS. COMPARISON METRICS BETWEEN SPEA  
AND DEA FOR DIFFERENT TRAFFIC SCENARIOS.

Net	a	Traffic Scenarios					
		low load			half load		
		$M_1$	$M_2$	$M_3$	$M_1$	$M_2$	$M_3$
NSF	SPEA	0.93	0.06	1	0.97	0.03	1
	DEA	0.13	1.2	0.29	0.03	6.81	0.08
NF	SPEA	1	0	1	1	0	1
	DEA	0	35.4	0	0	57.7	0
NTT	SPEA	1	0	1	1	0	1
	DEA	0	27.4	0	0	37.5	0
NSF		high load			saturation load		
	SPEA	1	0	1	0.97	1.18	1
	DEA	0	9.8	0	0.03	11.09	0.06
NF	SPEA	1	0	1	1	0	1
	DEA	0	56.7	0	0	34.7	0
NTT	SPEA	1	0	1	1	0	2
	DEA	0	54.4	0	0	50.6	0

ones calculated by DEA. Notice the huge difference (over 50 times) in favour of SPEA in the last column of Table II.

Table II  
TOTAL RUN TIME.

a	TRT	All Solutions		Solutions in $PF_{best}$	
		TSA	$\frac{TRT}{TSA}$	$TSA_{best}$	$\frac{TRT}{TSA_{best}}$
SPEA	486453 s	237 sol	2053 s/sol	234 sol	2079 s/sol
DEA	435171 s	113 sol	3851 s/sol	4 sol	108793 s/sol

## VI. CONCLUSION AND FUTURE WORK

This paper solves the WCA problem as a MOP using a MOEA, considering a direct-simulation approach. In this context, the main contribution of the proposed approach is its ability to find a complete set of Pareto optimal solutions to best satisfy designer's needs. Experimental results suggest that the proposed approach is promising for this network design problem outperforming state of the art DEA. However, it is important to emphasize that algorithms based on indirect-simulation approach are also effective when small size topologies are considered. As future work, a more realistic cost function of WDM network design will be considered.

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