A Multi-objective Evolutionary Algorithms Study applied to Routing and Spectrum Assignment in EON networks

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Abstract. In this work a new approach based on multi-objective evolutionary algorithms (MOEA) is proposed for the routing and spectrum assignment (RSA) Problem in elastic optical networks (EON); where, given a set of unicast requests, the proposed MOEA minimizes (a) the total cost, and (b) the spectrum used, simultaneously under optical layer constraints. The test experimental indicates that the proposal is suitable for the RSA when it is compared to another MOEA of the-state-of-the-art considering different quality measures. Basically, the proposed MOEA sequences the requests to be served under random-and-cost based strategy while that considered the-state-of-the-art is just random.

Keywords: Routing and Spectrum Assignment, Elastic Optical Networks, Multi-objective Optimization, Evolutionary Algorithms.

1 Introduction

For the resolution of the numerous problems that have multiple objectives, a good meta-heuristic for this type of problems are the evolutionary algorithms (EA - Evolutionary Algorithm). Traditional EAs are customized to adapt to multi-objective problems, through the use of specialized fitness functions and the introduction of methods to promote the diversity of the solution. There are general approaches to the optimization of multiple objectives. One is to combine the individual objective functions in a single compound function or move all, except one of them for the set of constraints. The next approach is to determine a whole set of optimal Pareto solutions or a representative subset. An optimal set of Pareto is a set of solutions that are not dominated with respect to the others [8]. This last approach is more convenient for making decision over a set of trade-off best solution instead of two first approaches. In this work, the main contribution is an approach based on a Multi-objective Evolutionary Algorithms (MOEA) for the RSA problem, in which it is determined that the proposed approach improves in terms of quality from the Pareto front to the work presented in [8]. The MOEA optimizes: (a) the spectrum used, and (b) the total cost, subject to the constraints of continuity, contiguity, and spectrum conflict imposed by the EON layer.

2   Elastic Optical Networks

We can define the EON as an OTN (Optical Transport Network) where all the equipment and the control plane can handle optical channels of variable bandwidth and all the switching elements can support different granularities in the spectrum of the channels that transmit information. EONs introduce fixed granularity into the bandwidth of the channels transported through the fiber. The ITU-T G.694.1, establishes a series of fixed spectral grids, which divide the optical spectrum between 1530-1565 nm, from the C band, ranging from 12.5 GHz. (Giga Herz) to 100 GHz, where most used are those of 50 GHz and 100 GHz [5]. The important change in the EON architecture is the replacement of the fixed grid (Fixed-grid) by a new flexible grid (Flexi-grid). The ITU-T is focused on the revision of a G.694.1 standard [5], for a division of the flexible optical spectrum called flexi-grid, for which the optical spectrum of the C band (1530-1565 nm) was defined, which is divided into FS (Frequency Slots) of fixed sizes of 6.25, 12.5, 25 and 50 GHz [6] and in addition a central frequency (CF, Central Frequency) is assigned to each elastic optical path (EOP - Elastic Optical Path) that must coincide with the beginning or the end of these slots existing differences in a fixed grid scheme and a flexible grid scheme In the case of the fixed grid scheme, we can observe the inefficient use of spectrum due to the fixed division that has the 50 GHz spectrum between each CF's, and if we observe the scheme of flexible grids can be noticed the free spectrum obtained thanks to the fine granularity that it offers and that allows to assign in a flexible way only the required bandwidth. The problem of RSA in Elastic Optical Networks is similar to the problem of Routing and Wavelength Assignment (RWA) in networks based on WDM. The difference between them (RSA and RWA) is the ability to flexibly assign the frequency spectrum. The RSA is classified into two types: Online/Dynamic and Offline/ Static traffic. In the case of the offline RSA problem, the list of all transmission requests is already entered as input, in order to proceed with the analysis and resolution with this input data. For the RSA online problem, the analysis and resolution is done as the requests arrive dynamically. In the first problem are can be applied optimization strategies; while in second one are usually developed heuristics.

3   Related Work

As the RSA is considered a NP-Complete problem [7], it has been treated with several techniques, exact and heuristic, both for dynamic traffic and for static traffic. Among the exact techniques are the ILP, while among the heuristics are optimizations with Colony of Bees (BCO, Bee Colony Optimization) [10], Genetic Algorithms (GA, Genetic Algorithm) [11] [12] [13], among others [14] [15].

   Different ILP models for small instances and different heuristics for more real scenarios have been used successfully to solve the RSA problem. As an example we can mention in [16] an ILP model was proposed to minimize the use of the spectrum to serve a traffic matrix in an EON. The authors propose a method that divides the problem into two sub-problems, the first is the routing and the second is the spectrum assignment and solves them sequentially, using a route-based approach. They also propose a

heuristic algorithm that serves the connections one by one sequentially. Then in [2], the authors extend their previous results including consideration of modulation level. With this new consideration, a new problem was defined routing, modulation level and spectrum assignment (RMLSA), being outside the scope of this work. Other problems such as Fragmentation Aware and Dynamic Traffic are also not considered. Another ILP formulation and the proof that the RSA problem is a NP-complete problem can be found in [7]. The work proposed in [8], presents the multi-objective RSA problem and its associated algorithm model. Each request has many possible routes, and in each routing it has several spectrum assignment options. The problem is to minimize the spectrum width to support all requests and minimize the overall cost of the spectrum in the link. The objective function for the work proposed in [8] is as following: there are two objectives associated with each solution. The first objective $f1$, is the width of the spectrum that indicates the maximum indexed slice used in the network. The second objective $f2$ is the total cost of the spectrum link. Given a set of requests, the route and channel are calculated for each one. After attending each demand sequentially and without any sort of ordering, the spectrum availabilities vector of each link is updated.

In this work it is developed a pure multi-objective approach to calculate a Pareto front. This approach is an extension of the work presented in [4] which has an approach based on weighted sum. In our work, as in [8] it has many possible routes, and in each routing it has several spectrum assignment options. The problem is to minimize the spectrum used and the overall cost of the link spectrum at the same time. The same objective function is taken from [8] and the requests are handled as follows: applications are ordered from highest to lowest, defined by the highest possible cost of said request, the first 30% of said list is attended in the first place, while the remaining 70% is treated in a random manner, unlike [8] it is a random ordering. More details are given in section 5.

4   Problem Statement

Given the physical topology, the matrix of demands and a list of pre-calculated routes (as K-shortest path), we need to satisfy all the demands of source-destination connection; i.e. to determine the route and spectrum assignment for each traffic demand with optimum spectrum utilization and he total cost. The spectrum utilization is given by the maximum index FS used on all fibers in the network while the total cost is depending on the distance traveled and the FS requested. For the proposed model, the following assumptions are established: The spectral resource of each optical fiber is divided into FS; the capacity of the fiber in terms of FS is limited in all links; the connection demands are bidirectional, and a complete end-to-end optical path must be found for each demand; A set of K specific route is given for a connection in advance; the request is represented by three tuples (s, d, α_{sd}), including the source node s, the destination node d, and the bandwidth / data rate demanded α considered in the quantity of FS requested.

4.1 Multi-Objective Formulation Problem

Given:
G	: Network topology, which represents an EON
E	: Set of links, in G
V	: Set of vertices, in G
GB	: Amount of FS for Band Guard
F_{total}	: Amount of FS available in each fiber
P	: Set of K routes for each demand
K	: Number of available routes
SD	: Quantity of demands

The notations and the formulation are presented below:
Constants:
dist_max	: Maximum distance traveled considering the longest routes.
espectrum_max	: Maximum FS index available.
cost_max	: Total cost of applications considering their maximum distances.
$dist_p^{sd}$	: Distance of the route *p*
α_{sd}	: Quantity of FS requested by the application where $s, d, \in V$

Indexes:
sd	: Demand index, $sd \in \{1, 2, ..., SD\}$
p	: Route index, $p \in \{1, 2, ..., SD\}$
mn	: Directional link index, $m \neq n$

Variables:
x_p^{sd}	: 1 if the path *p* is used to meet the request *sd*, Otherwise
Λ_{sd}	: First FS assigned to the request *sd*, $sd \in \{0,..., F_{total} - 1\}$
$\Delta_{sd, s'd'}$	: Indicator that is equal to 0 if $\Lambda_{s'd'} < \Lambda_{sd}$, and 1 in otherwise.

Objective function:
Minimize $f(x) = [f1, \; f2]$

Subject to:

- The Spectrum use:

$$f_1 = \frac{\max_{\forall sd}(\Lambda_{sd} + \alpha_{sd})}{spectrum_{max}} \tag{1}$$

- The total cost:

$$f_2 = \frac{\sum_{sd} \sum_p \left(\alpha_p^{sd} * dist_p^{sd} * x_p^{sd}\right)}{cost_{max}} \quad (2)$$

$$\sum_{p \in P_{sd}} x_p = 1, \forall(s,d) \quad (3)$$

$$\Lambda_{sd} + \alpha_{sd} * x_p^{sd} + GB - \Lambda_{s'd'} \leq (Ftotal + GB) * \quad (4)$$
$$\left(1 - \delta_{sd,s'd'} + 2 - x_p^{sd} - x_{p'}^{s'd'}\right)$$
$$\Lambda_{s'd'} + \alpha_{s'd'} * x_{p'}^{s'd'} + GB - \Lambda_{sd} \leq (Ftotal + GB) * \quad (5)$$
$$\left(1 - \delta_{s'd',sd} + 2 - x_p^{sd} - x_{p'}^{s'd'}\right)$$

$$\delta_{sd,s'd'} + \delta_{s'd',sd} = 1 \quad (6)$$

$$\Lambda_{s'd'} - \Lambda_{sd} < F_{total} * \delta_{sd,s'd'} \quad (7)$$

$$\Lambda_{sd} - \Lambda_{s'd'} < F_{total} * \delta_{s'd',sd} \quad (8)$$

The objective function (1) represents the maximum spectrum used, and (3) represents the total cost. On the other hand, we have that, for all request *sd, s'd'* and the paths $p \in P_{sd}$ and $p' \in P_{s'd'}$ with p and p' sharing at least one common link *mn* the constraints (3), (4), (5), (6), (7) and (8) represents the total cost. Restrictions (3), (4) and (5) ensure that the portions of spectrum that are assigned to connections that use paths that share a common link do not overlap and are adjacent. Also, for all requests *sd, s'd'* that have $p \in P_{s'd'}$, with p and p' sharing at least one common link ($\exists mn : nm \in p \wedge mn \in p'$), the constraints (6), (7) and (8) ensure that either $\delta_{sd,s'd'} = 1$ means that the initial frequency $\Lambda_{s'd}$ is smaller than the initial frequency $\Lambda_{s'd'}$, that is, $\Lambda_{sd} < \Lambda_{s'd'}$, o $\delta_{s'd',sd} = 1$, in which case $\Lambda_{sd} > \Lambda_{sd}$. Note that Λ_{sd} and $\Lambda_{s'd'}$ are always bounded superiorly by F_{total}, and that therefore their difference will always be less than F_{total}.

5 NSGA II Implementation

In the work presented in [8], a matrix of requests is generated which is attended sequentially by the algorithm. Our algorithm performs the same procedures as in [8] and our contribution in this work once the matrix of requests is generated is to order those requests from highest to lowest, defined by the highest possible cost of said request, the first 30% of said list it is attended first by the algorithm, while the remaining 70% is attended randomly. The algorithm deals with the requests in a certain order, which was taken from a document presented in [1].

Our algorithm, which is an extension of the algorithm MOEA presented in [4], begins with the creation of the initial population. This MOEA is called Non-dominated Sorting Genetic Algorithm II, NSGAII. The best solutions are found over several generations. Operators such as crossing and mutation explore other possible solutions. In this implementation, the objective is to find the route and the set of FS for each

request, such that the total distance traveled, the maximum FS used and the total cost are minimized; all this complying with the respective RSA restrictions. The implementation of the NSGAII is described below in Algorithm 1.

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Algorithm 1: NSGAII

INPUT: Route table P; Total amount of FS; List of demands;
Size of the population; Probability of mutation; Stop
Criterion; FS Assignment Algorithm; Total Distance, Maximum
FS, Maximum Cost
  OUTPUT: ParetoFront
  1: Initialize Population (P)
  2: While the stop criterion is not met
  3:      Q = generate individual (P) by selection, crossing
              and mutation
  4:      Q = Q ∪ P
  5:      R = Construct the Pareto front from Q based
              in dominance
  6:      Build Pareto fronts (R)
  7:      Calculate Distance of Crowding (R)
  8:      P = [0]
  9:      while P < PopulationSize
 10:           Include the solution R in population P
 11:      End while
 12: End while
 13: return ParetoFront (P)
```

In the NSGA II presented in this work, the chromosome represents a set of requests attended. Basically, the chromosome is a compound vector in which each gene represents an attended request. Each element of said vector contains: the index of the assigned route (taken from the table of pre calculated routes), and the index of the assigned FS of the request. The steps of the algorithm procedure can be described below:

Initial Population. The first step is to initialize the population. The NSGA II begins with an initial population of chromosomes, defined as explained below. At work, the order is defined as follows: orders are ordered from highest to lowest, defined by the highest possible cost of said request, the first 30% of said list is attended in the first place, while the remaining 70% is attended at random. This order is represented by the positions of the genes in the chromosome and is maintained throughout the execution of the algorithm. Then, randomly assign the routes and FS to the demands, taking into account the previously defined order. Each chromosome encodes a valid solution.

Selection of chromosomes for the next generation. The NSGA II algorithm shows us that the cycle begins with the selection of individuals, in step 3. The stochastic universal sampling method is used to select two parents to produce new individuals for the next generation [9].

Crossover operator. In this work we used the two-point cross operator [9] through which two cut points are randomly generated in each player, using the same points generated, assigning intercalary each segment generated from the parents to each child.

In algorithm 1 is applied in step 6. In Figure 1, we can observe the crossing procedure in which the cut points generated randomly were 1 and 2, dividing the player into 3 segments. The first segment of player 1 is assigned to the first segment of descendant 1, so the first segment of player 2 is assigned to the first segment of descendant 2. Then, the second segment of player 1 is assigned to the second descendant, while the second segment Player segment 2 is assigned as the second segment of the first descendant. Then the last segments are interspersed, resulting in both descendants shown in figure 4. This process is repeated until crossing the entire current population.
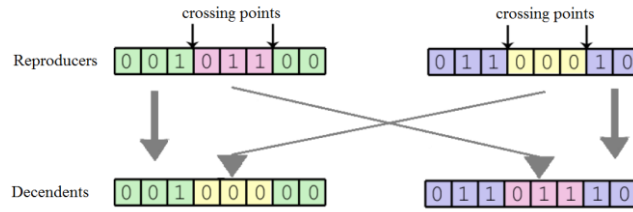
Figure 1: Crossing of 2 reproducers

Mutation. This procedure is applied after crossing, in each individual independently, in step 7 of algorithm 1. For the individual selected, according to the mutation probability obtained, a position of the vector is chosen randomly to change the route used in said position. Selecting a route from those available for said position, you have a higher probability of generating a feasible solution.

Pareto dominance. In step 4 the union of the two populations Q = Q ∪ P is performed, in step 5 and 6 the population is classified into categories (ranking) on the basis of non-dominance. Each solution is assigned a fitness value equal to its non-domain range (rank 0 is the best). Then the newly formed population is classified into categories (rank) according to their domain relation, and then, as explained in step 7, calculate the Crowding Distance of each individual, and then select the best ones in the next cycle that begins in the step 8, select the individuals with the best rank and crowding distance to fill the size of the population, as seen in steps 9, 10 and 11 of algorithm 1. Therefore, the algorithm starts all over again, from the election of breeders, until it reaches the stop condition.

Spectrum assignment. The algorithm used in this NASGA II is Random Fit, which randomly assigns the free FS found that complies with the constraints of the problem.

Stop criterion. A maximum execution time is used as stopping criterion.

6   Experimental Tests and results.

In this section we present the difference with the work proposed in [8] and the work presented by us, in addition the results of the experimental tests are presented and analyzed. The work proposed in [8], presents the multi-objective RSA problem and its associated algorithm model. Each request has many possible routes, and in each routing it has several spectrum assignment options. The problem is to minimize the spectrum

width to support all requests and minimize the overall cost of the spectrum in the link. The objective function for the work proposed in [8] is as follows: there are two objectives associated with each chromosome. The first objective $f1$, is the width of the spectrum that indicates the maximum indexed slice used in the network. The second objective $f2$ is the total cost of the spectrum link. Given a chromosome, the route and channel are calculated for each demand. After attending each demand sequentially and without any sort of ordering, the spectrum availabilities vector of each link is updated.

In this developed work, which is an extension of the work presented in [4] which has an approach based on weighted sum, a pure multi-objective approach with Pareto fronts is presented. In our work, as in [8] it has many possible routes, and in each routing it has several spectrum assignment options. The problem is to minimize the spectrum width to support all requests and minimize the overall cost of the link spectrum. The same objective function is taken from [8] and the requests are handled as follows: applications are ordered from highest to lowest, defined by the highest possible cost of said request, the first 30% of said list is attended in the first place, while the remaining 70% is treated in a random manner, unlike [8] it is a random ordering. The tests carried out considering different types of traffic load, on the NSF topology of 14 nodes, different K values (paths) and different amounts of demands, try to replicate various possible scenarios of the problem to solve. The experimental tests carried out show that our proposal for the ordering of the requests presents promising results.

6.1 Testing environment

The experiments were performed on a computer with an Intel Core i3 processor (3.40 GHz) and 8 GB of RAM. The implementation and execution of the MOEAs were carried out with JAVA 8. The traffic loads used were of the all-to-all type, that is, each node of the network makes a transfer request to all others in the network. In addition, the type of traffic load was random. The loads are divided into 3 categories, 50, 100 and 150 (low, medium, high), that is to say that for the category of 50 FS, for each demand a random value between 1 and 50 was generated as a requested quantity of FS; For category 100, for each demand a random value between 1 and 100 was generated as the requested quantity of FS and for category 150, a random value of 1 and 150 was generated as requested quantity of FS. Another variant that was taken was the number of shortest routes pre-calculated, that is, the value K. They were made with the following values of $k = 2$, 3, 4 and 5 for the network. For the executions of the NSGA II, the values shown in Table 1 were used as evolutionary parameters. The metric used for the comparison of the algorithms are hyper-volume and coverage [4].

Table 1. Parameters used for the execution of the NSGA II

Parameters	Value
Size of the population	50
Probability of mutation	0.1
Stop Criterion (in minutes)	5
Number of independent runs	15
Size of the population	50

6.2 Hyper-volume Metric and Coverage Metric

For the hyper-volume and coverage metric you can see the figure number 2, for load type 50 (low), with the number of paths k = 2, our proposed algorithm of order 30/70 obtains better results before the algorithm without ordering. With k = 3 paths, again our algorithm with order 30/70, exceeds the algorithm without ordering. With k = 4, the algorithm without ordering obtained better results with our algorithm 30/70. For k = 5, our algorithm 30/70 obtained good results. For the hyper-volume and coverage metric for load type 100 (average) for k = 2, the algorithm without ordering obtained better results, with k = 3, our algorithm with order 30/70, has better results before the algorithm without ordering, for k = 4, our 30/70 sorting algorithm improves the results before the algorithm without ordering. For k = 5, we obtained very good results with respect to the algorithm without ordination. For the hyper-volume and coverage metric for load type 150 (high) with k = 2, our sort algorithm 30/70 obtained better results compared to the algorithm without ordering. In k = 3, the algorithm without ordination obtained good results. Our 30/70 sorting algorithm got better results when k = 4 compared to the unordered algorithm. The unordered algorithm had better results when k = 5, compared to our 30/70 sorting algorithm.

Type of load (low, mid, High)	Number of roads (K)	Hypervolume (NORMALIZED VALUES)		COVERAGE	
		Sorting Algorithm 30/70	Unordered Algorithm	Sorting Algorithm 30/70	Unordered Algorithm
50	2	0,00450575727952277000	0,00373184833987698000	0,6	0,3
	3	0,03004763727709010000	0,00114619949446014000	1,0	0,0
	4	0,00107277586229790000	0,00608913898555240000	0,0	1,0
	5	0,01524133420666540000	0,01404235292493280000	0,5	0,0
100	2	0,00000000040137206552	0,00000000428130203222	0,0	1,0
	3	0,00235590742252450000	0,00192187663358532000	0,3	0,0
	4	0,00000000625575249301	0,00000000039930335062	1,0	0,0
	5	0,00000000560063877525	0,00000000040004562680	1,0	0,0
150	2	0,00000000437845029918	0,00000000027365314370	1,0	0,0
	3	0,00004759974150804820	0,00063478877339381300	0,0	1,0
	4	0,00036203376622539800	0,00003620284610853910	1,0	0,0
	5	0,00004690367773651360	0,00171967667778795000	0,0	1,0
AVERAGE		0,00447333048914869000	0,00244350750250017000	0,53333333333333300000	0,35833333333333300000

Figure 2: Comparison of algorithms, hyper-volume metric and Coverage metric.

7 CONCLUSIONS AND FUTURE WORK

In agreement with the exposed results, we can see that our algorithm of ordination 30/70, on average obtained better results with hypervolume metric, so also on average our algorithm has better coverage.

With the ordering of the requests, before generating populations, better Pareto solutions are obtained. Likewise if we give a treatment to the table of requests, ordering them from highest to lowest, defined by the highest possible cost of said request, and we divide the table of requests into two groups, one group of seniors and another group of random attendance we get better Pareto Fronts. As future work to develop we can mention several opportunities: study the performance of other spectrum assignment algorithms, consider other strategies of sorting the request to be served, extend this

approaches considering other issues as modulation level assignment or coded assignment.

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