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Survivable and Impairment-Aware Virtual Topologies for Reconfigurable Optical Networks: a Cognitive Approach

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***Abstract*—In this paper, we present a new version of a multiobjective genetic algorithm to design virtual topologies with the aim of reducing both the energy consumption and the network congestion. Moreover, we also propose an improved version of that algorithm, by including two cognitive techniques. Unlike the original version, the new proposals design survivable virtual topologies, as they provide shared path protection thus offering fault-tolerance capability with efficient resource utilization. Moreover, the proposed methods also take into account physical impairments in order to ensure that the survivable virtual topologies fulfill Quality of Transmission requirements in any scenario without failures or with a single cable failure. Finally, a simulation study demonstrates the advantages of the use of cognition.**

Keywords- Cognition; failure protection; multiobjective genetic algorithm; power consumption; QoT requirements; virtual topologies.

I. INTRODUCTION

Future transport networks require high capacity and flexibility. One of the architectures proposed to support those requirements is CHRON (Cognitive Heterogeneous Reconfigurable Optical Network) [1]. CHRONs are proposed to build a flexible optical infrastructure which relies on cognitive techniques to serve traffic demands while optimizing network resource utilization and ensuring energy-efficient operation. When a CHRON operates with centralized control, it supports the establishment of virtual topologies, like classic Wavelength-Routed Optical Networks (WRONs). In these networks, the basic element is the lightpath, i.e., an all-optical connection between two nodes not necessarily adjacent in the physical network. Then, the virtual (or logical) topology is the set of lightpaths established in the network. Such a virtual topology should be designed with the aim of optimizing (or at least satisfying) one or several parameters or performance criteria and, moreover, it could be dynamically reconfigured in order to better adapt to evolving traffic demands.

When designing a virtual topology, first of all, the lightpaths composing such a virtual topology should comply with Quality of Transmission (QoT) requirements, thereby ensuring a low Bit Error Rate (BER). Secondly, a key aspect that should be considered is energy consumption, as this parameter has grown exponentially during the last years (in line with increases in the Internet capacity). Thirdly, the design of the virtual topology should be robust enough –or be complemented with suitable control techniques– to effectively deal with occasional fiber failures in order to ensure survivability.

Two ways to support the survivability of the virtual topology are to provide either path or link protection. When path protection is used, the network can react when facing a cable failure by establishing a pre-computed end-to-end backup lightpath for each primary lightpath affected by the cable failure. Therefore, a dedicated set of resources must be reserved for each backup lightpath in a disjoint route of that used by its corresponding primary lightpath. In order to improve resource utilization, shared or backup multiplexing protection can be used. When that technique is employed, the same resources can be allocated to different backup lightpaths as long as their corresponding primary lightpaths are cable-disjoint.

In this paper, we focus on exploiting cognition for the design of survivable and reconfigurable virtual topologies. We propose two methods with the aim of simultaneously minimizing congestion (i.e., the maximum amount of traffic that is being carried by a lightpath) and energy consumption, while ensuring single-failure survivability by means of lightpath shared protection, and that all lightpaths in the virtual topology (including primary and backup ones) comply with QoT requirements in any scenario without failures or with a single cable failure.

This proposal expands previous work. In [2], we presented two multiobjective genetic algorithms: P-IA-GAPDELT (Power-Optimized Impairment Aware Genetic Algorithm to Provision and Design the Logical Topology) and P-SC^{T}-IA-GAPDELT (Power-Optimized, with Simple Cognition and Tabu list, Impairment Aware GAPDELT). These algorithms design non-survivable virtual topologies minimizing the congestion and the power consumption jointly, and the second one also includes cognitive techniques with the aim of improving its performance. However, even when they ensure that the virtual topologies provided satisfy QoT requirements, they do not design any protection mechanism to ensure the survivability of the network in case of a cable failure. In [3] we proposed another mechanism, also based on genetic algorithms, to design fault-tolerant virtual topologies, but without considering power consumption, QoT requirements or cognition. Hence, in this paper, we combine (and adapt) these two pieces of work and propose two algorithms to design survivable virtual topologies while considering QoT requirements. These new methods are called P-IA-GAPDELT+BMP (P-IA-GAPDELT with Backup Multiplexing Protection) and P-SC^{T}-IA-GAPDELT+BMP (P-SC^{T}-IA-GAPDELT with Backup Multiplexing Protection).

In the remaining of this paper, we first describe both methods. Then, we provide a brief overview of the model that we have used for power consumption estimation, and finally, we demonstrate, by means of simulation, the advantages of the second proposed algorithm, i.e., the advantages of using cognition.

II. Multiobjective Genetic Algorithms To Design Survivable Virtual Topologies in Optical Networks

The design of the virtual topology is an NP-Complete problem and it is usually divided into three different subtasks [4]:

a) Deciding which nodes should be connected by lightpaths and the number of them.
b) Finding a route in the physical network for every lightpath and assigning a wavelength to each one, i.e., solving the Routing and Wavelength Assignment (RWA) problem.
c) Routing the traffic over the virtual topology.

When virtual topologies are designed, different network parameters can be considered as optimization objectives, e.g., congestion, delay, cost, or energy consumption. However, many times the optimization of several parameters at the same time is necessary. In these cases, we talk about multiobjective optimization.

P-IA-GAPDELT and P-SC^{T}-IA-GAPDELT [2] are multiobjective genetic algorithms to design virtual topologies which minimize both the congestion and the power consumption. The difference between them is that the latter is enhanced with cognition to increase its performance, as demonstrated in that paper. Those algorithms obtain, in a single execution, a set of virtual topologies. In fact, they obtain an estimate of the Pareto Optimal Set (POS), i.e., a set of solutions where each solution cannot be simultaneously improved in terms of all the optimization objectives, that is, an objective cannot be improved without worsening the others.

In this work, we extend these algorithms by developing two new versions, P-IA-GAPDELT+BMP and P-SC^{T}-IA-GAPDELT+BMP, which include Backup Multiplexing Protection (BMP). They are also multiobjective genetic algorithms.

Genetic algorithms start from an initial population of individuals, which is then evolved by means of nature-inspired operators such as crossover and mutation. Each individual in the genetic algorithm corresponds to a possible solution (i.e., a virtual topology) and is represented by means of a chromosome. In the proposed algorithms, a chromosome is composed of a set of $N(N-1)$ genes, where N is the number of network nodes. Thus, each gene is associated to a source-destination node pair and it is encoded as a rational number between zero and one. The genes are used to determine how many lightpaths will be established between its associated pair of nodes, and the order in which lightpaths will be established. This chromosome structure is the same one as that employed in the first versions of the algorithms [5, 6]. The pseudo-code employed to translate a chromosome into a virtual topology is:

1. Take the gene with the highest value.
2. Solve the RWA problem for both the primary and the backup lightpath (as described later).
   2.1. If there are not enough resources to establish both lightpaths, set the value of the gene to zero.
   2.2. Otherwise, allocate resources to the primary and backup lightpaths. Subtract a fixed quantity, δ, from the gene.
3. Repeat the process from 1 until there are not free resources or genes with value higher than zero.

In order to solve the RWA problem for primary lightpaths, the shortest path (in terms of distance) is used to route the lightpath in the physical network, while the First Fit method [7] is used for wavelength assignment.

The RWA problem for backup lightpaths is solved by using a method based on the AUR-Exhaustive heuristic [8]. Let us assume that a backup lightpath should be computed between nodes *s* and *d*. First of all, a graph with a replica of the physical topology is created for each available wavelength in the network. Each of those graphs is called a layer. Then, a number of links are deleted in the different layers:

- The backup lightpath must be link disjoint with the primary lightpath. Therefore, the links traversed by the primary lightpath, as well as those same links but in the other direction, are deleted in each layer. This is due to the fact that a cable failure implies the failure of all wavelengths and all the fibers contained in it, and that we assume that each cable consists of two fibers, one per each direction.
- The resources used by primary lightpaths cannot be used to establish a backup lightpath. Hence, the links traversed by other primary lightpaths, but only in the layer that corresponds to the wavelength that they use, are deleted.
- Backup multiplexing is used, so the links used by backup lightpaths in the correspondent layer are deleted, if the primary lightpath of both connections share a part of the route. Otherwise, they are not deleted.

As previously stated, the third point guarantees single-failure protection, but minimizes the number of resources employed, because those primary lightpaths that do not share any physical cable can share the same backup resources.

Once the layers have been updated, the shortest distance path between nodes *s* and *d* is searched in each layer. The shortest of those paths is selected as the route for the backup lightpath, and the wavelength selected is that represented by the layer in which that path was obtained.

Fig. 1 represents the flow diagram of the new algorithms. The difference between both methods is that P-IA-GAPDELT+BMP does not include the gray area labeled as "cognition" in the figure. We will start by explaining this algorithm.

The initial population and the genetic operators are the same ones as in the initial version [5]. The initial population is randomly obtained, except some special individuals, designed ad-hoc with simple heuristics (see [5] for details). Then, by applying the evolution stages, the solutions evolve.

First of all, all the individuals of the parent population are copied to the descendant population, which is then further populated with new individuals created by means of crossover and mutation operations. The crossover operator randomly selects two individuals of the parent population, divides the parent chromosomes into two parts (by randomly selecting a position of the chromosomes) and creates two children by interchanging the second parts of those chromosomes. Then, the mutation operator is applied. This operator selects the genes of the chromosomes, one by one, and mutates them with probability $p_{mutation}$. When a mutation takes place, the value of that gene is randomly modified to another feasible value, i.e., to a random value between zero and one. The crossover and mutation operators are applied until the descendant population is composed by three times the number of individuals that there were in the parent population. Then, the fitness of the different solutions (virtual topologies) found is evaluated. For that aim, both the congestion and the power consumption of each solution are estimated. In order to estimate the congestion of a virtual topology, traffic is assumed to be routed following the shortest path in terms of the number of hops. To estimate the power consumption of a virtual topology, the model described in Section III is employed. Finally, those solutions composing the POS are selected to form the parent population of the new generation. This procedure is repeated until a stopping criterion is met, which has been set to the creation of a certain number of individuals during the evolution process.

At the end of the evolution stages, the algorithm checks whether the solutions obtained, i.e., whether the virtual topologies obtained, comply with QoT requirements. For that aim, the Q-factor [9] of all the lightpaths associated to each virtual topology are calculated and compared with a threshold, Q_{th}. The inclusion of this verification in the last stage, instead of using the Q-factor as an optimization criterion, or instead of checking the Q-factor at the end of each evolution stage, is due to computing time constraints. The current tools to estimate the Q-factors of a set of lightpaths are not fast enough [10] for the efficient execution of the genetic algorithm if such evaluation were performed during the evolution stages (where the Q-factors of all the lightpaths of thousands of virtual topologies should be calculated).

The verification of whether a survivable virtual topology complies with QoT requirements is done as follows. First of all, the Q-factors of all the primary lightpaths composing the virtual topology are calculated. If any of the lightpaths has a lower value than Q_{th}, that solution is discarded. If all primary lightpaths comply with QoT requirements, then an additional check must be performed, to ensure that when a failure takes place, and one or several backup lightpaths enter into operation, all lightpaths composing the restored virtual topology still comply with QoT requirements. Therefore, we analyze all potential failure scenarios by iteratively tearing down each of the cables of the network, activating the required backup lightpaths and calculating the Q-factors of the lightpaths established in the network. Only those solutions where the Q-factors of all the lightpaths (primary and backup) are higher than Q_{th} in all scenarios, i.e., with and without failures, are considered as the final solutions.

P-SC[T]-IA-GAPDELT+BMP extends the previous method by adding two cognitive techniques to improve the results in reconfigurable networks, as the algorithm is able to learn from its past executions. Thus, the algorithm also includes the gray box entitled "cognition" in the flow diagram shown in Fig. 1.

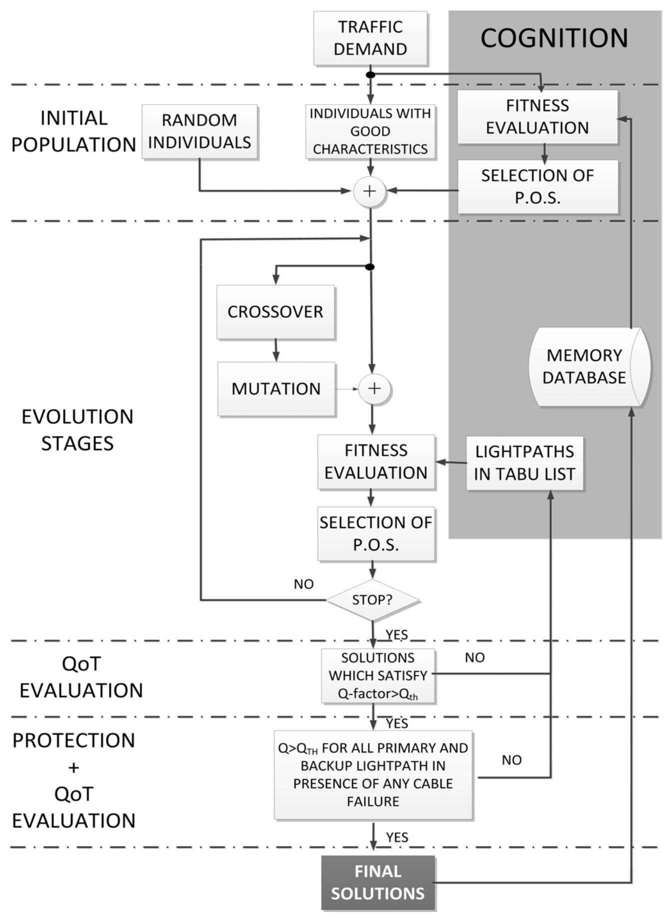

Fig. 1. Flow diagram of the survivable virtual topology design algorithms. The gray area labeled as "cognition" is only used in P-SC[T]-IA-GAPDELT+BMP.

In this algorithm, at the end of the evolution process, those final solutions fulfilling the QoT requirements are stored in a memory database. Then, when a new request for designing another virtual topology arrives later in time, the method uses the same initial population as P-IA-GAPDELT+BMP but complemented with the individuals from the memory database that better adapt to the current traffic demand. Hence, all the solutions stored in the memory are evaluated in terms of congestion and power consumption under the traffic demand included in the new virtual topology design request. Then, those individuals that belong to the POS are added to the initial population. In this way, the algorithm does not only learn from previous solutions but it also uses those ones that better adapt to the current scenario.

Moreover, another cognitive technique has been included in the fitness evaluation phase of P-SC^T-IA-GAPDELT+BMP. When the Q-factor of a lightpath is estimated to be below Q_{th}, the route and wavelength used by this lightpath is stored in a tabu list. Then, during the translation of the chromosome, the route and wavelength combinations stored in the tabu list are no longer considered as valid ones.

III. Power Estimation Model

The use of energy consumption as an optimization parameter implies to develop a model to estimate it. In the literature, different papers can be found considering this problem [11-15]. Shen and Tucker [14] propose a model to estimate the power consumption in an IP over WDM network. This model assumes that a lightpath traverses several nodes from its source node to the destination node without electronic conversion at intermediate nodes. The electronic routers are the main component in energy consumption, and thus, energy consumption can be saved by designing energy-efficient virtual topologies. This model enables or disables IP router cards and switches to sleep mode when there is low traffic load.

Our study can employ any of the methods proposed in the literature. However, the method that we have used to estimate power consumption follows the model by Shen and Tucker [14] but without including transponders in every input and output of the OXCs to perform wavelength conversion. In Fig. 2, the two-layered architecture that we have used to estimate the power consumption is shown. The power estimation model used in this studio is composed of the power consumption in the IP layer (i.e., at edge routers, E_r), in the transceivers (E_t) and the contribution of the amplifiers (E_e). The complete explanation of the estimation model can be found in [2].

IV. Simulations Results

Simulations have been made considering the physical topology of the 14-node Deutsche Telecom network [16], where each cable between two network nodes consists of two fibers, one per each direction. The capacity of a wavelength has been set to 10 Gbps, the maximum number of wavelengths per fiber to 12, the number of transmitters in each node to 26, and the number of receivers in each node has also been set to 26.

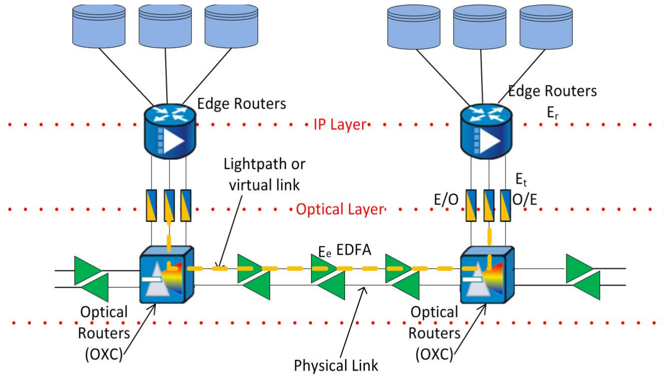

Fig. 2. Architecture of the IP over WDM optical network employed to estimate power consumption.

TABLE I. Power Consumption Per Element

Elements	Power consumption per element
Average power consumption per IP router card (E_r)[a]	1000 W
Power consumption per transceiver (E_t)[b]	73 W
Power consumption per EDFA (E_e)[c]	8 W

a. Router: Cisco 8-slot CRS-1 router data sheet.

b. Transponder: Alcatel-Lucent WaveStar OLS 1.6T ultra long-haul system.

c. EDFA: Cisco ONS 15501 EDFAs

The simulator has been developed in OMNeT++ [17] and the Q-factor of each lightpath in the survivable virtual topology has been estimated using a tool implemented in MATLAB [16]. The Q-factor threshold has been set to 9.54 dB. This Q-factor corresponds to a BER of approximately 10^{-3}. However, this BER value can be easily improved and can reach BER values of 10^{-12} (or even better) by means of second generation Forward Error Correction (FEC) codes, as it is stated in [18].

The model employed for power consumption estimation is that described in Section III. The power consumption of the different network elements shown in Fig. 2 is provided in Table I.

We have run simulations of two days of network operation where, each hour, one request to design a new survivable virtual topology arrives at the system. When facing each of these requests, the control node executes one of the algorithms previously presented to determine how to reconfigure the virtual topology of the network to better adapt to current traffic conditions. The traffic matrix is assumed to evolve with time according to the model by Gençata and Mukherjee [19]. It considers that the traffic from node s (source) to node d (destination) at time t (in seconds) is the given by Eq. (1) where:

- $\Lambda^{s,d}$ is the average traffic from s to d in one day, i.e., 86400 seconds.

- $\beta(t)$ adds the bursty character to the traffic demand and it is randomly generated each time that this function is invoked using a uniform random variable between [1-ε, 1+ε], where ε is a user-defined parameter which controls the amount of burstiness.

$$\lambda^{s,d}(t) = \Lambda^{s,d}\beta(t)\left[1+\frac{1}{2}\sin\left(\frac{2\pi 3600\,t}{86400}\right)\right] \quad (1)$$

The values of $\Lambda^{s,d}$ have generated randomly using an uniform distribution with mean 500 Mbps. The parameter ε, responsible of the burstiness of the traffic, has been set to 0.05 (i.e., 5% of the mean traffic in this period of the day). In order to obtain good statistical results, 40 simulations have been run. The results are then shown in average with 95% confidence interval.

In order to make a fair comparison of the cognitive and non-cognitive methods, the size of the initial population created when a new request for virtual topology design arrives is set to the same value in both cases. In contrast with the cognitive method, the non-cognitive one does not retrieve individuals for the initial population from a memory. Therefore, it completes the initial population with randomly generated individuals, if necessary. At the beginning of the simulation, the initial population is set to 10 individuals. The mutation probability has been set to 0.01, and the stopping criterion in the evolution stage of the algorithm (see Fig. 1) has been set to the creation of 100 individuals.

P-IA-GAPDELT+BMP and P-SC^T-IA-GAPDELT+BMP are multiobjective algorithms; thus, they do not provide a single feasible solution but a set of them in a single execution. In Fig. 3, the solutions obtained by the two algorithms for a single traffic matrix is presented. Each solution is represented in this figure in terms of its congestion and its power consumption.

Fig. 3 shows that both methods obtain several solutions in only one execution, i.e., an estimate of the Pareto optimal set. It is important to remark that all the solutions obtained can survive a cable failure by establishing the corresponding backup lightpaths (also included in the solution). Moreover, all lightpaths (principal and backup) comply with the QoT requirements in scenarios with and without a single cable failure.

In order to compare both methods, the common Pareto Optimal Set (POS) is calculated. The common POS is defined as the POS obtained when the solutions designed by both algorithms are considered jointly. Thus, the comparison will be done in terms of both the number of solutions found per each algorithm and the percentage of solutions that belong to the common POS that are designed by each algorithm. Hence, Fig. 3 shows that P-SC^T-IA-GAPDELT+BMP (the cognitive method) obtains, in this example, more solutions and also better solutions, as this algorithm provides most of the solutions in the common POS.

In order to generalize that conclusion, the average number of solutions found by both methods during the 40 simulations of two days is plotted in Fig. 4. The corresponding values of the percentage of the solutions in the common POS that have been designed by each algorithm is shown in Fig. 5.

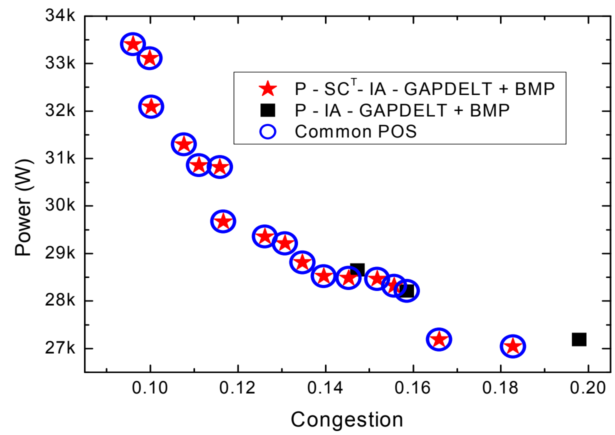

Fig. 3. Solutions found by P-IA-GAPDELT+BMP and P-SC^T-IA-GAPDELT+BMP for a single traffic matrix.

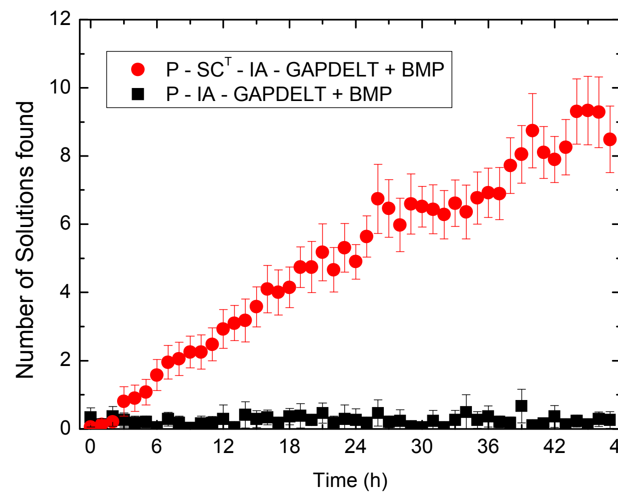

Fig. 4. Number of Solutions found per each algorithm depending on the time in which the request to design the virtual topology is created.

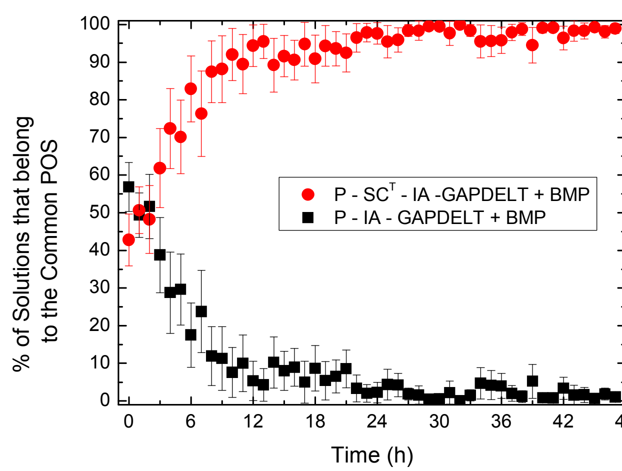

Fig. 5. Percentage of solutions that belong to the common POS depending on the time in which the request to design the virtual topology is created.

First of all, Fig. 4 shows that the non-cognitive method is usually unable to find even a single feasible solution. There are two reasons for this behavior. On the one hand, the problem we are facing is very hard, since not only the primary virtual topology, but also all the backup solutions (i.e., for all potential failures) must comply with QoT requirements, and we have assumed no regeneration along the lightpaths. On the other hand, with the aim of decreasing end-to-end delays, primary lighpaths are established following the shortest distance paths. That implies that backup lightpaths traverse longer distances and thus the difficulty for complying with QoT requirements (without using regenerators) increases.

In contrast, the cognitive method is able to find a set of feasible solutions. At the beginning of each simulation, the memory and the Tabu list of the cognitive method are empty, so that both algorithms obtain a similar number of solutions and with similar features. However, during the simulation, P-SC^{T}-IA-GAPDELT+BMP learns from the past and uses this learning to improve its results. In this way, in each new request to design a survivable virtual topology, the number of solutions found by the cognitive method grows. Therefore, the cognitive algorithm obtains more solutions than the non-cognitive one.

Finally, Fig. 5 shows that once P-SC^{T}-IA-GAPDELT+BMP learns, it provides almost all the solutions in the common POS. Therefore, the use of cognition leads to find more and better solutions in these hard scenarios in which all the primary and backup lightpaths should fulfill the QoT requirements in presence (or absence) of cable failures.

On the other hand, Table II shows the computing time of the cognitive method when obtaining the results depicted in Figs. 4 and 5. The simulations were run on a Debian GNU/Linux 6.0 machine using one core of an AMD Opteron 6128 processor. In particular, Table II shows the number of seconds employed by the different parts of the algorithm, as illustrated in Fig. 1: (1) initial population and evolution stages, (2) QoT evaluation of the primary virtual topologies, and (3) QoT evaluation of the backup virtual topologies for all possible single-failures. It is worthy to note that the computing time of steps (2) and (3) depends on the number of solutions found in step (1). However, for the sake of clarity, Table II only shows the time required to assess the QoT of *one* virtual topology and to evaluate the QoT of the backup virtual topologies for all the possible single-failure scenarios of *that* virtual topology.

As shown in Table II, the most time-consuming task of the algorithm is that devoted to the evaluation of the QoT of the lightpaths composing the virtual topology, or used as backup paths (steps 2 and 3). As previously discussed, this is due to the underlying MATLAB tool used in this study for that aim, which is relatively accurate but has a very high computing time [16, 10]. Note that this is a very severe drawback, as it limits how often reconfiguration can be applied. In fact, as shown in Table II, steps (2) and (3), i.e., assessing the QoT of a single virtual topology (and all its backup alternatives) requires nearly 25 minutes of computing time. Hence, reconfiguring the virtual topology every hour (as assumed in this study) would be unrealistic if using the same hardware and software than used in our study.

TABLE II
COMPUTING TIME OF EACH PART OF THE COGNITIVE ALGORITHM (P-SC^{T}-IA-GAPDELT+BMP)

Step of the algorithm (Fig. 1)	Computing time (s)
(1) Initial population and evolution stages	8.53 ± 0.29
(2) QoT evaluation of a primary virtual topology	54.72 ± 0.14
(3) QoT evaluation of the backup virtual topologies for all possible single-failures	1411.52 ± 3.71

Nevertheless, a solution for this drawback comes again from cognition, as the Q-factor evaluation mechanism employed in our study could be replaced by the Case-Based Reasoning QoT estimator recently presented in [20]. That cognitive estimator decreases the computing time required for QoT assessment in around three orders of magnitude when compared with the tool used in this study, while still providing reliable classifications of lightpaths into high/low QoT categories (>99% successful classifications). In that way, the utilization of that cognitive QoT estimator would address the limitation on the frequency of reconfiguration due to computing constraints.

V. CONCLUSIONS

In this paper, two new multiobjective genetic algorithms, P-IA-GAPDELT+BMP and P-SC^{T}-IA-GAPDELT+BMP, have been presented to design survivable virtual topologies in reconfigurable optical networks. The new proposals minimize both the network congestion and the energy consumption. Moreover, they provide not only a set of feasible virtual topologies in a single execution, but they also provide a backup lightpath for each primary lightpath to protect the network against a cable failure. Both methods also ensure that all the primary and backup lightpaths fulfil QoT requirements in presence (or absence) of cable failures. The difference between the two methods is that P-SC^{T}-IA-GAPDELT+BMP uses two cognitive techniques to improve its performance. The simulation results demonstrate that the use of cognition brings advantages in scenarios with hard QoT restrictions, as P-SC^{T}-IA-GAPDELT+BMP is able to find more and better solutions than the non-cognitive algorithm.

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