Wavelength Assignment Using a Hybrid Evolutionary Computation to Reduce Cross-Phase Modulation

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***Abstract*— In this paper, we propose a hybrid methodology based on Graph-Coloring and Genetic Algorithm (GA) to solve the Wavelength Assignment (WA) problem in optical networks, impaired by physical layer effects. Our proposal was developed for a static scenario where the physical topology and traffic matrix are known a priori. First, we used fixed shortest-path routing to attend demand requests over the physical topology and the graph-coloring algorithm to minimize the number of necessary wavelengths. Then, we applied the genetic algorithm to solve WA. The GA finds the wavelength activation order on the wavelengths grid with the aim of reducing the Cross-Phase Modulation (XPM) effect; the variance due to the XPM was used as a function of fitness to evaluate the feasibility of the selected WA solution. Its performance is compared with the First-Fit algorithm in two different scenarios, and has shown a reduction in blocking probability up to 37.14% when considered both XPM and residual dispersion effects and up to 71.42% when only considered XPM effect. Moreover, it was possible to reduce by 57.14% the number of wavelengths.**

***Index Terms*—** Cross-Phase Modulation, Dense Wave Division Multiplex, Evolutionary Computation, Wavelength Assignment Algorithms.

I. INTRODUCTION

Optical network based on Dense Wave Division Multiplex (DWDM) has been considered as a mature technology to be used in the backbone of optical networks. However, finding an optical solution for Routing and Wavelegnth Assintment (RWA) algorithm in the design and operation of the networks remains an open issue. One of the ways to simplify the RWA problem is to decompose it into two sub-problems: (i) Routing (R), and (ii) Wavelength Assignment (WA). RWA can be solved either offline (static case) or online (dynamic case).

A static solution occurs during the Wave Division Multiplex (WDM) network design phase while a dynamic RWA when the network is in operation. WDM network design is based on traffic forecasts where the traffic matrix is known in advance. The most common objective for a static solution is to minimize the network resources needed to support a given traffic matrix, e.g., the number of

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wavelengths used, or the number of fiber links traversed by the lightpaths. In the case of dynamic solution, the main objective is to minimize the blocking probability at the arrival of a connection request [1]. All these aspects make the RWA a NP-complete problem [2].

The algorithm has to consider another aspect which is the impact of physical layer impairments (PLIs). These algorithms are known as IA-RWA (Impairment Aware Routing and Wavelength Assignment) and their function is to ensure that the received signal quality is acceptable. The physical impairments affecting the quality of signals in an optical network can be divided into linear and nonlinear. Linear impairments affect each channel individually and do not depend on the signal power. On the other hand, nonlinear impairments not only impact each channel individually but also interfere with those channels with which they share the same optical fiber and/or optical component. The effect of nonlinear impairments is crucial at high bit rates, i.e., above 10 Gbit/s, and/or at high signal power [1].

Some of the most important linear impairments are: Amplified Spontaneous Emission (ASE) noise, Chromatic Dispersion (CD) and Polarized Mode Dispersion (PMD) [3], [4], and the accumulation of these impairments are directly proportional to the length of the link [5]-[8]. Hence, choosing the shortest route can reduce these impairments. Conversely, the most important nonlinear physical impairments are: Self-Phase Modulation (SPM), Cross-Phase Modulation (XPM) and Four-Wave Mixing (FWM) [3], [4]. However, Ten et al. [9] compared FWM and XPM penalties for a 40 x 10 Gb/s system with channel spacing of 100 GHz where they found that the degradation of the optical signal affected by XPM is several times greater than that of FWM [9]. This is the reason that our proposal limits to minimize XPM effect, as this non-linear impact is the one that dominates the scenario presented in our paper.

Literature presents several analytical models to compute XPM. In [10] the authors studied the spectral characteristics of XPM in multi-span optical systems and found that per span dispersion compensation is the most effective way to minimize its effect. In [11], a generalized model of the XPM degradation in fiber links consisting of multiple fiber segments with different characteristics and optical amplifiers is presented. It has also been shown that the total XPM-induced by intensity modulation (IM) is smaller in systems employing distributed dispersion compensation than in systems employing lumped dispersion compensation. An approach to minimizing setup times in an on-line provisioning paradigm by using guard bands, i.e., leaving unused wavelength channels between lightpaths in order to reduce the effect of XPM, is presented in [12]. In [13], a model that includes statistical estimation of XPM is used instead of an analytical model. It accelerates the computation time of XPM noise, but obtains an error of up to 6%. Even though analytical models are computationally more time consuming than the statistical estimation model, in certain situations it is preferable to use the analytical model because it is more accurate, as is the case when designing a network where time is not a crucial factor.

Our proposal is to be used in the design phase of the network (static scenario), as long as the physical topology and traffic matrix are known a priori. For the routing sub-problem, we used the Dijkstra algorithm [14] to find the shortest-path between a given source and destination pair. This algorithm uses the physical distance metric to evaluate the cost between two given nodes. We chose this algorithm because a shorter route possibly reduces some effects of the physical layer, such as ASE noise, PMD, chromatic dispersion and others.

With respect to wavelength assignment sub-problem, an approach to minimize the number of necessary wavelengths consists in formulating it as a graph-coloring problem [15], [16]. Graph-coloring can be applied to the static case in which all connections and their routes are known in advance [16]. After setting the number of necessary wavelengths, wavelength, in fact, has to be assigned. Several heuristics for this purpose have been proposed in the literature. The simplest and most commonly used among them are: Random, First-Fit (FF) and Most-Used (MU) [16]. However, these do not always show satisfactory results, especially regarding the quality of transmission, but, some studies have shown that metaheuristics are viable alternatives to efficiently solve the IA-RWA problem. The metaheuristics offer near optimal solution, but require a high computation time.

Literature shows instances of works that use metaheuristics to solve the RWA problem taking into account the linear physical layer impairments [8] and nonlinear physical layer impairments [17]. In [8], Monoyios and Vlachos proposed genetic algorithms for solving the IA-RWA problem without taking into account the nonlinear impairments. In [17], Bastos-Filho et al. presented a wavelength assignment algorithm inspired by evolutionary concepts that considers FWM and residual dispersion, but does not consider the XPM which can be a dominant nonlinear impairment [9]. Besides, some other papers also use metaheuristics to attempt to solve the routing and wavelength assignment problem [3], [18]-[22].

In this paper, the routing sub-problem was solved by Dijkstra algorithm, however, for the wavelength assignment sub-problem, we decided to develop a new methodology, based on the use of metaheuristics, since we did not find, in the investigated literature, any WA algorithm that seeks to reduce the XPM effect. Our approach minimized the total number of wavelengths required for the network and determined the wavelength activation order to reduce the XPM effect. The remainder of this paper is organized as follows. In Section II, we present the routing algorithm. Section III presents the XPM modeling. Section IV describes the proposed methodology and Section V presents the scenarios description and simulations results. Finally, we present our conclusions and provide future directions in Section VI.

II. ROUTING SUB-PROBLEM

For a scenario in which both the physical topology and traffic matrix are known a priori, the fixed routing is one of the most straightforward approaches used for solving the routing sub-problem. In this approach, the same pre-determined path is always selected as the route for all the connection requests between a specific source/destination pair. One commonly used fixed-routing approach is based on the shortest-path algorithm that computes the shortest route between a given source/destination pair. The most used shortest path implementations are based on the Dijkstra algorithm or Bellman-Ford algorithm [16].

In any shortest-path algorithm there is a cost parameter assigned to each network link. These algorithms will find a path of a minimum overall cost based on this parameter, corresponding to, for example: the length of the link, the number of hops, the load on the links or any physical impairment [23]. In our paper, the length of the link was used as the cost parameter of the shortest-path algorithm, since the accumulation of physical layer impairments are directly proportional to this metric.

III. CROSS-PHASE MODULATION MODELING

Cross-phase modulation (XPM) is a nonlinear phenomenon that occurs when two or more optical channels having different wavelengths propagate simultaneously inside an optical fiber. The phase of each channel is modulated by the intensity modulation (IM) of the other channels. XPM always accompanies the Self-Phase Modulation (SPM) in a nonlinear multi-wavelength link and it is a result of change in the effective refractive index of the fiber caused by the intensity of the all of co-propagating channels [24].

The analytic model developed by Cartaxo et all [25] analyzes the XPM effect in WDM systems based on intensity modulation and phase modulation. They are at the output of the transmission system of the channel that is being analyzed, i.e., probe channel (Continuous Wave – CW) and are caused by one or more interfering channels – pump channels (modulated carriers). The XPM-induced phase modulations in the probe channel are converted into intensity modulations by GVD and SPM. This model has been used to assess the influence of SPM and residual dispersion on the XPM-induced degradation. Cartaxo et all [25] also demonstrated that the influence of SPM cannot be neglected in the analysis of the XPM in dispersion compensated links but it can be significant.

According to [25] the Q factor is an important figure of merit to analyze XPM-induced power penalty in Intensity Modulation/Direct Detection (IM-DD) systems and can be written as:

$$Q = \frac{2k \cdot \bar{P} \cdot (r-1)/(r+1)}{\sqrt{\frac{2k_{sp} \cdot r \cdot \bar{P}}{r+1} + \left(\frac{2k \cdot r \cdot \bar{P}}{r+1}\right)^2 \cdot \sigma_n^2} + \sqrt{\frac{2k_{sp} \cdot \bar{P}}{r+1}}} \tag{1}$$

where $\bar{P}$ is the average optical power at the receiver input, r = P_1 / P_0 is the extinction ratio , k and k_{sp} are constants dependent on the receiver type. The power penalty is defined as the ratio between the required average power at receiver input with and without the influence of XPM and can be expressed in decibels as [25]:

$$P_P = -20.\log_{10}\left\{\frac{\sqrt{r}}{\sqrt{r}-1} \cdot \sqrt{1-\frac{r}{r-1}\sigma_n^2 \cdot Q^2} - \frac{1}{\sqrt{r}-1}\right\} \tag{2}$$

where σ_n^2 is the variance of the XPM-induced IM normalized, normalized by the square of the power at the symbol "1". Using (2), 1 dB of power penalty is obtained for was σ_n^2 = 4.2x10^{-3} and σ_n^2 = 2.6x10^{-3}, assuming r = ∞ and r = 10 dB, respectively. The Q-factor takes the value of 7, corresponding

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to a bit-error ratio (BER) of 10^{-12}.

In order to estimate the quality of the transmitted signal normalized, the variance of XPM-induced IM is employed. The variance shows the statistical dispersion of the power penalty induced by XPM, indicating how far are the values from the expected ones. σ_n^2 can be written as the integral of the power spectral density (PSD) of the probe channel IM, normalized by the square of the power at the symbol "1", as follows [25]:

$$\sigma_n^2 = \frac{1}{\bar{P}_i^2} \sum_{j=1}^{M} \int_{-\infty}^{+\infty} S_{p,j}(f) \cdot \left|H_{XPM,P,j}(f)\right|^2 \cdot |H_r(f)|^2 \cdot df \tag{3}$$

where $\bar{P}_i$ is the average optical power of the probe channel, M is the number of interfering channels, $S_{p,j}(f)$ is the power spectral density (PSD) of the *j'th* pump channel IM at the fiber input, $H_{XPM,P,j}(f)$ and $H_r(f)$ are the transfer functions of the equivalent linear model (ELM) of the XPM-induced IM associated with the *j'th* pump channel and of the electrical receiving filter, respectively.

The analytical model for characterizing XPM in multi-span optical systems used in this article, considers a transmission system, similar to that used in [25], where each section consists of a single-mode fiber (SMF) segment, followed by a dispersion-compensating fiber (DCF) segment, as shown in Fig. 1. An optical amplifier following each fiber segment is also considered, and the combined gain of both amplifiers in each section compensates for the power loss in that section.

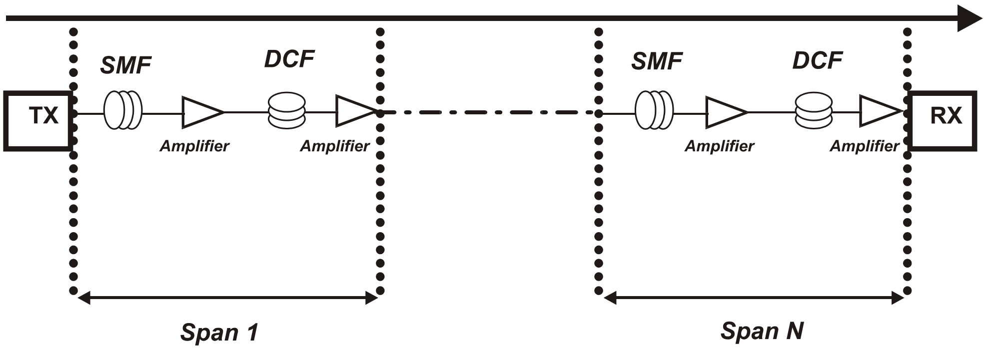

Fig. 1. Transmission system multi-span with dispersion compensation

Furthermore, also assumed are: the input power of the DCF segments is low enough to consider linear transmission, and the average power of the input channels in a determined span have identical values, regardless of being a probe or pump channel. The transfer functions of the equivalent linear model of the XPM-induced IM, generated in each span, is given by:

$$H_{i,j,s}(\omega) = \left[H_{i,j}^{(s)}(\omega).\, C_{eq}^{(s)}(\omega).\, C_{XPM}^{(s)}(\omega).\, C_{j,eq}^{(s)}(\omega)_{(1,1)}\right]_{(1)} \tag{4}$$

where superscript $^{(s)}$ represents a span s, subscript $_{(1)}$ represents the first element of the resulting vector that has size two, subscript $_{(1,1)}$ represents the first element of the matrix. $H_{i,j}^{(s)}(\omega)$ is the product of relative delays between pump channel *j* and the probe channel *i*, $C_{eq}^{(s)}(\omega)$ is the matrix that converts the XPM-induced phase and intensity (due to pump channel) into phase and intensity in the probe channel, $C_{XPM}^{(s)}(\omega)$ is the column vector with transfer functions to intensity and phase, and $C_{j,eq}^{(s)}(\omega)$ is

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the matrix that converts phase and intensity of the pump channel (due to SPM and GVD) along the optical path. The expressions for each of the described elements of equations (3) and (4), implemented in our paper, to calculate normalized variance of XPM effect, can be found in [25].

IV. PROPOSED METHODOLOGY

The proposed hybrid methodology consists of a graph coloring algorithm (used as a technique for pre-processing), followed by a Genetic Algorithm (used as an optimization technique). This methodology enables to assist in decision-making by network operators of optical transport, with respect to the wavelength activation order on the wavelengths grid in a given optical network scenario where the physical topology and traffic matrix are known a priori. However, this methodology should only be applied after the route is set for each demand contained in the traffic matrix of the network, as shown in Fig. 2.

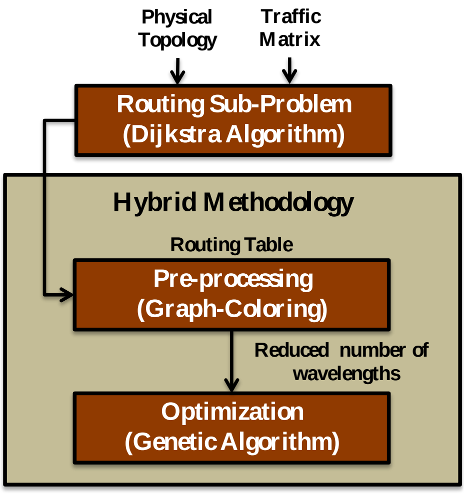

Fig. 2. General flowchart of the Proposed Methodology

A. Pre-processing

The pre-processing is the first step of our hybrid methodology. This phase is initiated immediately once the routes, that will meet the traffic matrix, are defined. The goal is to assist the wavelength assignment process by minimizing the number of necessary wavelengths, and an appropriate solution for this purpose is the graph-coloring algorithm [15],[16]. In this algorithm the vertices of the graph represent the optical paths (routes) and the edges represent the physical connections. The nodes of the graph must be colored so that each node is assigned to the first color not used by any of its adjacent nodes, thus minimizing the total number of colors used. For each color, obtained from the resolution of the graph, a distinct wavelength will be assigned. In our simulations, we could reduce this number by up to 57.14%.

B. Genetic Algorithm

After reducing the number of wavelengths by graph-coloring algorithm, the genetic algorithm (GA) is employed to perform an optimization iteratively evaluating the various candidate solutions. The result is a list containing the best solutions.

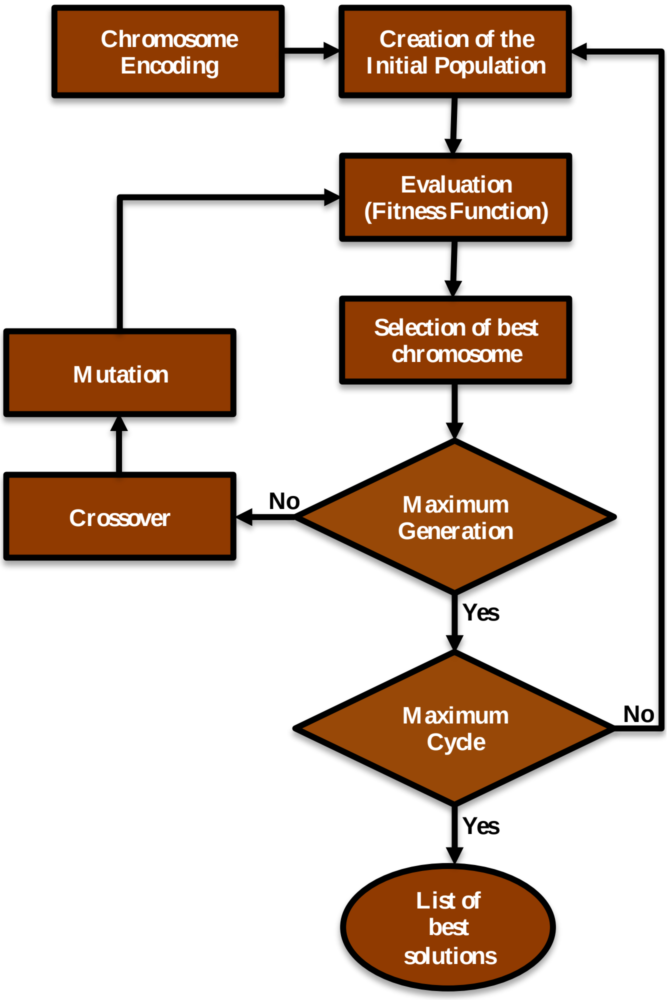

Fig. 3. Flowchart of Genetic Algorithm.

Figure 3 shows how GA works. It starts with the binary encoding of a chromosome followed by randomly generating an initial population, the first generation. Each chromosome of the population goes through an evaluation by means of a fitness function so that the best chromosome (solution) can be selected. The next step verifies whether the established number of generations has been reached which is when a given cycle terminates. If not, crossover and mutation operators are activated to generate new chromosomes to yield a new generation, that has to go through the previous step of evaluation and selection. In case the established number of generations is reached, a verification of established number of cycles is done. If the number of cycles is not reached, a new cycle will begin by creating a new initial population. This new initial population will also have to go through the steps of evaluation, selection, crossover and mutation. If the established number of cycles is reached, the optimization process is finalized resulting in list of chromosomes consisting of the best solution within each cycle.

Some details of implementing GA follow:

1) Chromosome encoding and initial population

A chromosome represents an encoded version of a wavelength activation order on the wavelengths grid, where the genes are bits representing each channel in the grid. If the bit is set to 1, then the

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wavelength it represents will be activated, otherwise remains disabled. The total number of genes that makes up the chromosome is the same as the number of channels in an optical link; however, the number of wavelengths that are activated is determined in the previous phase (graph-coloring to assign wavelengths).

The initial population consists of a set of chromosomes, where each individual is a potential solution for the problem that will be evaluated by the fitness function. The structure of the chromosome and of the initial population is depicted in Fig. 4, where each row represents one chromosome (labeled with a number from C_1 to C_m) and each column represents one wavelength (labeled with a number from W_1 to W_n according to its position on the wavelength grid).

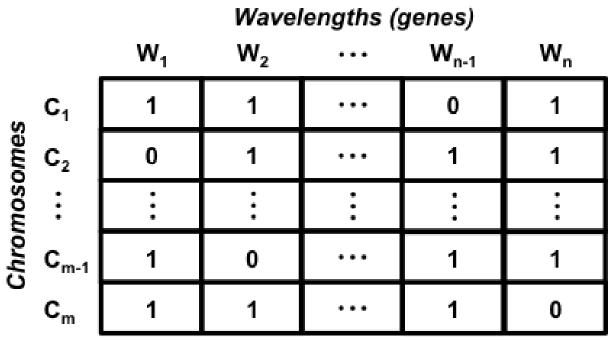

Fig. 4. Chromosome and initial population representation.

2) Evaluation

The next step employs a fitness function to evaluate each candidate solution (chromosome) of the population. This evaluation may: (i) identify the best solution; (ii) decide that a solution has to go through a crossover and mutation operations; or (iii) may not even select a solution. It is worth pointing out that the fitness function has been implemented based on the formulation described in Section III. The formulation considers as a maximum limit of normalized variance of XPM effect (σ_n^2), the value of $2.6\text{x}10^{-3}$ [25].

As a final result, the fitness function for each chromosome returns the number of channels blocked by XPM, residual dispersion or both. Residual dispersion is computed at the end of each route span, soon after the Dispersion Compensating Fiber (DCF); for each lightpath. DCF length has been adjusted to make the residual dispersion values negative in each span. This is because it has been demonstrated in [26], that, dispersion map, characterized by negative residual dispersion value per span, minimizes the degradation of XPM-induced degradation.

3) Selection of Best Chromosome and Maximum Generation

After evaluating each chromosome of a certain population, a chromosome that is fit is selected and this process is repeated in each generation of a same cycle. Once the generations of a given cycle are finalized, only the best out of the best solutions is stored.

Maximum Generation (Figure 3) is the criteria to terminate AG. In the performed simulations, it was possible to verify that from 20 generations onwards, the fitness of the chromosomes converge to close values. This is the reason that 20 was set as a maximum limit.

4) Crossover

This operation transfers genes from parents to children [27]. In our paper, the number of crossover operations performed to reproduce a new population, of the same size as the original population, is equal to half of the original population. The parents are chosen on the conventional Roulette Wheel selection scheme [17], and the crossing is conducted between pairs of chromosomes, where one has the best fitness and the other has the worst. New chromosomes named children are generated as shown in Fig. 5.

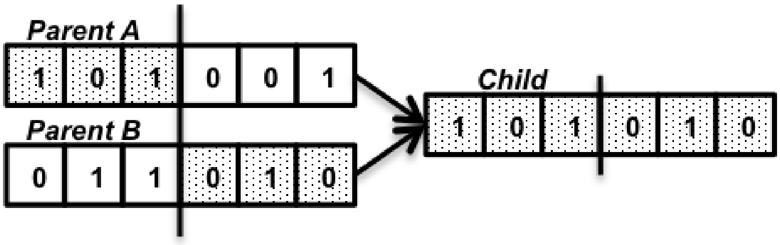

Fig. 5. Crossover phase.

5) Mutation

While crossover operations generate new combinations of existing gene values, mutation can introduce entirely new genes values into the population [27]. We use this operation to randomly modify some genes in each individual of the population in order to increase our search space and to avoid premature convergence. Genes are always modified in pair so that the number of wavelengths, defined in the Pre-processing (Graph-Coloring algorithm), is retained, as shown in Fig. 6.

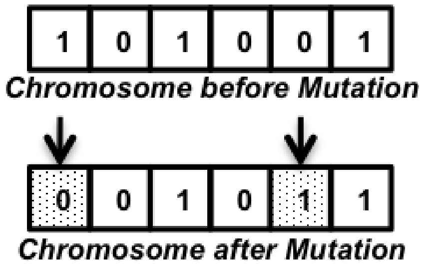

Fig. 6. Mutation phase.

6) Maximum Cycle

When the algorithm reaches the value of 20 for Maximum Generation, Maximum Cycle is activated so that it is verified whether the established number of cycles has been reached. In Maximum Cycle, a new initial population is generated and the process, of evaluation, selection, crossover and mutation, is repeated for 20 more generations. The number of cycles has been fixed to be 30 to enable expanding the search space in different regions, thus increasing the chances of finding optimal solutions. At the end of each cycle, the best solution found is stored so that the final result ends up in a list with the best solution in each of the 30 cycles.

V. SCENARIOS DESCRIPTION AND SIMULATIONS RESULTS

Several papers were analyzed in the development of this proposal, but all were implemented in a regular scenario, for example, with optical links of the same size, about 100 km. A major difference in our experiments is that they were performed in an optical network very close to the actual situation in terms of distance between nodes, which provides more realistic results. Figure 7 shows the network topology from the National Science Foundation network (NSF, U.S.) used to evaluate the effectiveness of our proposal. It has 16 OXC's (nodes origin and/or destination) nodes, 22 optical links (all links above 100 km were randomly divided in spans with size ranging from 50 to 100 km), and 302 passage nodes (nodes allocated in optical links, which may be used to add amplifiers and dispersion compensators, for creation of spans).

The configuration of the employed network in our paper enables to easily find routes with number of spans much above than one used in simulations by [25]. Nevertheless, studies on XPM-induced degradation were conducted by [26] in which a scenario, with a high number of spans, few active wavelengths and a dispersion management to reduce XPM (negative residual dispersion per span), was simulated. This scenario is very close to that we employed and therefore, validates our proposal.

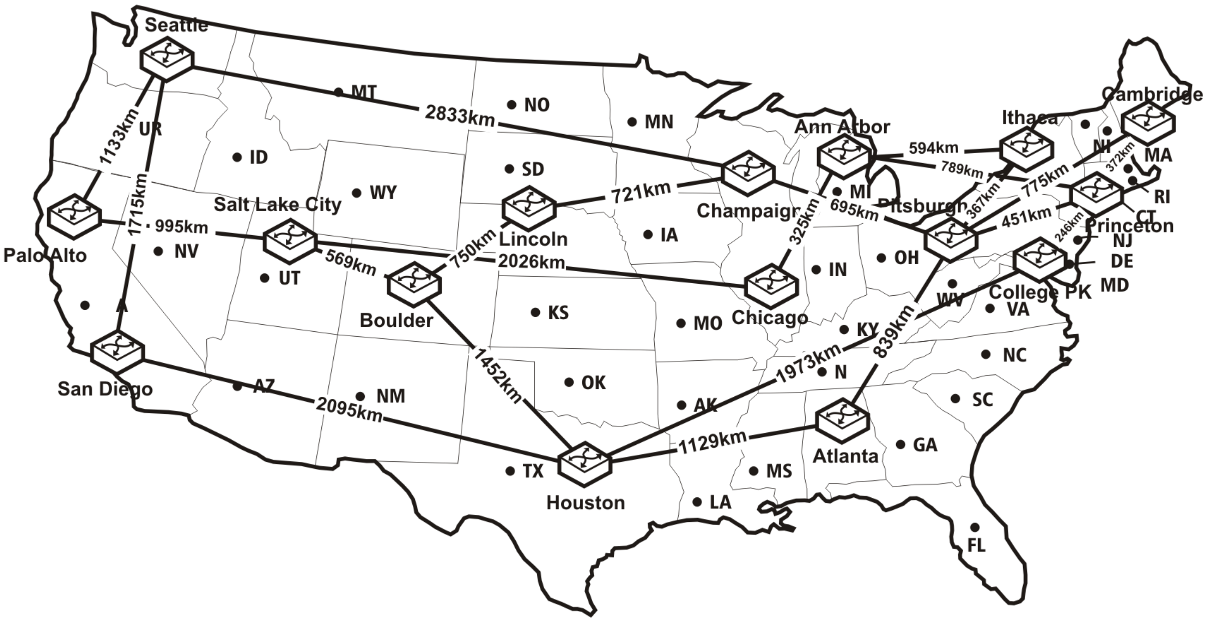

Fig. 7. NSFNET network topology.

The general configuration of the fiber link model, that we assumed, in each span consists of a sequence of alternating ITU-T G.652 fiber (SFM – single-mode fiber) and dispersion compensation fiber (DCF), as well as a set of amplifiers that can be: booster-, line- and/or pre-amplifier. One possible configuration is shown in Fig. 8.

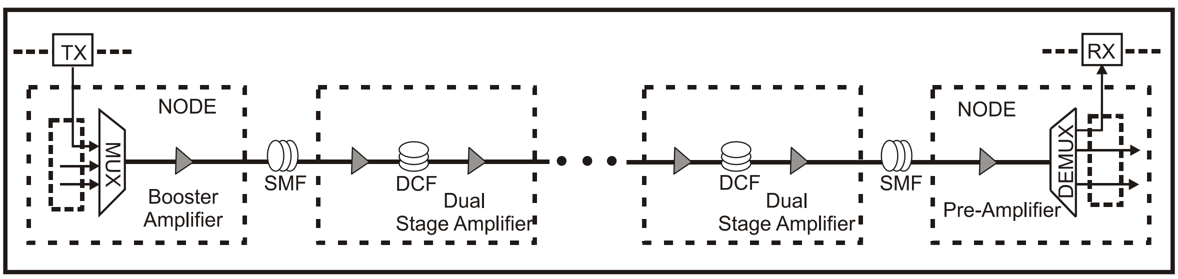

Fig. 8. General link architecture considered in our tests.

Our tests were performed with the number of connection requests ranging from 10 to 40, in two different scenarios, S1 and S2. S1 scenario considered blocked connections only by XPM effect, ignoring blocked lightpaths by residual dispersion, while S2 scenario considered blocked connections by both XPM and residual dispersion effects. In the latter scenario we considered blocked all lightpaths with residual dispersion values from 1175 ps/nm based on [28]. In both the scenarios we used the parameters listed in Table 1. The optical channels in a determined span have equal power values, but these values can be adjusted from -2 to 8 dBm depending on span length, in order to guarantee a convenient power budget.

TABLE I. DEFAULT SIMULATION PARAMETERS

Parameter	Values
Maximum number of wavelengths per path	40
DWDM grid spacing	100 GHz
Lowest wavelengths of the grid	1529.55 nm
Data rate per channel	10 Gbps
Span length	50 km to 100 km
Power of the pump and probe channels	-2 to 8 dBm
Amplifier noise figure	5.5 dB
SMF loss coefficient	0.22 dB/km
SMF dispersion coefficient for 1550.12 nm	17 ps/km.nm
Dispersion slope of the SMF	0.08 ps/km.nm^2
DCF loss coefficient	0.5 dB/km [29]
DCF Dispersion coefficient for 1550.12 nm	-100 ps/km.nm [29]
Dispersion slope of the DCF	-0.3 ps/km.nm^2 [29]
Fiber nonlinear coefficient	1.37 (W.km)$^{-1}$

Figures 9 and 10 compare the blocking probability in our proposal with the First-Fit algorithm as a function of the number of connection requests for two scenarios of the NSFNET topology. As can be seen, the First-Fit algorithm, which is the most used WA algorithm in the literature, presents the worst performance in all comparisons. This was expected since in this case adjacent channels were used, fact that enhances the XPM effect.

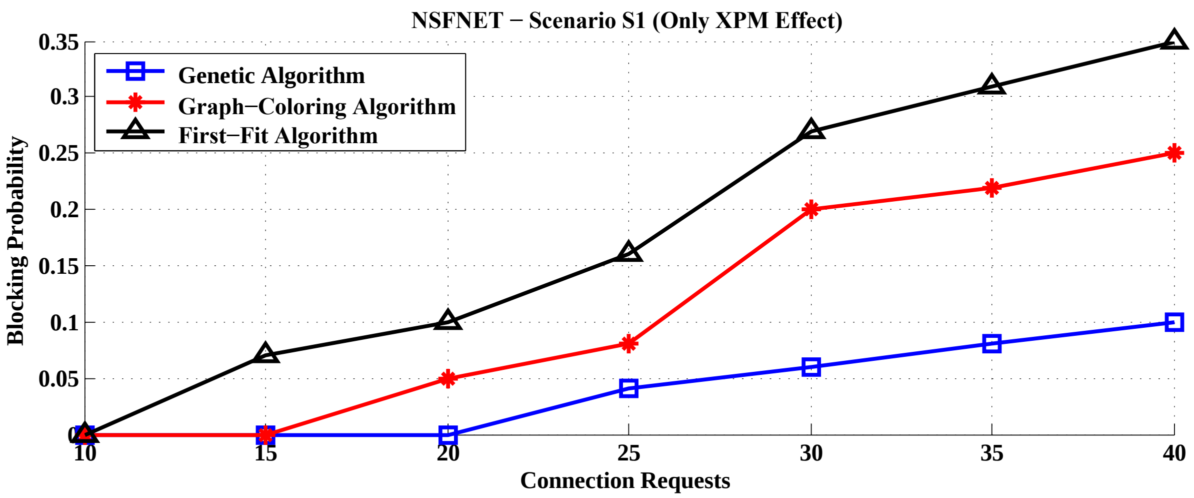

Fig. 9. Blocking probability as a function of the connection requests for the different WA algorithms accounted only XPM effect.

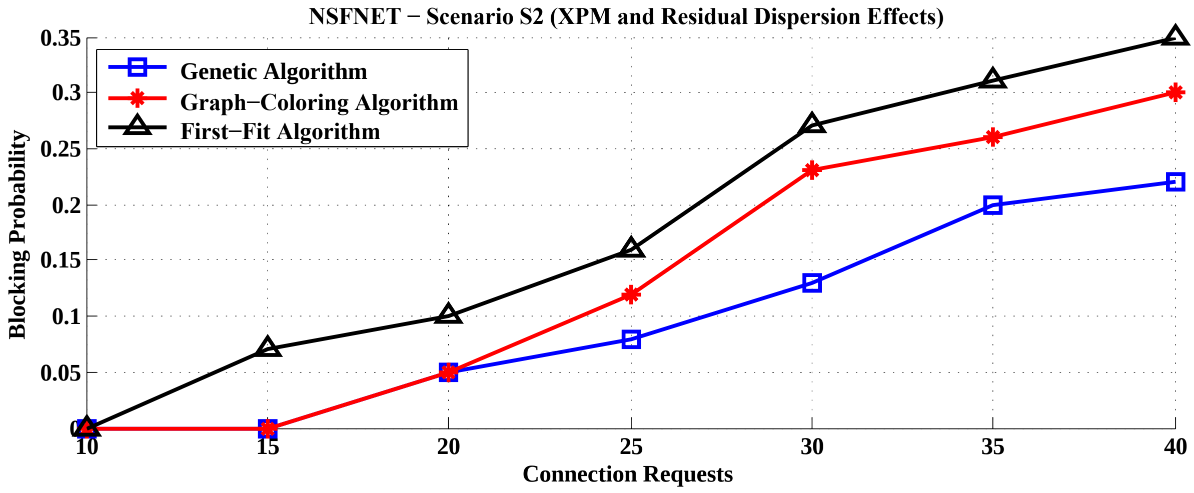

Fig. 10. Blocking probability as a function of the connection requests for the different WA algorithms accounted XPM and residual dispersion effects.

One can also notice that only using preprocessing Graph-Coloring algorithm it is possible to observe a significant improvement over traditional First-Fit algorithm, due to reduction the number of wavelengths (channels) needed to meet traffic matrix. One should also note that the Graph-Coloring algorithm shows a blocking probability acceptable when the number of connection requests is less than 25 (scenario S2), in which case it is not necessary to use the GA, avoiding the time consumed for its execution. However, the rate of blocking probability remained high when the number of demands reached this limit.

The Genetic Algorithm shows an improvement of rate of blocking probability. This is expected since GA tends to spread the wavelengths on the wavelengths grid, fact that minimizes the influence among channels. Therefore, our proposal is efficient when the number of demands below 40, and we considered only the XPM effect. When we also consider the residual dispersion our proposal presents good results for maximum of 25 demands. Soon, it will be possible to find tunable dispersion compensator, which may significantly reduce the effects generated by the residual dispersion [30], and thus the data presented in Fig. 9 will be more realistic.

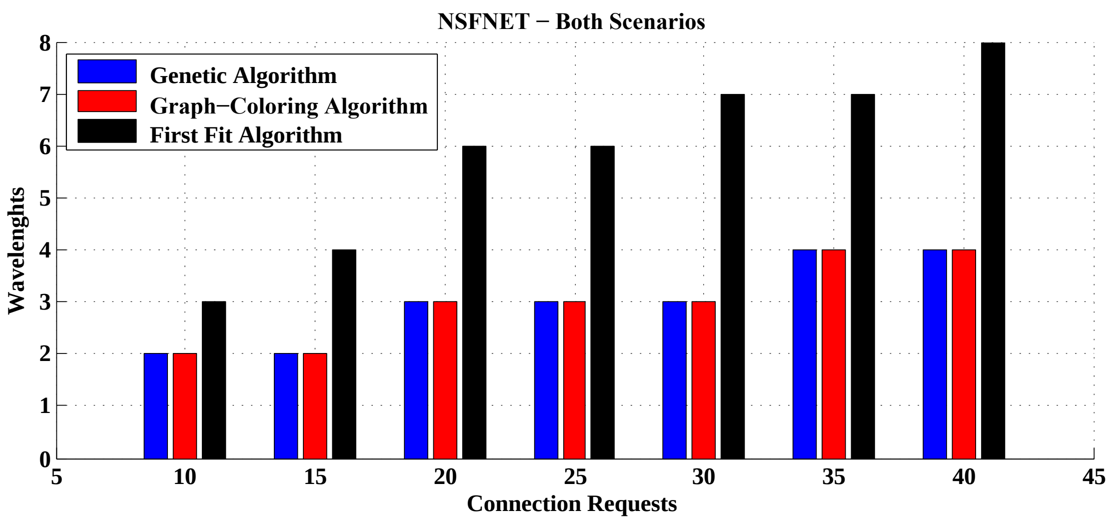

Fig. 11. Wavelengths as a function of the connection requests for the different WA algorithms in both scenarios

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One other advantage of our proposal concerns the reduced number of wavelengths through the graph-coloring technique, fact that not only impacts on network performance, but also on the cost of deployment. In Fig. 11 it can be noticed that for higher demands, the reduction can reach 57.14%. The number of wavelengths used in Genetic Algorithm is defined by Graph-Coloring Algorithm; the difference is that the latter uses the First-Fit as a method of allocating wavelengths.

Analyzing Figures 10 and 11, one can see that in the case the First-Fit algorithm the blocking probability reaches 7% for a demand of 15, which is attended by 4 wavelengths. While GA is able to meet almost double (25 demands) with nearly the same blocking probability, but with only 3 wavelengths. Thus, one can notice the reduction not only in the cost with equipment but also with the network energy consumption.

As expected, the performance and accuracy mainly depend on the population size, the number of generations and cycles. We performed several experiments in order to find out the parameters, which make the GA to achieve rapid convergence. So, we decided for the following configuration: the initial population of 10 individuals, with 20 generations and 30 cycles. To avoid premature convergence we used the operations of crossover and mutation rate of 0.8 and 0.01, respectively. The execution time grew exponentially according to the number of demands required. In order to perform 10 demands the optimization process took around 22 minutes, around 1 hour for 25 demands, and around 3 hours for 40 demands.

VI. CONCLUSIONS

In this paper we proposed a hybrid technique employing graph-coloring and genetic algorithm that present a near optimal solution to the WA problem. We have developed an optimization process that is able to significantly reduce the influence among channels by spreading wavelengths in the wavelength grid. This optimization process is flexible and in future it will be extended to incorporate other physical layer impairments, making the GA more efficient.

The results for GA showed the creation of multiple lists containing the best solutions in terms of blocking probability. Each list created in offline phase was generated by a different traffic matrix and could be used in the network operation phase according to the current network status. In all cases, it was found that the list generated by GA presented better results than the First-Fit and the Graph-Coloring algorithms. However in some situations the Graph-Coloring provides satisfactory results without the need to perform GA. This work demonstrated the applicability of computational intelligence and bio-inspired algorithms to solve different optimization problems involved in the design of networks.

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REFERENCES

[1] A. Jirattigalachote, Provisioning Strategies for Transparent Optical Networks Considering Transmission Quality, Security, and Energy Efficiency, Doctoral Thesis in Microelectronics and Applied Physics, Royal Institute of Technology, Stockholm, Sweden, March 2012.
[2] I. Chlamtac, A. Ganz, and G. Karmi, “Lightpath Communications: An Approach to High- Bandwidth Optical WANs”, IEEE Transactions on Communications, vol. 40, no. 7, pp. 1171-1182, July 1992.
[3] U. Bhanja, S. Mahapatra, and R. Roy, “FWM aware evolutionary programming algorithm for transparent optical networks”, Photonic Network Communications, v. 23, issue 3, p. 285-299, June 2012.
[4] S. Azodolmolky, et al., “Experimental demonstration of an impairment aware network planning and operation tool for transparent/translucent optical networks”, Journal of Lightwave Technology, v. 29, n. 4, 439 – 448, February 2011.
[5] F. Fidler, P. J. Winzer, M. K. Thottan, and K. Bergman, “Impairment-Aware Optical Networking Using Cross-Layer Communication”, IEEE Journal of Optical Communications and Networking, v. 5, n. 2, p. 144-158, February 2013.
[6] S. Pachnicke, T. Paschenda, and P. Krummrich, “Assessment of a constraint based routing algorithm for translucent 10 Gbits/s DWDM networks considering fiber nonlinearities”, Journal of Optical Networking, v. 7, n. 4, p. 365-377, April 2008.
[7] G. S. Pavani, L. G. Zuliani, H. Waldman, and M. F. Magalhães, “Distributed approaches for impairment-aware routing and wavelength assignment algorithms in GMPLS networks”, Computer Networks, v. 52, issue 10, 1905–1915, July 2008.
[8] D. Monoyios and K. Vlachos, “Multiobjective Genetic Algorithms for Solving the Impairment-Aware Routing and Wavelength Assignment Problem”, IEEE Journal of Optical Communications and Networking, v. 3, n. 1, p. 40-47, January 2011.
[9] S. Ten, K. Ennser, J. Grochocinski, S. Burtsev, and V. da Silva, “Comparison of four-wave mixing and cross phase modulation penalties in dense WDM systems”, in Optical Fiber Communication Conf. (OFC), 1999.
[10] R. Hui, K. Demarest, and C. Allen, “Cross-phase modulation in multispan WDM optical fiber systems, IEEE Journal of Lightwave Technology”, v. 17, issue 6, p. 1018–1026, 1999.
[11] A. Cartaxo, “Cross-phase modulation in intensity modulation-direct detection WDM systems with multiple optical amplifiers and dispersion compensators”, IEEE Journal of Lightwave Technology, v. 17, n. 2, p. 178-190, February 1999.
[12] N. Sambo, M. Secondini, F. Cugini, G. Bottari, P. Iovanna, F. Cavaliere, and P. Castoldi, “Modeling and distributed provisioning in 10–40–100-Gb/s multirate wavelength switched optical networks”, IEEE Journal of Lightwave Technology, v. 29, issue 9, p. 1248–1257, 2011.
[13] L. Velasco, A. Jirattigalachote, M. Ruiz, P. Monti, L. Wosinska, and G. Junyent, “Statistical Approach for Fast Impairment-Aware Provisioning in Dynamic All-Optical Networks”, IEEE Journal of Optical Communications and Networking, v. 4, v. 2, February 2012.
[14] Dijkstra, E. W. A Note on Two Problems in Connection with Graphs. In: Numerische Mathematik, vol. 1, pp. 269–271, 1959.
[15] B. Mukherjee, Optical Communication Networks, McGraw-Hill, New York, 1997.
[16] H. Zang, J. P. Jue, and B. Mukherjee, “A review of routing and wavelength assignment approaches for wavelength-routed optical WDM networks”, Optical Networks Magazine, v. 1, n. 1, p. 47–60, January 2000.
[17] C. J. A. Bastos-Filho, D. A. R. Chaves, F. S. F. e Silva, H. A. Pereira, and J. F. Martins-Filho, “Wavelength Assignment for Physical-Layer-Impaired Optical Networks Using Evolutionary Computation”, IEEE Journal of Optical Communications and Networking, v. 3, n. 3, p. 178-188, March 2011.
[18] U. Bhanja, S. Mahapatra, and R. Roy, “An evolutionary programming algorithm for survivable routing and wavelength assignment in transparent optical networks”, Journal of Information Sciences 222 (2013) 634–647.
[19] A. N. Patel, P. N. Ji, J. P. Jue, and T. Wang, “A Naturally-Inspired Algorithm for Routing, Wavelength Assignment, and Spectrum Allocation in Flexible Grid WDM Networks”, IEEE Globecom Workshop: Flexible Optical Networks, 2012.
[20] Y. S. Kavian, et al., “Routing and wavelength assignment in optical networks using Artificial Bee Colony algorithm”, Optik - Int. J. Light Electron Opt., 2012.
[21] C. Zhang, Z. L. Li, X. Zhang, and B. Zhang, “Two multi-objective genetic algorithms for the QoS based routing and wavelength allocation problem in WDM network”, Optik - Int. J. Light Electron Opt., 2012.
[22] A. Rubio-Largo, M. A. Vega-Rodríguez, J. A. Gómez-Pulido, and J. M. Sánchez-Pérez, “A Comparative Study on Multiobjective Swarm Intelligence for the Routing and Wavelength Assignment Problem”, IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews, v. 42, n.6, p. 1644-1655, December 2012.
[23] S. Azodolmolky, M. Klinkowski, E. Marín, D. Careglio, J. Solé- Pareta, and I. Tomkos, “A survey on physical layer impairments aware routing and wavelength assignment algorithms in optical networks”, Computer Networks, vol. 53, pp. 926–944, 2009.
[24] G. P. Agrawal, Nonlinear fiber optics, Academic Press, 2001.
[25] R. S. Luís and A. Cartaxo, “Analytical Characterization of SPM Impact on XPM- Induced Degradation in Dispersion-Compensated WDM Systems”, Journal of Lightwave Technology, v. 23, n. 3, p. 1503-1513, March, 2005.
[26] N. Costa and A. Cartaxo, “Influence of the Channel Number on the Optimal Dispersion Map Due to XPM in WDM Links”, Journal of Lightwave Technology, v. 26, n. 22, 3640 – 3649, November 2008.

[27] El-Sayed M. El-Alfy, S. N. Mujahid, and S. Z. Selim, "A Pareto-based hybrid multiobjective evolutionary approach for constrained multipath traffic engineering optimization in MPLS/GMPLS networks", Journal of Network and Computer Applications, February, 2013.
[28] International telecommunication union, "Optical fibers, cables and systems", Geneva, 2009.
[29] G. P. Agrawal, Fiber-optic communication systems, 3a ed. Wiley-Interscience, 2002.
[30] K. Tanizawa, J. Kurumida, M. Takahashi, T. Yagi, and S. Namiki, "In-Line Polarization-Insensitive Parametric Tunable Dispersion Compensator for WDM Signals", IEEE Journal of Lightwave Technology, v. 30, issue 11, p. 1750–1756, 2012.