A NOVEL APPROACH FOR WAVELENGTH ASSIGNMENT IN OPTICAL LINKS BASED ON MODIFIED GENETIC ALGORITHMS

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Abstract— This article presents a new strategy to search for satisfactory wavelengths assignments in an optical link considering the Four Wave Mixing (FWM) effect in optical fibers. The FWM effect is taken into account for the calculation of the fiber Noise Figure for each wavelength. In this work we analyze the assignments when there are additions and droppings of wavelengths, considering the best and satisfactory assignments by using exhaustive and genetic algorithms (GA), respectively. A new crossover operator for the GA utilized was developed and tested. With this approach the distributions of wavelengths are obtained from modified one genetic algorithm, which considers the quality of service criterion based on Bit Error Rate. We show that our new crossover operator outperforms the previous one presented in the literature.

Keywords— Optical Communications, Wavelength Assignment, Four wave mixing, Nonlinear effects, Search Algorithm, Genetic Algorithms.

1 Introduction

Due to the increasingly demand on telecommunication data traffic, the number of multiplexed channels in optical-transmission systems is growing considerably as well. However, the transmission of many high power optical channels in WDM systems causes nonlinear effects, such as *Four Wave Mixing* (FWM) [1-5], this, mainly in links that use dispersion shifted (DSF) [1] or non-zero dispersion shifted fibers (NZDSF) [2]. As a result, estimating the FWM impact on transmission performance is becoming very important for the design and the evaluation of system performance.

H. A. Pereira *et al* [6] described the problem and presented one technique to grow the number of active channels according to the power level overcoming the inconveniences of FWM. In Fig. 1 the arrows represent four assigned wavelengths in 16 channels grid in a given optical link. For the experiments of this work, the configurations 6/12, 8/16 and 10/20 were used. In all cases, the binary representation indicates that the states set to 1 means activated channel.

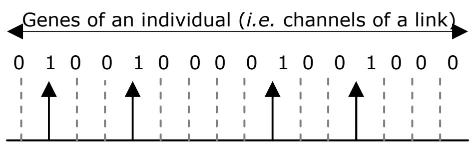

Fig. 1 - A 4 wavelength assignment in a 16 channels optical link.

Even though it is highly advisable to tackle the non-linearities of FWM in some systems, to evaluate the performance of all possible configurations can be very time consuming. For example, suppose we have a grid with N_t channels positions and N_i wavelengths assigned, the number of possibilities is given by (1).

$$C_F = \frac{N_t!}{N_i!\left(N_t - N_i\right)!} \tag{1}$$

Pereira *et al* [6], have already considered some improvements to the above mentioned problem using Genetic Algorithms (GA). However, after repeating their reported experiments, we have observed that the inheritance within the GAs utilized is not transmitted for the new generations.

In this paper we propose a novel approach to search solutions that minimizes the Four Wave Mixing problem by using elitism and improving performance of the crossover operator.

This work is organized as follows: Section 2 contains a brief review of optical transmission performance evaluation and the GAs used to search reasonable solutions. In Section 3 we present our approach to tackle the problem. In Section 4 we describe the experimental set-up and methodology. And in Sections 5 and 6, respectively, results and conclusions are provided.

2 Background

2.1 Optical Transmission Performance Evaluation

Hill *et al* were the first to investigate the FWM effect experimentally in a single mode fiber, estimating the power generated by the process [4]. Shibata *et al* proposed a formulation to include the efficiency dependence of the FWM with the channel frequency separation, fiber length, chromatic dispersion, and dispersion slope [5]. Whereas Song *et al* [2] proposed a more sophisticated model considering the depletion of the pump signals due to the fiber loss coefficient. Inoue [7] considered the balance of the amplifier noise and the FWM noise in a cascaded link through a simple expression, determining the system input signal power range.

On the other hand, the noise figure is an important parameter to determine the system performance and many formulations have been proposed; Baney *et al* [8] reported a noise figure definition in terms of measurable parameters considering an optoelectronic model. The noise factor is defined as the ratio between the *OSNR* in the optical fiber input ($OSNR_{in}$) and the *OSNR* in the optical fiber output ($OSNR_{out}$). The *OSNR* can be expressed as follows:

$$OSNR = \frac{< i_{Signal}^2 >}{< \Delta i_{Noise}^2 >}, \qquad (2)$$

where $< i_{signal}^2 >$ is the photocurrent generated by the optical signal of power level (P_{signal}) and it is proportional to the detected electrical signal power, and $< \Delta i_{Noise}^2 >$ is the mean-square value of a single-sided noise power spectrum [8].

The photocurrent generated by the optical signal can be expressed as

$$< i_{signal}^2 >= \Re^2 P_{signal}^2, \qquad (3)$$

where $\Re$ is the photo detector responsively. Whereas the noise corresponds to:

$$< \Delta i_{noise}^2 >= \Re^2 \int_{B_0} S_{noise}(f)df, \qquad (4)$$

where B_0 is the channel optical bandwidth and $S_{noise}(f)$ is the noise spectral power density.

Therefore, considering the additive source spontaneous emission in the input we have [8]:

$$OSNR_{in} = \frac{\Re^2 P_{signal}^2}{2q\Re P_{signal} B_0}. \qquad (5)$$

For the fiber output, with the FWM generated power added to the attenuated source spontaneous emission plus attenuated shot noise, we have:

$$OSNR_{out} = \frac{\Re^2 P_{signal}^2 \exp(-\alpha L)^2}{2q\Re B_0 P_{signal} \exp(-\alpha L) + < \Delta i_{FWM}^2 >}, \qquad (6)$$

where $< \Delta i_{FWM}^2 >$ corresponds to the noise square mean value due to additive noise components generated by FWM processes. L is the fiber length and α is the linear attenuation coefficient. Therefore, the noise factor of the optical fiber can be written as [6]:

$$F = \exp(\alpha L)\left[1 + \frac{< \Delta i_{FWM}^2 > \exp(\alpha L)}{2q\Re B_0 P_{signal}}\right]. \qquad (7)$$

In this approach there are many additive noise components interacting with the signal channel along the transmission. Considering a square law photo detector, one can evaluate the square mean value of noise considering the beating processes between the signal and the n additive noise components. The result is given by [6]:

$$< \Delta i_{FWM}^2 >= \Re^2\left[\left(\sum_{i=1}^{n} P_i + 2\sum_{i=0}^{n-1}\sum_{j=i+1}^{n}\sqrt{P_i P_j}\right)^2 - P_0^2\right],$$

where P_0 is the signal power attenuated in the fiber output and P_i (i=1,2,...,n) are the noise power components in the signal wavelength.

Therefore, one can calculate the linear output $OSNR_{out}$ that is equal to the linear input $OSNR_{in}$ divided the total noise factor as in (7). Furthermore, the Quality of service (*QoS*) of the channels can be evaluated through the *BER* estimation and the *BER* depends directly on $OSNR_{out}$. Therefore, one can determine a minimum acceptable $OSNR_{out}$ to maintain the *QoS* of every channel. In our case, the target is to find a wavelength assignment in a Grid so the channels respect these constrain, i.e., our fitness function should return the $OSNR_{out}$ of the worst channel. For a minimum *BER* of 10^{-12}, the minimum $OSNR_{out}$ is approximately 23 dB.

2.2 Evolutionary Computation

In 1975 John Holland published a seminal work about Evolutionary Computation based on Darwin and Mendel theories [9]. Since then, several applications that use GA have been put forward and utilized in many distinct domains to solve real-world problems. The use of GA is growing steadily in many domains where there is the need for searching of suitable solutions in high dimensional spaces.

GAs are mostly used in searching and optimization problems because of their robustness, efficacy and flexibility. This technique of the Computational Intelligence area, profits greatly from principles of natural competition and evolution. As opposed to that, conventional algorithms operate in a pre-established and rigid manner (*i.e.* script-like algorithm).

Normally a genetic algorithm considers the following concepts: (*i*) there is a space in which all possible solutions for the problem are mapped to, (*ii*) it is possible to devise a set containing candidate solutions for the problem, that is, population (*iii*) the fitness of each candidate solution is possible to be evaluated, (*iv*) candidate solutions can mix among themselves to share their “expertise” on solving the problem; (*v*) candidates with better fitness win the survival competition and will form the next generation of the population.

In a Darwinian perspective, GAs presents the following computational steps: (*i*) random generation of individuals to form the initial population, (*ii*) evaluation of fitness of individuals and (*iii*) selection of individuals with higher aptitude to be part of the next generation of candidate solutions. In the selection of individuals one may consider principles such as elitism, crossover and mutation. This process, in known as reproduction and as a whole it can be repeated until a satisfactory solution is achieved [10].

2.3 Representation, Selection and Genetic Operators

In GAs individuals of the population have a genotypic representation of the parameters of the solution mapped as genes, comprising their genotypes. This representation can be, for example, group of binaries values for every aspect related to the solution. As distinct values are actually assigned to the genes (phenotype) different fitness are evoked by each individual.

The rationale of GAs is that by combining characteristics of different individuals the resulting "offspring" might perform better (as a solution for the problem – hence, reducing the time of the search).

In this paper, as for the selection of individuals, we have applied the roulette wheel method. Complementary to that, in order to guarantee diversity and inheritance of good features, we also included modified forms of crossover and mutation operators [10].

3 The Contributed Approach

As described in the previous section, genetic algorithms (GA) can be defined by a set of integrated components, which can be implemented in many different ways. The flowchart in Fig. 2 shows a regular GA. Notice the presence of crossover, mutation and selection operators.

For the problem at hand a series of standard procedures present in GAs would not work. Therefore some adaptations have to be performed in order for the technique to be to excel in this particular problem (*i.e.* Wavelength Assignment in optical Links).

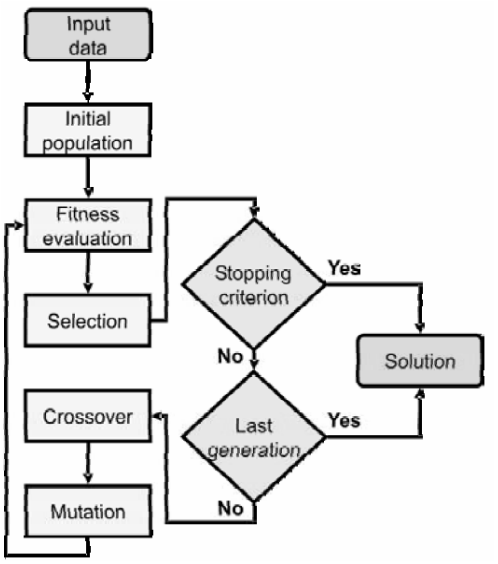

Fig. 2 - Schematic view of a regular Genetic Algorithm

3.1 The Existing Crossover Operator

Traditional one point crossover considers 50% of each parents' code for the descendants, i.e. 50% from one parent contribution and other 50% inherited from the second one. In the problem at hand, this could not be applied straightway. The reason is simple; the number of actives transmitters has to be the same at anytime through generations; hence, an especial crossover had to be adapted to this constraint.

One previous work have tackled this task and offered a reasonable contribution to the problem [6], where GAs were applied in the wavelength assignment in optical links for the first time. For the existing operator, refer to the steps below and also, to Fig. 3.

- Previous crossover step-1 – randomly select one position in the transmission grid where the transmitter is activated in Ind_1 (*i.e.* individual 1) and, an inactivated in Ind_2 (*i.e.* individual 2), then swap them over;
- Previous crossover step-2 – randomly select other position in the transmission grid where the transmitter is inactivated in Ind_1 and activated in Ind_2 and also swap them over;
- Previous crossover step-3 – keep the two just produced offspring as new candidate solutions for the problem.

	Step 1	Step 2	Offspring
Ind_1	01011001	00011001	00011101
Ind_2	01011001	00011001	00011101

Fig. 3 - Illustrative example of the previous crossover [6].

As a matter of fact, according to this implementation, just few cross inheritance will happen at maximum rate, refer to (9). Where i is the inheritance rate and N is genotype's length. If you want to guarantee that the maximum inheritance rate be achieved, you should force the chosen position to be equivalent in Ind_1 and Ind_2.

$$i = 2/N \cdot 100 \qquad (9)$$

The genetic information from just one parent to be copied to the offspring surpasses the expected 50%. It can be calculated by (10), and the obtained values suggest that this method is much similar to a mutation operator than a crossover one.

$$c = 100 - i \qquad (10)$$

For example: an experimental individual 12/6 which represent 6 actives channels in 12, has c = 83% and a maximum i = 17%.

3.2 The Proposed Crossover Operator

The major contribution proposed in this work regards to the previous crossover operator described in section 3.1.

The new proposed operator for crossover was out forward to allow better inheritance of features from parents to their offspring.

The novel crossover approach fixates one parent contribution towards the offspring as of 50%, while it allows the second parent inheritance rate to be 50% for individuals of any size. For the new operator, refer to the steps below and also, to Fig. 4.

- Novel crossover step-1 – given a pair of parents, split them right in the middle. Then, each second half of parent, Ind_{11} and Ind_{21}, will be crossed over, forming the first and second parts of Ind'_1 *of* Ind'_2, respectively (check bottom-left of Fig. 4. This procedure guarantees 50% of parents' genetic information passed on to the offspring;
- Novel crossover step-2 – calculate the difference (*diff*) of active channels in second half of the parents (check top-right of Fig. 4 and equations 11-12). This difference represents the number of activations or deactivations in individuals' genotype and directly affects the inheritance rate given by (13). A positive *diff* means activations in Ind_{12} and deactivations in Ind_{22}, while a negative *diff,* just the opposite. If *diff* equals to zero, the maximum inheritance rate 50% is achieved;

$$diff = sum(Ind_{11}) - sum(Ind_{21}) \quad (11)$$

$$sum(seq[]) = \sum i, i \in seq \quad (12)$$

$$i = \left(\frac{(N/2) - diff}{N} \right) \cdot 100 \quad (13)$$

- Novel crossover step-3 – randomly select the channels to be activated and deactivated, accordingly to step-2;
- Novel crossover final step – keep the two just produced offspring as new candidate solutions for the problem.

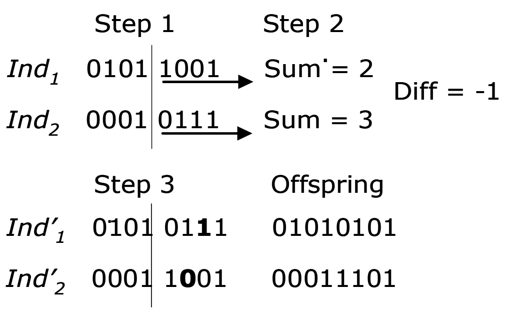

Fig. 4 – Illustrative example of the proposed crossover

Simulations indicate that the average inheritance rate is over 33%, refer to section 4 for more details.

It is important to highlight that the observed results depends on the probability of activation figures in the second half of each individual. So, performing a combinatorial analysis on the same example referred above, we obtained the results that are presented in Table 1 - Comparative results of probabilities inheritance rate using the novel crossover. (hence the mentioned average of inheritance is about 39%).

Table 1 - Comparative results of probabilities inheritance rate using the novel crossover.

Occurrence likelihood	Inheritance Rate
7%	17%
13%	25%
20%	33%
26%	42%
33%	50%

4 Methodology

In this section, we present the methodology applied to the development of all simulations carried out.

4.1 Experimental set-up

In order to find the best configuration of active channels over a transmission link using the binary codification, we must consider a satisfactory distribution when the OSNR will be greater than 22.9652 dB to a BER equal to 10^{-12}. Table 2 presents the values assumed for parameters used in all simulations.

Table 2 - Simulation Parameters of Communications.

Parameter	Value	Definition
λ_f	15503.12nm	First wavelength of the grid.
λ_0	1544nm	Zero dispersion wavelength.
L	19821m	Link length.
Δf	25GHz	Frequency spacing.
SNR_{in}	38.8dB	Input signal-to-noise ratio.
SNR_{QoS}	22.9652dB	SNR_{out} for QoS criterion.
P_{Signal}	-	Optical input ower/channel.
P	-	Initial population.
G	-	Number of generations.
P_{cross}	50%	Crossover probability.
P_{mut}	5%	Mutation probability.

In all experiments the: signal power, the individual length and the amount of active channels were variable parameters, according to each configuration used and presented in Table 3. The others parameters were kept constants, where N_t is the total numbers of channels and N_i are the active channels.

Table 3 - Optimized Genetic Parameters.

Configuration	Population	P_{Signal} (mW)
$N_t = 12$ and $N_i = 6$	30	1e-4 to 3.1e-4
$N_t = 16$ and $N_i = 8$	50	1e-4 to 2e-4
$N_t = 20$ and $N_i = 10$	85	1e-4 to 1.7e-4

4.2 Methodology and Results

We carried out 500 simulations for each GA configuration according to the Table 3. The results are shown in the tables and graphs below, which describe the observed behaviors of each specific algorithm under the established test-conditions. The tables present the algorithms used for simulation and the number of fitness function calls (fitness evaluations) named C_F.

Table 4 and Table 5 contains the values of C_F obtained for each algorithm using the first GA configuration (N_t = 12, N_i = 6 and Populations = 30) presented by Table 3 and assuming a specific critic value of P_{signal}.

Table 4 - Number of fitness function evaluations for grid size of 12 channels, 6 active channels, 1 feasible solution, at 0.25 mW of power.

Algorithm	C_F
GA Previous	111,83
GA Proposed	110,706
GA Previous + elitism	117,674
GA Proposed + elitism	79,182

Table 5. Number of fitness function evaluations for grid size of 12 channels, 6 active channels, 1 feasible solution, at 0.3 mW of power.

Algorithm	C_F
GA Previous	476,262
GA Proposed	448,97
GA Previous + elitism	490,864
GA Proposed + elitism	277,254

Notice that C_F values, obtained with the proposed approach of GA together with elitism, are much lower that all other technique we compared to (including the proposed GA without elitism); this, regardless of power used.

On the basis of the structure of previous Tables 4 and 5, Table 6 shows other results using a second GA configuration (N_t = 16, N_i = 8 and Populations = 50). Table 7 and Table 8 present the obtained results using a third GA configuration (N_t = 20, N_i = 10 and Populations = 85).

Table 6 - Number of fitness function evaluations for grid size of 16 channels, 8 active channels, 4 feasible solution, at 0.2 mW of power.

Algorithm	C_F
GA Previous	2573,49
GA Proposal	2386,516
GA Previous + elitism	2588,674
GA Proposal + elitism	593,018

Table 7 - Number of fitness function evaluations for grid size of 20 channels, 10 active channels, 29 feasible solution, at 0.16 mW of power.

Algorithm	C_F
GA Previous	6185,648
GA Proposed	6007,336
GA Previous + elitism	6562,522
GA Proposed + elitism	1071,664

Table 8 - Number of fitness function evaluations for grid size of 20 channels, 10 active channels, 4 feasible solution, at 0.17 mW of power.

Algorithm	C_F
GA Previous	31321,4
GA Proposed	30867,5
GA Previous + elitism	No solution found
GA Proposed + elitism	6746

Notice that C_F values shown in Tables 7 and 8 for the proposed approach of GA together with elitism are also much lower (approximately, five-fold better); this also, regardless of power.

By comparing our approach to others, we were able to consistently observe better results. Especially when the elitism operator was utilized.

For each GA configuration simulated, different behaviors have been acquired. Considering that elitism enhances the algorithms behavior, Fig. 5, Fig. 6 and Fig 7 show the behaviors of the algorithm that uses the proposed GA and the algorithm that uses the previous GA, both with elitism incorporated in them.

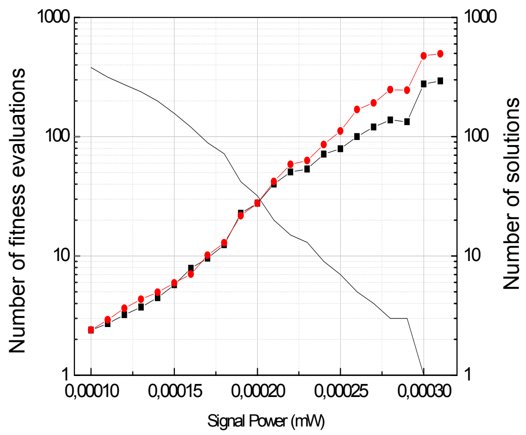

Fig. 5 - Proposed (dots) and previous (squares) GA, both using elitism with configuration N_t = 12, N_i = 6 and Population = 30.

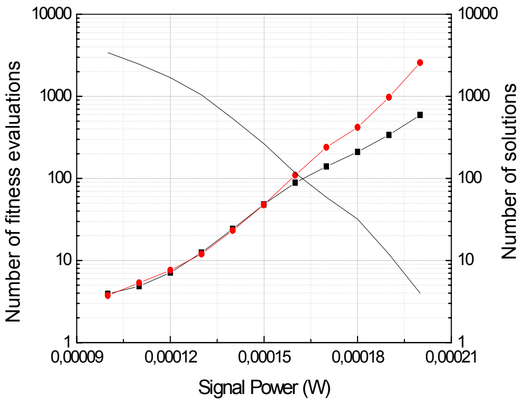

Fig. 6 - Proposed (dots) and previous (squares) GA, both using elitism with configuration $N_t = 16$, $N_i = 8$ and Population = 50.

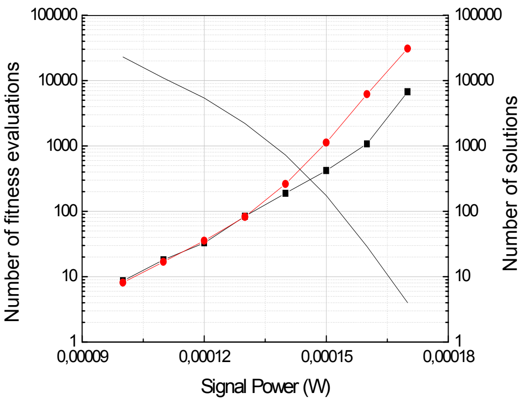

Fig. 7 - Proposed (dots) and previous (squares) GA, both using elitism with configuration $N_t = 20$, $N_i = 10$ and Population = 85.

5 Conclusions

A new approach using genetic algorithms has been proposed to the problem of wavelengths assignments in an optical link considering the Four Wave Mixing effect in fiber optics. Using this approach a large number of simulations were carried out in order to find solutions that minimize the impact of the four wave mixing effect.

One new crossover operator implementation was proposed to improve the simulations results. For every problem variation (network environment) the behavior of our proposal has produced better results than previous solution that utilize GA. Hence, we argue that the new crossover implementation is a better way to approach the problem revisited in this paper.

The proposed GA with elitism was proved to be more efficient than the all previous one simulated here. Hence, we are able to obtain lower C_F values for every tested critical P_{signal} value.

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