

Wavelength Assignment Optimization for All-Optical Networks Using Evolutionary Computation

Carmelo J. A. Bastos-Filho¹, Daniel A. R. Chaves², Felipe S. F. e Silva²,
Renan V. B. Carvalho³, Helder A. Pereira³, Joaquim F. Martins-Filho²

¹ Escola Politécnica de Pernambuco – Universidade de Pernambuco (UPE)
Departamento de Sistemas e Computação – Recife – PE – Brazil

²Centro de Tecnologia e Geociências – Universidade Federal de Pernambuco (UFPE)
Departamento de Eletrônica e Sistemas – Recife – PE – Brazil

³Escola Politécnica de Pernambuco – Universidade de Pernambuco (UPE)
Departamento de Engenharia Elétrica – Recife – PE – Brazil

cjabf@dsc.upe.br, helder.pereira@upe.poli.br, jfmf@ufpe.br

Abstract. *This paper presents a novel wavelength assignment algorithm for all-optical networks. The main idea is to determine the wavelength assignment order for a first fit algorithm taking into account the physical layer effects of four wave mixing and residual dispersion by using a training algorithm inspired in evolutionary computation concepts. The intelligent algorithm presents some concepts recently proposed in the computational intelligent field, such as an external archive to store the best solutions. The proposed wavelength assignment algorithm was compared with others classical algorithms such as regular first fit, best fit and random. In all the cases our proposal presented a better performance.*

1. Introduction

All-optical networks have been considered as the most reliable and economic solution to achieve high transmission capacities with quality of service (QoS). In these networks, the signal remains in the optical domain between the edge nodes, *i.e.* the signal propagates along the core of the optical network without any optical-electrical-optical conversion. One of the major challenges to manage these networks providing QoS is to define an appropriate routing and wavelength assignment algorithm (RWA) in order to obtain acceptable optical signal-to-noise ratio (OSNR) for every lightpaths [RFC 2005].

The RWA problem is a classic problem in optical networks. It can be divided in two minor problems: the routing process and the wavelength assignment process. A classical approach to solve routing problem is to represent the network topology by a graph, then use some metrics to evaluate the cost of each branch of the graph, and finally, use an algorithm that finds the minimum cost path between two given nodes [Mukherjee 2000, Zang et al. 1999]. Classical routing algorithms use some heuristic link cost function based on a pre-defined metrics, such as, the shortest path (SP), minor delay and load balance [Tanenbaum 2003]. After the routing procedure the wavelength assignment (WA) algorithm has to decide which available channel should be used to establish the call [Mukherjee 2000, Zhou and Yuan 2002]. Again, some heuristics are used in classical RWA to solve the wavelength assignment problem.

There are some well-known WA algorithms for all-optical networks [Zang et al. 1999, Stoica and Sengupta 2000, Alfouzan and Jayasumana 2003] among them, we can cite: first fit (FF), random-pick (RP), most used (MU), least used (LU), max-sum (MS) and relative capacity loss (RCL) [Zang et al. 1999]. The FF algorithm chooses the channel with the lowest index not used in the route. The RP algorithm selects randomly a channel available in the route. The MU algorithm chooses the most used wavelength in the entire network for the route. It plays a similar role of the FF algorithm, as it tends to use the wavelengths already used in other links of the network and lets other wavelengths for longer lightpaths. On the other hand, the LU algorithm chooses the least used wavelength in the entire network and spreads the used wavelengths like in the RP algorithm. The max-sum algorithm considers all possible paths in the network and attempts to maximize the remaining path capacities after the lightpath establishment. The relative capacity loss algorithm is based on max-sum by normalizing the evaluation formula used by max-sum.

However, the previous cited WA heuristics were not designed for networks with physical layer limitations. In transparent optical networks, the signal remains in the optical domain between the edge nodes, accumulating noise and other degrading effects, which are not removed. This is because in transparent networks there is no signal conversion from optical to electrical in regenerators, as in opaque networks. Therefore, a improper choice for wavelength assignment can severely degrade the signal quality and the network performance. Thus, recently, some impairment aware wavelength assignment (IA-WA) algorithms have been proposed to overcome this limitation. He and Brandt-Pearce [He and Brandt-Pearce 2006b] proposed a IA-WA algorithm (FFwO) using the idea of choosing the wavelength according to a list, as in the FF approach, but the order of the list is designed to minimize the occurrence of adjacent channels. The same authors [He and Brandt-Pearce 2006a] proposed other IA-WA algorithm (FFwSS) that tries to find the least physical impaired channel. In the sequence, He *et al.* [He et al. 2007] proposed a hybrid algorithm (AFFwSS) that combines the two previous approaches by switching between them based on a threshold pre-determined in a preliminary calibration simulation. Using a similar approach Fonseca *et al.* [Fonseca et al. 2004] proposed a wavelength assignment based on the first-fit algorithm using off-line optimized priority lists. These priority lists are determined using two different classes of heuristics aimed at finding sub-optimal solutions due to a four wave mixing (FWM) noise. Marsden *et al.* [Marsden and Maruta 2008] used a FF scheme in a network impaired by FWM noise, checking the QoS requirements before the connection is set up. In a network impaired by the residual dispersion (RD), Zulkifli *et al.* proposed [Zulkifli et al. 2007] two heuristics: best fit (BF), where wavelengths are indexed according to their end-to-end RD from the lowest to the highest value and just enough (JE), that assigns the wavelength that has the closest value of RD below the requested residual dispersion QoS threshold.

All these IA-WA algorithms tend to optimize the network performance for a single impairment, not considering a situation where many different impairments have impact on the signal quality and network performance. In a network scenario where many different impairments take place, it is difficult to find a first fit list that can balance all impairments together in order to improve the network performance. For example, one must spread the channels to minimize the FWM impairment. On the other hand, one must assign channels as close as possible to the zero residual dispersion wavelength to minimize the residual

dispersion effect.

In this paper we propose a novel wavelength assignment strategy for all-optical networks. The main idea is to determine the wavelength activation order in a first fit algorithm taking into account the physical layer impairments by using an optimization algorithm inspired in evolutionary computation concepts. Our algorithm is, in principle, well suitable for any number of physical impairments, since the first fit list is obtained according to overall network blocking probability. Thus, it tends to balance all relevant impairments to improve the network performance. The optimization algorithm presents some concepts recently proposed in the computational intelligent field, such as an external archive to store the best solutions. Our proposed IA-WA algorithm is compared to others WA algorithms such as first fit (FF), best fit (BF) and random pick.

This paper is organized as follows: In section 2, we describe our IA-WA algorithm based on evolutionary computation. In section 3 we present the details about the simulation setup. In section 4 we present the physical layer model used in the simulations. In section 5 we show the results. In section 6 we give our conclusions.

2. Wavelength assignment using evolutionary concepts

In this section, we describe the proposed wavelength assignment algorithm based on evolutionary concepts. We propose to use a computational intelligent search algorithm to find the wavelength assignment order that minimizes the overall blocking probability. Our proposed algorithm to select the wavelength assignment order is not a conventional evolutionary algorithm, such as genetic algorithms or differential evolution. It is an algorithm designed to satisfy the requirements imposed by our application constraints. Despite we are using a single objective, that is to minimize the blocking probability, it uses a novel concept from intelligent multi-objective algorithms called external archive. This external archive stores the best solutions obtained by the evolutionary algorithm obtained from previous iterations. The pseudo-code of our algorithm is shown in Table 1.

Table 1. Pseudo-code of our evolutionary algorithm used to determine the wavelength assignment order.

Pseudo code	
1	Initialize the external archive with a random population P
2	Evaluate the fitness of the individuals in the external archive
3	While the stopping criterion is not reached do
4	Select an individual from external archive using Roulette wheel ($ind1$)
5	Clone this individual
6	Mutate this individual
7	Select randomly other individual ($ind2$)
8	Perform binary tournament between ($ind1$) and ($ind2$)
9	If ($ind2$) wins do
10	Replace ($ind2$) in the position of ($ind1$) in the external archive
11	End

The external archive is composed by a population with P individuals, where an individual consists of a potential solution for the problem. In this case, each individual is a possible wavelength assignment list with W channels to be used by our WA algorithm. Each channel is labeled with a number from 1 to W according to its position on the

wavelength grid. One should note that a channel can not appear more than once on the same individual.

The fitness is evaluated for all the individuals separately. For each individual, we run a network simulation with the wavelength assignment order and the fitness of this individual is the blocking probability obtained from this simulation. The lower is the blocking probability, the stronger is the individual.

We perform the number of iterations necessary to reach the stopping criterion. In our case, we adopted a predefined number of iterations as the stopping criterion. In each iteration, the algorithm selects an individual from the external archive using roulette wheel, *i.e.* individuals with a lower blocking probability have more chance to be selected. It is because the better individuals will need less modifications to reach the best wavelength assignment order. Because of the constraint imposed by fact that an individual can not have repeated wavelengths, the crossover operator is not suitable for this application. Hence, a mutation operator based on swapping positions in the list were used.

After the selection, using the roulette wheel, the selected individual is cloned and a single swap mutation is applied, *i.e.* only one permutation is performed on the clone individual. Then, a binary tournament is performed between this new individual and other individual randomly selected from the external archive. If the modified clone wins, *i.e.* if it presents a lower blocking probability in the network simulation, this individual replaces the individual randomly selected for the tournament in the external archive.

Note that this evolutionary process to obtain the optimized first fit list for WA should runs offline, *i.e.* prior to the network operation. In the online operation of the network the list is already available. In fact, the optimized first fit list can be frequently updated, to account for any change in network topology or device characteristics, by a offline simulation process that should run in the background to the normal network operation. For this reason we call this offline optimization process as training stage.

3. Simulation setup

The optical network simulation is performed as follows: upon a call request, the route is defined by a routing algorithm using the shortest path cost function. Then a wavelength is selected by the WA algorithm. After that, the pulse broadening due to residual dispersion is evaluated. If it is above a maximum percentage of pulse broadening $\delta_{\%QoS}$, the call is blocked. Similar checking is performed to optical signal to noise ratio ($OSNR$) in the output of the chosen lightpath. If it is above the pre-determined level ($OSNR_{QoS}$) the call is established, otherwise it is blocked. The physical layer models used for the evaluation of the pulse broadening due to residual dispersion and evaluation of $OSNR$ will be described in the next section. The blocked calls are lost. The blocking probability is obtained from the ratio between the number of blocked calls and the total number of call requests. Our algorithm also blocks a call if there is no wavelength available for the respective lightpath.

For each network simulation a set of 10^7 calls are generated by choosing randomly (uniform distribution) the source-destination pair. The call request is characterized as a Poisson process. We assume circuit switched bidirectional connections in two different fibers and no wavelength conversion capabilities. The default parameters used in our

simulations are listed in Table 2. Amplifier gains are set to compensate for the link losses. According to equations 10 and 11, the residual dispersion is null at 1541.35 nm.

Table 2. Default simulation parameters.

Parameter	Value	Definition
P_{Laser}	-4 dBm	Output transmission power
P_{sat}	19 dBm	Amplifier output saturation power.
OSNR_{in}	30 dB	Input optical signal-to-noise ratio.
OSNR_{QoS}	23 dB	Optical signal-to-noise ratio for QoS criterion.
B	40 Gbps	Transmission bit rate.
B_o	100 GHz	Optical filter bandwidth.
W	32	Number of wavelengths in an optical link.
Δf	100 GHz	Channel spacing.
λ_i	1529.56 nm	The lower wavelength of the grid.
λ_0	1557 nm	Zero dispersion wavelength for transmission fiber.
$\lambda_{0\text{DCF}}$	1550 nm	Zero dispersion wavelength for compensation fiber.
α	0.2 dB/km	Fiber loss coefficient.
L_{Mx}	3 dB	Multiplexer loss.
L_{Dx}	3 dB	Demultiplexer loss.
L_{Sw}	3 dB	Optical switch loss.
F_0 (NF)	3.162 (5 dB)	Amplifier noise factor (Noise figure).
$D_{\text{TF}}(@1541.35 \text{ nm})$	0.939 ps/km.nm	Dispersion coefficient of the transmission fiber.
$S_{\text{TF}}(@1541.35 \text{ nm})$	0.06 ps/km.nm ²	Dispersion slope of the transmission fiber.
$D_{\text{DCF}}(@1541.35 \text{ nm})$	-1.87 ps/km.nm	Dispersion coefficient of the compensation fiber.
$S_{\text{DCF}}(@1541.35 \text{ nm})$	-126.18 ps/km.nm ²	Dispersion slope of the compensation fiber.
$\delta_{\%QoS}$	10%	Maximum percentage of pulse broadening.

Figure 1 show the network topology used in our simulations. It is a large network similar to the NSFNET.

4. Physical layer model used in the simulations

We used the physical layer model proposed by Pereira *et al.* [Pereira et al. 2008] to perform the network simulations. This model takes into account the spontaneous noise emitted by the optical amplifiers, as well as the gain saturation effect, at the output of the optical amplifiers. Considering the signal-spontaneous beating as the main noise source, this noise can be quantified by [Baney et al. 2000]:

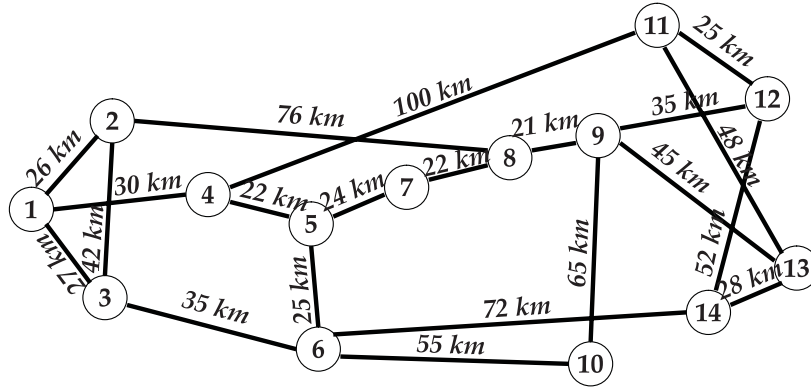


Figure 1. Network topology used in our simulations.

$$N_{\text{amp}} = P_{\text{ASE}} = \frac{hfB_oG_{\text{amp}}F_{\text{amp}}}{2}, \quad (1)$$

where h is the Planck constant, f is the optical signal frequency, B_o is the optical filter bandwidth, G_{amp} is the linear dynamic amplifier gain and F_{amp} is the amplifier noise factor. The amplifier gain saturation effect is taken into account by using the following expression [Martins-Filho et al. 2003]:

$$G_{\text{amp}} = \frac{G_0}{1 + \frac{P_{\text{out}}}{P_{\text{sat}}}}, \quad (2)$$

where G_0 is the non-saturated amplifier gain, P_{out} is the optical power at the amplifier output and P_{sat} is the amplifier output saturation power.

The four wave mixing is a nonlinear effect and it depends on the channel spacing, optical signal power per channel, number of wavelengths propagating in the optical fiber, fiber dispersion coefficient and the zero dispersion wavelength of the transmission fiber. Each FWM generated power can be evaluated using the following equation proposed by Song *et al* [Song et al. 1999]:

$$P_{\text{FWM}}(\lambda) = P_{ijk}(\lambda) = \frac{\eta}{9} D^2 \gamma^2 P_i P_j P_k e^{-\alpha L_{\text{TF}}} \left[\frac{(1 - e^{-\alpha L_{\text{TF}}})^2}{\alpha^2} \right], \quad (3)$$

where D is the degeneracy factor which is equal to three or six for degenerate and nondegenerate FWM, γ is the nonlinear coefficient, P_i , P_j and P_k are the input powers for the signals at frequencies f_i , f_j and f_k , respectively, α is the fiber attenuation coefficient and L_{TF} is the fiber length. η is the FWM efficiency and is given by:

$$\eta = \frac{\alpha^2}{\alpha^2 + \Delta k^2} \left(1 + \frac{4e^{-\alpha L_{\text{TF}}} \sin\left(\frac{\Delta k L_{\text{TF}}}{2}\right)}{(1 - e^{-\alpha L_{\text{TF}}})^2} \right), \quad (4)$$

where Δk is the phase matching factor, which depends on the fiber dispersion and the channel spacing. It can be expressed by:

$$\Delta k = \frac{2\pi\lambda_k^2}{c}\Delta f_{ik}\Delta f_{jk} \left(D_{TF} + S_{TF}(\Delta f_{ik} + \Delta f_{jk})\frac{\lambda_k^2}{2c} \right), \quad (5)$$

where D_{TF} and S_{TF} are the dispersion coefficient and dispersion slope for the transmission fiber, respectively. Δf_{ik} and Δf_{jk} are the frequency separation between wavelengths ik and jk , respectively.

The frequencies generated by FWM process can be determined by [Agrawal 1997]:

$$f_{ijk} = f_i + f_j - f_k, \quad (6)$$

where indexes i and j are different from k .

Considering every optical power component generated by FWM in the reference signal wavelength, we have:

$$N_{FWM} = \sum_{j=1}^m P_{FWM_j}(\lambda), \quad (7)$$

where N_{FWM} is the noise power due to FWM and $P_{FWM_j}(\lambda)$ is one of the m optical power components generated by the FWM effect that falls into the same propagating signal wavelength.

Figure 2 shows the network devices considered by the analytical model in each link [Pereira et al. 2008]. The links have the following elements: transmitter, optical switch, multiplexer, booster amplifier, optical fiber, pre-amplifier, demultiplexer, optical switch and receiver. The points **a** to **h** in Figure 2 are evaluation points where the signal and noise can be determined in the optical domain. For the lightpath with i links, the elements between **b** and **h** are repeated $i - 1$ times before the signal reaches the receiver in the destination node. At the point **h** in Figure 2, one can evaluate the output optical signal power (P_{out}) and the output optical noise power (N_{out}).

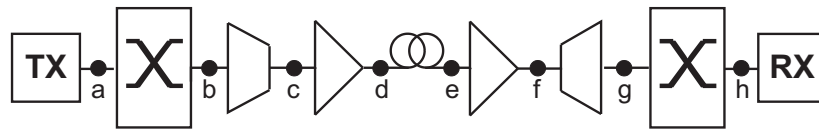


Figure 2. The link configuration for adjacent nodes, with optical devices considered in the analytical model.

Considering a route with i links, we have [Pereira et al. 2008]:

$$P_{out_i} = \left(\frac{G_{amp_{i,1}} e^{-\alpha d_i} G_{amp_{i,2}}}{L_{Mx} L_{Dx} L_{Sw}} \right) P_{out_{i-1}} \quad (8)$$

and

$$\begin{aligned}
N_{out_i} = & \frac{G_{amp1,i} e^{-\alpha d_i} G_{amp2,i}}{L_{Mux} L_{Demux} L_{Switch}} N_{out_{i-1}} + \frac{G_{amp2,i}}{L_{Demux} L_{Switch}} \sum_{j=1}^m P_{FWM_{i,j}}(\lambda) + \\
& + \frac{G_{amp1,i} e^{-\alpha d_i} G_{amp2,i}}{L_{Demux} L_{Switch}} \frac{h\nu(\lambda) B_o}{2} \left(F_{amp1,i} + \frac{F_{amp2,i}}{e^{-\alpha d_i} G_{amp1,i}} \right), \quad (9)
\end{aligned}$$

where $G_{amp1,i}$ and $G_{amp2,i}$ are the dynamic linear gains of the booster and pre-amplifier, α is the fiber loss coefficient, d is the fiber length, L_{Sw} , L_{Mx} and L_{Dx} are the optical switch, multiplexer and demultiplexer losses, $P_{out_0} = \frac{P_{in}}{L_{Sw}}$, $N_{out_0} = \frac{N_{in}}{L_{Sw}}$, P_{in} is the signal power and N_{in} is the noise power at the transmitter output.

Dividing P_{out} by N_{out} , one can obtain the $OSNR$ at destination node ($OSNR_{out}$). A threshold $OSNR$ ($OSNR_{QoS}$) can be established to guarantee the QoS for call requests on the network, and its value is given in Table 2.

The broadening of the optical pulses due to the residual dispersion effect is taken into account as follows [Zulkifli et al. 2007]:

$$\Delta t_{RD} = \Delta \lambda_{transmitter} \sum_{j=i}^i \left\{ \left[D_{TF}^{\lambda_{ref}} + (\Delta \lambda_j S_{TF}) \right] L_{TF_j} + \left[D_{DCF}^{\lambda_{ref}} + (\Delta \lambda_j S_{DCF}) \right] L_{DCF_j} \right\}, \quad (10)$$

where

$$L_{DCF_j} = \left| \frac{L_{TF_j} D_{TF}^{\lambda_{ref}}}{D_{DCF}^{\lambda_{ref}}} \right|. \quad (11)$$

$\Delta \lambda_{transmitter}$ represents the transmitter linewidth, $D_{TF}^{\lambda_{ref}}$, S_{TF} and L_{TF_j} are the chromatic dispersion coefficient in the reference wavelength, the chromatic dispersion slope and the optical fiber length, respectively. $\Delta \lambda_j$ is the difference between the transmitter wavelength and the wavelength where the residual dispersion is zero.

$\delta_{\%}$ represents the temporal broadening to the optical pulse, in percentage. It can be expressed by

$$\delta_{\%} = 100B\Delta t_{RD}, \quad (12)$$

where B represents the transmission bit rate. The maximum $\delta_{\%}$ is given in Table 2.

5. Results

In this section we present simulation results in order to demonstrate the effectiveness of our proposal for wavelength assignment, the optimized first fit (OpFF) WA algorithm. All the simulations were carried out in three different scenarios S_1 , S_2 and S_3 . S_1 scenario takes into account only the FWM effect, S_2 scenario considers both FWM effect and residual dispersion effect, whereas S_3 scenario just considers the residual dispersion. For these network operation simulations we used the same procedure described in section 3, where we can choose among four different wavelength assignment algorithms for comparisons: FF, BF, random pick and our OpFF.

Figure 3 presents the blocking probability distribution for the three scenarios S_1 , S_2 and S_3 for a network load of 60 Erlangs. For the simulations of figure 3 we used the BF as WA algorithm. One can note that the calls are blocked in S_1 due to $OSNR$ degradation (FWM), whereas in S_3 the calls are blocked only by dispersion effects. The causes for blocking in S_2 are balanced.

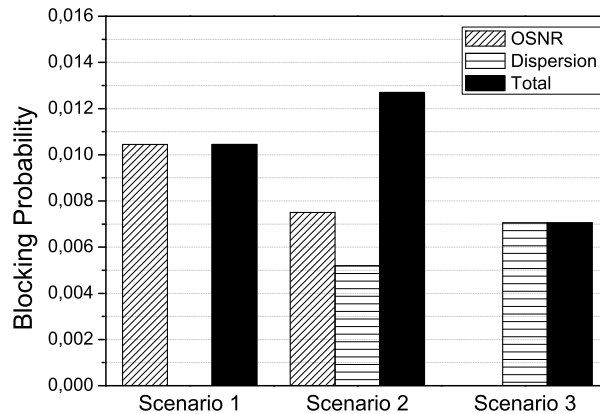


Figure 3. Blocking probability distribution for the three scenarios.

Figure 4 presents the convergence curves for the training stage for the three different scenarios S_1 (circles), S_2 (triangles) and S_3 (squares). As can be seen from Figure 4, the evolutionary algorithm achieved a stable state after 3000 iterations with a blocking probability around 0.00081 for S_1 , after 1000 iterations with a blocking probability around 0.0086 for S_2 and after 1200 iterations with a blocking probability around 0.0065 for S_3 . Note that in any case, after about 1000 iterations the blocking probability is reduced by about one order of magnitude. Table 3 presents the wavelength assignment lists for scenarios S_1 , S_2 and S_3 found by the evolutionary algorithm in the training stage. The list numbers represent the first to the 32th wavelength of the grid used in these simulations. For example, for the S_1 scenario the first wavelength to be used is the 5th wavelength in the grid.

Table 3. Optimized FF lists found after training stage.

Scenario	List
S_1	5 30 3 17 26 1 8 24 29 18 9 16 20 22 7 11 15 23 13 6 12 4 10 21 14 2 19 32 25 28 27 31
S_2	21 24 9 22 18 25 11 8 14 7 10 16 23 13 17 20 19 15 12 27 5 6 4 2 3 26 30 28 29 32 1 31
S_3	25 20 17 8 9 19 24 15 16 11 23 22 10 13 14 21 7 12 18 6 26 27 5 4 3 28 2 32 1 29 31 30

Figure 5 shows the number of noise components generated by FWM and relative difference between the number of generated noise components as a function of the number of active channels in the network in scenarios S_1 and S_2 . We do not present any result for S_3 since this scenario just considers the residual dispersion. Figure 5 was obtained for a single link, rather than for the network, to make it easier to control the number of active channels. The number of FWM noise components was obtained from Equation 3. solid symbols are used to present the number of noise components generated for three distinct situations: FF (squares), OpFF in scenario S_1 (triangles) and OpFF in scenario S_2 (circles). The open symbols are used to present the relative difference between the FF and OpFF cases. Figure 5 shows how effective the OpFF algorithm is in reducing the

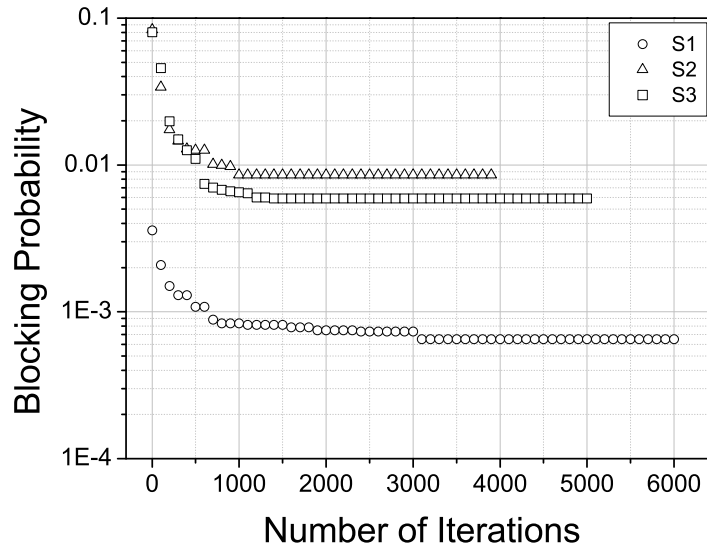


Figure 4. Evolution of the blocking probability as a function of the number of generations in the training stage, for the three scenarios.

detrimental effect of FWM, compared to the FF algorithm. For example, for 15 active wavelengths in a single link of the network the OpFF leads to the generation of half the number of noise components due to FWM than the FF algorithm, for scenario S_1 . For scenario S_2 the reduction in the number of noise components obtained from the OpFF is 20%. This is because in S_2 scenario the network is also impaired by residual dispersion. Figure 5 also shows that as the number of active channels increases, towards using 32 out of 32 possible channels, the benefit of using the OpFF decreases. However, one should keep in mind that in this extreme situation, where most of the channels are active at the same time, the network blocking probability would be too high anyhow, due to lack of available wavelengths.

Figures 6, 7 and 8 present the blocking probability as a function of the network load for 4 different WA algorithms in scenarios S_1 , S_2 and S_3 , respectively. The WA algorithms are first fit (squares), random (circles), best fit (up-triangles) and our proposed optimized first fit (down-triangles).

In all cases, the BF and OpFF WA algorithms outperformed the FF and the random algorithms. In the S_3 scenario BF and OpFF achieved a similar performance since the BF algorithm is designed to avoid dispersion effects. However, the OpFF algorithm obtained a slightly better performance for S_2 scenario. Furthermore, our proposal outperformed all others approaches, including the BF algorithm, for the S_1 scenario. This occurs because the BF algorithm can not treat other effects such as FWM.

6. Conclusions

We presented a novel strategy for impairment aware wavelength assignment in all-optical networks based on evolutionary concepts. The algorithm uses a list for wavelength assignment predetermined in a training stage by an intelligent optimization algorithm. We tested our proposal on a simulation environment that emulates a sophisticated physical

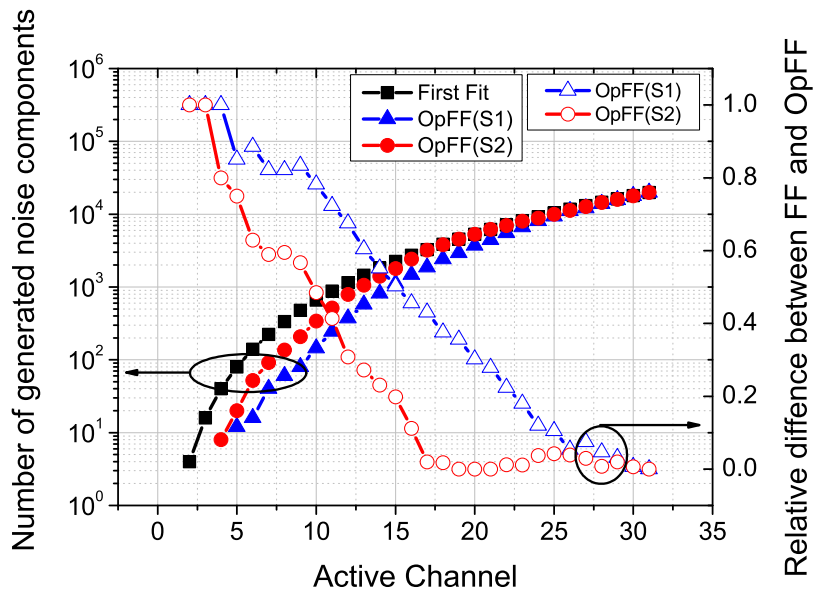


Figure 5. Number of noise components generated by FWM and relative difference between the number of noise components generated by the FF and by the optimized FF, as a function of the number of active channels in the network, in scenarios S_1 and S_2 .

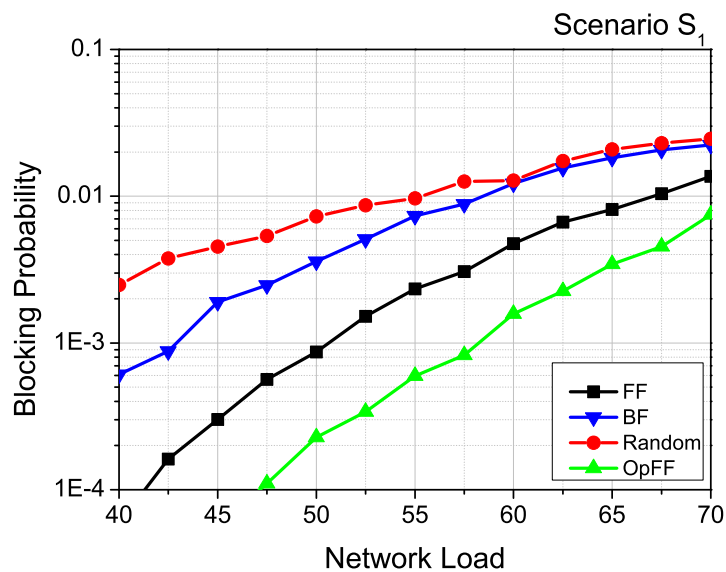


Figure 6. Blocking probability as a function of the network load for 4 different WA algorithms in scenario S_1 .

model based on OSNR degradation and temporal broadening penalties. The wavelength assignment algorithm was compared with others classical algorithms such as first fit, best fit and random pick. It achieved the best performance in all the cases. The best fit wavelength assignment algorithm achieved a similar performance for the case where the physical layer is limited by dispersion, but did not achieved such performance in other cases. It indicates that our algorithm is capable to learn and adapt itself to the network conditions during the training stage. Note that this training stage to obtain the optimized first fit list

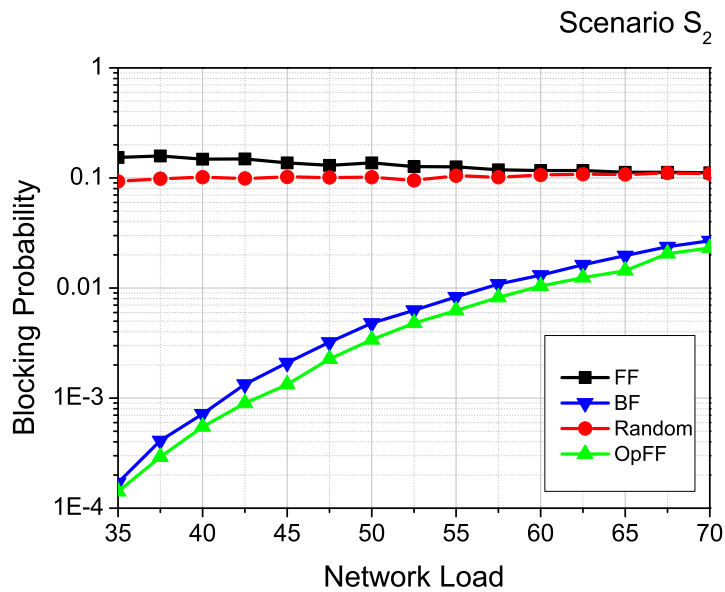


Figure 7. Blocking probability as a function of the network load for 4 different WA algorithms in scenario S_2 .

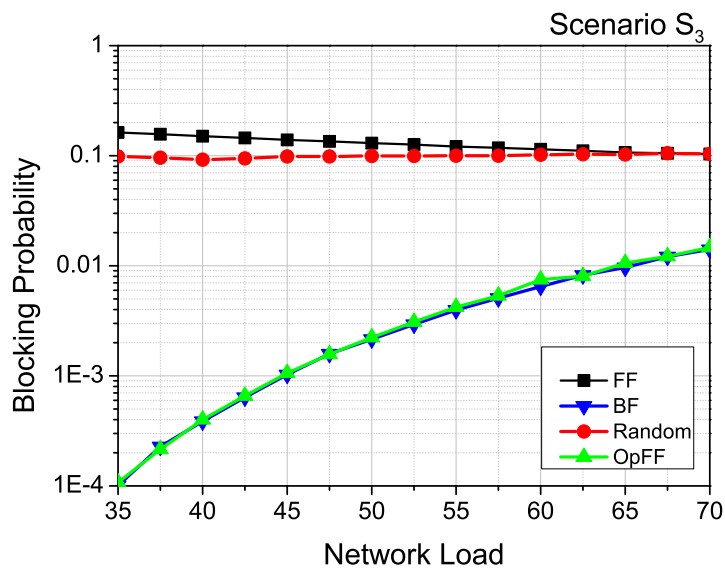


Figure 8. Blocking probability as a function of the network load for 4 different WA algorithms in scenario S_3 .

for WA should run offline, *i.e.* prior to the network operation. In the online operation of the network the list is already available. Therefore, the issues related to the computation complexity and time to find the solutions for our proposal are not critical.

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