Novel Adaptive Routing Algorithm for All-Optical Networks Based on Power Series and Particle Swarm Optimization

Daniel A. R. Chaves[1], Douglas O. Aguiar[1], Carmelo J. A. Bastos-Filho[2], Joaquim F. Martins-Filho[1]

[1]Department of Electronics and Systems, Federal University of Pernambuco, Recife-PE, CEP: 50740-530, Brazil

[2]Department of Computing and Systems, University of Pernambuco, Recife-PE, CEP: 52720-001, Brazil

email:jfmf@ufpe.br, cjabf@dsc.upe.br

Abstract. *In all-optical networks, signals are transmitted through physical layer with no regeneration. Therefore, noise accumulation along lightpath can severely impair optical signal-to-noise ratio. For this reason, many efforts have been made to develop impairment aware routing and wavelength assignment algorithms (IRWA) in order to mitigate the impairments effects, improving the network performance. In this paper we propose a systematic form to build an adaptive impairment aware cost function based on arbitrary set of chosen input network parameters. The cost function is based on power series expansion. Our routing algorithm is called Power Series Routing (PSR). An computational intelligence technique, Particle Swarm Optimization, is used to find the coefficients of the expansion.*

1. Introduction

All-optical networks have been considered as the most reliable and economic solution to achieve high transmission capacities with proper quality of service (QoS). There are two main challenges to manage these networks providing QoS: define an appropriate routing and wavelength assignment algorithm (RWA) and obtain acceptable optical signal-to-noise ratio (OSNR) for every channel.

The RWA problem is a classic problem in transparent 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. 2000]. The wavelength assignment algorithm has to decide which available channel should be used to establish the call [Mukherjee 2000], [Zhou and Yuan 2002]. Some routing algorithms use heuristics based on a pre-defined metrics. Some examples are: the shortest path (SP), minor delay, load balance [Tanenbaum 2003], lower noise figure in lightpath [Martins-Filho et al. 2003b].

Some RWA algorithms just consider the wavelength availability. However, this is a reasonable assumption only for opaque networks, in which the optical signals are regenerated at each node. In this scenario, many different link cost functions to guide the RWA process have been reported: Hops Based (HW), Distance Based (SP, shortest path), Available Wavelength (AW), Hop Count and Available Wavelengths (HAW), Total Wavelengths and Available Wavelengths (TAW), Hop Count and Total Wavelengths and Available Wavelengths (HTAW) [Bhide et al. 2001] and Least Resistance Weight (LRW) [Wen et al. 2005]. The main aim of these approaches is to achieve an improved load distribution or to minimize the use of the physical layer resources.

On the other hand, in transparent all-optical networks there is no signal regeneration at intermediate nodes along the lightpaths. Therefore, the signals accumulate noise due to transmission impairments. For this reason, the routing algorithm must be aware of these physical penalties to fetch routes that minimize OSNR degradation due to optical noise. Recently, many efforts have been made to develop RWA algorithms that consider physical impairments [Martins-Filho et al. 2003b], [Cardillo et al. 2005], [Chaves et al. 2007], [Tomkos et al. 2007]. The main goal of this approach is to minimize the blocking probability by finding routes considering physical layer status. Although routing schemes based on optical impairments outperform the most common approaches, the use of these algorithms implies in higher computational complexity.

In optical networks constricted by impairments, most reported studies concerning the solution of the RWA problem can be classified into three major categories. In the first category the RWA algorithm is treated in two steps: first a lightpath computation in a network layer module is provided, followed by a lightpath verification performed by the physical layer module. Different routing schemes have been proposed using this approach. In [Ramamurthy et al. 1999] the authors modeled their impairment-aware RWA algorithm taking into account the amplified spontaneous emission noise (ASE) generated in Erbium doped fiber amplifier (EDFA) and crosstalk added by the optical switch and compared the estimated bit error rate (BER) against a determined threshold. In [Huang et al. 2005] the authors modeled their impairment-aware RWA algorithm taking into account the polarization mode dispersion (PMD) and OSNR performance parameters separately and compared them against two threshold levels at the end of the route.

In the second category, the RWA algorithm is treated in three steps: first a lightpath computation in a network layer module is provided resulting in one (or none) feasible lightpath for each wavelength in network. Then, for each feasible lightpath found, a verification is performed by the physical layer module. Among the lightpaths that passed in physical layer module verification the best one is chosen, considering some metric. Pointurier *et al.* [Pointurier and Brandt-Pearce 2005] used this approach and developed a routing scheme based on Q-factor, which incorporates the effects of the compounded crosstalk in both physical layer module verification and choosing lightpath to set up the call. In [Anagnostopoulos et al. 2007] the authors developed a similar approach, nevertheless, considering the four wave mixing (FWM), cross phase modulation (XPM) and EDFA ASE noise effects.

In the third category, RWA algorithm itself is aware of physical impairments and uses the impairments information for routing procedure. Martins-Filho *et al.* proposed in [Martins-Filho et al. 2003a] a dynamic routing algorithm which selects the route based on lowest physical impairments, including ASE accumulation, amplifier gain saturation and wavelength dependent gain along the path and then calculate BER to check for the required signal quality. In [Cardillo et al. 2005] the authors proposed to use the OSNR model considered in [Huang et al. 2005] with some enhancements to consider non-linear penalties as well as the linear effects that occur along lightpath transmission. In [Kulkarni et al. 2005] the authors utilized the Q-factor as a performance parameter, and integrates the effects of the linear impairments (chromatic dispersion, PMD, ASE noise, cross-talk and filter concatenation).

In this paper we propose a systematic form to build the link cost function based on a set of relevant network parameters. It is a important tool for routing algorithm design, since the determination of the important parameters for link cost evaluation is a relatively easy task for a network specialist. However, to find the best cost function that combines these parameters is a much more complex task. We apply the proposed scheme to build an adaptive cost function for impairment aware routing, which we call PSR (Power Series Routing). We use PSR to provide the link cost for a lowest cost routing algorithm (*e.g.* Dijkstra's algorithm). The PSR is based on the expansion of the cost function in a power series. Simple network parameters such as link availability and link length were used as input variables for the cost function. The power series coefficients are found by the Particle Swarm Optimization (PSO) technique, and they take into account several physical impairments. The proposed PSR combines simplicity and fastness of the schemes commonly used in opaque networks with the high performance (*i.e.* low blocking probability) obtained from the impairment aware schemes. For this reason, PSR has similar mathematical formulation to the weight functions reported in [Bhide et al. 2001]. However, differently from those ones, PSR is trained based on physical impairments.

This paper is organized as follows: In section 2 we present our novel routing algorithm. In section 3 we describe the PSO technique used in this paper. In section 4 we present the optical physical layer models used to evaluate the performance of the routing algorithms. In section 5 we show the parameters and network topology used in our simulations. In section 6 we present the results. In section 7 we give our conclusions.

2. Power Series and Algorithm Description

In this section we present a new approach to build a link cost function for network routing. The proposed approach consists of 3 steps, basically: First, a number of input variables for the cost function is chosen by a network specialist. Then, the cost function is written in terms of a series of functions. And finally, an optimization algorithm is used to find the series coefficients that minimizes the network blocking probability.

It is well known that functions can be expressed in terms of series. Many of these representations use a complete set of orthogonal functions. For example, one can expand a single variable function $f(x)$ in a set of ortogonal functions as:

$$f(x) = \sum_{n=0}^{\infty} a_n \varphi_n(x), \tag{1}$$

where $\varphi_n(x)$ $n = 0, 1, 2...$ is a given set of ortogonal base functions. According to the different $\varphi_n(x)$ used, the series has different names *e.g.*, Taylor's series for $\varphi_n(x) = 1, x, x^1, x^2, ...$, Legendre's series for $\varphi_n(x) = L_n(x)$ (Legendre's polynomials), Fourier's series for $\varphi_n(x)$ as harmonic sine and cosine functions. The two former schemes make use of a set of orthogonal polynomials and the latter uses a set of orthogonal trigonometric functions.

In this paper, we focus our analysis in the series that make use of a set of orthogonal polynomials. By setting $\varphi_n(x) = 1, x, x^1, x^2, ...$, one can obtain from Eq. (1):

$$f(x) = \sum_{n=0}^{\infty} a_n x^n. \tag{2}$$

Assuming the continuity of the function and its derivatives, the expansion in Eq. (2) can also be done for a multivariable functions:

$$f(x_0, x_1, ..., x_k) = \sum_{n_0=0}^{\infty} \sum_{n_1=0}^{\infty} ... \sum_{n_k=0}^{\infty} b_{n_0,n_1,...,n_k} \prod_{j=0}^{k} x_j^{n_j}. \tag{3}$$

It is well known that one can find $b_{n_0,n_1,...,n_k}$ by means of derivatives (multivariable Taylor's series) [Lang 1970]. However, this approach works only for a function with derivatives. Despite the fact that there is no simple closed analytical form to find $b_{n_0,n_1,...,n_k}$ coefficients for piecewise continue functions, Eq. (3) can also represent these functions by using special polynomials such as Legendre's polynomials and Hermite's polynomials [Arfken and Weber 2005]. Nevertheless, the lack of an analytical form to find $b_{n_0,n_1,...,n_k}$ is not an obstacle if one is able to find these coefficients by a non analytical procedure.

Therefore, We use the proposed approach to build an adaptive cost function for impairment aware routing, which we call power series routing (PSR). The first step is to choose the input variables for the cost function. In optical networks the information about link length, link availability and number of hops have high correlation with noise accumulated along the lightpath. As the link length increases, higher gains must be provided by the optical amplifiers to compensate the losses. Therefore, more the ASE noise is added by optical amplifier in the lightpath. Link usage has impact in amplifier saturation and ASE noise generation, since the amplifier gain and noise figure depends on the total input signal power [Ramaswami and Sivarajan 2002], [Pereira et al. 2007a]. Furthermore, as the number of hops increases, more crosstalk noise is added in intermediate nodes. Therefore, these elementary network parameters could be used to build a simple routing scheme, instead of using the noise information, yet obtaining similar network performance results to schemes that use optical noise information to compose the cost function [Chaves et al. 2007]. For reasons above, we choose as input variables for the cost function two simple network parameters: normalized link availability and normalized route length.

The second step is to write the cost function in terms of a series as in Eq. (3), according to the number of network parameters chosen. Therefore, the link cost between nodes i and j can be expressed in a two variables form of Eq. (3) by:

$$f(x_{i,j}, y_{i,j}) = \sum_{n_0=0}^{\infty} \sum_{n_1=0}^{\infty} b_{n_0,n_1} x_{i,j}^{n_0} y_{i,j}^{n_1}, \tag{4}$$

where $x_{i,j}$, and $y_{i,j}$ are, respectively, the link availability and normalized link length between the nodes i and j. $x_{i,j}$ is defined as:

$$x_{i,j} = \frac{\lambda_{i,j}^{a}}{\lambda_{i,j}^{T}}, \tag{5}$$

where $\lambda^a_{i,j}$ and $\lambda^T_{i,j}$ are, respectively, the number of unused and total number of wavelengths in the link between nodes i and j. The normalized link length $y_{i,j}$ is defined as:

$$y_{i,j} = \frac{d_{i,j}}{d_{max}}, \tag{6}$$

where $d_{i,j}$ is link length between nodes i and j and d_{max} is the maximum link length in the network. Since it is not possible to have an infinite number of terms in Eq (4), one shall truncate the series in order to obtain an approximation with N terms:

$$f(x_{i,j}, y_{i,j}) = \sum_{n_0=0}^{N} \sum_{n_1=0}^{N} b_{n_0,n_1} x_{i,j}^{n_0} y_{i,j}^{n_1}. \tag{7}$$

One can note from Eq. (7) that this function has a constant term. This term includes a hop count computation.

The third step consists of using PSO to find the series coefficients that optimizes a network performance parameter. We used PSO because it achieves a better performance in high dimensionality problems than other optimization techniques (e.g. Genetic Algorithms) [Engelbrecht 2005]. For example, it can maximize the network throughput or minimize network blocking probability. In this paper we find the $b_{n_0,n_1,\ldots,n_k}$ coefficients that minimize blocking probability as will be described in the next section.

It must be highlighted that one can include an arbitrary number of input parameters in order to build the cost function, including direct information about the physical impairments.

3. Particle Swarm Optimization

In order find the b_{n_0,n_1} coefficients, as discussed in previous section we used an intelligent optimization technique called Particle Swarm Optimization (PSO) [Engelbrecht 2005]. PSO was proposed by Kennedy and Eberhart in 1995 and it is inspired in bird flocking [Kennedy and Eberhart 1995]. In PSO, each particle i is a possible solution of the problem and it has some properties such as its current velocity $\overrightarrow{v}_i$, its current position $\overrightarrow{x}_i$ and its best position in past $\overrightarrow{p}_i$. For the Swarm communication topology we used the local topology in a ring model, also known as *Lbest*, in which each particle has information about only two neighborhoods of the swarm [Bratton and Kennedy 2007]. It is recommend in [Bratton and Kennedy 2007] to use local best model, instead of global best model used in first PSO definition, since the global best approach has a higher probability to be trapped in local minima. Denoting by $v_{i,d}$ the d^{th} component of $\overrightarrow{v}_i$ vector and using the same notation for the other vectors we can state the pseudo code algorithm that we used to implement PSO optimizer as shown in table 1. $g()$ returns the fitness of one particle and $min_i(\overrightarrow{p}_{neighbors})$ returns the position $\overrightarrow{p}_{neighbor}$ of the fitter particle among the two neighbors of the particle i.

As one can see in the Table 1, particle velocity is updated using the *constriction* factor approach [Clerc and Kennedy 2002]. In this approach the particle velocity is updated using the following equation:

$$v_{i,d} = \chi[v_{i,d} + c_1\epsilon_1(p_{i,d} - x_{i,d}) + c_2\epsilon_2(p_{g,d} - x_{i,d})], \tag{8}$$

Table 1.

```
PSO algorithm for minimization
initialize randon population
Do
  For i = 1 to Population Size
    if g(x_i) < g(p_i) then  p_i = x_i
    p_g = min_i(p_neighbors)
    For d = 1 to Dimension
      v_{i,d} = χ(v_{i,d} + c1ε1(p_{i,d} − x_{i,d}) + c2ε2(p_{g,d} − x_{i,d}))
      x_{i,d} = (v_{i,d} + x_{i,d})
    Next d
  Next i
Until termination criterion is met
```

where the χ is evaluated by:

$$\chi = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}, \quad \varphi = c_1 + c_2. \tag{9}$$

In [Clerc and Kennedy 2002] the authors found that if $\varphi > 4$, the algorithm convergence is guaranteed. For this reason we have chosen the same approach for our PSO implementation.

4. Physical Impairments Modeling

In this section we describe the physical impairments model used in this work to evaluate optical noise. This model was proposed by [Pereira et al. 2007b]. The formulation quantifies the OSNR degradation along the optical signal propagation in the all-optical network. The impact of physical layer impairments is taken into account by considering both the signal power and the noise power at the destination node, both affected by gains and losses along the lightpath. Moreover, network elements add noise components. The optical amplifiers add ASE noise power and also suffer from gain saturation and ASE depletion as the total signal power increases. The optical switches add noise due to non-ideal isolation between ports. The effect of chromatic dispersion is neglected since we assume that group velocity dispersion (GVD) is totally compensated in the network links. We did not consider the PMD and FWM effects in the simulations presented in this paper. Fig. 1 shows the network devices considered in the model in each link. The links have the following elements: transmitter, optical switch, multiplexer, booster amplifier, optical fiber, pre-amplifier, demultiplexer, optical switch and receiver.

The points a until h are measurement points where the signal and noise can be determined in the optical domain. In point a, we have the input optical signal power (P_{in}) and the input optical noise power (N_{in}). The ratio between P_{in} and N_{in} defines the OSNR of the transmitter (OSNR_{in}). For the lightpath with k links, the elements between b and h are repeated k times before the signal reaches the receiver in the destination node.

At points b and h, the model considers the noise induced by homodyne crosstalk in the optical switch. This occurs basically because the energy of one optical sig-

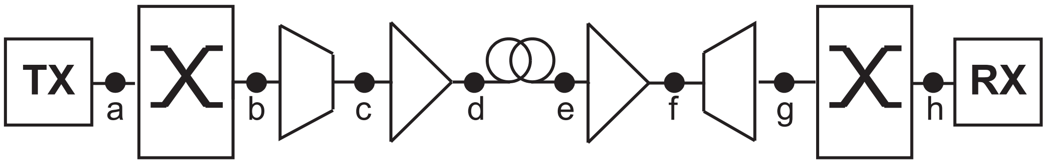


Figure 1. The link configuration with optical devices considered in our model.

nal can leak to other co-propagating signals due to non-ideal optical switches. The optical noise power generated by each optical switch in every wavelength is given by [Ramaswami and Sivarajan 2002]:

$$N_{Switch} = \varepsilon \sum_{j=1}^{n} P_{Sw_j}(\lambda), \tag{10}$$

where $P_{Sw_j}(\lambda)$ is the received optical power from the jth optical fiber in the same wavelength of the propagating optical signal, ε is the switch isolation factor and n is the number of signals in the same wavelength received from others links. At points c and g, it is just considered the multiplexer and demultiplexer losses.

At points d and f the noise induced by the optical amplifiers, as well as the gain saturation effect are taken into account. Considering the signal-spontaneous beating as the main noise source, this noise can be quantified by [Baney et al. 2000]:

$$N_{amp} = \frac{h\nu(\lambda) B_o G_{amp} F_{amp}}{2}, \tag{11}$$

where h is the Planck constant, $\nu(\lambda)$ is the optical signal frequency, B_o is the optical filter bandwidth, G_{amp} is the dynamic amplifier gain and F_{amp} is the amplifier noise factor.

The gain saturation effect is taking into account by using the following expression [Martins-Filho et al. 2003a, Martins-Filho et al. 2003b]:

$$G_{amp} = \frac{G_0}{1 + \frac{P_{out}}{P_{sat}}}, \tag{12}$$

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

Since F_{amp} depends on the input optical power, the following expression is used to model this effect [Pereira et al. 2007a], [Pereira et al. 2007b]:

$$F_{amp} = F_0 \left(1 + A_1 - \frac{A_1}{1 + \frac{P_{in}}{A_2}} \right), \tag{13}$$

where F_0 is the amplifier noise factor for low input optical powers, A_1 and A_2 are function parameters. These parameters were obtained by fitting experimental results from an Erbium doped fiber amplifier.

Finally, at the point h, one can evaluate the output optical signal power (P_{out}) and the output optical noise power (N_{out}). P_{out} is evaluated according to the gains and losses along the signal propagation and it is given by:

$$P_{out} = \frac{G_{amp_1} e^{-\alpha d} G_{amp_2}}{L^2_{Switch} L_{Mux} L_{Demux}} P_{in}, \tag{14}$$

where G_{amp_1} and G_{amp_2} are the dynamic linear gains of the booster and pre-amplifier, α is the fiber loss coefficient, d is the fiber length, L_{Switch}, L_{Mux} and L_{Demux} are the optical switch, multiplexer and demultiplexer losses.

N_{out} is evaluated from the source node to the destination node, including the additive noise component in the respective points along the lightpath and is given by:

$$\begin{aligned} N_{out} =& \frac{G_{amp_1} e^{-\alpha d} G_{amp_2}}{L_{Mux} L_{Demux} L^2_{Switch}} N_{in} + \frac{G_{amp_1} e^{-\alpha d} G_{amp_2}}{L_{Mux} L_{Demux} L_{Switch}} \varepsilon \sum_{j=1}^{n} P_{Sw_{1,j}}(\lambda) + \\ &+ \frac{G_{amp_1} e^{-\alpha d} G_{amp_2}}{L_{Demux} L_{Switch}} \frac{h\nu(\lambda) B_o}{2} \left(F_{amp_1} + \frac{F_{amp_2}}{e^{-\alpha d} G_{amp_1}} \right) + \varepsilon \sum_{j=1}^{s} P_{Sw_{2,j}}(\lambda), \end{aligned} \tag{15}$$

where N_{in} is the noise power at the transmitter output.

Dividing P_{out} by N_{out}, one can obtain the OSNR at destination node ($OSNR_{out}$). The $OSNR_{out}$ is related directly to the BER [Thyagarajan and Ghatak 1998]. Therefore, one can establish a threshold OSNR that guarantees the QoS ($OSNR_{QoS}$) for call requests on the network.

Considering a route with a number of i links:

$$P_{out_i} = \left(\frac{G_{amp_{i,1}} e^{-\alpha d_i} G_{amp_{i,2}}}{L_{Mux} L_{Demux} L_{Switch}} \right) P_{out_{i-1}}, \tag{16}$$

for the optical signal power and:

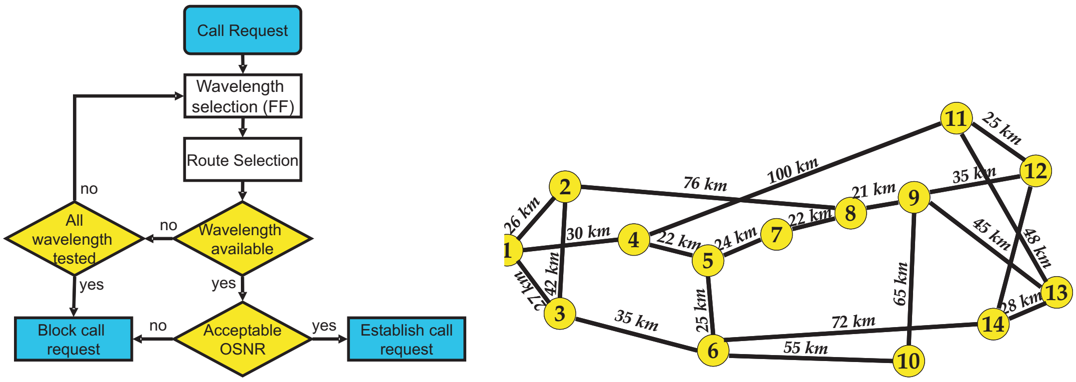
$$\begin{aligned} N_{out_i} =& \frac{G_{amp_{1,i}} e^{-\alpha d_i} G_{amp_{2,i}}}{L_{Mux} L_{Demux} L_{Switch}} N_{out_{i-1}} + \varepsilon \sum_{j=1}^{s} P_{Sw_{i+1,j}}(\lambda) + \\ &+ \frac{G_{amp_{1,i}} e^{-\alpha d_i} G_{amp_{2,i}}}{L_{Demux} L_{Switch}} \frac{h\nu(\lambda) B_o}{2} \left(F_{amp_{1,i}} + \frac{F_{amp_{2,i}}}{e^{-\alpha d_i} G_{amp_{1,i}}} \right), \end{aligned} \tag{17}$$

for optical noise, where $N_{out_0} = \dfrac{N_{in}}{L_{Switch}} + \varepsilon \sum_{j=1}^{n} P_{Sw_{1,j}}(\lambda)$ and $P_{out_0} = \dfrac{P_{in}}{L_{Switch}}$.

5. Simulations Setup

Our simulation software follows the flow chart shown in Fig 2(a). Upon a call request it selects an available wavelength from a list, using first fit algorithm. The route is defined by a routing algorithm that uses one of the following weight functions: Shortest

Path algorithm (SP), with physical length as the cost function, Least Resistance Weight (LRW) described in [Wen et al. 2005], an algorithm that uses the total noise figure of the lightpath as the cost function (OSNR-R) proposed in [Martins-Filho et al. 2003b], and our proposed PSR. Then the OSNR of lightpath is evaluated. If it is above the predetermined level $OSNR_{QoS}$ the call is established. Our algorithm blocks a call if there is no wavelength available or if the $OSNR_{out}$ for the respective wavelength is below the $OSNR_{QoS}$. The blocked calls are lost. The blocking probability is obtained from the ratio of the number of blocked calls and the number of call requests. 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 optical parameters used in our simulations are listed in Table 2. Amplifier gains are set to compensate link losses. We used network topology shown in figure 2(b). We used the PSO parameters shown in table 3.



(a) (b)

Figure 2. (a) Flow chart of the routing and wavelength assignment algorithm employed in our simulations (b) Network topology used in our simulations.

6. Results

The first step before the assignment of the Eq. (7) as a cost function for routing is to find the optimum values for the b_{n_0,n_1} parameters. We have performed a search in b_{n_0,n_1} space using PSO as described in section 3. The search was done using network load of 100 Erlangs. We propose to optimize for higher network loads since it is the worst case. The goal of this search is to minimize the network blocking probability (BP). In order to evaluate the fitness for a given particle each network was simulated for a set of 10^5 calls. The returned blocking probability BP is assigned as the fitness value for this particle. We call these network simulations as offline training process since it should be done prior to network operation.

Fig 3(a) shows the convergence of PSO algorithm. The lowest blocking probability found in each PSO iteration is shown. We performed the optimization for four different cases: $N = 3, 4, 5$ and 7. Since one can obtain a lower blocking probability by using $N = 5$ we chose this value as a default parameter to run PSO algorithm. Increasing N also increases the computational time for PSO convergence. $N = 7$ increases the dimensionality of the problem and it requires more than 5000 PSO interactions in order to achieve lower blocking probability than $N = 5$.

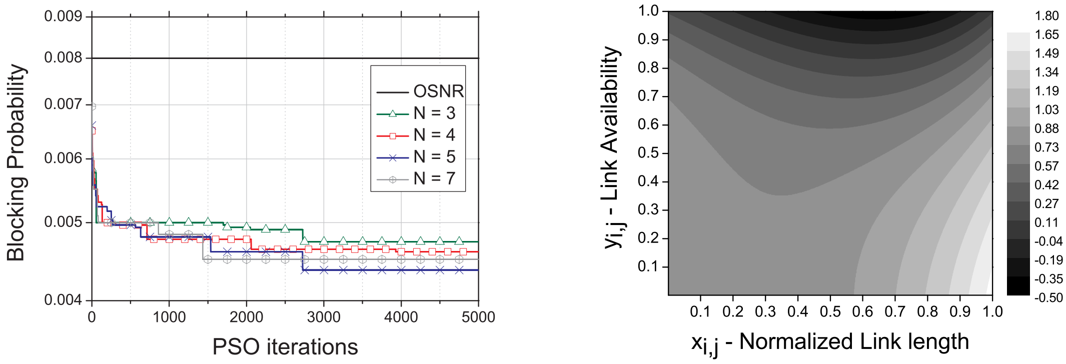
Table 2. Default optical parameters used in simulation .

Parameter	Value	Definition
P_{Sat}	16 dBm	Amplifier output saturation power
P_{in}	0 dBm	Transmitter output 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	36	Number of wavelengths in an optical link
Δf	100 GHz	Channel spacing
λ_i	1550.12 nm	The lower wavelength of the grid
λ_0	1510 nm	Zero dispersion wavelength
α	0.2 dB/km	Fiber loss coefficient
L_{Mux}	3 dB	Multiplexer loss
L_{Demux}	3 dB	Demultiplexer loss
L_{Switch}	3 dB	Switch loss
F_0	3.162	Amplifier noise factor that corresponds to $NF = 5$ dB
A_1	100	Noise factor model parameter
A_2	4 W	Noise factor model parameter
ϵ	-40 dB	Switch isolation factor

Table 3. PSO Simulation parameters.

Parameter	Value	Definition
P	50	Number of particles
G	5000	Number of interactions
c_1, c_2	2.05	Velocity update parameters
ϵ_1, ϵ_2	U[0,1]	Random numbers with uniform distribution
χ	0.72984	Constriction factor
S	[-1,+1]	PSO search space
V_{max}	+1	Maximum velocity
V_{min}	-1	Minumum velocity

As it was discussed in section 2 we chose two variables as a input parameters for PSR cost function: link availability $x_{i,j}$ and normalized link length $y_{i,j}$. Using the best parameters b_{n_0,n_1} found by PSO, we plot the link cost as a function of $x_{i,j}$ and $y_{i,j}$ in terms of level curves, as shown in Fig. 3(b). One can note that, as expected, the cost is high for long distances and low link availabilities (white regions in graph) and the cost is low for



(a) (b)

Figure 3. (a) PSO convergence (b) Cost function $f(x_{i,j}, y_{i,j})$ of (Eq. 7) found by PSO as a function of normalized link length and link availability.

short distances and high link availabilities (black regions in graph). Moreover, Fig. 3(b) shows that the cost function has a complex dependence with its variables. It demonstrates the need of using a systematic form to build the cost function from its input variables.

Since we have found a link cost function (fig. 3(b)) we can assign it as the network link cost and evaluate de network performance of the proposed scheme. For comparison purposes, we analyzed the PSR against three other cost function reported in literature: SP, LRW, OSNR-R. These algorithm were chosen for comparison due to following reasons: SP is simple and most largely used cost function for routing comparison purpose; LRW is an algorithm capable of finding less congested routes and, for this reason, leads to an improved network load distribution; and OSNR-R is a routing scheme that uses the physical impairments information during the routing procedure. Fig 4 shows the blocking probability as a function of total network load for these four different algorithms. One can note that our proposed PSR far outperforms the results obtained using either SP or LRW algorithms. Furthermore, when compared with the IRWA approach (OSNR-R), PSR has a very similar network performance in terms of blocking probability. It means that PSR is capable of reaching the high performance of the IRWA approach using no impairment information as input. The impairment information was considered in the offline (training) stage only.

PSR and OSNR-R routing algorithms have quite similar performance in terms of blocking probability. However, we must also compare the time spent by these approaches to solve the RWA problem for each call. We used an Intel® Core™2 @2.13 GHz with 3 GB of RAM to perform this comparison. The results for the average time spent to solve the RWA per call, performing 50000 calls, are shown in table 4. The PSR algorithm solves the RWA problem 8 times faster than OSNR-R. This is because in PSR the time consuming calculations to evaluate the physical impairments are performed offline, during the optimization of the b_{n_0,n_1} parameters. In the OSNR-R algorithm, as well as in other physical impairment based algorithm, these calculations occur during the online solution of the RWA problem. Table 4 also shows that PSR is up to 1.33 times slower than LRW. This small difference should be due to the simple mathematical formula of the LRW

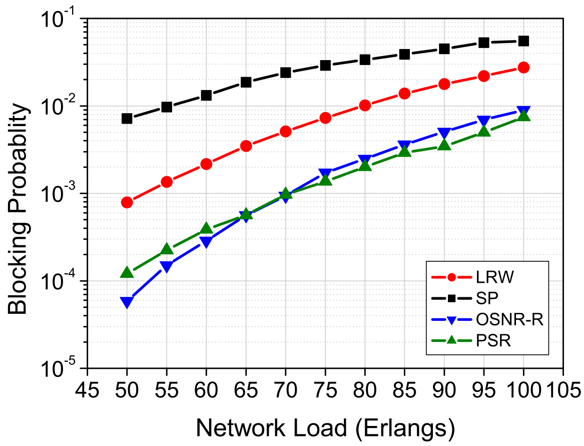


Figure 4. Network blocking probability as a function of network load for the LRW, SP, OSNR-R and PSR algorithms.

function, which involves just a single division operation. We did not consider the SP algorithm for computation time analysis since it is not an adaptive routing algorithm.

Table 4. Average Time Spent to Solve RWA per Call.

Algorithm	Time
LRW	0.12 ms
PSR	0.16 ms
OSNR-R	1.28 ms

7. Conclusions

In this paper we propose a systematic form to build the link cost function based on a set of relevant network parameters. We apply the proposed scheme to build an adaptive cost function (PSR) for impairment aware routing in all-optical networks. The proposed PSR is based on simple network parameters such as link availability, link length and hop count. Since PSR indirectly takes into account the network physical impairments we demonstrated that it outperforms or, in worst case, provides similar performance to other algorithm that use OSNR degradation as a weight function. However, the computation time for our weight function was 8 times faster than for the OSNR based one, for the network simulation conditions used.

It must be highlighted that the proposed weight function does not rely on online physical impairments evaluation to infer about signal noise in the network. Therefore, it is not mandatory to perform complex evaluations (as shown in section 4) to obtain values for optical noise based weight functions. However, PSR requires an offline simulation to store the awareness of physical impairments in the series parameters. This characteristic of a priori knowledge brings to our weight function a drastic reduction in the computation time for real time routing decision as compared to noise based approaches.

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