Using a Nature Inspired Technique to Train a Dynamic IA-RWA Algorithm

Konstantinos Manousakis and Emmanouel Varvarigos
Computer Engineering and Informatics Department, University of Patras, Greece, and
Research Academic Computer Technology Institute, Patra, Greece
{manousak, manos}@ceid.upatras.gr

Abstract—**In this work we add a training phase to an Impairment Aware Routing and Wavelength Assignment (IA-RWA) algorithm so as to improve its performance. The initial IA-RWA algorithm is a multi-parametric algorithm where a vector of physical impairment parameters is assigned to each link, from which the impairment vectors of candidate lightpaths are calculated. The important issue here is how to combine these impairment parameters into a scalar that would reflect the true transmission quality of a path. The training phase of the proposed IA-RWA algorithm is based on an optimization approach, called Particle Swarm Optimization (PSO), inspired by animal social behavior. The training phase gives the ability to the algorithm to be aware of the physical impairments even though the optical layer is seen as a black box. Our simulation studies show that the performance of the proposed scheme is close to that of algorithms that have explicit knowledge of the optical layer and the physical impairments.**

Keywords- Impairment-aware Routing and Wavelength Assignment; Particle Swarm Optimization

I. Introduction

In WDM optical networks, data are transmitted through lightpaths; that is, all-optical channels that may span multiple consecutive fibers. The problem of establishing a lightpath for a connection request involves selecting a route (path) and a free wavelength, and is called routing and wavelength assignment (abbreviated RWA) problem. The objective of the RWA operation is to minimize the network resources used or maximize the traffic served with limited network resources. In translucent or transparent networks where regenerators are only employed at some nodes or to no node at all, the quality of transmission (QoT) of the signal degrades due to physical layer impairments. The signal degradation can occur to the extent that the bit-error rate (BER) makes the signal detection infeasible at the receiver. RWA algorithms that consider the QoT of the candidate lightpaths are called impairment aware (IA)-RWA algorithms.

Several algorithms have been proposed to solve the IA-RWA problem. Most of these studies consider the online (dynamic) version of the problem [1]-[8] where connections arrive randomly and are served one-by-one, as opposed to the offline (static) version [9] where connections are known in advance. Among these online algorithms there are approaches that consider the quality of transmission (QoT) problem separately from the RWA problem. That is, they first solve the RWA problem and then consider the effects of the impairments, evaluating the feasibility of the chosen lightpaths in a separate modeling module [1]-[3]. This approach may not yield a solution with acceptable quality of transmission, and iterations are usually performed in order to improve the physical-layer blocking performance. Other online approaches incorporate physical impairments into the cost function of the algorithm and also consider the interference among the lightpaths [5]-[8]. A review of IA-RWA algorithms can be found in [10].

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Some studies have proposed swarm intelligence techniques to solve the RWA problem [11]-[13]. Swarm Intelligence algorithms are heuristic search methods that mimic the metaphor of natural biological evolution and/or the social behavior of species [15]. In Swarm Intelligence algorithms, a swarm is a collection of non-sophisticated members which cooperate with each other to perform complex tasks [16]. Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are well known and successful swarm intelligence optimization algorithms, while Genetic Algorithms (GAs) are evolutionary optimization. Some studies use techniques from ACO [13], GA [14] and PSO [11], [12] to solve the offline or online RWA problem.

Particle Swarm Optimization (PSO) was originally developed by Kennedy and Eberhart [17], [18]. It is a population based, optimization algorithm inspired by animal social behavior. Authors in [11] examine a PSO-based scheme to solve the dynamic RWA problem while considering ideal physical layer where signal transmission is error free. In [12] the authors propose and analyze the performance of an adaptive IA-RWA algorithm based on a set of input network parameters. The routing algorithm, called Power Series Routing (PSR), is trained by a PSO optimization technique, and its cost function is based on a power series expansion.

In [7] we investigated dynamic IA-RWA algorithms that use complex formulas in order to take *directly* into account the effects of physical impairments, by using physical layer models to calculate the QoT of the candidate lightpaths. In a different approach [8], we used an *indirect* multi-parametric approach that considers impairment-generating source parameters, such as the path length, the number of hops, the number of crosstalk and other inter-lightpath interferer sources. In this way, the QoT of each lightpath is characterized by several parameters that do not measure directly the impairment effects, but the sources that generate them. The lightpath to be used by a connection is selected using a transmission quality function that combines these parameters into an appropriate final scalar. Compared to [7], the approach in [8] is more general; however, the algorithm that accounts directly for physical impairments outperforms the indirect algorithm. This is because it is unclear in the multi-parametric algorithm which choice of the transmission quality function would yield the best performance, as expressed by the network blocking probability and the true quality of the chosen paths given by their Q-factor.

In this work we add a training phase to the indirect algorithm (Multi-Parametric) so as to improve its performance, while keeping the physical layer parameters as a black box. Each impairment-generating parameter of a link or path in the indirect algorithm has a coefficient that declares its relative importance in determining the transmission quality of that link or path. Our aim is to adjust these coefficients (equivalently, find the right transmission quality function) in order to improve the network performance of the algorithm. The performance metric used in comparing algorithms can be the blocking probability they achieve or the quality of the paths they select. We use a nature inspired algorithm for the training phase that is called particle swarm optimization (PSO). We present several approaches based on PSO to train the coefficients. Our simulation results show that the performance of the proposed algorithm is close to that of algorithms that have explicit knowledge of the optical layer and the physical impairments, even though our algorithm treats the physical layer as a black box.

The rest of the paper is organized as follows. In Section II we give a short description of the particle swarm optimization technique. In Section III we present the Multi-Parametric scheme. The training phase of the algorithm is presented in Section IV. Simulation results are presented in Section V. Our conclusions are given in Section VI.

II. Particle Swarm Optimization

In this section we give a short introduction to the particle swarm optimization (PSO) algorithm. PSO belongs to a class of population based optimization algorithms, called swarm intelligence, where population members evolve over time for problem solving. In PSO, a swarm (population) is a collection of particles (members) where each particle has both a position and a velocity. The position of a particle represents a candidate solution to the problem under consideration. The velocity of a particle moves it from one position to another over the problem search space.

Each individual in the particle swarm is composed of three d-dimensional vectors, where d is the dimensionality of the search space. These are the current position $\overline{x_i} = \left(x_{i1},...,x_{id}\right)$, the previous best position $\overline{p_i} = \left(p_{i1},...,p_{id}\right)$, and the velocity $\overline{u_i} = \left(u_{i1},...,u_{id}\right)$ vectors.

These particles move throughout the search space by a fairly simple set of update equations. The algorithm updates the entire swarm at each step by updating the velocity and position of each particle at each dimension according to:

$$u_{ij} = \chi \cdot \left(u_{ij} + \eta_1 r_1 \left(p_{ij} - x_{ij}\right) + \eta_2 r_2 \left(p_{gj} - x_{ij}\right)\right) \quad (1)$$

$$x_{ij} = x_{ij} + u_{ij}, \quad (2)$$

where parameter χ is called the constriction factor [19], and is used to avoid large values of velocity. $\overline{p_g} = \left(p_{g1},...,p_{gd}\right)$ is the best position found by any neighbor of the particle. The self-confidence factor η_1 is a positive constant that determines the influence of the particle itself over the problem search space, while the swarm-confidence factor η_2 is also a positive constant that determines the influence of the other members of the swarm. Finally, r_1 and r_2 are random variables taking real values inside the interval [0,1].

Below we present a pseudo-code of the particle swarm optimization algorithm:

PSO Algorithm

Initialize all particles in the swarm

for i = 1 : PopulationSize
  Random initialization of $\overline{x_i}$, $\overline{u_i}$
  $\overline{p_i} = \overline{x_i}$
end

while (iteration < MAX)
  for i = 1 : PopulationSize
    Evaluate $f\left(\overline{x_i}\right)$
    if $f\left(\overline{x_i}\right) < f\left(\overline{p_i}\right)$
      $\overline{p_i} = \overline{x_i}$
    end
    for j = 1 : d
      update velocity u_{ij} using equation 1
      update position x_{ij} using equation 2
    end
end
  return $\overline{p_i}$

III. IA-RWA Multi-Parametric Algorithm

We consider a WDM network with N nodes and L links, each of which carries m wavelengths, $\lambda_1, \lambda_2, ..., \lambda_m$. The WDM network employs no wavelength conversion. In contrast to the traditional single-cost approach, where each link is characterized by a scalar, in the multi-parametric approach a vector of impairment parameters is assigned to each link, from which the corresponding vectors of candidate lightpaths are calculated.

A. Impairment Generating Parameters

For a given lightpath (p,w), that is, wavelength w on path p, we record the following impairment parameters that affect its signal quality: (i) the path's length L_p, (ii) the number of hops

H_P of the path, (iii) the number A_{pw} of active adjacent channels of wavelength w across all the links of the lightpath, (iv) the number SA_{pw} of active second adjacent channels of wavelength w across all the links of the lightpath, (v) the number of intra-channel crosstalk sources X_{pw}, which is the number of lightpaths crossing the same switches and utilizing the same wavelength w along the lightpath. Note that the aforementioned parameters (i)-(v) are the key parameters for the majority of the physical impairments [20]. More specifically, amplified spontaneous emission (ASE) noise depends on the number of amplifiers, which is related to the length of the links, and the number of hops (switches). Chromatic dispersion (CD), self-phase modulation (SPM) and polarization mode dispersion (PMD) also depend on the length of the path. Filter concatenation (FC) depends on the number of filters over the path, and since it is a general practice that each all-optical switch employs two filters, FC depends on the number of hops. Moreover, the effects of the impairments that depend on the utilization of the other wavelengths are more severe when the interfering sources are the two adjacent channels. This is the case in cross-phase modulation (XPM), four-wave mixing (FWM) and inter-channel crosstalk (inter-XT). Finally, intra-channel crosstalk (intra-XT) depends on the utilization of the same wavelength of lightpaths crossing the same switch.

B. *Impairment Parameter Vectors*

The impairment vector characterizing a link l is given by

$$V_l = (L_l, H_l, \overline{A_l}, \overline{SA_l}, \overline{X_l}, \overline{W_l})$$

consisting of

(i) the length L_l of the link (scalar);

(ii) the hop count H_l of the link (scalar), which is by definition equal to 1 (it will help us count the number of hops of a path);

(iii) a vector $\overline{A_l} = (a_{l1}, a_{l2}, \ldots, a_{lm})$ whose i^{th} element a_{li} records the number of active adjacent channels on wavelength i of the link;

(iv) a vector $\overline{SA_l} = (sa_{l1}, sa_{l2}, \ldots, sa_{lm})$ whose i^{th} element sa_{li} records the number of active second-adjacent channels on wavelength i of the link;

(v) a vector $\overline{X_l} = (x_{l1}, x_{l2}, \ldots, x_{lm})$ whose i^{th} element x_{li} contains the number of intra-channel generating sources at the switch that link l ends;

(vi) the availability of wavelengths in the form of a Boolean vector $\overline{W_l} = (w_{l1}, w_{l2}, \ldots, w_{lm})$, whose i^{th} element w_{lm} is equal to 0 if wavelength λ_i is used and equal to 1 when λ_i is free.

The transmission quality TQ of a link is defined as

$$TQ(l, w) = c_{1l} \cdot L_l + c_{2l} \cdot H_l + c_{3l} \cdot A_{lw} + c_{4l} \cdot SA_{lw} + c_{5l} \cdot X_{lw}$$

where the coefficients c_i are used to account for the relative importance of each impairment parameter. Since the values of these coefficients that would result in the best network performance (as measured, e.g., by the blocking probability) are not known, a training procedure will be described in Section IV in order to estimate them.

Then the TQ of a lightpath (p,w) is equal to:

$$TQ(p, w) = \sum_{l\in p} c_{1l} \cdot L_l + \sum_{l\in p} c_{2l} \cdot H_l + \sum_{l\in p} c_{3l} \cdot A_{lw} + \sum_{l\in p} c_{4l} \cdot SA_{lw} + \sum_{l\in p} c_{5l} \cdot X_{lw}$$

C. *Multi-Parametric Impairment Aware RWA Algorithm*

The multi-parametric approach we use consists of two phases. In the first phase the algorithm computes the non-dominated paths from a given source to all network nodes (including the destination); this is done using a generalization of the single-parameter Dijkstra algorithm. The basic difference is that instead of a single path, a set of non-dominated paths between the origin and each node is obtained. A path that is dominated by another path, has worse wavelength availability, length and other impairment parameters than the other path, and there is no reason to consider it further [8]. During the calculation of the non-dominated paths when we expand a path we check the TQ metric of its wavelengths and we drop the path if it is not further extendable. In this way, the non-dominated paths returned at the end of the algorithm have at least one available wavelength. The lightpaths obtained have at least acceptable TQ metric performance, since lightpaths with unacceptable TQ values were made unavailable in the process of the algorithm. In the second phase of the proposed algorithm we apply a selection function (or policy) on the impairment vectors of each path. The function yields a scalar impairment cost per lightpath in order to select the optimal one. Note that the selection function applied to the impairment vector of a path has to be monotonic in each of the parameters.

D. *Quality of transmission, BER and Q factor*

Bit-error ratio (BER) is a very appropriate criterion to evaluate the true signal quality of a lightpath because it is a comprehensive parameter that takes all impairment effects into consideration. The Q factor is the electrical signal-to-noise ratio at the input of the decision circuit in the receiver's terminal, and, under the assumption of Gaussian shaped noise, is related to the system's BER through the function: $BER(Q) = \frac{1}{2} erfc\left(\frac{Q}{\sqrt{2}}\right)$.

We use the Q value as the true QoT measure of a path, in order to block lightpaths that do not satisfy the physical constraints.

IV. TRAINING PHASE OF THE MULTI-PARAMETRIC IA-RWA ALGORITHM

In this section we describe the techniques we use in order to train the coefficients of the selection function TQ used in the IA-RWA algorithm, so as to obtain the best network performance. In the first technique we use as performance metric the blocking probability (BP), so we try to train the coefficients of the selection function so as to minimize the blocking probability of the IA-RWA algorithm. In the second technique we use as performance metric the Q value of the lightpaths.

A. BP-training

We use particle swarm optimization to adjust the coefficients c_i's for the network under consideration in order to find the appropriate selection function that would optimize the desired network performance metric. Our main objective is to minimize the blocking probability (BP) achieved by the IA-RWA algorithm. Let this performance metric be denoted by $f\left(\overline{x_i}\right)$, where $\overline{x_i}$ (a particle of the swarm) corresponds to a set of values of the coefficients of the Multi-Parametric algorithm. The line "Evaluate $f\left(\overline{x_i}\right)$" of the PSO algorithm (Section II) corresponds to the blocking probability of the IA-RWA for a given number of wavelengths per link and traffic load. The evaluation of the blocking probability is performed through simulation for a given set of connection requests.

We distinguish two different approaches for defining the particles of the swarm based on the number of coefficients c_{il} that are adjusted. In the first approach, one coefficient for each impairment-generating source is used, meaning that these coefficients representing the relative importance of each impairment parameter are taken to be the same for all the links of the network and are adjusted in the same way. In the second approach, these coefficients are taken to be different for different links and are updated separately.

1) ScBP-training

In Same coefficients Blocking Probability (*ScBP*) training, the dimensions d of a particle are equal to the number of impairment parameters (equal to 5 considering the parameters defined in Section III.A). As a consequence, all the links of the network have the same coefficients (Sc) but every impairment parameter has its own coefficient. Therefore, the particle is defined as $\overline{x_i}=\left(c_1,\ldots,c_T\right)$, where c_1 is the coefficient for the path's length, c_2 for hop count, c_3 for active adjacent channels, c_4 for active second adjacent channels, and c_5 for the number of intra-channel crosstalk sources. Thus, every link of the network is characterized by the same vector $\overline{x_i}$.

2) DcBP-training

In Different coefficients Blocking Probability (*DcBP*) training, the dimensions d of a particle are equal to the number of impairment parameters multiplied by the number of network links. This means that *DcBP*-training differs from *ScBP* in the number of considered coefficients. While in *ScBP* the coefficients are different among impairment parameters and do not differ among links, in *DcBP* the coefficients are different among impairment parameters and among links. The particle is defined as a vector $\overline{x_i}=\left(c_{11},\ldots,c_{1T},\ldots,c_{L1},\ldots,c_{LT}\right)$, of dimension $L\cdot T$ where L is the number of links, and T is the number of impairment parameters.

B. Q-training

In the Q-training technique we adjust the coefficients c_{il} in the definition of the selection function TQ in order to approximate the true Quality of Transmission (QoT) of a lightpath as expressed by its Q-factor. The number of coefficients in this case is $L\cdot T$, since every coefficient c_{il} depends on the specific impairment parameter i and the specific link l. In order to compute the coefficients for every link the following equation has to be satisfied:

$$\begin{aligned} c_{1l}\cdot L_l+c_{2l}\cdot(H_l-1)+c_{3l}\cdot A_{lw}+c_{4l}\cdot SA_{lw}+c_{5l}\cdot X_{lw} \\ =T_{\max}-Q_{lw} \end{aligned} \quad (3)$$

where $T_{\max}$ is a large constant chosen so that the second part of the equation is always non-negative and Q_{lw} is the Q value of the lightpath under consideration. The left hand side of the equation declares the degradation of the lightpath. Below, we describe the way the coefficients of the impairment generating sources are computed.

1) Computing the coefficient for the length L

In order to adjust the coefficient c_{1l} (corresponding to the length) of each link l we assume that only one lightpath is present in the network, using link l and wavelength w. The coefficient c_{1l} is computed from $c_{1l}\cdot L_l=T_{\max}-Q_{lw}$, since the other terms of equation (1) are equal to zero.

2) Computing the coefficients for the XT

In order to adjust the coefficient c_{5l} (corresponding to intra-channel XT) we establish a lightpath *LP1* on link l and wavelength w as previously. Then we establish a new lightpath that may affect the lightpath *LP1*. For every newly established lightpath we calculate the new Q value of the *LP1*, and hence new values for c_{5l}. The coefficient of link l is then computed by the equation: $c_{1l}\cdot L_l+c_{5l}\cdot \mathrm{X}_{lw}=T_{\max}-Q_{lw}$, where X_{lw} is the number of intra-channel generating sources. In Fig. 1, the value k upon the link declares the order in which the new lightpaths are established. When a new lightpath is established the already established lightpaths remain unchanged. For example, in Fig. 1 we compute 6 different values for the coefficient c_{5l}. The coefficient c_{5l} is then equal to the mean value of the computed coefficients. The above procedure is repeated for every link of the network. It is worth noting that even though the lightpaths that produce intra-channel XT to an already established lightpath depend on the node architecture, the above procedure is independent of the node architecture since it tests all the possible lightpaths affecting the lightpath.

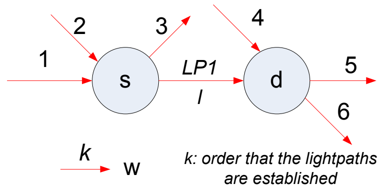

Figure 1: Intra-channel generating sources for lightpath *LP1*

3) Computing the coefficients for the channel interference

The coefficients c_{3l} (corresponding to adjacent channel interference) and c_{4l} (corresponding to second adjacent channel interference) are computed jointly. We first establish a lightpath *LP1* on link l and wavelength w, and then we establish every combination of lightpaths that occupy the adjacent (w-1, w+1) and second adjacent wavelength (w-2, w+2). The Q value of *LP1*, for every combination is computed. The coefficients have to satisfy $c_{1l} \cdot L_l + c_{3l} \cdot A_{lw} + c_{4l} \cdot SA_{lw} = T_{\max} - Q_{lw}$. This means that we have two variables (c_{3l}, c_{4l}) to approximate a value. We define a new optimization problem with these two variables with the objective of minimizing the difference between the second part and the first part of the equation. This minimization must stand for every combination of the adjacent and second adjacent channels. The algorithm that we use is particle swarm optimization. This procedure is performed for every link of the network.

4) Coefficient's of the number of hops H

In order to compute the coefficients c_{2l} (corresponding to the number of hops) we first modify equation (3) to:

$$c_{1l} \cdot L_l + c_{2l} \cdot H_l + c_{3l} \cdot A_{lw} + c_{4l} \cdot SA_{lw} + c_{5l} \cdot X_{lw} = T_{\max} - Q_{lw} \qquad (4)$$

We then establish a lightpath *LP1* on link l and wavelength w and sequentially we establish new lightpaths that may affect *LP1*. Having computed all the other parameters, we compute the coefficient c_{2l}. This coefficient is mainly used to balance all the coefficients together.

V. Simulation Results

In order to fairly compare the algorithms, we performed a number of simulation experiments with controlled and identical input parameters and an identical impairment estimation module (Q-Tool). In particular, we considered an all-optical transparent network, where connections arrive dynamically and have to be served as they come. The experiments were performed assuming the DT network topology (Figure 2), which is a transparent candidate network. We assumed 10Gbps transmission rates and channel spacing of 50 GHz. The span length in each link was set to 100 km. Each link was assumed to consist exclusively of SSMF fibers with dispersion parameter D=17 ps/nm/km and attenuation parameter a=0.25 db/km. For the DCF we assumed parameters a=0.5 dB/km and D=-80 ps/nm/km. The launch power was set to 3 dBm/ch for every SMF span and -4 dBm/ch for the DCF modules. The EDFAs' noise figure was set to approximately 6 dB with small variations (±0.5 dB) and each EDFA exactly compensates for the losses of the preceding fiber span. Connection requests (each requiring bandwidth equal to 10Gbps) are generated according to a Poisson process with rate λ (requests/time unit). The source and destination of a connection are uniformly chosen among the nodes of the network. The duration of a connection is given by an exponential random variable with average $1/\mu$ (time units). Thus, λ/μ gives the total network load in Erlangs.

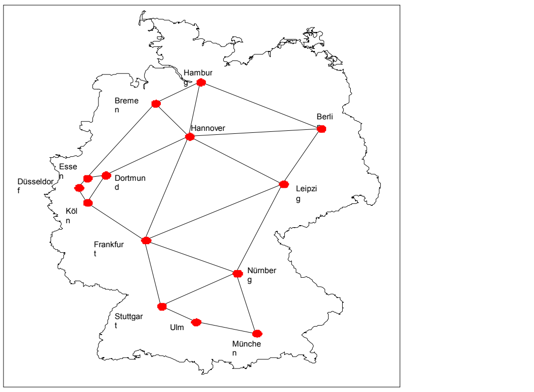

Figure 2: Generic DT network topology. 14 nodes, 23 links (we assumed 46 directed links).

The proposed training phase requires extra time but it does not affect the execution time of the algorithm during the network operation since this process is done once and offline. In Figures 3 and 4 we compare the proposed scheme presented in section IV with the Multi-parametric algorithm without training (no-training in the figures) and the Sigma-bound algorithm [7]. The Sigma-bound algorithm takes directly into account the effects of the physical impairments, by calculating the QoT of the candidate lightpaths. Note that Sigma-bound has explicit knowledge of the physical layer impairments and using this knowledge it can achieve a lower physical layer blocking probability than the other schemes.

In Fig. 3, we graph the blocking probability obtained for each of the algorithms as a function of the number of available of wavelengths for network load equal to 100 Erlangs. In Fig. 4, the blocking probability of each of the algorithms is depicted as a function of the traffic load, assuming 12 wavelengths per link. The algorithm depicted as "ideal" in the figure refers to the case of an ideal physical layer, without impairments. As a consequence, the blocking probability of this algorithm corresponds to network layer blocking, while the difference between the blocking probability of the algorithms and network layer blocking corresponds to physical layer blocking due to physical layer impairments.

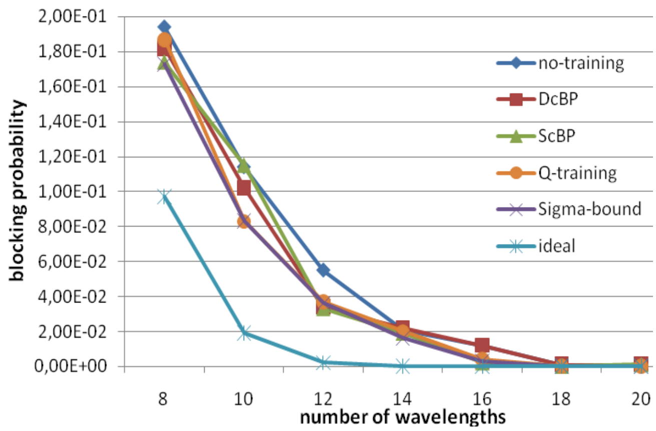

Figure 3: Blocking probability versus available number of wavelengths per link assuming traffic load equal to 100 Erlangs.

As can be seen in Figures 3 and 4, the Multi-Parametric algorithm with no-training has the worst performance among the algorithms compared, but its performance is significantly improved when the proposed training phase is used.

Regarding the training schemes *ScBP* and *DcBP* we observe that *ScBP* achieves better blocking probability. We would expect that using different parameters for different links (*DcBP*) would result in lower blocking probability, but this is not achieved because it is time consuming to train all these coefficients. We used the same number of iterations in the PSO algorithm when comparing these two schemes. The *DcBP* needs higher number of iterations to improve its performance.

Comparing *ScBP* and Q- training in Fig. 4 we observe that Q-training has better performance for light load, while *ScBP* is better for higher traffic load. From a network's perspective we are interested in loads the result in blocking performance in the range of 0 to 4%. Higher values of blocking probability would be unacceptable, and we would normally have to place more resources to satisfy the connection requests. Q-training achieves blocking performance that is close to that of Sigma-bound (in most cases). As expected, Sigma-bound is the best algorithm to be used, but it only applicable when we have explicit knowledge of the physical layer. If the physical layer is not known then a training phase to the multi-parametric algorithm is the best choice.

Also we observe that *ScBP* and *DcBP* (Fig. 3 and Fig. 4) yield the best blocking probability for load equals to 100 and 12 available wavelengths. This happens because the coefficients were trained using these parameters.

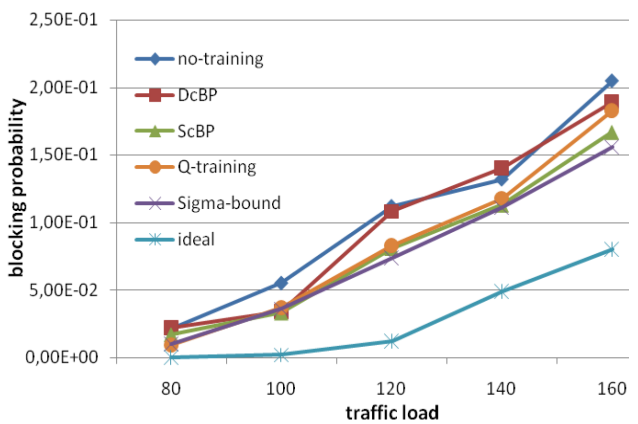

Figure 4: Blocking probability versus traffic load in Erlangs assuming 12 available wavelengths per link.

VI. Conclusion

We presented a training phase for the Multi-Parametric IA-RWA algorithm that is unaware of the physical layer. The training phase uses the particle swarm optimization technique to adjust the coefficients of the Multi-Parametric algorithm so as to optimize network performance metrics, such as the blocking probability. Simulation studies show that the training phase improves the performance of the algorithm so that it comes close to that of an algorithm (Sigma-Bound) that is aware of the physical layer.

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