DE GRUYTER OPEN

JAISCR, 2016, Vol. 6, No. 4, pp. 231 – 242
10.1515/jaiscr-2016-0017

ANT COLONY OPTIMIZATION APPLIED TO THE PROBLEM OF CHOOSING THE BEST COMBINATION AMONG M COMBINATIONS OF SHORTEST PATHS IN TRANSPARENT OPTICAL NETWORKS

Ítalo Brasileiro[1], Iallen Santos[1], André Soares[1], Ricardo Rabêlo[1], and Felipe Mazullo[2]

[1]*Computing Department, Federal University of Piauí, Terezina, Piaui, Brazil*

[2]*School of Systems and Information Engineering, University of Tsukuba, Tsukuba, Ibaraki, Japan*

Abstract

This paper presents an attempt to solve the problem of choosing the best combination among the *M* combinations of shortest paths in optical translucent networks. Fixed routing algorithms demands a single route to each pair of nodes. The existence of multiple shortest paths to some pairs of nodes originates the problem of choose the shortest path which fits better the network requests. The algorithm proposed in this paper is an adaptation of Ant Colony Optimization (ACO) metaheuristic and attempt to define the set of routes that fits in an optimized way the network conditions, resulting in reduced number of blocked requests and better adjusted justice in route distribution. A performance evaluation is conducted in real topologies by simulations, and the proposed algorithm shows better performance between the compared algorithms.

Keywords: optical networks, routing, ant colony, simulation

1 Introduction

The emergence of new technologies for audio and video services on demand, such as teleconferences and smart TVs, has led to a considerable increase in the demand for bandwidth in transport networks, which are the backbone components of telecommunication service providers. Optical network technology is a solution to this demand that is capable of reaching high transmission rates [1]. The optical transport networks use wavelength division multiplexing (WDM) [1], which allows the establishment of different parallel optical circuits in the same optical fiber.

Circuit-switched WDM optical networks allow for the establishment of an optical circuit for communication between the origin and destination nodes [2]. To establish an optical circuit in an WDM network, route selection and wavelength allocation are required. In a network under dynamic traffic in which there is no knowledge of the number of circuits that will be required, the routing and wavelength allocation algorithms focus on meeting the requests of the circuits by minimizing the blocking probability *(BP)* of future requests [3].

The *BP* is a commonly used metric to define the quality of service (QoS) of a network [3, 4]. Many of the connection requests of networks with high *BP* rates are blocked, which prevents data from being transferred between nodes. The main factor causing such blockages is the lack of available wavelength to establish the circuit. The load balance between the network links should be provided by the routing algorithms because they define the links that will be used to establish the circuit between the origin and destination of a request. An improper routing solution can lead to the overload of network links.

Different routing solutions are used to determine the shortest route between the origin and destination nodes [5, 6, 3]. For certain network topologies, there is more than one shortest route between a given pair of nodes. Hence, the selection of the shortest route can influence link congestion, which can represent a higher BP. The need to select the best existing shortest route between two nodes (origin and destination) is defined as the Problem of Choosing the Best Combination among M Combinations of Shortest Paths (MCSP) [5]. Solve this problem implies finding the best combination of routes which minimize the network blocking probability.

In transparent optical network, optical-electrical-optical (OEO) converters, which converts data from the optical to the electronic domain, are not used during transmission; therefore, signal conversion does not occur. The total transmission time is reduced because there is no delay related to signal processing between the origin and destination [7]. Futhermore, the financial cost associated with OEO converters is reduced in transparent optical networks.

Fixed routing algorithms provide lower complexity for the Control Planes protocols because the route computation for each sourcepair is not made online, i.e., it is made during a networks planning phase [1]. Thus, the complexity of fixed routing algorithms do not interfere in network performance, once their execution occur before network operational phase. According to the authors in [5], the majority of studies in the literature that address the routing and wavelength assignment (RWA) problem in transparent optical networks are based on the fixed routing class. These studies considered the use of shortest path algorithms to define a fixed route for each pair of origin-destination nodes. Among the shortest path algorithms, the Dijkstra algorithm (DJK) [6] is one of the most cited. In this study, the terminology shortest path will be used to indicate the shortest path in terms of number of loops in the route.

Authors [5] have defined the MCSP and proposed the best among the shortest routes (BSR) algorithm as a solution for the MCSP. Additionally, a comparison is made in [5] among the BSR, RRT (Resttricted Routing Algorithm) [4] and DJK [6] algorithms. The RRT algorithm creates a routing table for each pair of nodes, and critical links are temporarily removed from the search space, forcing the search for other routes disjoint from these links. The results showed a better performance of the BSR related to the *BP* for different network topologies. The Best among the Shortest Routes using Decision by Similarity (BSR-DS) algorithm is proposed in [3] to solve the MCSP. BSR-DS assesses the similarity between the shortest-path routes to perform a better load balancing. This characteristic of BSR-DS results in better performance compared with the BSR in terms of the BP.

Acquire results for some computational problems require high processing power and large time availability, making it infeasible to use traditional methods. Thus, emerges the need to use another ways to obtain results which are near of an optimum point. Consequently, several studies apply metaheuristics as attempt to obtain satisfactory results for their optimization problems [8, 9, 10]. The ACO (Ant Colony Optimization) metaheuristic is constantly present in current researches: in [8], is used to find a fiber-optic online solution for mixed-line-rate (MLR) networks, in [9], is used to minimize the total number of wavelength links used in the whole physical topology, and [10], used to solve the problem of routing and spectrum allocation (RSA) for elastic optical networks.

This study proposes the Ant Colony Optimization (ACO) BSR (ACO-BSR) algorithm to solve the MCSP. This algorithm is used to define the set of best routes between all the pairs of nodes according to important metrics to enhance load balancing, as the frequency of use for each link and similarity between routes. The route solution is obtained by applying and adapting a version of the ACO metaheuristics [11]. Furthermore, a comparative analysis between the proposed technique and DJK, BSR and BSR-DS algorithms is performed to real situations of transparent optical network topologies.

This study is organized as follows. Section 2 describes the problem related to the selection of the best combination among the *M* combinations of shortest paths, and Section 3 presents the adapted model of ACO meta-heuristic. An evaluation study is presented in Section 4 that compares the performance of the proposed algorithm with the performance of other existing algorithms in terms of BP, Fairness and Standard Deviation and Section 5 discusses the process of defining the parameters used in the proposed algorithm to maximize the performance. Finally, conclusions are presented in Section 6.

2 Problem of Selection the Best Combination Among *M* Combinations of Shortest Path

In this Section, the problem of selecting the best combination among the M combinations of shortest paths (MCSP) is presented [5]. Given an optical network topology with N nodes, the number of pairs of origin-destination nodes is $N \cdot (N-1)$. The $pair(o,d)$ notation is used to represent an ordered pair of nodes with its origin in node o and destination in node d. To perform the fixed routing, it is necessary to define a route for each $pair(o,d)$. In this study, $pair(o,d)$ is assumed to use the same route as $pair(d,o)$, with only the direction of the route changed; therefore, only routes in a single direction must be determined. Hence, $R = (N \cdot (N-1))/2$ routes are required for a given topology of N nodes, one for each $pair(o,d)$.

In this study, it is also assumed that the shortest path to a given $pair(o,d)$ is the route with the least amount of links between origin o and destination d, which results in a smaller number of hops. Each link in the route is also called a hop. Therefore, the cost of the path considers the number of hops in the route. Each $pair(o,d)$ can have more than one shortest path. In this study, such routes are called Candidate Routes (*CR*), and the set of *CRs* for a $pair(o,d)$ is represented by $CR_{pair(o,d)}$. The route selected for $pair(o,d)$ is named $r_{pair(o,d)}$. Figure 1 illustrates the $CR_{pair(1,4)}$ set for the R6NTL (Ring With 6 Nodes and a Transversal Link) topology.

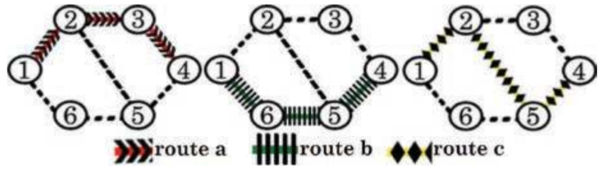

Figure 1. Candidate routes for $pair(1,4)$.

Because each $pair(o,d)$ can have more than one shortest route (*CR*), there are M different solutions for planning the fixed routes in a specific network topology [5]. If only the shortest-path routes are considered, the calculation of M, which represents the number of possible solutions, is given by Eq. (1).

$$M = \Pi_{i=1,j=1}^{N,N} |CR_{pair(i,j)}|, \tag{1}$$

where $CR_{pair(i,j)}$ is the amount of candidate routes for $pair(i,j)$ and $i \neq j$. Table 1 shows the pairs of nodes in the R6NTL topology according to their numbers of shortest paths.

Table 1. Pair of nodes in the R6NTL topology separated according to the number of candidate routes

N. of Shortest Paths (Candidate Routes)	**1**	**2**	**3**
Pairs	(1,2) (2,3) (3,4) (4,5) (5,6) (6,1) (1,3) (1,5) (4,6)	(1,5) (2,4) (3,5) (2,6)	(1,4) (3,6)

According to Eq. (1), the number of possible solutions, represented by M, can be found through the combination of all candidate routes. Thus, the value of M is given by $M = 1^9 \cdot 2^4 \cdot 3^2 = 144$. For a smaller topology, such as R6NTL, successive simulations can be performed to determine the best solution among the 144 possible route solutions. However, real topologies usually exhibit a greater number of nodes and links, leading to a significant increase in the value of M. Table 2 list the value of M for some topologies.

Table 2. Value of M for different topologies

Topology	Nodes	M
R6NTL	6	144
Abilene	11	9216
EON	19	$1.2 * 10^{32}$
USA	24	$7.14 * 10^{68}$
TORUS	25	$4.7 * 10^{101}$

The MCSP is used to identify a solution that includes the shortest-path routes (Sk) that satisfies $1 \leq k \leq M$ and provides a combination of Sk that results in better load distribution and smaller value in terms of network BP. Therefore, defining the Sk combination requires a definition of the shortest path to be used by each $pair(o,d)$ to establish a circuit during the network operation phase.

3 Ant Colony Optimization

Ant algorithms [12] are computational models inspired in the behavior of real ant colonies. Among the studied behaviors of ants (task division, nest building, foraging for food, etc.), the foraging for food behavior is particularly relevant. Such behavior allow the ants to find the shortest path between the nest and food source [13]. This allows faster food foraging, once the time spent on the route between the nest and food source is minimized, allowing a faster gatering, and it also increase the quality of the food source [14]. ACO algorithms were developed through studies on the food foraging behavior of ants. Initially, ACO algorithms were proposed to address discrete (or combinatorial) optimization problems. Thus, a population of artificial ants cooperates to solve search/optimization problems by exchanging information on the search space through depositing artificial pheromone. As an optimization technique based on intelligent (or computational intelligence) systems, the application of ACO algorithms has the following characteristics:

- It does not require special properties for the search space (objective function and equality/inequality constraints) such as convexity, existence of derivatives, continuity and unimodality;
- It is population-based, so the ACO algorithm evolves a population of candidate solutions that allows for sharing of information on the search space to improve convergence and the quality of the solutions;
- It includes stochastic (random) components to update solutions among the iterations, so the population evolution follows rules of probabilistic (stochastic) transition that reduce its dependence on the initial solution and the likelihood of the search process stagnating at local minima.

An ACO algorithm alternates the application of two basic principles:

- a procedure for creating solutions for the problem, where a set of n ants builds in parallel n solutions;
- a procedure for updating the pheromone trail, in which the pheromone concentration is changed (updated).

The main characteristics of the ACO algorithms are based on the following [15]:

- a colony of cooperative agents (artificial ants) to build solutions for the problem;
- a pheromone trail for indirect local communication;
- heuristic information that is dependent on the problem and influences the building of solutions;
- probabilistic decision (transition) rules to determine the next move of the ant.

Before presenting the ACO meta-heuristic in its adapted form, the concept of similarity between routes, which is used in the BSR-DS and ACO-BSR algorithms, must be clarified.

For the analysis of similarity, the shortest-path routes are analyzed in pairs. The calculation of the similarity between two routes a and b, which are CRs for a given $pair(o,d)$, is performed using Eq. (2).

$$Sml(a,b) = \frac{NE_{common}(a,b)}{H}, \tag{2}$$

where H is the number of links in route a and $NE_{common}(a,b)$ is the number of common links between routes a and b. It is important to highlight that the number of hops in route a is the same as in route b because both routes are shortest-path routes. Based on the concept of similarity between two routes, the similarity between all CRs for a given $pair(o,d)$ is provided by Eq. (3),

$$Sml_{pair(o,d)} = \frac{\gamma}{C^2_{|CR_{pair(o,d)}|}}, \tag{3}$$

where γ is the sum of similarity ($Sml(a,b)$) of all of the combinations of CRs for $pair(o,d)$; and C is the number of CR combinations for $pair(o,d)$.

Figure 2 shows the calculation of similarity between the CRs for $pair(1,4)$.

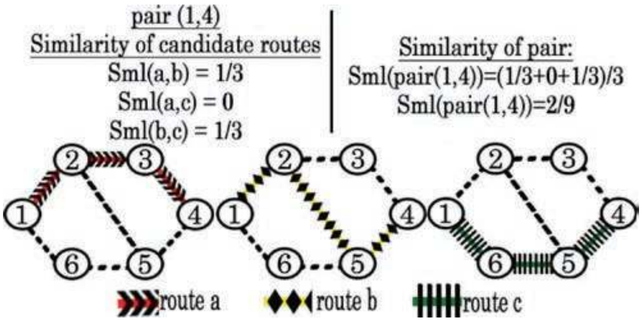

Figure 2. Candidate routes for $pair(1,4)$.

As observed in Figure 2, $pair(1,4)$ is composed of three alternative shortest-path routes: route a = nodes 1, 2, 3 and 4; route b = nodes 1, 2, 5 and 4; route c = nodes 1, 6, 5 and 4. In Figure 2, $Sml(a,b) = 1/3$ because routes a and b have only one link in common (from node 1 to node 2) and both have three hops; $Sml(a,c) = 0/3$ because the routes do not have links in common; $Sml(b,c) = 1/3$ because routes b and c only have one common link (from node 5 to node 4). Hence, the example of Figure 2 shows $Sml_{pair(1,4)} = ((1/3)+(0/3)+(1/3))/3 = 2/9$.

To apply the ACO meta-heuristic, the MCSP was modeled similarly to the travelling salesman problem [12]. Figure 3 shows an example of a graph (topology) for finding a solution to the MCSP. Initially, for each pair of nodes, the set of corresponding shortest paths is identified. Table 3 lists the set of shortest paths for the graph in Figure 3 (a).

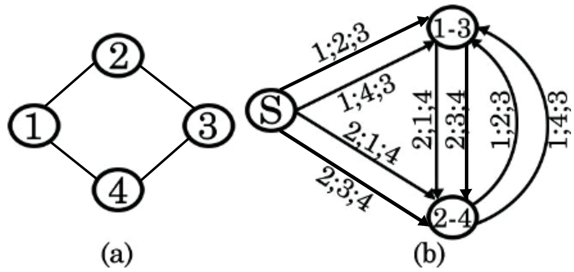

Figure 3. (a) Graph used to exemplify the application of the modified ACO meta-heuristics which generates graph in (b).

Table 3. Set of shortest routes for each pair of nodes in the topology

Pair	1-2	1-3	1-4	2-3	2-4	3-4
Shortest route	1-2	1-2-3 1-4-3	1-4	2-3	2-1-4 2-3-4	3-4

Next, a new graph is created with vertices that represent each $pair(o,d)$ of the topology. Additionally, an initial vertex S is inserted from which all ants start. Therefore, this artificial vertex plays the role of a starting node. The generated graph has edges between all vertices that are identified as the shortest-path routes in the table for $pair(o,d)$, towards which the edge is oriented. For example, between node S and node 1-3 the edges are 1,2,3 and 1,4,3, which are both possible shortest-path routes for $pair(1,3)$. Both edges are oriented towards node 1-3. Arcs 2,1,4 and 2,3,4 between S and node 2-4 represent the existing shortest routes between $pair(2,4)$ in the original graph (must be oriented towards node 2-4 in the generated graph). Figure 3(b) illustrates the new graph generated for the graph shown in Figure 3(a). In Figure 3(b), although the edges representing paths with single hops are not inserted (to provide a better visualization), they are considered (nodes 1-2, 1-4, 2-3 and 3-4).

Therefore, the graph that represents the search space that will be covered by the artificial ants is the graph generated from the topology under study; therefore, a solution for the travelling salesman problem in this graph is equivalent to a route solution for the topology in Figure 3. For instance, an ant positioned at the initial node S can go through the graph using the links 1;2;3 and 2;1;4. Along with the single-hop paths, which are not illustrated in the graph of Figure 3(b), such CRs will form a viable solution for the problem.

The application of the ACO meta-heuristics is based on [12]; when the ACO meta-heuristics are applied to the travelling salesman problem, it follows the steps, which are displayed in Figure 4.

Step 1: Initialization. The following values are defined: initial pheromone concentration; parameters (α, β and γ, explained in this Section); pheromone evaporation rate ρ, maximum t number of iterations to be performed; and n amount of ants. The n ants are positioned on the initial node S, which is representative of the starting point for the ant movement.

Step 2: Iterative process.

1. Building the solution. Step by step, the n ants select the next node to visit based on the following:

   – Pheromone concentration (τ);

   – Similarity (*Sml*), which is an important metric because it defines the routes that have the lowest degree of similarity and exhibit a lower probability of simultaneously composing two different circuits;

   – Link Utilization(u), which is a value that indicates the amount of routes that cross a link. Each link has a counter, which is increased by 1 everytime it is selected by a new route. The counter is reset to 0 in each colony iteration.

   Determining the node to visit at iteration t requires the use of a selection method. Hence, each ant performs a selection based on the roulette wheel method [16] among the existing elements of the routing table $Ai = [a_{ij}(t)]$ in each network node, which stores the values of a_{ij} for each neighbor j of the current node i:

$$a_{ij} = \frac{[\tau_{ij}(t)]^{\alpha}[1/u_{ij}(t)]^{\beta}[Slm_{ij}]^{\gamma}}{\sum_{l \in N_i}[\tau_{il}(t)]^{\alpha}[1/i_{il}(t)]^{\beta}[Sml_{il}]^{\gamma}}, \forall j \in N_i, \quad (4)$$

   where τ_{ij} indicates the amount of pheromones present in the arc i-j during iteration t; u_{ij} value indicates the use of the link, which has an inverse value, so lower u_{ij} values can have a higher chance on the roulette wheel; Sml_{ij} is the similarity between the candidate routes for $pair(i, j)$; and parameters α, β and γ are the weights used in the ants' decision-making process when determining the different levels of influence for the pheromone, frequency of use and similarity, respectively.

2. Pheromone updating

   After building the solution, each artificial ant sends its route solution to the analytical model [17], which calculates, through matematical formulations, the *BP* value for each of the solutions. The *BP* values return to the ants, which use them as parameter for the calculation of pheromone deposition. Each ant returns to the origin through the path found, depositing on each link an amount of pheromone ($\Delta\tau_{ij}$) that is inversely proportional to the *BP* of that route. Thus, a route with high *BP* will have a smaller amount of pheromone deposited on its links, which reduces the probability of being drawn in the roulette wheel (during step 2).

   It should be emphasized that pheromone evaporation occurs simultaneously with pheromone deposition, and it is mathematically represented as follows:

$$\tau_{ij}(t+1) = (1-\rho) * \tau_{ij} + \Delta\tau_{ij}(t), \quad (5)$$

   where ρ represents the pheromone evaporation rate.

Step 3: Stop criteria. The route building (search for a solution) and pheromone concentration updating processes are performed until the stop criterion is met. If the stop criterion is met, the iterative process is interrupted and the best obtained route solution up to that moment is defined as the final solution.

In ACO-BSR, the stop criterion is defined by the establishment of a maximum number of iterations. If a new set of routes with a better performance is found in any iteration, this set should be maintained because it will be a partial solution that will then be compared to future solutions or considered a final solution if results with a better performance are not found. Figure 4 displays the ACO-BSR operation flow.

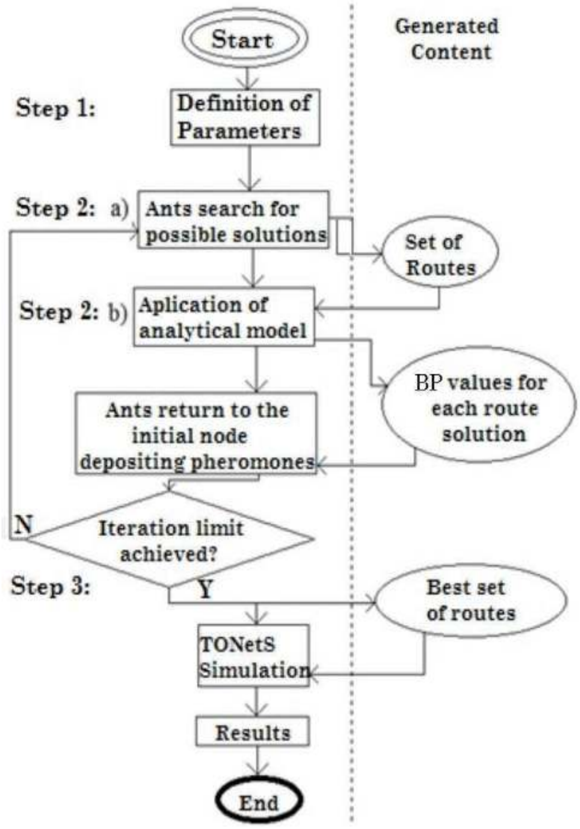

Figure 4. ACO-BSR application flow.

4 Performance Evaluation

This Section presents an evaluation that compares the performance of routing solutions obtained with the ACO (ACO-BSR) heuristic and three fixed routing algorithms: the DJK, BSR and BSR-DS algorithms. To apply the ACO-BSR, 20 ants and 400 iterations were used, and the determination of such values is explained in next Section. The presented analytical model [17] was used to obtain the network *BP*, which was used as an evaluation function (objective function) in the process of searching for the MCSP solution. Then, all four routing solutions obtained with the DJK, BSR, BSR-DS and ACO-BSR strategies were simulated using the TONetS (Transparent Optical Network Simulator), a simuation tool developed to study RWA algorithms, survivability techniques and wavelength converter placement in all-optical networks [3, 5, 7, 18]. The traffic load was uniformly distributed among all of the $pairs(o,d)$, and the requests were generated following a Poisson process with mean λ and an exponentially distributed time retention with mean $1/\mu$. The network traffic intensity was given by $\rho = \lambda/\mu$. All of the network links were two-directional and had 40 wavelengths in each direction. The *Random* algorithm was used for the wavelength allocation. For each simulation, 10 replications were performed with different seeds for the creation of random variables. For each replication, 100,000 optical circuit requests were generated. The topologies selected for the performance of the experiment were Abilene and USA, ilustrated in Figure 5. Both are real topologies located in US territory. Because the topologies occupy an extensive area and have an increasing number of users spread all around the US territory, both are frequently used in studies [2, 4, 5, 18]. Table 4 shows the values used for ACO-BSR parameters.

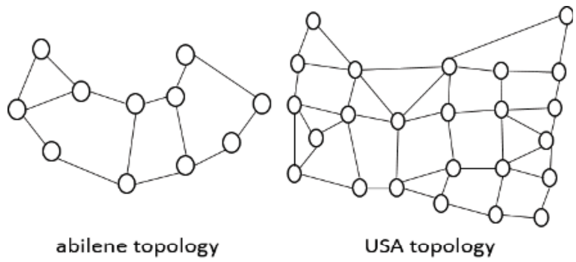

Figure 5. Abilene and USA topologies.

Table 4. Set of values used by the meta-heuristics parameters

Number of Ants	20
Number of Iterations	400
Evaporation Rate	0.25
α	1
β	0.1
γ	0.1

Figure 6 illustrates the variation of *BP* as a function of the increase in total network load for the Abilene and USA topologies. The results exhibit a confidence interval of 95%.

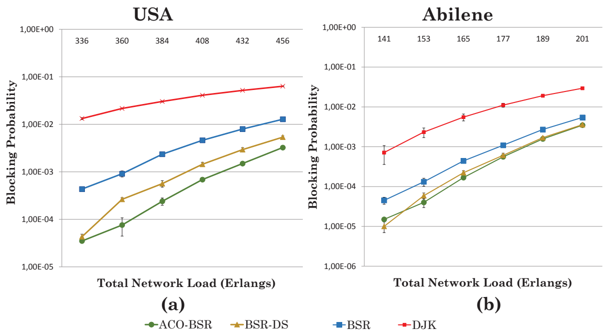

Figure 6. Variation of the BP for (a) USA and (b) Abilene topologies, with an increasing network load (in Erlangs).

The results for the Abilene topology show an inferior performance of the BSR compared with the results of the BSR-DS and ACO-BSR. There is a similarity between the graphical behavior of the BSR-DS and ACO-BSR. Because the Abilne topology displays a less robust structure, the quality of the solution obtained by the two algorithms can be close to a point where no significant improvement is possible, suggesting that the BSR-DS and ACO-BSR are the most indicated solutions for application in real scenarios of transparent optical networks.

For the USA topology, the ACO-BSR showed a better performance than the BSR-DS BSR and DJK, with the latter showing the worst performance. These results were related to the higher complexity of the USA topology and greater number of nodes and links, compared with the Abilene topology. Thus, the greater number of possible solutions was best analyzed by ACO-BSR, which had a Pb value 74.61% lower than that of the BSR and 39.48% lower than that of the BSR-DS. Another metric used to measure the quality of the route solution is fairness (Fr), which is defined in [7]. Considering $BP(o,d)$, which is the BP for a pair of nodes $pair(o,d)$, the value indicated by $1-BP(o,d)$ represents the probability that a $pair(o,d)$ will not suffer blocking. The Fr for a given topology is the proximity of a given value to the lowest and highest probability of not suffering blocking between all pairs of nodes. Reduction in Fairness value implies in more difficult to attend all users with similar BP rate. Equation (6) defines the Fr value.

$$Fr = \frac{1-(maxBP_{(o,d)})}{1-(minBP_{o,d})} \tag{6}$$

Figure 7 illustrates the variation of the Fr value with an increase in the network load for the USA(a) and Abilene(b) topologies.

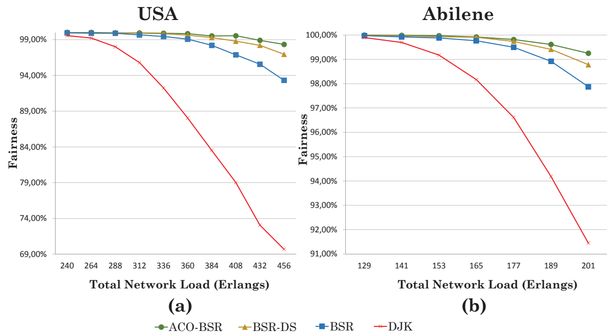

Figure 7. Fairness (Fr) as a function of the total network load (in Erlangs) to (a) USA and (b) Abilene topologies.

An analysis of the Fr value shows that the ACO-BSR has a better performance than the other three algorithms for both topologies. The algorithms DJK, BSR-DS and BSR do not provide simultaneous analyses of links similarity and frequency of use. Considering both heuristics, the ACO-BSR displays a more refined ability to select the lowest-cost route.

Although the BP values of the ACO-BSR are close to the values of the BSR-DS for the Abilene topology, the ACO-BSR has the advantage of exhibiting a more fair behavior, so it is more suitable for application in this topology.

Finally, a study based on the standard deviation values was also conducted. After calculating the average value of blocking probability for each load point, the standard deviation of the blocking probability value of all pairs was observed for each load point. Figure 8 shows the standard deviation values for USA and Abilene topologies.

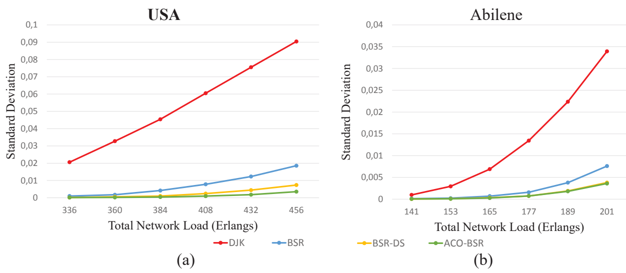

Figure 8. Standard Deviation values to (a) USA and (b) Abilene topologies.

For the USA topology, it is noted that the ACO-BSR presents a lower deviation between the average value and the blocking probability value of each pair, representing more uniform load distribution on the network. For the Abilene topology, there is a closeness of deviation values between the ACO-BSR and BSR-DS, demonstrating that both may exhibit similar behavior when evaluated in less complex topologies.

5 Impact of the ACO-BSR Heuristics Parameters in the MCSP Problem

To apply the ACO-BSR meta-heuristic, it is necessary to establish the values of certain parameters: weights of α (pheromone), heuristics β (frequency of use) and γ (similarity), total number of ants, maximum amount of iterations and pheromone evaporation rate. The performance achieved with variations of parameters is presented next and is based on the USA topology.

5.1 Number of Ants

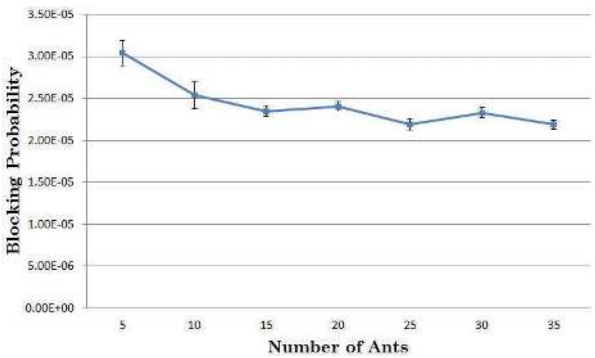

Figure 9. Variation of the *BP* with an increasing number of ants.

It is necessary to define the number of ants to be considered in the ACO-BSR algorithm. A greater number of ants tends to determine better results because it implies a better analysis of the set of routes (search space). Inversely, a great number of ants leads to an increase in the consumption of computational resources and execution time of the ACO meta-heuristic. Figure 9 shows the variation in the BP as a function of the number of ants. Notice that the value of BP tends to decrease with an increasing number of ants. The reduction of BP value does not occur linearly due to complexity of the problem. Additionally, the BP value tends to stabilize, suggesting that an increase in the number of ants does not provide further improvement of the solution.

The number of ants should vary according to the network size. For topologies with a greater number of nodes and links, a more refined analysis of all possible routes is required. During the experiment, 20 ants were used, which is a value that does not require great computational cost and has a *BP* value close to the value found by simulations with greater numbers of ants. Furthermore, an analysis of other studies that have employed the ACO algorithm suggests that 20 ants is an low cost number.

5.2 Number of Iterations

A greater number of iterations increases the chances of finding best-solution routes, although it implies a longer execution time. The *BP* exhibits greater variations in executions with less iterations (50, 100 and 150) because the *BP* is not as stable as it is in executions with more iterations (400, 450 and 500). Figure 10 shows the effect of the number of iterations on the *BP* value. Notice that after a maximum number of iterations, approximately 250, the optimization process stabilizes; therefore, 400 is a valid number for the maximum number of iterations.

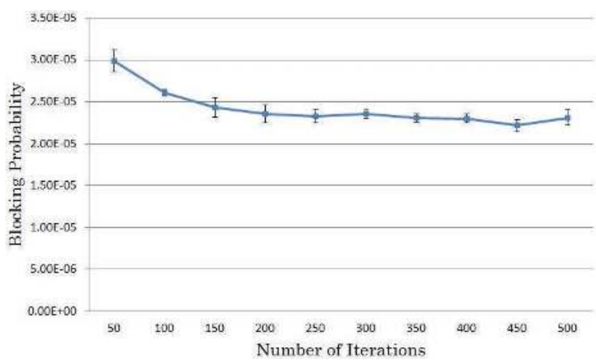

Figure 10. Variation of the *BP* with an increasing number of iterations.

5.3 Vary the weights of α, β and γ

The values of the weights (α for pheromone, β for frequency of use and γ for similarity) are normalized; therefore, to associate α, β or γ with a greater influence, an exponent with a value close to zero should be used. Providing the pheromone parameter with a high weight increases its influence on the value of A_{ij} and reduces the participation of both heuristics the constitution of the value for A_{ij}. This results in an improved probability of selecting routes with a greater frequency of use or similarity, which can affect the final result. To avoid such a scenario, the value of 1 is associated with the weight of the pheromone parameter. Figures 11 and 12 display the *BP* values when the weights of the other two heuristics (frequency of use and similarity, respectively) are changed. It is clear that the variation in the weight of the parameters does not exhibit a behavioral pattern. Therefore, to define the values that implies better performance, it is necessary to conduct initial experiments, which reaffirms the importance of the analytical model.

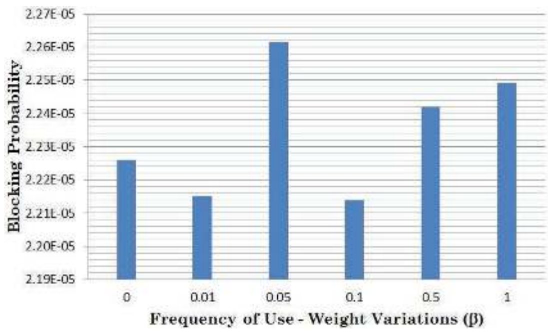

Figure 11. Variation of the *BP* caused by variation in the weights of frequency of use.

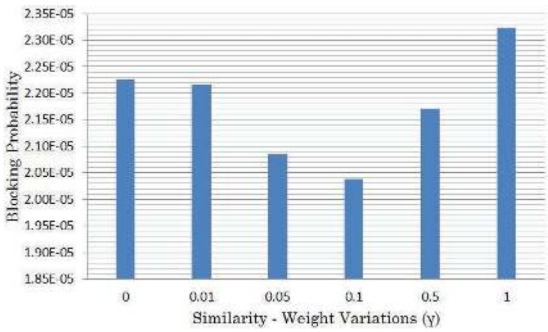

Figure 12. Variation of the *BP* caused by variation in the weights of similarity.

The plots in Figs. 13 and 14 compare the results (in *BP*) when the algorithms ACO-BSR and BSR-DS were applied to the USA and Abilene topologies, respectively. They also show the difference between the worst and best results found with variations of the weight for frequency of use (weight 0.05 for the worst and 0.1 for the best) and similarity (weight 1 for the worst and 0.1 for the best). The difference between the worst and best case is smaller compared to the variation of both parameters produced by the BSR-DS for the two topologies.

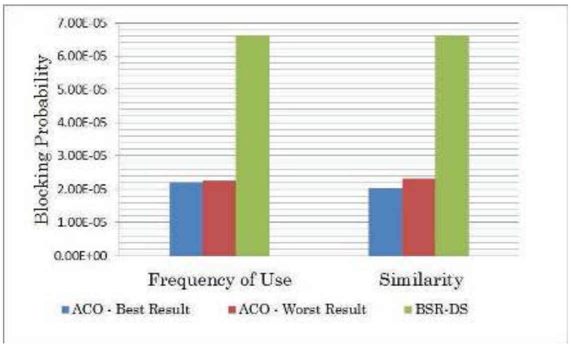

Figure 13. Best case, worst case and results of the BSR-DS obtained by the application of the analytical method to the USA topology.

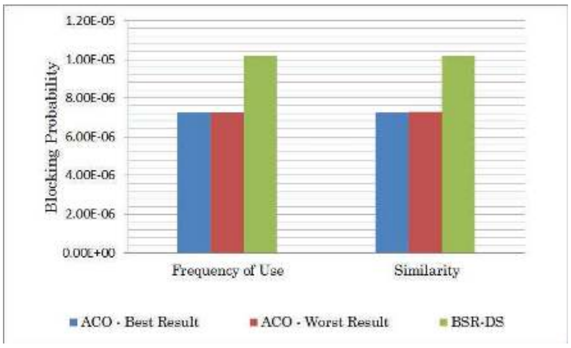

Figure 14. Best case, worst case and results of the BSR-DS obtained by the application of the analytical method to the Abilene topology.

6 Conclusions

Currently, the number of electronic devices with access to the internet has grown considerably. The popularity of such devices, along with the widespread use of robust applications, has created the need for greater bandwidth in transport networks. Hence, it is necessary to establish resource optimization strategies to guarantee a minimum level of QoS for the network users and avoid a greater number of blocked requests.

With the emergence of optical networks, new problems have occurred that must be addressed to optimize the network resources. One problem consists of selecting the best set of routes to establish circuits during network transmissions and determining the shortest route for a $pair(o,d)$ when more than one shortest route is presented. Considering the MCSP problem, this study proposes an algorithmic solution based on the Ant Colony Optimization, denominated ACO-BSR.

The search for the best combination of the shortest routes performed by the ACO-BSR considers three parameters that are essential for the proper functioning of the network: similarity, frequency of use and pheromone. The value of the similarity parameter depends on the degree of similarity between different shortest-path routes for the same pair of links. The value for the frequency of use parameter for a link is defined by the number of routes that cross it. Finally, the parameter pheromone has its value defined during the iterations of the ACO-BSR algorithm, and it exhibits higher results for the routes that provide better performance in terms of BP.

The ACO-BSR algorithm was applied to USA and Abilene topologies, and its performance was compared with the results obtained by the BSR-DS and BSR algorithms. For the USA topology, the ACO-BSR displayed better performance compared to the other two algorithms and provided a better mean value of network BP. The analysis of the Abilene topology showed that there was a similarity in *BP* values between the performance of the ACO-BSR and BSR-DS algorithms. However, the analysis of the Fairness parameter showed that there was more fair behavior when the ACO-BSR algorithm was used, implying that its use results in a better network load balance. A network with better load balance displays well-distributed routes among its links and allows for a better use of the networks capacity.

The use of the ACO-BSR algorithm does not require special properties for the search space; in addition, it is population-based and uses stochastic components for updating the solutions among its iterations. These main characteristics, along with the results of experiments performed for a scenario of transparent optical networks, show that the ACO-BSR algorithm can be as an alternative for fixed routing algorithms and indicate that it is adequate and efficient at solving the MCSP; therefore, it can be used and applied for real scenarios of transparent optical networks.

References

[1] A. Kretsis, K. Christodoulopoulos, P. Kokkinos, and E. Varvarigos, Planning and operating flexible optical networks: Algorithmic issues and tools, Communications Magazine, IEEE, vol. 52, no. 1, pp. 61–69, 2014.

[2] A. Stavdas, T. Orphanoudakis, and A. Drakos, Qos performance benchmarking of networking paradigms in core networks, in European Conference and Exhibition on Optical Communication (ECOC)(Turin, Italy, 2010), 2010.

[3] I. G. S. Santos, G. Duraes, W. Giozza, A. Soares, and B. Catu, A new routing algorithm to choose the best among shortest paths (in portuguese), in SBRC - Brazilian Symposium on Computer Networks and Distributed Systems, 2012.

[4] P. Rajalakshmi and A. Jhunjhunwala, Load balanced routing to enhance the performance of optical backbone networks, in Wireless and Optical Communications Networks, 2008. WOCN'08. 5th IFIP International Conference on. - IEEE, 2008, pp. 1–5.

[5] G. M. Duraes, A. Soares, J. R. Amazonas, and W. Giozza, The choice of the best among the shortest routes in transparent optical networks, Computer Networks, vol. 54, no. 14, pp. 2400–2409, 2010.

[6] E. W. Dijkstra, A note on two problems in connexion with graphs, Numerische mathematik, vol. 1, no. 1, pp. 269–271, 1959.

[7] A. Soares, W. Giozza, and P. Cunha, Classification strategy to mitigate unfairness in all-optical networks, in Networks, 2007. ICON 2007. 15th IEEE International Conference on. - IEEE, 2007, pp. 161–165.

[8] X. Wang, M. Brandt-Pearce, and S. Subramaniam, Distributed grooming, routing, and wavelength assignment for dynamic optical networks using ant colony optimization, Journal of Optical Communications and Networking, vol. 6, no. 6, pp. 578–589, 2014.

[9] F. C. Ergin, E. Kaldırım, A. Yayimli, and A. S. Uyar, Ensuring resilience in optical wdm networks with nature-inspired heuristics, Optical Communications and Networking, IEEE/OSA Journal of, vol. 2, no. 8, pp. 642–652, 2010.

[10] Y. Wang, J. Zhang, Y. Zhao, J. Wang, and W. Gu, Aco-based routing and spectrum allocation in flexible bandwidth networks, Photonic Network Communications, vol. 25, no. 3, pp. 135–143, 2013.

[11] M. Dorigo, M. Birattari, and T. Stutzle, Ant colony optimization, Computational Intelligence Magazine, IEEE, vol. 1, no. 4, pp. 28–39, 2006.

[12] M. Dorigo, E. Bonabeau, and G. Theraulaz, Ant algorithms and stigmergy, Future Generation Computer Systems, vol. 16, no. 8, pp. 851–871, 2000.

[13] A. P. Engelbrecht, Computational intelligence: an introduction. John Wiley & Sons, 2007.

[14] L. N. De Castro, Fundamentals of natural computing: basic concepts, algorithms, and applications. CRC Press, 2006.

[15] A. P. Engelbrecht, Fundamentals of computational swarm intelligence. John Wiley & Sons, 2006.

[16] L. Zhang, H. Chang, and R. Xu, Equal-width partitioning roulette wheel selection in genetic algorithm, in Technologies and Applications of Artificial Intelligence (TAAI), 2012 Conference on. IEEE, 2012, pp. 62–67.

[17] X. Chu, J. Liu, and Z. Zhang, Analysis of sparse-partial wavelength conversion in wavelength-routed wdm networks, in INFOCOM 2004. Twenty-third AnnualJoint Conference of the IEEE Computer and Communications Societies, vol. 2. IEEE, 2004, pp. 1363–1371.

[18] A. Fontinele, I. Santos, G. Duraes, J. Maranhao, and A. Soares, Regenerator preventive allocation in translucent optical networks (in portuguese), in SBRC - Brazilian Symposium on Computer Networks and Distributed Systems, 2014, pp. 721–734.

Ítalo Barbosa Brasileiro is in the Pos-graduation in Computer Science's Program at Federal University of Piaui and holds a BA in Computer Science course at Federal University of Piaui (UFPI). Participate of the Distributed Systems and Computer Network Laboratory (DisNeL) as researcher. Currently researches in computer network area, with emphasis on optical networks.

Iallen Gábio de Sousa Santos holds a degree in Computer Science from the Federal University of Piauí, currently in the Post-graduation in Computer Science's Program at Federal University of Piauí and member of Distributed Systems and Computer Network Laboratory (DiSNeL). Works in the area of computer networks with experience in area of vehicular networks and currently focused in the area of optical networks.

André Castelo Branco Soares was born in Teresina, Brazil. He received the BSc degree in Computer Science in 2001 from the Federal University of Piaui (UFPI), Teresina, Brazil; MSc degree in Computer Network in 2004 from the Salvador University, Salvador, Brazil; and PhD degree in Computer Science in 2009 from the Federal University of Pernambuco, Recife, Brazil. He is professor of the Computer Department at UFPI. Professor Soares coordinates the Distributed Systems and Network Computer Laboratory - DisNeL at UFPI. Currently, his research interest includes topics like optical network, survivability, RWA, RSA and hybrid optical switching.

Ricardo de Andrade Lira Rabelo received a PhD. degree in Power Systems from Sao Carlos Engineering School, University of Sao Paulo, Brazil in 2010. His areas of research interest are intelligent systems, power system planning and operation and power quality.

Felipe Eduardo do Nascimento Mazullo received the BE degree in Computer Science from the Universidade Federal do Piaui, Brazil, in 2011. In 2012, worked as a volunteer researcher at the Laboratory of Networks and Distributed Systems from Universidade Federal do Piaui. He joined as researcher student at the University of Tsukuba in Department of Systems and Information Engineering in 2013. He is currently a master's student in Graduate School of Systems and Information Engineering at the University of Tsukuba where he works developing research in the field of Optical Networks Elastic through the MEXT scholarship program of the Japanese Ministry of Education. His research focuses on routing algorithms and spectrum allocation. His research interests include, routing algorithms, MAC protocols, optical networks, wireless sensor networks, vehicular networks, distributed computing, simulation, big data.