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Routing and wavelength assignment in all-optical networks based on the bee colony optimization

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Abstract. Routing and Wavelength Assignment (RWA) problem in all-optical networks assumes determining the routes and wavelengths to be used to create the lightpaths for connection requests. The RWA problem belongs to a class of difficult combinatorial optimization problems. We propose the Bee Colony Optimization (BCO) heuristic algorithm tailored for the RWA problem (BCO–RWA) in all-optical networks without wavelength conversion in intermediate nodes. The BCO represents a new metaheuristic capable to solve difficult combinatorial optimization problems. The artificial bee colony behaves partially alike, and partially differently from bee colonies in nature. The proposed BCO–RWA algorithm has been performed for static case in which ligthpath requests are known in advance. We proved that BCO–RWA is able to produce optimal or near-optimal solutions in a reasonable amount of computer time.

Keywords: Bee colony optimization, lightpaths, metaheuristic, optical networks, routing and wavelength assignment

1. Introduction

Optical networks employing Wavelength Division Multiplexing (WDM) technique are believed to be the next generation networks that can meet ever increasing capacity requirements for advanced services. Recent developments in WDM technology have led to a tremendous research interest in WDM-based optical network design [3,21,31,38,39,45,49].

WDM technique brings out new problems in coordination of wavelengths usage in network. Each wavelength is a separate, circuit-switched communication channel, called a lightpath, carrying data up to several Gb/s. When it is needed to establish a lightpath between a node pair, a route must be found and a wavelength has to be assigned to carry the information. The problem is known as routing and wavelength assignment (RWA) [1,2,17,35–37,45,47,56]. In the case when the wavelength conversion at intermediate routing nodes is not possible, a lightpath has to be set up by assigning a dedicated wavelength to it on each physical link along its path between the end nodes in a network.

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Routing and wavelength assignment problem is a significant research topic. A number of papers devoted to the RWA problem proposed various both exact and heuristic approaches. A detailed survey of these methods can be found in [21] or in [56]. The RWA problem is combinatorial by its nature and belongs to a class of difficult combinatorial optimization problems [2,44,47]. The optimal solution is difficult to reach, especially in the cases of large networks. The RWA problem is found to be an NP-complete problem that cannot be solved exactly in polynomial time.

We concentrate here on the static version of the routing and wavelength assignment problem in which the connection requests are known in advance. Our objective is to maximize the number of established lightpaths, known as the Max-RWA problem. The Max-RWA problem could be formulated as an integer linear program (ILP). The reviews of various ILP formulations that have been proposed can be found in [25,26]. Two different 0-1 linear programming formulations of the Max-RWA problem are proposed in [32]. The solution approach in [32] is based on linear relaxations. Also, a new integer linear programming formulation is proposed in [42].

A range of heuristic and metaheuristic algorithms (Simulated Annealing, Tabu Search, Genetic Algorithms, Ant Colony Optimization) have been proposed for the RWA problem in [3–5,12,22,27,30,31,38,42,44,48,54].

In this paper, we propose a new metaheuristic algorithm for the RWA problem. Our approach is based on the bee colony optimization (BCO). The BCO heuristic algorithm is tailored for the Max-RWA problem in all-optical networks. The artificial bee colony behaves partially alike, and partially differently from bee colonies in nature and represents the new metaheuristic capable to solve difficult combinatorial optimization problems. The proposed BCO–RWA algorithm has been able to produce high quality solutions in a reasonable computation time. We compare the results of our algorithm with the results obtained by two different approaches applied to solve the same problem. The first one is the LP relaxation approach proposed in [32]. The second one is the Tabu metaheuristic algorithm recently proposed in [22]. The comparison shows that our algorithm gives better performances in terms of the number of established lightpaths.

The paper is organized in the following way. Problem statement is given in Section 2. Bee colony behavior in the nature is given in Section 3. Section 4 contains detailed description of the proposed BCO–RWA algorithm. Section 5 is devoted to the description of numerical experiments and obtained simulation results. Finally, the conclusion is given in the Section 6.

2. Statement of the problem

The Max-RWA problem that we consider in this paper is defined in the following way: *For a given traffic demand matrix and the given number of wavelengths, maximize the number of established lightpaths in a given optical network*. We assume a network in which wavelength conversion is not available. This means that a lightpath operates on the same wavelength across all fiber links that it traverses (a lightpath satisfies the wavelength-continuity constraint). We assume that a given optical network is single fiber which means that each physical link has one separate fiber for each direction. Each fiber supports the same number of wavelengths W.

An optical network composed of N nodes and L physical links can be represented by a corresponding graph with N nodes and L undirected edges. We use the mathematical formulation of the Max-RWA problem proposed by Krishnaswamy and Sivarajan in [32]. Let us introduce the following notation:

N – The set of nodes in given network,
$|N|$ – The total number of nodes,
L – The set of links in given network,
$|L|$ – The total number of links,
i, j – End points of a physical link, $i, j \in N$,
(s, d) – Source-destination node pair for a requested lightpath, $s, d \in N, s \neq d$,
SD – Set of node pairs (s, d),
$|SD|$ – The total number of (s, d) pairs,
Λ – The set of available wavelengths λ, where $\lambda \in \Lambda$,
W – The total number of available wavelengths $W = |\Lambda|$,
$\rho_{(s,d)}$ – The number of requested lightpaths for a node pair (s, d),
P – The ordinar number of a requested lightpath for given (s, d) pair, $P = [1, 2, \ldots, \rho_{(s,d)}]$,

$$C_{i,j} = \begin{cases} 1, & \text{if between two nodes } i \text{ and } j \text{ exists a physical link, } \forall i, j \in N, \\ 0, & \text{otherwise,} \end{cases}$$

$$x^{p}_{(s,d)} = \begin{cases} 1, & \text{if a lightpath } p \text{ for a node pair } (s,d) \text{ is established,} \\ 0, & \text{otherwise,} \end{cases}$$

$$x^{p,\lambda}_{(s,d)} = \begin{cases} 1, & \text{if a lightpath } p \text{ for a node pair } (s,d) \text{ is established using } \lambda, \\ 0, & \text{otherwise,} \end{cases}$$

$$x^{p,\lambda}_{(s,d),(i,j)} = \begin{cases} 1, & \text{if a lightpath } p \text{ for a node pair } (s,d) \text{ is established using } \lambda \text{ over a link } (i,j), \\ 0, & \text{otherwise.} \end{cases}$$

The following is the mathematical formulation of the Max-RWA problem:

$$\max F = \sum_{(s,d)=1}^{|SD|} \sum_{p=1}^{\rho_{(s,d)}} x^{p}_{(s,d)}, \tag{1}$$

$$\sum_{p=1}^{\rho_{(s,d)}} x^{p}_{(s,d)} \leqslant \rho_{(s,d)} \quad \forall (s,d), \tag{2}$$

$$\sum_{\lambda=1}^{W} x^{p,\lambda}_{(s,d)} = x^{p}_{(s,d)} \quad \forall p, (s,d), \tag{3}$$

$$x^{p,\lambda}_{(s,d),(i,j)} \leqslant x^{p}_{(s,d)} \quad \forall p, (s,d), \lambda, (i,j), \tag{4}$$

$$\sum_{(s,d)=1}^{|SD|} \sum_{p=1}^{\rho_{(s,d)}} x^{p,\lambda}_{(s,d),(i,j)} \leqslant 1 \quad \forall \lambda, (i,j), \tag{5}$$

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$$\sum_{i=1}^{|N|} C_{(i,j)} \times x^{p,\lambda}_{(s,d),(i,j)} - \sum_{i=1}^{|N|} C_{(j,i)} \times x^{p,\lambda}_{(s,d),(j,i)} = \begin{cases} \mathrm{x}^{p,\lambda}_{(s,d)}, & \text{if } j = s,\ \forall (s,d), p, \lambda, j, \\ -\mathrm{x}^{p,\lambda}_{(s,d)}, & \text{if } j = d, \\ 0, & \text{if } j \neq s \wedge j \neq d, \end{cases} \tag{6}$$

$$x^{p}_{(s,d)}, x^{p,\lambda}_{(s,d)}, x^{p,\lambda}_{(s,d),(i,j)} \in \{0, 1\}. \tag{7}$$

We try to maximize the total number of established lightpaths (relation (1)). The constraint (2) ensures that the total number of established lightpaths for a node pair (s, d) is at most $\rho_{(s,d)}$. The relations (3)–(6) ensure the wavelength continuity constraints. The constraint (3) ensures that if a lightpath p exists between node pair (s, d) then only one wavelength is assigned to it, between the W possible alternatives. Only those $x^{p,\lambda}_{(s,d),(i,j)}$ could be nonzero for which the $x^{p,\lambda}_{(s,d)}$ variables are nonzero (the constraint (4)). No two lightpaths traversing through the same link (i, j) will have the identical wavelength assigned to them (constraint (5)). The identical wavelength is kept at every node for a lightpath $x^{p}_{(s,d)}$ (constraint 6)). The constraint (7) ensures that all the variables are binary.

We solve the defined problem by the new metaheuristic algorithm based on the bee colony optimization (BCO).

3. Bees in the nature

A great number of traditional models and algorithms used to solve complex problems are based on control and centralization. Various natural systems (social insect colonies) lecture us that very simple individual organisms can create systems able to perform highly complex tasks by dynamically interacting with each other [7–10].

Bee swarm behavior in nature is, first and foremost, characterized by autonomy and distributed functioning and self-organizing. In the last couple of years, the researchers have started studying the behavior of social insects in an attempt to use the swarm intelligence concept in order to develop various artificial systems.

Self-organization of bees is based on a few relatively simple rules of individual insect's behavior [6,11,13, 15,16,18–20,23,24,28,29,43,49–53,55]. In spite of the existence of a large number of different social insect species, and variation in their behavioral patterns, it is possible to describe individual insects as capable of performing a variety of complex tasks [14]. The best example is the collection and processing of nectar, the practice of which is highly organized. Each bee decides to reach the nectar source by following a nestmate who has already discovered a patch of flowers. Each hive has a so-called dance floor area in which the bees that have discovered nectar sources dance. In that way, they try to convince their nestmates to follow them. If a bee decides to leave the hive to get nectar, she follows one of the bee dancers to one of the nectar areas. Upon arrival, the foraging bee takes a load of nectar and returns to the hive relinquishing the nectar to a food store bee. After she relinquishes the food, the bee can (a) abandon the food source and become again uncommitted follower, (b) continue to forage at the food source without recruiting the nestmates, or (c) dance and thus recruit the nestmates before the return to the food source. The bee opts for one of the above alternatives with a certain probability. Within the dance area, the bee dancers "advertise" different food areas. The mechanisms by which the bee decides to follow a specific dancer are not well understood, but it is considered that "he recruitment among bees is always a function of the quality of the food source" [14]. It is also noted that not all bees start foraging simultaneously. The experiments confirmed, "new bees begin foraging at a rate proportional to the difference between the eventual total and the number presently foraging".

Lučić and Teodorović [33,34] introduced the bee colony optimization (BCO) metaheuristic and tested it in the case of Traveling Salesman Problem. Teodorović and Dell'Orco [51] applied the BCO when trying to solve the Ride-Matching Problem. In this paper, we propose the BCO heuristic algorithm tailored for the Max-RWA problem.

4. The BCO–RWA algorithm

The agents that we call artificial bees collaborate in order to solve the Max-RWA problem. We create the artificial network shown in Fig. 1. The node depicted by the square in Fig. 1 represents hive. At the beginning of the search process all artificial agents are located in the hive. Bees depart from the hive and fly through the artificial network from the left to the right. Bee's trip is divided into stages. Bee chooses to visit one artificial node at every stage. Each stage represents the collection of all considered origin-destination pairs. Each artificial node is comprised of an origin and destination linked by a number of routes. Light-

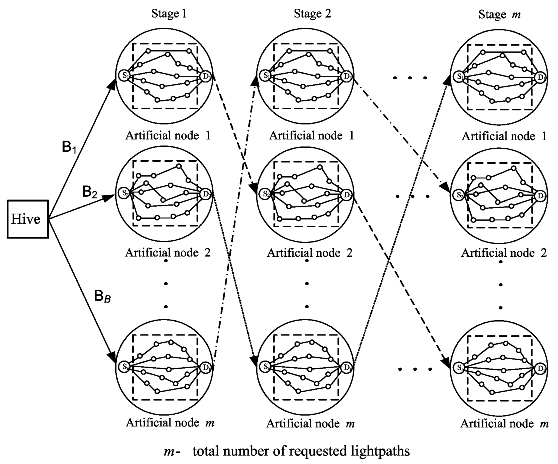

Fig. 1. The artificial network.

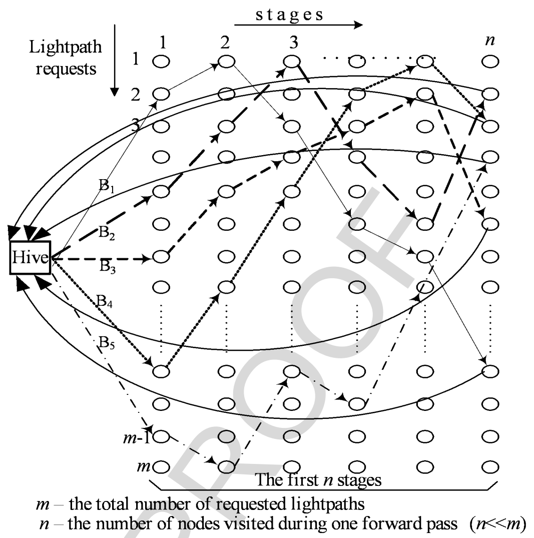

Fig. 2. The first forward and backward pass through the artificial network.

path is a route with assigned wavelength chosen by bee agent. Bee agent's entire flight is collection of established lightpaths. We have determined in advance the number of bees B and the number of iterations I (the concept of iteration will be explained later).

During the search process, artificial bees communicate directly. When flying through the space our bees perform forward pass or backward pass (Fig. 2). During forward pass every bee visits n stages (bee tries to establish n new lightpaths). In every stage a bee chooses one of the previously not visited artificial nodes. Sequence of the n visited artificial nodes generated by the bee represents one partial solution of the problem considered. Bee is not always successful in establishing lightpath when visiting artificial node. Bee's success depends on the wavelengths' availability on the specific links. In this way, generated partial solutions differ among themselves according to the total number of established lightpaths.

After forward pass, bees perform backward pass, i.e. they return to the hive. The number of nodes n to be visited during one forward pass is prescribed by the analyst at the beginning of the search process, such that $n \ll m$, where m is the total number of requested lightpaths.

In the hive, all bees participate in a decision-making process. We assume that every bee can obtain the information about solutions' quality generated by all other bees. In this way, bees exchange information about the quality of the partial solutions created (the number of established lightpaths). Bees compare all generated partial solutions. Based on the quality of the partial solutions generated, every bee decides whether to abandon the created partial solution and become again uncommitted follower, continue to expand the same partial solution without recruiting the nestmates, or dance and thus recruit the nestmates before returning to the created partial solution. Depending on the quality of the partial solutions generated, every bee possesses certain level of loyalty to the path leading to the previously discovered partial solution.

During the second forward pass (Fig. 3), bees expand previously created partial solutions (try to establish additional n lightpaths), and after that perform again the backward pass and return to the hive. In the hive bees again participate in a decision-making process, perform third forward pass, etc. The iteration ends when one or more feasible solutions of the RWA problem are created. The best discovered solution during the first iteration is saved, and then the second iteration begins. Within the second iteration, bees again incrementally construct solutions of the problem, etc. There is one or more created partial solutions at the end of each iteration. The parameter n reflects the granularity of the search process. The total number of forward passes U in a search process depends on the total number of requested lightpaths m, as well as on the value of the prescribed parameter n, where $U = \lceil m/n \rceil$.

For example, shown in Fig. 3, bees B_2, B_3 and B_4 participated in the decision-making process. By comparing the qualities of all generated partial solutions after the first backward pass, these bees decided to abandon its already generated paths (visited artificial nodes) and to join bees B_1 and B_5. Figure 3 illustrates the situation in which bee B_3 joined bee B_1, and bees

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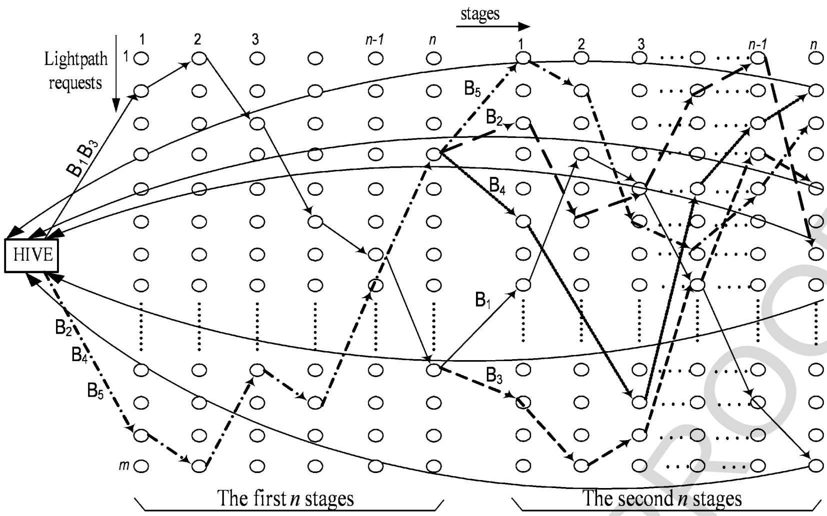

Fig. 3. Illustration of the bee's flight throughout the artificial network during the first and second n stages.

B_2 and B_4 joined bee B_5. During the second forward pass bees B_3 and B_1 fly together along the path generated by the bee B_1, while bees B_2 and B_4 fly together along the path generated by the bee B_5. When they reach the end of the path, they are free to make individual decision about next node to be visited. During the second forward pass, bees will visit n more unvisited nodes, expand previously created partial solutions, and after that perform again the backward pass and return to the hive. In the hive, bees will again participate in a decision making process, make a decision, perform third forward pass, etc.

4.1. *Bee's node and route choice mechanisms*

Bees choose some of the artificial nodes (not previously visited) in a random manner. Probability p that a specific unvisited artificial node will be chosen by the bee equals $1/n_{tot}$, where n_{tot} is the total number of unvisited artificial nodes. By visiting specific artificial node in the network shown in Fig. 3 bees attempt to establish the requested lightpath between one real source-destination node pair in optical network. Let us assume that the specific bee decided to consider the lightpath request between the source node s and the destination node d. In the next step, it is necessary to choose the route and to assign an available wavelength along the route between these two real nodes. In this paper, we defined for every node pair (s, d), the subset R_{sd} of allowed routes that could be used when establishing the lightpath. We defined these subsets by using the k shortest path algorithm. We calculated for every of the k alternative routes the bee's utility when choosing the considered route. The shorter the chosen route and the higher the number of available wavelengths along the route, the higher the bee's utilities are. We define the bee's utilities V_r^{sd} when choosing the route r between the node pair (s, d) in the following way:

$$V_r^{(s,d)} = a\frac{1}{h_r - h_{rmin} + 1} + (1-a)\frac{W_r}{W_{max}}, \qquad (8)$$

where:

- r – The route ordinary number for a node pair, $r = 1, 2, \dots, k$, $r \in R^{sd}$,
- h_r – The route length expressed in the number of physical hops,
- h_{rmin} – The length of the shortest route r,
- W_r – The number of available wavelengths along the route r,
- W_{max} – The maximum number of available wavelengths among all the routes,
- a – Weight (importance of the criteria), $0 \leqslant a \leqslant 1$.

Bees decide to choose a physical route in optical network in a random manner. Inspired by the well-known Logit model (one of the most successful and widely accepted discrete choice model), we have assumed that the probability p_r^{sd} of choosing route r in the case of origin-destination pair (s, d) equals:

$$p_r^{(s,d)} = \frac{e^{V_r^{sd}}}{\sum_{i=1}^{|R^{sd}|} e^{V_i^{sd}}}, \quad \forall r \in R^{sd}, \qquad (9)$$

where $|R^{sd}|$ is the total number of available routes between pair of nodes (s, d). The higher the bee's utilities V_r^{sd} along route r, the higher the probability p_r^{sd} of choosing route r. The route r is available if there is at least one free wavelength common along all the links that belong to the route r.

In order to assign bee to one of the considered routes we use roulette wheel. We divide the wheel into the segments. Every segment corresponds to one considered route. The size of each segment equals to the probability of choosing specific route. A segment is randomly selected by spinning the roulette wheel. In this way, we assign bee to a specific route connecting specific origin-destination pair. In the next step, using the random strategy, one of the available wavelengths is assigned to the route chosen by the bee.

4.2. *Bee's partial solutions comparison mechanism*

For every bee we now know the quality of the created partial solution. In the hive every bee makes the decision about abandoning the created partial solution or expanding it in the next forward pass. It is assumed in this paper that every bee can obtain the information about partial solution quality created by every other bee. The probability p_b^{u+1} that the bee b will at beginning of the $u+1$ forward pass use the same partial tour that is defined in forward pass u equals:

$$p_b^{u+1} = \mathrm{e}^{-\frac{C_{max} - C_b}{u}}, \tag{10}$$

where:

- C_b – The total number of established lightpaths from the beginning of the search process by the bth bee,
- C_{max} – The maximal number of established lightpaths from the beginning of the search process by any bee,
- u – Ordinary number of forward pass, $u = 1, 2, \ldots, U$, where $U = \lceil m/n \rceil$.

We can see from the relation (10) that if a bee has discovered the best partial solution in forward pass u ($C_b = C_{max}$), the bee b will continue to fly along the same partial tour in the $u + 1$ forward pass with the probability equal to one ($p_b^{u+1} = 1$). The smaller the number of the established lightpaths by the bee, the smaller is the probability that the bee will fly again along the same path. The smaller the ordinary number of the forward pass u (beginning of the search process) the higher the bees' "freedom of flight". The more forward passes we make, the bees have less freedom to explore the solution space.

The random number z is generated from the interval [0, 1]. When $z \leqslant p_b^{u+1}$, a bee will fly along the same partial tour. In the opposite case when $z > p_b^{u+1}$, bee will abandon the created partial solution and become the uncommitted follower.

4.3. *Recruiting process*

After making the decision to continue flight along the previously generated path, the bee flies to the dance floor area in the hive and starts dancing. Bee dancing represents the interaction between individual bees in the colony. This kind of communication between individual bees contributes to the formation of the "collective intelligence" of the bee colony. In the case when at the beginning of stage $u + 1$ bee does not want to fly along the same path, it will go to the dancing area and will follow another dancing bee. In this way, two groups of bees are formed in the dancing area – uncommitted followers ready to join some of the dancing bees, and dancing bees ready to recruit uncommitted followers. The probability p_P that the Pth advertised partial solution will be chosen by any of the uncommitted follower equals:

$$p_P = \frac{\mathrm{e}^{C_P}}{\sum_{i=1}^{Q} \mathrm{e}^{C_i}}, \tag{11}$$

where:

- C_P – The total number of the established lightpaths in the case of the Pth advertised partial solution,
- Q – The total number of advertised partial solutions.

The random number is generated from the interval [0, 1] for every uncommitted follower. Using these random numbers and the relation (11) every uncommitted follower is "assigned" to one of the dancing bees. In this way, the number of bees flying along specific path is changed before beginning of the new forward pass. Using collective knowledge and sharing information among themselves, bees concentrate on more promising search paths, and slowly abandon less promising paths.

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4.4. The pseudo-code of the bee colony optimization

The following is the pseudo-code of the bee colony optimization metaheuristic in the case when $n = 1$.

(1) Initialization. Determine the number of bees B, the number of iterations I and the number of artificial nodes n to be visited during each forward pass. Select the set of stages $ST = \{st_1, st_2, \ldots, st_m\}$. Find any feasible solution x of the problem. This solution is the initial best solution.
(2) Set $i := 1$. Until $i = I$, repeat the following steps;
(3) Set $j := 1$. Until $j = m$, repeat the following steps;
Forward pass: Allow bees to fly from the hive and to choose B partial solutions from the set of partial solutions S_j at stage st_j.
Backward pass: Send all bees back to the hive. Allow bees to exchange information about quality of the partial solutions created and to decide whether to abandon the created partial solution and become again uncommitted followers, continue to expand the same partial solution without recruiting the nestmates, or dance and thus recruit the nestmates before returning to the created partial solution. Set $j := j + 1$.
(4) If the best solution x_i obtained during the ith iteration is better than the best-known solution, update the best-known solution ($x := x_i$).
(5) Set $i := i + 1$.

Alternatively, forward and backward passes could be performed until some other stopping condition is satisfied. The possible stopping conditions could be, for example, the maximum total number of forward/backward passes, or the maximum total number of forward/backward passes between two objective function value improvements.

5. Numerical experiments

The proposed BCO–RWA algorithm was tested on a few numerical examples. We present here some computational and comparative results for the BCO–RWA algorithm. The first example is related to the optical network shown in Fig. 4. Each edge (link) represents a pair of directed fibers, one for each direction. We assumed that the total number of available wavelengths W is same for each fiber link.

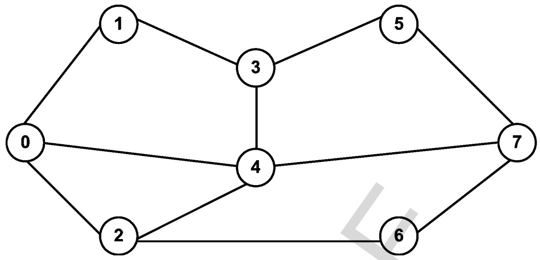

Fig. 4. The optical network with 8 routing nodes.

The traffic demands (requested lightpaths) used in this numerical experiment are presented by matrices D_i ($i = 1, \ldots, 6$) given below for $D_{1tot} = 28$, $D_{2tot} = 31$, $D_{3tot} = 34$, $D_{4tot} = 36$, $D_{5tot} = 38$ and $D_{6tot} = 40$. D_{itot} is the total number of requested lightpaths.

$$D_1 = \left[\begin{array}{c|cccccccc} d_{s,d} & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ \hline 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \\ 2 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 3 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 4 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 5 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 6 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 7 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 \\ 8 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 \end{array}\right],$$

$$D_2 = \left[\begin{array}{c|cccccccc} d_{s,d} & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ \hline 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 \\ 2 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 3 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 4 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 5 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 6 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 7 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 \\ 8 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \end{array}\right],$$

$$D_3 = \left[\begin{array}{c|cccccccc} d_{s,d} & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ \hline 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 \\ 2 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 \\ 3 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\ 4 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 5 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 6 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 7 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 \\ 8 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \end{array}\right],$$

$$D_4 = \left[\begin{array}{c|cccccccc} d_{s,d} & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ \hline 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 \\ 2 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 \\ 3 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\ 4 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 5 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 6 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 7 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 8 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \end{array}\right],$$

$$D_5 = \left[\begin{array}{c|cccccccc} d_{s,d} & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ \hline 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 \\ 2 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\ 3 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 \\ 4 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 5 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 6 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 7 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 8 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \end{array}\right],$$

$$D_6 = \left[\begin{array}{c|cccccccc} d_{s,d} & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ \hline 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 \\ 2 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\ 3 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 \\ 4 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 5 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 6 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 7 & 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 \\ 8 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \end{array}\right].$$

Each element $d_{s,d}$ in these matrices has one of the two possible values:

$$d_{(s,d)} = \begin{cases} 1, & \text{if a lightpath request exists} \\ & \text{between two end nodes } s \text{ and } d, \\ 0, & \text{otherwise.} \end{cases}$$

The first matrix D_1 is drawn at random. The next matrix D_2 is obtained by randomly converting three zero elements in the matrix D_1 into three ones. The third matrix is obtained by randomly converting three zeros in the matrix D_2 into three ones, etc.

The total number of bees engaged in discovering the optimal solution equals $B = 10$, while the total number of alternative routes between every node pair equals $k = 5$. We compared the obtained BCO–RWA results with the optimal solution for various number of connection requests that are to be established and different values of W. The comparison results are shown in the Table 1.

The proposed BCO–RWA algorithm produced results of a very high quality which can be seen from the Table 1. The BCO–RWA algorithm was able to obtain the objective function values that are very close to the optimal values of the objective function. The relative errors or relative deviations compared to optimal solutions are only few percents (less than 7% in the case of small number of available wavelengths). In cases of more complex problems (characterized by the higher number of available wavelengths) the BCO–RWA has produced the optimal solution.

The CPU times required to find the best solutions by the BCO–RWA are very low. In other words, the BCO–RWA was able to produce "very good" solutions in a "reasonable" computation time. Based on great number of performed tests, it could be shown that the number of bees significantly affects the required computational time, but the solution quality does not change much if the number of bees increases. The results for CPU times, shown in Table 1, are obtained for the case of $I = 10$ algorithm iterations. All the tests were performed on Intel(R) Pentium(R) computer processor with 1.73 GHz and 504 MB of RAM.

The second considered example is moderately large network, composed of 20 nodes and 39 links, which represents the European Optical Network (EON) [41]. The physical topology of the EON network is shown in Fig. 5. The RWA problem for this network was also solved in [32]. In order to solve the Max-RWA ILP problem the authors of [32] used the LP-relaxation technique. In order to round fractional values of the variables they developed two heuristic algorithms, named algorithm A and algorithm B.

We adopted the same traffic matrix (given by Table 2), as in [27], with the aim to provide the fair comparison between our BCO–RWA algorithm with the existing LP-relaxation approach in [32] and Tabu metaheuristic in [22].

The total number of requested lightpaths for this network was 374. The second comparison of various algorithms is given in Table 3 and illustrated in Fig. 6. From Table 3 it can be seen that our BCO–RWA always outperforms the proposed algorithms A and B, given in [32]. Also, our BCO–RWA algorithm outperforms the results of recently proposed Tabu metaheuristic algorithm in [22] for the larger number of available wavelengths. Note that our algorithm gives better performances for more complicated problem. The greater the number of wavelengths the closer the BCO–RWA value to the upper bound. When the number of available wavelengths is equal to 22 or more, we obtained the maximal number of established lightpaths (374).

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Table 1

The results comparison for the network shown in Fig. 4

Total number of requested lightpaths	Number of wavelengths	Number of established lightpaths		Relative error (%)	CPU time (s)	
		Optimal (ILP) solution	BCO–RWA solution		Optimal (ILP) solution	BCO–RWA solution
28	1	14	14	0	4	4.33
28	2	23	23	0	94	4.58
28	3	27	27	0	251	4.68
28	4	28	28	0	313	4.66
31	1	15	14	6.67	4	4.73
31	2	25	25	0	83	5.00
31	3	30	30	0	25	5.19
31	4	31	31	0	1410	5.21
34	1	15	14	6.67	14	5.19
34	2	27	26	3.70	148	5.50
34	3	33	33	0	216	5.64
34	4	34	34	0	906	5.64
36	1	16	15	6.25	23	5.64
36	2	27	26	3.70	325	6.09
36	3	34	34	0	788	6.11
36	4	36	36	0	1484	6.13
38	1	17	16	5.88	16	5.67
38	2	28	27	3.57	247	6.09
38	3	35	35	0	261	6.23
38	4	38	38	0	1773	6.33
40	1	17	16	5.88	31	6.00
40	2	28	27	3.57	491	6.28
40	3	35	35	0	429	6.61
40	4	40	40	0	1346	6.67

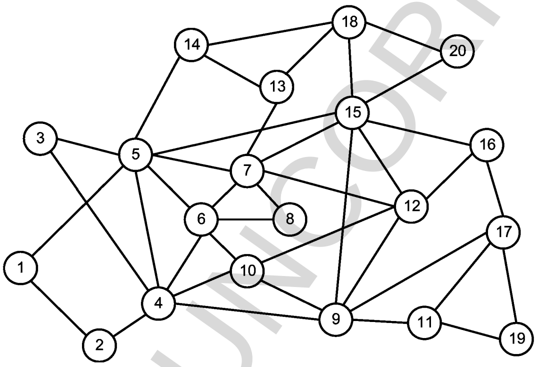

Fig. 5. The EON (European Optical Network) topology [41].

For the EON network topology, we predefined $k = 15$ alternative routes for each node pair (i, j) between which a lightpath need to be established. The number of artificial bees which participate in solving the RWA problem was limited to $B = 10$ due to computational complexity. For the maximal number of wavelengths, the computational time to obtain the solution is about a few tens of seconds for $I = 10$ performed iterations and the best results from these iterations are presented.

We compared our CPU times with those required for the Tabu search algorithm, proposed by Dzongang, et al. in [22]. They reported that "depending on the instance, the computing time of Tabu for each run ranges between 40 and 59 seconds for the EON network". These authors used Pentium 4, 2.4 GHz. Depending on the instance, the CPU times of the BCO–RWA algorithm varies between 10 and 40 seconds (depending on the number of bees and the number of algorithm iterations), for the EON network, which is similar to the CPU times of the Tabu search approach. On the other hand, the higher the number of available wavelengths,

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Table 2

Traffic matrix for the EON network [27]

i/j	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Σ
0	0	1	2	1	1	0	2	0	1	0	1	2	0	2	0	0	1	1	1	0	16
1	1	0	0	2	0	0	1	2	2	1	2	0	1	1	2	0	2	0	1	1	19
2	0	2	0	0	0	1	1	1	2	1	1	1	1	0	2	1	2	0	1	0	17
3	0	1	0	0	2	0	0	0	2	1	2	0	2	2	1	2	2	1	0	1	19
4	0	2	2	1	0	2	1	2	2	0	2	1	1	0	2	2	2	1	2	2	27
5	1	0	1	0	2	0	1	0	2	0	2	0	0	2	2	2	1	0	1	0	17
6	0	0	0	0	0	0	0	1	2	0	1	0	1	1	0	0	2	1	0	0	9
7	1	0	2	0	1	0	2	0	2	1	2	2	2	1	1	2	2	2	2	1	26
8	2	1	0	2	1	0	1	1	0	0	1	1	0	2	0	2	0	2	1	0	17
9	0	1	0	0	0	2	0	0	1	0	0	2	0	2	2	2	1	0	2	0	15
10	1	2	2	1	2	0	2	1	2	1	0	2	1	2	2	0	2	0	1	0	24
11	1	1	0	1	1	2	1	0	1	0	0	0	0	0	2	1	0	2	0	0	13
12	2	2	2	2	0	0	1	1	1	0	1	2	0	0	0	1	1	0	2	1	19
13	0	0	2	2	0	2	0	1	2	1	2	1	1	0	2	1	1	0	0	1	19
14	1	0	2	0	1	0	0	1	0	2	2	2	0	2	0	2	2	1	2	1	21
15	1	0	1	0	1	1	2	0	0	2	2	0	1	1	2	0	1	2	1	2	20
16	0	0	1	2	2	1	1	2	0	0	1	2	0	2	2	1	0	1	1	1	20
17	0	1	2	0	2	2	2	0	1	2	2	0	2	1	0	1	0	0	2	0	20
18	1	0	1	0	2	2	1	0	2	1	2	1	0	2	0	1	1	1	0	2	20
19	1	2	2	0	1	0	0	0	0	1	0	0	0	2	2	0	1	2	2	0	16
Σ	13	16	22	14	19	15	19	13	25	14	26	19	13	25	24	21	24	17	22	13	374

Table 3

The results comparison for EON network

Number of wavelengths	Number of established lightpaths				UB – Upper Bound [32]	(UB-BCORWA)/UB × 100 (%)
	Algorithm:					
	A [32]	B [32]	Tabu [22]	BCO-RWA		
10	262	250	281	264	285	7.37
11	274	265	294	285	301	5.32
12	284	278	307	301	317	5.05
13	295	290	318	315	329	4.25
14	310	308	328	326	337	3.26
15	316	314	338	338	344	1.74
16	319	318	345	348	350	0.57
17	333	325	352	354	356	0.56
18	339	334	356	361	362	0.28
19	340	337	361	365	367	0.54
20	341	340	366	370	370	0
21	347	347	370	372	373	0.27
22	355	352	372	374	374	0
23	361	361	374	374	374	0
24	367	364	374	374	374	0
25	370	367	374	374	374	0

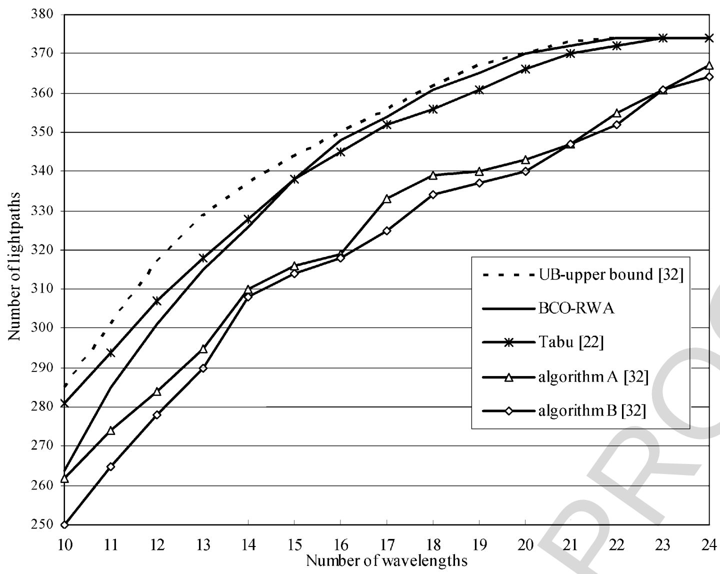

Fig. 6. The result comparison of various algorithms.

the higher the chance that the BCO–RWA algorithm will outperform Tabu approach (see Fig. 6).

The CPU times depend on the problem size, the total number of requested lightpaths, prescribed number of alternative routes for every node pair, prescribed number of algorithm iterations, as well as the total number of bees. In both of the performed numerical experiments the total number of bees was equal to $B = 10$. Both experiments were finished after $I = 10$ iterations. The total number of requested lightpaths, the prescribed numbers of alternative routes and the total number of links were different in two considered network examples. All these factors together caused differences in the required CPU times. The more detailed analyses of the CPU times and the BCO–RWA algorithm's complexity will be done in the future research.

6. Conclusion

We propose in this paper the BCO–RWA heuristic algorithm tailored for the routing and wavelength assignment problem (RWA) in all-optical networks. The proposed methodology is based on the concepts of collective intelligence. There are no theoretical results at this moment that could support proposed approach. Usually, development of various metaheuristic was based on experimental work in initial stage. Good experimental results usually motivated researchers to try to produce some theoretical results. The concepts proposed in this paper are not exception in this sense.

The proposed BCO–RWA algorithm has been able to produce optimal or near-optimal solutions in a reasonable computation time. The results obtained by applying our algorithm show that the network blocking performance, in terms of number of established lightpaths could be improved significantly compared to some previously proposed algorithms. The obtained results indicate that the development of new models based on swarm intelligence principles could significantly contribute to the solution of complex telecommunication problems.

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