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ORIGINAL PAPER

Routing and spectrum allocation in elastic optical networks using bee colony optimization

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Abstract Elastic optical network (EON) technology is considered as a very promising candidate for future high-speed networks due to its intrinsic flexibility and high efficiency in allocating the optical spectrum resources. The key issue that has to be addressed in EON is the routing and spectrum allocation (RSA) problem. RSA is NP-hard problem that has to be solved in an efficient manner. It is a highly challenging task particularly in the case of large problem instances. In this paper, we applied the bee colony optimization (BCO) metaheuristic approach to solve the RSA problem in EON with static traffic demands. The objective of the proposed BCO–RSA algorithm is to minimize both the network spectrum utilization and the average path length criterions. The results of numerous experimental studies show that our BCO–RSA algorithm performs superior compared to some benchmark greedy heuristics as well as to differential evolution (DE) metaheuristic algorithm recently proposed in the literature. The algorithm is evaluated in different realistic size optical networks, such as the NSFnet, two European optical networks (EON-19 and EON-28) and the USA network topology. Simulation results demonstrate that considerable spectrum savings could be achieved with our BCO–RSA algorithm compared to other considered approaches. In addition, we analyzed the efficiency of the BCO–RSA algorithm and compare it with the competitive DE approach according to the required CPU time and the convergence speed.

Keywords Bee colony optimization (BCO) · Elastic optical networks (EON) · Flexible lightpaths · Frequency slot (FS) · Routing and spectrum allocation (RSA)

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1 Introduction

At present, network operators are faced with the rapid growth of traffic in their communication networks due to ever-increasing bandwidth requirements and high popularity of various advanced bandwidth-hungry services, such as IPTV, video on demand, HDTV, online video gaming, and cloud and grid computing [1]. It is expected that future client demands will require more and more bandwidth capacities, ranging from several Gb/s up to Tb/s level. However, such heterogeneous and huge volume traffic demands could not be efficiently satisfied with traditionally deployed wavelength division multiplexing (WDM) technology. Although WDM is a cost-efficient technology, it has a serious drawback due to its coarse bandwidth granularity (at wavelength level) and rigid spectrum allocation [2]. That is, it allocates a fixed-grid optical spectrum for whole wavelength capacity regardless of the traffic to be served by a lightpath. Hence, if the traffic volume is smaller than the available wavelength capacity (sub-wavelength connections), a large part of spectrum assigned to a lightpath could be wasted, which results in inefficient resource utilization. It would be particularly evident with the deployment of contemporary WDM channels of higher capacity, such as ones with 40 or 100 Gb/s per wavelength [3]. Moreover, if client demands are greater than the capacity of one wavelength, two (or more) separate wavelengths should be used (super-wavelength channels) to satisfy given capacity demand. Since the guard bands (spectrum gaps) between wavelength channels have to be used, the efficiency of optical spectrum utilization is further reduced.

Recently, elastic optical network (EON) technology has been shown to be a promising candidate for more efficient optical spectrum utilization by supporting flexible sub- and super-wavelength granularity [1,2]. In EON, the available spectrum is divided into smaller granularity frequency slots

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(FS) and optical connections (flexible lightpaths) are allocated a proper number of FSs depending on the required capacity of client demands. Flexible lightpaths are established in elastic manner (capacity of an optical path can be adaptively expanded or contracted) by allocating a suitable number of FSs tailored to meet given traffic demand. As a result, the efficiency of resources utilization in EON is significantly improved compared to the traditional fixed-grid WDM networks [4]. Unlike the current WDM frequency channels of 100 or 50 GHz width, a FS in EON could be of finer granularity, such as 25 GHz, 12.5 GHz or even 6.25 GHz.

One of the key issues in designing, planning and operation of EON is addressed to the routing and spectrum allocation (RSA) problem [4]. A high-quality RSA solution leads to more efficient optical spectrum utilization. Considering that algorithms developed for fixed-grid networks could not be applied directly in case of EON, the efficient RSA solution is an indispensable and challenging task in future optical networks [5].

In this paper, we applied bee colony optimization (BCO) metaheuristic to solve the static (off-line) RSA problem in EON. Numerous prior studies prove that BCO is a fast, robust and efficient optimization tool, which is able to produce high-quality solutions together with small computational complexity [6–9]. Inspired by several successful BCO applications to WDM optical networking [10–13], our goal here is to demonstrate the quality and efficiency of BCO approach while solving the considered RSA problem in EON. Numerous experiments performed in various realistic optical networks prove that our BCO–RSA algorithm performs better compared to some other referenced algorithms from the literature. It indicates that BCO could be a promising approach to solve the RSA as well as some other complex optimization problems in future elastic optical networks.

The rest of the paper is organized as follows. Section 2 provides a literature review related to the RSA problem. In Sect. 3, the basic concept of RSA problem together with the problem statement is given, while Sect. 4 is dedicated to methods that we used to solve the researched RSA problem. In Sect. 5, the main principles of the proposed BCO metaheuristic applied to the RSA problem are introduced, while Sect. 6 brings an illustrative application of the proposed BCO–RSA algorithm. The comparative results of numerous simulation experiments between BCO–RSA and some other algorithms are given and discussed in Sect. 7. Some conclusions are given in the last section.

2 Related works

RSA is a well-known problem that attracts a rising attention among the researchers. It is widely considered in numerous studies related to elastic optical networking [1–5,14–27]. The applied methods to solve the RSA problem could be broadly classified into exact or approximate approaches. In [21], an overview of some optimization techniques which could be used to solve the RSA as well as other problems related to planning and operation of EON is given.

In case of small size optical networks with a limited number of traffic demands, integer linear programming (ILP) models could be successfully used to determine the optimal RSA solution. So far, various ILP RSA formulations are proposed in the literature [2,3,5,14,15]. The objective of majority formulations is to minimize the total or maximal number of occupied FSs in a network. It has been shown that static RSA is NP-complete problem (for which no polynomial time algorithm is known) even in the case of small network scenario [2]. In [3], an ILP RSA formulation that minimizes the spectrum used to serve traffic demands is proposed together with the decomposition method that breaks the complex RSA problem into two subproblems, the routing (R) and the spectrum allocation (SA), which are solved then sequentially. An ILP formulation proposed in [5] uses the concept of pre-computed channels for representation of spectrum contiguous frequency slots. It has been shown that the proposed approach allows solving the RSA problem more efficiently than some previous ILP models and that it can be applied even for realistic problem instances. The basic RSA problem can be further complicated by introducing the concept of adaptive (multi-level) modulation technique to tackle the problem of transmission reaches and signal impairments, which is known as the routing, modulation level and spectrum allocation (RMSA) problem. If modulation is not adaptive, RMSA reduces to RSA problem [25]. In [22], an ILP formulation is proposed to solve the static RMSA problem taking into consideration both linear and nonlinear impairments.

Due to large complexity and huge computational efforts to solve the ILP problems, they are usually intractable and could not be applicable in case of realistic size networks. Hence, the heuristic algorithms should be used to tackle more complex RSA scenarios in EON. Even though a heuristic algorithm cannot guarantee finding an optimal solution, sub-optimal solutions are often tolerable in numerous practical applications. On the other hand, heuristics are able to provide solutions at acceptable times, trading off optimality for speed [21]. There are various RSA/RMSA heuristic algorithms proposed in the literature, such as several related to static [2,3,14,15,22] as well as some to dynamic traffic demands [25–27]. In [2] authors proposed single-demand RMSA heuristic greedy algorithm that finds for each new connection demand the lowest feasible starting subcarrier among the set of pre-calculated candidate paths. In [3], three simple greedy heuristics based on first fit (FF), most subcarriers first (MSF) and longest path first (LPF) ordering strategies are proposed. They process demands in sequential manner (i.e., one by one) according to the selected ordering criteria. We will describe these heuristics later in more detail (in Sect. 4.2) and use them as benchmarks to compare the performances of the BCO algorithm we propose in this paper. In [14], the authors proposed a heuristic called the adaptive frequency assignment–collision avoidance (AFA-CA) that is also sequential algorithm in which demands are processed in decreasing order of requested FSs. Differently from the MSF algorithm [3], the AFA-CA algorithm works in an adaptive way, i.e., it selects the next demand to be processed according to previously allocated demands as well as the current usage of FSs in the network [14]. In [15], two heuristic algorithms, namely shortest path with maximum spectrum reuse (SPSR) and balanced load spectrum allocation (BLSA), are proposed to choose the routing paths and maximize the reuse (i.e., minimize the maximal number) of frequency slots in spectrum allocation. In [22], two low-complexity heuristics, group ILP (GILP) and connection list (CL) are proposed to solve the static RMSA problem. Zhu et al. [25] proposed a dynamic multi-path provisioning heuristic algorithm that considers differential delay constraint and bandwidth allocation granularity. They have shown that the multi-path scheme outperforms two single-path ones by providing lower bandwidth blocking probability and improving the average network throughput. Further, in [26] the authors proposed several dynamic service provisioning algorithms that incorporate a hybrid single-/multi-path routing (HSMR) scheme combining both the online and off-line path computation with various path selection policies. Within dynamic lightpath provisioning, spectrum fragmentation is very common and it degrades notably the bandwidth utilization in EON. In [27], two joint RSA heuristic algorithms, namely fragmentation aware (FA) and fragmentation aware with congestion avoidance (FA-CA), to alleviate the spectral fragmentation issue are proposed. Simulation results show that the proposed FA and FA-CA algorithms achieve better blocking probability performance compared to some other referenced algorithms. For a comprehensive review of various proposed RSA/RMSA heuristics, we referred to recent publication [28].

Although heuristic algorithms are computationally straightforward and could produce solutions of acceptable quality, a more promising approach is to use metaheuristic algorithms with the intention of further improving the solution quality compared to heuristic algorithms. Unlike the heuristics, which are problem-specific, metaheuristics are global search methods, which examine solutions produced by a heuristic algorithms and move to better ones in a sophisticated manner [21]. To this point, various metaheuristics have been used to solve the RSA/RMSA problem in EON networks [17–24]. In [21], the simulated annealing (SA) approach is used to modify the connection ordering policy in order to improve the performance of the heuristic algorithms. In [20], an evolutionary genetic algorithm (GA) approach is used to solve the static RSA problem in flexible grid optical networks with dedicated path protection consideration, and in [23] an adaptive GA algorithm is proposed to solve the dynamic RMSA problem in EON. In addition, in [24] a two population- based GA approach that divides the individuals into two populations and makes them evolve in parallel with different selection and mutation strategies is proposed to optimize the RMSA. Besides, some other popular metaheuristics are also used to solve the RSA problem in EON, such as the differential evolution (DE) [17], ant colony optimization (ACO) [18] or tabu search (TS) [19].

For the first time, we explore in this study the application of bee colony optimization (BCO) metaheuristic while solving the (off-line) RSA problem in EON. We tested the performances of the proposed BCO–RSA algorithm in different realistic sized optical network topologies. The results are promising and indicate that our BCO–RSA algorithm performs better compared not only to the referred sequential FF, MSF and LPF simple heuristics from [3], but also outperforms the competitive DE metaheuristic approach, recently proposed in [17] to solve the same problem.

3 RSA problem in EON

3.1 Basic concept of RSA

The RSA problem in EON is to find the route and assign the appropriate number of FSs along the route to establish a flexible lightpath [4]. RSA is similar to the traditional routing and wavelength assignment (RWA) problem that has been previously solved in fixed-grid WDM optical networks [11]. However, there is a difference between the two problems, that is, the RSA is a general and more complex problem compared to the RWA. To be precise, only in a special case if all lightpaths would require just one FS, RSA will be reduced to the RWA problem. Namely, it is well known that RWA involves only one wavelength to be assigned to the lightpath along the route (in networks without wavelength converters), while flexible lightpaths in EONs typically require a number of FSs (according to the bandwidth demand of a connection request) to be combined to create the variable-width (or elastic) channels. Keeping this in mind, the wavelength continuity constraint in fixed-grid WDM networks is transformed into FSs *continuity constraint* in EON and the single wavelength assignment constraint is transformed into the FSs *non-overlapping constraint* in combination with the FSs *contiguous constraint* [23].

To establish a flexible lightpath with the capacity of f frequency slots, the *spectrum contiguity constraint* assumes that f consecutive subcarrier slots must be allocated to it and the *spectrum continuity constraint* requires that the same FSs have to be allocated on every physical link along the chosen route for a given lightpath. The *non-overlapping constraint* ensures that the FS at the given fiber link has to be allocated only to one flexible lightpath that traverses over this link. In other words, there are no two lightpaths established over common link using the same FS. These constraints significantly increase the complexity of the RSA problem. Therefore, it is usually simplified by splitting into two subproblems: (i) the routing subproblem, and (ii) the spectrum allocation subproblem, which could be solved sequentially. For the routing subproblem, various algorithms could be used, such as the fixed routing (FR), fixed-alternate routing (FAR), least congested routing (LCR) or adaptive routing (AR) [4]. The spectrum allocation could be performed using different policies, such as the first fit (FF), random fit (RF), last fit (LF), first-last fit (FLF), least used (LU), most used (MU) or exact fit (EF). A detailed explanation of these routing and spectrum allocation techniques could be found in [4].

Based on traffic demand scenario, RSA problem can be classified into static (or off-line) and dynamic (or online) cases. In the case of static traffic, the connection requests are completely known in advance, where the duration of each demand is considered as infinity. Such scenario typically appears during the planning or designing phase of EON. In case of dynamic traffic that is associated within the network operation phase, connection requests arrive to and depart from the network in a stochastic manner. In this study, we focused entirely on the static traffic scenario.

3.2 Problem statement

We are looking to solve the off-line RSA problem in EON. It is assumed that the connection request r_i between the source–destination node pair (s, d) is represented by a given number of frequency slots f_i to meet the required capacity (in terms of bit rate) between these nodes in a given optical network topology. The total number of requests in traffic demand list is assumed to be R. We assumed that a given optical network topology can be modeled as a graph, specified by the set of nodes N and set of links L, which interconnect some node pairs. It is assumed that each optical link consists of two separate fibers, one for each direction. For each traffic demand, the RSA procedure involves solving the routing and frequency allocation subproblems. For the routing subproblem, we used the FAR method [4], which assumes that k-shortest paths are predetermined for each node pair (s, d), which form the set of candidate paths K to be considered for lightpath establishing. For the frequency allocation subproblem, the FF policy [4] is applied, which assumes that FSs are indexed and a list of indexes of available and used slots is maintained. This policy always attempts to choose the lowest indexed slot from the list of available slots and allocates it to the lightpath to serve the connection request [4]. While establishing the lightpaths, a guard band of GB frequency slots has to be used to separate adjacent spectrum optical paths.

The considered RSA problem can be stated as follows: For a given optical network topology and traffic demands expressed by the number of requested FSs between network nodes, it is necessary to serve all traffic demands such that the spectrum utilization (SU) (i.e., the maximal index of utilized FS in any network link) is minimized, subject to the continuity and the contiguity constraints. In order to make a more fair comparison between BCO and DE approaches, we assumed the same objective (fitness) function F, as proposed in [17]:

$$\min F = a_1 \frac{\mathrm{SU}}{b_1} + a_2 \frac{\mathrm{APL}}{b_2} \tag{1}$$

which is to minimize the weighted sum of the spectrum utilization (SU), i.e., the number of used FSs and the average path length (APL). The weighted parameters a_1 and a_2 in the objective function ($a_1 \in [0, 1]$ and $a_2 = 1 - a_1$) are used to manage the importance of either criteria (SU or APL), while b_1 and b_2 are the normalizing constants (i.e., the upper bound values for SU and APL, respectively). In other words, the normalizing constant b_1 represents the sum of FSs for all requests in traffic demand list R, while the constant b_2 is the average path length that is calculated by assuming that all traffic demands are routed through the longest available path from the set of alternate paths K for node pair (s, d). The normalizing constants b_1 and b_2 are described in more detail in [17], Sect. 3.2. The motivation behind using these two terms in the objective function is as follows: (i) by minimizing the maximal index value of the frequency slot (SU) used on any link in a given network, more efficient spectrum utilization (or spectrum saving) as well as network-traffic load balancing is achieved, and (ii) by minimizing the APL, the overload of network resources, transmission delays or signal impairments could be improved [17]. We assumed that the path length is expressed by the number of links (or hops) along the route between two end nodes. More details related to SU and APL terms could be found in [17], Sect. 3.1.

4 Methods used to solve the RSA problem

4.1 BCO metaheuristic

BCO metaheuristic is at first proposed by Lučić and Teodorović [9] to solve the complex transportation engineering problems. So far, BCO has been applied to various combinatorial optimization problems. A comprehensive overview of BCO with its various applications could be found in [6–8].

BCO is a population-based stochastic random-search technique that is inspired by the foraging habits of natural bees looking for nectar sources [6–13]. Similar to the behavior of bees in nature, the artificial bees in BCO "fly" around the search space looking for the most excellent solution. Every bee b in population of B bees creates ones solution to the considered optimization problem. The searching procedure is performed during a predefined number of iterations I, with a number of partial flies (or steps) that bees perform during iteration.

In brief, BCO procedure could be explained as follows [6–13]: At the beginning of the searching process, all artificial bees start their flies from the hive in parallel. During each step, every bee starts with the forward pass to discover its partial solution and after that makes the backward pass (i.e., fly-back to the hive) to evaluate and compare the quality of its solution. In each forward pass, every bee generates its partial solution independently from other bees such that there are total of B self-contained partial solutions during each step. In order to find the best solution, the bees perform cooperative decisions in the hive by exchanging the information about the quality of their solutions. By performing intelligent decisions, bees slowly discover more hopeful solutions and bit by bit leave ones of inferior quality. During each step, every bee decides with a probability whether to discard the created partial solution and become an uncommitted follower or to continue to expand its current solution with (or without) recruiting other bees. Depending on the solution quality, each bee possesses a certain level of loyalty to the previously discovered partial solution. In such a way, before beginning of each new step all bees are divided into two sets: the followers and the recruiters. It is accomplished during the recruitment procedure in a probabilistic manner, such that a probability of the recruiter bee's partial solution would be chosen by any uncommitted bee depending on the objective function value (solution quality) of the recruiter bee. Using this probability, every uncommitted follower is "assigned" to one of the recruiter's bees (it accepts the current solution of its recruiter) and continues to expand its solution in the next step independently. When a given number of steps are performed, iteration is finished and the best-found solution is saved. The procedure is repeated for a specified number of iterations, and the best obtained solution during this iterative procedure is chosen as the final best solution. More details about the BCO optimization method are described later in Sects. 5 and 6 and could be also found in [6,7].

4.2 Benchmark algorithms

In order to compare the quality and efficiency of BCO metaheuristic while solving the considered RSA problem in EON, we used some benchmark algorithms like the FF, MSF and LPF sequential greedy heuristics proposed in [3] together with the competitive DE metaheuristic approach, recently proposed in [17]. They will be described here very briefly.

In FF heuristic [3], the requests are served one by one as they appear in the traffic demand list (i.e., without the ordering). In MSF heuristics, the requests are firstly ordered in decreasing number of required FSs and served one by one beginning from the top of list, while in the case of LPF policy demands are sorted in decreasing order of the number of links their shortest path contains [3]. Although the FF, MSF and LPF heuristics are simple to implement, it is obvious that the spectrum utilization (solution quality) greatly depends on the applied ordering policy.

DE is a stochastic global optimization metaheuristic technique that emulates a complex process of natural evolution [17]. Like other metaheuristics, DE uses a population of individuals (solutions) and iterates by creating new populations until a satisfactory solution is obtained or a computational limit is exceeded. The evolution procedure in DE is based on three control parameters: the mutation constant (M), which controls the mutation strength, the recombination constant (RC), which increases the diversity in the mutation process, and the population size (NP). Using the differences between populations and with the manipulation of control parameters, the solution quality is intelligently improved by generations. More comprehensive explanation of DE metaheuristic approach could be found in [17].

5 BCO applied to the RSA problem

In this section, we present the application of BCO metaheuristic to the considered RSA problem in more detail. The proposed BCO–RSA algorithm contains the following phases: (i) initialization phase, (ii) partial solutions generation phase, (iii) solutions comparison phase and (iv) recruitment phase.

5.1 Initialization

In this phase, the input data required for BCO optimization procedure have to be defined, such as the number of iterations I, number of steps S (forward and backward passes), number of bees in population B, physical network topology given by the set of nodes N and set of physical links L, set of pre-computed shortest paths K for each node pair (s, d), set of traffic demands R expressed by the (integer) number of required frequency slots (FSs) for each node pair (s, d), guard band value GB, the values of weighted parameters a_1 and a_2 in objective function given by (1) and the ordered set of traffic demands. Inspired by very well performances that could be obtained with the MSF heuristic, we applied the following rule for initial ordering of traffic demands: With the intention to provide diversification of initial solutions for different bees in population, the set of demands ordered by MSF heuristics is modified such that the (integer) numbers of FSs in the sorted list are multiplied by a constant number randomly chosen from an interval $[x, 1]$, $0.5 < x < 1$ and the reordering of demands is performed again for each bee based on modified (non-integer) values of FSs. These (non-integer) values of FSs are used only for the purpose of demands ordering, but actual traffic demands remain to be of original (integer) values in terms of number of FSs. Some other heuristics (such as the random, FF or LPF ordering) could be also used to obtain initial ordering, but it has been shown that better final results could be obtained by applying the described rule for traffic demands ordering.

5.2 Partial solutions generation

During each forward pass (or algorithm's step) $s = 1, 2, \ldots, S$, every bee investigates a given number of requests r from the ordered traffic demand list R. The number of demands r to be tested is pre-specified in advance. Hence, the total number of forward passes S during iteration is given as $S = \lceil R/r \rceil$, where R is the total number of requested traffic demands in given optical network and r is the number of demands tested by every bee during one algorithm's step s. For each demand tested by every bee during one step, the routing and spectrum allocation subproblems have to be performed. For the routing subproblem, a set of candidate shortest paths K between node pairs (s, d) is pre-computed for each request $r \in R$. For every route in set K, the maximal index of the occupied FS is determined and the route with minimal FS index value is chosen to establish the lightpath. A set of contiguous FSs is assigned for a lightpath to serve the connection request r, starting from the lowest indexed frequency slot (first fit) from the list of available slots on the chosen route. In such a way, every bee creates its own partial RSA solution, which is independent from other bee's solution in a population.

5.3 Solutions comparison

After the partial solutions are generated by individual bees, all bees return back to the hive to compare the quality of their solutions. It is assumed that a quality of solution could be represented by the value of objective function F, given by Eq. (1). Lesser the value of objective function F, better the solution quality. The bees with better solution quality have more chance to keep their solutions. Bees which are loyal to their solutions form the set of recruiter bees (RB), while the rest (uncommitted) bees from the colony become follower bees (FB). Recruiter bees promote their solutions trying in such way to attract uncommitted followers to join them during the recruitment process. Each uncommitted follower has to decide whether it will continue to explore its own solution or to start jointly exploring one of the solutions being advertised by the recruiter bees. It is assumed that solutions with better qualities have greater chance to be chosen by follower bees. In order to decide which bee will keep its partial solution, we assumed the probability $p_{b,\text{loyal}}$ that bth bee will be loyal to its partial solution as follows:

$$p_{b,\text{ loyal}} = 1 - \log[1 + (O_{\max} - O_b)], \quad b = 1, 2, \ldots, B \tag{2}$$

where O_b denotes the normalized objective function value for solution created by the bth bee, and $O_{\max}$ represents the maximum over all normalized values of solutions to be compared.

The normalized value O_b of the objective function for solution created by the bth bee could be defined as follows [6,7]:

$$O_b = \frac{F_{\max} - F_b}{F_{\max} - F_{\min}}, \quad b = 1, 2, \ldots, B \tag{3}$$

where $F_{\min}$ and $F_{\max}$ are minimal and maximal values of the objective function obtained by all engaged bees, respectively, and F_b is the objective function value of the solution obtained by the bth bee. Lesser objective function value F_b (better solution quality of the bee b) produces greater normalized value O_b, which then also increases the probability $p_{b,\text{loyal}}$. Using Eq. (2) and a randomly generated number (rnd), each artificial bee decides whether to become uncommitted follower or to become the recruiter bee, which continues further to expand its own solution. If rnd $\leq p_{b,\text{loyal}}$, the bee b stays loyal to its own solution. Otherwise, she becomes uncommitted follower bee.

5.4 Recruitment

Within the recruiting phase, an uncommitted bee decides what recruiter bee it could follow, taking into account the quality of all advertised solutions by recruiters. The probability that an uncommitted bee will choose the solution of the recruiter bee b could be defined as follows [6,7]:

$$p_{b,\text{ recruit}} = \frac{O_b}{\sum_{r=1}^{\text{RB}} O_r}, \quad b = 1, 2, \ldots, \text{RB} \tag{4}$$

where O_r represents the normalized value of the objective function of the rth advertised solution, $r = 1, 2, \ldots, \text{RB}$, and RB denotes the number of recruiter bees.

Using Eq. (4) and a random number generator, each uncommitted bee joins to one recruiter bee based on a roulette wheel method. In this way, each uncommitted bee accepts previously created partial solution of the recruiter bee b, but in the next forward pass every bee is free to continue the solution exploration independently of each other.

The described exploration procedure is performed until all traffic demands are tested during iteration. The best-found solution among B created solutions in iteration is saved and used as initial solution in the next iteration. The algorithm iterates through the pre-specified number of iterations I, and the best solution obtained during all iterations is chosen as the global best solution.

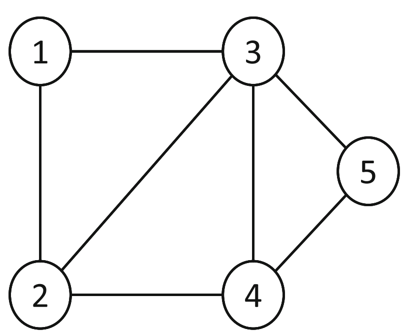
6 Illustrative example

With the intention to explain the BCO optimization procedure in more detail, we present an illustrative example of the BCO–RSA algorithm applied to a small optical network topology with $R = 16$ traffic demands, as shown in Fig. 1. We assumed the equal network-traffic scenario as in [17] to make a comparison of the BCO and DE approaches, both applied on the same example. We assumed also that each physical link in given optical network represents a single bidirectional fiber with maximal capacity of $C = 20$ frequency slots per link. A guardband of GB = 1 frequency slot is also assumed. For every node pair (s, d), $k = 4$ shortest paths are calculated in advance using the Yen's algorithm. We used the population of $B = 5$ bees to keep the parity with the number of individuals NP used in DE algorithm. The number of traffic demands tested by bees during one algorithm's step s is assumed to be $r = 4$. Hence, the total number of steps S in one algorithm iteration is $S = \lceil R/r \rceil = \lceil 16/4 \rceil = 4$, and the total number of iterations is assumed to be $I = 10$. The following values of weighted parameters in the objective function are assumed $a_1 = 0.5$ and $a_2 = 0.5$. The calculated values of normalizing parameters are $b_1 = 38$ (sum of the requested FSs for all traffic demands) and $b_2 = 3.4375$ (the averaged path length obtained by choosing the longest path from set K for each node pair in traffic demand list R).

Assume that the initial ordering of traffic demands to be tested by individual bees is represented by rows in Table 1. It is obtained based on the randomization procedure in the initialization phase described previously in Sect. 5.1.

During the first forward pass, i.e., in the step $s = 1$, every bee tests the first $r = 4$ requests from the ordered list (for example, the first requests tested by bee B_1 are R_3, R_{13}, R_4 and R_8) trying to establish r lightpaths in given optical network. At the end of this procedure, every bee creates its partial solution with the quality defined by the objective (fitness) function value F_b. During the backward pass, bees perform the comparison of their generated partial solutions. A probable scenario of the BCO–RSA parameters value obtained during the first algorithm's step ($s = 1$) is given in Table 2.

It could be seen from Table 2 that the best (minimal) fitness value is achieved by the bee B_4 ($F_{\min} = 0.0890$) and the worst (maximal) fitness is obtained by the bee B_1 ($F_{\max} = 0.1598$). Consequently, the maximal and minimal normalized objective function values O_b are obtained (based on Eq. 3) by the bees B_4 and B_1, respectively. The corresponding probabilities of loyalty $p_{b,\text{loyal}}$ are calculated for every bee b using Eq. 2. By choosing a random number rnd (in this case rnd = 0.6256) and comparing it with the values of $p_{b,\text{loyal}}$, we obtain the set of uncommitted followers (bees B_1 and B_3) which abandon from their solutions and try to follow some of the recruiters bees (B_2, B_4 or B_5). The recruitment procedure is performed based on the probability values $p_{b,\text{recruit}}$, which are calculated for every recruiter bee using Eq. 4. In the applied roulette wheel method, the cumu-



Request #	s	d	FS	Request #	s	d	FS
R_1	1	2	1	R_9	3	2	2
R_2	1	3	1	R_{10}	3	4	2
R_3	1	5	4	R_{11}	3	5	1
R_4	2	1	3	R_{12}	4	1	2
R_5	2	3	2	R_{13}	4	3	4
R_6	2	4	2	R_{14}	5	2	3
R_7	2	5	2	R_{15}	5	3	3
R_8	3	1	3	R_{16}	5	4	3

Fig. 1 Small network topology with $R = 16$ requested traffic demands [17]

Table 1 Ordering of traffic demands in the first step ($s = 1$)

Bee#	Request #															
B_1	R_3	R_{13}	R_4	R_8	R_{14}	R_{15}	R_{16}	R_5	R_6	R_7	R_9	R_{10}	R_{12}	R_1	R_2	R_{11}
B_2	R_{13}	R_{15}	R_6	R_{16}	R_7	R_5	R_{14}	R_{10}	R_4	R_{11}	R_{12}	R_9	R_2	R_1	R_3	R_8
B_3	R_3	R_6	R_{10}	R_{12}	R_7	R_{15}	R_5	R_2	R_4	R_8	R_{16}	R_{14}	R_9	R_{13}	R_{11}	R_1
B_4	R_4	R_{16}	R_9	R_{15}	R_{12}	R_3	R_6	R_{14}	R_7	R_8	R_{13}	R_{10}	R_2	R_1	R_{11}	R_5
B_5	R_{13}	R_3	R_{12}	R_{16}	R_{14}	R_5	R_2	R_4	R_1	R_9	R_{15}	R_8	R_7	R_6	R_{11}	R_{10}
	$s = 1$															

Table 2 The values of BCO–RSA parameters during the first step ($s = 1$)

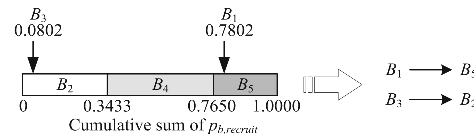
Bee #	F_b	O_b	$p_{b,\text{loyal}}$	rnd	Followers	Recruiters	$p_{b,\text{recruit}}$	Recruitment procedure
B_1	0.1598	0	0.3069	0.6256	B_1	–	–	
B_2	0.1022	0.8142	0.8296		–	B_2	0.3433	
B_3	0.1335	0.3716	0.5124		B_3	–	–	
B_4	0.0890	1.0000	1.0000		–	B_4	0.4217	
B_5	0.1203	0.5574	0.6336		–	B_5	0.2350	

Table 3 Ordering of traffic demands in step $s = 2$

Bee#	Request #															
B_1	**R_{13}**	**R_3**	**R_{12}**	**R_{16}**	R_{14}	R_4	R_{15}	R_8	R_5	R_9	R_7	R_6	R_{10}	R_2	R_1	R_{11}
B_2	**R_{13}**	**R_{15}**	**R_6**	**R_{16}**	R_7	R_5	R_{14}	R_{10}	R_4	R_{11}	R_{12}	R_9	R_2	R_1	R_3	R_8
B_3	**R_{13}**	**R_{15}**	**R_6**	**R_{16}**	R_3	R_{14}	R_4	R_8	R_7	R_5	R_{10}	R_{12}	R_9	R_{11}	R_2	R_1
B_4	R_4	R_{16}	R_9	R_{15}	R_{12}	R_3	R_6	R_{14}	R_7	R_8	R_{13}	R_{10}	R_2	R_1	R_{11}	R_5
B_5	**R_{13}**	**R_3**	**R_{12}**	**R_{16}**	R_{14}	R_5	R_2	R_4	R_1	R_9	R_{15}	R_8	R_7	R_6	R_{11}	R_{10}
	$s = 1$				$s = 2$											

Table 4 Ordering of traffic demands in step $s = 3$

Bee#	Request #															
B_1	R_{13}	R_3	R_{12}	R_{16}	R_{14}	R_4	R_{15}	R_8	R_5	R_9	R_7	R_6	R_{10}	R_2	R_1	R_{11}
B_2	**R_{13}**	**R_{15}**	**R_6**	**R_{16}**	**R_7**	**R_5**	**R_{14}**	**R_{10}**	R_4	R_{11}	R_{12}	R_9	R_2	R_1	R_3	R_8
B_3	R_{13}	R_{15}	R_6	R_{16}	R_3	R_{14}	R_4	R_8	R_7	R_5	R_{10}	R_{12}	R_9	R_{11}	R_2	R_1
B_4	**R_{13}**	**R_{15}**	**R_6**	**R_{16}**	**R_7**	**R_5**	**R_{14}**	**R_{10}**	R_3	R_4	R_8	R_{12}	R_9	R_{11}	R_2	R_1
B_5	R_{13}	R_3	R_{12}	R_{16}	R_{14}	R_5	R_2	R_4	R_1	R_9	R_{15}	R_8	R_7	R_6	R_{11}	R_{10}
	$s = 1$				$s = 2$				$s = 3$							

lative sum of the probability values $p_{b,\text{recruit}}$ is determined and the random numbers for each uncommitted followers are generated in order to select the matching recruiter bee. In the given example, the randomly generated number for uncommitted bee B_1 is 0.7802, which belongs to the cumulative sum region of the recruiter bee B_5. Hence, the uncommitted bee B_1 is assigned to the bee B_5 and consequently, the generated partial solution of bee B_1 is replaced with the solution of the recruiter bee B_5. Similar decision was made for the uncommitted bee B_3, which is assigned to the recruiter bee B_2.

In the next step ($s = 2$), all the bees further explore the search space individually (using the described ordering policy), but with the partial solutions updated based on the recruitment decisions made in previous step ($s = 1$). In this example, the bee B_1 takes the same partial solution of the bee B_5 in previous step and the bee B_3 takes the partial solution from the bee B_2. The ordering of requests for bees B_1 and B_3 in the next step ($s = 2$) is performed again using the described randomized ordering policy such that the rest of demands (by omitting the demands tested in the first step) are sorted. Table 3 illustrates the ordering of traffic demands in the next step ($s = 2$). The updated partial solutions of corresponding bees are signed as bold in Table 3 (and also later in Tables 4 and 5).

All calculations shown in Table 2 are also performed in the next step $s = 2$. Assume that the results of the recruitment process in the second step are as follows: The only uncommitted follower bee B_4 is recruited by the bee B_2, i.e., the partial solution of bee B_4 is replaced by the solution of the recruiter bee $B_{2.}$ Table 4 illustrates the ordering of requested traffic demands in the step $s = 3$.

Finally, in the last step ($s = 4$), assume that the uncommitted followers are the bees B_3 and B_4, both of which are recruited by the bee B_2. The created partial solutions in the last step are given in Table 5. It could be seen that the bees B_3 and B_4 have joined to the partial solution of recruiter bee B_2.

At the end of first iteration (i.e., in the last step $s = 4$), the obtained fitness values for individual bees are $F = [0.1993; 0.1993; 0.2124; 0.2124; 0.1902]$. It could be seen

Table 5 Ordering of traffic demands in step $s = 4$

Bee#	Request #															
B_1	R_{13}	R_3	R_{12}	R_{16}	R_{14}	R_4	R_{15}	R_8	R_5	R_9	R_7	R_6	R_{10}	R_2	R_1	R_{11}
$\boldsymbol{B}_2$	$\boldsymbol{R}_{13}$	$\boldsymbol{R}_{15}$	$\boldsymbol{R}_6$	$\boldsymbol{R}_{16}$	$\boldsymbol{R}_7$	$\boldsymbol{R}_5$	$\boldsymbol{R}_{14}$	$\boldsymbol{R}_{10}$	$\boldsymbol{R}_4$	$\boldsymbol{R}_{11}$	$\boldsymbol{R}_{12}$	$\boldsymbol{R}_9$	R_2	R_1	R_3	R_8
$\boldsymbol{B}_3$	$\boldsymbol{R}_{13}$	$\boldsymbol{R}_{15}$	$\boldsymbol{R}_6$	$\boldsymbol{R}_{16}$	$\boldsymbol{R}_7$	$\boldsymbol{R}_5$	$\boldsymbol{R}_{14}$	$\boldsymbol{R}_{10}$	$\boldsymbol{R}_4$	$\boldsymbol{R}_{11}$	$\boldsymbol{R}_{12}$	$\boldsymbol{R}_9$	R_3	R_8	R_2	R_1
$\boldsymbol{B}_4$	$\boldsymbol{R}_{13}$	$\boldsymbol{R}_{15}$	$\boldsymbol{R}_6$	$\boldsymbol{R}_{16}$	$\boldsymbol{R}_7$	$\boldsymbol{R}_5$	$\boldsymbol{R}_{14}$	$\boldsymbol{R}_{10}$	$\boldsymbol{R}_4$	$\boldsymbol{R}_{11}$	$\boldsymbol{R}_{12}$	$\boldsymbol{R}_9$	R_3	R_8	R_2	R_1
B_5	R_{13}	R_3	R_{12}	R_{16}	R_{14}	R_5	R_2	R_4	R_1	R_9	R_{15}	R_8	R_7	R_6	R_{11}	R_{10}
	$s = 1$				$s = 2$				$s = 3$				$s = 4$			

FF (SU=20; APL=1.4375; F=0.4722)

LINK\FS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1↔2	R_1	GB	R_4	R_4	R_4	GB	R_8	R_8	R_8	GB										
1↔3	R_2	GB	R_3	R_3	R_3	R_3	GB	R_{12}	R_{12}	GB										
2↔3	R_5	R_5	GB	R_9	R_9	GB	R_8	R_8	R_8	GB		GB	R_{14}	R_{14}	R_{14}	GB				
2↔4	R_6	R_6	GB	R_7	R_7	GB														
3↔4	R_{10}	R_{10}	GB				GB	R_{12}	R_{12}	GB		GB	R_{15}	R_{15}	R_{15}	GB				
3↔5	R_{11}	GB	R_3	R_3	R_3	R_3	GB	R_{13}	R_{13}	R_{13}	R_{13}	GB	R_{14}	R_{14}	R_{14}	GB				
4↔5			GB	R_7	R_7	GB	GB	R_{13}	R_{13}	R_{13}	R_{13}	GB	R_{15}	R_{15}	R_{15}	GB	R_{16}	R_{16}	R_{16}	GB

LPF (SU=18; APL=1.5625; F=0.4641)

LINK\FS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1↔2	R_1	GB	R_4	R_4	R_4	GB								GB	R_{14}	R_{14}	R_{14}	GB
1↔3	R_2	GB	R_8	R_8	R_8	GB	R_3	R_3	R_3	R_3	GB	R_{12}	R_{12}	GB	R_{14}	R_{14}	R_{14}	GB
2↔3		GB	R_{16}	R_{16}	R_{16}	GB	R_5	R_5	GB	R_9	R_9	GB	R_{13}	R_{13}	R_{13}	R_{13}	GB	
2↔4		GB	R_{16}	R_{16}	R_{16}	GB	R_6	R_6	GB	R_7	R_7	GB	R_{13}	R_{13}	R_{13}	R_{13}	GB	
3↔4	R_{15}	R_{15}	R_{15}	GB	R_{10}	R_{10}	GB				GB	R_{12}	R_{12}	GB				
3↔5	R_{11}	GB	R_{16}	R_{16}	R_{16}	GB	R_3	R_3	R_3	R_3	GB			GB	R_{14}	R_{14}	R_{14}	GB
4↔5	R_{15}	R_{15}	R_{15}	GB					GB	R_7	R_7	GB						

MSF (SU=11; APL=1.3125; F=0.3356)

LINK\FS	1	2	3	4	5	6	7	8	9	10	11
1↔2	R_4	R_4	R_4	GB	R_8	R_8	R_8	GB	R_1	GB	
1↔3	R_3	R_3	R_3	R_3	GB	R_2	GB	GB	R_{12}	R_{12}	GB
2↔3	R_5	R_5	GB	GB	R_8	R_8	R_8	GB	R_9	R_9	GB
2↔4	R_{14}	R_{14}	R_{14}	GB	R_6	R_6	GB	GB	R_7	R_7	GB
3↔4	R_{13}	R_{13}	R_{13}	R_{13}	GB	R_{10}	R_{10}	GB	R_{12}	R_{12}	GB
3↔5	R_3	R_3	R_3	R_3	GB	R_{15}	R_{15}	R_{15}	GB	R_{11}	GB
4↔5	R_{14}	R_{14}	R_{14}	GB	R_{16}	R_{16}	R_{16}	GB	R_7	R_7	GB

DE (SU=11; APL=1.3125; F=0.3356)

LINK\FS	1	2	3	4	5	6	7	8	9	10	11
1↔2	R_{12}	R_{12}	GB	R_4	R_4	R_4	GB	R_1	GB		
1↔3	R_8	R_8	R_8	GB	R_2	GB	R_3	R_3	R_3	R_3	GB
2↔3	R_6	R_6	GB	R_9	R_9	GB	R_5	R_5	GB		
2↔4	R_{12}	R_{12}	GB	GB	R_{14}	R_{14}	R_{14}	GB	R_7	R_7	GB
3↔4	R_6	R_6	GB	R_{13}	R_{13}	R_{13}	R_{13}	GB	R_{10}	R_{10}	GB
3↔5	R_{15}	R_{15}	R_{15}	GB	R_{11}	GB	R_3	R_3	R_3	R_3	GB
4↔5	R_{16}	R_{16}	R_{16}	GB	R_{14}	R_{14}	R_{14}	GB	R_7	R_7	GB

BCO (SU=11; APL=1.3125; F=0.3356)

LINK\FS	1	2	3	4	5	6	7	8	9	10	11
1↔2	R_4	R_4	R_4	GB	R_8	R_8	R_8	GB	R_1	GB	
1↔3	R_3	R_3	R_3	R_3	GB	R_2	GB	GB	R_{12}	R_{12}	GB
2↔3	R_5	R_5	GB	GB	R_8	R_8	R_8	GB	R_9	R_9	GB
2↔4	R_{14}	R_{14}	R_{14}	GB	R_6	R_6	GB	GB	R_7	R_7	GB
3↔4	R_{13}	R_{13}	R_{13}	R_{13}	GB	R_{10}	R_{10}	GB	R_{12}	R_{12}	GB
3↔5	R_3	R_3	R_3	R_3	GB	R_{15}	R_{15}	R_{15}	GB	R_{11}	GB
4↔5	R_{14}	R_{14}	R_{14}	GB	R_{16}	R_{16}	R_{16}	GB	R_7	R_7	GB

Fig. 2 The results of FF, LPF and MSF ordering heuristics as well as DE and BCO metaheuristics for network example shown in Fig. 1

that the bee B_5 achieves the best (minimal) value of the objective function F. Hence, its solution is used to create the population of initial solutions for the next algorithm iteration using again the described randomization procedure. The optimization results obtained after $I = 10$ iterations are given in Fig. 2 together with other considered RSA algorithms. Figure 2 shows the network state (i.e., occupation of FSs on different network links) after all requests R in traffic demand list are served by each algorithm. One can see that BCO approach outperforms significantly the considered FF and LPF sequential heuristics according to the SU, APL and F values, while producing the comparative results with MSF as well as DE approaches. Note that in this small network example with quite a few traffic requests, MSF heuristic performs well enough as the BCO and DE metaheuristic approaches do. However, in more complex traffic scenarios, the metaheuristics could have significant benefits in terms of the achieved solution quality.

7 Experimental evaluations and results

To evaluate the performances of the proposed BCO–RSA algorithm, we have carried out extensive simulation experiments in four realistic size optical network examples, such as the National Science Foundation Network (NSFNet) with $N = 14$ nodes, European Optical Network (EON) with $N = 19$ and $N = 28$ nodes, EON-19 and EON-28, respectively, and USA network with $N = 40$ nodes. The physical topologies of these networks are shown in Fig. 3. For each network example, 15 different traffic demand lists R are generated randomly, with a number of requested FSs for every node pair (s, d), where $s \neq d$. Hence, the total number of requests R in each traffic demand list is $R = N * (N - 1)$, where N is the number of nodes in a given network topology. It is assumed that the number of FSs for each request $r \in R$ is chosen randomly from the range $[0, Y_{\max}]$ with uniform distribution. According to the assumptions in [17], we also assumed that $Y_{\max} = 4$ for NSFNet and EON-19 network examples, while the value of $Y_{\max} = 5$ is used for other two network examples. The number of shortest paths for each node pair is assumed to be $k = 3$ in case of NSFNet and EON-19 and $k = 5$ for EON-28 and USA. The weighted parameters a_1 and a_2 in the objective function are set to the equal (best [17]) values of $a_1 = a_2 = 0.5$ (unless in some special cases, when the value of $a_1 = 1$ is used to optimize just the SU criterion in the objective function), while the normalizing constants b_1 and b_2 are calculated specifically for different network-traffic scenarios. A guard band of one FS (i.e., GB = 1) is also assumed.

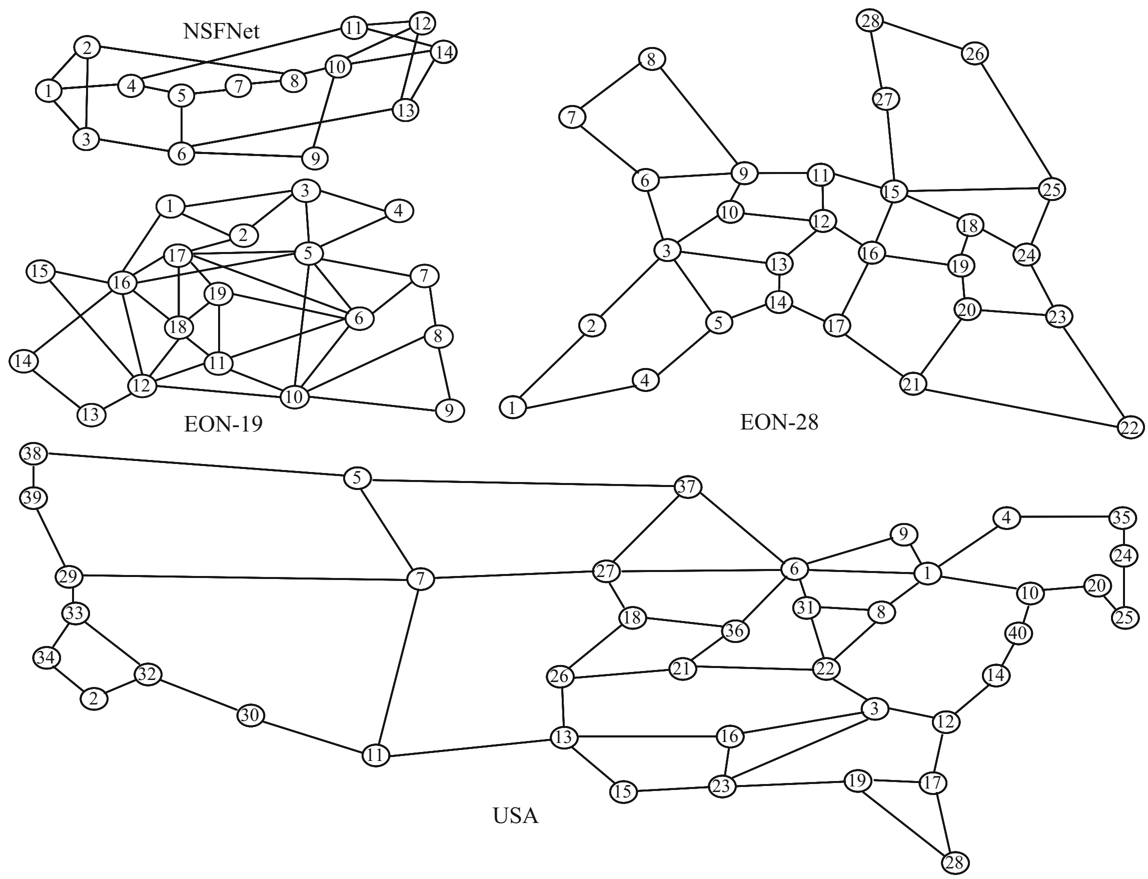


Fig. 3 Topology examples of some realistic optical networks

The BCO-related parameters are the following: The number of bees in population is assumed to be $B = 10$ (only in some experiments, we used the population of $B = 20$ and $B = 30$ bees to investigate the impact of population size to the solution quality), the number of requests served in each step of the algorithm $r = 5$ and the maximal number of iterations is assumed to be $I = 500$ (in case of NSFNet, EON-19 and EON-28 network examples) and $I = 200$ (in case of USA network topology) so as to constrain the required CPU time. All simulation tests have been performed by running the particular programming code that is implemented in MATLAB, using the PC with the processor on 2.4 GHz and installed RAM of 8 GB.

There are two versions of DE-RSA algorithm proposed in [17]: DE-relative position index (DE-RPI) and DE-general combinatorial (DE-GC) approach. For comparison purposes, we simulated the DE-RPI version due to its little better performances compared to DE-GC approach [17]. As suggested in [17], we used the same set of DE parameters: $M = 0.2$, RC = 0.5 and NP = 20. To make a fair comparison, we used the same number of generations *Gen* in DE approach as the number of iterations I in BCO approach.

Figures 4, 5, 6 and 7 show the comparison results (of the FF, MSF and LPF heuristic ordering policies as well as both metaheuristic algorithms, DE and BCO), for NSFNet, EON-19, EON-28 and USA networks, respectively. Graphics (a, b, c, d) on the left part of each figure show: (a) the spectrum utilization (SU), i.e., the minimal required number of frequency slots (FSs) to serve all requests in traffic demand list in a given network, (b) the average path length (APL), (c) the fitness (or objective function) value F and (d) the SU for two values of weighted parameter a_1 in the objective function: a default value of $a_1 = 0.5$, which means that both criteria (SU and APL) are optimized simultaneously with the equal weighted parameter values, while the value of $a_1 = 1$ minimizes only the SU criterion of the objective function by omitting the APL part. The results on all figures refer to the default value of weighted parameter $a_1 = 0.5$, unless it is specifically indicated that the value of $a_1 = 1$ is used. We performed the separate simulations for 15 independently generated traffic scenarios, for each considered algorithm (FF, LPF, MSF, DE, BCO, DE ($a_1 = 1$) and BCO ($a_1 = 1$)) in each network topology. Hence, a total of 15 * 7 * 4 = 420 simulation experiments are performed for results comparison in this section. Graphics (e, f, g and h) shown on the right side of each figure represent the averaged (SU, APL and F) values obtained over 15 traffic demand instances.

It could be seen that FF heuristic produces the worst results according to both the averaged values of SU and APL, and to integral fitness value F, followed by the LPF and MSF ordering policies. With DE metaheuristic, the results could be further improved, specifically according to the APL and F values. However, it could be noticed (see Fig. 4a–c) that our BCO–RSA algorithm is superior because it almost always (for all generated traffic scenarios) outperforms the results of other approaches according to all considered terms (SU, APL and F). In addition, the results of averaged values for SU, APL and F (Fig. 4e–g) show that our BCO–RSA algorithm provides the best performances. The results shown in Fig. 4d, h compare the BCO and DE approaches more clearly according to the SU performance. It could be seen that when both terms, the SU and APL, are optimized simultaneously (in the case of $a_1 = 0.5$), BCO approach decreases the averaged required number of FSs compared to DE metaheuristic (the results shown by first two bars in Fig. 4h).

It could be also seen that our BCO–RSA algorithm is better compared to DE metaheuristic if only the SU is optimized (case of $a_1 = 1$). If the objective function should minimize the SU only, both approaches (BCO and DE) provide better results with the weighted parameter $a_1 = 1$ compared to $a_1 = 0.5$, but in either case, our BCO–RSA algorithm offers the best performances compared to any other considered algorithms.

Similar results are obtained for other considered network examples (see Figs. 5, 6, 7). They confirm the superiority of the BCO–RSA algorithm in more complex network-traffic scenarios, such as the case of networks with larger number of nodes and links as well as with greater total number of requested frequency slots.

To get a more explicit goodness measure of BCO–RSA solution quality, we compare the results according to the SU performance in different network topologies in terms of the percent of spectrum (FSs) savings achieved with some benchmark algorithms. The results of maximal and average spectrum savings (over 15 different traffic scenario instances) relative to the FF heuristic (which always produces the worst solutions) are illustrated in Fig. 8. It could be seen that the most spectrum savings could be achieved using our BCO–RSA algorithm compared not only to simple heuristics (FF, LPF, MSF), but also with the competitive DE approach in different network topologies. As it is intuitively expected, more spectrum saving could be achieved if the weighted parameter $a_1 = 1$ is used compared to the default value of $a_1 = 0.5$.

Hereinafter, we investigate the computational complexity and efficiency of our BCO–RSA algorithm. The computational complexity is analyzed according to the CPU times required to perform the predefined maximal number of iterations I. Figure 9 shows the CPU time performance for different number of bees B and various values of searching granularity r (i.e., the number of requests tested during each algorithm step) in different network topologies. It could be seen that the increase in the number of bees B has a huge impact on the CPU time performance. However, the greater number of bees does not necessarily lead to the improvement of the solution quality. It could be noticed from Table 6 that by increasing the number of bees, the solution quality (SU, APL, F) does not change significantly. Our experiences show that the population of $B = 10$ bees is more than enough to obtain a high-quality solution within acceptable computational time.

It could be noticed from Fig. 9 that CPU time depends on the value of searching parameter r, too. The greatest CPU time is required with the finest searching granularity ($r = 1$), while the larger values of parameter r, for example $r = 5$ or $r = 10$, cause a less amount of CPU time values. Keep in mind that the results given in Fig. 9 show the total required CPU times for $I = 500$ iterations in case of NSFNet, EON-19 and EON-28 networks and $I = 200$ iterations in case of USA topology.

Further, we have explored in more detail the influence of parameter r to the solution quality along with the CPU time values. Table 7 shows the comparison results of SU, APL and F performances for a range of values of parameter r in case of NSFNet network example. The results for minimal (min), maximal (max) and average (avg) values are obtained throughout $I = 100$ iterations for randomly generated traffic demands with $Y_{\max} = 4$. It could be noticed that parameter r does not (or just a small) affect the SU, APL or F performances. By increasing the searching granularity r, less forward passes (or solution comparisons) are needed. As a result, the CPU time is decreased by increasing the value of r. However, it could be seen that CPU values are not reduced notably when $r > 5$ (this is why we chose the value of $r = 5$ in our simulation experiments). Similar findings are obtained for other considered network examples, but due to space limit, we presented here only the results for NSFNet topology.

Additionally, the CPU times of various considered algorithms in different network topologies are also compared and shown in Table 8 assuming the same number of iterations/generations $I = Gen = 500$ and the population size of $B = NP = 10$ in case of BCO and DE approaches.

Finally, we analyzed the convergence speed of our BCO–RSA algorithm, i.e., its ability to find the best quality solution during a predefined number of iterations. Figure 10 gives the comparative results between BCO and DE approaches related to the convergence speed obtained within total of $I = 500$ iterations in different network topologies. By performing numerous simulation experiments, it was observed that the convergence speed could vary depending on the assumed

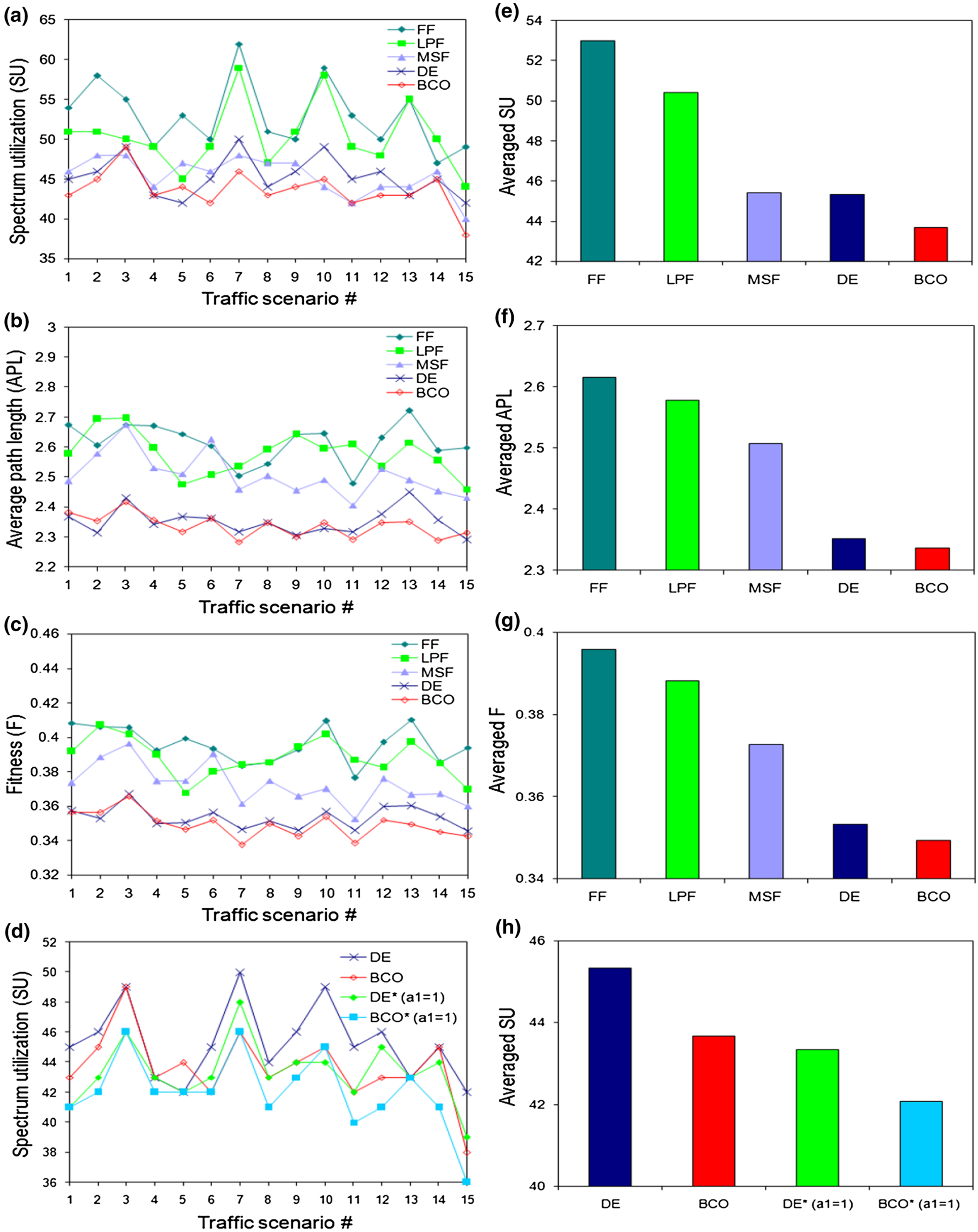


Fig. 4 The comparison results for NSFNet topology

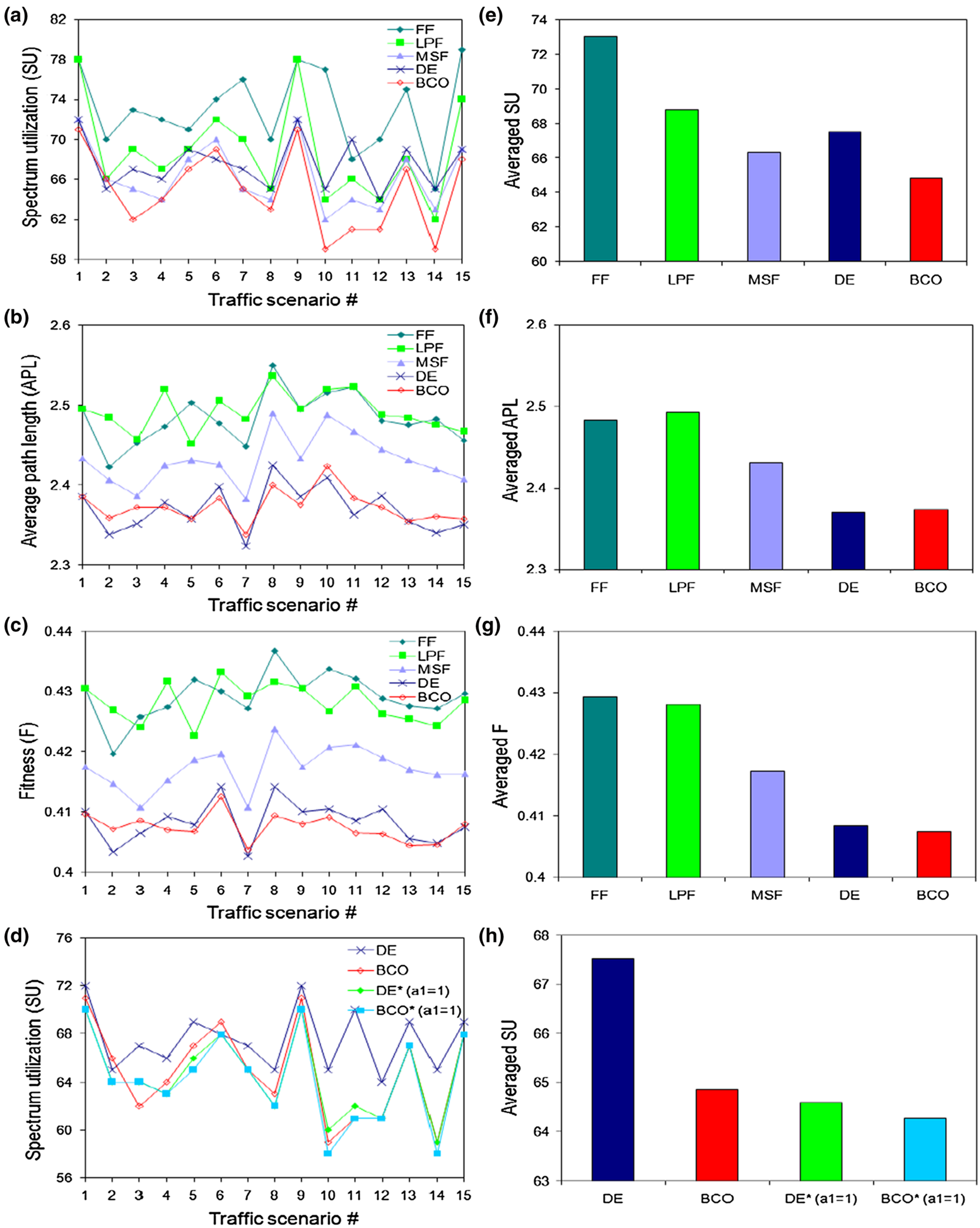


Fig. 5 The comparison results for EON-19 topology

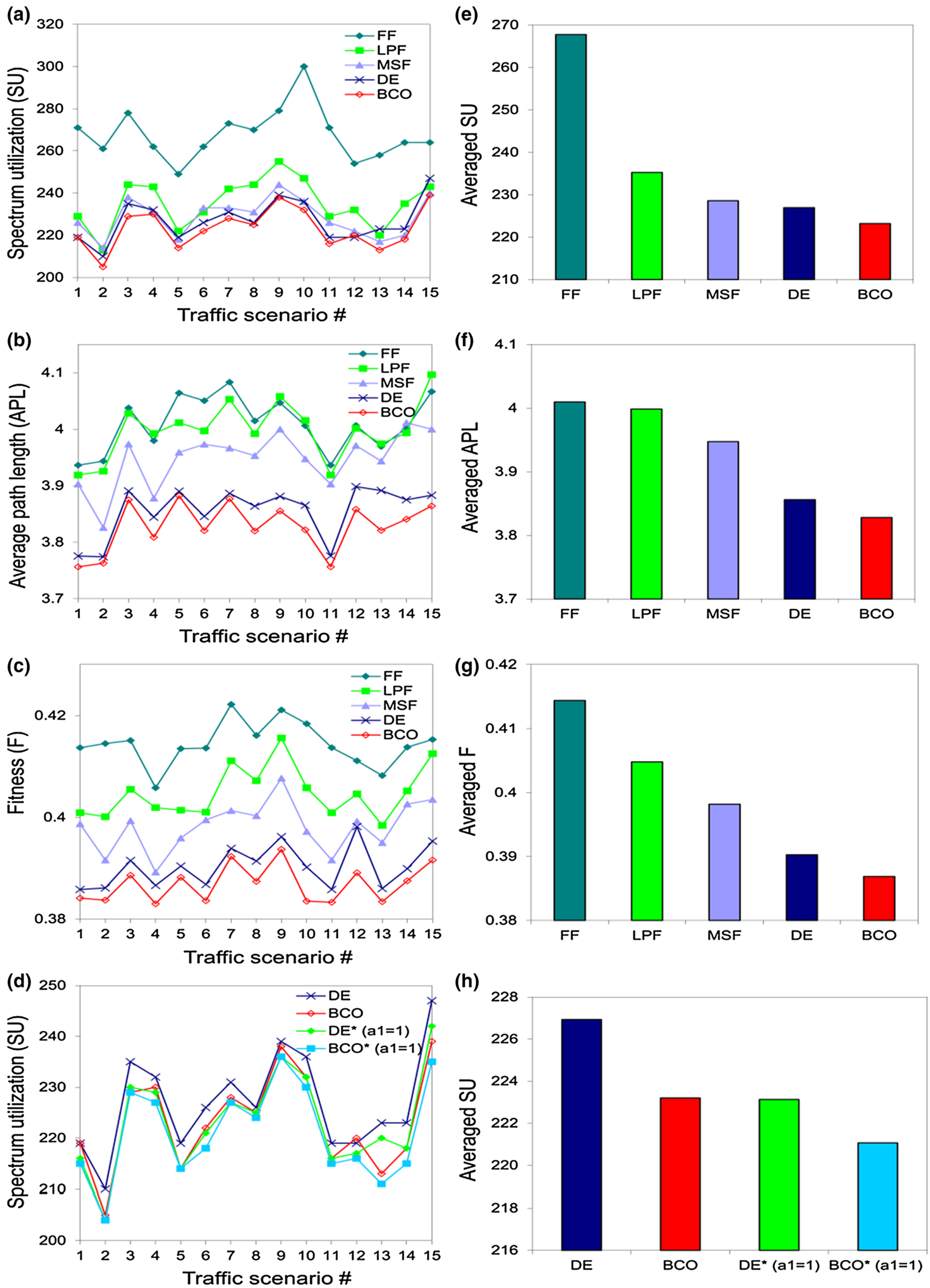


Fig. 6 The comparison results for EON-28 topology

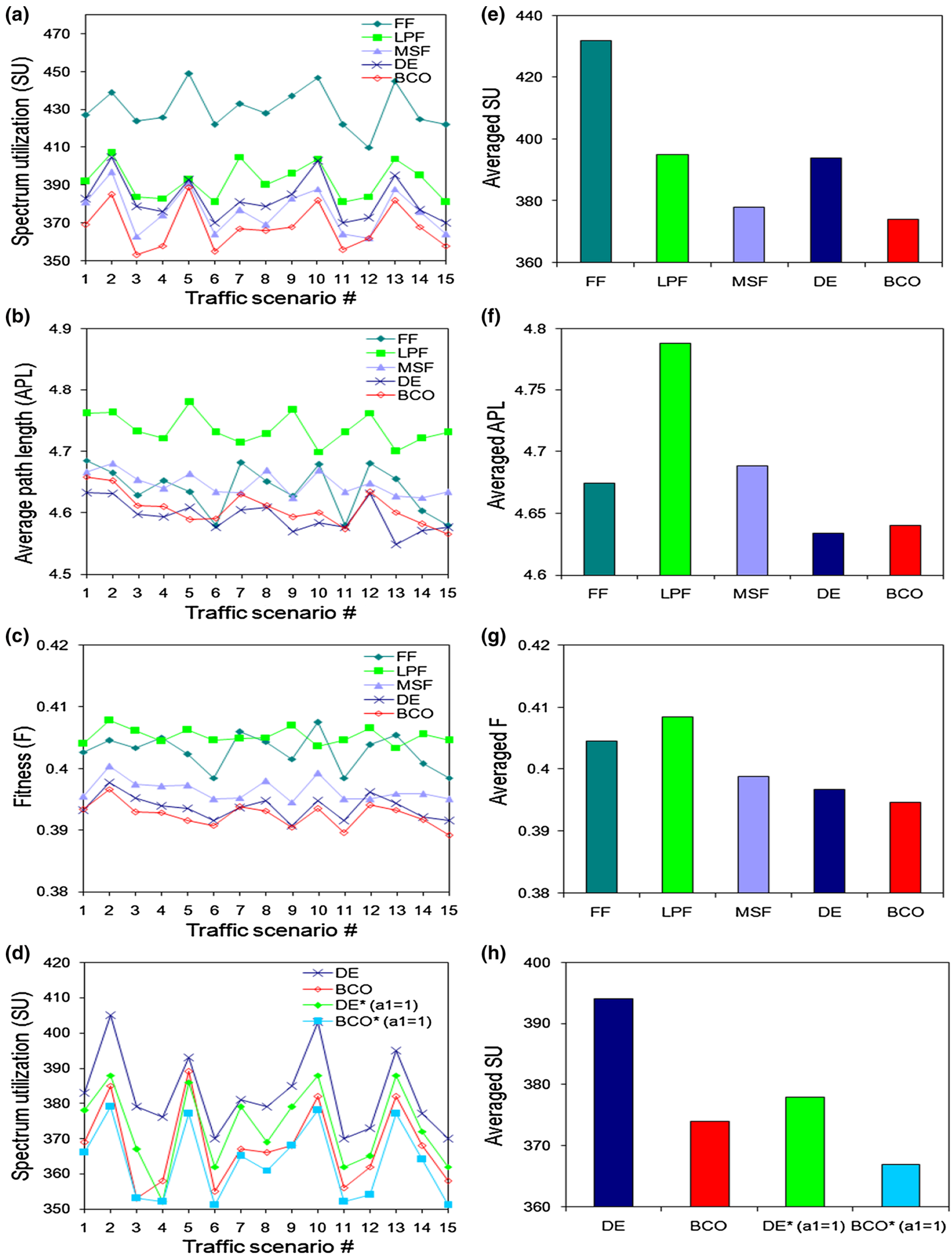


Fig. 7 The comparison results for USA topology

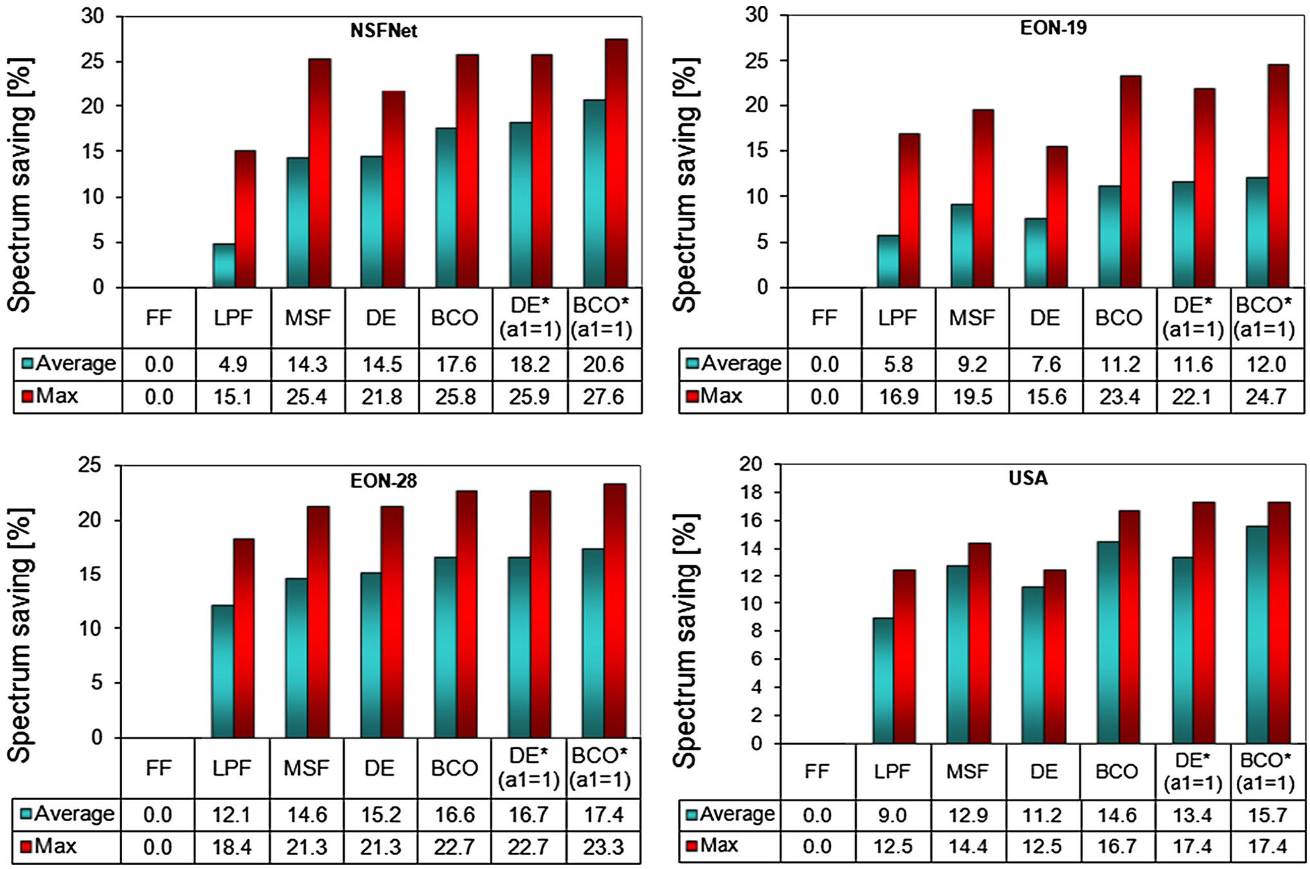


Fig. 8 Spectrum savings (relative to FF heuristic) achieved by various algorithms in considered networks

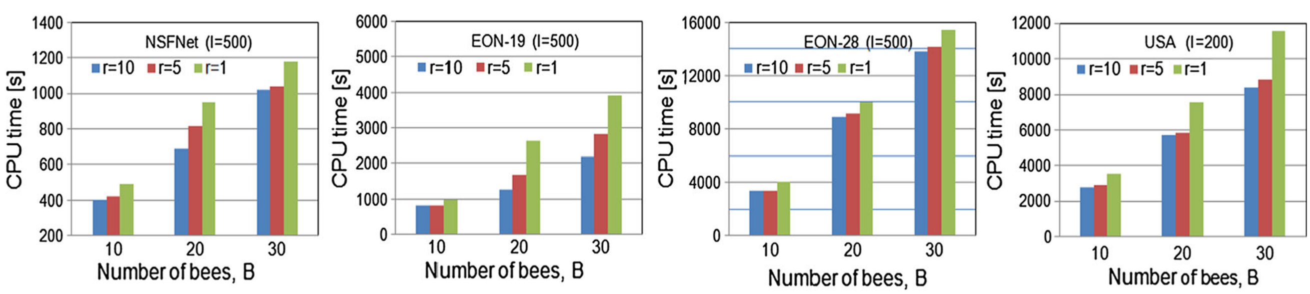


Fig. 9 The required CPU time of BCO–RSA algorithm in various considered network topologies

Table 6 Solution quality analysis for different number of bees B

B	NSFNet			EON-19			EON-28			USA		
	SU	APL	F	SU	APL	F	SU	APL	F	SU	APL	F
10	43	2.3586	0.3557	50	2.3630	0.4050	218	3.8344	0.3863	359	4.5790	0.3904
20	43	2.3448	0.3539	52	2.3593	0.4059	218	3.8296	0.3859	361	4.5652	0.3896
30	42	2.2759	0.3439	51	2.3356	0.4045	217	3.8360	0.3862	356	4.5775	0.3898

traffic demand scenario in a given network. However, due to space limitation we presented here only the results of a particular (randomly chosen) traffic demand scenario for each network topology. It could be seen that after a certain number of iterations (always less than $I = 500$ in all considered network topologies and traffic scenarios) our BCO approach outperforms DE approach, i.e., it is able to produce better solution quality (less fitness value) within a given number of iterations. Regardless that the solution quality of BCO approach could be somewhat weaker (higher fitness value)

Table 7 Influence of the searching granularity parameter r to the solution quality (SU, APL and F)

r	SU			APL			F			CPU (s)
	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	
1	39	45	42.61	2.3546	2.5603	2.4699	0.3468	0.3793	0.3661	124
5	41	45	42.69	2.3262	2.5532	2.4517	0.3474	0.3775	0.3640	87
10	41	45	42.79	2.3191	2.5390	2.4282	0.3465	0.3731	0.3611	86
15	40	47	42.94	2.3404	2.5390	2.4341	0.3506	0.3708	0.3612	83
20	41	46	42.86	2.3404	2.5603	2.4333	0.3506	0.3687	0.3611	82
30	41	50	43.94	2.3404	2.5532	2.4475	0.3501	0.3750	0.3617	81
40	40	47	43.69	2.3333	2.5745	2.4418	0.3469	0.3700	0.3624	81
50	42	49	44.03	2.3688	2.5816	2.4540	0.3509	0.3706	0.3625	80

Table 8 Comparison of CPU times for various considered algorithms and network examples (I = Gen = 500; B = NP = 10; r = 5)

CPU time (s)	NSFNet	EON-19	EON-28	USA
BCO	420	830	3408	7914
DE	416	814	3361	7556
FF	0.17	0.20	0.61	1.45
LPF	0.18	0.22	0.65	1.54
MSF	0.14	0.21	0.63	1.45

for a smaller number of iterations, it has better convergence speed (greater slope of fitness function), which indicates more frequent solution improvements between iterations. Hence, it is able to provide better final solutions compared to DE approach for appropriately chosen number of iterations. In other words, due to its better convergence speed, BCO is able to find the same solution quality within the smaller number of iterations. It proves our preliminary statement that BCO is able to produce high- quality solutions in an efficient manner. Hence, the algorithm such as the one we proposed

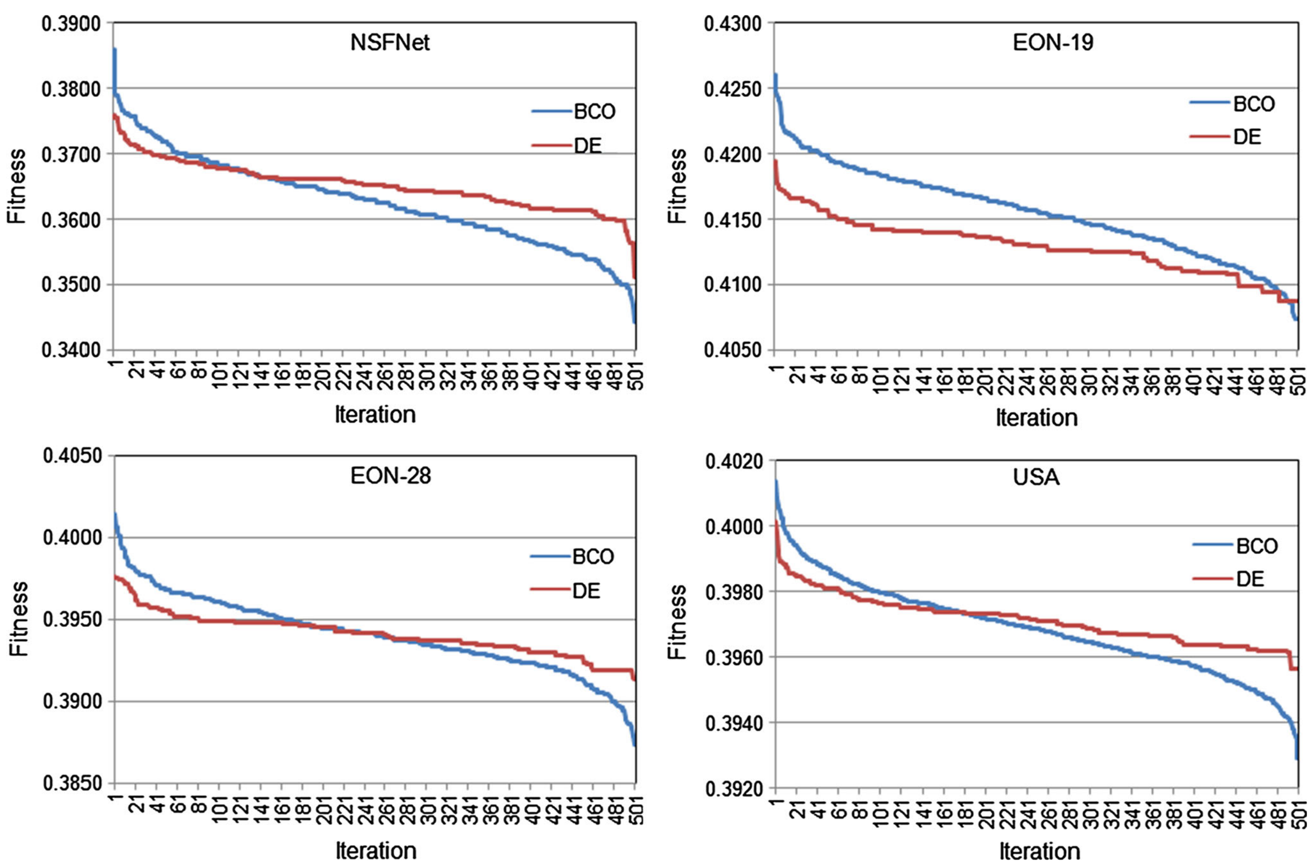


Fig. 10 Convergence speed comparison of BCO and DE approaches

in this paper is highly recommended for solving the complex RSA problem in next-generation elastic optical networks.

8 Conclusion

In this paper, we have suggested the application of BCO metaheuristic to solve efficiently the complex RSA problem in realistic size elastic optical networks. To the best of our knowledge, this is the first application of BCO method to the considered problem. The proposed BCO–RSA algorithm optimizes the SU and APL criterions at once by minimizing the integral objective (fitness) function. To evaluate the performances of the BCO–RSA algorithm, we performed numerous simulation experiments in four practical optical network topologies under various traffic scenarios. Numerical results show that our BCO–RSA algorithm is capable of producing the solutions of superior quality compared to other referenced algorithms. Although "studies show that DE in many instances outperforms other evolutionary algorithms" [17], it has been shown that our BCO–RSA algorithm is able to still overcome DE metaheuristic approach. This allows a preferred choice and proves the strength of the BCO approach compared to other competitive approaches while solving hard combinatorial problems. Overall, the quality solutions and high efficiency of the proposed BCO–RSA algorithm confirm that it is fully indispensable to be used for designing and operation of next-generation elastic optical networks.

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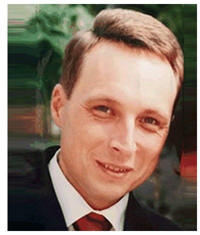

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