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Spectrum Defragmentation in Elastic Optical Networks: Two Approaches With Metaheuristics

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ABSTRACT This work introduces two novel approaches for the selection of active lightpaths that perform a spectrum defragmentation process in elastic optical networks (EONs). The algorithms, named *DF-Ants* and *DF-Gen*, are based on ant colony optimization and genetic metaheuristics, respectively, and their objective is to minimize the fragmentation of the entire network, evaluated with two different fragmentation metrics. In this way, the blocking probability is expected to be minimized with the fewest number of reconfigured possible connections. Furthermore, a new performance metric for spectrum defragmentation is also presented, named *weighted blocking rate* (WBR). Unicast traffic simulations were conducted, showing the feasibility of the proposal.

INDEX TERMS Ant colony optimization, elastic optical networks, genetic algorithms, metaheuristics, spectrum defragmentation.

I. INTRODUCTION

Optical networks are experiencing an exponential growth in terms of bit rates and bandwidth. This growth is caused by the expansion of cloud-based services, video on demand, and virtual datacenters [1], [2], and it is expected that in the near future, the capacity of the current optical networks will become saturated (a phenomenon known as ‘‘capacity crunch’’) [3], [4].

Elastic optical networks (EONs), also known as *flex-grid* networks, were proposed by Jinno et al. [5] as an alternative for facing the capacity crunch through the efficient use of fiber optic spectrum. This technology provides superior flexibility in spectrum assignment strategy for heterogeneous optical connection requirements, in contrast to traditional WDM (wavelength division multiplexing) optical networks with fixed-bandwidth channels. EONs operate following the G.694.1 ITU-T recommendation, using channels with a flexible bandwidth and allocating just the necessary spectrum composed of an entire number of 12.5 GHz frequency slots (FSs) [6]. In this way, a better efficiency of spectrum utilization of each optical link is achieved, and it is possible to accommodate a higher number of optical connections on a given fiber.

The bandwidth fragmentation problem is caused by the dynamic assigning and releasing of connection demands in EONs, and it can have an important impact on the efficient use of the spectrum [7]. It consists in the appearance of isolated unused FS blocks in contiguous fiber links. These blocks may not be used, considering that optical connections, or lightpaths, must comply with the continuity and contiguity bandwidth restrictions in EONs in the absence of wavelength conversion [8]. As a consequence, bandwidth fragmentation has a direct influence in the blocking probability of connection demands.

One way to address the bandwidth fragmentation is by rerouting or reconfiguring a subset of active lightpaths in the network for accommodating the spectrum use of active connections. This process is known as *spectrum defragmentation* [9].

Spectrum defragmentation can cause disruptions in the use of existing lightpaths and therefore a decrease in the final quality of service (QoS). For this reason, it is desirable to reduce network fragmentation, reconfiguring the fewest number of active lightpaths as possible. Therefore, the selection of active lightpaths for a subsequent defragmentation process is critical for maintaining a high QoS and decreasing the operational cost of each defragmentation procedure.

In this work, two novel algorithms are presented for the selection of active lightpaths in a defragmentation process.

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Both algorithms are based on already mature metaheuristics (ant colony optimization and genetic algorithm) that aim to minimize two different fragmentation metrics for the entire network. Therefore, subsequent rejections of connection demands can be expected to be minimized.

In addition, a new performance metric for the defragmentation process is introduced, named the *weighted blocking rate* (WBR). This metric aims to lead with a trade-off between two important performance metrics in any of the defragmentation procedures, namely, the blocking probability and the number of reconfigured connections.

In Section II, the defragmentation problem is presented. Section III discusses aspects of the first algorithm, named *DF-Ants*. In Section IV, a genetic algorithm for the selection of active lightpaths is presented, named *DF-Gen*. Section V shows experimental results using traffic simulation over two EON topologies. Finally, Section VI concludes this work.

II. SPECTRUM DEFRAGMENTATION OVER EONS

Fig. 1 shows the spectrum, divided into 10 FSs, of two adjacent links l_1 and l_2. Due to dynamic traffic, their spectrum shows fragmentation and only FSs 2, 3 and 7 are available for simultaneous use by new lightpaths. If a new lightpath requires two contiguous FSs, only FSs 2 and 3 may be assigned. Although only 50% of the total available bandwidth is used in both links, it cannot be used efficiently because of bandwidth fragmentation.

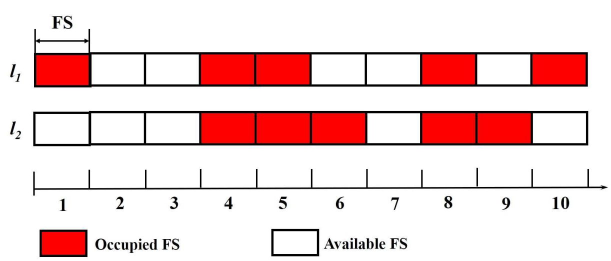

FIGURE 1. Spectrum fragmentation in two links of an EON.

Spectrum defragmentation seeks to reaccommodate the used FS blocks in order to leave more FS blocks aligned in contiguous optical links. A typical classification of the spectrum defragmentation process is as follows:

- *Reactive defragmentation* [10], [11]: It is performed when a blocking of a connection demand appears. Its main objective is to obtain the establishment of the blocked demand, and it typically involves only a partial region of the network.
- *Proactive defragmentation* [10], [11]: The objective of this process is to decrease the fragmentation state of the entire network and therefore to achieve a smaller blocking probability of subsequent demands. It can be performed periodically, or it can be triggered by a specific event, when some previously defined threshold is reached.

This work is focused on proactive defragmentation, performing a complete reconfiguration procedure to a subset of existing lightpaths (i.e., allowing a rerouting and spectrum reassigning).

Zhang et al. published in [12] a comprehensive analysis of the defragmentation process in EONs, identifying four subproblems:

1) *How to reconfigure:* Which RSA (routing and spectrum assignment) algorithm to use in the defragmentation process.
2) *How to migrate the traffic:* Which strategy should be used in the migration of reconfigured lightpaths to the new assigned paths and spectrum in order to minimize disruptions in existing connections.
3) *When to reconfigure:* What method should be used for determining the period of time to perform a defragmentation process.
4) *What to reconfigure:* To decide which lightpaths must be included in the reconfiguration process in order to obtain the best results in decreasing fragmentation.

This work studies the fourth subproblem, i.e., the selection of the lightpaths set to reconfigure, considering two main objectives: (i) to minimize the number of blocking demands in a certain period of time, i.e., the blocking probability; and (ii) to minimize the number of reconfigured lightpaths to diminish the probability of disruptions.

The physical EON can be modeled as a nondirected graph $G\{N, L\}$ with a set of physical nodes N and a set of physical links L. The bandwidth of each fiber link $l \in L$ is divided in W frequency slots or FSs. Before the defragmentation procedure, a set of active lightpaths R are installed in the network. Each lightpath $r_i \in R$ is defined by a path of k physical links, connecting the source and destination nodes, and a set of contiguous FSs.

The selection of lightpaths for a defragmentation procedure consists in the determination of a subset of active lightpaths $R^D \subseteq R$ that are to be re-routed.

A complete survey on this problem can be found in [9]. To our best understanding, only Zeng et al. [13] use metaheuristics to select connections for the defragmentation process. They present a simulated annealing-based "multistep" defragmentation process that consists in reconfiguring one connection at a time, seeking to decrease the fragmentation state of the network. However, they do not study how to determine the rate of reconfigured lightpaths for each defragmentation process. Other works, such as [14], propose an integer linear programming (ILP)-based method, seeking to minimize the maximum number of occupied wavelength slots in the network. The defragmentation problem is classified as *NP-Complete* [11], [9], so exact methods are not scalable to complex instances.

Other works focus on heuristics to solve this problem. As an example, [15] considers the holding time of connections to reduce fragmentation, while the authors of [16] propose a make-before-break (MBB) defragmentation, rejecting connections that cannot be reconfigured by this strategy.

Neither of these two strategies considers the complete universe of possible solutions.

This work performs an evaluation of two different metaheuristics used for the planning of the defragmentation process, considering two objectives: the blocking probability and the number of reconfigured connections. These metrics are evaluated at the end of a dynamic traffic simulation.

III. ANT COLONY OPTIMIZATION DEFRAGMENTATION ALGORITHM: DF-ANTS

This section presents *DF-Ants*, an ant colony optimization (ACO) algorithm for the selection of lightpaths to reconfigure. This algorithm is based on the *ant system algorithm* [17].

DF-Ants seeks to optimize a metric that evaluates the fragmentation state of the network, measured after a reconfiguration process made with a specific set of active lightpaths. In this way, the rate of future demand blockings is expected to be minimized.

The considered fragmentation metrics (or FM) are as follows:

- *External Fragmentation Metric (EFM)* [18]: EFM, for a specific optical link l, is calculated as:

$$EFM_l = 1 - \frac{MaxBlock}{FS_{free}} \tag{1}$$

  where *MaxBlock* is the size of the largest FS free block (in terms of the number of free FSs), and FS_{free} is the total number of free FSs in the link.
  A value of EFM = 0 indicates a nonfragmented link, while an EFM value tends to 1 for a very fragmented link.
- *Maximum Slot Index (MSI):* MSI, for a specific optical link l, is defined as the highest FS index unavailable in the link [19]:

$$MSI = Max\ j\ :\ FS_j = 1 \tag{2}$$

  where $FS_j = 1$ if it is occupied and $FS_j = 0$ if it is available.
  A low value of MSI indicates low fragmentation, while a value of MSI near W indicates a high fragmentation.
  It is important to note that this defragmentation metric can only be used when the RSA algorithm used for routing the connection demands uses a *first-fit* [20] criterion for spectrum assignment.

The values of EFM and MSI for the network will be the average of the considered metric for all the optical links in a specific time. Similarly, EFM and MSI for each lightpath will be equal to the average of the metric for all the component links in a specific time.

A. DEFINITION OF SUBPROBLEMS.

Initially, FM_{Prev}, which is the initial value of the FM used in the algorithm, is calculated for comparison purposes, and the set of active lightpaths to reconfigure R^D is empty.

Algorithm 1 ACO Algorithm: *DF-Ants*

Require: Physical network G, set of active lightpaths R, parameter FM_{tar}

Calculate visibility values η_i for each active lightpath $r_i \in R$ and FM_{prev}
Initialize pheromone values τ_i
for each artificial ant **do**
  $R^D = R^{best} = \emptyset$; $FM_{ants} = FM_{prev}$
  while $FM_{ants} < FM_{tar}$ **or** $|R^D| < |R|$ **do**
    Select an active lightpath r_j by equation (5)
    Add r_i to R^D ($R^D = R^D + r_i$)
    Delete physical network lightpaths $r_i \in R^D$ in an auxiliary graph $G_{aux} = G^F$
    Reroute in G_{aux} lightpaths r_i in nonascending order according to the number of required FS
    if all lightpaths are rerouted **then**
      Calculate FM_{ants}
    else
      Block()
    end if
  end while
  if $|R^D| < |R^{best}|$ **then**
    $R^{best} = R^D$
  end if
  Perform *evaporation* process
  update *pheromone* table τ_j according to *fitness* value $|R^D|$
end for
return Best solution R^{best}

Each step of an artificial ant consists in the addition of one active lightpath to the set of lightpaths to reconfigure R^D. Therefore, the artificial ant will select consecutively an active lightpath and will include it in R^D.

After each addition, the artificial ant will perform a simulated reconfiguration of the network, with the set of lightpaths calculated until this step, using an auxiliary graph G_{aux}. The objective is to evaluate the value of the fragmentation metric of the entire network.

If the value of this metric reaches a predetermined value FM_{tar}, the artificial ant stops and returns the set of lightpaths selected at this period of time.

B. FITNESS FUNCTION

The *fitness* function used to evaluate the solution found by each artificial ant is the number of active lightpaths to be rerouted. If R is the set of the total active lightpaths in the network at the time of the defragmentation procedure, and $R^D \subseteq R$ is the set of lightpaths to be rerouted, the fitness function will be:

$$fitness = |R^D| \tag{3}$$

where $|.|$ denotes cardinality.

C. PROPOSED ALGORITHM

Two versions of the *DF-Ants* algorithm are proposed, differing only in the fragmentation metrics *FM* used to evaluate the fragmentation state of the network (EFM or MSI).

Considering that the algorithm tries to minimize the *fitness*, the values of pheromone trails τ_i associated with each active lightpath r_i will be proportional to the multiplicative inverse of this value.

The visibility η_i of each lightpath r_i is calculated once for all the artificial ants. Its value is the multiplicative inverse of the fragmentation metric FM_i used for each lightpath:

$$\eta_i = \frac{1}{FM_i} \tag{4}$$

The probability that an active lightpath r_i could be selected to be part of the set of lightpaths to be reconfigured will be calculated with the well-known ACO probability formula:

$$p(r_i \in R^D) = \frac{\tau_i^\alpha \cdot \eta_i^\beta}{\sum_{r_j \in R} \tau_j^\alpha \cdot \eta_j^\beta} \tag{5}$$

The parameters α and β adjust the relative influence of visibility and pheromones, respectively.

Algorithm 1 presents the proposed process. Given a physical network G and the objective value of the fragmentation metric FM_{tar}, visibility values are calculated and pheromone values are initialized for each active lightpath in the network.

Then, each artificial ant selects an active lightpath at each step, and adds it to set R^D (lines 6 and 7). Subsequently, a reconfiguration of R^D is performed over an auxiliary network graph G_{aux}.

This process is carried out while the fragmentation metric FM_{ants} is larger than the objective value FM_{tar} (line 5). Otherwise, the artificial ant ends its trip. Finally, the *fitness* function is evaluated, the best solution is updated, and the *evaporation* (a gradual reduction of all pheromone values considering an evaporation parameter ρ) and pheromone update processes are performed.

IV. GENETIC ALGORITHM DF-GEN

This section describes the genetic algorithm *DF-Gen*, which selects a set of active lightpaths to reconfigure with a predefined number of components.

Similar to *DF-Ants*, each version of *DF-Gen* uses one of the fragmentation metrics to characterize the fragmentation state of each optical link, each lightpath or the entire network.

However, *DF-Gen* performs the rerouting of a fixed ratio of active lightpaths γ, which is defined a priori.

A. REPRESENTATION OF A CHROMOSOME

A feasible solution (or *chromosome*) is represented by a vector R^D with size $|R^D| = \gamma \cdot R$, where R is the set of active lightpaths at the moment of the defragmentation. This vector consists of natural numbers i, each one representing an active lightpath in the network $r_i \in R$.

i	1	2	3	4	5	6
r_i	21	8	43	16	32	5

FIGURE 2. An individual chromosome of the *DF-Gen* algorithm.

Figure 2 represents a chromosome in which lightpaths r_{21}, r_8, r_{43}, r_{16}, r_{32} and r_5 were selected for rerouting. In this case $|R^D| = 6$.

B. GENERATION OF THE INITIAL POPULATION

The initial population set, with *Pob* elements or different solutions, is generated as follows:

- for 30% of the elements, the roulette selection method [21] is used, assigning to each active lightpath a probability proportional to the value of the fragmentation metric used. In this way, the worse lightpaths (considering the fragmentation of their links) have higher priority to be included in the chromosomes;
- the remaining 70% is generated randomly, with a uniform probability distribution for all the lightpaths (all the connections have the same probability to be selected).

C. GENETIC OPERATORS

1) MUTATION

Mutation consists in randomly selecting one lightpath $r_i \in R^D$ and its replacement by another lightpath $r_j \notin R^D$.

2) CROSSOVER

For the *crossover* operation, the *1-point crossover* method is used [22].

First, two parents (solutions) are selected using the roulette selection method, giving to each lightpath a probability proportional to its fragmentation metric. Then, a point of crossing is selected in the vector solution. Both fragments are combined to generate two different solutions. Figure 3 shows the implemented crossover method.

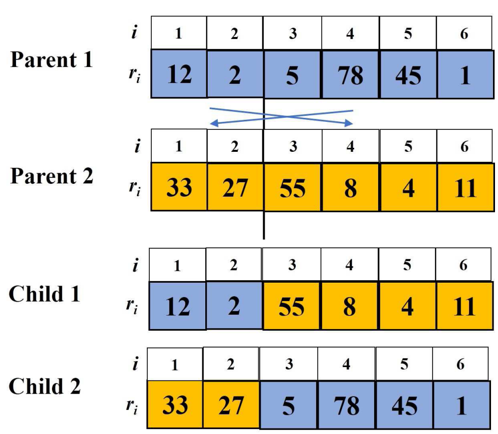

FIGURE 3. The crossover operation.

D. FITNESS FUNCTION

The *fitness* function of each solution is equal to the fragmentation metric used, after performing rerouting of all the *lightpath* components of the solution:

$$fitness = FM_{post} \tag{6}$$

Algorithm 2 illustrates the process. The first step is to calculate the initial population (lines 1 to 8). Then, the fitness function of each solution (each chromosome) is calculated. The parent chromosomes are selected on line 12.

Algorithm 2 Genetic Algorithm: *DF-Gen*

Require: Physical network G^F, set of active lightpaths R, parameters γ and Pop

1: Calculate values of FM_i for each lightpath $r_i \in R$
2: Calculate size of chromosome $|R^D| = \gamma \cdot |R|$
3: **for** each chromosome $R_k^D \in Pob$ **do**
4:     **if** $k \leq 0.7 \cdot Pob$ **then**
5:         Select randomly $|R^D|$ lightpaths and add them to R_k^D
6:     **else**
7:         Select R^D lightpaths using the roulette selection method, considering values of FM_i
8:     **end if**
9: **end for**
10: **while** not given stop condition **do**
11:     Evaluate *fitness* function of each *chromosome* in Pob
12:     Select chromosomes *parents* using the roulette selection method considering values of FM
13:     Perform *crossover* y *mutation* operations
14:     Select best chromosomes for new generation population Pop
15: **end while**
16: **return** Best chromosome of last generation's Pop

The operations of crossover and mutation are performed in line 13. The best solutions are chosen for the next generation, using *elitism*. The stop condition is the number of generations.

V. EXPERIMENTAL RESULTS

Experimental simulations have been conducted with the objective of determining the feasibility of the proposed algorithms in decreasing demand blockings. A dynamic unicast traffic simulator was implemented over two different EON topologies: NSFNET (with 14 nodes and 22 optical links) [23] and USNET (with 24 nodes and 43 links) [24].

As a baseline, we have also implemented the *Defragmentation with Fixed Timing and Fixed Ratio* (DF-FT-FR) algorithm, proposed by Zhang et al. [12]. This algorithm also calculates the value of the FM_i for each active lightpath and then selects a number ($\gamma \cdot |R|$) of them with the worst values to reroute. For the presented simulations, $\gamma = 0.3$ was employed, which appeared to achieve the best results [12].

A. PARAMETERS OF DF-ANTS ALGORITHM

Two versions of this algorithm were implemented, each one trying to minimize a different FM (EFM or MSI). The parameters applied to this algorithm for the experiments were defined after preliminary executions, and they are as follows:

- Number of artificial ants = 30
- Parameter $\alpha = 1$
- Parameter $\beta = 1$
- Evaporation parameter $\rho = 0.1$
- Objective improvement in the value of FM for the entire network $FM_{tar} = 0.75 \cdot FM_{prev}$.

B. PARAMETERS OF DF-GEN ALGORITHM

Similar to the previous case, two different fragment metrics were used in different versions of the *DF-Gen* algorithm.

In addition, the values of the γ parameter were taken from the set $\{0.2; 0.3; 0.4; 0.5; 0.6; 0.7\}$ in order to analyze the effect of γ in the blocking ratio. Hence, experimental testing was performed with 12 different versions of *DF-Gen*. As an example, *DF-Gen-40-MSI* is the *DF-Gen* algorithm that considers the fragmentation metric MSI with $\gamma = 0.4$ in the considered period of time.

Other parameters applied to this algorithm are as follows:

- Size of population $Pop = 50$ (each generation works with 50 different solutions)
- Mutation probability $p(mt) = 0.05$
- Cross over probability $p(cr) = 0.5$
- Stop criterion: Number of generations = 50.

It is important to note that these parameters were chosen with the objective of having the same execution times for both algorithms (a few seconds for each defragmentation procedure).

C. PARAMETERS OF THE OPTICAL NETWORK SIMULATOR

The parameters for the generation of testing instances were:

- Total number of FSs for each optical link: 300
- Selection of source and final nodes for each demand connection: randomly, with a uniform distribution of probabilities
- Each demand requires a random number of FSs between 1 and 8
- Each test instance is executed in 1000 periods of discrete time.

The FA-RSA (*Fragmentation Aware-Routing and Spectrum Assignment*) algorithm, presented in [25], was used twice: (i) for the initial routing of each demand and (ii) in the defragmentation process.

Instances of testing with fixed values of traffic volume were considered, taking values of 400, 500, 550 and 600 *Erlangs* for NSFNET and 400, 450, 550, 650 and 700 *Erlangs* for the USNET network.

The arrival of each demand follows a Poisson distribution with $\lambda = 5$. The holding time HT of each lightpath follows an exponential distribution.

TABLE 1. Experimental values of blocking probability and reconfigurations - NSFNET network.

	Fragmentation Metric	400 Erlangs		450 Erlangs		500 Erlangs		550 Erlangs		600 Erlangs	
		Blocking Prob. (%)	γ (%)	Blocking Prob. (%)	γ (%)	Blocking Prob. (%)	γ (%)	Blocking Prob. (%)	γ (%)	Blocking Prob. (%)	γ (%)
DF-FT-FR	*EFM*	1.4	30	4.4	30	4.9	30	8.4	30	11.4	30
	MSI	1.5	30	3.8	30	4.8	30	7.6	30	11.1	30
DF-Ants	*EFM*	**0.9**	66	3.6	66	4.6	62	7.8	70	10.6	67
	MSI	1.0	47	4.1	65	5.1	30	8.5	16	11.8	36
DF-Gen-20	*EFM*	1.4	20	4.3	20	5.0	20	8.4	20	11.9	20
	MSI	1.3	20	4.0	20	4.8	20	8.1	20	11.2	20
DF-Gen-30	*EFM*	1.4	30	4.1	30	4.9	30	8.3	30	11.1	30
	MSI	1.1	30	3.7	30	4.5	30	7.8	30	10.6	30
DF-Gen-40	*EFM*	1.2	40	3.9	40	4.7	40	7.9	40	11.2	40
	MSI	1.0	40	3.4	40	4.3	40	7.4	40	10.6	40
DF-Gen-50	*EFM*	1.3	50	3.9	50	4.6	50	7.7	50	10.9	50
	MSI	**0.9**	50	**3.3**	50	4.2	50	7.2	50	**10.2**	50
DF-Gen-60	*EFM*	1.2	60	3.7	60	4.6	60	7.6	60	10.7	60
	MSI	1.1	60	**3.3**	60	**4.0**	60	7.2	60	10.6	60
DF-Gen-70	*EFM*	**0.9**	70	3.4	70	4.6	70	7.5	70	10.6	70
	MSI	**0.9**	70	**3.3**	70	4.1	70	**7.0**	70	**10.2**	70
With no Defragmentation		1.6		4.4		5.2		8.7		12.3	

The defragmentation processes were performed periodically each 100 time slots, i.e., nine defragmentation processes were performed with each instance.

For each testing instance (with a fixed value of *Erlangs* and in a determined network topology), three different executions were considered, taking the average value of the results as a representative value of the testing instance.

In addition, one testing instance with no defragmentation was also considered for comparison purposes.

D. PERFORMANCE METRICS

The most representative performance metric used to evaluate the efficiency of a defragmentation process is the *blocking rate*, which is equal to the number of blocking number of demands over the total number of demands in a test instance.

Another important performance metric is the rate of reconfigured lightpaths over the total active lightpaths γ, which evaluates the complexity of the defragmentation process operation.

Clearly, the defragmentation algorithm obtains a great decrease of blocking demands as the value of γ increases, which is undesirable since it means an increase in the operative cost of each defragmentation process. Furthermore, it generates an increase in the probability of disruptions in the service of lightpaths.

Therefore, it is important to find a balance between these two metrics in trade-off. This work proposes a new defragmentation performance metric, named *Wavelength blocking ratio* (WBR), defined as:

$$WBR = \Delta Bl \cdot (1 - \gamma) \tag{7}$$

where ΔBl is the difference between the number of blocking demands that occurs in the testing instance without performing any defragmentation process, and the number of blocking demands obtained performing the defragmentation processes. In this sense, ΔBl evaluates the obtained benefit (number of avoided blocking demands) achieved due to the defragmentation process. This value is weighted by $(1 - \gamma)$, which indicates the rate of nonconfigured demands connections. Clearly, this value indicates the simplicity of defragmentation in operative terms, and moreover, it describes the number of disruptions that could be generated in each process.

E. OBTAINED RESULTS

Tables 1 and 2 show values of the blocking probability and γ for each testing instance, obtained by *DF-Ants*, *DF-Gen* and the reference DF-FT-FR algorithms, with NSFNET and USNET network topologies respectively. The values of blocking probability without performing any defragmentation process, for the same set of connection demands, are also presented.

As can be observed, the value of γ is fixed for all the experiments except for the *DF-Ants* algorithm, which performs a variable number of reconfigurations.

It can also be noted that the best results for blocking probability (in bold) are reached with higher values of γ, especially for *DF-Gen*, as expected.

We can also observe that the *DF-Ants* algorithm seems to reach good results only for low rates of traffic. Its experimental results are comparable to other values of *DF-Gen* only for 300 *Erlangs*.

The concept of *Pareto dominance* [26] is explained as follows: In a multiobjective optimization problem, a solution A *dominates* another solution B if A is better than B in at least one objective and is not worse in any other objective.

Using this concept, we can ascertain that no solution exists that in the Pareto sense, *dominates* the rest of the solutions, considering each instance separately. That is, no algorithm is the best in blocking probability and γ simultaneously. To compare both proposals, we then use the WBR metric.

Tables 3 and 4 show experimental values of WBR for each instance and a column with average values of each algorithm. The best results are shown in bold.

TABLE 2. Experimental values of blocking probability and reconfigurations - USNET network.

	Fragmentation Metric	*400 Erlangs* Blocking Prob. (%)	γ (%)	*450 Erlangs* Blocking Prob. (%)	γ (%)	*550 Erlangs* Blocking Prob. (%)	γ (%)	*650 Erlangs* Blocking Prob. (%)	γ (%)	*700 Erlangs* Blocking Prob. (%)	γ (%)
DF-FT-FR	*EFM*	1.1	30	2.6	30	5.8	30	6.6	30	8.7	30
	MSI	1.0	30	2.8	30	5.7	30	6.3	30	8.7	30
DF-Ants	*EFM*	1.1	63	3.0	69	5.6	69	5.9	88	8.4	84
	MSI	**0.7**	44	2.6	42	5.8	11	6.3	26	9.0	22
DF-Gen-20	*EFM*	1.0	20	3.3	20	5.9	20	7.1	20	9.2	20
	MSI	0.9	20	2.7	20	5.6	20	6.5	20	8.9	20
DF-Gen-30	*EFM*	1.0	30	3.0	30	5.9	30	6.8	30	9.1	30
	MSI	0.8	30	2.6	30	5.4	30	6.5	30	8.6	30
DF-Gen-40	*EFM*	1.0	40	2.9	40	5.9	40	6.6	40	8.9	40
	MSI	0.8	40	2.4	40	5.3	40	6.0	40	8.5	40
DF-Gen-50	*EFM*	1.0	50	2.7	50	5.5	50	6.4	50	8.7	50
	MSI	**0.7**	50	2.3	50	**5.0**	50	5.9	50	8.4	50
DF-Gen-60	*EFM*	0.9	60	2.6	60	5.6	60	6.3	60	8.5	60
	MSI	**0.7**	60	**2.2**	60	**5.0**	60	5.9	60	8.1	60
DF-Gen-70	*EFM*	**0.7**	70	2.6	70	5.4	70	6.2	70	8.5	70
	MSI	**0.7**	70	2.3	70	**5.0**	70	**5.7**	70	**7.8**	70
With no Defragmentation		1.3		3.5		6.1		8.2		9.5	

TABLE 3. Values of WBR metric - NSFNET network.

		400 Erlangs	*450 Erlangs*	*500 Erlangs*	*550 Erlangs*	*600 Erlangs*	*Average*
DF-FT-FR	*EFM*	7,0	0,0	10,5	13,3	29,4	12,0
	MSI	4,9	18,9	13,3	39,9	41,3	23,7
DF-Ants	*EFM*	11,9	13,6	11,0	14,7	27,7	15,8
	MSI	15,9	5,3	4,9	11,8	14,7	10,5
DF-Gen-20	*EFM*	6,4	4,8	8,8	12,0	16,0	9,6
	MSI	10,4	14,4	16,0	27,2	44,0	22,4
DF-Gen-30	*EFM*	6,3	11,2	10,5	14,7	39,9	16,5
	MSI	18,9	23,8	26,6	32,2	**58,1**	31,9
DF-Gen-40	*EFM*	10,8	13,2	15,0	25,8	33,6	19,7
	MSI	**19,2**	**28,8**	**28,8**	**39,6**	51,0	**33,5**
DF-Gen-50	*EFM*	8,0	11,0	15,0	26,0	34,0	18,8
	MSI	17,0	27,0	24,5	38,0	51,0	31,5
DF-Gen-60	*EFM*	8,0	14,4	12,4	22,0	31,6	17,7
	MSI	10,8	21,6	24,0	31,2	34,0	24,3
DF-Gen-70	*EFM*	9,9	15,3	8,7	18,3	25,5	15,5
	MSI	9,9	16,8	16,5	26,4	31,8	20,3

TABLE 4. Values of WBR metric - USNET network.

		400 Erlangs	*450 Erlangs*	*550 Erlangs*	*650 Erlangs*	*700 Erlangs*	*Average*
DF-FT-FR	*EFM*	7,0	30,8	11,2	18,2	29,4	19,3
	MSI	9,8	23,8	11,9	28,7	30,8	21,0
DF-Ants	*EFM*	3,0	7,4	7,8	7,6	9,1	7,0
	MSI	16,8	26,1	11,6	31,8	21,8	21,6
DF-Gen-20	*EFM*	9,6	10,4	6,4	3,2	15,2	9,0
	MSI	15,2	32,0	20,8	27,2	24,8	24,0
DF-Gen-30	*EFM*	9,1	19,6	5,6	14,0	15,4	12,7
	MSI	**17,5**	**32,9**	24,5	23,8	32,2	26,2
DF-Gen-40	*EFM*	7,8	19,2	6,6	17,4	20,4	14,3
	MSI	15,0	32,4	23,4	**34,2**	**32,4**	**27,5**
DF-Gen-50	*EFM*	6,0	21,0	15,5	20,0	21,5	16,8
	MSI	15,5	30,5	**26,0**	30,5	29,5	26,4
DF-Gen-60	*EFM*	7,2	17,6	10,0	17,6	20,8	14,6
	MSI	12,4	26,8	21,2	24,8	28,4	22,7
DF-Gen-70	*EFM*	8,4	13,8	10,8	14,4	15,6	12,6
	MSI	9,3	18,6	15,9	21,6	26,4	18,4

For both network topologies, the best average results were obtained by *DF-Gen-40-MSI*. Furthermore, this algorithm reaches the best results for 80% of the instances in NSFNET and 40% of instances for USNET. Clearly, the optimum value of γ seems to be 0.4. Higher values can obtain better results of blocking probability, but they are penalized with higher rates of reconfigurations.

The findings also draw attention to the low values reached by the *DF-Ants* algorithm, which performs similar to or even worse than the reference heuristic algorithm. This result suggests that this metaheuristic is not efficient for the studied problem.

F. FRAGMENTATION METRICS PERFORMANCE

It is also interesting to compare the results by each FM to observe which metric is more efficient in avoiding demand blockings.

Figures 4 and 5 show the average values of the WBR metric for each defragmentation algorithm, considering the FM used and the network topology. It is evident that MSI is the FM that reaches the best results, overcoming EFM in almost all cases. However, this result must be taken with care, considering that it may be specifically related to the RSA algorithm used to allocate each demand or to reconfiguring the active lightpaths.

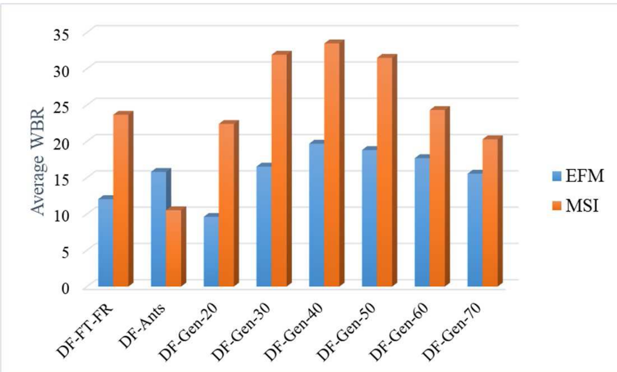

FIGURE 4. Average values of WBR - NSFNET network.

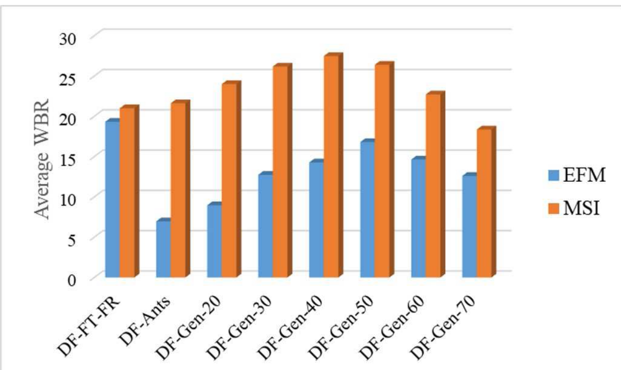

FIGURE 5. Average values of WBR - USNET network.

VI. CONCLUSION

This work presents two algorithms based on well known metaheuristics to select active connections to be reconfigured in a bandwidth defragmentation procedure for elastic optical networks. The studied defragmentation process is proactive, i.e., the fragmentation state of the entire network is considered. Moreover, this work analyzed the effect of two fragmentation metrics in avoiding future blockings: EFM and MSI.

The two chosen metaheuristics are a genetic algorithm, *DF-Gen*, and an ant colony optimization algorithm named *DF-Ants*, considering the maturity of those strategies. The efficiency of both algorithms in minimizing the blocking probability was analyzed through unicast traffic simulations over two different EON topologies. In addition, the increase in the number of reconfigured lightpaths necessary for each case was analyzed, which is a negative effect since it makes the operative process of each defragmentation procedure difficult and increases the probability of service disruptions.

A new performance metric for the defragmentation process evaluation was also proposed, named weighted blocking rate (WBR), to address both mentioned metrics (a trade-off between the blocking probability and number of reconfigured lightpaths).

According to the experimental results, the genetic algorithm *DF-Gen*, with a fixed rate of reconfigured lightpaths of 40%, obtained the best performance.

In the experiments, each algorithm tried to minimize a different fragmentation metric, namely, EFM and MSI. The best results were reached when MSI is considered. However, this result might be closely linked to the routing and spectrum assignment (RSA) algorithm used in the simulations, which will be further studied by the authors.

Ultimately, considering the low values of execution times, these experiments show the feasibility of using metaheuristics for selecting active lightpaths in defragmentation processes.

As future work, the authors propose a comparison to other metaheuristics as swarm particle optimization and bee colony optimization, using the same metrics or alternatively, proposing new metrics, and also considering execution time and convergence.

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