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RESEARCH ARTICLE

A Bandwidth-Balanced RMLSA Solution for Static Elastic Optical Network: A Two Stages Approach

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ABSTRACT This paper addresses one of the main tasks in transparent static elastic optical networks (EONs), known as the routing, modulation level, and spectrum assignment (RMLSA) problem. We present, for the first time, a two-stage RMLSA solution, focusing on reducing spectrum consumption (or network capacity). The first macro stage, called least demand bandwidth balance (LDBB), relies on a physical layer impairment (PLI) model to jointly compute the connections' route and modulation level (RML). We use a new balancing criterion that effectively distributes each network link's frequency slot unit (FSU) demands, exemplifying three different balancing functions based on the maximum number of FSUs on the links and the total number of FSUs demanded and the cost of the route. In the last macro stage, using all connections chosen paths, we perform the spectrum assignment (SA) process using two specific connections prioritization criteria. We propose two SA algorithms, called sliding-fit (SF) and parcel-fit (PF), reducing the spectrum consumption. These algorithms change the SA paradigm by searching connections for a given subset of the frequency spectrum, contrary to the search of FSUs for a given connection in standard approaches. In all cases, our solution exhibited a lower total network capacity than the commonly used strategies found in the literature, with an average network capacity reduction of 5.7 % FSUs. In addition, our proposal may be used to easily dimension network capacity and determine how many extra resources may be needed to attend to all network users.

INDEX TERMS Elastic optical network, modulation level, routing, spectrum assignment.

I. INTRODUCTION

IN the last decade, a new network architecture paradigm, called elastic optical networks (EON), has been proposed to address the inefficient fixed-spectrum grid currently used in wavelength division multiplexing (WDM) optical communications [1]. In EON, the frequency grid is divided into narrow bands (e.g., 3.125, 6.25 or 12.5 GHz per channel), denoted frequency slot unit (FSU). Thus, considering the bandwidth requirements of each connection, several consecutive FSUs that best suit their spectral requirements is provided. Consequently, more efficient management of the spectrum is achieved [2], [3].

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EON operators must face a long-standing problem: routing, modulation-level, and spectrum assignment (RMLSA). The RMLSA problem involves finding a route, a suitable modulation format, and a portion of spectrum for each connection to be transmitted. Furthermore, in transparent optical networks, where there is no opto-electronic conversion, this problem is subject to continuity and contiguity constraints [4], [5]. The continuity constraint refers to the use of the same FSUs for each connection along its entire route. In addition, when the bandwidth demands of the connection must be satisfied with more than one FSU, they must be contiguous throughout the frequency spectrum. Because of any solution to the RMLSA problem, unusable FSUs may appear among those assigned, a problem known as spectrum fragmentation [2], [6]–[8]. In transparent optical networks, the spectral fragmentation problem may represent a significant waste of bandwidth because there are no signal conversion capabilities. Therefore, network operators must avoid them as much as possible.

In EONs the traffic pattern can be static or dynamic [9]. In static network operation, all the required connections are known and the resources are set permanently at the beginning of the network operation. In contrast, in dynamic optical networks, resources are constantly allocated and released, allowing the same resource, if available, to be used by different connections. Optical networks operate statically because their design and implementation are simpler than those of dynamic networks [3]. For this reason, in this study, we focused on static optical networks.

Proposals for the RMLSA problem are focused on optimization, machine learning (ML), or heuristic approaches. Optimization techniques may achieve optimal solutions but with limited scalability to real-size topologies [10]–[13], because the RMLSA problem has a nondeterministic polynomial-time complete (NP-C) computational complexity [14].In contrast, ML methods achieve near-optimal solutions but they commonly lack generalization to non-trained topologies. Finally, ad-hoc methods can provide good and scalable solutions for different network topologies.

A standard procedure for assessing RMLSA using heuristics schemes is to subdivide the problem into simpler subproblems, dealing with each routing, modulation-level, and spectrum assignment sub-parts in separate and sequential stages [14]–[17]. Nevertheless, by dividing the problem into different stages, the final RMLSA solution may not be as efficient the a global solution. For example, choosing a modulation format depends on the physical-layer impairments (PLI), which limit the optical transmission reach [18]. Therefore, solutions that consider the modulation format in the calculation of routes may achieve a better performance than those that do not. In this sense, RMLSA proposals may solve sub-problems together to achieve better global solutions.

The purpose of this study is to solve the RMLSA problem in joint macro stages, focusing on reducing the spectrum consumption, or what is equivalent, minimizing the network capacity required for transparent elastic optical networks with static network operation. The first macro stage involves the routing and modulation format decision in a single procedure, first computing a set of candidate routes with the minimum FSUs demand possible, and then selecting the final route using a novel network FSUs balancing strategy. We call this macro-stage strategy the least demand bandwidth balance (LDBB). For the last macro stage we use a demand prioritization strategy to sort the connections using two different sorting criteria. Subsequently, we propose two novel techniques for spectrum assignment, called sliding-fit (SF) and parcel-fit (PF). These techniques change the standard paradigm of searching spectrum for each connection demanding transmission into searching for connections for a given subset of the frequency spectrum.

As a result of these contributions, better resource allocation efficiency is obtained in comparison with existing solution methods in transparent static elastic optical networks, with low complexity and ease of implementation. In addition, the methodology presented here may be used by network operators to dimension network capacity (determine how many extra optical fibers, spectral bands, or optical cores are needed), and evaluate the extra costs implied by the solution.

The remainder of this paper is organized as follows. In Section II we present an overview of the different RMLSA solutions found in the literature. In Section III, the RMLSA solution strategy is presented. Next, we summarize the main simulation parameters used in our experiment in Section IV. In Section V, we present some simulation exams, comparing our results with those achieved by the common RMLSA solution approaches found in the literature. Finally, in Section VI, we present some concluding remarks on this work.

II. RELEVANT WORKS

EONs have been considered promising candidates to support future Internet cost-efficiently. First, we must solve the RMLSA problem correctly. Therefore, in this section, we present an overview of the different RMLSA solution methods found in the literature and their main advantages and disadvantages.

All the solutions to the RMLSA problem consist of finding a transmission route, choosing an appropriate modulation format, and selecting an available portion of the spectrum to transmit each network connection. Standard RMLSA solution approaches include optimization, machine learning, and heuristic.

Optimization methods solve the RMLSA problem by reducing the spectrum consumption in the network. Several optimization techniques proposed in the literature use integer linear programming (ILP) models [17], [19] to obtain the best possible solution. However, the extensive number of variables makes these models have NP-C computational complexity [14]. Therefore, optimization models present scalability difficulties for real-size topologies [10]–[12]. For instance, in [13], the authors proposed a pure ILP model for ring network topologies computed until eight nodes. To avoid this, some authors use mixed-integer linear programming (MILP) [20], which solves only one part of the problem using ILP methods.

As an alternative to optimization techniques, ML methods can obtain near-optimal solutions in real-size topologies. Therefore, ML has gained popularity in recent years [21], [22]. Nevertheless, despite ML techniques achieving near-optimal results, they also have some disadvantages. For example, in [23], the authors proposed a deep reinforcement learning algorithm to search for the optimal RMLSA solution by relating the network states and rewards. However, this method requires predicting future requests, which induces additional complexity and oscillations in the cumulative rewards.

Additionally, ML solution strategies also lack generalization to other network topologies; therefore we need to retrain the model for different networks [24]. Finally, to maintain optical networks, configuration actions should have exact reasons to be taken. However, most ML algorithms are not interpretable, making it difficult for network operators to troubleshoot problems when the network performance is not as good as expected [24].

A feasible strategy to overcome these issues is to find suitable solutions by any means available. Thus, applying heuristics to solve the RMLSA problem may be a good approach for obtaining acceptable solutions in real-size network topologies. Common heuristic strategies subdivide the RMLSA problem into routing, modulation-level, and spectrum assignment sub-problems [14]–[17].

In the routing stage (R), algorithms found in the literature compute the routes that choose the shortest paths (e.g., Dijkstra's algorithm [25]–[27]) or paths that balance the number of connections on each network link (e.g., Baroni's algorithm [25]–[27]). In the modulation level stage (ML), the best modulation format for each transmission route is selected to satisfy a given quality of transmission (QoT). Common approaches consider this relationship by associating any modulation format available in the transponder with its maximum achievable reach (MAR) [28]–[30]. Finally, in the spectrum assignment stage (SA), the standard techniques found in the literature are first-fit (FF), most-used (MU), and best-fit (BF) [28], [31]–[33]. However, it is unclear whether using an approachable substage to solve the RMLSA yields a well-integrated and efficient global solution.

Furthermore, several studies [34], [35] claim that balancing network connections achieves significant capacity savings compared with using the shortest paths. However, elastic transmissions allow different connection classes based on the bandwidth requirements. Therefore, balancing the number of connections may not be sufficient to achieve a proper network balance. Concerning the SA stage, as pointed out by [16], more elaborate techniques are needed to reduce spectrum fragmentation as much as possible.

Finally, in Table 1, we present a summary of the main advantages and disadvantages of the different RMLSA solution methods.

III. RMLSA SOLUTION STRATEGY

Conventional methods to solve the RMLSA problem subdivide the global problem into more straightforward and affordable sub-problems, approaching them in tandem. However, this strategy does not ensure a well-suited global solution [14]–[17]. In this work, as displayed in Fig. 1, we face the routing and modulation-level sub-problems (RML) together in a macro-stage. We then allocated the connection demands in the spectrum assignment (SA) stage.

In Fig. 1, the network topology is represented by the graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ is the set of network nodes, and $\mathcal{L}$ is the set of unidirectional links. The set $\mathcal{C} = \{c_\ell | \forall \ell \in \mathcal{L}\}$ is conformed by the capacities of each network link, where c_ℓ

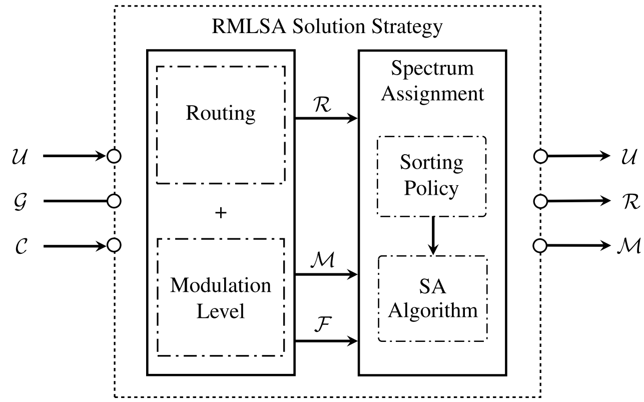


FIGURE 1. Solution diagram to the RMLSA problem.

is the capacity (number of available FSUs) of link $\ell \in \mathcal{L}$ and c is the maximum c_ℓ in $\mathcal{C}$. We additionally define $\mathcal{U}$ as the set of all connections (all source-destination node pairs) demanding communication on $\mathcal{G}$. Here, we specify each connection $u \in \mathcal{U}$ as $u = (\mathcal{S}_u, \mathcal{D}_u, t_u)$, where the parameters $\mathcal{S}_u$, $\mathcal{D}_u$ and t_u represent the source node of the connection, the destination node and the transmission bit rate requirements.

Let $\mathcal{R} = \{r_u | \forall u \in \mathcal{U}\}$ be the set of paths computed for all $u \in \mathcal{U}$, where r_u denote the route selected for connection u to transmit. Here, $|r_u|$ represents the route length, measured as the number of hops from the source to the destination nodes. Let $\mathcal{M} = \{\mu_u | \forall u \in \mathcal{U}\}$ be the set of modulation formats, where μ_u is the modulation format chosen for the connection u to transmit along route r_u.

Finally, let $\mathcal{F} = \{\mathcal{F}_u \mid \forall u \in \mathcal{U}\}$ be the set of FSUs demanded, where $\mathcal{F}_u \in \mathcal{F}$ denotes the number of FSUs demanded by connection u with path r_u. Furthermore, we define $\mathcal{F}_\ell$ as the total bandwidth demanded (in FSUs) to link ℓ by all network connections using the routes given in $\mathcal{R}$, that is,

$$\mathcal{F}_\ell = \sum_{\forall u,\ \ell \in r_u} \mathcal{F}_u. \tag{1}$$

The notation we use throughout this paper is outlined in Table 2.

A. PHYSICAL LAYER IMPAIRMENTS MODEL

Fiber-optic communication systems are deeply affected by physical layer impairments (PLI) accumulated by the signal during propagation. A connection is established only if certain QoT is achieved. However, amplified spontaneous emission (ASE) noise, dispersion, and nonlinear distortions limit the maximum QoT obtained [36].

For a given QoT, a complex spectrum modulation format require fewer FSUs than simpler formats. Nevertheless, a significant number of bits per symbol increases the transmission sensitivity to degradation, making the transmission shorter for more complex modulation formats [18]. In this sense, the existing trade-off between route length and proper modulation format is vital for solving the RMLSA problem.

TABLE 1. Advantages and disadvantages of the different RMLSA solution methods.

Method	Advantages	Disadvantages
Optimization [13], [17], [19]	Reachable Optimality	NP-C complexity of EON problems Limited scalability
Machine learning [21]–[23]	Good solution Non trivial solutions may be found	Requires large training process Hyperparameter Tunning is needed Lack of generalization Actions are difficult to interpret
Ad-hoc [14]–[17] [28], [31]–[33]	Good solutions Scalable Interpretable	Require previous knowledge of the problem Bias solution may be obtained

TABLE 2. Summary of the notation used.

Notation	Description
$\mathcal{C}$	Set of links capacities
c_ℓ	Capacity of link ℓ
$\mathcal{F}$	Set of FSUs demanded
$\mathcal{F}_\ell$	Total FSUs demanded to link ℓ
$\mathcal{F}_u$	Number of FSUs demanded by connection u with path r_u
$\mathcal{G}$	Network graph
$\mathcal{L}$	Set of unidirectional links
$\mathcal{M}$	Set of modulation formats
μ_u	Modulation format selected for user u with path r_u
$\mathcal{N}$	Set of network nodes
$\mathcal{R}$	Set of user's path
r_u	Path selected for user u
$\mathcal{U}$	Set of all connections

In this work, we use the Gaussian noise model presented in [36] considering an optical system using super-channels with single-polarization and selecting a bit error rate (BER) threshold of 10^{-6} for each communication request. As shown in Table 3, with this model the maximum achievable reach (MAR) is obtained, which is limited by ASE noise and nonlinear interferences at the optimum launch power. The fiber parameters used for the MAR calculation can be found in [36]. Table 3 also lists the number of FSUs required for each possible modulation format and bit rate. The available modulation formats are binary phase-shift keying (BPSK), quadrature phase-shift keying (QPSK), and Λ-quadrature amplitude modulation (Λ-QAM), where Λ takes values of 8, 16, 32, and 64.

To obtain the number of FSUs, we first select a more complex modulation format that satisfies the MAR of the route for each connection. Then, according to the bit rate requirements of the connection (10, 40, 100, 400, or 1000 Gbps), we select the number of FSUs demanded by each connection. For example, considering a route with 2000 km and a connection bit rate requirement of 400 Gbps, the more complex modulation format that meets the MAR is QPSK, resulting in a connection demand of 16 FSUs.

B. ROUTING AND MODULATION-LEVEL MACRO-STAGE

In the RML macro-stage, we propose a new routing and modulation-level algorithm to compute each network connection's transmission path and its corresponding modulation format. We refer to this as the least demand bandwidth balance (LDBB) algorithm. Our method computes the transmission path for each network connection, attempting to evenly distribute the total bandwidth demanded in all the links of the network while considering the cumulative effects of PLI in optical communications. The LDBB algorithm uses one of three possible balancing functions for route selection to determine the appropriate route within the possible ones. These balancing functions have the same goal of balancing the bandwidth demanded for each network link, but using different criteria to do so. Hereafter, we first define the balancing functions used, and then explain the LDBB algorithm.

1) BALANCING FUNCTIONS

Let $r_{k,u}$ be the k-th candidate route to be chosen for transmit connection u, which is computed using, for example, the algorithm given in [25]. Then, considering the number of FSUs demanded by connection u with route $r_{k,u}$, the first variant of the balancing functions refers to the maximum value of the number of FSUs obtained on any of the links

TABLE 3. Spectrum requirements in terms of FSUs and MAR for each bit rate and modulation format pair.

Modulation Format	MAR (km)	Bit rate (Gbps)				
		10	40	100	400	1000
BPSK	5520	1	4	8	32	80
QPSK	2720	1	2	4	16	40
8-QAM	1360	1	2	3	11	27
16-QAM	560	1	1	2	8	20
32-QAM	240	1	1	2	7	16
64-QAM	80	1	1	2	6	14

of candidate route k. This is:

$$\hat{\mathcal{F}}_{k,u} = max(\mathcal{F}_\ell | \forall \ell \in r_{k,u}). \tag{2}$$

Consequently, we choose the candidate route that presents the minimum $\hat{\mathcal{F}}_{k,u}$ among all candidate routes. We denote this first variant as " Minimum " (M).

The second variant of the balancing functions depends on the number of FSUs demanded by the entire candidate route $\mathcal{P}_{k,u}$. The other balancing function was evaluated as follows:

$$\mathcal{P}_{k,u} = \sum_{\forall \ell \in r_{k,u}} \mathcal{F}_\ell. \tag{3}$$

For this second variant, the value of r_u was selected by selecting the candidate route with the minimum value of $\mathcal{P}_{k,u}$. We denote this variant as " Sum " (S).

The last variant of the balancing function aims to select routes based on cost measures. To this end, the cost of a link is first evaluated as:

$$cost_\ell = e^{(\mathcal{F}_\ell - \bar{\mathcal{F}}_\ell)/\hat{\mathcal{F}}_\ell}, \tag{4}$$

where:

$$\bar{\mathcal{F}}_\ell = \frac{1}{|\mathcal{L}|} \sum_{\forall \ell \in \mathcal{L}} \mathcal{F}_\ell, \tag{5}$$

$$\hat{\mathcal{F}}_\ell = max(\mathcal{F}_\ell | \forall \ell \in \mathcal{L}), \tag{6}$$

are the average and maximum values of the FSUs required in the network links, respectively. The use of $\hat{\mathcal{F}}_\ell$ in the calculation of $cost_\ell$ aims to mitigate the large differences that could exist between the FSUs demand of the different links in the network. On the one hand, when $\mathcal{F}_\ell$ is greater than $\bar{\mathcal{F}}_\ell$, the cost of the link will be defined in the range $1 < cost_\ell \leq e$; whereas, otherwise ($\mathcal{F}_\ell \leq \bar{\mathcal{F}}_\ell$), the cost of the link will be given between $e^{-1} < cost_\ell \leq 1$.

Finally, we select the path that requires the minimum route cost ($cost_{k,u}$) among all candidate routes, where $cost_{k,u}$ is obtained as:

$$cost_{k,u} = \sum_{\forall \ell \in r_{k,u}} cost_\ell, \tag{7}$$

This last metric is denoted as " Cost " (C).

2) PROPOSED RML METHOD

Next we explain in details the routing and modulation level macro-stage algorithm.

Least Demand Bandwidth Balance: To implement the LDBB algorithm, we follow the following steps:

1) For each network connection, we calculate K shortest paths (measured in the number of links) as candidate routes, using for example [25]. Each candidate path is denoted by $r_{k,u}$, with $1 \leq k \leq K$.
2) For each candidate route, we choose the more complex modulation format complying with the maximum achievable reach of the path as shown in Table 3. Accordingly, we store the number of FSUs demanded by the candidate path on the parameter $\mathcal{F}_{k,u}$.
3) Then, we filter the candidate routes of each connection, selecting the routes that present the lowest overall FSUs demand value $\mathcal{FR}_{k,u} = |r_{k,u}| \cdot \mathcal{F}_{k,u}$.
4) For each connection, one by one, we replace its transmission route r_u with one of the candidates, if and only if the given balancing function of the path is lower on the alternative route. It should be noted that, by default, the route chosen for each connection is the first of the corresponding set of routes, that is, $r_u = r_{1,u}$.
5) Step **4** is repeated until there are no more possible substitutions.
6) Finally, the sets $\mathcal{R}$, $\mathcal{M}$, and $\mathcal{F}$ are obtained, composed of the paths chosen for each connection, their corresponding modulation formats and FSUs demands.

3) LDBB ALGORITHM COMPUTATIONAL COMPLEXITY

The computational complexity of the LDBB algorithm can be determined by the computational complexity of the first five steps. First, for each connection of the network, the shortest k routes were computed using the algorithm described in [25]. In this algorithm, each route is calculated using Dijkstra's algorithm, which is known to have a time complexity of $\mathcal{O}(|\mathcal{N}|^2)$. Consequently, the time complexity of the first step is $\mathcal{O}(K \cdot |\mathcal{U}| \cdot |\mathcal{N}|^2)$.

The modulation format was determined for each of the k candidate routes in the second step. Because this task is simple and performed only once for each connection, its associated cost is $\mathcal{O}(K \cdot |\mathcal{U}|)$. The next step of the LDBB algorithm is to filter candidate routes that have the lowest value of $\mathcal{FR}_{k,u}$, so that the associated cost is $\mathcal{O}(K \cdot |\mathcal{U}|)$.

The greatest cost of the algorithm is given in steps four and five. Specifically, the best route for each connection and candidate route in the fourth step was chosen based on the balance metric used. The worst situation in calculating the balancing function occurs for the C function case, because it involves calculating the cost of each link, the average demand per link, and the maximum demand value among all of these. In this case, evaluating the balancing function has an associated complexity of $\mathcal{O}(|\hat{r}| \cdot |\mathcal{L}|)$, where $|\hat{r}|$ is the maximum number of hops among all routes; then, the fourth step, in its entirety, has a complexity of $\mathcal{O}(K \cdot |\hat{r}| \cdot |\mathcal{U}| \cdot |\mathcal{L}|)$.

The fifth step of this algorithm involves repeating the fourth step several times. Because the number of repetitions is unknown in advance, the number of iterations that must be performed is represented by the letter i. However, it should be noted that this step was run three times on average among all simulations. Thus, the complexity of steps 4 and 5 is given by $\mathcal{O}(iK \cdot |\hat{r}| \cdot |\mathcal{U}| \cdot |\mathcal{L}|)$. Consequently, the LDBB algorithm has computational complexity $\mathcal{O}(K \cdot |\mathcal{U}| \cdot |\mathcal{N}|^2 + 2K \cdot |\mathcal{U}| + iK \cdot |\hat{r}| \cdot |\mathcal{U}| \cdot |\mathcal{L}|)$.

From the previous expression, if we assume that $iK \cdot |\hat{r}| \cdot |\mathcal{U}| \cdot |\mathcal{L}| \approx 2K \cdot |\mathcal{U}| \cdot |\mathcal{N}|^2$, and that $i \cdot |\hat{r}| \cdot |\mathcal{U}| \cdot |\mathcal{L}| \gg 2 \cdot |\mathcal{U}|$, then the computation time of the LDBB algorithm was three times the time require to evaluate the Dijkstra algorithm. As can be seen, the LDBB algorithm requires a short execution time, which is comparable to that of the Dijkstra algorithm. This allows the LDBB algorithm to adapt quickly to changes in network demand, as is the case in incremental traffic scenarios.

C. SPECTRUM ASSIGNMENT STAGE

In the SA stage, the goal is to serve all connections with the least possible capacity. This stage is performed by considering the perceived gains for assigning each network connection. The entire process consist of two substages. First, we take advantage of the static network operation to sort the connections before the spectrum assignment task. Next, the connections were served using one of the proposed SA algorithms.

1) CONNECTIONS SORTING POLICIES

The different connections were sorted before the spectrum-assignment process. According to [37]–[39], sorting connections according to their FSUs demand or route length (measured in terms of the number of hops), both in decreasing order, allows greater efficiency in the use of resources. For this reason, we decided to use both sorting policies and then performed spectrum assignments. To specify the use of each one of them, these criteria are denoted as decreasing bandwidth (DB) and decreasing length (DL), respectively.

2) PROPOSED SA METHODS

In this study, two SA algorithms, sliding-fit (SF) and parcel-fit (PF), were developed.

To assign the spectrum of the different connection demands on the network, we use the ''Fit'' sub-procedure for both algorithms. The input parameters required by this sub-procedure are the selected connection u, connection route r_u, connection FSUs demand $\mathcal{F}_u$, and the first (s_1) and last (s_2) FSU indexes of the portion of the spectrum to be analyzed.

a: FIT

To perform the Fit sub-procedure, we execute the following steps:

1) We iterate for all possible consecutive (contiguous) FSUs between s_1 and s_2.
2) If a subset of $\mathcal{F}_u$ size is available and satisfies the continuity constraint in r_u, the algorithm assigns the connection demand and finishes by returning the first index of the assigned FSUs subset.
3) Otherwise, if there is no available subset of $\mathcal{F}_u$ size between s_1 and s_2, the algorithm returns 0 to indicate that the connection demand remains unassigned.

To represent the evaluation of this algorithm, we symbolically use this procedure as the Fit$(u, r_u, \mathcal{F}_u, s_1, s_2)$ function.

The input parameters of the SF and PF algorithms are the set of connections $\mathcal{U}$, the selected routes $\mathcal{R}$ and the corresponding modulation formats $\mathcal{M}$, the set of connections' demands $\mathcal{F}$, and the highest FSUs demand among all connections $m = max(\mathcal{F}_u \mid \forall u \in \mathcal{U})$.

b: SLIDING-FIT (SF)

This algorithm can be performed using the following steps:

1) First, we divide the total network capacity into $c - m + 1$ sections of m consecutive FSUs. The first section uses FSUs from 1 to m, the second section uses FSUs from 2 to $m + 1$, etc.
2) For each section of m consecutive FSUs, we try to assign as many connection demands as possible using the Fit$(u, r_u, \mathcal{F}_u, s_1, s_2)$ function. Here, s_1 and s_2 refer to the first and last FSU indices of the m section analyzed.
3) The process ends once all connections have been served or the network capacity is exhausted. In the latter case, some connections could not be served.

In the SF algorithm, the search for FSUs for all connection requests was limited to a subsection of the entire available spectrum. If a connection can not be assigned in a section (after trying the rest of the connections), an attempt is made to allocate it again in the next FSU section. In this way, the SF algorithm completely changes the spectrum assignment paradigm, by searching connections for a given portion of the spectrum, instead of searching for availability for each connection request (as is the case with the FF algorithm).

The name of this algorithm refers to the way it operates: a fixed-size section that assigns connections as it slides through capacity.

c: PARCEL-FIT (PF)

In contrast, the PF algorithm uses the same idea of limiting the search in a subset of FSUs. Here, the term ''parcel'' is used to refer to a specific subset of FSUs. However, the number of sections to be analyzed was significantly lower. The main steps of the PF algorithm are as follows:

1) First, we sort the set of connections $\mathcal{U}$ according to the chosen ''order'' policy (see Section III-C1).
2) Then, we divide the link capacity into $\lceil c_\ell/m \rceil$ parcels, each having as many m FSUs.
3) For each parcel, we attempt to assign as many connections as possible, considering two cases. In the first case, we attempt to assign the connections strictly within the limits of the parcel, whereas in the second

case, connections are served if at least one FSU is within the limits of the parcel. To this end, we used the Fit algorithm in both cases.

4) The process ends once all connections have been served or the network capacity is exhausted. In the second case, some connections could not be served.

3) SF AND PF ALGORITHMS COMPUTATIONAL COMPLEXITY

The SF computational complexity is determined by the number of sections, whereas the number of sections is determined by each link capacity and the maximum FSUs demand among all connections. For this algorithm, the number of sections is equal to the capacity of each link c_ℓ minus the size of the section (m) added 1, that is, $c_\ell - m + 1$.

Then, in each section, the SF attempts to assign all the network connections. A connection is assigned if a subset of consecutive FSUs (complying with the contiguity constraint) is available in all links (complying with the continuity constraint) of its route. Considering these constraints, for the worst case, the number of operations required to verify whether a connection is assignable is equal to the maximum FSUs demand among all connections by the maximum number of hops among all routes, that is, $m|\hat{r}|$. Finally, all these operations lead to an SF computational complexity of $\mathcal{O}([c_\ell - m + 1]m|\hat{r}||\mathcal{U}|)$.

In the case of the PF algorithm, an attempt is made to serve all network connections twice for each parcel, one strictly within the boundaries of the parcel, and another that may exceed the upper boundary of the parcel. In both cases, because m is the maximum FSUs demand, the number of FSUs to be analyzed is m and $2m$ respectively. Consequently, for each of the $\lceil c_\ell/m \rceil$ parcels, the PF must perform $m|\hat{r}|||\mathcal{U}| + 2m|\hat{r}|||\mathcal{U}|$ operations; thus, the PF computational complexity is given by $\mathcal{O}(\lceil c_\ell/m \rceil\, 3m|\hat{r}|||\mathcal{U}|)$.

According to these results, it is evident that the SF algorithm is more complex than the PF algorithm, thus, it is more time-consuming. Additionally, the computational complexity of the SF and PF algorithms depends on c_ℓ. Consequently, the higher the network capacity, the longer it takes to obtain a solution.

IV. SIMULATION PARAMETERS

The RMLSA solution algorithms were programmed on a python-based specific-purpose simulator using six well-known network topologies, as shown in Fig. 2. The entire code of our work as well as the distance of the different links can be accessed from GitHub[1]; while in Table 4 we summarize the number of nodes, links, and connections of these topologies.

The proposed algorithms were evaluated for each topology assuming that there was as much capacity per link as necessary to serve all network connections. Then, our algorithm also serves as a dimensioning technique, by computing the amount of capacity required to attend to all network connection requests. Standard fiber communications use the C band spectral capacity for transmission. However, if more capacity is required than the one available in the C band, it can be satisfied by installing more fibers, using multi-core fibers, or increasing the available bandwidth using the L-band [40], [41]. Nonetheless, each of these solutions would require an update to Table 3 to consider the additional physical impairments limiting the maximum achievable reach in multi-fiber, multi-core or multi-band contexts. Additionally, because initially, the capacity of each link is unknown, and to evaluate the spectrum assignment algorithms, the unlimited capacity per link is assumed to serve all network connections. The real capacity of each link is then given by the index of its last assigned FSU.

For each topology, the RMLSA problem is solved using different variants of the proposed RMLSA strategy. Each of these solution variants was achieved by choosing five candidate routes in the first stage, a balancing function, a connection sorting policy, and a spectrum assignment algorithm. Finally, as shown in Table 5, for each variant, 100 simulations were performed with aleatory bit rate requirements, and the final result corresponded to the average of the simulations.

Finally, to compare our solution strategy, we additionally evaluated the commonly used Dijkstra's algorithm (Dk) [25] and Baroni's algorithms (Ba) [34] in the routing stage, and the first-fit algorithm (FF) [33], in the SA stage under the same conditions. We decided to use these algorithms because they are widely used and are recognized for their good performance and simplicity.

TABLE 4. Network features.

Topology	Nodes	Links	Connections
UKNet	21	78	420
ITALIAN	21	72	420
EuroCore	11	50	110
EON	20	78	380
ARPANet	20	62	380
NSFNet	14	42	182

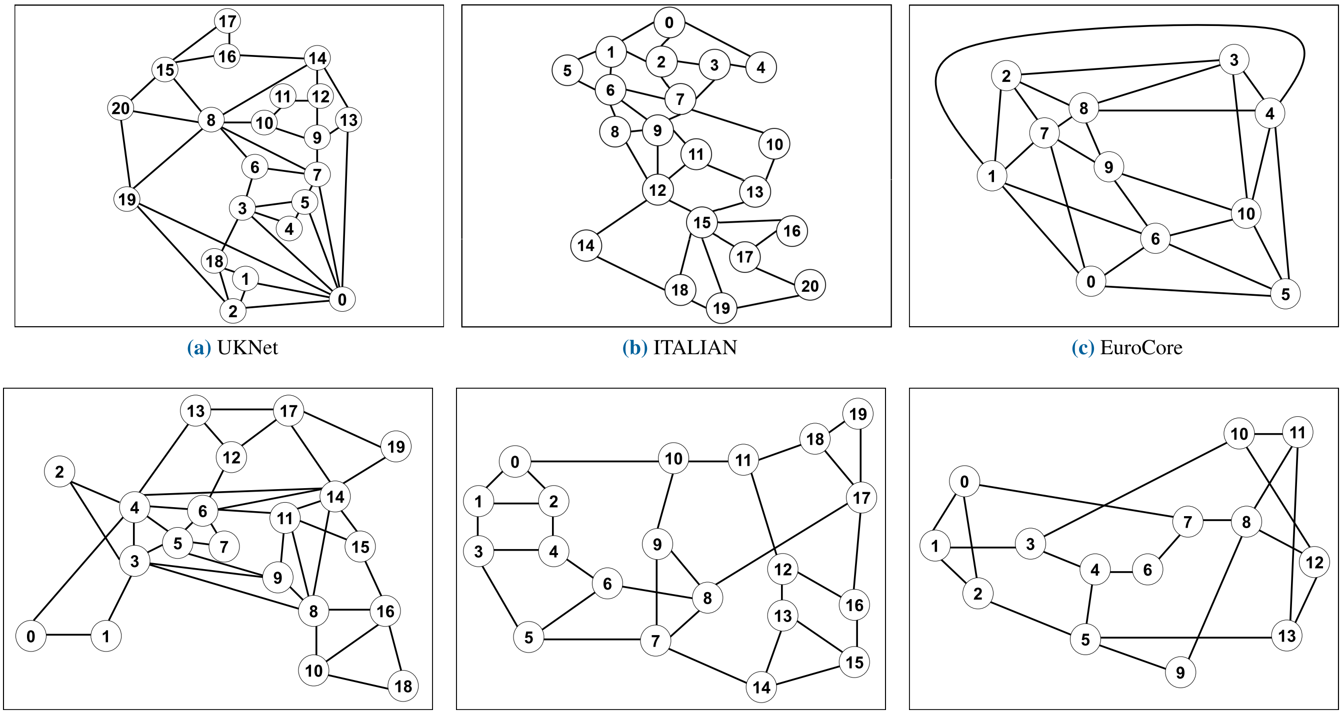
TABLE 5. Simulation parameters.

Parameter	Value
Number of simulations	100
Candidate routes (K)	5
Bit rate (Gbps)	10, 40, 100, 400, 1000

A. CONNECTION'S FSUs DEMAND

The bit rate requirements of each connection are assigned by a demand generator, which chooses a random value between

[1] https://github.com/jbcedeno930806/code



(a) UKNet **(b)** ITALIAN **(c)** EuroCore

(d) EONet **(e)** ARPANet **(f)** NSFNet

FIGURE 2. Network topologies.

10, 40, 100, 400, and 1000 Gbps. For a fair comparison between the different solution variants, the demand generator uses the *n-th* seed for the *n-th* simulation. In this way, we ensured that the connection bandwidth requirements of the connections were the same regardless of the variant used.

The conversion of bit rate requirements to FSUs demands was performed using the data shown in Table 3, complying with the MAR of each route. Because we do not consider signal regeneration in this study, in cases where the distance of the chosen route exceeds the maximum achievable range, the worst possible modulation format (BPSK) is assigned.

B. PERFORMANCE METRICS

Several metrics are used to evaluate the performance of the RMLSA solution strategy, as described in this subsection.

1) NETWORK CAPACITY AND SPECTRAL FRAGMENTATION

The total network capacity $\mathcal{C}_{net}$ corresponds to the number of FSUs assigned to all network links. This is:

$$\mathcal{C}_{net} = \sum_{\forall \ell \in \mathcal{L}} c_\ell. \tag{8}$$

However, this metric can be decomposed by the total capacity demanded by all connections $\mathcal{F}_{\mathcal{U}}$ and fragmented capacity. Fragmented FSUs correspond to the amount of unused FSUs among those that were assigned. Let $\mathcal{W}$ be the network fragmentation, composed of the sum of all the spectral fragmentation of the links ($\mathcal{W}_\ell$, $\ell \in \mathcal{L}$), that is,

$$\mathcal{W} = \sum_{\forall \ell \in \mathcal{L}} \mathcal{W}_\ell, \tag{9}$$

then, the total network capacity $\mathcal{C}_{net}$ can be decomposed as:

$$\mathcal{C}_{net} = \mathcal{F}_{net} + \mathcal{W}, \tag{10}$$

where:

$$\mathcal{F}_{net} = \sum_{\forall u \in \mathcal{U}} \mathcal{F}_u \cdot |r_u| \tag{11}$$

is the total number of FSUs demanded to the network.

2) CAPACITY SAVINGS

Let $\mathcal{Q}(A)$ be the percentage of capacity savings achieved by the solution variant A, compared to that obtained by the strategy based on the Dijkstra algorithm (Dk) when analyzing different routing algorithms, or the first-fit algorithm (FF) when analyzing different SA algorithms. Thus, for each variant analyzed, $\mathcal{Q}(A)$ was evaluated as follows:

$$\mathcal{Q}(A) = \frac{\mathcal{C}_{net}(Dk) - \mathcal{C}_{net}(A)}{\mathcal{C}_{net}(Dk)} \cdot 100 \tag{12}$$

3) LEVEL OF ROUTING UNBALANCE

Let $\sigma_{\mathcal{F}}$ be the standard deviation of the number of FSUs demanded for each link in the network; that is:

$$\sigma_{\mathcal{F}} = \frac{1}{\mathcal{L}^2}\sqrt{\sum_{\forall \ell \in \mathcal{L}} (\mathcal{F}_\ell - \bar{\mathcal{F}}_\ell)^2}. \tag{13}$$

Then the coefficient of variation CV of the network can be evaluated using:

$$CV = \frac{\sigma_{\mathcal{F}}}{\bar{\mathcal{F}}_{\ell}}. \tag{14}$$

A perfectly balanced network had CV of 0. However, because the actual network topologies and bandwidth demand are hardly symmetric, it is difficult to obtain this condition. Thus, the larger CV, the more unbalanced the network. Therefore, the value of CV can be used to quantify the level of imbalance.

4) SPECTRAL EFFICIENCY

The spectrum assignment efficiency η_{SA} is defined as the ratio between the total capacity demanded and the total capacity of the network:

$$\eta_{SA} = \frac{\mathcal{F}_{net}}{\mathcal{F}_{net} + \mathcal{W}} \cdot 100. \tag{15}$$

Thus, for the same demand for FSUs, a higher value of η_{SA} indicates a better relationship between the capacity demanded and used.

V. SIMULATION RESULTS

This section presents the results obtained when evaluating the proposed RMLSA solution strategy for the six topologies shown in Fig.2. Three possible evaluation scenarios were considered. In the first scenario, the proposed solution strategy is evaluated using the LDBB, Dk, and Ba algorithms for the routing and modulation-level stages (the last two are used for comparison), while the spectrum assignment is solved using the common FF spectrum assignment algorithm. For the second scenario, the RMLSA problem was solved again, but this time using the SF, PF, and FF algorithms for the spectrum assignment stage (the FF was used for comparison), wheras the typical routing algorithms (Dijkstra and Baroni) were used in the routing and modulation-level stages. Finally, we used both the LDBB algorithm and the SF and PF algorithms to solve the RMLSA problem for the third evaluation scenario. For comparison, in this type of scenario, the Dk and Ba algorithms were used for routing, and the FF algorithm was used for spectrum assignment.

A. FIRST SCENARIO

Table 6 lists the percentage of capacity savings obtained by the different routing variants in Dijkstra's routing approach. Here, we grouped the solution variants according to the sorting policy of the connections. As shown in Table 6, in all topologies, the variants based on the LDBB routing algorithm achieved the most significant capacity savings, surpassing even the variant based on the Ba algorithm. For the ITALIAN topology, the capacity-saving percentage shows a similar value between the variants based on the Ba and LDBB algorithms. In this case, only the LDBB variant using the M balancing function achieved a greater capacity saving percentage, and the one that obtained the best results in most topologies.

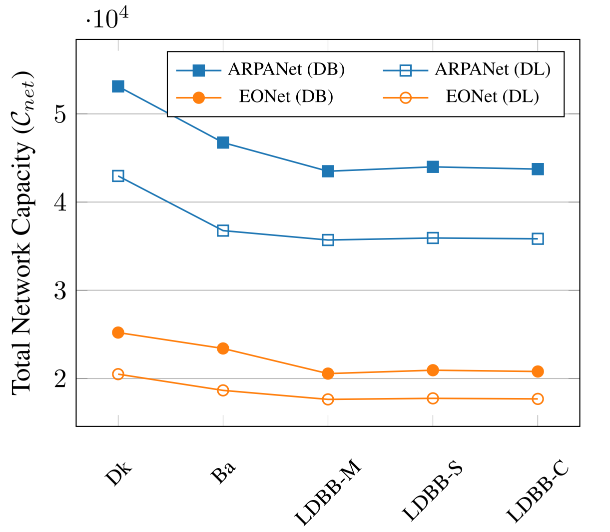


FIGURE 3. Total network capacity obtained for the ARPANet (square) and EONet (circle) topologies using the DB (filled) and DL (outline) sorting policies.

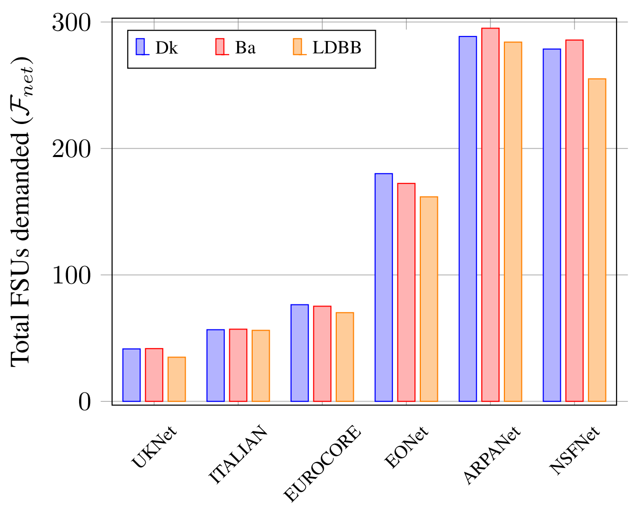


FIGURE 4. Total number of FSUs demanded to the network for each routing algorithm and topology analyzed.

Furthermore, for the same topology and solution variant, the capacity savings obtained when using the DB sorting policy, in general, presented a better percentage. However, as shown in Fig.3 for the ARPANet and EONet topologies, the lowest total network capacity ($\mathcal{C}_{net}$) was obtained by the DL sorting policy. This result is fulfilled in the remaining topologies, although with a minor difference.

To explain the reasons for the different performances obtained by the methods compared herein, we foresee two possible factors: the total number of FSUs demanded by the network, and the bandwidth unbalance presented in the links of the network.

First, the total number of FSUs required by the network depends on the routes selected to transmit each connection. Different routes for the same connection may present different FSUs demands because the routes do not necessarily

TABLE 6. Total capacity savings $\mathcal{Q}(A)$ obtained by the different solution variants compared to the Dk based variant.

Topology	DB				DL			
	Ba	LDBB-M	LDBB-S	LDBB-C	Ba	LDBB-M	LDBB-S	LDBB-C
UKNet	27.16	44.61	43.9	44.24	28.52	39.7	39.65	39.82
ITALIAN	32.49	33.6	30.94	31.69	29.17	29.63	27.82	28.49
EuroCore	11.83	22.11	20.72	21.22	13.46	17.37	16.76	17.19
EONet	7.15	18.44	16.93	17.5	8.97	13.95	13.38	13.69
ARPANet	11.99	18.11	17.18	17.66	14.43	16.9	16.37	16.58
NSFNet	7.45	14.89	14.11	14.33	9.77	15.15	15.22	15.42

TABLE 7. Coefficient of variation.

Topology	Dk	Ba	LDBB-M	LDBB-S	LDBB-C
UKNet	0.9402	0.5404	0.4875	0.4602	0.4604
ITALIAN	0.9095	0.6002	0.6172	0.59	0.5901
EuroCore	0.8377	0.65	0.5485	0.5334	0.5337
EONet	0.6979	0.6652	0.5977	0.5734	0.5739
ARPANet	0.7718	0.6501	0.6295	0.6119	0.6132
NSFNet	0.6359	0.5504	0.5226	0.5097	0.51

have the same distance (km). Thus, as shown in Fig.4, the LDBB algorithm attempts to balance the FSU's demand on each link of the network using routes that require the least amount of network resources. Thus, it is possible to reduce the total network capacity before spectrum assignment. This reduction occured because the total number of FSUs demanded by the network was lower in the LDBB algorithm.

Second, as shown in Table 7, variants based on the LDBB algorithm present a better balance of the FSUs demanded on the network links, and, from Table 7, these variants also have lower network capacity requirements; whereas variants based on the shortest routes (Dk) and connections balancing (Ba) highly unbalance the number of FSUs demanded on the network links, leading to higher network capacity requirements as shown in Table 7. This observation allows us to conclude that balancing the number of FSUs demanded by the network links is key to achieving a lower network capacity in EON.

B. SECOND SCENARIO

The total capacity savings obtained for the spectrum assignment algorithms in comparison with the Dk-FF approach are listed in Table 8. As can be seen, all variants outperform Dk-FF in terms of capacity saving. However, regardless of the sorting policy used and the routing algorithm, for each topology, the best results were obtained by the SF and PF based variants. In addition, we must note that despite the variants using the DB sorting policy achieving a more significant percentage of capacity saving, the least total network capacity in all topologies was obtained using the DL policy. This result is consistent with the result obtained in the first scenario.

On the other hand, Fig.5 shows the spectral efficiency obtained for each topology and solution variant. When connections are sorted by their FSUs demand (Fig.5a), it can be seen that the majority of the solution variants obtain a performance below 60 %. This indicates that at least 40 out of 100 FSUs of capacity were due to network fragmentation. In contrast, when connections are sorted according to the length of their route (Fig.5b), a better utilization ratio of the available spectrum is achieved, obtaining a spectrum assignment efficiency above 60 % (at most 40 out of 100 FSUs correspond to fragmentation) for most of the analyzed variants. Finally, as expected from Table 8, for both connection sorting policies, regardless of the routing algorithm, the PF and SF spectrum assignment algorithms overpass the FF algorithm, with the Ba-SF variant showing the best performance, with the highest spectral efficiency in most of the topologies.

At this point, it is clear that the SF and PF algorithms show better use of resources than the FF algorithm. To the best of our knowledge, this is mainly because to the search for FSUs available for each connection. Commonly used spectrum allocation algorithms, including the FF algorithm, prioritize connection allocation over allocation location. In this sense, for each connection, a portion of the spectrum available for all capacities was sought. However, when operating with sections (or parcels), the SF and PF algorithms choose a subset of FSUs in the frequency spectrum and later determine the connections for the selected FSUs. Thus, the priority lies in the assignment place. Consequently, better accommodation of connections is achieved, which translates into a lower requirement for total network capacity.

Finally, it must be noted that the FF algorithm presents a computational complexity of $\mathcal{O}(c_\ell|\hat{r}||U|)$ [33], which in turn, results in a faster solution than the SF and PF algorithms. For example, in our simulations of the NSFNet topology, the SF and PF algorithms required 0.3084s and 0.0125s more than

TABLE 8. Second scenario total capacity savings $\mathcal{Q}(A)$ obtained by the different solution variants compared to the Dk-FF based variant.

Topology	DB					DL				
	Dk-PF	Dk-SF	Ba-FF	Ba-PF	Ba-SF	Dk-PF	Dk-SF	Ba-FF	Ba-PF	Ba-SF
UKNet	0.24	18.74	27.16	28.06	39.89	1.23	5.89	28.52	29.84	30.5
ITALIAN	1.7	16.7	32.49	33.67	37.42	2.72	7.52	29.17	29.85	30.25
EuroCore	2.69	1.73	11.83	12.25	12.16	0.15	0.32	13.46	13.38	13.44
EONet	1.03	21.27	7.15	7.92	28.17	2.56	4.62	8.97	11.08	14.05
ARPANet	0.32	24.65	11.99	12.78	32.91	4.43	9.83	14.43	16.87	19.27
NSFNet	0.56	18.59	7.45	8.23	26.37	3.07	5.23	9.77	14.02	15.2

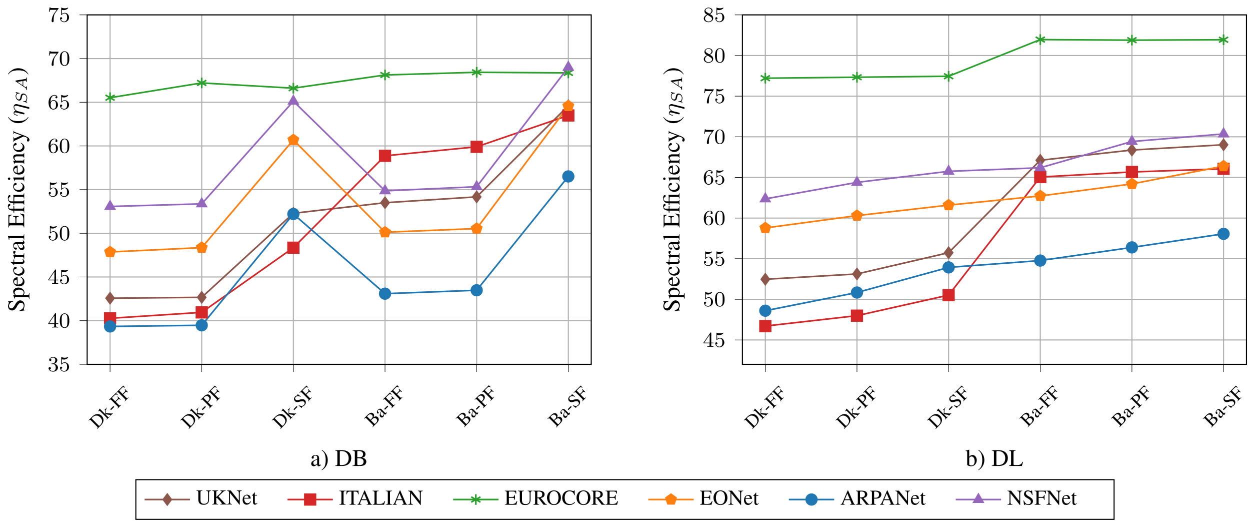


FIGURE 5. Spectrum assignment efficiency obtained for the different variants analyzed, sorting the connections by the number of FSUs demanded in decreasing order (Fig. 5a), and the number of links of the route in decreasing order (Fig. 5b).

TABLE 9. Third scenario total capacity savings $\mathcal{Q}(A)$ obtained by the different solution variants compared to the Dk-FF based variant.

Topology	DB							DL						
	FF	PF			SF			FF	PF			SF		
	Ba	LDBB-M	LDBB-S	LDBB-C	LDBB-M	LDBB-S	LDBB-C	Ba	LDBB-M	LDBB-S	LDBB-C	LDBB-M	LDBB-S	LDBB-C
UKNet	27.16	45.19	44.53	44.77	49.82	49.82	49.91	28.52	39.88	40.07	40.13	40.42	40.48	40.53
ITALIAN	32.49	35	32.48	33.21	39.78	37.71	38.14	29.17	30.37	28.53	29.32	31.11	29.1	29.71
EuroCore	11.83	22.12	20.76	21.26	22.12	20.76	21.26	13.46	17.38	16.75	17.19	17.37	16.75	17.18
EONet	7.15	19.06	17.42	18.09	32.07	31.4	31.42	8.97	15.56	14.94	15.44	17.15	16.27	16.27
ARPANet	11.99	18.61	17.72	18.13	34.71	33.44	33.62	14.43	19.13	18.87	18.85	21.8	20.34	20.51
NSFNet	7.45	15.43	14.66	14.85	31.47	31.08	31.12	9.77	19.32	19.16	19.19	21.16	20.63	20.73

the FF approach, respectively. However, a in static network operation, where there is as much time as necessary to obtain a solution, this time difference is not relevant and can therefore be ignored.

C. THIRD SCENARIO

Thus far, the algorithms proposed for the spectrum routing and allocation stages have been analyzed separately. However, these approaches are not mutually exclusive, and it is possible to integrate them into a single solution. In addition, the solution strategies based on the Dijkstra and Baroni algorithms (for the routing stage) and first-fit algorithm (for spectrum allocation) were also analyzed.

Table 9 shows the percentage of capacity savings achieved by the different variants compared with the Dk-FF solution. Overall, regardless of the connection sorting policy used, the proposed strategy outperformed both the Dk-FF and Ba-FF solutions in terms of capacity saving, while the lowest total network capacity was obtained with the DL sorting policy. Among all variants for this scenario, we observed that the LDBB variant, using the M balancing function, DL sorting policy, and SF spectrum allocation algorithm, generally achieved the best results in all topologies.

Finally, from Fig. 6 and Table 9 it can be seen that variants with lower total network capacity present a better relationship between the total number of FSUs demanded by the network and the actually used ($\mathcal{C}_{net}$), ratifying the DL policy as the most efficient in the use of spectral resources. In this case, all the proposed variants reached spectral efficiencies greater than 55 %, assigning an average of 65 FSUs of demand for every 100 (at most 35 of 100 FSUs correspond to fragmentation) FSUs of capacity.

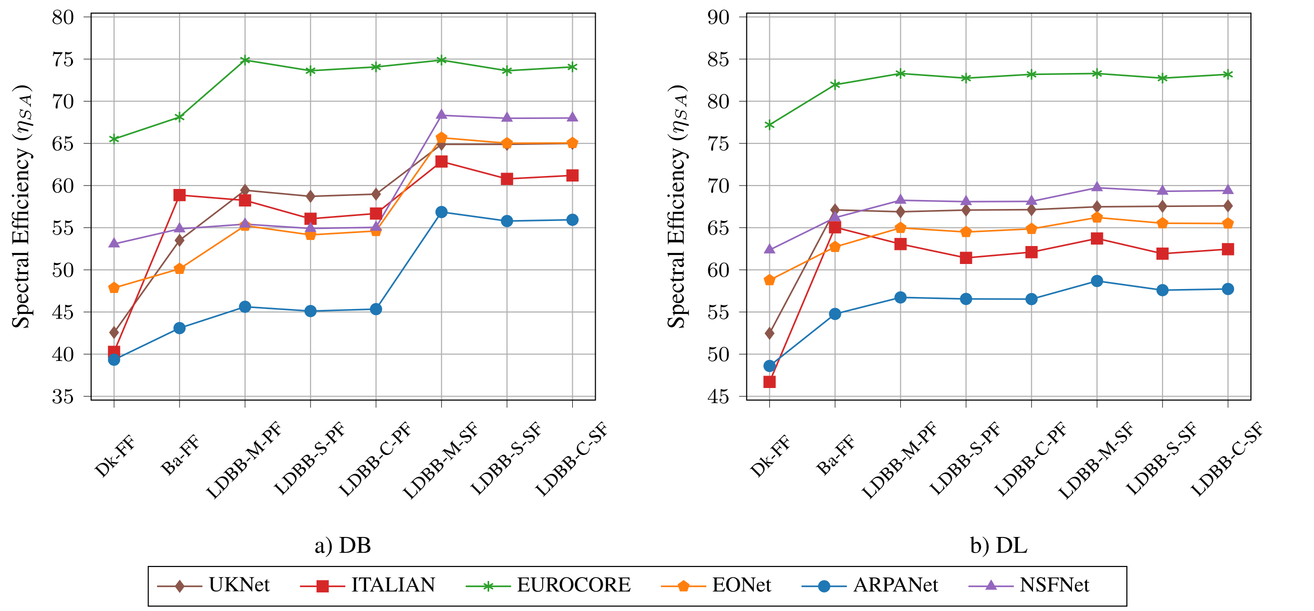


FIGURE 6. Spectrum assignment efficiency obtained for the different variants analyzed, sorting the connections by the number of FSUs demanded in decreasing order (Fig. 6a), and the number of links of the route in decreasing order (Fig. 6b).

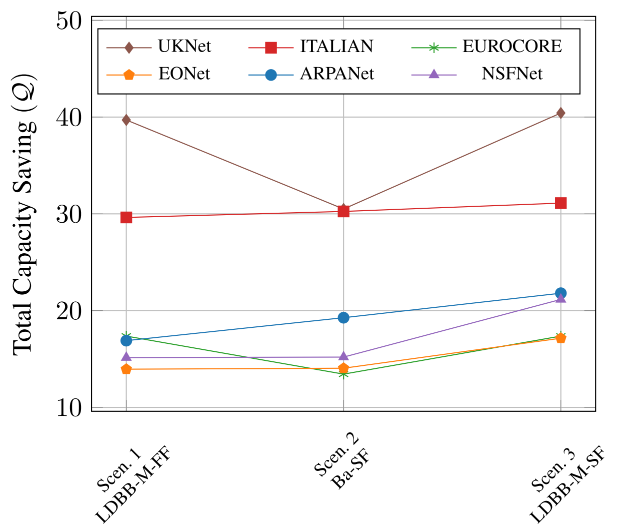


FIGURE 7. Total capacity savings achieved for the best variants (in most of topologies) using the DL sorting policy for each scenario.

These results are in accordance with those observed in the first and second scenarios. However, as shown in Fig.7, when using the entire RMLSA solution strategy (third scenario), for each topology, the total capacity savings are greater than those in the other two scenarios. It should be noted that, for a fair comparison, Fig.7 only shows the variants that present the greatest total capacity saving in most topologies for each scenario, using the DL sorting policy.

VI. CONCLUSION

In this study, we solved the RMLSA problem in EONs with static network operation. To this end, we used a two-stage solution approach to solve the RML sub-problems in the first stage, and the SA sub-problem in the second stage.

For the RML stage, we proposed a new algorithm, called LDBB, to compute the routes with the lowest FSU demand and achieves better network bandwidth balance. On the other hand, for the SA stage, we proposed two new spectrum assignment algorithms, called parcel-fit and sliding-fit. These algorithms focus on minimizing network capacity by searching connections for a given subset of the frequency spectrum. In this sense, our proposal allows dimensioning the network capacity in such a way that it uses the least possible number of FSUs per link, or even computes how many extra optical fibers, spectral bands or optical cores may be needed in multi-fiber, multi-band or multi-core environments.

We compared our proposal with common routing and spectrum assignment algorithms by using six well-known network topologies under three different scenarios. In the first and second scenarios, we evaluated the RML and SA stages, respectively; in the third scenario we evaluated the entire RMLSA solution strategy (both the RML and SA stages).

For the first scenario, the simulation results show that algorithms that balance network resources achieve better performance, with a significant impact on high connection topologies. Additionally, we demonstrated that balancing the number of FSUs required for each link of the network minimizes the total network capacity required. In this sense, the LDBB algorithm outperformed Dijkstra's and Baroni's routing algorithms.

On the other hand, for the second scenario, the proposed algorithms achieved better spectrum utilization, reducing the total capacity required in the network with a significant saving of FSUs in all evaluated scenarios and topologies. In this way, to perform spectrum assignment, it is convenient to search connections for a section of the available spectrum contrary to commonly used approaches of searching available spectrum for connections.

Finally, when we use all the proposed algorithms in a single solution (third scenario), the total network capacity is reduced even more than in the first and second scenarios with an average savings of 5.7 % FSUs in all topologies.

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