Scalable Multi-objective Optimization of Reliable Latency-constrained Optical Transport Networks

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***Abstract*—In the evolving scenario of 5G end-to-end networks, optical transport networks provide the connectivity between the mobile edge and the mobile core network. According to the functional decoupling of the base station into the Remote Radio Unit (RRU) and the Baseband Unit (BBU), the latter can be virtualized into a cloud computing platform to access the mobile core. As a consequence, BBU virtual network functions related to different RRUs can be centralized and replicated in a subset of the nodes of the transport network with the aim of optimized reliable design.**

In this paper a scalable methodology, based on lexicographic optimization, is proposed for the solution of a multi-objective optimization problem to achieve, among other goals, the minimization of the number of active nodes in the transport network while supporting reliability and meeting latency constraints. The proposed solution method is compared to an aggregate optimization approach, showing that the former is capable of proving the optimality of the most relevant components of the multi-objective function (minimization of the number of active nodes and of the number of hops) for instances of medium size, and finds better solutions for instances with a larger number of nodes, namely several tens. The computing times to find an optimal solution for the most relevant objectives are much shorter than those required to solve the aggregate model, even for networks of several tens of nodes.

***Index Terms*—Optical Transport Networks, Optimization, Reliability, C-RAN, Latency**

I. Introduction

Optical transport networks represent the aggregation infrastructure to support the increasing radio access capacity of fifth generation mobile networks, namely 5G networks. Optical transport networks provide interconnection based on the Cloud Radio Access Network (C-RAN) model, where the functionality of the Baseband unit (BBU) is fully decoupled from the Remote Radio Unit (RRU) and virtualized into a cloud computing platform. RRUs exchange digitized radio samples with the cloud platform using a high capacity fronthaul connection.

A backhaul network is then responsible of the connection of virtualized BBU functions to the mobile core. As a consequence of virtualization, BBU functions related to different RRUs can be hosted in the same node, called BBU Hotel. This approach has the advantage to reduce the number of active processing nodes in the transport network, with some advantage in cost reduction (pooling gain), but it is expected to need additional connectivity to support the fronthaul, which requires very costly dark fibers used in a circuit switched basis [2]. An evolution of the pure C-RAN scheme is represented by the Next Generation Fronthaul Interface that introduces packet-based interconnection and further functional split in the optical transport network [1].

One of the major challenges for optical transport network design is represented by the Ultra Reliable Low Latency Communication (URLLC) service class, as defined in the 5G context. This class of service is referred to emerging applications with particular time critical and reliability requirements, like autonomous driving or industrial processes. When allocating BBU functions to a BBU hotel, delay constraints need to be met, according to service requirements, that impact on the distance between the BBU Hotel and the served RRU. In any case the BBU hotel, as hosting multiple BBU functions, result in a critical system as far as reliability requirements which call for proper redundancy of the BBU function in the transport network and further impact on the scalability [3], [4].

By considering all the aspects above, the optimized design of the optical transport network results in a multi-objective problem, whose solution is rather complex and suffers of scalability issues in relation to the value of the parameters that characterize the system, like the number of nodes of the transport network and the number of wavelengths on the optical links.

Previous works from the literature consider the optimization problem of reliable C-RAN transport network and apply Integer Linear Programming (ILP) modelling, showing some limitations on the size of the transport network (in terms of number of nodes) that can be solved in acceptable execution time by using a commercial solver [3], [5]. In [3] the optimization of transport network cost with respect to the number of nodes, connections and interfaces with reliability support in the presence of single BBU hotel failure is provided, showing the effectiveness of the approach mainly for network of a few tens of nodes. In real networks, the number of nodes could sensibly increase in the future, especially in scenarios where the processing capability is further split and distributed over the geographical area. Investigating algorithmic solution methods capable of easily calculating the optimal allocation of BBU functions while providing reliability are, as a consequence, of particular interest.

Given that the components of the multi-objective function are not equally important but rather characterized by different relevance [3], the idea of this paper is to adopt a lexicographic approach that optimizes a sequence of single-objective problems, each one having as goal one term of the multi-objective function. These problems are solved in decreasing order of the importance of the associated objective function. For each subsequent problem, a constraint is imposed that limits the value of the objective function associated with the previous problem.

The proposed lexicographic approach is compared to an aggregate multi-objective ILP model [3], showing that the former is capable of better handling networks of larger size: it is capable of proving the optimality of the most relevant components of the multi-objective function (minimization of the number of active nodes and of the number of hops) for instances of medium size, and finds better solutions for larger size networks with 100 nodes. In addition, the results for the most relevant objectives are obtained by the lexicographic approach in shorter computing times than by solving the aggregate ILP model.

The paper is organized as follows. In section II the reference scenario and the problem statement are introduced. In section III the lexicographic method is described. In IV the result obtained are discussed. In section V conclusions are drawn and further work is presented.

II. Reference scenario and problem statement

In figure 1 the reference transport network with the main elements considered in the model is presented, according to [3]. A set of RRUs equipped with antennas covers a geographical area. Each RRU is connected to a node to access the transport network where BBU functionality is located. The transport network consists of a set of nodes interconnected by WDM optical fibers acting as fronthaul segments, according to the C-RAN principle. A node enabled to perform BBU processing as virtual network function is called BBU hotel. Support for reliability is provided with reference to single BBU hotel failure by assigning primary and backup BBUs to each RRU in distinct nodes. The access to BBU functionalities, either primary or backup, is referred as port. Backup ports can be shared by RRUs with different primary nodes. RRUs with the same primary node need to have distinct backup ports. As a consequence, the main elements of a transport networks to support C-RAN are the nodes, the ports within nodes and the wavelengths on each link. The C-RAN model allows to centralize BBU functions in a few nodes thus reducing the number of nodes in the transport network that needs to be activated. This means cost saving in terms of power consumption and network management. At the same time a larger number of wavelength is required when centralizing due to longer paths to reach the BBU hotel. Furthermore, higher number of hops, and consequently higher delay, is introduced with centralization. Transport network cost can be optimized in relation to a cost function associated to these elements and this results in a multi-objective optimization function.

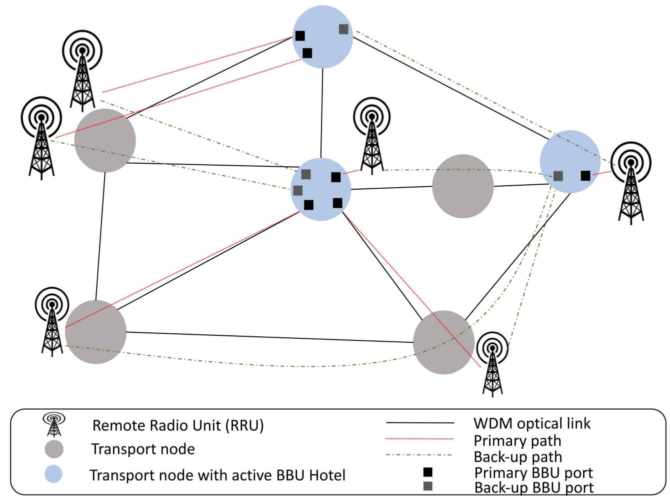

Fig. 1. Main elements of the transport networks.

In the past, different approaches, based on ILP models or heuristics, have been proposed for the solution of the above optimization problem, each one showing its pros and cons [3], [5], [6]. In particular, solving the ILP models by a solver has been shown to have scalability limitations that the heuristics are typically suited to overcome [6].

The method proposed in this paper aims at improving the scalability performance of previous proposals by adopting a lexicographic optimization approach [7], based on multiple-step optimization made of single-objective problems which are solved in decreasing order of the priority of the associated objective function. Previous application of lexicographic methodology at communication systems can be found in literature, such as [8], [9].

The optimization problem considered here is NP-hard and is characterized by a multi-objective goal aiming at the minimization of three terms, with decreasing priority order as assumed in [3] and according to the considered application: the cost C_B of activating nodes for hosting BBU hotels, the cost C_H of the total hops needed to connect BBU hotels and RRUs, and the cost C_P of installing backup ports (the number of primary ports does not have to be optimized since it is equal to the total number of RRUs). As a consequence, the overall optimization consists of a three-step optimization approach with each optimization step being NP-hard.

III. Lexicographic Optimization

In this section, the objective function and the constraints of each single-objective problem that need to be solved at each step are described. All the parameters and decision variables used in this section are reported in Table I.

A. Step 1: Minimization of C_B

This step is used to determine the optimal activation cost of BBU hotels in transport nodes. The ILP model solved in this step reads as follows:

TABLE I
MODEL PARAMETERS AND VARIABLES

Parameters	
S	Set of transport nodes. $\|S\| = s$
H	$s \times s$ matrix. h_{ij} is the distance in hops between nodes i and j computed with the shortest path.
α	Weight for the distance in the cost function.
β	Activation cost for a single BBU hotel.
γ	Cost for a BBU hotel port.
r_i	Number of RRUS at site i, $i \in S$.
δ^l_{ij}	1 if shortest path between i and j is using link l, 0 otherwise, i, $j \in S$, $l \in L$
M_W	Maximum number of wavelengths available in each link.
M_H	Maximum allowed distance in hops between RRU and BBU.
L	Set of links.
Variables	
B_j	1 if node $j \in S$ hosts a BBU hotel, 0 otherwise
p_{ij}	1 if BBU hotel j is assigned as primary for RRUs at node i, i, $j \in S$, 0 otherwise.
b_{ij}	1 if BBU hotel j is assigned as backup for RRUs at node i, i, $j \in S$, 0 otherwise.
y_j	Number of BBU ports required at hotel site j for backup purposes, $j \in S$.
$c_{ijj'}$	1 if RRUs at node i are using destination j as primary and j' as backup hotel site, i, j, $j' \in S$, 0 otherwise.

$$\min C_B, \quad C_B = \sum_{j \in S} B_j \tag{1}$$

$$\sum_{j \in S} p_{ij} = 1 \quad \forall i \in S \tag{2}$$

$$\sum_{j \in S} b_{ij} = 1 \quad \forall i \in S \tag{3}$$

$$p_{ij} + b_{ij} \leq B_j \quad \forall i, j \in S \tag{4}$$

$$(p_{ij} + b_{ij}) \cdot h_{ij} \leq M_H \quad \forall i, j \in S \tag{5}$$

$$\sum_{i \in S} \sum_{j \in S} (p_{ij} + b_{ij}) \cdot \delta^l_{ij} \cdot r_i \leq M_W \quad \forall l \in L \tag{6}$$

$$B_j \in \{0, 1\} \quad \forall j \in S \tag{7}$$

$$p_{ij} \in \{0, 1\} \quad \forall i \in S, j \in S \tag{8}$$

$$b_{ij} \in \{0, 1\} \quad \forall i \in S, j \in S \tag{9}$$

The objective function (1) requires to minimize the activation cost expressed as the number of nodes hosting a BBU hotel. Constraints (2) and (3) impose, respectively, that one primary node and one backup node are associated with each node where a RRU is located. Constraints (4) are used to count the number of active nodes and to impose that each node can only be used as primary or as backup (but not both). The maximum distance, expressed as number of hops, between any two nodes is limited to M_H in constraints (5). Constraints (6) limit the number of wavelengths over each link to M_W. Due to constraints (4), either p_{ij} or b_{ij} can be equal to 1 in constraints (5) and (6). Finally, constraints (7)-(9) define the variable domains.

B. Step 2: Minimization of C_H

In this step, the objective is the minimization of the distance, expressed as the number of hops needed to connect BBU hotels and RRUs. The ILP model solved in this step reads as follows:

$$\min C_H, \quad C_H = \sum_{i \in S} \sum_{j \in S} (p_{ij} + b_{ij}) \cdot h_{ij} \tag{10}$$

$$(2) - (9)$$

$$\sum_{j \in S} B_j \leq C^*_B \tag{11}$$

The objective function (10) is the minimization of the total number of hops. All the constraints defined in the ILP model of step 1 are imposed: indeed, here we have to define the optimal assignment of primary and backup nodes (and, consequently, the number of active nodes) so as to minimize the number of hops. However, the number of active nodes is limited to C^*_B with constraint (11): this means that the optimal solution value of step 1 reduces the search space in step 2.

C. Step 3: Minimization of C_P

The last step deals with the complete problem, where, however, there is a single objective (the minimization of the cost of installing backup ports), and the optimal values of the first two objectives are imposed as constraints (see constraints (11) and (15)). The ILP model solved in this step reads as follows:

$$\min C_P, \quad C_P = \sum_{j \in S} y_j \tag{12}$$

$$(2) - (9), \quad (11)$$

$$c_{ijj'} \geq p_{ij} + b_{ij'} - 1 \quad \forall i, j, j' \in S, \, j \neq j' \tag{13}$$

$$y_{j'} \geq \sum_{i \in S} c_{ijj'} \cdot r_i \quad \forall j, j' \in S, \, j \neq j' \tag{14}$$

$$\sum_{i \in S} \sum_{j \in S} (p_{ij} + b_{ij}) \cdot h_{ij} \leq C^*_H \tag{15}$$

$$\sum_{j \in S} y_j \geq \frac{\sum_{i \in S} r_i}{C^*_B - 1} \tag{16}$$

$$y_j \geq 0, \quad \textit{integer} \quad \forall j \in S \tag{17}$$

$$c_{ijj'} \in \{0, 1\} \quad \forall i \in S, j \in S, j' \in S, j \neq j' \tag{18}$$

The objective function (12) requires to minimize the installation cost of backup ports. All constraints of step 1 are imposed, since the choice of active nodes and of primary and backup nodes are not imposed from the previous steps. However, we limit the search space by the optimal values obtained in the previous steps (constraints (11) and (15)). Constraints (13) is used to define if a node i is using destination j as primary and j' as backup nodes ($i, j, j' \in S$, $j \neq j'$), and constraints (14) determine the number of needed backup ports for each active BBU hotel. As expected, this step is the hardest to be solved, especially due to the large number of variables $c_{ijj'}$. By preliminary computational experiments, we observed that weak lower bounds were obtained by solving the Linear Programming relaxation of this model. In order

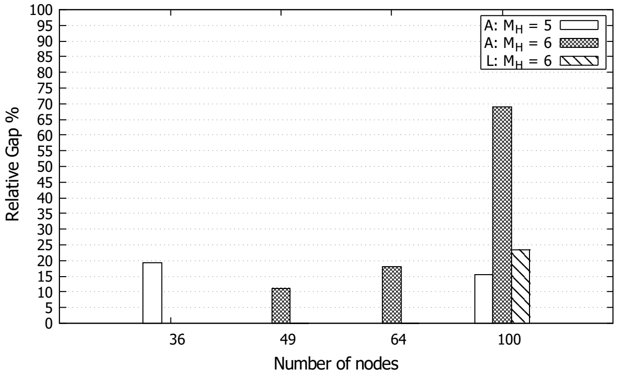

Fig. 2. Relative gaps of the two approaches for different instances, varying the maximum distance M_H. A:= Aggregate, L = Lexicographic.

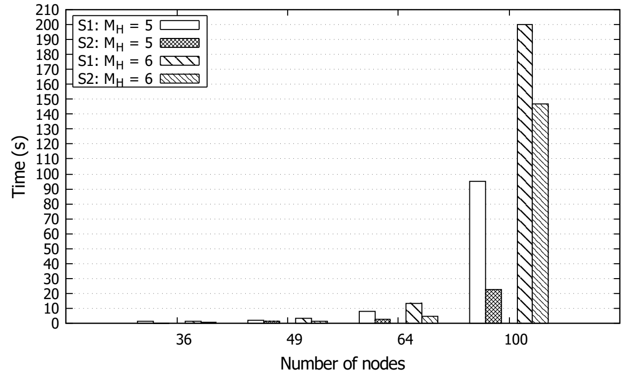

Fig. 3. Execution times of the first two steps of the lexicographic for different instances. S1 = Step 1, S2 = Step 2, varying the maximum distance M_H.

to improve this lower bound, we added constraint (16) that computes the minimum number of backup ports required in any optimal solution. It corresponds to the ratio between the total number of RRUs and the number of active nodes minus one. Indeed, recall that RRUs can share backup ports if they have different primary BBU hotels. Therefore, the minimum number of backup ports is obtained by considering the largest number of different primary nodes: the latter coincides with the number of active nodes, but we cannot assign the same node as primary and as backup (see constraints (4)), hence we subtract one.

The aggregate multi-objective model consists of considering the minimization of the weighted sum given by $\beta \cdot C_B + \alpha \cdot C_H + \gamma \cdot C_P$ with $\beta \gg \alpha \gg \gamma$ (as in [3]) under all constraints reported in step 3, except for constraint (16) since it would lead to a non-linear model.

The aggregate model and each step of the lexicographic approach will be solved by a general-purpose ILP solver.

There are two main advantages of the lexicographic method with respect to solving the aggregate multi-objective model: the first one is that in the first and second steps only a subset of variables and constraints has to be considered, thus leading to models that are "easier" than the aggregate multi-objective one; the second advantage is that, when the optimal solution to the problem cannot be found due to time limits, we may still be able to guarantee the optimality of some steps (typically, the first two steps).

IV. Numerical evaluations

In this section the effectiveness of the lexicographic approach is evaluated and compared with the aggregate multi-objective model developed in [3]. The numerical results were obtained by using the commercial solver CPLEX 12.10, running on an Intel Core i9-9900K@4.8GHz with 32GB@3000MHz RAM. The time limit for execution was set to 1 hour. In the lexicographic approach, the time limit was set to 200 seconds for step 1, 200 seconds for step 2, and 3200 seconds for step 3. Four regular Lattice networks of 36, 49, 64 and 100 nodes were considered, with $r_i = 10$ RRU per node ($i \in S$) and a maximum of $M_W = 80$ wavelengths per link. In the numerical evaluations, $\beta = 10^6$, $\alpha = 10^3$, and, $\gamma = 1$ were used as weights in the multi-objective function of the aggregate model as in [3], thus imposing the hierarchy among objectives required by the application scenario. The lexicographic approach bypasses the use of such large weights, avoiding potential numerical issues during execution. Since the two approaches have different objective values, the equivalent gap for the lexicographic is defined as follows:

$$\mathrm{G_{eq}} = \frac{C_{\mathrm{eq}} - \mathrm{LB_{eq}}}{C_{\mathrm{eq}}} \tag{19}$$

$$C_{\mathrm{eq}} = \beta \cdot C_B^* + \alpha \cdot C_H^* + \gamma \cdot C_P^* \tag{20}$$

$$\mathrm{LB_{eq}} = \beta \cdot \mathrm{LB}(C_B) + \alpha \cdot \mathrm{LB}(C_H) + \gamma \cdot \mathrm{LB}(C_P) \tag{21}$$

where $\mathrm{LB}(\cdot)$ is the best lower bound value achieved by the solver in the execution time limit for the corresponding model in each step, and C^* is the objective value of the best solution found in that step.

Figure 2 reports the relative percentage gaps of the two approaches for the four networks and M_H equal to 5 or 6 (see Table II for more details). When $M_H = 5$, the relative percentage gap of the lexicographic approach is at most 0.0042% for all instances, hence it is not reported, while the aggregate model has a gap of about 15% for two instances. When $M_H = 6$, near-optimal solutions are obtained by the lexicographic approach for all the instances with up to 64 nodes, while the aggregate model shows much larger gaps (more than 10%). For the network with 100 nodes, the relative gap increases also for the lexicographic approach, in particular for $M_H = 6$, but it is significantly smaller (about $1/3$) than the gap of the aggregate model.

In Figures 3 and **??** the computing times required by the lexicographic approach (steps 1 and 2) and by the aggregate model are reported, respectively.

For all instances but the largest one (no matter the M_H value), the lexicographic approach requires very short computing times and obtains optimal or near-optimal solutions. For the network with 100 nodes, the computing time increases: when $M_H = 5$, the lexicographic approach obtains a near-optimal solution, while, when $M_H = 6$, step 1 reaches the time limit of 200 seconds. The aggregate model requires much

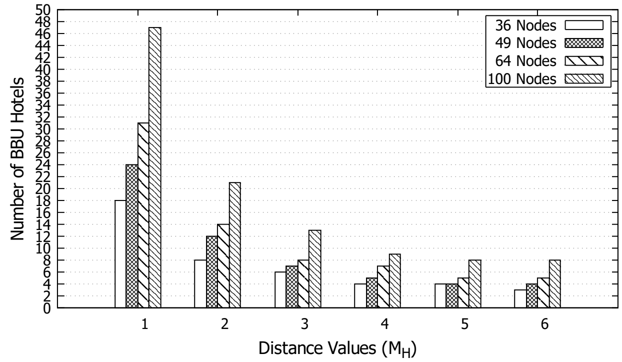

Fig. 4. Number of active BBU hotels as a function of the distance value varying the network size.

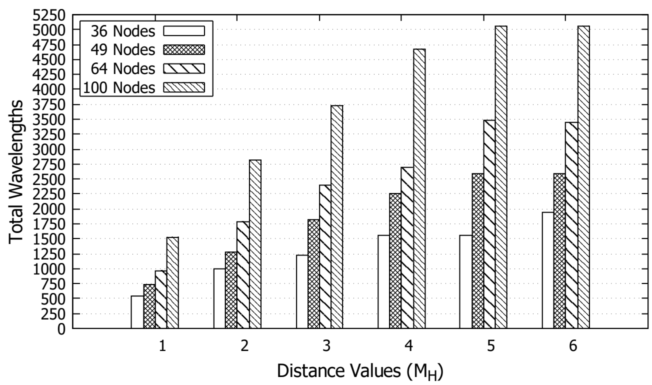

Fig. 5. Total number of wavelengths as a function of the distance value varying the network size.

longer computing times (see Figure 3) and reaches the time limit of 3600 seconds for most instances.

Although the third step of the lexicographic approach reaches the time limit for most instances, the advantage of this method is that it is able to obtain proven optimal solutions for what concerns the first two objectives. Since the third component of the objective function has a much smaller weight than the first two, these solutions are also near-optimal ones for the multi-objective problem.

In Figure 4 the required number of BBU Hotels in the considered networks for different distance values are shown. As the distance value increases, the number of required BBU hotels decreases sharply. Correspondingly, as shown in Figure 5, the total number of wavelengths increases with the distance value. In fact, as the number of BBU hotels decreases, more wavelengths are required in the interconnection networks to connect RRUs to their assigned primary and backup BBU hotels. In addition, as the distance value increases, further minimization of the number of BBU hotels becomes increasingly difficult. This is because as the number of BBU hotels decreases, constraints (6) become more tight due to the greater number of total wavelengths to distribute in the links.

In Figure 6 the average number of hops required by RRUs to reach their BBU primary or backup hotel is shown. In our reference networks, as the distance constraints get less tight,

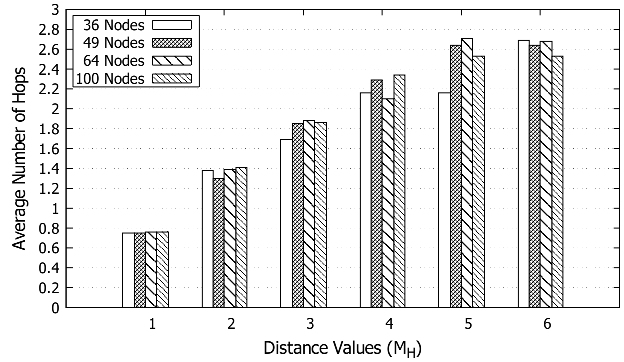

Fig. 6. Average number of hops required in different networks, for different distance values.

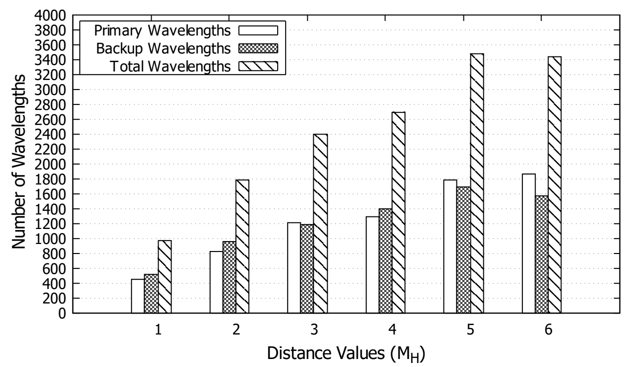

Fig. 7. Number of primary and backup wavelengths required in the 64 nodes network for different distance values.

the average number of hops does not exceed 3. In particular, considering figure 4, one can observe that centralization does not result in a severe increase of the average number of hops, furthering our choice for the lexicographic ordering of the objectives. In addition, since our reference networks have the same structure, the average number of hops results to be mostly independent from the number of nodes.

In Figure 7 the number of needed primary and backup wavelengths for the 64 node network is shown. The additional backup wavelengths, for each distance value, show similar

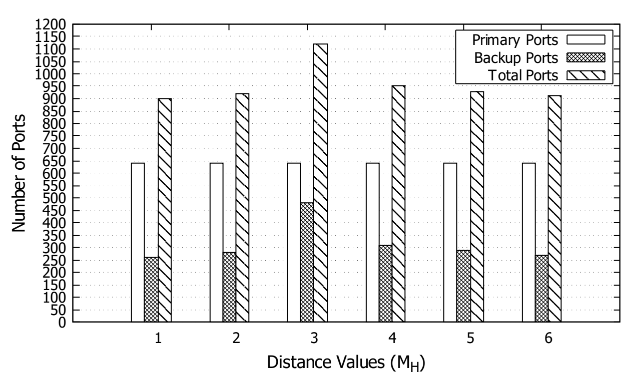

Fig. 8. Number of primary and backup ports required in the 64 nodes network for different distance values.

TABLE II
RESULTS OF THE LEXICOGRAPHIC AND AGGREGATE APPROACHES.

Approach	$\|S\|$	M_H	C_B	C_H	C_P	Gap%
Lexicographic	36	5	4	156	180	0
Aggregate	36	5	4	156	180	19.16
Lexicographic	36	6	3	194	180	0
Aggregate	36	6	3	194	180	0
Lexicographic	49	5	4	259	250	0.0022
Aggregate	49	5	4	259	250	0
Lexicographic	49	6	4	259	250	0.0022
Aggregate	49	6	4	259	250	11.21
Lexicographic	64	5	5	348	300	0.0026
Aggregate	64	5	5	348	290	0.0002
Lexicographic	64	6	5	344	270	0.002
Aggregate	64	6	5	356	220	18.16
Lexicographic	100	5	8	506	500	0.0042
Aggregate	100	5	8	535	470	15.37
Lexicographic	100	6	8	506	540	23.5
Aggregate	100	6	18	607	280	68.9

values as the needed primary wavelengths. This is because primary and backup hops were given the same level of priority in our lexicographic ordering.

In Figure 8 the number of needed primary and backup ports for the 64 nodes network is shown. As mentioned before, the number of primary ports is constant, since they cannot be shared, and equal to the sum of all RRUs. The overall sum of backup ports is minimized, albeit with lowest priority. As an example, for M_H = 3 a larger number of backup ports is obtained as a consequence of the higher priority in minimizing the total number of hops.

In Table II the objective values and relative percentage gaps obtained by the lexicographic and aggregate approaches are reported. Results for the aggregate approach are based on [3]. Except for a few cases (36 nodes with $M_H = 6$, 49 nodes with $M_H = 5$, and 64 nodes with $M_H = 5$) in which both methods have comparable performance, the lexicographic approach performs significantly better than the aggregate model. For instances with up to 64 nodes, it finds optimal or near-optimal solutions, being able to guarantee the optimality of the first two steps, while the aggregate model shows, in some cases, much larger gaps, thus providing worse information regarding the actual quality of the solutions obtained. Not only the relative gap is smaller for the lexicographic approach, but also better solutions are obtained. For the largest instance, it finds a near-optimal solution, characterized by a smaller number of hops than the aggregate model, when $M_H = 5$. When $M_H = 6$, even if the lexicographic approach has 23.5% gap, it finds a significantly better solution with 8 active nodes and 506 hops compared to the 18 nodes and 607 hops required by the aggregate model.

V. CONCLUSIONS

A lexicographic approach is proposed to solve a multi-objective optimization problem, aiming at achieving scalability in optimal transport network design. The multi-objective problem is divided into three single-objective steps which are analyzed in terms of execution time and accuracy. Compared to a previously defined aggregate model, the lexicographic approach shows much better performance and accuracy when applied to large networks: it allows to calculate the optimal (or near-optimal) solution in a few tens of seconds for the most relevant objectives, also in those situations that the aggregate model was not able to solve. The main bottleneck of the approach is represented by port optimization, which is anyway assumed as the lowest priority objective. In addition, an in-depth understanding of the optimization procedure has been achieved that can be applied for future development with additional constraints in slice automation perspective.

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