On The Design of Resilient and Reliable Wireless Backhaul Networks

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***Abstract*—The exponential growth of traffic in mobile networks is leading to an increased pressure on the infrastructure of mobile networks and in particular on their backhaul networks. It is more critical than ever to carefully plan backhaul networks. In this paper, we formulate and solve the problem of hierarchical wireless backhaul network design. In our problem, we cover different requirements, namely: topology simplicity, network resiliency and link reliability. We formulate the problem as an Integer Linear Programming (ILP) problem, allowing us to solve the problem to optimality. Furthermore, we provide a graph theory based algorithm that allows to solve the problem over large scale. The proposed algorithm exploits the properties of the graph representing the network. The results of our evaluations in various network scenarios demonstrate the efficiency of our ILP formulation and the provided algorithm in keeping the backhaul network simple, resilient and reliable. Using a practical channel propagation model and different node densities that are representative of small-scale and large-scale urban environments, our results also show that even with high resiliency requirements, the network traffic can be backhauled with only $5-10\%$ of the nodes for the considered densities. Our results also demonstrate that our algorithm leads to near-optimal solutions in different scenarios.**

***Index Terms*—Hierarchical network topology, resilient and simple topology, graph theory based algorithm, wireless backhaul networks.**

I. Introduction

Cellular networks have witnessed a drastic traffic growth in the last few years. This successive increase in the traffic demand is no more a result of human activities only. The massive integration of connected devices with innovative services and applications is another factor. Globally, mobile data traffic reached 50EB per month in 2020 and is projected to reach 226EB per month in 2026 [1].

Consequently, mobile network operators are currently facing significant challenges. On the economic plan, their revenues are not growing at the same pace of the traffic load, making further investments, targeting the improvement of the network, harder to consider. On the technical plan, challenges span from increasing the network capacity, and providing higher data rates to ensuring low latency.

To tackle these challenges, network densification continues to be a prominent solution adopted by mobile operators. However, network densification implies the need for designing an appropriate bachkaul network capable of handling in turn the anticipated traffic. The backhauls of wireless networks vary depending on a network's objectives and requirements. While wired backhaul networks (e.g., optical fiber (OF) links) provide very reliable solution against weather disruptions and failures, the cost of such links hinders their extended deployment. On the other hand, wireless backhauls offer many advantages such as cost efficiency and ease of deployment. Yet, wireless backhauls suffer from link quality degradation due to weather related factors.

Hence, designing the topology of wireless backhaul network requires particular attention. At the individual link level, it is critical to ensure reliability. At the network level, guaranteeing network resiliency is of utmost importance, allowing the network to react to potential failures and ensure an acceptable level of service at all times [3].

In this work, we focus on the topology design of a wireless backhaul network. We consider a hierarchical (i.e., tree) network topology as it is both simple to manage and flexible enough to meet the reliability and resiliency requirements [2].

The hierarchical topology consists of a tree with one or more root nodes (i.e., Internet gateways) to which all the leaves (i.e., base stations (BSs)) are connected in a multi-level fashion. Many questions must be answered to efficiently map this type of topology to the wireless backhaul. For example, what is the optimal number of levels for this tree? How many nodes can be included at each level? What is the role of each node in such a topology? As the answers to these questions are crucial in the design of a wireless backhaul network, we aim to answer some of them in our proposed work while considering multiple requirements, such as the topology simplicity, the reliability and resiliency of the network.

Several research works have investigated the planning of wireless backhaul networks [4]- [7], as discussed in the next section. However, to the best of our knowledge, no work has formulated the problem while addressing all of the following aspects: a) topology simplicity, defined by obtaining a simple network structure with the smallest possible number of intermediate management nodes; b) the link reliability requirement, defined by ensuring that only the links that meet a certain reliability metric are utilized; and c) network resiliency, defined by having redundant links connecting each node to other nodes in the network.

The contributions of this work lie in solving the hierarchical backhaul wireless network design problem and are as follows:

- We propose a general Integer Linear Porgramming (ILP) mathematical formulation of the problem. For a given set of communication nodes, the formulation allows to determine the level to which each node belongs and the links existing among them.
- Considering the complexity of the problem, we introduce a graph theory based algorithm that allows to solve the problem. We carefully design its steps in the light of the peculiarities of the problem.

- We solve the problem to optimality based on the ILP model and analyze the obtained solutions in different scenarios. Moreover, we assess the performance of our algorithm and compare its solution to the ILP-based one. Our evaluations confirm that our formulation and the algorithm allow to derive high quality solutions that meet our requirements.

The rest of this paper is organized as follows: section II introduces a brief review of the literature related to our work. Section III presents the problem statement and the mathematical formulation. Section IV presents our proposed graph theory based algorithm to solve the problem. The simulation and the results are detailed in section V, and Section VI concludes the work.

II. Related work

The problem of designing a backhaul network topology was studied in a number of research works [4]- [7]. Here, we present the most relevant ones to our problem. In [4], the authors introduced a hybrid framework for selecting either a Free Space Optics (FSO), an Optical Fiber (OF), or a Radio Frequency (RF) link to construct a backhaul network topology. They aim to do so while maximizing the connectivity of the network.

The closest to our work is the study in [5]. There, the authors study self-backhauling where the same radio spectrum is used for both backhaul and access traffic and derive decisions on the role of each node in a hierarchical topology while taking into account network resiliency.

In [6], the joint optimization of user association and radio resources allocation in different backhaul network topologies was studied. The authors discussed the effect of two different topologies, namely star and tree topologies, on the network performance and user quality of service. The star topology showed a limitation when long links are used, while the tree topology performed well for a limited number of multi-hubs between the root and the destination.

Building an Unmanned Aerial Vehicles (UAVs) based wireless backhaul topology has been proposed as a simple and flexible solution. The authors in [7] discussed link and path reliability in this wireless backhaul network to maximize the network resiliency.

Overall, none of the existing works presents an optimal solution to the wireless backhaul topology design problem while considering topology simplicity, links reliability and network resiliency, as we do. For instance, the study in [4], it does not cover the role of each node in the backhaul topology. Again, in [5] neither the link reliability, nor the selection of the network root node were covered in the optimization problem. Resiliency instead is not covered in the topology design problem in [6]. Finally, in [7]; only sub-optimal solutions through heuristic algorithms were proposed in the topology design problem.

III. Problem Statement and Formulation

In this section, we present our problem statement and detail our mathematical problem formulation.

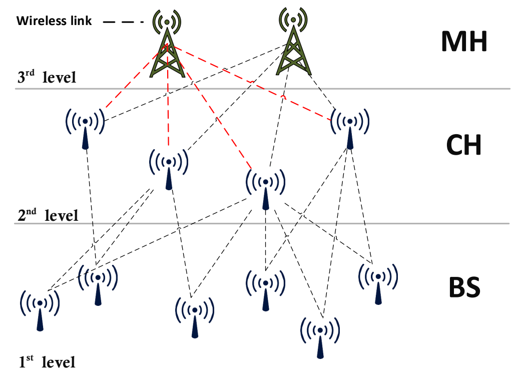

Figure 1. The considered hierarchical wireless backhaul topology network: the 3rd level contains the Master Hubs (MHs), the 2nd level contains the Cluster Heads (CHs), and the 1st level contains the Base Staions (BSs).

A. Problem Statement

We assume a set of communication nodes distributed in a certain topographical area. Based on their locations, the path loss between every pair of nodes is estimated using a specific channel model. We study the problem of designing a tree topology wireless backhaul network, given the inter-node path loss information. We assume a topology as shown in Fig. 1. The topology includes 3 tiers. The upper tier (i.e., the 3rd level of the network) is represented by one or more master hubs (MHs), which are nodes that collect all the traffic from the middle tier, i.e. the 2nd level. In turn, the middle tier includes a set of Cluster Heads (CHs). A CH is a hub node that is responsible for backhauling the traffic from the lower tier to the upper tier. Finally, the lower tier, i.e. the 1st level consists of a set of Base Stations (BSs).

We aim to design a backhaul topology that is simple to manage, reliable and resilient against propagation impairments and equipment/site failures. Our task is to decide the level to which each node belongs and thus its role in the backhaul network. Parallel to these decisions, we need to identify the links among these nodes that will connect the intended tree topology. The resiliency of the designed backhaul network is modeled as k-connectivity links: we guarantee a number of k links between each BS and the CHs and we guarantee a number of k links between a CH and the MHs.

To meet the link reliability requirements, only the links that achieve a specific quality level from a propagation perspective are considered to be valid for use by the network. In this work, we use the Signal-to-Noise-Ratio (SNR) as the metric to define the quality of each link. We assume that the interference effect among the different clusters of the network can be mitigated through: a) proper frequency planning that takes advantage of the geographical distribution of the nodes, and b) the use of directive antennas at the uplink direction of each link (i.e., from the BSs to the CHs, and from the CHs to the MHs).

B. Mathematical Formulation

In our system model, the input network is modeled as a connected graph. In this graph $G(\mathcal{N}, \mathcal{L})$, $\mathcal{N}$ is the set of communication nodes and $\mathcal{L}$ is the set of links among them.

Table I
SYSTEM MODEL NOTATIONS

Notation	Description
$\mathcal{N}$	Set of nodes
m,$n \in \mathcal{N}$	communication nodes in the set $\mathcal{N}$
$\mathcal{L}$	Set of links
$\mathcal{M}$	Set of MHs, a subset of $\mathcal{N}$
$\mathcal{C}$	Set of CHs, a subset of $\mathcal{N}$
$\mathcal{N}_m^{\mathcal{C}}$	Set of neighbors of node m in set $\mathcal{C}$
d_m	the degree of node m
P_t	Transmitted power
$P_{r\_(m,n)}$	Received power for a link between nodes m and n
P_r^{th}	Received power threshold
G_m	The gain of the antenna at node m
G_n	The gain of the antenna at node n
α	PPP density
$PL_{(m,n)}$	Path loss between node m and node n
f_c	the carrier frequency
$\mathcal{S}$	Resiliency parameter
$x_{(m,n)}$	Binary variables = 1, if edge (m,n) is included between node m that is a BS and a node n that is a CH
$w_{(m,n)}$	Binary variables = 1, if edge (m,n) is included between node m that is a CH and a node n that is a MH
y_m	Binary variables = 1, if node $m \in \mathcal{C}$
z_m	Binary variables = 1, if node $m \in \mathcal{M}$

Based on this input graph, we aim to build the hierarchical wireless backhaul topology among the communication nodes. The problem is modeled as an ILP optimization problem. Four binary decision variables are used in the formulation and can be summarized as:

$$y_m = \begin{cases} 1 & \text{if a node } m \in \mathcal{N} \text{ is considered a CH (i.e. } m \in \mathcal{C}) \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$z_m = \begin{cases} 1 & \text{if a node } m \in \mathcal{N} \text{ is considered a MH (i.e. } m \in \mathcal{M}) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$x_{(m,n)} = \begin{cases} 1 & \text{if a link } (m,n) \in \mathcal{L} \text{ is included between} \\ & \text{node } m \text{ that is a BS and } n \text{ that is a CH} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$w_{(m,n)} = \begin{cases} 1 & \text{if a link } (m,n) \in \mathcal{L} \text{ is included between} \\ & \text{node } m \text{ that is a CH and } n \text{ that is a MH} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The notations used for modeling the problem are listed and detailed in Table I.

The optimization problem can be stated as given below in Eqs. (5-14).

$$\underset{w,x,y,z}{\text{minimize}} \sum_{m \in \mathcal{N}} y_m + \sum_{(m,n)\in\mathcal{L}} w_{(m,n)} + \sum_{(m,n)\in\mathcal{L}} x_{(m,n)} \tag{5}$$

$$\text{s.t.} \quad w_{(m,n)} - z_m \geq y_n - 1, \quad \forall \quad (m,n) \in \mathcal{L}, \tag{6}$$

$$w_{(m,n)} - z_n \geq y_m - 1, \quad \forall \quad (m,n) \in \mathcal{L}, \tag{7}$$

$$\sum_{m \in \mathcal{N}} z_m = \mathcal{S}, \tag{8}$$

$$x_{(m,n)} \leq \quad y_m + y_n, \quad \forall \quad (m,n) \in \mathcal{L}, \tag{9}$$

$$\sum_{n \in \mathcal{N}} x_{(m,n)} \geq \mathcal{S} * (1 - z_m - y_m), \quad \forall \quad m \in \mathcal{N} \tag{10}$$

$$(P_{r\_(m,n)} - P_r^{th}) * x_{(m,n)} \geq 0, \forall \quad (m,n) \in \mathcal{L} \tag{11}$$

$$(P_{r\_(m,n)} - P_r^{th}) * w_{(m,n)} \geq 0, \forall \quad (m,n) \in \mathcal{L} \tag{12}$$

$$x_{(m,n)}, w_{(m,n)} \quad \in \{0,1\}, \quad \forall \quad (m,n) \in \mathcal{L} \tag{13}$$

$$y_m, z_m \quad \in \{0,1\}, \quad \forall \quad m \in \mathcal{N} \tag{14}$$

Equation (5) presents our multi-objective cost function. The first term of (5) minimizes the total number of CHs, determined by the binary variable $y_m \,\forall\, m \in \mathcal{N}$. The second and the third terms of (5) serve to minimize the number of links that are required to form the topology in the 1st and 2nd levels, that are determined by the binary variables $x_{(m,n)}, w_{(m,n)} \,\forall\, (m,n) \in \mathcal{L}$, respectively.

Constraints (6) and (7) are used to organize the relations between nodes and links in the 2nd level of the topology. These constraints force that each MH (z_m or z_n) should be linked to all CHs (y_m or y_n) by the 2nd level links $w_{(m,n)}$.

To ensure resiliency at the level of MHs, we consider $\mathcal{S}$ BSs to act as MHs. Thus, $\mathcal{S}$ MHs are needed in the network. This is guaranteed by constraint (8).

Constraint (9) coupled with (10) ensure the resiliency of the network by forcing $\mathcal{S}$-connectivity. With these constraints, if a node m is a BS, then it must be linked to at least $\mathcal{S}$ CHs. By that, resiliency at the 1st the 2nd level of the topology are satisfied.

Constraints (11) and (12) ensure the reliability of individual links at each tier, by assuring that the received power of each active link ($x_{(m,n)}$, $w_{(m,n)}$) is greater than a certain threshold $i.e.$, P_r^{th}.

Finally, equations. (13,14) define the nature of the four decision variables.

IV. GRAPH THEORY BASED ALGORITHM

The ILP can be implemented and solved to optimality using optimization software (e.g. IBM ILOG CPLEX Optimization Studio [13]). However, reaching the optimal solution for the large-scale scenarios is very time consuming. Therefore, we propose a Graph Theory based algorithm that allows to reach a sub-optimal solution in a reasonable time.

Our Graph Theory based algorithm allows to determine the design of the backhaul network. By operating over the set of nodes, it determines first the set of CHs. It then selects the set of MHs. Finally, it identifies the set of links to activate in the backhaul network. The decisions are derived while considering the degrees of the nodes. In graph theory, the degree d_m of a node m in a graph is defined as the number of links that are incident to the node. For the purpose of our algorithm, we define $\mathcal{N}_m^{\mathcal{C}}$ as the set of neighbors of a node m in the set of CHs (i.e., $\mathcal{C}$).

The inputs to our algorithm are the graph $\mathcal{G}(\mathcal{N}, \mathcal{L})$, the required resiliency level $\mathcal{S}$, the link reliability threshold P_r^{th}, and the received power for each link $P_{r\_(m,n)}$. The outputs of the algorithm are the set of CHs $\mathcal{C}$, the set of MHs $\mathcal{M}$, and the set of active links $\mathcal{L}^{active}$.

In the following we present the details of our algorithm, outlined also in Algorithm 1. First, we scan the links of the graph ($(m, n) \in \mathcal{L}$) and remove the links that do not meet the reliability threshold criteria from the set $\mathcal{L}$; in lines $(1-3)$. Second, in line (4) of the Algorithm, we sort the nodes in the graph $\mathcal{G}$ in a decreasing order of their degrees d_m $\forall$ m in $\mathcal{N}$. Third, in lines $6-8$, we select the CHs. For that, we iterate over the set of sorted nodes. If a node does not have $\mathcal{S}$ neighbors in the set of CHs, we select it itself as a CH. By that, we favorize having nodes with higher degrees as CHs and avoid having isolated nodes.

Next, for each node in the set $\mathcal{N}$, if the node has links to all CHs, it will be added to the set of MHs (i.e., $\mathcal{M}$). This step is repeated as long as the number of MHs hasn't reached the limit set by the resiliency requirement $\mathcal{S}$; in lines $(10-14)$.

Finally, in lines $(15-21)$, the links among nodes in the two tiers will be activated to form the set of active links $\mathcal{L}^{active}$.

A. Complexity Analysis

To demonstrate the effectiveness of our proposed graph-based algorithm, we are going to discuss the time complexity of the algorithm compared to the optimization problem.

Defintion - Dominating Set. *For any undirected graph $\mathcal{G}(\mathcal{N}, \mathcal{L})$, the subset of nodes $C \in \mathcal{N}$ to be a dominating set, if for all nodes $m \in \mathcal{N}$, either $m \in C$ or a neighbor n of m is in C. The minimum dominating set (MDS) problem is to find a minimum such C for given graph $\mathcal{G}$.*

Lemma. *The minimum dominating set (MDS) is a special case of our proposed optimization problem with no consideration of resiliency and assigning the network gateways (MHs). In specific, finding the minimum set of CHs that will be able to backhaul the network traffic with no consideration of resiliency ($\mathcal{S}$ = 1) such that each BS to be connected to $\mathcal{S}$ CHs is equal to find the MDS of the graph $\mathcal{G}$.*

Theorem 1. *Our proposed problem is NP-hard*

Proof. In a simple scenario of our model, if each BS connected to one of the CHs in the covering set C (i.e., CHs), the selected set of CHs is equal to the dominating set C. Hence, MDS problem is a special case of our proposed problem without considering resiliency and finding Gateways (MHs). Given the previous Definition and Lemma, since the minimum dominating set problem is a well known NP problem [14], we can claim that our proposed problem is NP-hard.

Theorem 2. *The graph based algorithm can be solved in a polynomial time. In specific, the time complexity of our graph-based algorithm is $\mathcal{O}(|\mathcal{N}|^2)$.*

Proof. As shown in 1, the unqualified links removal step takes $\mathcal{O}(|\mathcal{L}|)$ time. the sorting of the nodes takes $\mathcal{O}(|\mathcal{N}| \log |\mathcal{N}|)$ time. The *for* loop at lines $(6-8)$ will take $\mathcal{O}(|\mathcal{N}|)$ time. The same is applied at the *for* loop at lines $(10-14)$, so it will take $\mathcal{O}(|\mathcal{N}|)$ time. The outer *for* loop at line (16) is upper-bounded by S and the inner loop is upper bounded by $|\mathcal{N}| - \mathcal{S} - 1$, so the time complexity for these loops is $\mathcal{O}(|\mathcal{N}|\mathcal{S}^2 - \mathcal{S})$. Finally, at lines$(19-21)$ the time complexity is the product of $\mathcal{O}(|\mathcal{N}| - \mathcal{S} - 1)$, $\mathcal{O}(|\mathcal{N}| - 2\mathcal{S} - 1)$. Therefore, the time complexity of the complete algorithm is $\mathcal{O}(|\mathcal{N}|^2)$.

Algorithm 1: Graph Theory Based Algorithm

Input: $\mathcal{G}(\mathcal{N}, \mathcal{L})$, $\mathcal{S}$, $P_{r-(m,n)}$, P_r^{th}
Output: $\mathcal{C}$, $\mathcal{M}$, $\mathcal{L}^{active}$
1 **for** (m, n) *in* $\mathcal{L}$ **do**
2   **if** $P_{r-(m,n)} < P_r^{th}$ **then**
3         $\mathcal{L} \leftarrow \mathcal{L} - \{(m, n)\}$ // (m, n) removed
4 Sort nodes in $\mathcal{N}$ based on degree
5 $\mathcal{C} \leftarrow \phi$
6 **for** m *in* $\mathcal{N}$ **do**
7   **if** $|\mathcal{N}_m^{\mathcal{C}}| < \mathcal{S}$ **then**
8         $\mathcal{C} \leftarrow \mathcal{C} \cup \{m\}$ // m added to CHs
9 $\mathcal{M} \leftarrow \phi$
10 **for** m *in* $\mathcal{N}$ **do**
11   **if** $\mathcal{C} \subseteq \mathcal{N}_m^{\mathcal{N}}$ **then**
12         $\mathcal{M} \leftarrow \mathcal{M} \cup \{m\}$ // m added to MHs
13   **if** $|\mathcal{M}| = \mathcal{S}$ **then**
14   Break
15 $\mathcal{L}^{active} \leftarrow \phi$
16 **for** m *in* $\mathcal{M}$ **do**
17   **for** n *in* $\mathcal{C}$ **do**
            // activating links
18         $\mathcal{L}^{active} \leftarrow \mathcal{L}^{active} \cup \{(m, n)\}$
19 **for** m *in* $\mathcal{C}$ **do**
20   **for** n *in* $\mathcal{N} \backslash (\mathcal{C} \cup \mathcal{M})$ **do**
21         $\mathcal{L}^{active} \leftarrow \mathcal{L}^{active} \cup \{(m, n)\}$

V. Evaluation

This section covers the evaluation of our problem formulation and the proposed algorithm. First, in Sec V-A the evaluation scenario will be introduced. Then, we are going to evaluate the performance of our proposed algorithm against the optimal solution in Sec V-B. Later, we will proceed with a deeper analysis of the network topology according to different parameters in Sec.V-C.

A. Evaluation scenario

To evaluate our problem formulation, we solve it using simulations. We focus on a scenario of a Rapidly Deployable Network (RDN) for use as the tactical backhaul in an isolated

Table II
SIMULATION PARAMETERS

Parameter	Value
Simulation area	25 km^2
f_c	2 GHz and 5 GHz
P_t	20 dBm
G_m or G_n	6 dB (at 2 GHz) and 8 dB (at 5 GHz)
G_m or G_n	20 dB (at 2 GHz) and 28 dB (at 5 GHz)
α	1 : 10 BS / KM^2
Minimum inter-node distance	200 m
A, B, C	23.5, 42.5, 20

area or where a commercial network is unavailable. In this scenario, the nodes are distributed according to a type II Matern Hard-Core process (MHCP) with a minimum distance of R. The MHCP is a Poisson Point Process (PPP) that maintains a minimum distance between the nodes and is a common process for modeling wireless networks [8], [9]. We consider different node distribution densities that vary from 1 BS/KM^2 to 20 BS/KM^2.

We use the WINNER-II B5a (i.e., rooftop to rooftop) model to estimate the inter-node path loss [10]. WINNER-II B5a path loss model can be given by:

$$PL_{(m,n)} = A\log_{10}(d_{(m,n)}) + B + C\log_{10}\left(\frac{f_c}{5}\right) + X \quad (15)$$

where, $d_{(m,n)}$ is the distance between node m and node n in meters, , f_c is the frequency in GHz, X is an optional environment-specific factor, A is a fitting parameter that includes the path loss exponent, B is the intercept, and C describes the path loss frequency dependence. Furthermore, practical antenna gains for two different frequencies are considered. For each link, we assume the node at the higher layer is provided with an Omni antenna; i.e., the MHs uses Omni antennas to communicate with the CHs and the CHs use Omni antennas to communicate with their BSs. On the other hand, for each link, we assume the node at the lower layer is provided with a directive antenna, so that the CHs use directive antennas to communicate with the MHs and the BSs use directive antennas to communicate with the CHs [11]. The simulation parameters are summarized in Table II.

B. Graph Theory Based Solution vs. Optimal Solution

We implement and solve our ILP formulation using IBM ILOG CPLEX [13], leading to the optimal solution to the problem. In addition, we solve the problem using our proposed Graph Theory based Algorithm. We assume an SNR threshold of 10 dB with no fade margin and $\mathcal{S} = 2$. In Fig. 2, we compare the results obtained based on the two approaches. The figure shows the average ratio of CHs and the average ratio of links for scenarios with a different number of nodes. The values are averaged over 20 runs for each scenario.

As can be seen, the Graph Theory based algorithm presents near-to-optimal results, with different densities of the network. The difference between the two is about 0.01 only in terms of CHs ratio. However, the ratio of the links is the same for both approaches, since the total number of CHs and MHs obtained

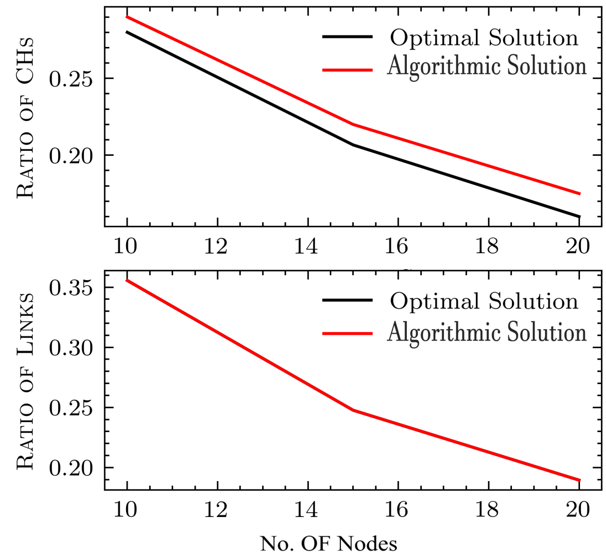

Figure 2. Optimal vs. Greedy solution (Average of 20 runs)

is always the same according to the two approaches, leading by that to the same minimum number of links (i.e., $\mathcal{S}$).

C. Evaluation of optimal solution

In this section, we study the impact of different parameters on the optimal wireless backhaul network topology generated according to our ILP problem formulation.

We show in Fig.3 the impact of the resiliency parameter $\mathcal{S}$ (i.e., representing the number of redundant links and the number of MHs) on the wireless backhaul network topology. We assume an SNR threshold of 10 dB, while not accounting for a fade margin against weather disruptions. In Fig.3(a), we show the ratio between the number of CHs utilized and the set of all nodes on the left axis, as well as the number of CHs utilized on the right axis, for different densities of network nodes. Fig.3(a) clearly shows that the larger the value of S (i.e., the more restrictive the resiliency requirements), the larger the number of CHs utilized. A similar trend appears in Fig.3(b), which presents the ratio between the links used in the topology and the set of possible links.

Moreover, we can notice the ratios of CHs and links are considerably higher when the network is less dense, and vary between 15% and 25%; respectively. However, as the network gets denser, this ratio goes below 5% when $\mathcal{S}$ is set to 2. This behavior shows that our formulation allows to keep the network simple and can significantly reduces the management cost, even when the density of the network is increased, as expected for the next generation networks.

We now investigate the impact of different propagation scenarios in Figures 4 and 5 on the derived wireless backhaul network topology. Figure 4 allows to compare the performance of our model at two different frequencies (2 and 5 GHz) for $\mathcal{S} = 2$. We also assume an SNR threshold of 10 dB, while not accounting for a fade margin against weather disruptions. Figure 4(a) shows the ratio between the number of CHs utilized and the set of all nodes for different densities of network nodes. Figure 4(b) presents the ratio between the links

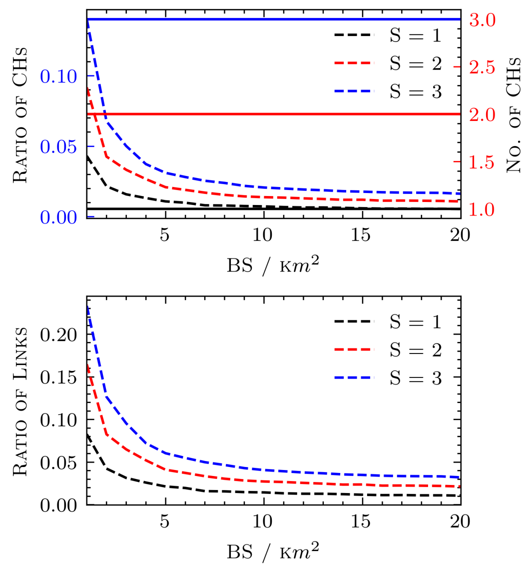

Figure 3. Ratio of utilized CHs and Links for different resiliency levels. (a) Left-axis: Ratio of CHs (i.e., no. of utilized CHs / no. of all nodes - **dashed lines**). Right-axis: No. of CHs (no. of utilized CHs - **solid lines**). (b) Ratio of utilized links (no. of utilized links / No. of all available links).

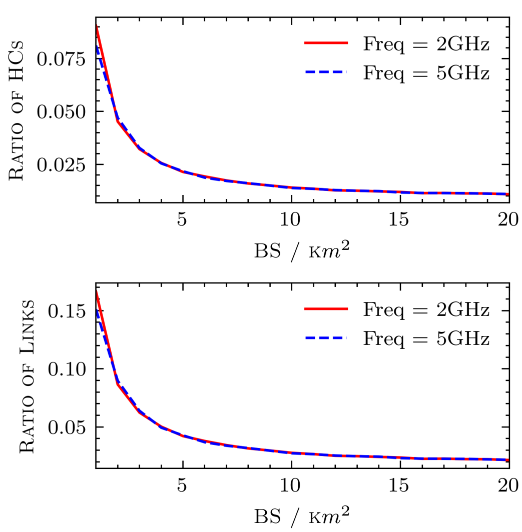

Figure 4. Ratio of CHs (a) and ratio of links (b) for two operating frequencies

used in the topology and the set of possible links for different densities of network nodes. As can be seen, the two ratios present almost the same behavior for different frequencies. This identical response occurs because our formulation forces the solver to find the minimum possible number of CHs to backhaul the network's traffic: four CHs in total (two MHs, as per Eq. (8) + two additional CHs to satisfy the resiliency requirements for $\mathcal{S} = 2$, as per Eq. (10)). The effect of having higher path loss at 5 GHz compared to 2 GHz is (almost completely) compensated for by the higher antenna gain at the higher frequency.

From our previous analysis it is clear that the resiliency requirement, controlled by $\mathcal{S}$, is a major factor in the decision on the number of required CHs. We now investigate the impact of the reliability thresholds on the network topology in Fig.5.

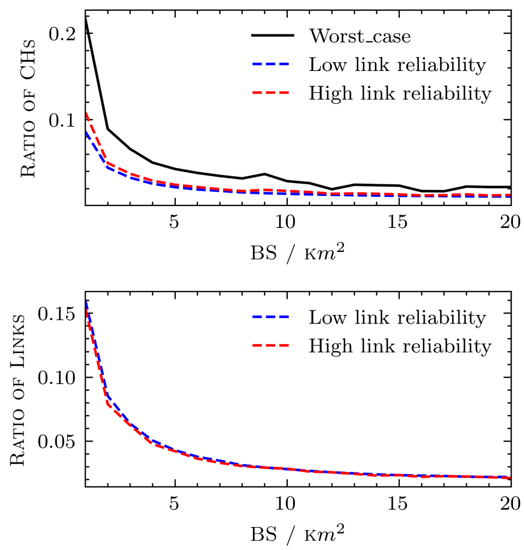

Figure 5. Ratio of CHs (a) and ratio of links (b) for different link reliability requirements. Worst case represents the ratio of the maximum number of CHs to the average number of nodes.

Here we compare two cases: a) A low-reliability case, where no fade margin against weather disruptions is considered. In this case, each link, by definition, will meet the reliability requirements only 50% of the time. b) A high-reliability case, where a 20 dB fade margin against weather disruptions is accommodated for the calculation of the link budget. Based on the Olsen-Segal model and our simulation parameters, this fade margin guarantees a link reliability of 99.99% [12].

Fig.5(a) shows the ratio of CHs for the low-reliability and high-reliability cases (averaged over 20 simulation runs). As it can be seen, for high reliability requirements, a slightly higher number of CHs are required. Furthermore, the ratio of CHs at the high link reliability level obtained from the worst simulation run (i.e., the ratio of the maximum number of CHs to the average number of nodes) is shown in solid black in Fig.5(a), where about 20% of the nodes are required to backhaul the traffic at dense networks after a density of 1BS/km^2. A similar trend appears in Fig.5(b), where the ratio between the links used in the topology and the set of possible links is presented in both link reliability cases.

VI. Conclusion

In this paper, we study the problem of hierarchical backhaul wireless network design. We present an ILP mathematical formulation for the problem that allows to derive a simple, resilient and reliable backhaul network design. The ILP allows to derive optimal solutions to our problem. It is complemented by a graph theory based algorithm to solve the problem over large scale scenarios. The two approaches are evaluated in various network scenarios. Our evaluations demonstrate that our formulation allows to keep the backhaul network simple, reliable and resilient. Our results showed that even with high resiliency requirements, the network traffic can be backhauled using only $5-10\%$ of the total nodes. Moreover, our results show that our algorithm can provide near-optimal solutions in different network densities.

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