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Abstract: In this work, we investigate on minimizing the energy consumption of a wireless backhaul communication network through a joint optimization of data routing and radio configuration. The backhaul network is modeled by a digraph in which the nodes represent radio base stations and the arcs denote radio links. According to the scenario under consideration, a power-efficient configuration can be characterized by a modulation constellation size and a transmission power level. Every link holds a set of power-efficient configurations, each of them associating a capacity with its energy cost. The optimization problem involves deciding the network's configuration and flows that minimize the total energy expenditure, while handling all the traffic requirements simultaneously. An exact mathematical formulation of the problem is presented. It relies on a minimum cost multicommodity flow with step increasing cost functions, which is very hard to optimize. We then propose a piecewise linear convex function, obtained by linear interpolation of power-efficient configuration points, that provides a good approximation of the energy consumption on the links, and present a relaxation of the previous formulation that exploits the convexity of the energy cost functions. This yields lower bounds on the energy consumption, and finally a heuristic algorithm based on the fractional optimum is employed to produce feasible solutions. Our models are validated through extensive experiments that are reported and discussed. The results verify the potentialities behind this novel approach. In particular, our algorithm induces a satisfactory integrality gap in practice.

Key-words: Backhaul communication networks, radio channels, power efficiency

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Réseaux radio backhaul:
minimisation de la consommation d'énergie par la configuration des liens radios

Résumé : Nous étudions la minimisation de la consommation d'énergie des réseaux de communication sans-fil de type backhaul par l'optimisation jointe du routage des flux de données et de la sélection de la configuration des liens. Le réseau backhaul est modélisé par un graphe orienté dont les nœuds représentent les stations radio et les arcs les liens de communication radio. Dans le scénario que nous considérons, une configuration efficace en énergie peut être caractérisée par la taille de la modulation choisie et la puissance de transmission. Chaque lien dispose d'un ensemble de configuration efficaces, chacune associant une capacité à sa consommation en énergie. Le problème d'optimisation à résoudre inclu le choix de la configuration du réseau et le flot minimisant la consommation totale d'énergie, sous la contrainte de satisfaire toutes les demandes de traffic. Nous présentons une formulation mathématique exacte basée sur un multiflot entier de coût minimum avec des fonctions de coût en escalier, rendant le problème très difficile à résoudre. Nous proposons ensuite une fonction linéaire par morceaux convexe, obtenue par interpolation linéaire des points de configuration efficaces en énergie, qui fournit une bonne approximation de la consommation d'énergie sur les liens, et présentons une relaxation qui exploite la convexité des fonctions de coût. Ceci rapporte des limites inférieures sur la consommation d'énergie, et finalement un algorithme heuristique basé sur l'optimum fractionnaire est utilisé pour produire des solutions réalisables. Les résultats de simulations attestent du potentiel de notre nouvelle approche. En particulier, notre algorithme heuristic tire profit de la convexité de la fonction de coût pour fournir des solutions à faible écart avec l'optimal.

Mots-clés : Réseaux Backhaul, canaux radio, efficacité énergétique

1 Introduction

The term *backhaul* often refers to transmitting from a remote site to a main site. In telecommunications, the backhaul typically comprises high capacity links to transport traffic between the backbone network and the small subnetworks at the edge of the entire network. Nowadays, microwave radio links are considered as one of the key technologies to build backhaul communication networks, and they are becoming a common preference over leased lines for many reasons, such as economical equipment cost, easy installation, and disaster resiliency [1]. Despite that, wireless network operators are now challenged to reduce operation costs while supporting the rapid growth in bandwidth intensive applications and the very bursty traffic behaviors. In addition, the tremendous rise of energy has yielded a strong social and economical incentive for researchers and manufacturers to investigate on how to reduce energy expenditure of communication systems.

Fostered by the poor behavior of wireless networks when their size increases [2, 3], backhaul and mesh networks have been intensively studied in the recent years with a specific focus on capacity or other QoS parameters and installation costs [4, 5, 6]. Conversely, many researches have focused on minimizing the energy consumption in wireless network, such as minimum energy broadcasting, backbone construction or monitoring in sensor and adhoc networks [7, 8]. In particular, most existing solutions are per-device power optimization while one should focus on a system-wide approach to reach a global energy expenditure minimum. Thus, it is quite consensual that there is still much room for the conceptualization of more sophisticated solutions in this research area.

Furthermore, the optimum configuration choice for wireless backhaul networks is quite different from classical wired networks. Indeed wired channels are stationary and predictable, while wireless links are time-varying by nature (weather conditions can create instantaneously variations in the communication channel) and present a dynamic behavior (for instance, transmission power and modulation format can be adjusted to traffic requirements) [9]. Therefore, wireless communication systems should be flexible to operate efficiently in several different circumstances. As an example, when the traffic demand increases, operators can intensify the transmission power or alternatively change the modulation format to provide additional capacity. In this context, we have to deal with a complex decision for setting the radio link's parameters. This decision consists in determining the optimal system's configuration, taking into account a specific situation and a set of concurrent requirements, such as power consumption, throughput, and latency.

In this work, we are concerned with minimizing energy consumption in wireless backhaul communication networks, focusing on power-efficient radio configuration. The backhaul network is modeled as a digraph in which the nodes represent radio base stations (RBS) and the arcs represent radio links. Every link holds a set of power-efficient configurations, each of them associating a capacity with its energy cost. The optimization problem involves deciding both the network's configuration and flows that minimize the total energy expenditure, while handling all the traffic requirements simultaneously. It can be seen as a special case of the minimum cost multicommodity flow (MCMCF) problem, which is largely used for optimal design and dimensioning of telecommunication networks. Nevertheless, to our knowledge, the specific application studied here, i.e. determining optimal radio link's configuration while minimizing energy consumption, has seldom been addressed in the literature in the role of multicommodity flow problems.

In [10], various special cases of the MCMCF problem are reported, each of them associated with an appropriate choice of link cost function. Generally, the optimization criterion refers to the total cost of the equipment to be installed on the various links of the network. When the cost function is considered to be linear, then the MCMCF problem can be formulated as a large scale continuous linear program, and many efficient algorithms are available (see the survey [11]). On the other hand, when considering realistic situations, we have commonly to deal with piecewise linear concave cost functions or step increasing cost functions, giving rise to large scale integer linear programs, much more difficult to solve in practice (see [12] and references therein). These cases usually address the economy of scale phenomenon, where the link's average cost decreases as the installed capacity increases.

In this paper, we consider the power efficiency abstraction, related to many concepts of digital and wireless communications, such as modulation schemes, signal-to-noise rate (SNR), bit error rate (BER) performance, and channel capacity. Notably, in this context, we perceive that the link's average energy cost raises as the channel capacity increases. We then propose a piecewise linear convex cost function, obtained by linear interpolation of power-efficient configuration points, that provides a good approximation of the energy consumption on the links, and present a problem relaxation that exploits the convexity of the energy cost functions. This yields lower bounds on the total energy expenditure, and finally a heuristic algorithm based on the fractional optimum is employed to produce feasible solutions. In particular, our algorithm induces a satisfactory integrality gap in practice.

The remainder of the work is organized as follows. In Section 2, we convey more information with regard to the radio link's characterization, focusing on channel capacity and power efficiency. In Section 3, we introduce an exact formulation for the application considered here. It relies on a minimum cost multicommodity flow with step increasing energy cost functions. In Section 4, we propose a relaxation of the previous formulation, associated with a piecewise linear convex energy cost function on the links. A simple heuristic algorithm based on the fractional optimum is introduced. In Section 5, we discuss some computational results that we have achieved by experimenting with benchmark problem instances. In Section 6, some final remarks and comments on future work conclude the paper.

2 Link Characterization

The analysis of communication systems involves detailed knowledge of the physical channels through which the information is transmitted [13]. There are a lot of electromagnetic phenomena behind the radio wave propagation, such as free space loss, refraction, and reflection. Traditionally, the performance of wireless communications is focused on computing signal levels at the receiver, and it begins with a link power budget, that is, a calculation involving the gain and loss associated with the antennas, transmitters, transmission lines, as well as the signal attenuation due to propagation [1], [9]. The result is an estimation of the signal-to-noise rate value, from which we can obtain some implications in terms of channel capacity and bit error rate. Given the allocated channel bandwidth B and the signal-to-noise ratio value S/N, expressed as a linear power fraction, we can determine an upper bound for the channel capacity C, assuming that the bit error rate approaches zero if the data transmission rate is below the channel capacity, according to the following Shannon's capacity theorem [14]:

$$C[bits/s] = B[Hz] * log_2(1 + \frac{S[W]}{N[W]})$$

Actually, the degree to which a communication system can approximate this limit depends on receiver noise and modulation technique [15]. The receiver noise is generated by components used to implement the communication system. Other sources of noise may arise externally to the system, such as interference from other users of the channel. With regard to the modulation technique, there are several features which influence the preference for some modulation scheme. Roughly speaking, a desirable modulation scheme provides low BER at low SNR, and occupies a minimum of bandwidth. These requirements are conflicting, and existing modulation schemes do not simultaneously perform all of them. Some modulation schemes perform well in terms of BER performance, while others are better in terms of bandwidth efficiency [9].

While focusing on energy expenditure, an important factor that must be considered is the power efficiency: a measure of the received power needed to achieve a specific bit error rate for a given modulation scheme. In other words, power efficiency represents the ability of a modulation technique to preserve the fidelity of the digital message at low power levels. Unfortunately, the most power-efficient modulation methods, like binary phase shift keying (BPSK) and quadrature phase shift keying (QPSK), present a rather modest number of bits per transmitted symbol for a given bandwidth [16].

Commonly, to support broadband applications, modern communications systems use M-ary digital modulation techniques. The modulating signal is represented as a time sequence of symbols, where each of them has m finite states and represents n bits of information (with $n = log_2 m$). Nowadays many fixed wireless radio systems use quadrature amplitude modulation (QAM), which presents high bandwidth efficiency and, when compared to other M-ary modulation techniques, offers a good trade-off between occupied bandwidth and power efficiency. Fig. 1 illustrates the signal constellations for 16-QAM and 64-QAM. To increase the data rate, symbols that convey more information bits with more signal constellation states are required. Because the constallation states are closer together, high-level modulations will be obviously more susceptible to noise than low-level modulations [16].

Modern communication systems implement digital modulators and demodulators completely in software. Instead of having a particular modem design permanently frozen as hardware, embedded software implementations now allow to work with different modulation schemes without having to redesign or replace the modem [9]. In practice, as the modulation scheme changes to accommodate higher data rates, the SNR requirement increases to preserve the BER performance. Since we can increase noise immunity by increasing signal

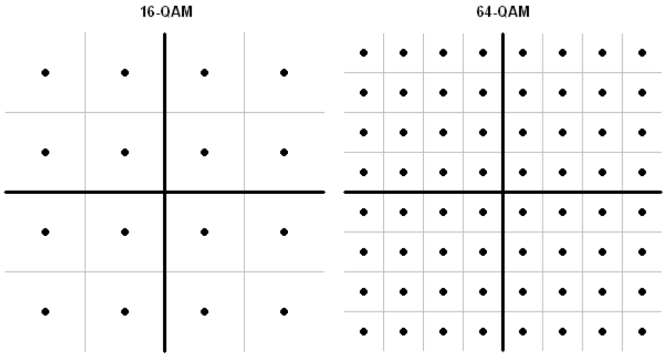


Figure 1: Signal constellations for 16-QAM and 64-QAM

power, there is a trade-off between bandwidth efficiency and power efficiency. Fig. 2 shows the theoretical capacity (given by Shannon's theorem), the practical bitrate (using QAM schemes), and the signal-to-noise rate achieved for a typical radio link scenario in wireless backhaul networks.

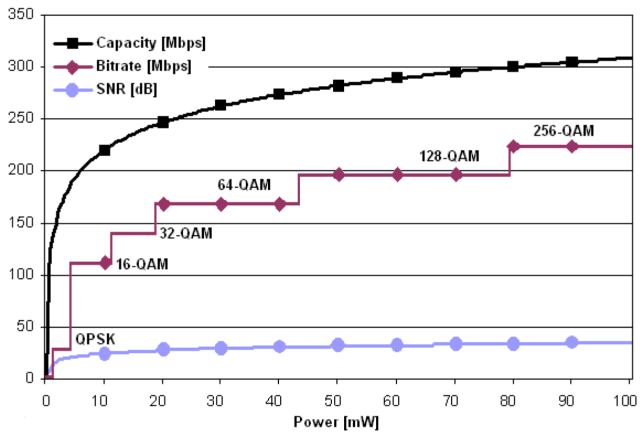


Figure 2: Theoretical versus practical channel capacities

Under this scenario, a power-efficient configuration can be characterized by a modulation constellation size and a transmission power level. Every radio link holds a set of power-efficient configurations, each of them associating a capacity with its energy cost. Fig. 3 illustrates both a discontinuous step increasing and a piecewise linear convex energy cost functions on the links. The latter is obtained by linear interpolation of power-efficient configuration points and provides a good approximation of the energy consumption on the links. Note that, for each modulation scheme, only the most right point of the curve represents a power-efficient configuration.

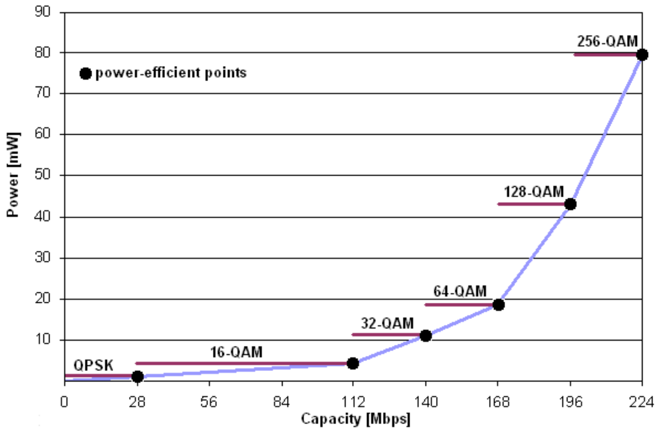


Figure 3: Step increasing and piecewise linear convex energy cost functions

3 Mathematical Model

In this section, we introduce an exact mathematical formulation to the problem of how to minimize energy consumption in wireless backhaul networks by power-efficient radio configuration. The optimization problem involves deciding both the network's configuration and flows, while handling all the traffic requirements simultaneously. Particularly, by configuration, we mean the choice of the transmission power level and the modulation scheme for each radio link, assuming a finite set of power-efficient configuration points. The energy consumption on each link is given by a step increasing cost function, as shown in Fig. 3, and depends on the traffic volume that is supposed to pass through it.

This problem can be seen as a MCMCF with step increasing cost functions, and it can be formally stated as: Given the network's topology as a digraph $G = (V, E)$, where each node $v \in V$ denotes a RBS and each arc $uv \in E$ represents a radio link from u to v, with $u, v \in V$ and $u \neq v$. Let M_{uv} be the number of power-efficient configurations held by the arc uv, each of them associating a radio link's capacity b_{uv}^m with its energy cost c_{uv}^m, for $m = 1, \ldots, M_{uv}$. We are also given the traffic requirements defined by K oriented pairs of terminals (s_k, t_k), with $s_k, t_k \in V$ and $s_k \neq t_k$, and by the expected demand on them d_k, with $k = 1, \ldots, K$. We want to determine the network's configuration planning and traffic flow that minimize the total energy expenditure. Consider the binary decision variable y_{uv}^m which alludes whether the link's configuration m is active for the arc uv, and let x_{uv}^{mk} be the flow through the arc uv under the configuration m with respect to the traffic requirement k. Finally, the optimization problem can be formulated as:

$$\begin{aligned}
min \quad & \sum_{uv \in E} \sum_{m=1}^{M_{uv}} c_{uv}^m y_{uv}^m && (1)\\
s.t. \quad & \sum_{uv \in E} \sum_{m=1}^{M_{uv}} x_{uv}^{mk} - \sum_{vu \in E} \sum_{m=1}^{M_{vu}} x_{vu}^{mk} = -d_k, && (2)\\
& \forall v \in V, k = 1 \ldots K, v = s_k &&\\
& \sum_{uv \in E} \sum_{m=1}^{M_{uv}} x_{uv}^{mk} - \sum_{vu \in E} \sum_{m=1}^{M_{vu}} x_{vu}^{mk} = 0, && (3)\\
& \forall v \in V, k = 1 \ldots K, v \neq s_k, v \neq t_k &&\\
& \sum_{uv \in E} \sum_{m=1}^{M_{uv}} x_{uv}^{mk} - \sum_{vu \in E} \sum_{m=1}^{M_{vu}} x_{vu}^{mk} = d_k, && (4)\\
& \forall v \in V, k = 1 \ldots K, v = t_k &&\\
& \sum_{k=1}^{K} x_{uv}^{mk} \leq b_{uv}^m y_{uv}^m, && (5)\\
& \forall uv \in E, m = 1 \ldots M_{uv} &&\\
& \sum_{m=1}^{M_{uv}} y_{uv}^m \leq 1, \forall uv \in E && (6)\\
& x \in \mathbb{R}^+, y \in \mathbb{B} && (7)
\end{aligned}$$

In this formulation, the objective function (1) represents the total energy expenditure that we want to minimize. For each link, it counts the energy consumption due to the radio operation at a given transmission power level, defined by its configuration. The flow conservation property is expressed by (2), (3), and (4). It provides the routes for each demand pair, guaranteeing that the traffic requirements are entirely attended. By (5), it is assured that, on each link, the available capacity according to its configuration supports all the traffic to be routed through it. Finally, the link's configuration choice is determined by (6). For each radio link, it forces a single selection among the possible power-efficient configurations.

Unfortunately, this formulation results in large scale integer linear programs, which are very hard to solve in practical cases. In addition, solution methods for this problem have received little attention in the literature. In [17], a relaxation that combines both column and constraint generation is used to derive lower bounds to this problem. In [18], a difference of convex function algorithm is applied to provide feasible solutions. These studies consider general step increasing functions, where "convexification" may derive poor approximations.

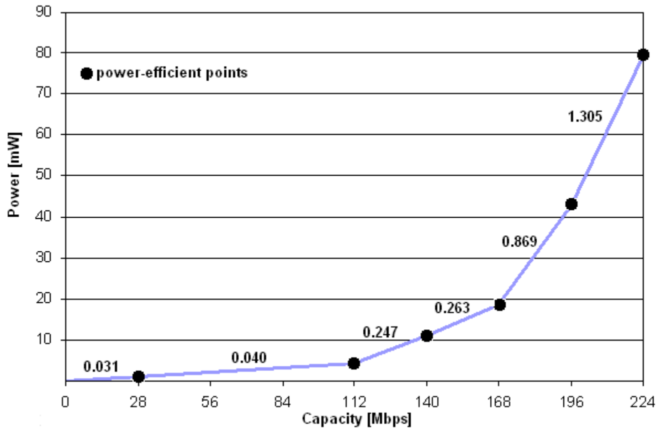


Figure 4: Energy cost per unit of capacity

In the sequel, we introduce a convexification-based relaxation that takes advantage of the inherent convex shape of the energy cost functions on the links to obtain lower bounds on the power consumption and determine the network's configuration.

4 Model Relaxation

In the subsequent formulation, in order to obtain an approximation of the energy consumption on the links, we use linear interpolation of power-efficient points. In Fig. 4, for each interval, the endpoints represent power-efficient configurations and the decimal numbers denote the additional energy cost per unit of capacity, considering a real world scenario of radio communication. Note that the link's energy cost per unit of capacity increases as the modulation scheme changes to accommodate higher data rates.

The problem can be rewritten as a MCMCF with piecewise linear convex cost functions, giving rise to large scale continuous linear programs. Consider the problem statement, as in the previous section, and the following modifications: now b_{uv}^m represents the incremental of capacity on the arc uv when we move from the configuration $m-1$ to the immediate higher level m, and c_{uv}^m denotes the marginal energy cost into this configuration. As the marginal cost for routing an amount of traffic over higher QAM schemes is always increasing, the modulation and the transmission power for each link can be determined by the variable x of highest-level configuration and non-zero value, i.e. by the flow at the highest QAM scheme. The problem can be then formulated as:

$$min \quad \sum_{uv \in E} \sum_{m=1}^{M_{uv}} \sum_{k=1}^{K} c_{uv}^{m} x_{uv}^{mk} \tag{8}$$

$$s.t. \quad \sum_{uv \in E} \sum_{m=1}^{M_{uv}} x_{uv}^{mk} - \sum_{vu \in E} \sum_{m=1}^{M_{vu}} x_{vu}^{mk} = -d_k, \tag{9}$$

$$\forall v \in V, k = 1 \dots K, v = s_k$$

$$\sum_{uv \in E} \sum_{m=1}^{M_{uv}} x_{uv}^{mk} - \sum_{vu \in E} \sum_{m=1}^{M_{vu}} x_{vu}^{mk} = 0, \tag{10}$$

$$\forall v \in V, k = 1 \dots K, v \neq s_k, v \neq t_k$$

$$\sum_{uv \in E} \sum_{m=1}^{M_{uv}} x_{uv}^{mk} - \sum_{vu \in E} \sum_{m=1}^{M_{vu}} x_{vu}^{mk} = d_k, \tag{11}$$

$$\forall v \in V, k = 1 \dots K, v = t_k$$

$$\sum_{k=1}^{K} x_{uv}^{mk} \leq b_{uv}^{m}, \tag{12}$$

$$\forall uv \in E, m = 1 \dots M_{uv}$$

$$x \in \mathbb{R}^{+} \tag{13}$$

The total energy cost is now given by a continuous linear function (8). The flow conservation constraints (9), (10), and (11) remain as in the previous model and implicitly provide, besides the routes for each demand pair, the network's configuration. Finally, by (12), we guarantee that, through every link, the flow over each configuration level does not exceed its capacity.

This formulation gives rise to continuous linear programs and can be easily solved even if we have to deal with very large problem instances. Despite the fact that the resulting optimal solution of the associated linear program is not a practical one, it yields lower bounds on the energy consumption. Furthermore, quite satisfactory solutions can be obtained by means of simple heuristics based on the fractional optimum. Particularly, we consider a direct heuristic algorithm that considers the optimal solution of the relaxation and assigns, for each radio link, the lowest-level power-efficient configuration capable of routing the network's flows.

5 Computational Results

In a manner as to testify the potentialities behind the novel approach, we have performed computational experiments on standard benchmark grid network instances [19]. We consider that the radio base stations use directional antennas and the transceivers devices present identical characteristics, and all radio links are operated at the same frequency and bandwidth. We assume here the free space path loss attenuation model and do not consider interference, but receiver noise. The following parameters are assumed:

- Channel Bandwidth: 28 MHz;
- Operated Frequency: 13 GHz;
- Antenna Gain: 30 dBi;
- Receiver Sensitivity: -90 dBm;
- Distance: 1000 m.

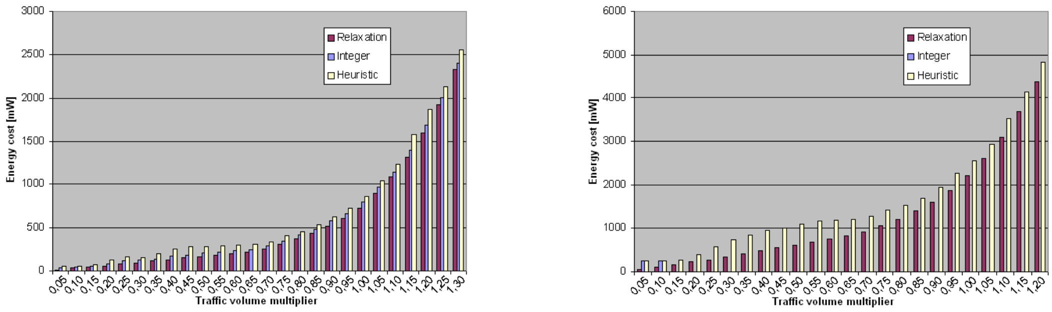
We can then compute the data related to the power-efficient configurations. Table 1 shows the modulations supported, along with the transmission power levels, the channel capacities, the marginal energy costs, and the SNR requirements for a BER of 10^{-6}.

Table 1: Power-efficient configurations data

Modulation	Power	Capacity	Marginal Cost	SNR
QPSK	0.88 mW	28 Mbps	0.031 mW	14.21 dB
16-QAM	4.20 mW	112 Mbps	0.040 mW	21.02 dB
32-QAM	11.10 mW	140 Mbps	0.247 mW	25.24 dB
64-QAM	18.47 mW	168 Mbps	0.263 mW	27.45 dB
128-QAM	42.81 mW	196 Mbps	0.869 mW	31.10 dB
256-QAM	79.34 mW	224 Mbps	1.305 mW	33.78 dB

We performed experiments on grid networks using the traffic matrix given in [19]. In order to observe the evolution of the energy cost as a function of the traffic amount, we have multiplied the traffic matrix by a traffic volume factor λ, initiated at 0.05 and increased by 0.05 until the network's infrastructure does not support the traffic anymore. We have used CPLEX to execute both the discrete and the continuous program models associated with the MCMCF with step increasing and piecewise linear convex energy cost functions, respectively. Fig. 5 illustrates that the energy cost evolves exponentially as the traffic volume increases. Overall, the computational results show that the heuristic algorithm performs well compared to the exact model and allows solving instances that are not reachable with the exact model. Note that, for the exact formulation, after 2 hours of computation, integer solutions were found for all 5×5 grid instances. However, for the 10×10 grid, feasible solutions were found just for the two first instances. None of the feasible solutions for the exact formulation was proven to be optimal.

Considering the MCMCF with piecewise linear convex cost functions, fractional optimal solutions were found for all problem instances, and the execution time has never exceeded few seconds. Furthermore, heuristic feasible solutions based on the fractional optimum were



(a) 5 × 5 grid (b) 10 × 10 grid

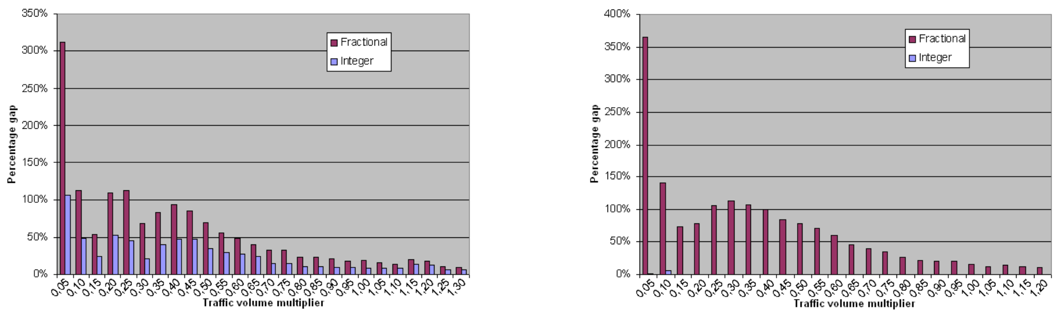
Figure 5: Solutions comparison in terms of energy consumption

generated for all problems. As a drawback, instances on which the network's traffic was small have not presented good heuristic solutions. As expected, the relaxation spreads the traffic among several radio links. Therefore, by rounding up the links' capacity, many links may use a higher-level modulation to carry a small extra amount of traffic that could be routed through other links.

As an example, consider 4 radio base stations A, B, C, D, 4 radio links AB, AC, CD, DB, and a traffic matrix with 4 demands of 10 Mbps each, AB, AC, CD, DB. The relaxation routes the demands on different links, for an overall cost of $4 \times 10 \times 0.031 = 1.24\ mW$. Actually, this solution does not represent a real world radio configuration. Thus, in order to obtain a feasible solution, the heuristic rounds the capacity up of all links from 10 Mbps to 28 Mbps, for a total cost of $4 \times 0.88 = 3.52\ mW$. The exact model, however, avoids the use of the link AB, routing the demand AB through the links AC, CD, DB, for an overall cost of $3 \times 0.88 = 2.64\ mW$. This partially explains why the gap is large in Fig. 6 when λ is small. Many links are under-used to transport a small amount of traffic. This also explains why the gap increases as the traffic volume factor λ moves from 0.15 to 0.20 or from 0.30 to 0.35 in Fig. 6(a). Despite this fact, good heuristic solutions have been obtained with few seconds of computation. Particularly, our algorithm induces a very satisfactory integrality gap in instances on which the amount of traffic is large.

6 Conclusion

In this paper, we presented mathematical formulations for the joint optimization of data routing and radio configuration in wireless backhaul networks. In particular, we proposed an approximation of the energy consumption on the links by a piecewise linear convex cost function. A heuristic based on the fractional optimum is used to generate feasible solutions.



(a) Grid 5 × 5 (b) Grid 10 × 10

Figure 6: Percentage gap of heuristic solutions compared to integer and fractional energy costs

As future work, we intend to investigate alternative relaxations and heuristics to decrease the gap to the exact solution.

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