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Energy and Throughput Optimization of Wireless Mesh Network with Continuous Power Control

Anis Ouni*†, Hervé Rivano‡†, Fabrice Valois†, Catherine Rosenberg§†

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Abstract: Providing high data rate with minimum energy consumption is a crucial challenge for next generation wireless networks. This paper focuses on wireless mesh networks using a MAC layer based on S-TDMA (Spatial Time Division Multiple Access). We investigate on the optimization issues combining throughput and energy consumption. Our contributions are two-fold. First, we formulate and solve using column generation a new MILP to compute the energy-throughput tradeoff curve under a physical interference model when the nodes can perform continuous power control and can use a discrete set of data rates. Second, we highlight some network engineering insights. In particular, we show that power control and multi-rate functionalities allow to reach optimal throughput with lower energy consumption using a mix of single hop and multi-hop routes.

Key-words: Mesh networks, capacity, energy, scheduling, resource allocation.

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Optimisation de la la consommation d'énergie et de débit des réseaux radio maillés avec un contrôle de puissance continu

Résumé : Offrir un haut débit avec une consommation d'énergie faible est un défi pour les réseaux sans fil de nouvelle génération. Ce papier se focalise sur les réseaux maillés sans fil à large bande utilisant la technique S-TDMA (Spatial Time Division Multiple Access). Nous nous intéressons en particulier à la problématique motivante de l'optimisation de la capacité du réseau et de la consommation d'énergie. Nous développons des modèles d'optimisation en programmation linéaire intégrant un modèle d'interférences SINR avec un contrôle de puissance continu et une variation de taux de transmission. Nous utilisons la technique de génération de colonnes pour résoudre le problème d'une manière efficace. Ensuite, Nous mettons en lumière un ensemble de règles d'ingénieries. En particulier, nous montrons que le contrôle de puissance et la variation de taux de transmission sont nécessaires pour un fonctionnement optimale du réseau offrant un débit maximal avec une consommation efficace en énergie.

Mots-clés : Réseaux Radio Maillés, capacité, consommation énergétique, allocation de ressource.

1 Introduction

Providing high data rate to users, irrespective of their position, is a challenge for next generation cellular networks. In this paper, we consider a managed wireless mesh network (WMN) organized in a tiered architecture: *i)* clients are connected to Mesh Routers (MR) and *ii)* a multi-hop wireless backhaul topology interconnects the MRs with the core network (Fig. 1). The MRs aggregate the uplink traffic generated by mobile clients and forward it through multi-hop communications to dedicated MRs, denoted gateways, that bridge the backhaul network to the core network. Downlink traffic goes similarly from the gateways to the MRs then to the clients. We assume that mobile-to-MR and MR-to-MR traffic use independent resources. This work focuses on the backhaul network and does not take into account the users requests but rather their flows aggregated by the MRs. Optimizing the capacity of multi-hop wireless networks, defined as the maximum achievable total throughput in the network topology under a fairness criteria, has been one of the main research issues since the seminal work of Gupta and Kumar [1]. Besides, minimizing the energy expenditure and electromagnetic pollution of such infrastructures are also hot societal and economical challenges [2, 3]. Several works in the literature have studied how to maximize the capacity or to minimize the energy consumption, but the works were done under strong assumptions and tradeoffs between achievable throughputs and energy have received very little attention.

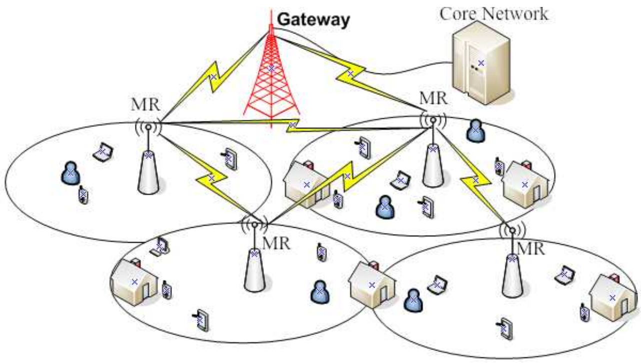


Figure 1: Wireless mesh network architecture: mesh routers collect the traffic from clients (mobile or static) and forward it to the core network.

The first contribution of this work is to develop a flexible optimization framework based on linear programing to study multi-hop mesh networks. Several such optimization tools have been proposed in the literature [4, 5, 6]. The main novelty of this framework is to combine the following features.

1. The routing is computed by a path-based multi commodity flow formulation, and the joint routing and scheduling is solved by a column generation algorithm. By computing a restricted set of decision variables, this algorithm allows us to solve reasonable size instances with a detailed modeling of the links.

2. The modeling of links relies on two notions. A *logical link* representation is used for an efficient formulation of routing issues where only origin-

destination pairs are relevant. While a *physical link* is described by the parameters of the radio transmission and is used for dealing with physical layer issues.

3. This combination of link models allows us to have a tractable formulation while using a detailed Signal-to-Noise-and-Interference-Ratio (SINR) interference model with continuous power control and multi-rate functionality at each mesh router or gateway.

This framework is used to compute an optimal system setting of the backhaul network to minimize the energy consumption (resp. to maximize the capacity) under some network capacity (resp. energy consumption) requirements. We mean by system setting the parameters configuration for operating the backhaul network such as routing paths and scheduling, including the transmission power and rate assigned to each transmission. The impact of these mechanisms on the performances of the network is investigated in depth as well as the energy-throughput tradeoffs.
Our second contribution, is to provide practical engineering insights on WMN.

Our numerical results highlights that:

- Combining continuous power control and multi-rate functionalities allow to reach the optimal achievable throughput with significantly lower energy consumption; in such tradeoffs some nodes actually use several combinations of power and rate at different times.
- The ratio of uplink over downlink traffic demands does not have a significant impact on the network capacity and energy consumption tradeoffs.
- In the case of fixed transmission power, single-hop communications are more energy efficient than multi-hop ones; in the case of continuous power control, it is the opposite.
- The clique area around the gateway plays a critical role in the energy-throughput tradeoff. The predominance of the clique in the capacity determination of a WMN has already been highlighted in the literature. We obtain similar results concerning the energy-throughput tradeoff.

The rest of the paper is organized as follows. Section 2 reviews related works. Section 3 gives the problem statement and the network model. Then, we present, in Section 4, our framework based on linear programming and column generation. Section 5 studies the energy-capacity tradeoff and highlights the benefits of power control. In Section 6, we provide practical engineering insights on WMN. Finally, we conclude the paper in Section 7.

2 Related work

There exists a vast amount of literature devoted to improving the capacity of WMN and to minimizing the energy consumption even if these two issues are mainly considered separately. To increase the throughput provided to nodes, several studies have investigated TDMA scheduling techniques, i.e., to identify sets of links that can be simultaneously activated [4, 7]. [4] studies the problem

of routing and scheduling in IEEE 802.11 based networks. It provides an optimization framework for determining optimal routing and scheduling needed by the traffic in the network considering a binary interference model and fixed transmission power. In a practical system, transmission power is an important tunable parameter to provide reliable and energy efficient communications: higher transmission power increases the SINR at the receiver to enable successful reception on a link, while lower transmission power mitigates interferences to other simultaneously utilized links. The joint problem of power control and scheduling link transmissions in wireless network in order to optimize performance objectives (throughput, delay, energy) received a lot of attention in the recent years [8, 5, 9, 10]. In [5], a joint scheduling, routing and power control strategy is proposed. The authors develop a computational tool using column generation to maximize the minimum throughput among all flows. They highlight the usefulness of power control on the performance of multi-hop wireless networks. In this work, the power control is restricted to a small set of power levels. In [8], the problem of finding a minimum-length schedule that satisfies a set of specified traffic demands is addressed. It is shown that power control improves the spatial reuse, which leads to further improvements on the schedule length compared to a fixed transmit power. Because scheduling with power control using a SINR model is NP-hard [7, 11], several papers proposed heuristic algorithms to minimize the schedule length with and without power control [7, 12].
The optimization of energy consumption also has been extensively addressed in the literature. The energy expenditure in a node is typically linear with the transmission power [13, 14]. From the energy efficiency standpoint, the most effective solution is to put the wireless nodes in sleep mode [15, 16, 17]. In order to produce an effective energy-efficient network, [18] proposed an optimization framework which allows to compute jointly a planning and energy management solution for WMN. The authors showed that the highest energy savings are achieved when network planning and management are handled at the same time.

To the best of our knowledge, only few papers investigate jointly capacity and energy consumption of WMN. [19] studied energy, latency and capacity tradeoff existing in multi-hop ad-hoc wireless networks. The authors assume a linear topology with a simple energy model. They propose an analytical study that does not take into account a realistic interference model. The tradeoff between energy consumption and capacity is investigated using a binary interference model and a fixed transmission power in [20]. The relation between energy minimization and throughput maximization of a 802.11 WLAN is analyzed in [21]. In [6], the authors formulated optimization problems to study the max-min node lifetime and the max-min throughput of a multi-hop wireless network. They show that the optimal tradeoffs between throughput and lifetime are usually not obtained at the minimum power that enables network connectivity.

[22] has investigated the problem of the joint allocation of Modulation and Coding Scheme (MCS), resource blocks and power assignment to users in LTE cellular systems, while minimizing the overall power consumption. To achieve this objective, the authors break down the problem in two loops based on a linear program and a metaheuristic algorithm. They show that to provide a minimum bit rate per user, it is better to use more resource blocks with lower

MCS and less transmission power, rather than few resource blocks with higher MCS but more power.

The lack of papers on both the capacity and energy consumption in the literature leads to this in-depth study to investigate the tradeoff between them using a continuous power control.

3 Assumptions and Problem Definition

3.1 Assumptions and network properties

In this work, we consider a synchronized multi-hop single channel WMN where the MAC layer is based on S-TDMA. The time is divided into time slots allocated to nodes to transmit their traffic. These resources (slots) should be optimally allocated to the nodes in order to offer maximum throughput with efficient energy consumption. We assume that the channel gains are quasi time-invariant. Under the assumption of quasi-static traffic and quasi time-invariant channel gains, it is reasonable to consider a static network. We assume that each mesh router is equipped with an omni-directional antenna and that its transmit power can be adjusted continuously at each transmission. The network capacity can be improved by increasing the number of gateways if they are sufficiently spaced from each other [23]. In this paper, our scenarios are restricted to the single gateway case, though our models could address multi gateways scenarios. We assume that there is an uplink flow from each MR to the gateway and a downlink flow from the gateway to each MR. These flows require several resources to be transmitted and are routed through multi-hop paths to be computed (see Fig. 1).

3.2 Network model and notations

A wireless mesh network is a fixed infrastructure made of set V of nodes, composed of a set of mesh routers, denoted V_{MR}, and a gateway Gw. This section is dedicated to the modeling of the WMN.

3.2.1 Node model

Each mesh router is characterized by its identity $u \in \mathrm{V}_{\mathrm{MR}}$, geographic position and a weight $d_{UL}(u)$ (resp. $d_{DL}(u)$) that reflects its uplink (resp. downlink) throughput requirement. The uplink throughput requirement is needed to forward the uplink traffic generated by mobile clients to the gateway.

During each time slot, a node can be either idle, receiving, or transmitting. When transmitting, the transmit power of the node u is denoted $P_t(u)$ and bounded by a maximum value P_{max}. The nodes have a continuous power control capability in order to reduce the interferences and to use the appropriate transmission rate as explained in the following section. The energy consumption of a node, which depends on its activity as detailed in Section 3.3.2, is denoted $J(u)$.

In the following, we present the modeling of the links by introducing an aggregated notion of *logical links* and a more detailed notion of *physical links*. The former completes, with V, a graph representation of the network which is convenient for computing optimal routings. The latter describes all the parameters of a transmission needed for computing capacity and energy efficient resource allocations.

3.2.2 Links and SINR interference model

When a communication occurs between two nodes, traffic is sent over the link at a rate r which belongs to a set of transmission rate $R = \{r_j\}$, $N_r = |R|$, $0 < r_1 < r_2 < ... < r_{N_r}$. Note that each transmission rate r_j is the result of the use of a modulation and coding scheme MCS_j. In this work, we introduce two notions of (directed) links. Let us denote a *logical link* $e = (u, v)$ identified only by an origin-destination pair. E is the set of feasible logical links and $G = (V, E)$ is the graph representation of the WMN. Such a representation is convenient for handling efficiently the routing issues described further. However to assess the achievability of a logical link, hence define E, and cope with interference and energy issues, a more detailed notion of link is required. Let us denote a *physical link* by l and identified by the following parameters (e, P_t, r).

- $e = (o(l), d(l)) \in E$ the logical link between the origin-destination pair $(o(l), d(l))$.
- $P_t \in [0, P_{max}]$: the transmit power of the node $o(l)$ during this communication.
- $r \in R$: the transmission rate, in bits per second, used during this communication.

Each rate r has a corresponding SINR requirement $\beta(r)$ for the communication to be established with some given parameters such as a maximum bit error rate ($\beta(r_i) > \beta(r_{i-1})$). It means that a physical link $l = (e, P_t, r)$ is established if and only if the power received from $o(l)$ in $d(l)$ is enough to reach the SINR requirement of the rate r. The power received at $d(l)$ is proportional to P_t and to the channel gain function, denoted $G(l)$, which takes into account a given radio propagation model (path loss, fading and shadowing). Altogether, the SINR condition at receiver $d(l)$, in the presence of a set s of other simultaneously active transmissions, is expressed as follows.

$$SINR_{d(l)} = \frac{P_t * G(o(l), d(l))}{\mu + \sum\limits_{l'=(e', P'_t, r') \neq l, l' \in s} P'_t * G(o(l'), d(l))} \geq \beta(r), \quad (1)$$

where $\mu \in \mathbb{R}^+$ represents the thermal noise at the receiver.

The set of feasible physical links is denoted $\mathcal{L}$ and a logical link e exists if and only if there exists $P_t \in [0, P_{max}]$ such that $l = (e, P_t, r_1) \in \mathcal{L}$. The set of logical links can therefore be defined as $E = \{e = (u, v), \exists P_t < P_{max}, (e, P_t, r_1) \in \mathcal{L}\}$. One can note that $\mathcal{L}$ is infinite while E is finite and tractable for routing issues.

3.2.3 Conflict free scheduling

A set I of physical links $(l^1, l^2, ..., l^n)$ is said an *independent set* (*ISet*) if and only if Eq. (1) holds at all receivers and $\forall l^i, l^j \in s$, $i \neq j$, $o(l^i) \neq o(l^j)$, $d(l^i) \neq d(l^j)$ and $o(l^i) \neq d(l^j)$. All the links in this set can be scheduled at the same time without creating any decoding conflict. The set of all possible *ISets* is denoted $\mathcal{I}$.

Table 1: Network model parameters and notations

E, $\mathcal{L}$	Set of logical and physical links
Gw, $\mathrm{V_{MR}}$	Gateway and set of mesh routers
μ, $\beta(.)$	Thermal noise and SINR threshold function
$G(.)$	Channel gain function
$P_t(.)$	Transmit power
$P_r(.)$	Power consumed by the receiver
$d_{UL(.)}, d_{DL(.)}$	Resp. Uplink and Downlink weight
I	An ISet
$\mathcal{I}$	Set of all possible ISets
R, N_r	Set of available rates: $R = \{\mathrm{r_j}\}$, $\lvert R\rvert = N_r$
Cc	Fixed cost of circuit consumption

Note that, because we consider continuous power control, the set of physical links is infinite. However $\mathcal{I}$ can be reduced to a finite set of "minimal ISets" with respect to transmission powers: we only consider ISets in which transmission power cannot be reduced without modifying the transmission rate of link. This does not provide a tractable and easy to generate set of ISets, but column generation allows for generating only a subset of useful ISets (this will be discussed in details in Section 4.2).
By scheduling only ISets, we will make sure that the schedule is conflict free. Let $w(\mathrm{I})$ be the fraction of time allocated to the ISet I, we have $\sum_{I\in\mathcal{I}} w(\mathrm{I}) = 1$. Our optimization problems will compute the $(w(\mathrm{I}))$'s to maximize the objective function.

3.2.4 Routing model

The activation of an ISet I provides to each logical link, $e \in E$, a rate $r_e(\mathrm{I})$ equal to $r(l) \in R$ if it exists $l = (e, P_t(l), r(l)) \in \mathrm{I}$, and to 0 otherwise. Hence each logical link e sees a total rate equal to $\sum_{\mathrm{I}\in\mathcal{I}} r_e(\mathrm{I})w(\mathrm{I})$. These rates are used to route the traffic between the mesh routers and the gateway. We define a routing path as a set of logical links through intermediate nodes from source to destination. For each mesh router $u \in \mathrm{V_{MR}}$, let $\mathcal{P}^u_{UL}$ (resp. $\mathcal{P}^u_{DL}$) denote the set of uplink (resp. downlink) paths between u and the gateway, and let $\mathcal{P}_{UL} = \cup_u \mathcal{P}^u_{UL}$ (resp. $\mathcal{P}_{DL} = \cup_u \mathcal{P}^u_{DL}$) denote the set of uplink (resp. downlink) paths in the network. The uplink traffic is modeled by the flow function $f_{UL} : \mathcal{P}_{UL} \rightarrow \mathbb{R}^+$. The traffic sent by u is hence $\sum_{\mathrm{P}\in\mathcal{P}^u_{UL}} f_{UL}(\mathrm{P})$ (same thing for the downlink traffic flow). The flow over a logical link e is the sum of the uplink and downlink traffic on the paths going through e. This flow has to be below the total rate of e. The problem of routing is to calculate the flow function that maximize the throughput or minimize the energy consumption.

3.3 Network capacity and energy consumption model

3.3.1 Network capacity

we assume that the throughput requirements of the mesh routers are heterogeneous. This can be explained by the number of clients connected to each mesh router. To model this, each mesh router is allocated a weight that reflects its greedy throughput requirement with respect to a common base λ. We consider a fair notion of network capacity in which every router receives at least its weighted share of the global throughput. The resources are therefore assigned so that each node $u \in V$ receives an end-to-end uplink throughput $\lambda_{UL}(u)$ (resp. downlink $\lambda_{DL}(u)$), so that : $\lambda_{UL}(u) \geq d_{UL}(u) * \lambda$, where $d_{UL}(u)$ (resp. $d_{DL}(u)$) is the uplink (resp. downlink) weight of node u and λ is the common base throughput (in bps) to be optimized. The network capacity is hence at least $\sum\limits_{u \in V_{MR}} (\lambda_{DL}(u) + \lambda_{UL}(u)) \geq \sum\limits_{u \in V_{MR}} d_u * \lambda$, where $d_u = d_{UL}(u) + d_{DL}(u)$. Maximizing λ achieves a fair maximization of the network capacity.

An insight of a throughput-optimal scheduling policy would be to schedule as many links as possible in each time slot, that is to maximize the spatial reuse of system resources. This objective has to be mitigated with interferences and energy consumption constraints.

3.3.2 Energy consumption model

We propose a generic energy consumption model that is based on the node activity (idle, transmission, reception). When the radio part of the node is not on operation, some components are always on and they consume a given quantity of power denoted Cc, this state is called *Idle State*. When the radio part is on operation, the node u can either be in *Transmission State* ($u = o(l)$) or in *Reception State* ($u = d(l)$) and it consumes, respectively, $(Cc + a(u) * P_t(o(l)))$ and $(Cc + P_r(u))$. The coefficient $a(u)$ characterizes the amplifier. In this work we assume that $P_r(u)$ is fixed for all nodes. The relation between transmission power and node energy consumption is nearly linear [13, 14].

Each ISet I has an power consumption (Watts), $J(\mathrm{I})$, and is calculated as follows:

$$J(\mathrm{I}) = |V| * Cc + \sum_{l \in \mathrm{I}} a(o(l)) * P_t(o(l)) + \sum_{l \in \mathrm{I}} P_r(d(l)) \tag{2}$$

The total energy consumption of the network is $\sum_{\mathrm{I} \in \mathcal{I}} w(\mathrm{I}) J(\mathrm{I})$ when the scheduling is done using the $(w(\mathrm{I}))$'s.
Tables 1 summarizes all the network model parameters and notations.

In the next section we formulate two different linear programming problems: the first one maximizes the network capacity subject to a constraint on the total energy consumption while the second one minimizes the total energy consumption subject to a capacity constraint. We also present the column generation algorithm that we use to cope with the combinatorial complexity of the paths and the set of ISets.

4 Linear Models for Capacity and Energy Consumption Optimizations

4.1 Master formulation

The joint routing and scheduling problem can be expressed in two linear programs (LP) depending on the objective. The first one maximizes the capacity with an energy budget constraint. It is called the Master Problem to Maximize Capacity (MPMC) and formulated as follows.

$$\max_{\lambda,(w(I))_{I\in\mathcal{I}},f_{UL}(u)_{u\in V},f_{DL}(u)_{u\in V}} \lambda$$

$$\text{subject to } \forall u \in V_{MR} \quad \sum_{\mathrm{P}\in\mathcal{P}^u_{UL}} f_{UL}(\mathrm{P}) \geq d_{UL}(u) * \lambda \tag{3}$$

$$\forall u \in V_{MR} \quad \sum_{\mathrm{P}\in\mathcal{P}^u_{DL}} f_{DL}(\mathrm{P}) \geq d_{DL}(u) * \lambda \tag{4}$$

$$\forall e \in E \quad \sum_{\mathrm{P}\in\mathcal{P}_{DL},\mathrm{P}\ni e} f_{DL}(\mathrm{P}) + \sum_{\mathrm{P}\in\mathcal{P}_{UL},\mathrm{P}\ni e} f_{UL}(\mathrm{P}) \leq \sum_{\mathrm{I}\in\mathcal{I}} r_e(\mathrm{I})w(\mathrm{I}) \tag{5}$$

$$\sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I}) \leq 1 \tag{6}$$

$$\sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I})J(\mathrm{I}) \leq J \tag{7}$$

$$\lambda > 0, \quad (w(I))_{I\in\mathcal{I}} \geq 0, \quad f_{UL}(u)_{u\in V} \geq 0, \quad f_{DL}(u)_{u\in V} \geq 0 \tag{8}$$

The objective function imposes the maximization of the end-to-end base throughput λ. Equations (3)-(5) express the routing part as flows between the MRs and the gateway. Constraints (5) impose that the total flow on the logical link e does not exceed the capacity of the link itself while constraints (3) (resp. (4)) ensure that each MR achieve a maximum uplink (resp. downlink) throughput taking into account the nodes weights. Eq. (7) constraints the total energy expenditure of the network to a budget J.

The second LP formulation minimizes the total energy expenditure under a capacity guarantee and is called the Master Problem to Minimize Energy consumption (MPME).

$$\min_{\lambda,(w(I))_{I\in\mathcal{I}},f_{UL}(u)_{u\in V},f_{DL}(u)_{u\in V}} \sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I})J(\mathrm{I})$$

subject to Equations (3)-(6) and

$$\lambda \geq \lambda_{min} \tag{9}$$

The flow equations of MPME remain the same as Eq. (3)-(5) while the upper bound on the energy consumption (Eq. (7)) is replaced by a lower bound on the network capacity (Eq. (9)). Finally, the objective is to minimize the energy expenditure of the network.

The physical links parameters (like transmission power and link rate) are explicitly taken into account by each ISet I $\in \mathcal{I}$: recall that an ISet is a set of physical links and will be calculated by a mixed integer linear program, detailed in the following.

The MPMC and MPME formulations allow us to calculate the Pareto front between the network capacity and the energy consumption. Fig. 2 explains how we calculate this Pareto front. The first step is to calculate the two extremal points, $P0 = (J_{min}, \lambda_{min})$ and $P1 = (J_{max}, \lambda_{max})$, which present the minimum energy consumption, J_{min}, and the maximum base throughput λ_{max}. Recall that the network capacity is equal to $\sum_v d_v * \lambda$. $P0$ and $P1$ are calculated as follows:

$$P0 \begin{cases} J_{min} = \min \sum_{\mathrm{I} \in \mathcal{I}} w(\mathrm{I})J(\mathrm{I}) \quad | \quad \lambda > 0 \quad (using \quad MPMC) \\ \lambda_{min} = \max \lambda \quad | \quad \sum_{\mathrm{I} \in \mathcal{I}} w(\mathrm{I})J(\mathrm{I}) \leq J_{min} \quad (using \quad MPME) \end{cases}$$

$$P1 \begin{cases} \lambda_{max} = \max \lambda \quad | \quad \sum_{\mathrm{I} \in \mathcal{I}} w(\mathrm{I})J(\mathrm{I}) \leq \infty \quad (using \quad MPMC) \\ J_{max} = \min \sum_{\mathrm{I} \in \mathcal{I}} w(\mathrm{I})J(\mathrm{I}) \quad | \quad \lambda \geq \lambda_{max} \quad (using \quad MPME) \end{cases}$$

Once determined the two extremal points, we use one of the two linear programs to plot the rest of the curve. For example if we use the MPMC linear program, then we vary J between J_{min} and J_{max}.

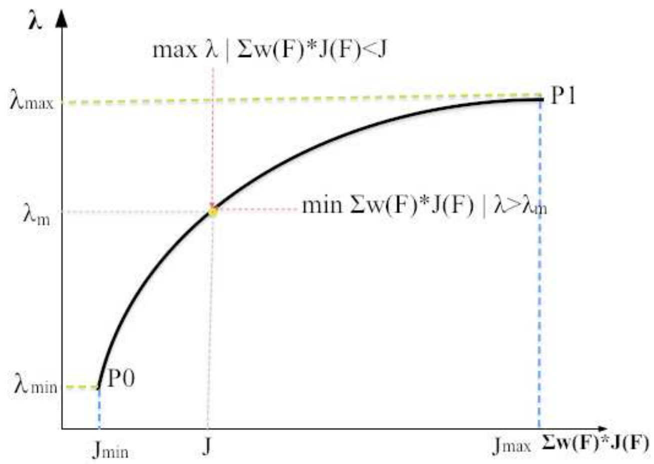


Figure 2: The Front Pareto description.

Because the numbers of paths and ISets are exponential with the size of the network, these formulations are not scalable as such. Column generation [4,5] is a prominent and efficient technique to cope with this situation. Based on linear programing duality results, it avoids the complete enumeration of the variable sets. The column generation that we have implemented is described below.

4.2 Column generation

Column generation is an algorithmic technique for solving linear programs with an exponential set of variables which takes its roots in the duality theory [24]. Each linear program, denoted *master* in this context, has an associated and unique *dual* program. For each constraint of the master, there is a dual variable that is defined. Similarly, for each variable of the master, there is a constraint in the dual, which binds the dual variables related to the master constraints in which the concerned master variable appears. This is done in a way that the duality association is reflexive (the dual of the dual of a LP is the original LP). The dual formulations of MPMC is detailed in the following section. Each

Table 2: LP Model Notations

$J(\mathrm{I})$	Total energy cost of ISet I
$w(\mathrm{I})$	Fraction of time allocated to ISet I
$\mathrm{P_{UL}}$, $\mathrm{P_{DL}}$	Resp. UL and DL Path
$\mathrm{f_{UL}(P)}$, $\mathrm{f_{DL}(P)}$	Resp. UL and DL Flow of path P
J	Energy budget
λ_{min}	Minimum throughput requirement
$\theta_{UL}(.), \gamma(.), \sigma$	Dual variables
n	Number of nodes

instantiation of the master variables is similarly associated to an instantiation of the dual variables such that the master values represent a sub-optimal feasible solution if and only if the dual values is a non feasible solution, i.e. at least one constraint of the dual is violated. Both set of master and dual values represent a feasible solution if and only if there are both optimal (with the property that the master and dual optimal objectives values are the same).

Exploiting this property, the column generation principle is to first solve the master on a restricted set of variables (also called columns, hence the column generation), considering that the non considered variables are zero. In our case, the variables are the flow over the paths and the weights of the ISets. We are then considering a restricted set of paths $\mathcal{P}_0$ and ISets $\mathcal{I}_0$ which have to be carefully chosen to ensure the existence of an initial feasible solution. Generally, $\mathcal{P}_0$ contains a shortest path between each mesh router and the gateway (uplink/downlink paths), and $\mathcal{I}_0 = \{\{l = (\mathrm{e}, P_t, r_1)\}, \mathrm{e} \in \mathrm{E}, P_t = \frac{\beta(r_0)*\mu}{G(l)}\}$.

The solving of the master on this restricted set of variable is thus fast and, if there exists a feasible solution, it is related to a set of dual values. If the solution of the master is suboptimal, the aforementioned property of the duality claims that the dual values describe is a non feasible solution of the dual. There is then at least one constraint of the dual that is violated and which is in bijection with a variable of the master, here a path or an ISet. The separation theorem claims that solving again the master on the set of variables increased by this new variable will improve the solution [24]. The process loops until no such variable exists as depicted in Fig. 3. When reaching this state, it means that the dual variables represent a feasible solution. Since the master does to, the theory of duality claims that both the master and the dual are optimal. Finding the new variables in the column generation process consists in solving the auxiliary programs described in Section 4.2.2.

4.2.1 Dual formulation

We present below the dual formulation of MPMC, the one for MPME being very similar. Recall that in this LP, there is a constraint for each variable of the master, be it the flow on a path or the weighting of an ISet. We denote $\theta_{UL}(.)$, $\theta_{DL}(.)$, $\gamma(.)$, Ω, and σ, respectively, the dual variables associated to constraints (3), (4), (5), (6) and (7). o(P) denotes the source node of path P. $J(u)$ is the power consumption (Watts) of node u.

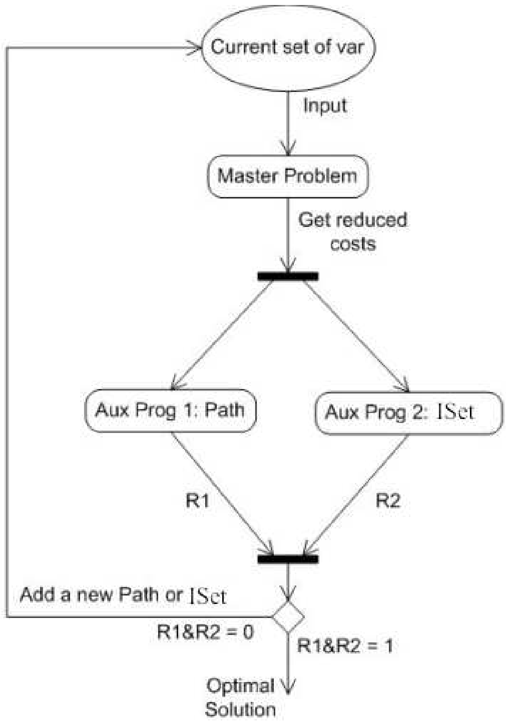


Figure 3: The column generation process

$$\min_{(\theta_{UL}(u))_{u\in V},(\theta_{DL}(u))_{u\in V},\sigma,\Omega,(\gamma(e))_{e\in E}} \Omega + J * \sigma$$

$$\text{subject to:} \qquad \forall \mathrm{P} \in \mathcal{P}_{UL} \qquad \theta_{UL}(\mathrm{o(P)}) \leq \sum_{e\in \mathrm{P}} \gamma(e) \tag{10}$$

$$\forall \mathrm{P} \in \mathcal{P}_{DL} \qquad \theta_{DL}(\mathrm{o(P)}) \leq \sum_{e\in \mathrm{P}} \gamma(e) \tag{11}$$

$$\mathrm{I} \in \mathcal{I} \qquad \sum_{e\in E} r_e(\mathrm{I})\gamma(e) - \sigma J(\mathrm{I}) - \Omega \leq 0 \tag{12}$$

$$\sum_{u\in V_{MR}} (\theta_{UL}(u)d(u) + \theta_{DL}(u)d(u)) \geq 1 \tag{13}$$

4.2.2 Auxiliary programs

We now describe the two auxiliary programs which determine if there are uplink/downlink paths or ISets that violate the constraints of the dual program. The first one, associated to constraints Eq. (10)-(11), finds, for each source node, a weighted path with a weight lower than the dual variable associated to the source node. If the minimum weighted path fits the constraint then all other paths do. This problem is hence solved by any shortest path algorithm like Dijkstra.

The second auxiliary problem is associated to constraint Eq. (12). We need to decide if it exists an ISet I such that $\sum_{e\in E} r_e\gamma(e) - \sigma J(\mathrm{I}) - \Omega > 0$. One more time, if the maximum weight communication set respects Eq. (12) then all other ISets do. Our auxiliary program can consider two scenarios:

Generation of ISets with continuous power control and multi-rate In this case, each node can continuously control its transmission power and choose the best MCS (or rate $r \in R$) depending on the SINR achieved at the receiver. Given a set of dual variables $(\gamma(.), \sigma)$ obtained from the master problem (MPME or MPMC), we can generate a new ISet by solving the following Mixed Integer Linear Program:

$$\max_{\Psi, P_t, J} \sum_{e\in E} (r_e\gamma(e)) - \sigma \sum_{u\in V} J(u) - \Omega \tag{14}$$

$$\forall u \in V \qquad J(u) \geq a(u) * P_t(u) + \sum_{v\in V} \sum_{1\leq i\leq N_r} P_r(u)\Psi^i_{(v,u)} + Cc \tag{15}$$

$$\forall (u,v) \in E, i \in [1, N_r] \qquad P_t(u) * G(u,v) \geq$$
$$\beta(r_i) * \left(\sum_{u'\neq u,v} P_t(u') * G(u',v) + \mu \right) - \left(1 - \Psi^i_{(u,v)}\right) n * P_{max} \tag{16}$$

$$\forall u \in V \qquad \sum_{v\in V} \sum_{1\leq i\leq N_r} \Psi^i_{(u,v)} + \sum_{w\in V} \sum_{1\leq i\leq N_r} \Psi^i_{(w,u)} \leq 1 \tag{17}$$

$$\forall e = (u,v) \in E \qquad r_e = \sum_{1\leq i\leq N_r} r_i \Psi^i_{(u,v)} \tag{18}$$

$$\forall u \in V \qquad P_t(u) \leq P_{max} \tag{19}$$

The decision variables of this linear program are $P_t(u)$, $J(u)$ and $\Psi^i_{(u,v)}$ where $(u,v) \in E$ and $i \in [1, N_r]$. $\Psi^i_{(u,v)}$ is a binary variable which is equal to 1 if the communication between u and v is active, in the new ISet, with a transmission rate equals at least r_i, and to 0 otherwise. The goal is to find a new ISet I where $(\sum_{e\in E} r_e\gamma(e) - \sigma \sum_{u\in V} J(u))$ is maximum (Eq. (14)). If this ISet violates Eq. (12), it may improve the solution of the master program. If not, no other ISet can do and the solution of the master is optimal. The constraints of this ILP define the ISet structure as follows. The energy consumption model, detailed in Subsection 3.3.2, is presented by constraints (15). The constraint (16) ensures that the SINR condition is satisfied for all active links, in the ISet, taking into account the transmission rate used by each one. Note that $(1 - \Psi^i_{(u,v)})n * P_{max}$ equals 0 when the link (u,v) is active, hence the constraint (16) reverts back to the classical interferences constraint (1). Otherwise ($\Psi^i_{(u,v)} = 0$), and finally $n * P_{max}$ ensures that $P_t(u)$ can be equal to 0 (constraint (16) is always respected), where n is the number of nodes. Finally, constraints (17) implies that each node is active in at most one link with one transmission rate in each time-slot. This constraint also ensure the half duplex property where a node cannot transmit and receive simultaneously.
This auxiliary program builds a new ISet I which contains the following physical links: for all $e = (u,v) \in E$ such that $\Psi^i_{(u,v)} = 1$, $l = (e, P_t(u), r_i) \in I$.

Generation of ISets with single-rate In this case, we assume that only a single rate, $r \in R$, is available and that each node can continuously control its transmission power. We study this case using the previous auxiliary program by setting $N_r = 1$.

In this section, we have presented our linear programs, to optimize the network capacity and the energy consumption, and the column generation to solve them. Next, we investigate deeply on energy-capacity tradeoff. We calculate an optimal system setting of the network to minimize the energy consumption (resp. to maximize the capacity) under the requirements of high network capacity (resp. low energy consumption).

5 SINR based model: continuous power control and single-rate

In this section, we assume that each node operates at a fixed transmission rate (fixed MCS) and can tune its transmit power at each transmission. We calculate an optimal routes for data, transmission powers, resources allocation and link schedules.

5.1 Scenarios and Model Parameters

Both the capacity-oriented and energy-oriented formulations, and the column generation algorithm are implemented and tested using AMPL/CPLEX [25,26]. In all our numerical results, we consider the classic path-loss attenuation which is equal to $(\frac{d(u,v)}{d_0})^{-\alpha}$ where $\alpha = 3.6$ is the path loss exponent and $d_0 = 1m$ is the near-field crossover distance. The noise power density is -174 dBm/Hz. We assume that the five MCSs presented in Table 4 are available. Table 3 summarizes all physical parameters. Numerical values are adapted from the models of the EARTH project for small cells [2]. Combining equations (2) and (6), one can get that the energy cost is $Cc * |V|$ plus the variable part of the energy cost which does not depend on Cc. Indeed, the fixed cost of circuit consumption has no impact on the optimization of the transmit power assignment and can therefore be considered as null in the following, up to a constant shift of the numerical results.
We consider both regular and random topologies. The regular network topology has its nodes positioned on a grid. The random topologies are generated with a Poisson process in the Euclidean plane (an example of such topology is depicted in Fig. 8(a)). In all our scenarios, we consider 24 MRs and a gateway located in the network center. Except when otherwise stated, all MRs have the same throughput requirement (the impact of non uniform throughput requirement is investigated in Subsection 6.2). Note that, in ours results, the energy consumption is presented as J/bit, obtained by divided the total power consumption (Watts) by the network capacity (bits/s).

Table 3: Physical layer parameters

Noise power density	-174 dBm/Hz
Scheduling block size	1ms/180 Khz
$Path - lossfunction$	$(\frac{d(u,v)}{d_0})^{-\alpha}$, $\alpha = 3.6, d_0 = 1m$
Maximum transmit power (P_{max})	30dBm
Antenna gain	5dB
Amplifier coefficient (a)	10
Power consumed by the receiver (P_r)	0.5Watt

Table 4: Modulation and Coding Schemes: MCS [22]

MCS	Modulation	CR	$\beta[dB]$	Throughput	Efficiency
MCS1	QPSK	1/2	1	164 Kb/s	0.933 b/s/Hz
MCS2	16QAM	1/2	10	328.12 Kb/s	1.866 b/s/Hz
MCS3	16QAM	3/5	11.40	393.75 Kb/s	2.24 b/s/Hz
MCS4	64QAM	1/2	11.80	492.18 Kb/s	2.8 b/s/Hz
MCS5	64QAM	3/5	13.80	590.625 Kb/s	3.36 b/s/Hz

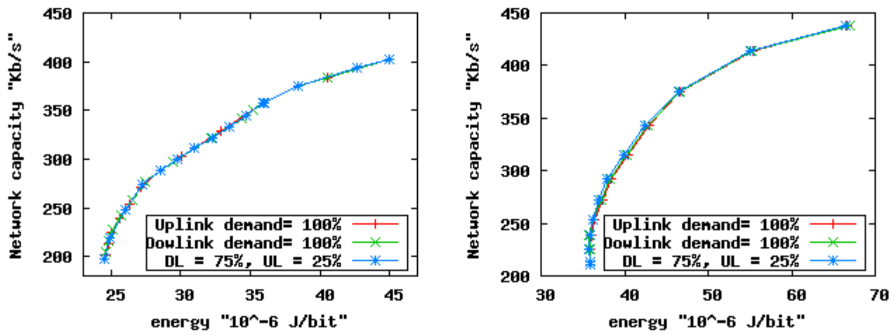
5.2 Capacity and energy tradeoff in case of 1 MCS

5.2.1 Insensitivity of the mix of UL/DL traffic to the energy-capacity tradeoff

the Pareto front of the capacity/energy tradeoff is depicted in Fig. 4 for a grid and a random network using only MCS4. In this study, we consider three scenarios: uplink-only, downlink-only and mixed traffic with 25% uplink and 75% downlink. In each case, a minimal energy budget for the network is required to route all traffic between the MRs and the gateway. We observe that there is no significant impact of the mix of uplink and downlink flows on the energy-capacity tradeoffs. In fact, the capacity is constrained by the activity inside a bottleneck zone around the gateway [27, 23]. In this area, there is no spatial reuse as only one link can be activated at each time either in uplink or downlink. Hence, the network capacity cannot be improved by combining the uplink and downlink flows. Note that the paths of uplink and downlink flows are not necessarily the same since the ISets are different due to the asymmetric interferences.

5.2.2 Impact of the maximum power transmission on energy-capacity tradeoff

Fig. 5 depicts the energy-capacity Pareto fronts on a random topology when the maximum power transmission takes one of three values (10dBm, 15dBm and 21dBm). It shows that increasing the maximum transmission power increases the magnitude of the energy-capacity tradeoff and the maximum network capacity. It also shows that we can achieve a larger network capacity with the same energy expenditure. Indeed, the limit on the power transmission forbids solutions in which a better spatial reuse is achieved with the same energy budget. Higher transmission power induces a higher connectivity in the network, in



(a) Grid network (b) Random network

Figure 4: Capacity and energy tradeoff, using MCS4 and $P_{max} = 15dBm$, in the case of uplink-only, downlink-only and mixed traffic (25% uplink + 75% downlink).

particular around the gateway. Intuitively, in the bottleneck area, going directly to the gateway saves time despite a lesser spatial reuse.

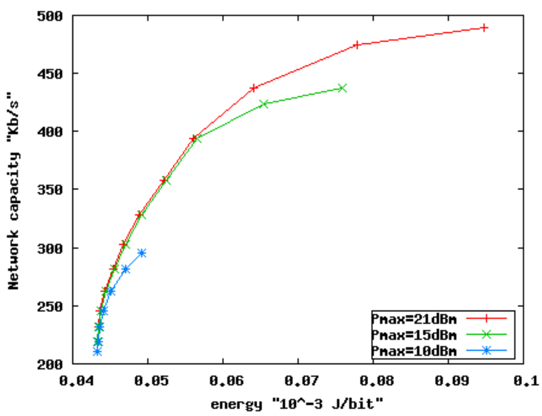


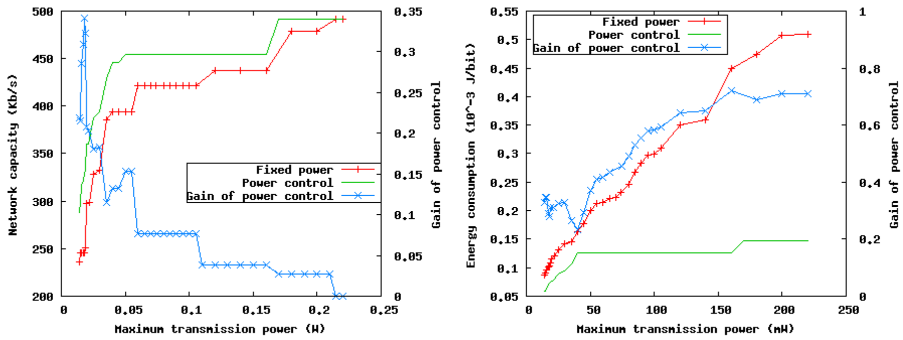
Figure 5: Impact of maximum power transmission on energy-capacity tradeoff: random network with MCS4.

5.2.3 Gain due to power control

The gain of enabling continuous power control is illustrated in Fig. 6(a) and Fig. 6(b) which present, respectively, the network capacity and the energy consumption in the case of power control and fixed power[1]. Let P_{1hop} be the transmission power which allows all MRs to communicate with the gateway directly at single-hop (single-hop network). Fig. 6(a) shows that when $P_{max} < P_{1hop}$, the use of continuous power control is very beneficial to increase the network

[1]The fixed power is equal to the maximum transmission power

capacity and the energy consumption. It adjusts the transmit power in order to reduce the interferences, which increases the spatial reuse and thus improves the throughput. When $P_{max} \geq P_{1hop}$, continuous power control and fixed power leads to the same network capacity. In the case of fixed power, this capacity is obtained with high transmission power and, hence, with high energy consumption. Interestingly, power control allows to achieve this capacity with multi-hop communications and lower transmission power which provides about 70% of energy conservation.
To summarize, it is obvious that there is a key advantage of using continuous power control: firstly, the network capacity is higher (about 13% of average gain). Secondly, the energy consumption is much lower (energy conservation between 30% and 70%). It is important to highlight that in the case of continuous power control, the energy consumption increases only if the network capacity increases.



(a) Network capacity (b) Energy consumption

Figure 6: Impact of maximum transmission power and gain due to power control: random network using MCS4

6 Multi-rate transmission and optimal system setting

Given an ISet I, each link $l = (u, v, P_t, r) \in$ I is activated during w(I) with the transmission rate $r(l) \in R$. An optimal system setting consists in finding, for each communication, the best MCS_j with a transmission power that minimizes the overall energy consumption and maximizes the network capacity. The main question to be addressed is how $MCSs$ and power should be allocated to each transmission.
In this section, we consider the five MCS presented in Table 4. Note that the energy consumption and the capacity are linked to the MCS used. Intuitively, higher modulation means higher throughput and capacity but require more power transmission to meet the SINR threshold constraint. This increases the tradeoff between capacity and energy consumption.

To further illustrate this tradeoff, we study a simple scenario of a single communication between a source and destination. The energy consumption per bit (J/bit) for each transmission rate (or MCS) is depicted in Table 5 and calculated

Table 5: MCS vs energy consumption per bit (J/bit)

MCS	Energy consumption per bit
MCS1	2.43 10^{-6} J/bit
MCS2	9.64 10^{-6} J/bit
MCS3	11.09 10^{-6} J/bit
MCS4	9.73 10^{-6} J/bit
MCS5	12.85 10^{-6} J/bit

by divided the energy consumption by the total number of bits transmitted in a time-slot. We observe that MCS1 is the most energy efficient but it is the lowest in terms of throughput while MCS5 leads to the higher throughput.

Under this scenario with an isolated link, transmitting power and throughput are bounded by the MCS characteristics which results in a tradeoff on the energy efficiency. As seen in Section 5, in a scenario with several nodes and concurrent communications, the interferences and the spatial reuse induce a tradeoff between the overall energy consumption and capacity. In the following section, we study the tradeoff in a network when the nodes can perform continuous power control and use a multi-rate transmission.

Next, we assume that the MCS presented in Table 4 are available for each node. For each network, an optimal solution is calculated: network capacity, energy consumption, routing, resource allocation, physical parameters of each node (transmit power and MCS used for each transmission), and activation time of each communication.

6.1 Energy and Capacity Tradeoff

To reduce the complexity and the computing time, but without loss of generality, we eliminate the MCS1 (which dramatically increases the number of available links and leads to prohibitive computation times) and use only the 4 other MCSs. The tradeoff between energy consumption and network capacity is depicted in Fig. 7 which presents the fixed power case and the continuous power control one. This figure shows an important tradeoff between capacity and energy consumption. This tradeoff is the result of the use of different MCS and the impact of the spatial reuse. In the control power case, the most energy efficient solution (J_{min}) activates only one link on each time-slot with the lowest MCS. This is, of course, at the cost of achieving the worst network capacity: increasing the number of simultaneous communications and using high modulations increase the capacity but consume more energy.

Comparing the energy-capacity tradeoff obtained with the two scenarios highlights that the continuous power control increases the magnitude of the tradeoff (the capacity varies between 140 and 450 Kb/s), and allows to achieve higher network capacity with lower energy consumption.

6.2 Impact of topology and throughput requirement

Most of previous results are obtained with random network and homogeneous throughput requirement. We investigate on the impact of throughput require-

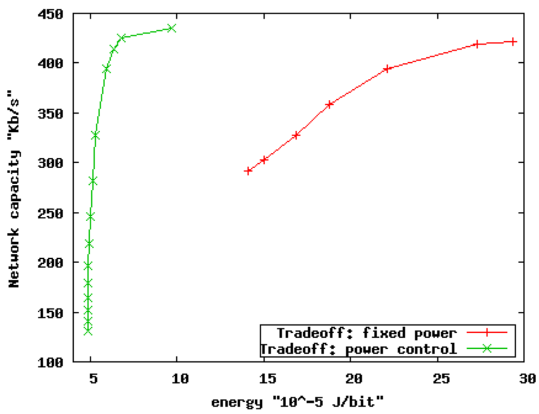


Figure 7: Energy and capacity tradeoff: fixed power vs continuous power control (random network and mutli-rate transmission)

ment distribution (represented by the weight d_u) and the topology on the energy-capacity tradeoff.

6.2.1 Impact of topology

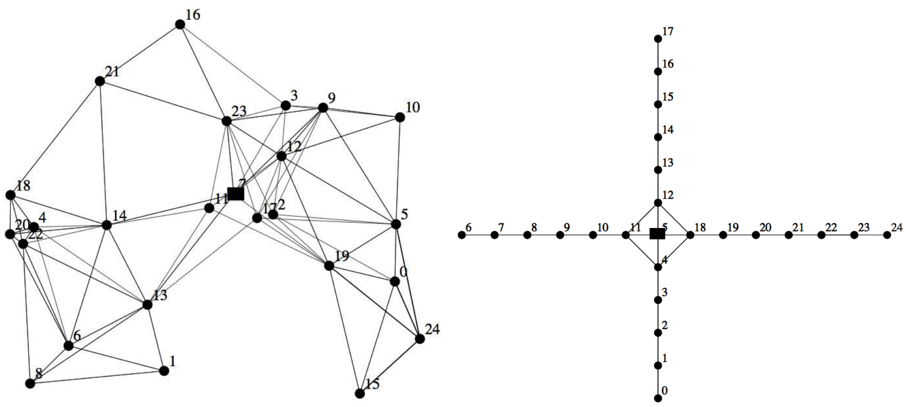
In addition to the grid and the random topologies, we consider an urban network where 24 MRs are placed around a street crossing with fixed inter-node distance, the gateway being placed at the intersection (marked as a square node). The maximum connectivity graph of the random and urban topologies are presented, respectively, in Fig. 8(a) and Fig. 8(b). The characteristics of these networks are presented in Table 6. The maximum and the minimum number of links are obtained, respectively, if all nodes use the lowest and highest MCS.

The impact of the topology is illustrated by Fig. 9. The three curves (grid, random and urban network) evolve similarly but with different interval and slope. The random network have the highest capacity compared to the others. This can be explained by the fact that in this network the number of nodes connected directly to the gateway is more important than the others. This increases the capacity and minimizes the energy consumption. Following the characteristics of the networks presented in Table 6[2], the urban network has the largest average number of hops. Consequently, it needs more energy consumption to achieve the same network capacity than grid or random network.

Table 6: Characteristics of different topologies:

Characteristics	Grid	Random	Urban
Nodes number	25	25	25
Max links cardinality	144	170	56
Min links cardinality	80	108	56
Average number of hops	1.66	1.58	3.5

[2]Due to the continuous power control and the MCS used, the radio links cardinality evolves.



(a) Random topology (b) Urban topology

Figure 8: Random and urban networks

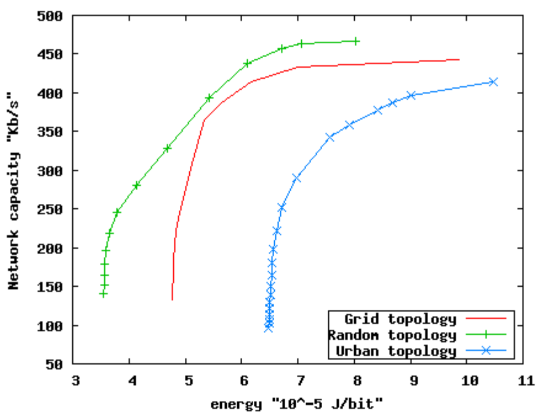


Figure 9: Capacity and energy tradeoff with multi-rate transmission and continuous power control: impact of topology.

6.2.2 Impact of throughput requirement

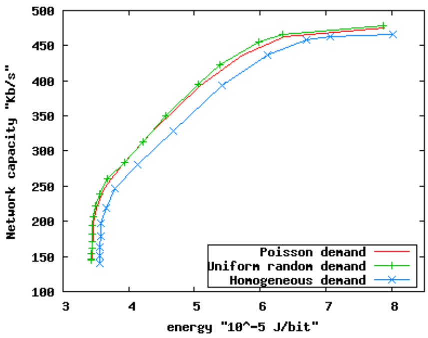
We study here the impact of the throughput requirement distribution on the energy-capacity tradeoff. We compare the following distributions with the same mean value [3].

- Homogeneous distribution: all MRs have the same weight.
- Uniform random distribution: weights are distributed uniformly and independently.

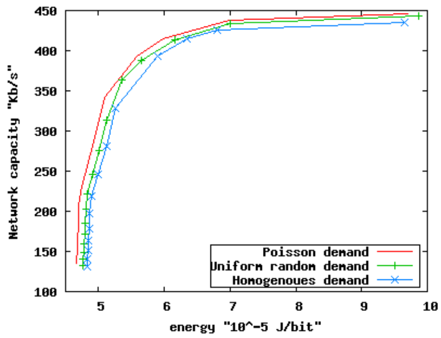
[3] The optimization problem being linear and the results being reported as J/b and Kn/s, the actual value of the mean requirement has no impact on the numerical results. For our simulations it was set to 2.

- Poisson random distribution: weights are distributed according to a Poisson distribution.

The results are reported in Fig. 11 which presents the energy-capacity tradeoff as a function of weight distribution in the case of grid and random networks. The impact of the throughput requirement on the energy-capacity tradeoff is very low. Indeed, the traffic load distribution is not very important, the bottleneck area around the gateway has the most impact on capacity. We also studied the case of high traffic load concentrated in an area. Fig. 11(b) showed that the impact of the weight distribution is significant when there is a traffic load concentrated in an area creating another bottleneck area. Fig. 11(a) shows an impact of the distance between the bottleneck and the gateway: the energy consumption decreases when the bottleneck is near the gateway, while the network capacity is almost the same. Based on this observation, it is worth considering the bottleneck-gateway distance parameter upon the network planning and design.



(a) Random topology, continuous power control



(b) Grid topology, continuous power control

Figure 10: Capacity and energy tradeoff with multi-rate transmission and continuous power control: impact of weight distribution.

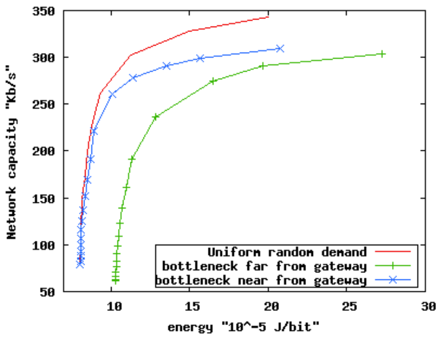
7 Discussion and Conclusion

7.1 Discussion

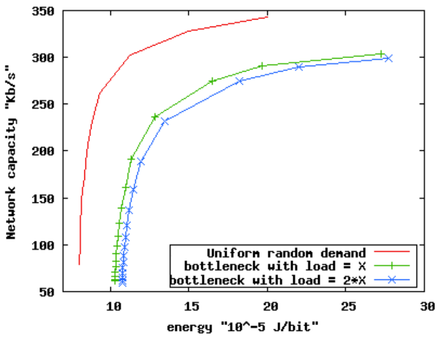
In this section we discuss the main contributions of this paper with respect to other results of the literature. This discussion is divided into two parts: the first is about our optimization framework presented in Section 4. The second part is about the network design insights which can be deduced from our results.

7.1.1 Optimization framework

In this work, we presented a flexible framework based on a linear program model and a column generation algorithm. In contrast to [4,27] which present a binary interference model with fixed power, our optimization model is generic and can



(a) Impact of the distance between the bottleneck and the gateway on the energy-capacity tradeoff



(b) Impact of the magnitude of bottleneck on the energy-capacity tradeoff

Figure 11: Impact of bottleneck on energy-capacity tradeoff with MCS3 and continuous power control.

Table 7: Total solve time for each scenario.

Scenario	Total solve time (s)
Binary model	2.6
SINR with continuous power control: single-rate	80.03
SINR with power control and multi-rate	2523.98

take any interferences and energy model into account. The complexity of this framework depends on the degree of accuracy of used functionalities (power control, multi-rate and SINR-based model). The deeper we investigate, the higher the computing complexity is. Table 7 presents the total computation time[4] for some scenarios. The total solve time of a scenario with five MCS on a 25 nodes grid network is about 10^3 times greater than the case of binary interference model. A deeper challenge is to minimize this complexity to cope with larger network size.

Most of the works in the literature are restricted to the optimization of the capacity. Furthermore, the power control used is restricted to a small set of power levels [8,5,9,10]. Our framework is based on a linear program and allows maximizing the capacity or minimizing the energy consumption. In addition to that, we modeled a more realistic physical layer based on SINR interferences, continuous power control, and multi-rate transmission.

7.1.2 Network design guidelines

Several works in the literature have focused on maximizing the capacity or minimizing the energy consumption, but investigating the tradeoff between them has received less attention. The study of this tradeoff is one of the main contributions of this paper. We showed that the magnitude of the energy-capacity tradeoff increases with continuous power control (Section 5) and the multi-rate

[4]The sum of user CPU time and system CPU time used to solve commands.

transmission (Section 6). [28] discussed under which circumstances energy efficiency and throughput can be jointly maximized, and when they constitute different objectives. In the context of p-persistent CSMA based WLAN, the authors highlighted that power saving and throughput do not constitute antagonistic objectives and can be jointly achieved. The advantages of the continuous power control are shown in section 5 and 6. The network capacity and the energy consumption are optimized by reducing the power transmission and the interferences. This confirms the results of [8,5,6] which show that power control (set of power levels) improves the spatial reuse and hence improves the throughput. Ours results show that the use of multi-rate transmission is beneficial to give the best capacity and energy consumption. Moreover, we investigate several topologies and weight distribution. We highlighted that the weight distribution has no impact on the energy and capacity: only the congestion area around the gateway's neighborhood is important and influences the energy-capacity tradeoffs, which is coherent with previous works on capacity [4, 5, 27].

7.2 Conclusion and perspectives

Operating a wireless mesh networks, while the goal is to achieve high data rate with minimum energy consumption, is a crucial challenge. In this paper, we addressed the problem of network capacity and energy consumption optimization in WMN using a MAC layer based on S-TDMA. A set of novel linear programming models using a column generation algorithm was presented. The later computes a linear relaxation of the Routing and Scheduling Problem with a realistic SINR model and continuous power control. Since the objective of maximizing the network capacity is often in conflict with the objective of energy minimization, we carried out a thorough study of the tradeoff between them. We investigated the problem of the joint resources, MCS, and transmission power allocation to find an optimal system setting of the backhaul network.

Among our goals of using optimization tools is to develop protocols based on optimization results to maximize the capacity with efficient energy consumption. Based on the studies presented in this paper, we obtained a strategy of routing and MCS distribution. Communicate directly with the gateway in the congestion area (around the gateway), using MCS with high throughput (MCS4 and MCS5), and with multi-hop communications in the outside combined with spatial reuse is the most valuable way to significantly increase the network capacity with respect to a minimum energy consumption. The implementation and testing of a protocol based on this approach is one of our goals of future work.

8 Acknowledgment

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