Energy Consumption Optimization for Multihop Cognitive Cellular Networks

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Abstract—Cellular networks are faced with serious congestions nowadays due to the recent booming growth and popularity of wireless devices and applications. Opportunistically accessing the unused licensed spectrum, cognitive radio can potentially harvest more spectrum resources and enhance the capacity of cellular networks. In this paper, we propose a new multihop cognitive cellular network (MC^{2}N) architecture to facilitate the ever exploding data transmissions in cellular networks. Under the proposed architecture, we then investigate the minimum energy consumption problem by exploring joint frequency allocation, link scheduling, routing, and transmission power control. Specifically, we first formulate a maximum independent set (MIS) based energy consumption optimization problem, which is a non-linear programming problem. Different from most previous work assuming all the MISs are known, finding which is in fact NP-complete, we employ a column generation based approach to circumvent this problem. We develop an ϵ-bounded algorithm, which can obtain a feasible solution that are less than $(1+\epsilon)$ and larger than $(1-\epsilon)$ of the optimal result of MP, and analyzed its computational complexity. We also revisit the minimum energy consumption problem by taking uncertain channel bandwidth into consideration. Simulation results show that we can efficiently find ϵ-bounded approximate results and the optimal result as well.

Index Terms—Multihop cognitive cellular networks, energy consumption, cross-layer optimization

1 Introduction

The booming growth and popularity of wireless devices like smartphones have resulted in the surge of various mobile applications, such as anywhere anytime online social networking, mobile gaming, and mobile video services, which have exacerbated the congestion over cellular networks. On the other hand, recent studies show that many licensed spectrum blocks are not effectively used in certain geographical areas and are idle most of the time [1], [2]. Since Federal Communications Commission (FCC) opens the discussions on intelligently sharing licensed spectrum, there has been a flux of research activities on cognitive radio (CR), which enables unlicensed users to opportunistically access the unused licensed spectrum as long as their usage does not cause disruptive interference to the licensed holders' service provisioning. Moreover, enabling multihop communications between nodes and base stations (BS), multihop cellular network has been proposed as an extension of the conventional single-hop cellular network. Previous works like [3] have shown that multihop cellular networks can achieve higher capacity than traditional cellular networks. Therefore, a new architecture taking advantage of such promising technologies is in dire need to improve the performance of cellular networks.

In this paper, we propose a multihop cognitive cellular network (MC^{2}N) architecture by jointly taking the advantage of CR techniques and multihop cellular networks to support the ever-exploding traffic demand in cellular networks. In particular, we propose to equip both cellular base stations and network users with CRs. Instead of delivering all the traffic between base stations and users in one hop like that in traditional cellular networks, we propose to carry such traffic in hybrid mode, i.e., either in one-hop or via multiple hops depending on the local available spectrums and the corresponding spectrum conditions. In so doing, we can further take advantage of local available channels, frequency reuse, and link rate adaptivity to provide higher network throughput and decrease energy consumption.

Since the users' wireless devices are usually battery-powered, energy consumption is obviously a crucial issue in cellular networks. Although there have been quite a few works on energy consumption optimization in wireless networks [4]–[19], unfortunately, so far there has been a lack of a complete cross-layer solution to the energy consumption problem. Besides, the architecture of MC^{2}Ns makes the minimum energy consumption problem unique and even more challenging. Thus, under the proposed architecture, in this study we investigate the minimum energy consumption problem by exploring joint frequency allocation, link scheduling, routing, and transmission power control, with Physical Model being the interference model. We consider M-order quadrature amplitude modulation (M-QAM) schemes at the physical layer.

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We first formulate a maximum independent set (MIS) based energy consumption problem, which we call Master Problem (MP) and is a non-linear programming (NLP) problem. We notice that finding all the maximal independent sets is NP-complete when transmission powers are fixed, and hence even more difficult when transmission powers are controllable as in our case. Although most previous research simply assumes that MISs are given [20], [21], we do not make such assumptions. Instead, we employ a column generation (CG) based approach to decompose MP into a Restricted Master Problem (RMP) and a Pricing Problem (PP). Noticing that RMP can be solved in polynomial time but PP is still very difficult to solve, we further decompose PP into two separate problems, namely, Link-Band Pair Selection (LBPS) and Power Allocation (PA), which are a Binary Integer Programming (BIP) problem and an LP problem, respectively. By iteratively solving these two problems, we are able to find a suboptimal result for PP. Although the result for PP obtained by our proposed scheme is suboptimal, we can still find the optimal solution to MP due to the intrinsic iterative nature of column generation. Besides, it has been observed in the context of column generation algorithms [22], [23] that one can usually determine solutions that are at least 95–99 percent of the global optimality fairly quickly. Subsequently, we develop an ϵ-bounded approximation algorithm, which can obtain a feasible solution that achieves less than $(1+\epsilon)$ of and larger than $(1-\epsilon)$ of the optimal result of MP. We also theoretically analyze the computational complexity of the proposed algorithm. Simulation results show that we can efficiently find ϵ-bounded approximate results and the optimal result as well, i.e., when $\epsilon = 0\%$ in the algorithm. In other words, we are able to solve MP very efficiently without having to find the maximum independent sets.

Moreover, although most previous research on CR networks assumes that the harvested spectrums have constant bandwidths, in practice, due to the unpredictable activities of primary users, the vacancy/occupancy of licensed spectrum are uncertain in nature [1], [24]. In this study, we also revisit the minimum energy consumption problem by taking uncertain spectrum occupancy into consideration.

The rest of this paper is organized as follows. Section 2 introduces the most related work. In Section 3, we briefly explain our system models, including network architecture, network model, and link capacity model. We then formulate a minimum energy consumption problem for MC^{2}Ns in Section 4. After that, we propose in Section 5 a column generation based ϵ-bounded approximation algorithm which can efficiently find ϵ-bounded approximate solutions and the optimal solution when $\epsilon = 0$. Subsequently, we revisit the minimum energy consumption problem by considering dynamic spectrum bandwidth in Section 6. The impact of adaptive M-QAM schemes on the system performance is studied in Section 7. Simulations are conducted in Section 8 to evaluate the performance of the proposed algorithms. We finally conclude this paper in Section 9.

2 Related Work

In this section, we discuss related work on multihop cellular networks, energy consumption in wireless networks, and the column generation approach.

In traditional cellular networks, ad hoc communications are introduced to deliver information among users [25]–[27], but every user still communicates with base stations directly in one hop, which leads to low frequency spatial reuse and hence low throughput. Considering multi-hop communications between nodes and base stations, some works such as [3] investigate the capacity of multihop cellular networks, which has been shown to be much higher than that of traditional cellular networks. The works [28], [29] also show that multihop transmissions can improve the multicast throughput of cellular networks. However, these works only consider the case where nodes share the cellular channels and have not exploited the local available secondary channels as we propose in this study. Moreover, the energy consumption optimization problem is not discussed.

In the literature, energy consumption has always been a primary concern in wireless networks. A big chunk of work addresses this problem by developing energy-efficient medium access control [4]–[7] or routing [8], [9] algorithms. In ad hoc networks, some researchers [10]–[12] try to minimize energy consumption by controlling transmission power. Energy efficiency is also studied in CR ad hoc networks [13]–[19]. [13]–[17] focus on energy efficiency in cooperative spectrum sensing. Buzzi and Saturnino [18] investigate energy-efficient power control and receiver design in CR networks by proposing a noncooperative power control game among the users. Bayhan and Alagz [19] study the energy efficiency in CR networks considering link capacity and channel switching cost. However, these works do not give a complete cross-layer solution to the energy consumption problem.

As an efficient method to solve large-scale optimization problems, column generation has been utilized in cross-layer optimization in wireless networks [30]–[36]. Patrik et al. [30] and [31] employ column generation to find suboptimal solutions to their optimization problems. Fu et al. [32] develop a column generation based fast algorithm for joint power control and scheduling in single-hop wireless network. Zheng et al. [33] study joint congestion control and scheduling, without considering routing. Johansson and Xiao [34], Cao et al. [35], Kompella et al. [36] propose cross-layer design for wireless network under the multi-commodity flow model, where each link is assumed to operate at one of predetermined data rates. Note that many previous works cannot bound the gaps between their suboptimal results and the optimal results. Compared with the above works adopting column generation, our problem formulation and the algorithm design are completely different.

3 System Models

3.1 Network Architecture

We consider a multihop cognitive cellular network in which both base stations and network users are equipped with cognitive radios, as shown in Fig. 1. In particular, base stations and more powerful terminals (e.g., laptops and tablets) can have higher cognitive capability and span a larger range of frequency spectrum (e.g., from MHz bands to GHz bands), while less powerful devices (e.g., smart phones and

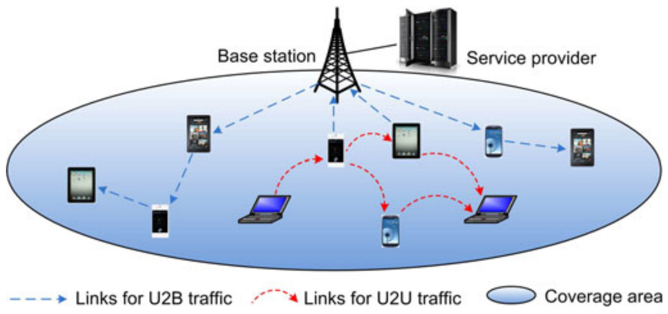

Fig. 1. The architecture of a multihop cognitive cellular network.

cellular phones) may just access several typical spectrum bands, such as the cellular band, the 2.4 GHz ISM bands, and the TV band which has large bandwidth and good penetration and propagation performances. We call cellular band "the basic band", and other bands "the secondary bands". The service provider uses the basic channel for signaling, controlling, handling handoffs, accommodating users' voice traffic, etc., and uses all the available channels to support users' data traffic. As a central coordinator, the service provider purchases secondary bands, and performs network optimization to find out the optimal transmission power, radio and frequency allocation, link scheduling, and routing schemes for satisfying users' traffic demands, based on the observed, collected, and predicted channel information [24], [37], [38] in the coverage area. The control messages can be exchanged over a dedicated channel called cognitive pilot channel (CPC) or common control channel as illustrated in IEEE 802.22 [39] and in [40].

As shown in Fig. 1, we consider supporting two types of traffic in the network: the traffic between users and base stations (U2B) and the traffic between users (U2U). Notice that as discussed in our previous work [41], [42], the service provider can decide to route U2U traffic through the backhaul network when the source and the destination are far away from each other, e.g., when they are not in the same cellular cell or not within certain number of hops of each other, in order to maximize network capacity. In that case, one U2U communication changes into two U2B communications, i.e., uplink and downlink communications in the source cell and destination cell, respectively. Without loss of generality, we simply refer to U2U traffic as the traffic that does not go through the backhaul network in what follows. Note that instead of delivering all the U2B traffic in one hop like that in traditional cellular networks [41]–[43], we propose to carry U2B traffic either in one-hop or via multiple hops, depending on the local available channels and the corresponding channel conditions. Therefore, the proposed architecture can enhance the performance of cellular networks by taking advantage of local secondary bands and link rate adaptivity.

3.2 Network Model

Consider a cell in a multihop cognitive cellular network consisting of $\underline{\mathcal{N}} = \{1, 2, \ldots, n, \ldots, N\}$ users and a set of available secondary spectrum bands $\underline{\mathcal{M}} = \{1, 2, \ldots, m \ldots, M\}$ with different bandwidths. We denote the base station by B and the basic band by 0, and consequently let $\mathcal{N} = \underline{\mathcal{N}} \cup \{B\}$ and $\mathcal{M} = \underline{\mathcal{M}} \cup \{0\}$. The bandwidth of band m is denoted by W^m. The transmission power of node i to node j on band m is denoted by P_{ijm}. Suppose there are a set of $\mathcal{L} = \{1, 2, \ldots, l, \ldots L\}$ sessions, including uplink U2B, downlink U2B, and U2U traffic. We let $s(l)$ and $d(l)$ denote the source node and the destination node of session $l \in \mathcal{L}$, respectively, and also denote by $r(l)$ the traffic demand of session l, with the unit of bits per second (bps). The users are allowed to access the secondary bands when the primary services on these bands are not active, but they must evacuate from these bands immediately when primary services return. Besides, due to their different geographical locations, the users in the network may have different available secondary spectrum bands. Let $\mathcal{M}_i \subseteq \mathcal{M}$ represent the set of available licensed bands at node $i \in \mathcal{N}$. Then $\mathcal{M}_i$ might be different from $\mathcal{M}_j$, i.e., $\mathcal{M}_i \neq \mathcal{M}_j$, where $j \in \mathcal{N}$ and $j \neq i$[1].

3.3 Achievable Data Rate

Here we discuss the achievable data rate over a channel.

We employ a widely used model [44]–[46] for power propagation gain between node i and node j, denoted by g_{ij}, as follows:

$$g_{ij} = [d(i,j)]^{-\gamma},$$

where i and j also denote the positions of node i and node j, respectively, $d(i,j)$ refers to the Euclidean distance between i and j, and γ is the path loss exponent.[2]

We consider that the network adopts a constant M-order quadrature amplitude modulation scheme in an additive white Gaussian noise (AWGN) wireless environment with a target bit error rate (BER) of P_b. According to [44], the BER of M-QAM on an AWGN channel is shown to be well approximated by

$$P_b \approx 0.2\exp\left(\frac{-1.5\mathrm{SINR}}{M-1}\right), \tag{1}$$

where SINR is the received signal-to-interference plus noise ratio at the receiver. In addition, we adopt the Physical Model [50], [51] as the interference model, which means that a data transmission is successful only if the received SINR is above a certain threshold Γ. In particular, if node i sends data to node j on link (i,j) using band m, the achievable data rate over link (i,j) on band m is

$$c_{ijm} = \begin{cases} C^m \text{ bits/sec}, & \text{if } \mathrm{SINR}_{ijm} \geq \Gamma \\ 0, & \text{otherwise,} \end{cases} \tag{2}$$

where SINR_{ijm}, the SINR of the signal received at j from i on channel m, is

1. Note that in this study we only consider the energy consumption optimization in one cell. The interference from other cells can be addressed, for example, by frequency planning. The technique presented in this paper can also be directly applied to address multiple-cell scenarios.

2. In this paper, we assume that the coherence bandwidth of each band is larger than its bandwidth so that each band is flat, and that the coherence time of the channel is larger than the duration of a time slot so that the fading remains constant in each time slot. This is a common assumption made in the literature on resource management in cellular networks, such as [47]–[49].

$$\mathrm{SINR}_{ijm} = \frac{g_{ij}P_{ijm}}{\eta_j W^m + \sum_{k\in\mathbb{T}_i^m, v\neq j} g_{kj}P_{kvm}}.$$

Here, $\mathbb{T}_i^m$ is the set of nodes transmitting on channel m at the same time as i, and η_j is the thermal noise power density at the receiver j.

From both (1) and (2), in order to achieve BERs which are no larger than P_b, the threshold Γ can be set as

$$\Gamma = -\frac{(M-1)\ln(5P_b)}{1.5}. \quad (3)$$

Assume that the modulation uses ideal Nyquist data pulse. Then, the spectral efficiency of M-QAM is $\log_2 M$ bps/Hz [44]. Therefore, in (2), C^m, i.e., the constant data rate on band m, can be calculated as

$$C^m = W^m \log_2 M.$$

In other words, the achievable data rate on a channel is proportional to its bandwidth under a given modulation scheme M-QAM.

Note that when an adaptive M-QAM scheme is used instead, the constellation size can be $M = 2^t, t = 1, 2, \ldots, T$, making the spectral efficiency equal to $t = 1, 2, \ldots, T$ bps/Hz. Thus, the achievable data rates over a channel can be T discrete values. This is in fact the case in some current off-the-shelf IEEE 802.11 compliant products [52], [53]. In this study, we will first consider a constant M-QAM modulation scheme and then an adaptive M-QAM modulation scheme (in Section 7) to fully characterize the achievable data rates.

4 Energy Consumption Optimization

In this section, we investigate the energy consumption optimization problem for an MC^{2}N by joint frequency allocation, link scheduling, routing, and transmission power control, considering a constant M-QAM modulation scheme.

4.1 Link Scheduling and Routing Constraints

We define a link-band pair $((i,j),m)$, which indicates a transmission link (i,j) (from i to j) operating on band m. We also define an independent set as a set in which each element is a link-band pair standing for a transmission, and all the elements (or transmissions) can be carried out successfully at the same time, i.e., $\mathrm{SINR}_{ijm} \geq \Gamma$ for any $((i,j),m)$ belonging to the IS. If adding any more link-band pairs into an IS results in a non-independent one, this IS is defined as a maximum independent set. We denote the set of all the MISs in the network by $\mathcal{K} = \{\mathcal{I}_1, \mathcal{I}_2, \ldots \mathcal{I}_q, \ldots, \mathcal{I}_Q\}$, where $Q = |\mathcal{K}|$. We will show in the next section that we do not really need to find the maximum independent sets. In what follows, we present the link scheduling and routing constraints.

4.1.1 Link Scheduling Constraints

Denote the maximum independent set $\mathcal{I}_q$'s $(1 \leq q \leq Q)$ time share (out of unit time 1) to be active by w_q. Since at any time instance, there should be only one active maximum independent set to ensure the success of all the transmissions, we have

$$\sum_{1\leq q\leq Q} w_q \leq 1, \quad w_q \geq 0 \ (1 \leq q \leq Q). \quad (4)$$

Let $c_{ijm}(\mathcal{I}_q)$ be the data rate on link (i,j) over band m when $\mathcal{I}_q$ is active. Then, $c_{ijm}(\mathcal{I}_q)$ is equal to 0 if the link-band pair $((i,j),m) \notin \mathcal{I}_q$, and determined according to (2) otherwise. For node $i, j \in \mathcal{N}$, we denote by $f_{ij}(l)$ the flow rate of session l over link (i,j). Thus, the schedule of the maximum independent sets should satisfy the following:

$$\sum_{l\in\mathcal{L}}^{i\neq d(l), j\neq s(l)} f_{ij}(l) \leq \sum_{q=1}^{Q} w_q \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ijm}(\mathcal{I}_q). \quad (5)$$

4.1.2 Routing Constraints

At the network level, a source node may need a number of relay nodes to route its data packets toward the intended destination node. Clearly, routing packets over a single path may not be able to fully take advantage of local available channels. Therefore, in this study, we employ multipath routing to deliver packets more effectively and efficiently.

Recall that $f_{ij}(l)$ is the data rate on link (i,j) that is attributed to session l. If node i is the source of session l, i.e., $i = s(l)$, then we have the following constraints:

$$\sum_{j\neq s(l)} f_{js(l)}(l) = 0, \quad (6)$$

$$\sum_{j\neq s(l)} f_{s(l)j}(l) = r(l). \quad (7)$$

The first constraint means that the incoming data rate of session l at its source node is 0. The second constraint means that the traffic for session l may be delivered through multiple nodes on multiple paths, and the total data rate on all outgoing links is equal to the corresponding traffic demand $r(l)$.

If node i is an intermediate relay node for session l, i.e., $i \neq s(l)$ and $i \neq d(l)$, then

$$\sum_{j\neq s(l)} f_{ij}(l) = \sum_{p\neq d(l)} f_{pi}(l), \quad (8)$$

which indicates that the total incoming data rate at a relay node is equal to its total outgoing data rates for the same session.

Moreover, if node i is the destination node of session l, i.e., $i = d(l)$, then we have

$$\sum_{j\neq d(l)} f_{d(l)j}(l) = 0, \quad (9)$$

$$\sum_{p\neq d(l)} f_{pd(l)}(l) = r(l). \quad (10)$$

The first constraint means that the total outgoing data rate for session l at its destination $d(l)$ is 0, while the second constraint indicates that the total incoming data rate for session l at the destination $d(l)$ is equal to the corresponding traffic demand $r(l)$.

4.2 Energy Consumption Optimization

The objective of this study is to exploit both the basic and the secondary spectrum bands to minimize the total energy consumption in the network required to support certain traffic demands. Gathering information about spectrum availability in the network, the service provider can achieve this goal by optimally determining end-to-end paths, scheduling the transmissions and selecting transmission power on each active link-band pair.

We consider the network works in a time-slotted fashion and denote the length of a time slot by T. Let $P_{ijm}(\mathcal{I}_q)$ denote the power consumption on link (i,j) over band m when $\mathcal{I}_q$ is active. Then, $P_{ijm}(\mathcal{I}_q)$ is equal to 0 if the link-band pair $((i,j),m) \notin \mathcal{I}_q$, and equal to $P_{ijm} + P_r$ otherwise, where P_r is the receiver's power for receiving a packet, which we assume to be a constant for all nodes on all the bands. Thus, in an MC^{2}N, the energy consumption optimization problem under the aforementioned link scheduling and routing constraints can be formulated as follows:

$$\begin{aligned} &\textbf{Min} \quad \psi = \sum_{q=1}^{Q} w_q T \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} P_{ijm}(\mathcal{I}_q) \\ &\textbf{s.t.} \quad \text{Constraints } (4)-(10) \\ &f_{ij}(l) \geq 0 \;\; (l \in \mathcal{L}, i,j \in \mathcal{N}) \end{aligned} \tag{11}$$

$$0 \leq P_{ijm} \leq P^i_{\max} \;\; (i,j \in \mathcal{N}, m \in \mathcal{M}_i \cap \mathcal{M}_j), \tag{12}$$

where w_q's, $f_{ij}(l)$'s and P_{ijm}'s are the optimization variables. In this optimization problem, the objective function is the total energy consumption in one time slot in the network, (4) indicates that the total scheduling length can be no larger than one time unit, (5) shows that the total flow rate over link (i,j) cannot exceed the link capacity, (6)–(10) are the routing constraints, (11) means the flow rate is non-negative, and (12) indicates that the transmission power of node i cannot exceed its maximum transmission power, i.e., $P^i_{\max}$.

Given all the maximum independent sets in the network, we find that the formulated optimization problem is a linearly constrained quadratic programming (QP), or a quadratic programming problem. Although it is shown in [54] that a QP can be transformed to an LP problem, finding all the maximal independent sets in a network is still an NP-complete problem [55], [56]. Moreover, in our problem the MISs are coupled with the selection of transmission powers, which makes the problem even more difficult to solve. In the rest of this paper, we call this optimization problem the master problem, and denote the minimum total energy consumption by ψ^*.

5 A Column Generation Based Efficient ϵ-Bounded Approximation Algorithm

Notice that MP is formulated given that we have already known all the maximum independent sets $\mathcal{K}$. However, finding all the maximum independent sets is an NP-complete problem [55], [56]. In this section, to circumvent this difficulty and efficiently solve MP, we propose a column generation based ϵ-bounded approximation algorithm, which can efficiently find the ϵ-bounded approximate results and the optimal result as well, i.e., when $\epsilon = 0$ in the algorithm, without enumerating all the maximum independent sets.

5.1 Column Generation

Column generation is an iterative approach for solving huge linear or nonlinear programming problems, in which the number of variables (columns) is too large to be considered completely [22]. Generally, only a small subset of these variables are non-zero values in an optimization solution, while the rest of the variables (called *nonbasis*) are zeros. Therefore, CG leverages this idea by generating only those critical variables that have the potential to improve the objective function. In our case, MP is decomposed into a Restricted Master Problem and a Pricing Problem. The strategy of this decomposition procedure is to operate iteratively on two separate, but easier, problems. During each iteration, PP tries to determine whether any columns (i.e., independent sets) uninvolved in RMP exist that have a negative reduced cost,[3] and adds the column with the most negative reduced cost to the corresponding RMP, until the algorithm terminates at, or satisfyingly close to, the optimal solution.

Notice that the optimal result of MP remains the same when we consider all the independent sets $\overline{\mathcal{K}}$ which include all the maximum independent sets $\mathcal{K}$. Thus, we consider that RMP starts with a set of initial feasible independent sets, say $\mathcal{K}'$, and certain fixed transmission power for each link-band pair in each independent set. In particular, $\mathcal{K}'$ can be easily formed by placing just one link-band pair $((i,j),m)$ in each of them, with the initial transmission power P_{ijm} for each link-band pair set to its maximum value $P^i_{\max}$. Consequently, RMP can be formulated as follows:

$$\begin{aligned} &\textbf{Min} \; \overline{\psi} = \sum_{1\leq q\leq|\mathcal{K}'|} w_q T \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} P_{ijm}(\mathcal{I}_q) \\ &\textbf{s.t.} \quad \text{Constraints}(6)-(11) \\ &\sum_{l\in\mathcal{L}} f_{ij}(l) \leq \sum_{q=1}^{|\mathcal{K}'|} w_q \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ijm}(\mathcal{I}_q) \\ &(i,j \in \mathcal{N}, \text{ and } \mathcal{I}_q \in \mathcal{K}'), \end{aligned} \tag{13}$$

where $P_{ijm}(\mathcal{I}_q)$'s are known, and the optimization variables are w_q's and $f_{ij}(l)$'s. Thus, RMP is a small-scale linear programming (LP) problem that can be easily solved in polynomial time by thepolynomial interior algorithm introduced in [57]. We can thus obtain its primal optimal solution and a Lagrangian dual optimal solution. Since RMP uses only a subset of all the independent sets (i.e., columns) used by MP, i.e., $\mathcal{K}' \subseteq \overline{\mathcal{K}}$, the optimal result of RMP serves as an upper bound on the optimal result of MP. By introducing more independent sets to RMP, column generation may be able to decrease the upper bound. Therefore, we need to determine which column can potentially improve the optimization result the most and when the optimal result of RMP is exactly the same or satisfyingly close to the optimal result of MP. Notice that the formulated RMP does not consider the constraint (4). This is because RMP only includes a few

3. Reduced cost [22] refers to the amount by which the objective function would have to improve before the corresponding column is assumed to be part of optimal solution. In the case of a minimization problem like in this paper, improvement in the objective function means a decrease of its value, i.e., a negative reduced cost. In finding the column with the most negative reduced cost, the objective is to find the column that has the best chance to improve the objective function.

independent sets in the beginning iterations, in which $\sum_{1\leq q\leq|\mathcal{K}'|} w_q$ might be larger than 1, resulting in no feasible solution to RMP. Instead, we consider the constraint (4) after the final solution is obtained. If $\sum_{1\leq q\leq|\mathcal{K}'|} w_q$ is less than or equal to 1, the final solution is feasible. Otherwise, it is infeasible, i.e., the network cannot support all the traffic demands. We denote by $\overline{\psi}^*$ the minimum total energy consumption obtained by RMP. Since RMP is formulated only based on a subset of all the ISs in the network, we have $\overline{\psi}^* \geq \psi^*$.

Note that a few works like [32] develop heuristic algorithms to find a good initial set $\mathcal{K}'$, which can reduce the number of iterations required in column generation. We focus on the problem itself in this study. In addition, we will show by simulations later that in fact our initial set $\mathcal{K}'$ can be quickly improved and that the solution to RMP can be efficiently found. Furthermore, although the initial set will influence the convergence speed of our approach, we will show in Section 5.4 that we can always find the optimal solution to MP regardless of the choice of initial set.

5.2 Introducing More Columns to RMP

During every iteration, when RMP is solved, we need to check whether any new independent set with certain transmission power allocation can further improve the current objective function. In particular, for each independent set $\mathcal{I}_q \in \overline{\mathcal{K}} \setminus \mathcal{K}'$, we need to examine if any of them has a negative reduced cost. The reduced cost u_q for a column $\mathcal{I}_q \in \overline{\mathcal{K}} \setminus \mathcal{K}'$ can be calculated as [58]

$$u_q = \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\left(\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} TP_{ijm}(\mathcal{I}_q) - \lambda_{ij}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ijm}(\mathcal{I}_q)\right),$$

where λ_{ij}'s are the Lagrangian dual optimal solution corresponding to (13). Since there are totally $|\mathcal{N}|\times(|\mathcal{N}|-1)$ constraints generated from (13), the total number of λ_{ij}'s is also $|\mathcal{N}|\times(|\mathcal{N}|-1)$.

Notice that we need to find the column which can produce the most negative reduced cost. Consequently, this column to be added to RMP can be obtained by solving

$$\underset{\mathcal{I}_q\in\overline{\mathcal{K}}\setminus\mathcal{K}'}{\textbf{Min}} \qquad u = u_q,$$

or equivalently

$$\underset{\mathcal{I}_q\in\overline{\mathcal{K}}\setminus\mathcal{K}'}{\textbf{Min}}\ u = \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}\big(TP_{ijm}(\mathcal{I}_q) - \lambda_{ij}c_{ijm}(\mathcal{I}_q)\big), \quad (14)$$

which is called a Pricing Problem. Denote by u^* the optimal solutions to the above problem. Then, if $u^* \geq 0$, it means that there is no negative reduced cost and hence the current solution to RMP optimally solves MP. Otherwise, we add to RMP the column derived from (14) as well as the transmission power assignment for each link-band pair in this column, and then re-optimize the updated RMP. We leave how to solve PP in the following two sections.

5.3 Formulating PP

Next, we study how to solve PP, i.e., the optimization problem formulated in (14). Our objective is to find out the independent set, i.e., all the link-band pairs that can be active at the same time, and the transmission power on each of the link-band pairs in the set, which can minimize u.

Assume band m is available at both node i and node j, i.e., $m \in \mathcal{M}_i \cap \mathcal{M}_j$. We define

$$s_{ijm} = \begin{cases} 1, & \text{if node } i \text{ transmit to node } j \text{ using channel } m \\ 0, & \text{otherwise.}\end{cases}$$

Then, the result we need to find out is $\{((i,j),m), P_{ijm} \mid s_{ijm} = 1\}$ that can minimize u in (14).

Since a node is not able to transmit to or receive from multiple nodes on the same frequency band, we have

$$\sum_{j\in\mathcal{N},j\neq i} s_{ijm} \leq 1, \text{ and } \sum_{i\in\mathcal{N},i\neq j} s_{ijm} \leq 1. \quad (15)$$

Besides, a node cannot use the same frequency band for both transmission and reception at the same time, due to "self-interference" at physical layer, i.e.,

$$\sum_{i\in\mathcal{N},i\neq j} s_{ijm} + \sum_{q\in\mathcal{N},q\neq j} s_{jqm} \leq 1. \quad (16)$$

Moreover, recall that in this study, we consider each node is only equipped with a single radio, which means each node can only transmit or receive on one frequency band at a time. Thus, we can have

$$\sum_{m\in\mathcal{M}_j}\sum_{i\in\mathcal{N},i\neq j} s_{ijm} + \sum_{n\in\mathcal{M}_j}\sum_{q\in\mathcal{N},q\neq j} s_{jqn} \leq 1. \quad (17)$$

Notice that (15)-(16) will hold whenever (17) holds.

In addition to the above constraints at a certain node, there are also constraints due to potential interference among the nodes. In particular, according to the Physical Model discussed in Section 3.3, if node i uses band m for transmitting data to node j, the cumulative interference from all the other nodes transmitting on the same band at the same time plus the noise power level should be small enough so that the SINR of the signal received at node j is above the threshold Γ, or

$$g_{ij}P_{ijm} \geq \Gamma\left(\eta_j W^m + \sum_{k\in\mathbb{T}_i^m, v\neq j} g_{kj}P_{kvm}\right). \quad (18)$$

Rewriting the above expression in the form of a constraint that accommodates all the link-band pairs in the network, we have

$$g_{ij}P_{ijm} + M_{ijm}(1 - s_{ijm}) \geq \Gamma\left(\eta_j W^m + \sum_{k\neq i, v\neq j} g_{kj}P_{kvm}s_{kvm}\right), \quad (19)$$

where M_{ijm} is set as the sum of interferences from all the other nodes and the noise, i.e.,

$$M_{ijm} = \Gamma\left(\eta_j W^m + \sum_{k\neq i, v\neq j} g_{kj}P^k_{\max}s_{kvm}\right).$$

Note that if a link-band pair $((i,j),m)$ is part of the new independent set generated by PP, i.e., $s_{ijm} = 1$, then (19) converts back to the expression in (18). If $((i,j),m)$ doesn't belong to the independent set, i.e., $s_{ijm} = 0$, then M_{ijm} ensures that the interference constraint (19) is redundant.

Let $\overline{P_{ijm}} = P_{ijm} + P_r$. Consequently, considering the above constraints, the pricing problem of finding the optimal column and the corresponding transmission power allocation can be formulated as follows

$$\begin{aligned}
\textbf{Min} \quad & u = \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}\left(T\overline{P_{ijm}}s_{ijm} - \lambda_{ij}c_{ijm}s_{ijm}\right)\\
\textbf{s.t.} \quad & \text{Constraints } (12), (17) \text{ and } (19)\\
& \sum_{((i,j),m)\in\mathcal{I}_q} s_{ijm} < |\mathcal{I}_q|, \text{ for any } \mathcal{I}_q \in \mathcal{K}' \qquad (20)\\
& s_{ijm} = 0 \quad \text{or} \quad 1, \qquad (21)
\end{aligned}$$

where both P_{ijm}'s and s_{ijm}'s are the optimization variables. Recall that λ_{ij}'s are the Lagrangian dual optimal solutions to RMP, and c_{ijm}'s are calculated according to (2). Note that (20) indicates the obtained independent set is a new one, i. e., not in $\mathcal{K}'$. Since s_{ijm}'s can only take value of 0 or 1, PP is a mixed integer quadratically constrained quadratic programming (MIQCQP) problem, which, unfortunately, is still very difficult to solve.

5.4 Solving PP

Although there exist some approximation techniques for solving MIQCQP problems, such as generalized benders decomposition [59], outer approximation [60], and branch-and-bound or branch-and-cut [61], they have prohibitively high complexities which are unbearable in the iterative column generation approach described above. In the following, we propose a more efficient method, which further decomposes PP into two separate problems, namely, link-band pair selection with given transmission power profile, and power allocation with given link-band pair selection.

In particular, LBPS can be formulated as

$$\begin{aligned}
\textbf{Min} & \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}\left(T\overline{P_{ijm}}s_{ijm} - \lambda_{ij}c_{ijm}s_{ijm}\right)\\
\textbf{s.t.} \quad & \text{Constraints } (17), (19){-}(21),
\end{aligned}$$

where $\overline{P_{ijm}}$'s are given and the only variables are s_{ijm}'s. Thus, LBPS is a binary integer programming problem. Then, we follow a similar idea to that in [62], [63] to develop a greedy algorithm to find a suboptimal solution to LBPS, which is called the sequential-fix (SF) algorithm.

The main idea of SF is to fix the values of s_{ijm}'s sequentially through a series of relaxed linear programming problems. Specifically, in each iteration, we first relax all the 0-1 integer constraints on s_{ijm}'s to $0 \le s_{ijm} \le 1$ to transform the problem to a linear programming problem. Then, we can solve this LP to obtain an optimal solution with each s_{ijm} being between 0 and 1. Among all the values, we set the largest s_{ijm} to 1. After that, by (17), we can fix $s_{pjn} = 0$ and $s_{jqn} = 0$ for any $n \in \mathcal{M}_j$ and $p, q \in \mathcal{N}$.

Having fixed some s_{ijm}'s in the first iteration, we remove all the terms associated with those already fixed s_{ijm}'s, eliminate the related constraints in (17), and update the problem to a new one for the second iteration. Similarly, in the second iteration, we solve an LP with a reduced number of variables, and then determine the values of some other unfixed s_{ijm}'s based on the same process. The iteration continues until we fix all s_{ijm}'s to be either 0 and 1.

Besides, PA can be formulated as follows:

$$\begin{aligned}
\textbf{Min} & \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}\left(T\overline{P_{ijm}}s_{ijm} - \lambda_{ij}c_{ijm}s_{ijm}\right)\\
\textbf{s.t.} \quad & \text{Constraints } (12) \text{ and } (19),
\end{aligned}$$

where s_{ijm}'s come from the results of LBPS and are considered as known values. Therefore, PA is an LP problem with P_{ijm}'s being the variables, which can be easily solved.

With LBPS and PA being formulated above, we can now find the solution to PP by solving these two problems iteratively as follows. First, the power allocation (P_{ijm}'s) is initialized with an arbitrary power allocation, e.g., the maximum value $P^i_{\max}$ for each link-band pair. Based on this given power allocation, we solve LBPS to obtain the link-band pair selection results. With such results, we then solve PA to get updated power allocation profile P_{ijm}'s and replace the corresponding values in LBPS. The above iteration continues until the objective function of LBPS (i.e., that of PP) does not change any more or the maximum number of iterations is reached. Algorithm 1 details the above process for solving PP.

Algorithm 1 Solving PP

Input: Dual solution of RMP λ_{ij}'s, maximum iteration number max_iter_num
Output: P_{ijm}'s, s_{ijm}'s

```
Initialize P_ijm's with P^i_max, and set iter_num to 0;
while iter_num < max_iter_num or u does not change any more do
    while not all s_ijm's are fixed do
        Given {P_ijm}, solve LBPS by relaxing s_ijm between 0 and 1;
        Search for the s_ijm with the largest value, and set the found s_ijm to be 1;
        Set s_pjn = 0, s_jqn = 0 for (n ∈ M_j, p, q ∈ N);
        Remove fixed s_ijm's from (17);
    end while
    Construct a new column I_q = {s_ijm | s_ijm = 1};
    Solve PA with calculated s_ijm's using the polynomial interior algorithm [58];
    Update {P_ijm} according to the result of PA;
    iter_num = iter_num + 1;
end while
```

Recall that when the optimal result of PP is larger than or equal to 0, i.e., $u^* \ge 0$, it means that there is no negative reduced cost and MP have been optimally solved. Unfortunately, our decomposition approach developed above does not find the optimal solution to PP. However, when the optimal result of the relaxed PP, denoted by $\underline{u^*}$, is larger than or equal to 0 (i.e., $u^* \ge \underline{u^*} \ge 0$), MP can be optimally solved. Notice that the relaxed PP is a Quadratic Programming problem. As proved in [54], a QP can be transformed to an LP problem with $m + n$ constraints, where m and n are the number of constraints and the number of variables in the original QP, respectively. Thus, the relaxed PP can be easily solved. Moreover, notice that in each iteration, PP finds a new independent set that is different from the previously found ones due to constraint (20). Besides, PP also finds the corresponding $\overline{P_{ijm}}$'s for this new independent set that minimize the objective of PP. This is because PA is always calculated at last in Algorithm 1 when solving PP, which is an LP problem whose optimal result can be easily calculated. Therefore, when there is no new solution found to the original PP, it means that we have found all the independent sets and the corresponding optimal transmission power allocations, and hence can also optimally solve MP. As a result, MP can be guaranteed to be optimally solved, and thus the optimal result of RMP will always converge to the optimal result of MP.

5.5 ϵ-Bounded Approximate Solutions

Since the number of independent sets in $\overline{\mathcal{K}}$ increases exponentially as the number of link-band pairs in the network, the number of iterations (of PP) needed to find all the independent sets producing negative reduced cost can be very large, especially in large-size networks. However, it has been observed in the context of column generation algorithms [22], [23] that one can usually determine solutions that are at least 95–99 percent of the global optimality fairly quickly, although the tail-end convergence rate in obtaining the optimal solution can be slow in many classes of problems. Here, we design an algorithm to find ϵ-bounded approximate solutions to MP.

We first give the definition of ϵ-bounded approximate solutions as follows.

Definition 1. *Let $0 \le \epsilon < 1$ be a predefined parameter, and ψ^* the optimal result. Then, a solution is called an ϵ-bounded approximate solution if its corresponding result ψ satisfies*

$$(1-\epsilon)\psi^* \le \psi \le (1+\epsilon)\psi^*.$$

Then, we can have the following lemma.

Lemma 1. *Denote by ψ_u and ψ_l the upper bound and lower bound on the optimal result ψ^* of MP, respectively. Then, ϵ-bounded approximate ($0 \le \epsilon < 1$) solutions can be obtained when there is no new independent set found by PP, or the iteration stops at $\underline{u^*} \ge 0$, or*

$$\frac{\psi_l}{\psi_u} \ge \frac{1}{1+\epsilon}. \tag{22}$$

Proof. When $\frac{\psi_l}{\psi_u} \ge \frac{1}{1+\epsilon}$, we can get that $\psi_u \le (1+\epsilon)\psi_l \le (1+\epsilon)\psi^*$ and $\psi_l \ge \psi_u/(1+\epsilon) \ge (1-\epsilon)\psi_u \ge (1-\epsilon)\psi^*$. Thus, any obtained result between the upper and lower bounds, i.e., $\psi_l \le \psi \le \psi_u$, satisfies $\psi \le \psi_u \le (1+\epsilon)\psi^*$ and $\psi \ge \psi_l \ge (1-\epsilon)\psi^*$, and hence is an ϵ-bounded approximate solution by definition. Besides, when $\underline{u^*} \ge 0$ or there is no new independent set found by PP, as mentioned before, the obtained solution is the optimal solution and hence an ϵ-bounded approximate solution as well. □

Notice that in (22), ϵ is predetermined, e.g., 3 percent. As mentioned before, the optimal result of RMP in each iteration is an upper bound on the optimal result of MP, i.e., ψ_u. A lower bound can be obtained by [58]

$$\psi_l = \psi_u + \mathcal{R}u^* \le \psi^*,$$

where u^* is obtained by solving PP optimally, and $\mathcal{R} \ge \sum_{1 \le q \le |\overline{\mathcal{K}}|} w_q$ holds for the optimal solution to RMP. We set $\mathcal{R} = 1$. Then, if a traffic demand can be supported, the optimal solution must satisfy $\sum_{1 \le q \le |\overline{\mathcal{K}}|} w_q \le \mathcal{R} = 1$. Thus, if an optimal solution leads to $\sum_{1 \le q \le |\overline{\mathcal{K}}|} w_q > 1$, then the corresponding traffic demand cannot be supported. Since we actually do not obtain u^* with the decomposition algorithm, the lower bound can be set to $\psi_l = \psi_u + \mathcal{R}\underline{u^*}$ which is less than $\psi_u + \mathcal{R}u^*$ and hence ψ^*. In addition, since u^* is negative, ψ_l may be negative as well. Thus, we finally calculate ψ_l by

$$\psi_l = \max\{\psi_u + \mathcal{R}\underline{u^*}, 0\}. \tag{23}$$

Consequently, according to Lemma 1, the feasible solution obtained by solving RMP, which leads to a result ψ_u, is an ϵ-bounded approximate solution since we have found the corresponding scheduling and routing solutions. We finally describe an ϵ-bounded approximation algorithm for the energy consumption optimization problem in Algorithm 2.

Algorithm 2 An ϵ-Bounded Approximation Algorithm

Input: approximal factor ϵ, traffic demand $r(l)$'s, initial IS $\mathcal{K}_{ini}$, $\psi_u = \infty$, $\psi_l = \infty$, $\underline{u^*} = -\infty$
Output: w_q's, $f_{ij}(l)$'s, P_{ijm}'s

while There is no new independent set found by PP or $\frac{\psi_l}{\psi_u} < \frac{1}{1+\epsilon}$ or $\underline{u^*} > 0$ **do**
  Solve RMP under current $\mathcal{K}'$ using the polynomial interior algorithm [58], obtain its optimal result ψ_u and dual optimal solution λ_{ij}'s;
  Solve PP based on calculated λ_{ij}'s following Algorithm 1 and a new column $\mathcal{I}_q$;
  Obtain optimal result $\underline{u^*}$ of relaxed PP;
  Update $\mathcal{K}' = \mathcal{K}' \cup \mathcal{I}_q$;
  $\psi_l = \psi_u + \mathcal{R}\underline{u^*}$;
end while

5.6 Computational Complexity Analysis

As we mentioned before, although MP can be transformed to an LP problem, solving it directly still requires a high computational complexity since finding all the independent sets is an NP-complete problem and coupled with the selection of transmission powers. Note that in a network, the number of link-band pairs in it, denoted by G, will be $O(|\mathcal{N}|^2|\mathcal{M}|)$. Thus, the number of independent sets is at most 2^G, i.e., $O(2^{|\mathcal{N}|^2})$. Since usually only a small number of independent sets would be useful in a scheduling problem, the developed column generation based algorithm finds the useful ones one-by-one iteratively. We analyze the computation complexity of our algorithm as follows.

Theorem 1. *The computational complexity of our proposed column generation based algorithm for MP is $O(K^4 + K|\mathcal{N}|^9)$ when there are K iterations in the algorithm, and $O(2^{4|\mathcal{N}|^2})$ in the worst case.*

Proof. In our proposed column generation based algorithm, one RMP and one PP are solved in each iteration. In RMP, the variables include w_q's and $f_{ij}(l)$'s. Note that the initial independent sets are formed by placing one link-band-pair in each of them. Thus, in the kth iteration, the numbers of w_q's and $f_{ij}(l)$'s are $G + k$ and $|\mathcal{N}|^2 L$, respectively. Since RMP is an LP problem, it can be solved by the polynomial interior algorithm introduced in [57], whose computation complexity is $O(n^3)$ where n is the number of the variables in a problem. Therefore, the computation complexity of RMP in the kth iteration is $O((G + k + |\mathcal{N}|^2 L)^3)$. For PP, we further decompose it into an LBPS and a PA. As LBPS is a BIP problem, we develop an SF algorithm that consists of multiple rounds of computation for relaxed LP problems with a decreasing number of variables, i.e., s_{ijm}'s, in each round. Note that the number of variables is clearly upper bounded by G. Thus, the computation complexity in each round is no larger than $O(G^3)$. Besides, notice that in each round, SF fixes one of s_{ijm}'s to 1 and other interfering variables to 0 according to constraints (17). Particularly, from the first inequality in (15), we can know that if $s_{ijm} = 1$, then $s_{izm} = 0$ $(z \neq j)$. Therefore, all the variables s_{ijm}'s in LBPS can be determined in at most $|\mathcal{N}||\mathcal{M}|$ rounds. Consequently, the computation complexity of LBPS is upper bounded by $O(G^3|\mathcal{N}||\mathcal{M}|)$. As PA is an LP problem with G variables, its computation complexity is $O(G^3)$. Besides, LBPS and PA are calculated iteratively until the objective function of LBPS does not change any more or the maximum iteration number is reached. We set the maximum iteration number to $O(G)$ in our algorithm. Therefore, the computation complexity for PP is $O(G^4|\mathcal{N}||\mathcal{M}| + G^4)$, i.e., $O(G^4|\mathcal{N}|)$.

In all, the computation complexity for column generation based approach when there are K iterations is

$$\begin{aligned} &O\left(\sum_{k=1}^{K}\left[(G+k+|\mathcal{N}|^2L)^3 + G^4|\mathcal{N}|\right]\right) \\ &= O\left((G+K+|\mathcal{N}|^2L)^4 + K(G^4|\mathcal{N}|)\right) \\ &= O(K^4 + K|\mathcal{N}|^9). \end{aligned}$$

The first step is due to $\sum_{k=1}^{K} k^3 = K^2(K+1)^2/2$. In the worst case that all the independent sets need to be found, our algorithm needs to have at most $2^G - G$ iterations and hence its computational complexity is $O\big((2^{|\mathcal{N}|^2})^4 + 2^{|\mathcal{N}|^2} \cdot |\mathcal{N}|^9\big)$, i.e., $O(2^{4|\mathcal{N}|^2})$. □

Note that our later simulations show that usually only a small number of iterations are needed, which means our algorithm has a very low computational complexity according to Theorem 1. In contrast, if we solve MP directly, the computational complexity is always $O((2^G + |\mathcal{N}|^2L)^3)$, i.e., $O(2^{3|\mathcal{N}|^2})$.

6 UNCERTAIN SPECTRUM AVAILABILITY

So far we have assumed that the availability of frequency bands in MC^{2}Ns is constant. However, in practice, the vacancy/occupancy of the licensed bands is unpredictable. To model this unique feature of MC^{2}Ns, let $\delta_{ijm} \in [0,1]$ denote the available time of band m at link (i,j) within one unit time slot, which is a random variable. As shown in [38], the statistical characteristics of δ_{ijm} contain abundant knowledge about band m's spectrum availability at link (i,j) for opportunistic accessing.[4] Taking uncertain stochastic spectrum availability into consideration, constraint (13) in RMP can be reformulated as follows:

$$\sum_{q=1}^{|\mathcal{K}'|} w_q \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} c_{ijm}(\mathcal{I}_q)\delta_{ijm} \geq \sum_{l\in\mathcal{L}}^{i\neq d(l), j\neq s(l)} f_{ij}(l). \quad (24)$$

Note that the interference constraint (19) remains the same since the bandwidth W^m does not change. Thus, the variables δ_{ijm}'s contained in (24) change RMP from a linear programming problem into a stochastic optimization problem (SOP), which needs to be solved carefully.

Inspired by the concept of value at risk (VaR) in [64], we leverage a parameter $\beta \in [0,1]$ to define temporal spectrum availability at confidence level β, and denote it by $X_\beta(W)$ as follows:

$$\begin{cases} H_W(t) = \int_t^\infty h_W(w)dw, \quad t \in \mathcal{R} \\ X_\beta(W) = \sup\{t : H_W(t) \geq \beta\}, \quad \beta \in [0,1], \end{cases}$$

where $h_W(\cdot)$ is the probability distribution function of the random variable W. Based on the above definition, we can reformulate (24) as

$$\sum_{q=1}^{|\mathcal{K}'|} w_q \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} X_\beta\big(c_{ijm}(\mathcal{I}_q)\delta_{ijm}\big) \geq \sum_{l\in\mathcal{L}}^{i\neq d(l), j\neq s(l)} f_{ij}(l), \quad (25)$$

Denote by $F_W(\cdot)$ the cumulative distribution function (CDF) of the random variable W, we can get $X_\beta(W) = F_W^{-1}(1-\beta)$. Thus, we have $X_\beta(c_{ijm}(\mathcal{I}_q)\delta_{ijm}) = F^{-1}_{c_{ijm}(\mathcal{I}_q)\delta_{ijm}}(1-\beta)$. Therefore, given the distributions of random variables δ_{ijm}'s, (25) is a linear constraint. Replacing (24) with (25), RMP becomes an LP problem again, which can be easily solved as described in Section 5.4.

7 THE IMPACT OF ADAPTIVE M-QAM

In order to better characterize the achievable data rates, we revisit the energy consumption optimization problem for MC^{2}Ns by considering an adaptive M-QAM modulation scheme. Since the algorithm proposed above still works well under this new modulation scheme, we only describe the main changes incurred in formulating and solving PP in the following.

7.1 Achievable Data Rate Under Adaptive M-QAM

Similar to that in (3), in order to achieve the target BER P_b under an adaptive M-QAM ($M = 2^1, 2^2, \ldots, 2^T$) scheme, we need to determine a set of SINR thresholds $\{\Gamma_1, \Gamma_2, \ldots, \Gamma_T\}$ as follows:

$$\Gamma_{\log_2 M} = -\frac{(M-1)\ln(5P_b)}{1.5}, \quad M = 2^1, 2^2, \ldots, 2^T.$$

Let $\Gamma_{T+1} = \infty$. Then, the achievable data rate for (i,j) on band m when $\Gamma_{\log_2 M} \leq \mathrm{SINR}_{ijm} < \Gamma_{\log_2 M+1}$ ($M = 2^1, 2^2, \ldots, 2^T$) can be calculated by

$$c_{ijm} = W^m \log_2 M,$$

i.e., the achievable data rate on a link depends on the adopted modulation type and the spectrum bandwidth.

7.2 Formulating PP

Let s^t_{ijm} be a binary indicator of whether the transmission from node i to node j on band m satisfies $\Gamma_t \leq \mathrm{SINR}_{ijm} < \Gamma_{t+1}$ $(1 \leq t \leq T)$. Then, we have

4. Chen et al. in [38] carried out a set of spectrum measurements in the 20 MHz to 3 GHz spectrum bands at four locations concurrently in Guangdong province of China. They used these data sets to conduct a set of detailed analysis on statistics of the collected data, including channel occupancy/vacancy statistics, channel utilization, also spectral and spatial correlation of these measures.

$$\sum_{t=1}^{T} s_{ijm}^{t} \leq 1. \quad (26)$$

Besides, since each active link-band pair $((i,j),m)$'s SINR must be above one of the thresholds in $\{\Gamma_1,\ldots,\Gamma_t,\ldots,\Gamma_T\}$, we have

$$s_{ijm} = \sum_{t=1}^{T} s_{ijm}^{t}. \quad (27)$$

Therefore, under an adaptive M-QAM scheme, (18) needs to be reformulated as

$$g_{ij}P_{ijm} \geq \left(\sum_{t=1}^{T} s_{ijm}^{t}\Gamma_t\right)\left(\eta_j W^m + \sum_{k\in\mathbb{T}_i^m, v\neq j} g_{kj}P_{kvm}\right). \quad (28)$$

Note that if $((i,j),m)$ is not active, i.e., $s_{ijm} = \sum_{t=1}^{T} s_{ijm}^{t} = 0$, we have $s_{ijm}^{t} = 0$. Then, the right-hand-side of (28) is 0, which makes it a redundant constraint. Thus, the above constraint can accommodate all the link-band pairs in the network.

Consequently, the PP under the new discrete link capacity model can be formulated as follows:

$$\begin{aligned}
\textbf{Min} \quad & u = \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}\left(T\overline{P_{ijm}}s_{ijm} - \lambda_{ij}c_{ijm}s_{ijm}\right)\\
\textbf{s.t.} \quad & \text{Constraints (12), (17), (27), and (28)}\\
& \sum_{((i,j),m)\in\mathcal{I}_q} s_{ijm} < |\mathcal{I}_q|, \ \text{for any } \mathcal{I}_q \in \mathcal{K}'\\
& s_{ijm}, s_{ijm}^{t} = 0 \quad \text{or} \quad 1,
\end{aligned} \quad (29)$$

7.3 Solving PP

Following the similar decomposition algorithm introduced before, we can solve PP by decomposing it into two smaller and easier problems: LBPS and PA.

Specifically, by replacing s_{ijm} with $\sum_{t=1}^{T} s_{ijm}^{t}$, LBPS can be formulated as

$$\begin{aligned}
\textbf{Min} & \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}\sum_{t=1}^{T}\left(T\overline{P_{ijm}}s_{ijm}^{t} - \lambda_{ij}c_{ijm}s_{ijm}^{t}\right)\\
\textbf{s.t.} \quad & \text{Constraints (28)}\\
& \sum_{m\in\mathcal{M}_j}\sum_{i\in\mathcal{N}, i\neq j}\sum_{t=1}^{T} s_{ijm}^{t} + \sum_{n\in\mathcal{M}_j}\sum_{q\in\mathcal{N}, q\neq j}\sum_{t=1}^{T} s_{jqn}^{t} \leq 1.\\
& \sum_{((i,j),m)\in\mathcal{I}_q}\sum_{t=1}^{T} s_{ijm}^{t} < |\mathcal{I}_q|, \ \text{for any } \mathcal{I}_q \in \mathcal{K}'\\
& s_{ijm}^{t} = 0 \quad \text{or} \quad 1,
\end{aligned}$$

where $\overline{P_{ijm}}$'s are given and the only variables are s_{ijm}^{t}'s. Thus, LBPS is a Binary Integer Programming problem. Then, we can also apply the SF algorithm to find a suboptimal solution.

Besides, PA can be formulated as follows:

$$\begin{aligned}
\textbf{Min} & \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j}\sum_{t=1}^{T}\left(T\overline{P_{ijm}}s_{ijm}^{t} - \lambda_{ij}c_{ijm}s_{ijm}^{t}\right)\\
\textbf{s.t.} \quad & \text{Constraints (12) and (28)},
\end{aligned}$$

where s_{ijm}^{t}'s come from the results of LBPS and are considered as known values. Therefore, PA is an LP problem with P_{ijm}'s being the variables, which can be easily solved.

In addition, note that according to Section 6, no other changes need to be made when uncertain spectrum availability is considered.

8 Simulation Results

In this section, we carry out extensive simulations to evaluate the performance of the proposed algorithm. Simulations are conducted using CPLEX 12.4 and C++ on a computer with two 2.27 GHz CPUs and 24 GB RAM. Our goals are to demonstrate the efficiency as well as the convergency property of the proposed algorithms, to show the performance improvement over other schemes, to understand the cross-layer optimization under the Physical Model, and to study the system performance under the discrete link capacity model. Notice that most of the previous works obtain suboptimal results that are either unbounded or far away from the optimal results, and many works do not fully consider the joint frequency allocation, link scheduling, routing, and transmission power control. Besides, many works based on conflict graphs assume all the maximum independent sets are given. Therefore, it is not very fair to compare our ϵ-bounded approximation algorithm with other algorithms.

In the simulations, we consider a square network of area 1,000 m $\times$ 1,000 m, with a base station located at the center. We study three cases where 20, 30, and 40 nodes are randomly distributed in the network, respectively. We assume the bandwidth of the basic band, which is available at both the BS and CR nodes, is 1 MHz, and there are three secondary spectrum bands in the network with their bandwidths being 1.2, 1.4 and 1.6 MHz, respectively. At each node (including the base station), only a random subset of the secondary bands are available. In all the three cases, we assume that there are three uplink U2B sessions, three downlink U2B sessions, and three U2U sessions. The source and destination for each session are randomly selected, and each session has a traffic demand of 500 Kbps. We set the length of each time slot T to 100 seconds. Some other important simulation parameters are listed as follows. The path loss exponent is 4. In the case of a constant M-QAM scheme, we adopt 8-QAM and set the target BER to $P_b = 10^{-3}$, resulting in the SINR threshold $\Gamma = 24.73$ following (3). In the case of an adaptive M-QAM scheme, we consider 8-QAM, 16-QAM, and 32-QAM. With the objective BER of $P_b = 10^{-3}$, we set the SINR thresholds to $\{24.73, 52.98, 109.50\}$. The noise power spectral density is $\eta = 10^{-20}$W/Hz at all nodes. According to the FCC regulations on TV white space cognitive radio operation [39], we set the maximum transmission power of CR nodes to $P_{\max}^{i} = 100\,\text{mW}$ for any $i \in \mathcal{N}$, and that of the base station to 4 W. Besides, in the simulations we assume the power needed by a receiver to receive a packet is negligible compared to transmission power, so that we can focus on the impact of transmission power. In addition, in the case of uncertain spectrum availability, we consider that all the secondary bands' available durations in a unit time follow the same uniform distribution over $[0, 1]$.

8.1 Cost of Solving RMP

We first study the cost of solving RMP under different network settings. Note that in order to well investigate the cost of solving RMP, we apply a traditional algorithm (provided

TABLE 1
Solving RMP with Different ϵ's

ϵ	Iteration Number	Running Time (S)
5%	156	9.05
3%	169	10.14
1%	177	10.95
0%	183	11.35

TABLE 2
Solving RMP with Different Network Sizes

Network Size	Iteration Number	Running Time (S)
$N = 20$	183	11.35
$N = 30$	197	14.78
$N = 40$	224	19.98

by CPLEX) which can solve MIQCQPs to solve PP in inner iterations. Table 1 shows the iteration number and running time needed to solve RMP in order to obtain ϵ-bounded approximate solutions. The results are obtained when there are 20 CR nodes in the network. We can see that it takes 156 iterations and 9.05 seconds to solve RMP so as to get optimal results, i.e., when $\epsilon = 0\%$[5]. Table 2 gives the cost of solving RMP when $\epsilon = 0\%$ in networks of different sizes. We can observe that as the number of CR nodes increases, the iteration number and the total running time both increase. Intuitively, this is because when the number of nodes increases, the number of variables increases as well and the searching space becomes larger.

Besides, Fig. 2 illustrates the convergence property of upper and lower bounds on the optimal energy consumption when we use traditional algorithms to solve PP in inner iterations, given that $\epsilon = 0\%$ and there are 20 CR nodes in the network. In each iteration, we compute the lower and upper bounds on the minimum energy consumption of MP and track their progresses. Recall that in each iteration the upper bound ψ_u is the optimal result of RMP, while the lower bound ψ_l is calculated according to (23). We can find that although the gap between the lower and upper bounds is initially large, the gap narrows down quickly in the first 140 iterations. Particularly, note that there is a sharp decrease of ψ_u at the beginning. This is because the initial set of independent sets $\mathcal{K}'$ used for solving RMP is very small and simple, and can be easily well improved. Thus, it demonstrates that we can efficiently find the ϵ-bounded approximate solution with our simple initial set $\mathcal{K}'$. In addition, we find that the minimum total energy consumption in one time slot finally converges to 22.1 joules (J).

8.2 Cost of Solving PP

We then evaluate the cost of solving PP in networks of different sizes when $\epsilon = 0\%$. We set $max\_iter\_num = 10 \times G$ where $G = |\mathcal{N}|^2|\mathcal{M}|$ in Algorithm 1. Table 3 shows the running time of a traditional algorithm provided by CPLEX and that of the proposed decomposition scheme, i.e., LBPS plus PA, which is the total running time of solving PP until an optimal result for MP is obtained. Obviously, the proposed decomposition outperforms (in terms of running time) the traditional algorithm. Specifically, when $N = 40$, the running time needed by our decomposition method is 11.42 seconds, which is only 0.33 times of that needed by the traditional algorithm, i.e., 34.53 seconds.

Fig. 3 shows the convergence property of upper and lower bounds on the optimal energy consumption when we use decomposition scheme to solve PP in inner iterations, given that $\epsilon = 0\%$ and there are 20 CR nodes in the network. We find that the minimum energy consumption is also 22.1 J, which is the same as that in Fig. 2. We also notice that compared to using the traditional algorithm to solve PP, using the decomposition scheme leads to slightly more iterations, i.e., we need to solve RMP for more times. However, the total running time when using the decomposition scheme is $11.35 + 5.56$, i.e., 16.91 s, which is much less than the total running time when using traditional algorithms, i.e., $11.35 + 16.49 = 27.84$ s. This is due to the fact that the decomposition scheme is more efficient and hence takes less time in each iteration. Note that since this running time is obtained on a general-purpose PC with modest computation capability, it can be further reduced if a more powerful server is used. Besides, Chen et al. [38] carried out a set of spectrum measurements in the 20 MHz to 3G Hz spectrum bands at four locations concurrently in Guangdong province of China, and found that most of channel vacancy duration last longer than 150 seconds, which is much larger than the running time of our algorithm. Therefore, our algorithm can work well under the dynamic availability of secondary spectrum bands.

We further illustrate the convergence speed of our scheme in Fig. 4 when there are 20 CR nodes in the network. Following the similar idea of rate of convergence as described in [65], we define the convergence rate in the kth iteration as $\alpha(k) = \frac{|\psi_u(k+1)-\psi^*|}{|\psi_u(k)-\psi^*|}$[6], where $\psi_u(k)$ stands for ψ_u obtained in the kth iteration. Thus, the lower $\alpha(k)$ is, the faster convergence our scheme achieves in the kth iteration. Besides, when the result converges in the kth iteration, we have $\psi_u(k) = \psi_u(k+1) = \psi^*$ and hence $\alpha(k) = 1$. As shown in Fig. 4, we can see that the convergence rate $\alpha(k)$ approaches 1 as the iterations continue, indicating the convergence speed slows down. Moreover, when k is smaller than 185, $\alpha(k)$'s are obviously lower than 1, indicating fast convergence of our scheme. Besides, we obtain from Fig. 3 that $\psi_u(185) = 22.9$ J, i.e., $\epsilon = 3.6\%$ when $k = 185$. This reveals similar results observed by [22], [23] that column

5. Note that the simulations are conducted on a general-purpose PC with modest computation capability. In practice, the optimization problems will be solved by the service provider, which usually has much higher computation capability. Thus, the computation time in practical cellular systems can be much shorter.

6. Rate of convergence [65] is usually employed to analyze the convergence speed of an algorithm or a sequence $\{x_k\}$. For example, if there exists a number $\mu \in (0,1)$ such that $\lim_{k\to\infty} \frac{x_{k+1}-L}{x_k-L} = \mu$, we say that the sequence $\{x_k\}$ converges linearly to L with μ being the rate of convergence. Although there are other kinds of definitions, this metric does not tell clearly the convergence performance at each node of a sequence. Since in our algorithm, the convergence speed is very dynamic in different iterations, we design a similar metric, convergence rate in an iteration, to show the convergence speed more clearly and in more detail. Fig. 4 shows that the convergence speed of our algorithm tend to slow down as it proceeds.

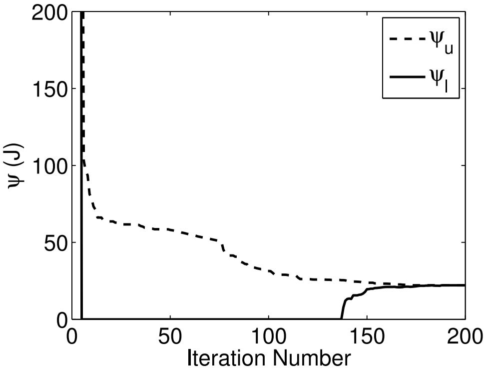

Fig. 2. Convergence property when using traditional algorithms to solve PP in a 20-node network.

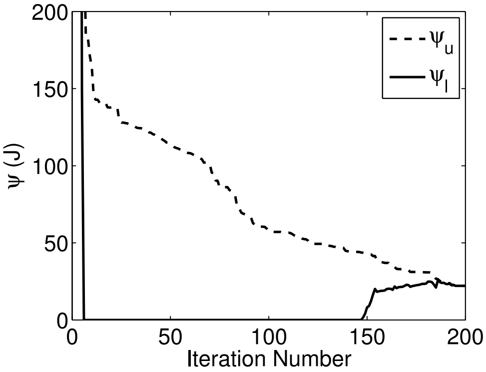

Fig. 3. Convergence property using the proposed decomposition scheme to solve PP in a 20-node network.

generation approaches can determine solutions that are at least 95–99 percent of the global optimality fairly quickly.

8.3 Performance Comparison

Here, we demonstrate the energy consumption and the maximum end-to-end throughput achieved by the cellular (CN) architecture and the proposed MC^{2}N architecture with or without considering energy consumption optimization. We assume that the CN architecture works in TDMA/TDD mode, i.e., the transmission from each user is scheduled one by one for either upstream or downstream traffic. In addition, if energy consumption optimization is not considered, we set $P_{ijm} = P^i_{max}$ $(i \in \mathcal{N})$ and formulate a scheduling length minimization problem. Specifically, we formulate an optimization problem with the objective of minimizing the total scheduling length, i.e., $\sum_{q=1}^{|\mathcal{K}'|} w_q$, to support all traffic, considering link scheduling and routing constraints.

Fig. 5a shows the energy consumption under different node numbers in four scenarios, i.e., CN architecture without energy consumption optimization, CN architecture with energy consumption optimization, MC^{2}N architecture without energy consumption optimization, and MC^{2}N architecture with energy consumption optimization. We find that the energy consumption of MC^{2}N architecture with energy optimization is the lowest. Besides, as N increases, the energy consumption of the CN architecture (with or without energy optimization) stays the same since the traffic are delivered in one hop and its scheduling and routing schemes do not change. On the other hand, the energy consumption of the MC^{2}N architecture with energy consumption optimization decreases when there are more nodes in the network, because we can utilize shorter links to deliver data packets with lower energy consumption.

We further show in Fig. 5b the maximum end-to-end throughput in the same four scenarios as mentioned

TABLE 3
Running Time Comparison

Network Size	Traditional Algorithm (S)	LBPS+PA (S)
$N = 20$	16.49	5.56
$N = 30$	25.21	7.18
$N = 40$	34.53	11.42

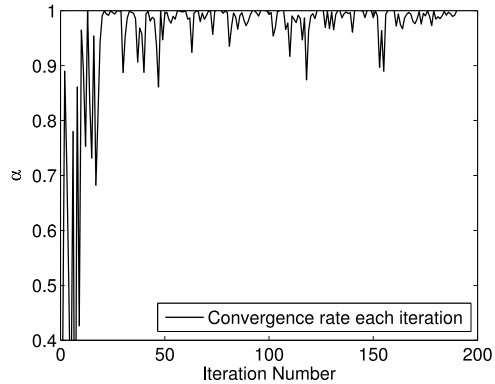

Fig. 4. Convergence rates using the proposed decomposition scheme to solve PP.

above. Note that the maximum end-to-end throughput $r^*(l)$, i.e., the saturated throughput when the minimum scheduling length is 1, can be calculated as $r^*(l) = \frac{r(l)}{\sum_{q=1}^{|\mathcal{K}'|} w_q}$ under the assumption that all the sessions still have equal traffic demands. We find that the maximum end-to-end throughput achieved under the MC^{2}N architecture is generally higher than that achieved under the CN architecture, since the MC^{2}N architecture also takes advantage of local available channels and frequency reuse. Besides, under the MC^{2}N architecture, the maximum end-to-end throughput achieved without energy consumption optimization is higher than that achieved with energy consumption optimization, since the former is optimized with an objective of minimum

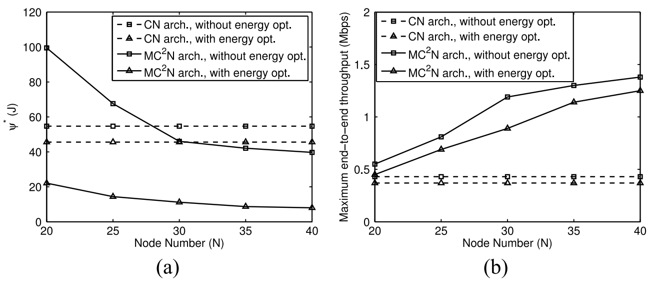

Fig. 5. Performance comparison in four different scenarios. (a) Energy consumption. (b) Maximum end-to-end throughput.

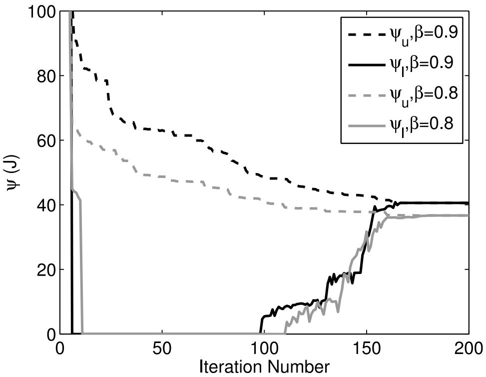

Fig. 6. Performance comparison with different β's under uncertain spectrum supply.

scheduling length and hence a higher maximum end-to-end throughput.

8.4 Energy Consumption Optimization Under Uncertain Spectrum Supply

Both the lower and upper bounds on the minimum energy consumption under uncertain spectrum supply with different β's are illustrated in Fig. 6. Note that we consider a network of 20 CR nodes. We can see that the minimum energy consumption (when the results are stable) when $\beta = 0.9$, i.e., 40.6 J, is higher than that when $\beta = 0.8$, i.e., 36.7 J. This is intuitively true because a smaller β indicates a lower requirement on service quality, and hence the minimum energy consumption can be lower.

8.5 Impact of Adaptive M-QAM

We first compare the running time of our decomposition scheme under these two link capacity models. As we explained above, only the cost of solving PP is influenced by the link capacity model. Thus, we compare the running time of solving PP under constant M-QAM with that under adaptive M-QAM in Table 4. The results are obtained under different N's by setting $\epsilon = 0\%$. We find that the running time required to find the optimal result under the adaptive M-QAM is higher than that under the constant 8-QAM. This is because PP formulated under the constant 8-QAM only includes variables s_{ijm}'s, while that under the adaptive M-QAM includes both s_{ijm}'s and s^t_{ijm}'s as variables, resulting in higher computation complexity.

Fig. 7a compares the minimum energy consumption ψ^* achieved under the two modulation schemes. We find that the minimum energy consumption under the constant 8-QAM is higher than that under the adaptive M-QAM model. Specifically, when $N = 20$, the former is equal to 22.1 J, while the latter is equal to 19.7 J. This is because with the same transmission power, the achievable data rate can be larger under the adaptive M-QAM model. Therefore, the scheduling length required to support the same traffic is shorter under the adaptive M-QAM model, which results in lower energy consumption. We also show in Fig. 7b the maximum end-to-end throughput comparison between these two models. We find that the maximum end-to-end throughput under the adaptive M-QAM model is higher than that under the constant 8-QAM model. Particularly, when $N = 20$, the former is equal to 0.61 Mbps, while the latter is equal to 0.45 Mbps.

Table 5 compares the energy consumption under these two models when β takes different values. We find that energy consumption under both models increases as β increases, because a larger β indicates a higher requirement on spectrum availability. Besides, under the same β, the energy consumption under the adaptive M-QAM model is lower than that under the constant 8-QAM model.

TABLE 4
Running Time Comparison under Different Modulation Schemes

Network Size	Constant 8-QAM (S)	Adaptive M-QAM (S)
$N = 20$	5.56	5.79
$N = 30$	7.18	9.44
$N = 40$	11.42	15.27

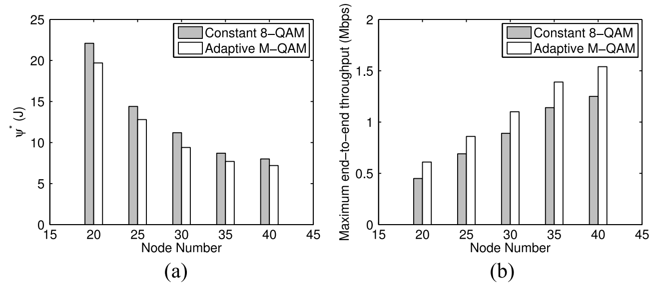

Fig. 7. Performance comparison under different modulation schemes. (a) Energy consumption. (b) Maximum end-to-end throughput.

9 Conclusions

In this paper, we have proposed a novel multihop cognitive cellular network architecture to accommodate the ever-exploding traffic demand in cellular networks. We have studied a minimum energy consumption problem in MC^{2}Ns, and formulated it as a joint scheduling, routing, and transmission power control optimization problem, which we call MP and is a QP problem. We have solved MP utilizing column generation, without having to find the maximum independent sets which are assumed to be known by most previous works. We have also investigated the minimum energy consumption problem considering uncertain spectrum bandwidth, which has been largely overlooked in former research.

TABLE 5
Energy Consumption Comparison under Different Modulation Schemes

Confidence Level	Constant 8-QAM (J)	Adaptive M-QAM (J)
β=0.8	36.7	33.5
β=0.85	38.2	34.9
β=0.9	40.4	37.3
β=0.95	45.6	41.2

Moreover, both constant M-QAM and adaptive M-QAM physical-layer modulation schemes have been considered in the energy consumption problem.

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