Energy-Efficient Cooperative Communications for Multimedia Applications in Multi-Channel Wireless Networks

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Abstract—The dramatic growth of mobile multimedia communications imposes new requirements on quality-of-service and energy efficiency in wireless networks. In this paper, we study the energy- and spectrum-efficient cooperative communication (ESCC) problem by exploiting the benefits of cooperative communication (CC) for mobile multimedia applications in multi-channel wireless networks. In a static network, it is formulated as a mixed-integer nonlinear programming problem. To solve this problem, we use linearization and reformulation techniques to transform it into a mixed-integer linear programming problem that is solved by a branch-and-bound algorithm with enhanced performance. To deal with the problem in dynamic networks, we propose an online algorithm with low computational complexity and deployment overhead. Extensive simulations are conducted to show that the proposed algorithm can significantly improve the performance of energy efficiency in both static and dynamic networks.

Index Terms—Energy efficiency, cooperative communication, multi-channel, optimization, online algorithm

1 Introduction

The demands of mobile multimedia communications have dramatically increased in recent years with the emergence of various mobile devices, e.g., smart phones and tablets. For example, it is now quite common for mobile users to share photos and videos with others. Mobile games are also popular because they are portable and offer entertainment anywhere and anytime. These mobile multimedia applications impose new requirements on the wireless networks: (1) *Quality-of-service (QoS)*. A specified transmission rate should be achieved to guarantee a certain level of QoS. (2) *Energy efficiency*. Since mobile devices are powered by batteries with limited capacity, the transmission of data produced by mobile multimedia applications should be conducted in an energy-efficient manner. (3) *Spectrum efficiency*. In modern wireless networks with booming growth of various wireless applications, the spectrum has become a scare resource that should be efficiently utilized.

Some new emerging cellular technologies, such as device-to-device (D2D) communication that allows two devices in proximity of each other to establish a direct link for data transmission, are rarely considered by existing work. It can significantly improve spectral efficiency because multiple D2D links may work simultaneously in the same channel. However, transmissions on D2D links are prone to be impaired by many factors like fading. The low capacity of wireless links [1], [2] motivates us to exploit the benefits of cooperative communication (CC), which has shown its effectiveness in combating fading to achieve high channel capacity and reliability in a low-cost way well suited to the context of D2D communication. It has been proposed to achieve spatial diversity by employing several single-antenna nodes to form a virtual antenna array without requiring multiple antennas on the same node. The outage probabilities and channel capacity of several CC transmission schemes are analyzed in [3]. Throughput maximization for both unicast and broadcast sessions using CC is studied in [4]. Simic et al. [5] have compared the energy-efficiency of two major cooperative diversity schemes, virtual-multiple-input-single-output (MISO) and decode-and-forward, in wireless sensor networks. Spectrum efficiency in cognitive radio network where CC is applied has been studied in [6].

Although many efforts have been made to exploit the benefits of CC, they fail to satisfy all the requirements of mobile multimedia communications simultaneously. In this paper, we study the energy and spectrum efficiency of mobile multimedia communications empowered by CC. Specifically, we consider a multi-channel wireless network consisting of multiple communication pairs and a set of relay nodes. We formulate an optimization problem called energy- and spectrum-efficient cooperative communications (ESCC) with the objective of minimizing the total energy consumption of a given set of communication pairs by power control, relay assignment, and channel allocation. Our main contributions are summarized as follows.

- First, we define the ESCC problem based on our system model and prove its NP-hardness. To formally describe this problem, we formulate it as a mixed-integer nonlinear programming (MINLP) problem.
- Second, to solve the ESCC problem, we transform it into a mixed-integer linear programming (MILP) problem that can be solved by a branch-and-bound algorithm. To accelerate the solving process, we

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exploit several problem-specific characteristics to enhance the proposed algorithm.

- Third, we propose an online algorithm for dynamic networks where nodes can join and leave the network at any time. It achieves low computational complexity and deployment overhead.
- Finally, extensive simulations are conducted to show that the proposed optimal algorithm can significantly reduce energy consumption in static networks. In dynamic networks, our online algorithm has close performance to the global optimal solution.

The rest of this paper are organized as follows. The related work is reviewed in Section 2. Section 3 introduces some preliminaries of CC and the system model considered in this paper. Problem formulation and solution are presented in Section 4 and Section 5, respectively. An online algorithm is proposed in Section 6. Simulation results are shown in Section 7. Finally, we conclude the paper in Section 8.

2 Related Work

2.1 Mobile Multimedia Communications

Energy efficiency and QoS are both critical for wireless networks [7], especially in video communication systems. He and Wu [8] have studied the optimal power allocation for video encoding and wireless transmission, and introduced a mechanism called achievable minimum distortion to quantify the distortion under a total power constraint. They consider two scenarios in wireless video sensing: small-delay wireless video monitoring and large-delay video surveillance. A general framework that takes into account multiple factors, including source coding, channel resource allocation, and error concealment, for the design of energy-efficient wireless video communication systems is presented in [9]. It can be applied to achieve the optimal tradeoff between energy consumption and video delivery quality during wireless video transmission. Sun et al. [10] have set up a measurement system to reveal the battery capacity consumption behavior and its footprinting in a video delivery system using H.264 codec. A systematic optimization framework which jointly considers the coding parameters and transmission parameters is proposed to achieve the tradeoff between battery consumption and QoS. For mobile multimedia communications, Wang et al. [11] have proposed a novel time slicing technique where the cyclic prefix is replaced with the precoded pseudo-random sequence for MSE-OFDM system. This technique can be used for both uplink and downlink transmissions of mobile multimedia communications with variable data rates.

While wireless technologies like long term evolution (LTE)/LTE-Advanced are capable of providing high speed, large capacity, and guaranteed QoS mobile multimedia service, the D2D communication will become a key feature supported by the next generation cellular networks because of its many beneficial features. The major ones are to provide extended coverage [12], to make offloading [13], and to improve throughput and spectrum efficiency [14] for cellular networks.

2.2 Cooperative Communications

The basic idea of CC is proposed in the pioneering paper [15]. Later, Laneman et al. [3] have studied the mutual information and outage probability between a pair of nodes using CC under both amplify-and-forward (AF) and (decode-and-forward (DF) mode. We summarize the most relevant work as follows. The energy efficiency of CC in wireless body area networks is investigated in [16]. To minimize the energy consumption, the problem of optimal power allocation is studied with the constraint of targeted outage probability. In [17], the energy consumption is optimized by taking amplifier power and circuit power into consideration in cooperative wireless sensor networks. An energy-efficient relay selection scheme integrated with a routing protocol is proposed in [18] for wireless sensor networks.

In [19], Zhao et al. show that it is sufficient to choose one "best" relay node instead of multiple ones for a single unicast session under AF mode. Moreover, they propose an optimal power allocation algorithm based on the best relay selection to minimize the outage probability. For multiple unicast sessions, Sharma et al. [20] consider the relay node assignment with the goal of maximizing the minimum data rate among all concurrent sessions. With the restriction that any relay node can be assigned to at most one source-destination pair, an optimal algorithm called ORA is developed. By relaxing this constraint to allow multiple source-destination pairs to share one relay node, Yang et al. [21] have proven that the total capacity maximization problem can be also solved with an optimal solution within polynomial time.

In [22], Gong et al. propose a cooperative relay scheme to increase the SINR at secondary receivers in cognitive radio networks. However, they focus on the spectrum sharing at relay nodes under the assumption that all relay nodes are deployed at the same location. A joint optimization problem of channel pairing, channel-user assignment and power allocation in a dual-hop relaying network with multiple channels is studied in [23]. It deals with a simple scenario that a source communicates with multiple users via a fixed relay. More recently, Luo et al. [24] study by the first time the tradeoff between the achievable data rate and network lifetime in cognitive radio cooperative communication systems. They propose an energy-efficient joint relay selection and power allocation scheme, and formulate a multi-armed restless bandit problem where the optimal policy is decided in a distributed way.

3 Preliminaries and System Model

In this section, we first introduce some necessary preliminaries of CC and then present the system model considered in this paper.

3.1 Preliminaries of CC

The basic idea of CC can be presented using a well-known three-node model, where a source node s transmits data to a destination node d under the assistance of a relay node r. All transmissions are conducted on a frame-by-frame basis under a channel b with bandwidth W. We consider the decode-and-forward mode in CC, where each frame is partitioned into two time slots. In the first time slot, source s transmits a signal to destination d with power P_s. Due to the broadcast nature of

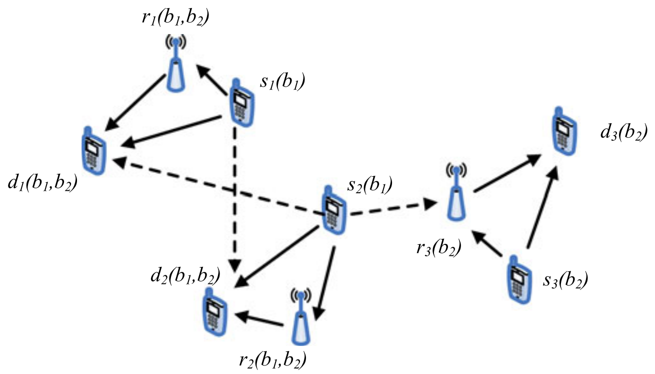

Fig. 1. Network model.

wireless communication, this transmission is also overheard by relay r. After decoding the received signal, relay r forwards it to destination d in the second time slot using power P_r.

We let $\beta_{uv} = \frac{|h_{uv}|^2}{\sigma_v^2}$, where σ_v^2 is the variance of the received background noise at node v and h_{uv} represents the effect of path-loss, shadowing and fading between nodes u and v. Following the analysis in [3], channel capacity between s and d under the assistance of relay r can be calculated by:

$$C(s,r,b) = \frac{W}{2}\min\{\log_2(1+\beta_{sr}P_s), \log_2(1+\beta_{sd}P_s+\beta_{rd}P_r)\}. \tag{1}$$

Under direct transmission (DT), source s transmits data to destination d in both time slots. The channel capacity between s and d using power P_s under channel b is given as follows:

$$C(s,\emptyset,b) = W\log_2(1+\beta_{sd}P_s). \tag{2}$$

By observing (1) and (2), we find that CC is not always better than direct transmission. In fact, a poor choice of relay node could make the achievable data rate under CC even lower.

3.2 System Model

In this paper, we consider a number of single-hop unicast sessions over source-destination (S-D) pairs (s_i, d_i), $s_i \in S = \{s_1, s_2, \ldots, s_n\}$ and $d_i \in D = \{d_1, d_2, \ldots, d_n\}$, under the support of a set $R = \{r_1, r_2, \ldots, r_m\}$ of m dedicated relay nodes in a multi-channel wireless network with a set of l available channels denoted by $B = \{b_1, b_2, \ldots b_l\}$. All nodes are equipped with a single antenna and work in a half-duplex mode, which means that they cannot transmit and receive simultaneously, with a transmission power within the range $[0, P^{max}]$. Following the discussion in [19], [25], each source-destination pair is assigned to at most one relay node. Each node $v (v \in S \cup D \cup R)$ identifies a set of accessible channels denoted by $B(v)$. Due to geographical differences, the set of accessible channels may be different at each node. For any pair (s, d), a common channel $\mathcal{B}(s)$ should be assigned to support a CC transmission with its associated relay node $\mathcal{R}(s)$, or a direct transmission (i.e., $\mathcal{R}(s) = \emptyset$). A relay node is allowed to work under a single channel to avoid frequent channel switching and potential conflicts. An examples is shown in Fig. 1, where the associated channels are given in the brackets beside each node and the possible interfering links are denoted by dotted arrows.

Such a network configuration for a communication session has been widely adopted in the literatures, e.g., [26], and is denoted as a 3-tuple $(s, \mathcal{R}(s), \mathcal{B}(s))$ in this paper. Multiple source-destination pairs may work over the same channel that will be shared by time division multiplexing. In order to guarantee a certain level of QoS, each source-destination pair $(s_i, d_i), 1 \le i \le n$, must afford a specified transmission rate λ_i.

Based on the system model, we study an energy and spectrum efficient cooperative communication problem that is defined as follows.

Definition 1. *The energy and spectrum-efficient cooperative communication problem: given a group of communication sessions, and a set of relay nodes in a multi-channel wireless network, the objective of the ESCC problem is to find the optimal power control, relay assignment, and channel allocation such that all transmission rate requirements are satisfied and the total energy consumption is minimized.*

4 Problem Formulation

In this section, we present the formulation of the ESCC problem. For relay assignment, we define a binary variable u_{ij} as follows:

$$u_{ij} = \begin{cases} 1, & \text{if relay } r_j \text{ is assigned to pair } (s_i, d_i), \\ 0, & \text{otherwise.} \end{cases}$$

We let u_{i0} denote direct transmission between s_i and d_i. Each S-D pair communication is established by either direct transmission or or CC with a single relay [19], [25], leading to the following constraint:

$$\sum_{j=0}^{m} u_{ij} = 1, \forall 1 \le i \le n. \tag{3}$$

To model the channel allocation, we define the following binary variables for sources and relays:

$$v_{ik} = \begin{cases} 1, & \text{if channel } b_k \text{ is allocated to pair } (s_i, d_i), \\ 0, & \text{otherwise,} \end{cases}$$

$$w_{jk} = \begin{cases} 1, & \text{if channel } b_k \text{ is allocated to relay } r_j, \\ 0, & \text{otherwise.} \end{cases}$$

Due to the channel constraint at each node, we have:

$$v_{ik} = 0, \forall b_k \in B - B(s_i) \cap B(d_i), \forall 1 \le i \le n, \tag{4}$$

$$w_{jk} = 0, \forall b_k \in B - B(r_j), \forall 1 \le j \le m. \tag{5}$$

Each source-destination pair (s_i, d_i) and each relay r_j involved in CC must be allocated a channel, which lead to the following constraints:

$$\sum_{k=1}^{l} v_{ik} = 1, \forall 1 \le i \le n, \tag{6}$$

$$\sum_{k=1}^{l} w_{jk} \le 1, \forall 1 \le j \le m. \tag{7}$$

Moreover, a common channel should be assigned to the nodes in the same unicast session using either cooperative communication or direct transmission. Such network configuration for cooperative communication has been widely adopted in the literature [26] and can be represented by:

$$u_{ij} + v_{ik} - 1 \le w_{jk} \le v_{ik} - u_{ij} + 1, \quad \forall 1 \le i \le n, 1 \le j \le m, 1 \le k \le l. \tag{8}$$

When relay assignment is made, i.e., $u_{ij} = 1$, constraint (8) becomes $w_{jk} = v_{ik}$, implying that the same channel is used for (s_i, d_i) and r_j. Otherwise, it becomes a redundant one $v_{ik} - 1 \le w_{jk} \le v_{ik} + 1$, which is always true.

When multiple sessions are allocated on channel b_k, the transmission pattern with T frames using time multiplexing can be described by a binary variable e_{ik}^t:

$$e_{ik}^t = \begin{cases} 1, & \text{if pair } (s_i, d_i) \text{ is scheduled in the } t\text{th frame under channel } b_k, \\ 0, & \text{otherwise.} \end{cases}$$

Each frame can accommodate at most one source-destination pair on any channel, i.e.,

$$\sum_{i=0}^{n} e_{ik}^t \le 1, \forall 1 \le k \le l, 1 \le t \le T, \tag{9}$$

and $e_{ik}^t = 1$ only if $v_{ik} = 1$, which can be expressed by:

$$0 \le e_{ik}^t \le v_{ik}, \forall 1 \le i \le n, 1 \le k \le l, 1 \le t \le T. \tag{10}$$

Finally, the transmission time fraction assigned to each pair (s_i, d_i) must guarantee the transmission rate λ_i to be achieved, i.e.,

$$\lambda_i \le \sum_{k=1}^{l} \left(\frac{W}{T} \sum_{t=1}^{T} e_{ik}^t \sum_{j=0}^{m} u_{ij} I_{ij} \right), \forall 1 \le i \le n, \tag{11}$$

where variables $I_{ij} (1 \le i \le n, 1 \le j \le m)$ are defined as mutual information between s_i and d_i under the assistance of relay r_j. These variables should satisfy the following constraints according to (1):

$$I_{ij} \le \frac{1}{2} \log_2 \left(1 + \beta_{s_i r_j} P_{s_i}\right), \forall 1 \le i \le n, 1 \le j \le m, \tag{12}$$

$$I_{ij} \le \frac{1}{2} \log_2 \left(1 + \beta_{s_i d_i} P_{s_i} + \beta_{r_j d_i} P_{r_j}\right), \quad \forall 1 \le i \le n, 1 \le j \le m. \tag{13}$$

As a special case, the mutual information I_{i0} between source s_i and d_i under direct transmission is:

$$I_{i0} = \log_2 (1 + \beta_{s_i d_i} P_{s_i}), \forall i, 1 \le i \le n. \tag{14}$$

The ESCC problem can be formally presented as follows:

$$\textbf{ESCC}: \quad \min \sum_{1 \le i \le n} P_{s_i} + \sum_{1 \le j \le m} P_{r_j}, \text{ subject to: } (3)\text{-}(14).$$

We observe that above formulation is a MINLP problem due to the logarithm functions in constraints (12)-(14), and multiplication of variables in constraints (11). This problem cannot be efficiently solved because it combines the difficulties from nonlinear constraints and integer variables.

Theorem 1. *The ESCC problem is NP-hard.*

Proof. In order to prove an optimization problem NP-hard, we need to show the NP-completeness of its decision form, which is formalized as follows.

The ESCC problem

INSTANCE: Given a set of source nodes S, a set of destination nodes D and a set of relay nodes R in a CRN with channel set B, where each source-destination pair (s_i, d_i) should transmit under a rate λ_i, and a positive number $\mathcal{E}$.

QUESTION: Is there a relay assignment $\mathcal{R}$ as well as a channel allocation $\mathcal{B}$ such that the total energy consumption per bit of all pairs is no greater than $\mathcal{E}$?

It is easy to see that the ESCC problem is in NP class as the objective function associated with a given $\mathcal{R}$ and $\mathcal{B}$ under optimal power control can be evaluated in a polynomial time. The remaining proof is done by reducing the well-known 3DM problem to the ESCC problem.

The 3DM problem

INSTANCE: Given three disjoint sets X, Y and Z with $|X| = |Y| = |Z| = \psi$, set $T \subseteq X \times Y \times Z$ consisting of a set of 3-tuples (x_i, y_i, z_i), $x_i \in X$, $y_i \in Y$ and $z_i \in Z$, and an integer ϵ.

QUESTION: Is there a subset $M \subseteq T$ such that any two 3-tuples in M are disjoint, and $|M| \ge \epsilon$?

For each node $x_i \in X$, we create a source-destination pair, i.e., $S = X$ and $D = X$. Each node in Y corresponds to a channel in B, i.e., $B = Y$. The relay node set is created by letting $R = Z$. Each 3-tuple (x_i, z_j, y_k) in T specifies a configuration including a source-destination pair x_i, a relay node z_j and a channel y_k. For each configuration (x_i, z_j, y_k), we set the energy consumption under the optimal power control to $\overline{E}$, i.e., $E^*(x_i, z_j, y_k) = \overline{E}$ and $E^*(x_i, \emptyset, y_k) > \overline{E}$. The transmission rate λ_i is set to the value such that $\overline{E}$ can be achieved only when x_i exclusively uses the relay z_j and channel y_k, i.e., $|\mathcal{S}(y_k)| = 1$. Finally, we let $\mathcal{E} = \epsilon \overline{E}$.

It is a straightforward exercise to verify that the solution of the ESCC problem according to the configurations specified by $M (|M| \ge \epsilon)$ is exactly to assign each channel and relay only one source-destination pair such that their transmission rate can be satisfied and the total energy consumption per bit is no greater than $\mathcal{E}$. Then, we suppose that the ESCC problem has a solution no greater than $\mathcal{E}$. When multiple source-destination pairs work under the same channel in our constructed instance, they have to increase their transmission power to meet the rate requirements, leading to a higher energy consumption per bit. In order to satisfy the rate requirement while achieving the minimum total energy consumption $\mathcal{E}$, each source-destination pair should be assigned a relay on an exclusive channel in the solution of ESCC problem, which forms a solution of the 3DM problem including ϵ disjoint 3-tuples. □

5 SOLUTION

In this section, we first linearize the formulated MINLP problem, and then propose a branch-and-bound algorithm to solve the problem by exploiting several problem-specific characteristics.

5.1 Linearization and Reformulation

In this section, we transform the nonlinear constraints into linear ones, which can be easier to handle, using linearization and reformulation techniques.

We first consider to linearize constraint (11). For this purpose, we define a new variable δ_{ij} as:

$$\delta_{ij} = u_{ij} I_{ij}, \forall 1 \leq i \leq n, 0 \leq j \leq m, \tag{15}$$

such that constraint (11) can be rewritten as:

$$\lambda_i \leq \frac{W}{T} \sum_{k=1}^{l} \sum_{t=1}^{T} \left(e_{ik}^t \sum_{j=0}^{m} \delta_{ij} \right), \forall 1 \leq i \leq n. \tag{16}$$

The nonlinear constraint (15) can be equivalently replaced by the following linear ones:

$$0 \leq \delta_{ij} \leq I_{ij}^{max} u_{ij}, \forall i, j, 1 \leq i \leq n, 0 \leq j \leq m, \tag{17}$$

$$\begin{aligned} &I_{ij} - I_{ij}^{max}(1 - u_{ij}) \leq \delta_{ij} \leq I_{ij}, \\ &\forall i, j, 1 \leq i \leq n, 0 \leq j \leq m, \end{aligned} \tag{18}$$

where I_{ij}^{max} is the maximum mutual information of pair (s_i, d_i) using power P^{max} under the assistance of relay $r_j (1 \leq j \leq m)$ or direct transmission $(j = 0)$. The equivalence holds for the following reasons: when $u_{ij} = 1$, both constraints (15) and (18) become $\delta_{ij} = I_{ij}$, and (17) is redundant. When $u_{ij} = 0$, both constraints (15) and (17) become $\delta_{ij} = 0$, and (18) is redundant.

Constraint (16) still contains product of variables and can be further linearized as:

$$c_i \leq \frac{W}{T} \sum_{k=1}^{l} \sum_{t=1}^{T} \theta_{ik}^t, \forall 1 \leq i \leq n, \tag{19}$$

where θ_{ik}^t is defined by:

$$\theta_{ik}^t = e_{ik}^t \sum_{j=0}^{m} \delta_{ij}. \tag{20}$$

In a similar way, the above constraint can be further replaced by the following linear ones:

$$0 \leq \theta_{ik}^t \leq \sum_{j=0}^{m} \delta_{ij}, \forall 1 \leq i \leq n, 1 \leq k \leq l, 1 \leq t \leq T, \tag{21}$$

$$\begin{aligned} &\sum_{j=0}^{m} \delta_{ij} - I_i^{max}(1 - e_{ik}^t) \leq \theta_{ik}^t \leq I_i^{max} e_{ik}^t, \\ &\forall 1 \leq i \leq n, 1 \leq k \leq l, 1 \leq t \leq T, \end{aligned} \tag{22}$$

where I_i^{max} is defined as $I_i^{max} = \max_{0 \leq j \leq m}\{I_{ij}^{max}\}$.

Then, we consider to linearize the constraints (12) to (14) by adopting a similar approach given in [27]. A set of line segments are used to approximate the logarithm function as shown in Fig. 2, where $y^q = \log_2(x^q), 1 \leq q \leq Q$. Thus, these nonlinear constraints can be replaced by a number of linear constraints as:

$$\begin{aligned} &I_{i0} \leq \frac{y^{q+1} - y^q}{x^{q+1} - x^q}(1 + \beta_{s_i d_i} P_{s_i} - x^q) + y^q, \\ &\forall 1 \leq i \leq n, 1 \leq q \leq Q - 1, \end{aligned} \tag{23}$$

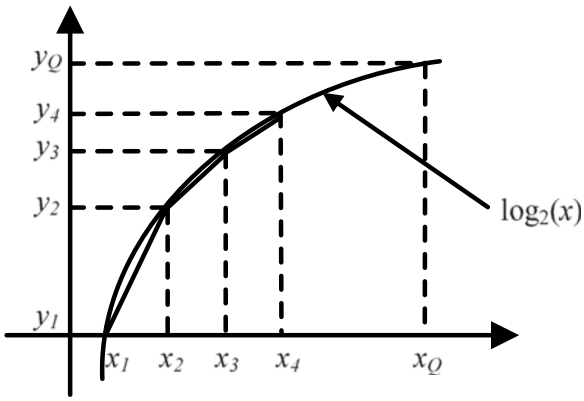

Fig. 2. Approximation of $\log_2(x)$ function.

$$\begin{aligned} &I_{ij} \leq \frac{y^{q+1} - y^q}{x^{q+1} - x^q}(1 + \beta_{s_i r_j} P_{s_i} - x^q) + y^q, \\ &\forall 1 \leq i \leq n, 1 \leq q \leq Q - 1, \end{aligned} \tag{24}$$

$$\begin{aligned} &I_{ij} \leq \frac{y^{q+1} - y^q}{x^{q+1} - x^q}(1 + \beta_{s_i d_i} P_{s_i} + \beta_{r_j d_i P_{r_j}} - x^q) + y^q, \\ &\forall 1 \leq i \leq n, 1 \leq q \leq Q - 1. \end{aligned} \tag{25}$$

We finally obtain a MILP for the ESCC problem as follows:

$$\textbf{ESCC\_L}: \quad \min \sum_{1 \leq i \leq n} P_{s_i} + \sum_{1 \leq j \leq m} P_{r_j}, \text{ subject to: } (3)\text{-}(10), (17)\text{-}(19), \text{ and } (21)\text{-}(25).$$

5.2 A Branch-and-Bound Algorithm

To deal with the integer variables in problem ESCC_L, we propose an algorithm based on a branch-and-bound framework as formally described in Algorithm 1.

Algorithm 1. Solving the ESCC_L Problem

$\mathcal{P} = \{p_0\}, \mathcal{U} = \infty$;
set $\overline{L}_{p_0}$ as the optimal solution of the relaxed problem p_0;
while $\mathcal{P} \neq \emptyset$ **do**
  select a problem $p \in \mathcal{P}$ with the minimum $\overline{L}_p$ and let $\mathcal{L} = \overline{L}_p$;
  set U_p as the solution of p by rounding;
  if $U_p < \mathcal{U}$ **then**
    $U^* = U_p, \mathcal{U} = U_p$;
    if $\mathcal{L} \geq (1 - \epsilon)\mathcal{U}$ **then**
      return the $(1 - \epsilon)$-optimal solution U^*;
    else
      remove all problems $p' \in \mathcal{P}$ with $\overline{L}_{p'} \geq (1 - \epsilon)\mathcal{U}$;
    end if
  end if
  $(p_1, p_2) = \textbf{Problem Decomposition}(p)$;
  solve problems p_1 and p_2 by relaxing all unfixed integer variables and obtain the results $\overline{L}_{p_1}$ and $\overline{L}_{p_2}$;
  if $\overline{L}_{p_1} < (1 - \epsilon)\mathcal{U}$, **then** put p_1 into $\mathcal{P}$; **end if**
  if $\overline{L}_{p_2} < (1 - \epsilon)\mathcal{U}$, **then** put p_2 into $\mathcal{P}$; **end if**
end while
return the $(1 - \epsilon)$-optimal solution U^*;

In Algorithm 1, we use $\mathcal{P}$ to denote a problem set with a lower bound $\mathcal{L}$ and an upper bound $\mathcal{U}$, that are tightest found so far, of the optimal solution. Initially, $\mathcal{P}$ only includes the original problem denoted by p_0 that is constructed by relaxing all the integer variables in ESCC_L formulation. For any problem $p \in \mathcal{P}$, the optimal solution of the corresponding relaxed problem can be obtained by solving a linear programming (LP) problem and it can serve as a lower bound, denoted as $\overline{L}_p$, of the solution to the original problem. Then, the algorithm proceeds iteratively as follows. In each round, we find a problem $p \in \mathcal{P}$ with minimum $\overline{L}_p$ and then set $\mathcal{L} = \overline{L}_p$. While any feasible solution of p can serve as an upper bound, the one obtained by rounding under the satisfaction of all constraints is used and denoted by U_p. The tightest upper bound $\mathcal{U}$ is updated from line 6-13. If the performance gap between $\mathcal{L}$ and $\mathcal{U}$ is less than a predefined small number ϵ, a $(1-\epsilon)$-optimal solution U^* is returned. Otherwise, we replace problem p with two subproblems p_1 and p_2 constructed by function **ProblemDecomposition**, which is shown in Algorithm 2, with different variable domains.

Algorithm 2. Problem Decomposition(p)

1: construct two problems p_1 and p_2 according to formulation ECC_L;
2: **if** there are unfixed $v_{ik}, 1 \le i \le n, 1 \le k \le l$ in problem p **then**
3: Find an unfixed v_{ik} with maximum value in the result of p and denote it by x;
4: **else if** there are unfixed $e^t_{ik}, 1 \le i \le n,\ 1 \le k \le l, 1 \le t \le T$ in problem p **then**
5: Find an unfixed e^t_{ik} with maximum value in the result of p and denote it by x;
6: **else if** there are unfixed $u_{ij}, 1 \le i \le n, 1 \le j \le m$ in problem p **then**
7: Find an unfixed u_{ij} with maximum value in the result of p and denote it by x;
8: **end if**
9: In problem p_1, set $x = 1$ and fix associated variables according to (6), (8), (9), and (10);
10: In problem p_2, set $x = 0$ and fix associated variables according to (6), (8), (9), and (10);
11: construct a set $S' = \{s_i | s_i \in S \text{ and its associated } \mathrm{e}^{\mathrm{t}}_{\mathrm{ik}} \text{ and } u_{ij} \text{ are fixed}\}$;
12: calculate the optimal transmission power $P^*_{s_i}$ and $P^*_{r_j}$ for all $s_i \in S'$ and its associated relay if CC is used, respectively;
13: replace constraints (9), (10),(17)-(19), and (21)-(25) for all sources in S' in both p_1 and p_2
14: **return** problems p_1 and p_2;

5.3 Execution Acceleration

To accelerate the execution of the branch-and-bound algorithm, we exploit some problem-specific characteristics in Algorithm 2 that can reduce not only the complexity of the relaxed ECC_L problem in each iteration of Algorithm 1, but also the number of iterations to achieve the specified performance gap.

In Algorithm 2, we consider to decompose problem p into two subproblems p_1 and p_2 by branching binary variables v_{ik}, e^t_{ik} or $u_{ij}, 1 \le i \le n, 1 \le j \le m, 1 \le k \le l, 1 \le t \le T$. Other variables can be quickly determined after they have been fixed because the resulting problem becomes a tractable linear programming problem. In particular, we fix integer variables in an order of $v_{ik}(1 \le i \le n, 1 \le k \le l)$, $e^t_{ik}(1 \le i \le n, 1 \le k \le l, 1 \le t \le T)$ and $u_{ij}(1 \le i \le n, 1 \le j \le m)$, and for each type of variables, in an decreasing order of their solutions to the relaxed problem p. The idea of the first criteria is that by fixing one variable, other integer variables could be fixed right away as many as possible due to the constraints regarding these correlated variables. The second criteria is a greedy approach similar to rounding such that the solution with desired performance could be reached as early as possible.

After a variable, denoted by x, is selected to branch, we set its value to 1 and 0 in subproblem p_1 and p_2, respectively, as shown in lines 9 and 10. Simultaneously, other variables are fixed according to constraints (6), (8), (9), and (10). For example, when $v_{ik} = 0$ is fixed, many other related variables can be fixed immediately as well, i.e., $e^t_{ik} = 0$ for all $t(1 \le t \le T)$ since source-destination pair (s_i, d_i) is not allowed to transmit under channel b_k. On the contrary, when $v_{ik} = 1$, at least one of the variables $e^t_{ik}(1 \le t \le T)$ should be 1 to guarantee the non-zero channel capacity.

Furthermore, we find out that the fixed variables are also beneficial to lower the complexity of decomposed subproblems by replacing the original constraints with some equivalent and much simplified ones. In line 11, we construct a set $\mathcal{S}'$ to include the sources whose associated variables e^t_{ik} and u_{ij}, $1 \le j \le m, 1 \le k \le l, 1 \le t \le T$ are all fixed. For any source $s_i \in S'$, the transmission time fraction α_i allocated to the corresponding pair can be calculated by:

$$\alpha_i = \frac{\sum_{k=1}^m \sum_{t=1}^T e^t_{ik}}{T}. \tag{26}$$

If $u_{i0} = 1$, the optimal transmission power $P^*_{s_i}$ under direct transmission can be easily calculated by:

$$P^*_{s_i} = \frac{2^{\frac{\lambda_i}{\alpha_i}} - 1}{\beta_{s_i d_i}}, \tag{27}$$

according to (14). Otherwise, we suppose $u_{ij'} = 1, j' \ne 0$ and the optimal transmission power $P^*_{s_i}$ and $P^*_{r_{j'}}$ can be obtained by solving the following problem:

$$\begin{aligned} &\min P_{s_i} + P_{r_{j'}}, \text{subject to:} \\ &\lambda_i \le \frac{\alpha_i}{2} \log_2(1 + \beta_{s_i r_{j'}} P_{s_i r_{j'}}), \end{aligned} \tag{28}$$

$$\lambda_i \le \frac{\alpha_i}{2} \log_2(1 + \beta_{s_i d_i} P_{s_i} + \beta_{r_{j'} d_i} P_{r_{j'}}), \tag{29}$$

which can be written into a linear form as:

$$\begin{aligned} &\min P_{s_i} + P_{r_{j'}}, \text{ subject to:} \\ &2^{\frac{2\lambda_i}{\alpha_i}} - 1 \le \beta_{s_i r_{j'}} P_{s_i}, \end{aligned} \tag{30}$$

$$2^{\frac{2\lambda_i}{\alpha_i}} - 1 \le \beta_{s_i d_i} P_{s_i} + \beta_{r_{j'} d_i} P_{r_{j'}}. \tag{31}$$

Thus, constraints (9), (10), (17)-(19), and (21)-(25) for any sources $s_i \in S'$ can be eliminated to simplify the formulation. Furthermore, we notice that the larger the size of S' is, the less the constraints are involved in the subproblems. In other words, this technique will allow decomposed subproblems to be solved faster and faster as Algorithm 1 proceeds. The equivalence is given in Theorem 2 below.

Theorem 2. *The transmission power obtained by local optimization is also the global optimal solution of the ESCC_L problem.*

Proof. This theorem can be proved by contradiction. Suppose P'_{s_i} is the transmission power of s_i in the global optimal solution, but $P'_{s_i} \neq P^*_{s_i}$. Since the value of α_i used in the local optimization is the same with that in global optimization, and $P^*_{s_i}$ is the optimal solution of local optimization, we have $P^*_{s_i} < P'_{s_i}$. Thus, the global optimal solution can be improved by replacing P'_{s_i} with $P^*_{s_i}$, which contradicts the fact that P'_{s_i} is the global optimal solution. □

6 An Online Algorithm

In this section, we consider a dynamic network where S-D pairs can join and leave the network at any time. A straightforward method to handle network dynamic is to apply the global optimal algorithm proposed in the last section when any joining or leaving event happens. Although total energy consumption can be always minimized under such a method, it incurs high computational complexity due to frequent execution of the global algorithm. Moreover, deploying a new global solution that would be significantly different from current network status may lead to high overhead of channel switching and relay reassociation for many nodes.

In this section, we design an online algorithm to deal with network dynamic with the following three important objectives.

Efficiency. The online algorithm should have low computational complexity such that it can quickly respond to network events.

Simplicity. To reduce the overhead of deployment, the number of nodes that need to be reconfigured should be as small as possible.

Performance. Although the total energy consumption of the online algorithm cannot always achieve the performance of the global optimal algorithm, their performance gap should be small such that users have incentive to adopt this algorithm.

Note that the above objectives may contradict with each other, and they cannot be satisfied at the same time. Thus, our online algorithm should make a good tradeoff among these objectives. The initial channel allocation, relay selection and power control of a network can be obtained by applying the global optimal algorithm. We first consider the case that an S-D pair (s_x, d_x) joins the network. The corresponding participation algorithm is shown in Algorithm 3. As shown in lines 1 and 2, pair (s_x, d_x) is allocated an accessible channel b_k that accommodates nodes whose total energy consumption is the lowest among all possible channels. Then, each existing pair under channel b_k, which is included in set S^k, contributes a fraction $\frac{1}{|S^k|}$ of its transmission time to pair (s_x, d_x), whose transmission time is calculated in line 4. After that, we consider the relay selection by applying the local optimization proposed in last section for each available relay that is not assigned under channel b_k. The one with the minimum energy consumption will be chosen as the relay node for pair (s_x, d_x). Finally, we update the transmission time of pairs in S^k in line 7, and recalculate their transmission power by applying the local optimization.

Algorithm 3. Participation Algorithm for an S-D Pair (s_x, d_x)

1: find a channel b_k that can be accessed by pair (s_x, d_x) and accommodates nodes with minimum total energy consumption;
2: $\mathcal{B}(s_x) = b_k$;
3: $S^k = \{s_i | \mathcal{B}(s_i) = b_k, s_i \neq s_x\}$;
4: $\alpha_x = \frac{\sum_{s_i \in S^k} \alpha_i}{|S^k|}$;
5: the set of available relay nodes are maintained in set R^k;
6: apply local optimization to determine the relay selection, i.e., $\mathcal{R}(s_x) = \arg\min_{r_j \in R^k}(P_{s_x} + P_{r_j})$, and corresponding transmission power;
7: $\alpha_i = \frac{\alpha_i(|S^k - 1|)}{|S^k|}, \forall s_i \in S^k$;
8: update the transmission power of nodes in S^k and their associated relay nodes by local optimization;

We then consider the case that an S-D pair (s_x, d_x) leaves the network. As shown in Algorithm 4, the transmission time α_x is equally shared by the set of pairs in S^k that still work under the same channel. If pair (s_x, d_x) uses direct transmission, i.e., $\mathcal{R}(s_x) = \emptyset$, we finish the departure process by updating the transmission power of nodes in S^k using local optimization. Otherwise, we replace the current relay node of an S-D pair in S^k by $\mathcal{R}(s_x)$ if the energy consumption can be reduced, as shown in lines 4 to 15.

Note that our online algorithm can be easily extended to handle the dynamic of channels in wireless networks. When the set of accessible channels of an S-D pair or a relay node changes such that they cannot work under the current channel, we tackle the problem by first removing the corresponding S-D pair by Algorithm 4, and then adding it into the network with updated accessible channel set using Algorithm 3. In D2D scenarios, the network operator with global information can manage the switching between direct links and conventional cellular links by executing the proposed online algorithms.

The time complexity of our online algorithms is analyzed as follows. We first consider the participation algorithm shown in Algorithm 3. The algorithm first checks all channels, with complexity of $O(l)$, to identify the one that satisfies the requirement in line 1. Then, the operations from line 2 to 5 can be finished within $O(1)$. The relay selection in line 6 needs to conduct at most m times of local optimization, each of which is with complexity of $O(1)$, to find out the best relay. Finally, the complexity of updating the transmission power of nodes in S^k is $O(n)$ in the worst case. Therefore, the overall complexity of the participation algorithm is $O(l + n + m)$. In the departure algorithm shown in

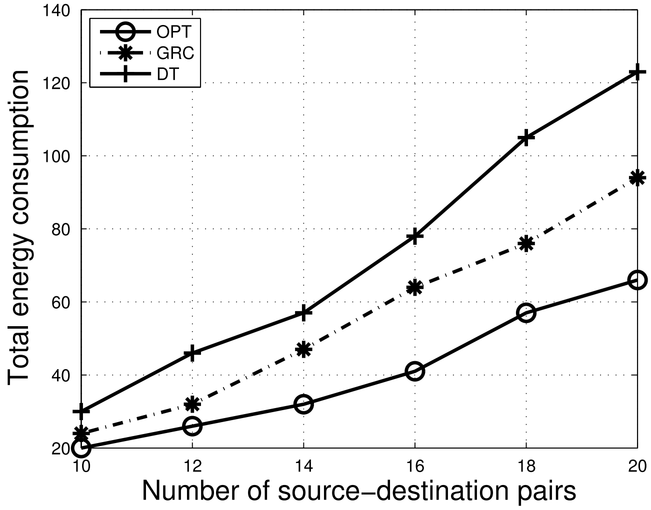

Fig. 3. Energy consumption vs. number of S-D pairs.

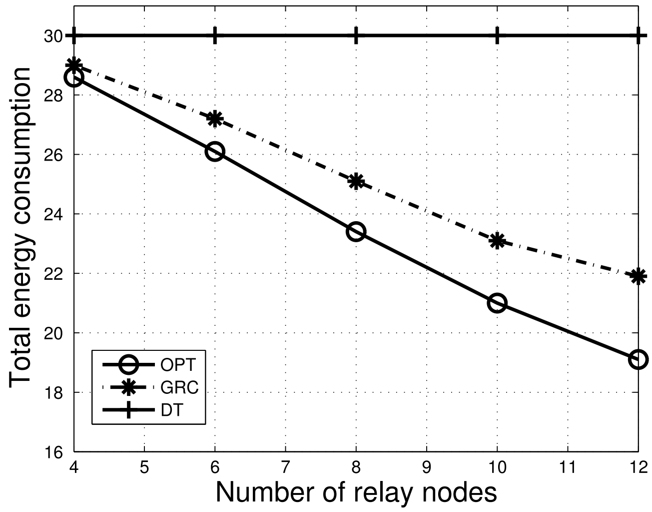

Fig. 4. Energy consumption vs. number of relay nodes.

Algorithm 4, each pair in S^k tries to reduce its energy consumption if a relay is released by the leaving pair from line 4 to 15, leading to a time complexity of $O(n)$. The updates of transmission time fraction in line 3 and the transmission power in line 16 are both with $O(n)$ complexity. Thus, the overall complexity of departure algorithm is $O(n)$.

Algorithm 4. Departure Algorithm for an S-D Pair (s_x, d_x)

1: $\alpha_x = 0$, $b_k = \mathcal{B}(s_x)$;
2: $S^k = \{s_i | \mathcal{B}(s_i) = b_k, s_i \neq s_x\}$;
3: $\alpha_i = \alpha_i + \frac{\alpha_x}{|S^k|}, \forall s_i \in S^k$;
4: **if** $\mathcal{R}(s_x) \neq \emptyset$ **then**
5:   **for** each $s_i \in S^k$ **do**
6:     $r' = \mathcal{R}(s_i)$;
7:     apply the local optimization by letting $\mathcal{R}(s_i) = \mathcal{R}(s_x)$;
8:     **if** the energy consumption can be reduced **then**
9:       $\mathcal{R}(s_i) = \mathcal{R}(s_x)$;
10:       break;
11:     **else**
12:       $\mathcal{R}(s_i) = r'$;
13:     **end if**
14:   **end for**
15: **end if**
16: update the transmission power of nodes in S^k by local optimization;

Both participation and departure algorithms have low computational complexity. Moreover, only transmission time and relay association (only in Algorithm 4) of each pair under one channel need to be adjusted, leading to low overhead of deployment. Finally, the proposed online algorithm can achieve close performance with global optimal solution, which will be shown in next section.

7 Performance Evaluation

7.1 Simulation Setting

In our simulation setting, all the nodes in a network instance are distributed randomly within a $1{,}000 \times 1{,}000$ square region. We set the variance of the background noise power at the destination and the relay to 10^{-10}W. The bandwidth of each channel is specified as a uniform distribution in the range from 20 to 30 MHz and the channel gain $|h_{uv}|^2$ between two nodes with a distance $||u - v||$ is calculated as $|h_{uv}|^2 = ||u - v||^{-4}$. We set the rate requirement of each node randomly within $[1, 5]$.

For static networks, we compare the optimal results obtained by our proposed algorithm, which is denoted by OPT, with the following two algorithms.

Direct transmission: All pairs use direct transmission.

Greedy relay assignment and channel allocation (GRC): We follow the basic idea of the GRC algorithm proposed in [6] that considers a similar network environment with our work. Instead of optimizing the transmission rate as [6] does, we iteratively assign a relay node and a channel to a pair such that the resulting energy consumption is minimized at each step.

For dynamic network, we compare our online algorithm with the global approach that always update the network according to the optimal solution as we introduced in the beginning of Section 6.

7.2 Simulation Results

We first investigate the effect of number of source-destination pairs on the energy consumption under 10 relay nodes and 10 channels. All results are obtained by averaging over 20 random network instances. As shown in Fig. 3, energy consumption grows as the number of S-D pairs increases for all algorithms. That is because more source-destination pairs will share a channel in larger networks. In order to achieve the required transmission rate, they have to use higher transmission power to increase channel capacity. Moreover, OPT and GRC always outperform DT with lower energy consumption because of the benefits of CC.

We then evaluate the energy consumption under different number of relay nodes. The number of source-destination pairs and channels are both fixed to 10. As shown in Fig. 4, the relay node number does not affect the performance of DT, and the energy consumption of both OPT and GRC can be improved in the networks with more relay nodes. For

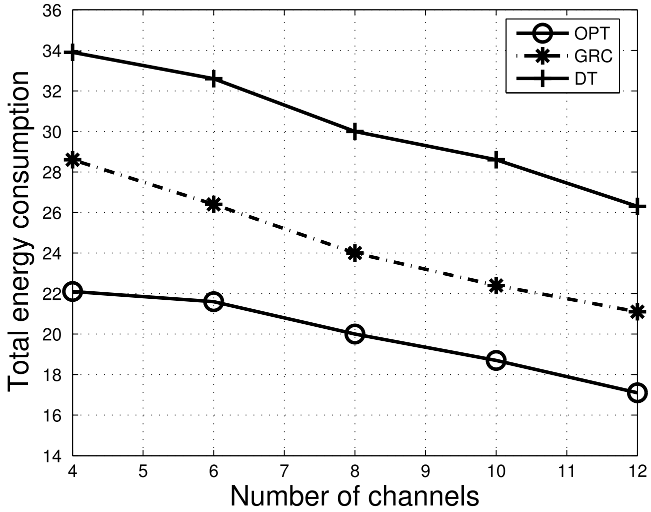

Fig. 5. Energy consumption vs. number of channels.

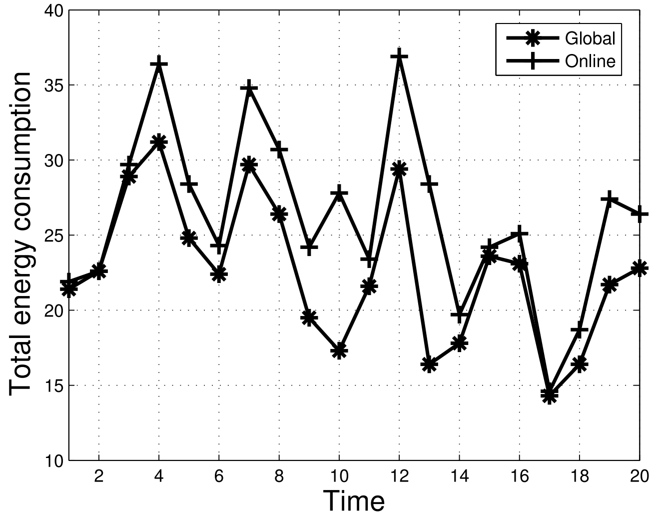

Fig. 7. Energy consumption of the online algorithms.

example, the energy consumption of OPT and GRC is reduced by 40 and 32 percent, respectively, as the number of relay increases from 4 to 12. We attribute this phenomenon to the fact that each source-destination pair has more chances to select a better relay node when larger number of relays are available in the network.

The influence of channel number to the energy consumption is investigated by changing its value from 4 to 14. The results under 10 S-D pairs and 10 relay nodes are shown in Fig. 5. The performance of all algorithms decreases as channel number grows because the channel contention is mitigated when large number of channels is available in the network. For example, when the number of channels increases from 4 to 14, the reduction of energy consumption of OPT is nearly 30 percent.

We evaluate the time efficiency of the proposed acceleration approach by comparing the execution time of the branch-and-bound algorithms with and without acceleration. We plot the cumulative distributed function (CDF) of execution time in Fig. 6. The execution time of some network instances is greater than 5 seconds if acceleration is not applied. However, the maximum execution time will be reduced to 3.6 seconds with acceleration. The average execution time of the algorithms with and without acceleration is 1.63 and 1.85 seconds, respectively.

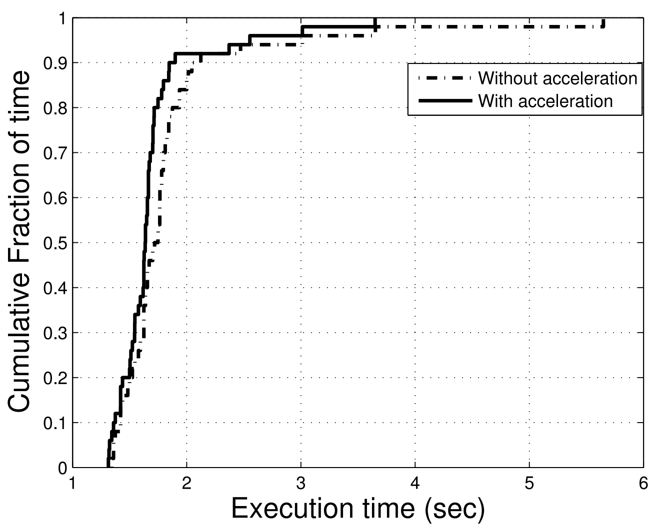

Fig. 6. Time efficiency of the acceleration approach.

To evaluate the performance of our online algorithm, we consider a network that initially contains 10 S-D pairs and 10 relay nodes. Then pair participation and departure events happen subsequently according to a Poisson process, in which the inter-arrival time and residence time of these communication pairs obey a negative exponential distribution with parameters $\lambda_a = 0.5$ and $\lambda_r = 0.1$, respectively. We show the performance of our online algorithm and the global approach within 20 time units in Fig. 7. We observe that our online algorithm incurs only 17 percent extra energy consumption to the global approach.

8 Conclusion

In this paper, we exploit the great potential of CC for energy-efficient multimedia communications in multi-channel networks. With the objective of minimizing total energy consumption, the problem is formulated as a MINLP problem by taking power control, relay selection, and channel allocation into consideration. After linearizing all the nonlinear constraints, we propose a branch-and-bound algorithm with enhanced performance to solve the problem. To deal with the dynamic of networks, we propose an online algorithm with low complexity and overhead. Extensive simulations are conducted to show that the proposed algorithm can significantly reduce the energy consumption compared with existing work.

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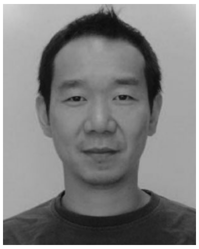

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