DAFEE: A Decomposed Approach for Energy Efficient Networking in Multi-Radio Multi-Channel Wireless Networks

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***Abstract*—As wireless networks are gaining increasing popularity, the network energy efficiency has become a critical issue. In this paper, we focus on energy-efficient networking in a generic multi-radio multi-channel (MR-MC) wireless network where transmission scheduling, transmit power control, radio and channel assignment are coupled together in a multi-dimensional resource space, thus requiring joint optimization and low complexity algorithms. We propose a novel Decomposed Approach For energy-efficient (DAFEE) networking in MR-MC networks, with the objective to minimize network energy consumption while guaranteeing a certain level of performance. In particular, we leverage a multi-dimensional tuple-link based model and a concept of resource allocation pattern to transform the complex optimization problem into a linear programming (LP) problem. The LP problem however has a very large solution space due to the exponentially many possible resource allocation patterns. We then exploit delay column generation and distributed learning techniques to decompose the problem and solve it with an iterative process. Furthermore, we propose a sub-optimal algorithm to speed up the iteration with constant-bounded performance. Simulation results are presented to demonstrate the effectiveness of the proposed algorithm.**

***Index Terms*—Multi-radio multi-channel networks, optimization, resource allocation, energy efficiency**

I. Introduction

Wireless network energy efficiency is a compound of both network performance (e.g., throughput) and energy consumption. Since performance and energy consumption are usually conflicting objectives, a common modeling approach for energy-efficient networking is minimizing energy consumption while guaranteeing a certain level of performance requirement [1]–[3], which is to be adopted in this paper.

We study energy-efficient networking in a generic multi-radio multi-channel (MR-MC) network. The problem is to allocate transmissions wisely such that network traffic demands are satisfied with least amount of energy consumption. Since an MR-MC network consists of nodes equipped with multiple radio interfaces operating on different channels, a transmission decision can be viewed as a resource allocation strategy in a multi-dimension resource space involving selection of transmitters and receivers for establishing transmission links, radio and channel assignment, transmit power control and link scheduling. On one hand, the multi-dimensional resource space in MR-MC networks provides a broad range of resource allocation choices to improve network performance [4]–[6]. On the other hand, the large scale of resource space incurs significant complexity in finding an optimal solution, which thus motivates us to explore a Decomposed Approach For Energy-Efficient networking (DAFEE) in MR-MC networks.

Energy-efficient networking in MR-MC networks requires joint optimization solution over coupled resource allocation issues including link scheduling, radio/channel assignment and power control. The existing studies have addressed resource allocation issues in MR-MC networks over different dimensions, but a generic joint optimization solution over the whole multi-dimensional space (especially when power control is involved) is still not available, to the best of our knowledge. Radio/channel assignment and transmission scheduling in MR-MC networks have been well studied with the objective to maximize network capacity [7]–[10]. Specifically, the protocol interference model is widely adopted to characterize the link conflict relationships within the network into a conflict graph, over which independent set based scheduling is then used to facilitate a linear programming (LP) based formulation [11], [12]. However, such a model simplifies transmission links into an on-off manner with fixed transmit power, which can neither model dynamic power assignment nor accurately reflect the practical interference magnitude. The signal-to-interference-plus-noise ratio (SINR) based physical interference model is more realistic and models transmissions under the power control. Link scheduling for capacity optimization under the physical interference model has been studied in [13]–[15], but limited to single-channel scenarios. How to incorporate physical interference model based power assignment into MR-MC networks for energy-efficient resource allocation remains a challenging issue to be addressed.

In this paper, we adopt the multi-dimensional tuple-link model, proposed in [9], to develop the DAFEE approach in MR-MC networks under the physical interference model. With tuple-link based modeling, joint resource allocation solution can be reduced into scheduling and power assignment over tuple-links, where radio/channel assignments are implicitly achieved by the activation of channel/radio dimensions associated with the scheduled multi-dimensional tuple-links.

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To further decouple the issue of scheduling and power assignment, we propose a new concept of *resource allocation pattern* (RAP) which is defined as a vector of transmit power assignment over all of the tuple-links in the network. Under an RAP, the receiver of each tuple-link will achieve a certain SINR and the transmission capacity of a tuple-link is then determined according to the Shannon-Hartley equation. By considering discretized transmit power levels, the joint scheduling and power assignment problem is finally transformed into a scheduling problem over a finite number of RAPs, which facilitates an LP formulation, in a similar manner as independent set based scheduling [6], [9].

The RAP based scheduling however suffers from the complexity issue due to exponentially many RAPs. We then leverage delay column generation (DCG) to decompose the optimization problem, by starting with an initial subset of RAPs and then iteratively adding new RAPs for improved objective. The key challenge in DCG based solution lies in the sub-problem of searching for a new entering column, which in our case is a new RAP. We demonstrate that the sub-problem is equivalent to a utility based optimization problem which can be solved by distributed learning algorithm. Moreover, we propose a sub-optimal algorithm to speed up the iteration, and conduct theoretical analysis of the performance of this algorithm.

The main contributions of this paper is the development of the DAFEE framework with the following techniques

1) We formulate an optimization framework over multi-dimensional resource space for energy-efficient networking over multi-dimensional tuple-links, which can jointly solve the resource allocation issues of radio/channel assignment, power control and transmission scheduling.
2) We propose a new concept of RAP that enables translating the original optimization problem into an RAP based scheduling problem, which is an LP optimization.
3) To effectively solve the RAP-based scheduling problem, we develop DCG based decomposition techniques and exploit distributed learning algorithm in searching new RAPs. We propose a sub-optimal algorithm to speed up the iterative process, which approximates the optimal solution with constant performance bound.
4) We present numerical results to demonstrate the performance of DAFEE approach in improving energy efficiency.

The remainder of this paper is organized as follows. Section II reviews more related work. Section III describes the system model. Section IV and V present the problem formulation and decomposition algorithms of the DAFEE framework, respectively. The DAFEE algorithm and related theoretical analysis are developed in Section VI with convergence and optimality analysis. Performance evaluations are presented in Section VII. Section VIII gives the conclusion.

II. Related Work

Energy-efficient networking has gained increasing interest in recent research, especially for networks with multi-dimensional resource space such as cognitive radio networks [16]–[18] and device-to-device communications [19], [20]. Resource allocation for heterogeneous cognitive radio network is studied in [16], where a Stackelberg game approach is adopted with gradient based iteration algorithm as solution. Channel assignment and power control is investigated in [17] to maximize energy efficiency for cognitive radio networks, where problem is solved by mapping it to a maximum matching problem. Similarly, a joint solution of channel and power allocation is proposed in [18], with the objective of maximizing overall throughput. Physical interference model is applied and the problem is solved by bargaining based cooperative game. An energy efficiency maximization problem is formulated in [19] as a non-convex problem. The problem is transformed into a convex optimization problem with nonlinear fractional programming and solved with iterative optimization algorithm. The authors of [20] propose a joint radio resources and power allocation scheme with energy efficiency as objective, which is formulated and solved with auction game. The above works target on specific network scenarios or configurations, which could not be applied to generic MR-MC networks. Furthermore, as most of them focus on channel and power allocation, link scheduling problem is not considered.

Energy efficiency in generic MR-MC network is discussed in [21] that an optimization problem is formulated to derive radio/channel assignment and scheduling solutions to optimize energy efficiency under full network capacity. A similar approach is adopted in [1] to minimize energy consumption with guaranteed capacity requirement. The problem is solved with a decomposed approach due to the large scale solution space. While these work take protocol interference model to simplify the scheduling problem, the more realistic physical interference model is applied in [22] for a joint scheduling and radio configuration problem. However, they all use fixed transmit power in the formulation, which cannot lead to the most energy-efficient solution. In existing literature, a joint solution over the whole multi-dimensional resource space including link scheduling, radio/channel assignment as well as power allocation has not been fully investigated, which is to be studied in this paper.

III. Problem Formulation

A. System Model

Consider a generic MR-MC network with node set $\mathcal{N}$. Each node $v \in \mathcal{N}$ is equipped with one or multiple radios which are denoted as radio set $\mathcal{R}_v$. Define the set of all radios in the network as $\mathcal{R}$ which is the union set of all $\{\mathcal{R}_v | v \in \mathcal{N}\}$. We assume that the transmit power of each radio can take value only from a discrete set of power levels which is denoted as $\mathcal{P} = \{0, 1, 2, \ldots, |\mathcal{P}|\}$. Suppose the maximum transmit power of a radio is denoted as $p_{\max}$, then the transmit power can take values from $\{0, p_{\max}/(|\mathcal{P}|-1), 2p_{\max}/(|\mathcal{P}|-1), \ldots, p_{\max}\}$. The set of non-overlapping channels in the network is denoted as $\mathcal{C}$. For each radio, all the other radios within its maximum transmission range but not locating on the same node are defined as its neighbors. For a non-isolated node, there are directional physical links from it (as the transmitter) to its neighbors (as the receivers). Denote $\mathcal{L}$ as the set of all such physical links. For simplicity, we focus on single-hop transmissions and suppose that the traffic demand information for each physical link l (i.e., the amount of data required to be transmitted through a link) is known, and is denoted as $b_l, \forall l \in \mathcal{L}$. Such a model is also used in [22].

The objective is to minimize the total energy consumption in the network under the above traffic demand constraint by jointly addressing: link scheduling, radio and channel assignments, and transmit power control. In this optimization, the scheduling problem is to select transmission links and decide the transmission time for them. It can be seen that the joint optimization problem involves both continuous and discrete decision variables, making it a mixed-integer problem which is known of high complexity. In what follows, we present a tuple-link based framework to remodel the network, which facilitates an LP formulation and problem decomposition.

A *tuple-link* is defined as a combined resource allocation for a transmission indicating the transmitter radio, the receiver radio[1] and the operating channel. Denote $\mathcal{T}$ as the set of all the tuple-links in the network. Tuple-link only exists when there exists a corresponding physical link; a physical link l can be mapped to multiple tuple-links, denoted as set $\mathcal{T}_l$. Accordingly, the traffic demand of l is to be fulfilled by the tuple-links in $\mathcal{T}_l$. Figure 1 gives examples of tuple-links with 2 channels in the network. As shown by the dash lines, the physical link between the two nodes is mapped to 8 tuple-links. With this tuple based

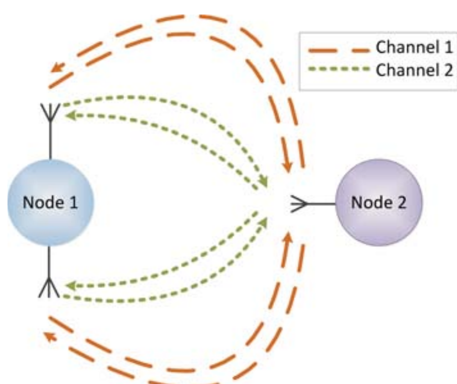


Fig. 1. Tuple-link example.

framework, the above optimization problem becomes to jointly solve scheduling and power control of the tuple-links.

In a wireless network, interference between two concurrent transmissions will degrade the transmission quality of both links. In this paper, we consider physical interference model, in which the transmission quality over a tuple-link is characterized by the SINR at the receiver. For a tuple-link $t \in \mathcal{T}$, the received SINR is defined as

$$\gamma_t = \frac{h_t p_t}{I_t + \sigma^2} = \frac{h_t p_t}{\sum\limits_{t' \in \mathcal{T} \setminus t} h_{t't} p_{t'} + \sigma^2} \tag{1}$$

where h_t, p_t, I_t, σ^2 denote the channel gain, transmit power, received interference and the noise power, respectively. Particularly, $h_{t't}$ stands for the interference channel gain from t''s transmitter to t's receiver. If t' and t are in different channel, $h_{t't} = 0$ which indicates t' will not generate interference to t. Then the achievable transmission rate of tuple-link t can be expressed as

$$a_t = B_t \log_2(1 + \gamma_t) \tag{2}$$

where B_t is the corresponding channel bandwidth of tuple-link t.

B. Optimization Problem Formulation

Generally, a tuple-link may use different transmit power at different time such that the mutual interference can be dynamically coordinated and the transmission rate can be adjusted. At a time instance, the transmit power levels of all the tuple-links form a *resource allocation pattern* (RAP). Based on (2) and definition of tuple-links, an RAP implies the transmission state of all the links in the network, including which radios and channels are being used as well as the corresponding transmit power. Therefore, the scheduling problem is to select the RAPs and decide transmission time for them.

Since the sets of tuple-links and transmit power levels are finite, the total number of possible allocation patterns is finite. In each RAP, if a tuple-link is assigned a non-zero transmit power level, the tuple-link is considered to be active. Let $\mathcal{A}$ be the set of all RAPs in the network. Denote the transmission time assigned to pattern α as x_α. The power level and the achieved data rate of tuple-link t in pattern α are $p_{t,\alpha}$ and $a_{t,\alpha}$, respectively. Since each RAP defines the transmit power levels of all tuple-links, $a_{t,\alpha}$ can be expressed as a function of $p_{t,\alpha}$ as $a_{t,\alpha} = B_t \log_2(1 + \frac{h_t p_{t,\alpha}}{\sum_{t' \in \alpha \setminus t} h_{t't} p_{t',\alpha} + \sigma^2})$. Thus, the energy-efficient resource allocation problem can be formulated as an RAP based scheduling to minimize energy consumption and satisfy traffic demand:

Problem 1:

$$\min_{\{x_\alpha\}} \quad E = \sum_{\alpha \in \mathcal{A}} \sum_{t \in \mathcal{T}} p_{t,\alpha} x_\alpha \tag{3}$$

$$s.t. \quad \sum_{t \in \mathcal{T}_l} \sum_{\alpha \in \mathcal{A}} a_{t,\alpha} x_\alpha \geq b_l, \quad \forall l \in \mathcal{L} \tag{4}$$

$$x_\alpha \geq 0, \quad \forall \alpha \in \mathcal{A} \tag{5}$$

The optimization variables are transmission time x_α's to be assigned to RAPs. The objective function in (3) stands for the total energy consumption which is the summation of energy consumption over all the tuple-links in all RAPs. The constraints in (4) indicate that for each physical link l, the total traffic over all l's corresponding tuple-links should satisfy l's traffic demand b_l.

[1]Tuple-link is directional since the transmitter and receiver are specified.

It can be seen that Problem 1 is an LP problem; however, since the allocation patterns can be significantly many, searching the optimal scheduling of the patterns across such a large solution space is difficult, which motivated us to develop a decomposition method to find the optimal solution.

IV. DAFEE Framework

The complexity of Problem 1 is mainly determined by the size of RAP set $\mathcal{A}$. For example, consider that if all nodes have the same number of radios $|\mathcal{R}_v|$ and radio conflict (see Section IV-B1) is ignored, the size of $\mathcal{A}$ can be expressed as $|\mathcal{A}| = |\mathcal{P}|^{(|\mathcal{L}|\cdot|\mathcal{R}_v|^2\cdot|\mathcal{C}|)}$, which will be significantly large.

Our experiments in tuple-link scheduling indicate that only a subset of $\mathcal{A}$ (called the critical set) will be scheduled. Therefore, we apply the delayed column generation (DCG) technique to iteratively find such a critical subset [23].

A. DCG-Based Decomposition

Starting from an initial feasible solution obtained based on a small subset of $\mathcal{A}$, the DCG method iteratively searches for new columns or RAPs that are promising in improving the objective. Let $\mathcal{A}^{(k)}$ denote the subset of RAPs already found at the beginning of iteration k. In this iteration, first, the optimal solution based on $\mathcal{A}^{(k)}$ is obtained as follows.

Master Problem

$$\min \quad E^{(k)} = \sum_{\alpha\in\mathcal{A}^{(k)}} \left(\sum_{t\in\mathcal{T}} p_{t,\alpha}\right) x_\alpha, \tag{6}$$

$$s.t. \quad \sum_{\alpha\in\mathcal{A}^{(k)}} \left(\sum_{t\in\mathcal{T}_l} a_{t,\alpha}\right) x_\alpha \geq b_l, \quad \forall l\in\mathcal{L}, \tag{7}$$

$$x_\alpha \geq 0, \quad \forall\alpha\in\mathcal{A}^{(k)} \tag{8}$$

The above master problem can be easily solved if the subset $\mathcal{A}^{(k)}$ is of moderate size. The solution of the master problem provides the scheduling time $x_{\alpha,k}$ for each pattern α in $\mathcal{A}^{(k)}$ along with the dual variable $w_l^{(k)}$ associated with each of the constraint in (7). For any other pattern $\alpha\notin\mathcal{A}^{(k)}$, whether it can be added to the Master Problem for deciding its transmission time is evaluated based on the following reduced cost (improvement to objective):

$$\begin{aligned}&\sum_{l\in\mathcal{L}}\sum_{t\in\mathcal{T}_l} a_{t,\alpha}w_l^{(k)} - \sum_{t\in\mathcal{T}} p_{t,\alpha}\\ =&\sum_{t\in\mathcal{T}}\left(a_{t,\alpha}w_t^{(k)} - p_{t,\alpha}\right),\end{aligned} \tag{9}$$

where $w_t^{(k)} = w_l^{(k)}$ if $t\in\mathcal{T}_l$ and $w_t^{(k)} = 0$ if otherwise. In the above equation, we have used the fact that each tuple-link belongs to only one physical link. A new pattern will be added to $\mathcal{A}^{(k)}$ if it maximizes the reduced cost, i.e., it solves the following optimization problem:

Sub-Problem (Problem 2):

$$\max_{\alpha\in\mathcal{A}\setminus\mathcal{A}^{(k)}} \quad \sum_{t\in\mathcal{T}}\left(a_{t,\alpha}w_t^{(k)} - p_{t,\alpha}\right) \tag{10}$$

In the objective function of the sub-problem, the term $a_{t,\alpha}w_t^{(k)} - p_{t,\alpha}$ can be viewed as the utility of tuple-link t in pattern α which consists of the profit in satisfying the traffic demand (i.e., $a_{t,\alpha}w_t^{(k)}$, since $w_t^{(k)}$ is the dual of (7)) and the power cost; the objective function is thus the total utility of all tuple-links (system utility) of a pattern. Hence, the sub-problem is indeed to search for an RAP with maximal utility. The new RAP, if found, is then added to current subset to form $\mathcal{A}^{(k+1)}$. The master problem is then updated and solved to provide a new set of solutions. The process is repeated until no new RAP with positive utility can be found in the sub-problem.

Remark 1. *The physical meaning of the solving process can be explained as follows. Each time solving the master problem will provide an updated evaluation on all the tuple-links regarding to their capabilities in satisfying traffic demand based on their performance in existing RAPs, and such evaluation are conveyed through dual variables $w_t^{(k)}$. Then according to this evaluation, a new RAP that can maximize the system utility is searched and fed back to the master problem. With this new information, all the tuple-links will be re-evaluated by solving the updated master problem.*

Theorem 1. *The optimal solution of the decomposed problem is also optimal for the original problem (Problem 1), which is achieved when no new RAP of positive utility can be found in the sub-problem.*

Proof: When the sub-problem cannot find any allocation pattern with positive utility $\sum_{t\in\mathcal{T}}(w_t a_t - p_t)$, it means the value of the objective function in the master problem cannot be further reduced, in other words the master problem achieves the optimal solution. Since the number of allocation patterns is finite, this solution also optimizes the original problem (Problem 1). ■

B. Learning Based Algorithm for Solving the Sub-Problem

In this subsection we focus on solving the sub-problem, which is to find an RAP that maximizes the system utility. First of all, to form valid RAPs, we need to deal with radio constraints.

1) radio constraint: In an RAP, there are three types of radio constraints:

- transmitters of different tuple-links cannot use the same radio
- receivers of different tuple-links cannot use the same radio
- transmitter and receiver from different tuple-links cannot use the same radio

The first constraint can be resolved by applying a requirement that each radio can assign positive power level to at most one of its outgoing tuple-links. In the following we will introduce an algorithm where radios act as players to make transmission decisions so that this requirement can be easily incorporated in the design of player strategy set.

For the second and the third constraints, we formulate a relaxed version of the sub-problem where these two types of constraints are ignored. Then the solution from the relaxed problem is further processed to satisfy radio constraints and make it a feasible solution. Hereafter, we denote the relaxed problem as **Problem 3**.

2) distributed learning: Based on our tuple-link based network model, each radio is associated with a number of incoming and outgoing tuple-links. Therefore, solving the relaxed problem is to let each radio select exactly one outgoing tuple-link and assign a power level (the other out-going tuple-links are assigned zero power level). The decision is made towards maximizing the system utility as indicated in Problem 2. The sub-problem is still of large searching space. In order to further decompose the problem, we exploit utility based distributed learning algorithm [24] to solve the sub-problem.

Consider the radios in the network as players, denoted as $\mathcal{R} = \{1, \ldots, |\mathcal{R}|\}$. s_j denotes a strategy of player j, which indicates the outgoing tuple-link that is chosen with an associated power level. The strategy set of player j is denoted as S_j. The strategies of all players, denoted as $\mathbf{s}$, if satisfying the radio constraints, provide power assignments for all tuple-links and therefore form an RAP. Since for each player, there can be at most one tuple-link scheduled for transmission, the utility of a player is the same as the utility of the chosen tuple-link. Then the system utility can be expressed as the sum of player utilities

$$U(\mathbf{s}) = \sum_{j \in \mathcal{R}} U_j(\mathbf{s}) \tag{11}$$

where, the utility of each player can be obtained by

$$u_j = U_j(\mathbf{s}) = w_j a_j - p_j \tag{12}$$

with w_j, a_j and p_j the corresponding dual value, rate and power level of the selected tuple-link of radio j, respectively.

The basic idea of the learning algorithm is to recursively update the players' strategies based on their moods, where the mood of player j, denoted as m_j, takes two types – content (C) and discontent (D). In the following, define (s_j, u_j, m_j) as the state of player j. The learning algorithm is then run iteratively where each player updates its strategy and mood as follows: Suppose the current state of player j is $(\bar{s_j}, \bar{u_j}, \bar{m}_j)$.

Update strategy:

If the current mood $\bar{m}_j$ is content, choose a new strategy s_j from S_j with probability

$$\Pr(s_j) = \begin{cases} 1 - \epsilon^q & \text{for } s_j = \bar{s}_j \\ \frac{\epsilon^q}{|S_j|-1} & \text{for } s_j \neq \bar{s}_j \end{cases} \tag{13}$$

where $\epsilon > 0$ is the experimentation rate and q is a constant larger than the number of players $|\mathcal{R}|$. If the current mood $\bar{m}_j$ is discontent, randomly choose a strategy from S_j, i.e.,

$$\Pr(s_j) = \frac{1}{|S_j|}, \forall s_j \in S_j \tag{14}$$

After a new strategy s_j is chosen, calculate the new utility u_j based on (12) and then update the mood.

Update mood:

If the mood is content and the new state is the same as the current one, then m_j remains content. Otherwise, if the new state is different from current one or the current mood is discontent, set mood to content with probability ϵ^{1-u_j} and to discontent with probability $1 - \epsilon^{1-u_j}$, respectively.

The updating processes are summarized as follows:

Algorithm 1: State Updating of Player j

Input: current state $(\bar{s}_j, \bar{u}_j, \bar{m}_j)$;
//Update strategy
if $\bar{m}_j = C$ **then**
  Update strategy s_j according to Eq. (13);
else
  Update strategy s_j according to Eq. (14);
end
Calculate utility u_j using s_j;
//Update mood
if $\bar{m}_j = C$ *and* $(s_j, u_j) = (\bar{s}_j, \bar{u}_j)$ **then**
  $m_j = C$;
else
  $m_j = C$ with probability ϵ^{1-u_j} and
  $m_j = D$ with probability $1 - \epsilon^{1-u_j}$;
end
Output: new state (s_j, u_j, m_j).

Definition 1 (Interdependence [24])**.** *An $|\mathcal{R}|$-player game $G(\mathcal{R}, \{S_j\}_{j \in \mathcal{R}}, \{U_j\}_{j \in \mathcal{R}})$ is interdependent if for every strategy $s_j \in S_j, (j \in \mathcal{R})$ and every subset of players $\mathcal{R}_b \subset \mathcal{R}$, there exists a player $n \notin \mathcal{R}_b$ and strategies $\{s'_r\}_{r \in \mathcal{R}_b} \in \{S_r\}_{r \in \mathcal{R}_b}$ such that*

$$U_n(\{s'_r\}_{r \in \mathcal{R}_b}, \{s_j\}_{j \in \mathcal{R}/\mathcal{R}_b}) \neq U_n(\{s_r\}_{r \in \mathcal{R}_b}, \{s_j\}_{j \in \mathcal{R}/\mathcal{R}_b}) \tag{15}$$

Lemma 1. *$G(\mathcal{R}, \{S_j\}_{j \in \mathcal{R}}, \{U_j\}_{j \in \mathcal{R}})$ is an interdependent $|\mathcal{R}|$-player game on a finite strategy space.*

Proof: For a connected network and any radio subset $\mathcal{R}_b \subset \mathcal{R}$, we can always find a radio $n, n \notin \mathcal{R}_b$ such that n is the neighbor of some radio (radios) in $\mathcal{R}_b$ or n belongs to a node which has radios in $\mathcal{R}_b$. In other words, we can always find a radio outside $\mathcal{R}_b$ that will be affected by radios inside $\mathcal{R}_b$. Suppose radio n is affected by r, which is either a neighbor of n or locates at the same node with n. With the current strategy, if n and r are working on the same channel, then r can change the power level in its strategy which changes n's utility. If not, r can switch to the same channel as n that will change n's utility. In either case, (15) holds. ■

As can be seen, Algorithm 1 runs at each radio in a distributed manner. According to Theorem 1 in [24], the stochastically stable state of an interdependent game maximizes the system utility. Then, one can easily prove the following theorem, which shows that this distributed algorithm converges.

Theorem 2. *The distributed learning can converge to the optimal solution of* **Problem 3** *with probability 1 if the experiment rate ϵ is sufficiently small.*

3) post-processing: The previous learning algorithm provides solution for the relaxed Problem 3 which allows a radio being used by multiple tuple-links. In order to satisfy all the radio constraints, we need to deactivate (set power level to zero) some of the active tuple-links in the solution such that each radio is used by at most one tuple-link.

Consider a graph V where the vertices correspond to radios in the network. An edge[2] exists between two vertices if there is an active tuple-link connecting them, with a weight equal to the tuple-link's utility. Then the radio constraint becomes that a vertex in V cannot be incident to more than one edge, which is to find a matching in V. Therefore the problem of deactivating tuple-links to maximize remained utilities is equivalent to finding the maximum weighted matching of graph V. Algorithms of finding the maximum weighted matching of a graph can be found in many literatures such as [25], [26], which can be applied to the deactivation procedure. After processing the solution of Problem 3, we can obtain a solution to the sub-problem (Problem 2).

Remark 2. *In some network scenarios, the second or the third radio constraint may not apply. When a receiver applies multiplexing techniques such as CDMA, receiving from multiple transmitters is allowed. A full-duplex radio can allow transmitting and receiving at the same time. In these scenarios, the deactivation post-processing may not be necessary.*

After the deactivation procedure, since there may be less transmissions in the network, the utilities of the remaining active tuple-links are updated. Then, the power levels of all tuple-links, which form a new RAP, is fed back to the master problem.

V. DAFEE Algorithm and Performance Analysis

In the master stage, the master problem is solved by a central agent who can collect the transmission strategy of each radio in the network to form an RAP. Based on the obtained patterns, the central agent can perform RAP based scheduling and obtain an optimal solution of the master problem. The solution also comes with dual values, which will be distributed to the tuple-links in the network.

In the sub-problem stage, each radio can distributedly update its strategy and utility, where the latter is calculated based on the received interference of the selected tuple-link. At the end of the sub-problem stage, radios will report their strategies to the central agent and the latter will perform the maximum matching algorithm to deactivate tuple-links and remove radio conflict, if needed. The new RAP is then added to central agent's constraint matrix for next iteration.

When solving the sub-problem with learning algorithm, it may take a long time to converge to the optimal solution. In fact it may not be necessary to wait for the optimal solution in sub-problem, any pattern with positive utility can improve the objective of master problem, which can update scheduling solution and dual values (as more accurate evaluations of tuple-links). With this consideration, we propose the DAFEE algorithm as follows.

[2]In this problem the edge is used to imply radio conflict relationship which is nondirectional.

A. Algorithm Design

Define a short period of time TL_1 and a longer period of time TL_2. Each time when starting sub-problem stage, the learning process runs only for TL_1 time, followed by the matching process (if necessary). Then the current utility is calculated; if the utility is larger than a predefined value β, the sub-problem stage stops and the current tuple-link strategies are returned to the master problem as a new RAP. Otherwise, the learning process continues to run for another TL_1 of time and checks the utility again. Every time when a utility exceeds a certain threshold β, the sub-problem stage stops. If after TL_2 there is no utility exceeding β, the entire algorithm stops, outputting the current solution as the final result. The entire algorithm is summarized in Algorithm 2.

Algorithm 2: DAFEE Algorithm

```
Initial allocation pattern sets A^(0)
(e.g. randomly assign non-zero power to all tuple-links);
//Master stage
Formulate Master Problem with RAPs A^(k);
Solve for schedule x^(k), energy E^(k) and dual variables
w^(k);
Distribute dual variables to corresponding radios;
//Sub-problem stage
reset timer1 and timer2;
while timer2 < TL_2 do
    while timer1 < TL_1 do
        Initialize with random strategy;
        for radio j = 1, ..., |R| do
            Update state according to Algorithm 1 ;
        end
    end
    Collect strategies and utilities of radios;
    Deactivation procedure with maximum weighted
    matching algorithm, if needed;
    Form a new RAP and calculate the sum utility;
    if sum utility > β then
        Add the new RAP to form A^(k+1);
        Go to master stage;
    end
    Reset timer1;
end
```

B. Performance Analysis

For ease of exposition, we rewrite Problem 1 into standard matrix form:

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{c}'\mathbf{x} \\ \textit{s.t.} \quad & \mathbf{A}\mathbf{x} \geq \mathbf{b} \\ & \mathbf{x} \geq \mathbf{0} \end{aligned}$$

where $\mathbf{c}, \mathbf{x}, \mathbf{b}$ are the vector forms of $\{\sum_{t\in\mathcal{T}} p_{t,\alpha}\}$, $\{x_\alpha\}$ and $b_l\}$, respectively. $\mathbf{A}$ denotes the $|\mathcal{L}|$ by $|\mathcal{A}|$ constraint matrix with elements $\sum_{t\in\mathcal{T}_l} a_{t,\alpha}$.

Suppose the optimal objective of Problem 1 is E^* and the result obtained from DAFEE is E_{DAFEE}, we have the following performance bound:

Theorem 3. *The approximation ratio of DAFEE algorithm is bounded as*

$$\frac{E_{DAFEE}}{E^*} \leq (|\mathcal{P}|-1)(|\mathcal{R}|+\beta/p_{max}) \tag{16}$$

where $|\mathcal{P}|$ is the number of power levels, $|\mathcal{R}|$ is the number of radios and β is the parameter in Algorithm 2.

Proof: Suppose $\mathbf{x}^*$ and $\mathbf{w}^*$ are the optimal solutions of the original problem (Problem 1) and its dual problem, respectively, where the dual problem is

Problem 4:

$$\begin{aligned} \max \quad & \mathbf{w}'\mathbf{b} \\ s.t. \quad & \mathbf{w}'\mathbf{A} \leq \mathbf{c}' \\ & \mathbf{w} \geq \mathbf{0}. \end{aligned}$$

Suppose the final solution of the DAFEE algorithm is $\hat{\mathbf{x}}$, and the corresponding dual variable is $\hat{\mathbf{w}}$. When the algorithm ends, there may be columns whose utilities are positive but less than β (according to the definition of utility below (10)). Define Δ as the index set of such columns. Therefore

$$0 < \hat{\mathbf{w}}'\mathbf{A}_\alpha - c_\alpha \leq \beta, \quad \forall \alpha \in \Delta \tag{17}$$

$$\hat{\mathbf{w}}'\mathbf{A}_\alpha - c_\alpha \leq 0, \quad \forall \alpha \in \mathcal{A} \setminus \Delta \tag{18}$$

where $\mathbf{A}_\alpha$ is the α'th column of $\mathbf{A}$ and c_α is the α'th element of $\mathbf{c}$. Denote the sub-matrix constructed with $\mathbf{A}$'s columns in Δ as $\mathbf{A}_\Delta$. Suppose $\mathbf{H}_\Delta$ is the left inverse of $\mathbf{A}_\Delta$ such that $\mathbf{H}_\Delta\mathbf{A}_\Delta = \mathbf{I}$ where $\mathbf{I}$ is identity matrix. Expand $\mathbf{H}_\Delta$ to size $|\mathcal{L}| \times |\mathcal{A}|$ by adding all-zero rows. Denote $\boldsymbol{\beta}$ as an $|\mathcal{A}| \times 1$ vector whose elements are equal to β if located at Δ, and 0 otherwise. Hence, combining (17) and (18) we will have

$$\begin{aligned} & \hat{\mathbf{w}}'\mathbf{A} - \mathbf{c}' \leq \boldsymbol{\beta}' \\ \Longrightarrow\ & (\hat{\mathbf{w}}' - \boldsymbol{\beta}'\mathbf{H})\mathbf{A} \leq \mathbf{c}' \end{aligned}$$

When β is small enough, $\hat{\mathbf{w}}' - \boldsymbol{\beta}'\mathbf{H}$ will be nonnegative and therefore a feasible solution of Problem 4. Hence,

$$\mathbf{w}^{*\prime}\mathbf{b} \geq (\hat{\mathbf{w}}' - \boldsymbol{\beta}'\mathbf{H})\mathbf{b} = \hat{\mathbf{w}}'\mathbf{b} - \boldsymbol{\beta}'\mathbf{H}\mathbf{b}$$

Since $\hat{\mathbf{w}}'\mathbf{b} = \mathbf{c}'\hat{\mathbf{x}}$,

$$\mathbf{w}^{*\prime}\mathbf{b} \geq \mathbf{c}'\hat{\mathbf{x}} - \boldsymbol{\beta}'\mathbf{H}\mathbf{b}$$

We may ignore the columns corresponding to negative elements in $\mathbf{Hb}$ since it can only make $\boldsymbol{\beta}'\mathbf{Hb}$ even smaller and decrease the gap between solution and optimum. For the other columns, we have $\mathbf{HAx}^* \geq \mathbf{Hb} \geq \mathbf{0}$. Then $\boldsymbol{\beta}'\mathbf{Hb} \leq \boldsymbol{\beta}'\mathbf{HAx}^* = \boldsymbol{\beta}'\mathbf{x}^*$.

According to weak duality,

$$\begin{aligned} & \mathbf{c}'\mathbf{x}^* \geq \mathbf{w}^{*\prime}\mathbf{b} \geq \mathbf{c}'\hat{\mathbf{x}} - \boldsymbol{\beta}'\mathbf{x}^* \\ \Longrightarrow\ & \mathbf{c}'\hat{\mathbf{x}} \leq (\mathbf{c}' + \boldsymbol{\beta}')\mathbf{x}^* \end{aligned}$$

Finally,

$$\begin{aligned} \frac{E_{DAFEE}}{E^*} &= \frac{\mathbf{c}'\hat{\mathbf{x}}}{\mathbf{c}'\mathbf{x}^*} \\ &\leq \frac{\sum_{\alpha\in\mathcal{A}}(c_\alpha + \beta)x_\alpha^*}{\sum_{\alpha\in\mathcal{A}} c_\alpha x_\alpha^*} \\ &\leq (|\mathcal{P}|-1)(|\mathcal{R}|+\beta/p_{\max}) \end{aligned}$$

The last inequality holds since c_α cannot be larger than $|\mathcal{R}|p_{\max}$ (where all radios are transmitting with maximum power) or smaller than $p_{\max}/(|\mathcal{P}|-1)$ (where only one radio is transmitting with minimum non-zero power level). The bound can be interpreted as the extra energy consumption introduced by approximation is no larger than adding β to the consumption of each scheduled RAP. ■

VI. Numerical Results

The simulation is performed in a connected MR-MC network environment with 30 nodes which are randomly deployed in a 1000×1000 m^2 area. Each node is equipped with two radio interfaces, with 5 or 8 channels available for transmissions. $p_{\max}$ is set to one and the transmit power can take values on $\{0, 1/(|\mathcal{P}|-1), 2/(|\mathcal{P}|-1), \ldots, 1\}$.

We will use energy efficiency of the network as the performance metric, which is defined as the ratio of sum traffic demands ($\sum_{l\in\mathcal{L}} b_l$) and total energy consumption (the objective function of Problem 1). In order to demonstrate the effect on energy efficiency from including power assignment into joint allocation, we vary the power strategy size (number of available power levels) and compare the achieved energy efficiency. Notice that when $|\mathcal{P}| = 2$, transmit power can only take values of zero or maximum transmit power, which can be viewed as the solution without power control.

The energy efficiency corresponding to different power strategy sizes $|\mathcal{P}|$ is shown in Fig. 2, where we fix all the other network parameters and take records at the same number of master iteration for all cases. As can be seen from this figure, the lowest energy efficiency is achieved when no power allocation is used. It is because that whenever a tuple-link is scheduled for transmission, the maximum power is used, which will cause extensive interference that degrades the transmission efficiency. A more delicate power strategy can increase the possible patterns of power allocation in the network, as well as better allocate co-channel transmissions to reduce mutual interference. Therefore involving power control into joint resource allocation and increasing number of power levels can improve the achieved performance.

We further evaluate the performance of joint resource allocation under different network configurations in terms of variable numbers of channel, traffic demands and traffic densities. The total link demand in the network depends on the number of links with positive demands and the traffic demand

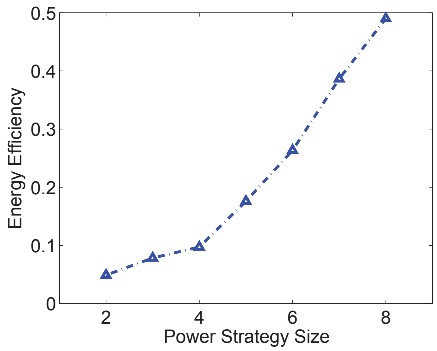
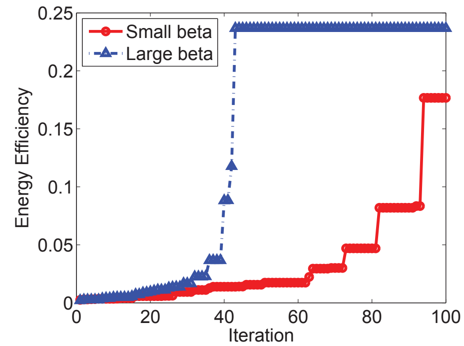
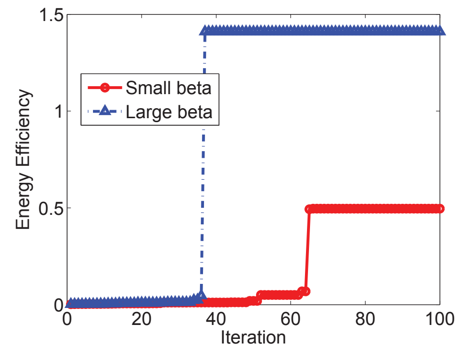


Fig. 2. Energy efficiency with different power strategy size.



(a) PSS-5



(b) PSS-8

Fig. 5. Effect of β

for each link. To simulate a higher traffic demand, the traffic demands in each link increases but the number of links with positive demand is unchanged. For a higher traffic density, the number of links with positive demand increases but the total demands keeps unchanged. The energy efficiency comparison is shown in Fig. (3) and (4), along with the iteration process. Iteration in x-axis counts for the master problem. Denote a case with power strategy size n as PSS-n.

In Fig. 3 and 4, we compare the energy efficiency under different power strategy size (PSS). It is observed that PSS-8 can outperform PSS-5 and PSS-2 in all scenarios. As mentioned previously, more choices of power levels can provide more allocation and solution patterns, which gives higher probability in finding a better solution at each round. This can also be supported by the observation that the performance of PSS-8 improves faster than others.

As traffic demand or traffic density increases, the energy efficiency will be lower than that of light traffic, since more traffic may lead to more intensive interference which impacts energy efficiency. Another observation is that the case with a higher traffic density has more dynamic increase in the solution compared with the other cases. This is because a higher density indicates the strategy of a tuple-link may have a higher chance to affect others' utilities and cause a larger change in the objective. Therefore the curve will stay in flat in a relatively shorter period and gradually evolve soon.

The choice of β also has an influence on the convergence speed. As shown in Fig. 5, a larger β will drive up performance quickly since a larger β means each round in the master problem is only triggered by a larger improvement. However, a large β also indicates that after several rounds the sub-problem is less likely to find any further improvement exceeding β and probably miss possible small improvement. Therefore the case with a larger β tends to stop earlier, while the case with a smaller β is still able to improve the solution gradually. In practice, we can first use a larger β to run the algorithm such that the result can be improved rapidly. Then switch to a smaller β to check for further improvement.

VII. Conclusion

In this paper we have investigated energy-efficient resource allocation in MR-MC networks. We have formulated an optimization problem to minimize energy consumption in the network while satisfying the traffic demand requirements. The large scale problem has been solved by decomposition algorithm based on DCG and distributed learning methods. The solution of this problem provides a joint allocation of radio, channel, and transmit power. We have proposed an efficient algorithm to speed up the solution process and shown the performance bound. Numerical results demonstrated that the proposed algorithm can improve energy efficiency of MR-MC networks.

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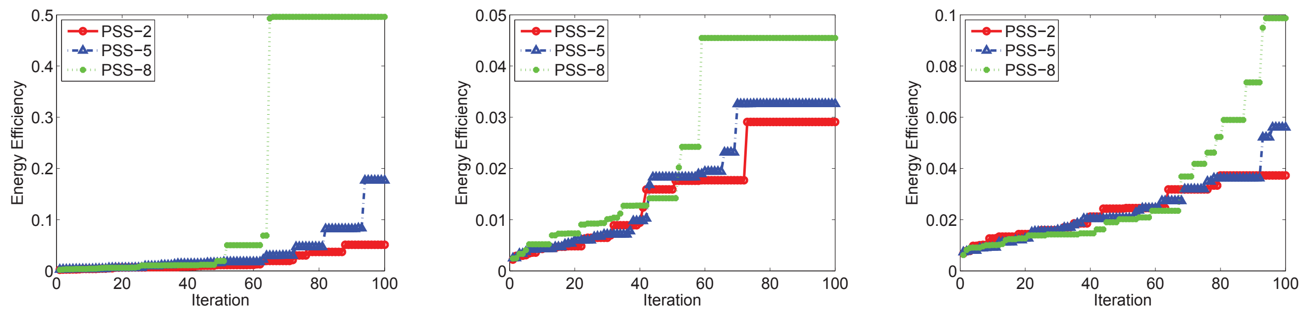
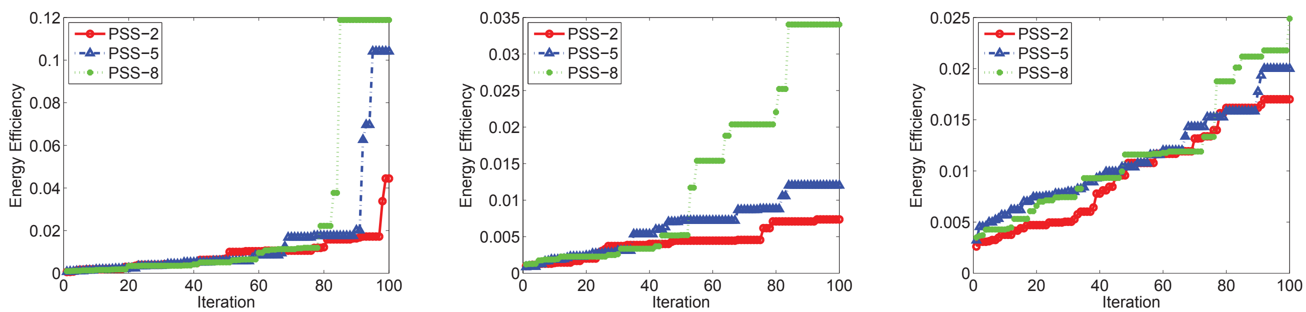


(a) default.

(b) higher traffic demand.

(c) higher traffic density.

Fig. 3. Energy efficiency comparison under different network parameters with 5 channels.



(a) default.

(b) higher traffic demand.

(c) higher traffic density.

Fig. 4. Energy efficiency comparison under different network parameters with 8 channels.

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