A Cross-Layer Optimization Framework for Multihop Multicast in Wireless Mesh Networks

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***Abstract*— The optimal and distributed provisioning of high throughput in mesh networks is known as a fundamental but hard problem. The situation is exacerbated in a wireless setting due to the interference among local wireless transmissions. In this paper, we propose a cross-layer optimization framework for throughput maximization in wireless mesh networks, in which the data routing problem and the wireless medium contention problem are jointly optimized for multihop multicast. We show that the throughput maximization problem can be decomposed into two subproblems: a data routing subproblem at the network layer, and a power control subproblem at the physical layer with a set of Lagrangian dual variables coordinating interlayer coupling. Various effective solutions are discussed for each subproblem. We emphasize the network coding technique for multicast routing and a game theoretic method for interference management, for which efficient and distributed solutions are derived and illustrated. Finally, we show that the proposed framework can be extended to take into account physical-layer wireless multicast in mesh networks.**

***Index Terms*— Convex optimization, dual decomposition, mesh network, multicast routing, network coding, power allocation, game theory.**

I. INTRODUCTION

Wireless mesh networks have emerged as a practical solution for the broadband wireless Internet. In a wireless mesh network, nodes at different locations communicate with each other by relaying information over wireless links. An important consideration in the design of a mesh network is the network's ability to efficiently support high-throughput multicast applications (e.g., video streaming broadcast) over wireless links. This paper addresses architectural and network optimization issues for such applications in a wireless mesh network.

The design of wireless mesh networks for high-throughput multicast involves at least two sets of technical challenges. The first set of challenges involves multicast routing (i.e., the ability for a single source node to send information to multiple destinations at the same time[1].) Recently, a technique called *network coding* was proposed [2] to implement multicast by information encoding at the relay nodes. Network coding has proven to be effective in increasing the multicast throughput [1] [2] [3]. Network optimization with the use of network coding is one of the main emphases of this paper.

The second set of challenges arises due to the shared nature of the wireless medium. Since geographically nearby transmissions often interfere with each other, the traditional 'bit-pipe' assumption on link capacity no longer holds. It is possible to tradeoff the capacity of one link with the capacity of another by power adaptation. This necessitates the use of power control techniques for interference mitigation at the physical layer.

This paper addresses both sets of challenges together by considering a joint optimization of multicast routing and power control for a wireless mesh network. We focus on achieving maximum multicast throughput and propose a cross-layer optimization framework to model and to solve the optimal throughput problem in an efficient and distributed manner.

In our framework, the utility of the overall throughput is maximized subject to three groups of constraints: (1) the dependence of overall throughput on per-link data flow rates, (2) the dependence of per-link flow rates on link capacities, and (3) the dependence of link capacities on radio power levels. Our main contribution is that the joint optimization problem can be decomposed into two subproblems: a multicast routing subproblem at the network layer and a power control subproblem at the physical layer. We present a general primal-dual algorithm that iteratively solves these two disjoint subproblems and globally converges to the optimal solution of the throughput maximization problem. We further illustrate how each subproblem can be solved efficiently with different techniques. More specifically, at the network layer, we discuss the multicast routing subproblem with or without network coding; at the physical layer, we discuss geometric programming method as well as game theoretic approach. The primal-dual algorithm and the effective solutions for each subproblem together constitute an integrated modelling and solution framework for optimal multicast in wireless mesh networks. The optimization framework proposed in this paper represents a cross-layer strategy, which strikes a balance between the *demand* of link bandwidth at the network layer and the *supply* of link capacity at the physical layer.

The remainder of this paper is organized as follows. We first discuss related work in Section II, then motivate the necessity of a cross-layer design through a simple example in Section III. In Section IV, we propose the joint optimization framework and the layering approach, together with an efficient primal-dual algorithm to solve the problem. In Section V, we discuss the modular structure of subproblems, point out several new

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[1]Since unicast and broadcast may be viewed as special cases of multicast [1], multicast routing represents a general problem at the network layer.

techniques at the network and physical layers, and show how the subproblems are incorporated in the overall framework. In Section VI, we address the distributed implementation of wireless mesh networks. Section VII presents simulation results to illustrate the main concept. In Section VIII, we discuss possible extensions such as hybrid/hierarchical networks and the utilization of physical-layer wireless multicast. Finally, we conclude the paper in Section IX.

II. Related work

Recent fundamental work by Ahlswede, Cai, Li and Yeung [2] and Koetter and Médard [3] showed that coding operations at relay nodes can improve the overall throughput for multicast in a directed network. Such coding operations are referred to as *network coding*. In addition, Li, Yeung and Cai [4] showed that linear coding suffices to achieve the maximum rate. With the assistance of network coding, the problem of achieving optimal multicast throughput in undirected networks has been studied by Li *et al.* [1][5]. Recently, two groups have studied the distributed implementation of routing with network coding. Lun *et al.* [6] proposed a subgradient-based distributed algorithm in dual domain, while Wu and Chiang [7] proposed a subgradient-based distributed method in primal domain. However, most of existing literature in network coding assumes fixed link capacities, which is not realistic in multihop wireless networks, where link capacities are subject to interference from other neighboring transmissions. In this paper, we propose a framework that takes the physical layer interference into account when solving the optimal throughput problem for multihop wireless mesh networks.

The main technique used in this paper is the method of dual decomposition for convex optimization problems. Our dual decomposition approach is inspired by the duality analysis of TCP flow control protocol by Low [8] and Wang *et al.* [9], in which network congestion parameters are interpreted as primal and dual optimization variables and the TCP protocol is interpreted as a distributed primal-dual algorithm. Our work is also related to the extension of the above work to multihop wireless networks by Chiang [10], in which power levels and TCP window sizes are jointly optimized. In a related work, Johansson, Xiao, and Boyd [11] carried out a similar convex optimization approach to jointly perform routing and resource allocation in wireless code division multiple access systems. Recently, Lin and Shroff [12] employed a dual decomposition technique to study the impact of imperfect scheduling on cross-layer rate control. In our previous work [13], we have also studied a dual method for the joint source coding, routing, and power allocation problem for sensor networks, where the focus is a lossy source coding problem at the application layer. All of the above work treat the multi-session unicast problem only. The main idea of the present work is to propose a similar framework for multicast problems in a network coding context.

For wireless multicast in ad hoc networks, Wu *et al.* [14][15] studied the issue of network planning and solved a cost (e.g., power consumption or congestion) minimization problem with centralized control. Both the focus and solution approaches of our paper are different as compared to [14][15]. We focus on maximum throughput, which is critical to the provisioning of high network capacity especially in mesh networks. We target distributed solutions. We further present a general solution framework that decomposes the optimization into different layers with modular structures.

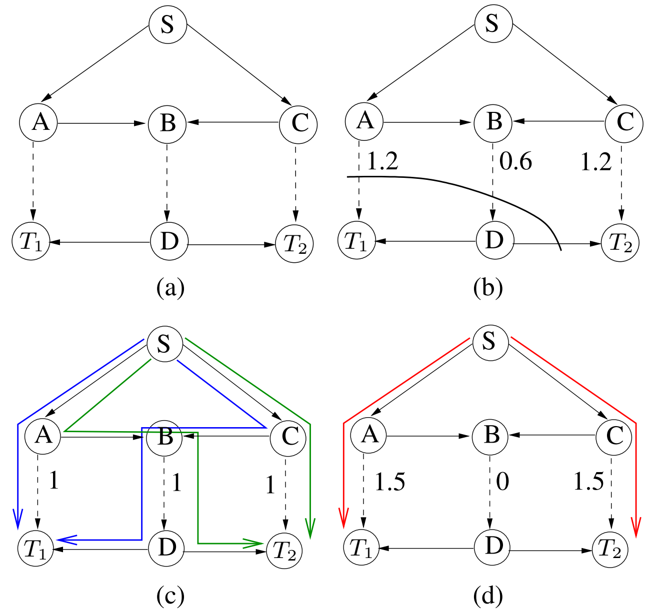


Fig. 1. Motivating example: (a) A multicast session in a mesh network. Solid lines represent wireline links, dashed lines represent wireless links. S is the multicast source, and T_1, T_2 are multicast destinations. (b) Naive power allocation with equal transmission power at each wireless link: AT_1, BD, CT_3. Multicast throughput is bounded by 1.8. (c) Radio power increased for the middle wireless link BD, and radio power decreased for the side wireless links AT_1, CT_2. Multicast throughput becomes 2 with network coding. (d) Power allocation scheme optimized for multicast routing using a tree.

III. Motivating Example

In this section, we present a simple example to illustrate the necessity of joint flow routing and power control in a multicast session. Consider a mesh network with mixed wireline and wireless communication links as shown in Fig. 1(a). The solid lines represent wireline links with fixed high capacities. The three dashed vertical lines represent wireless links established between radios, which have relatively low capacities. Each wireless link capacity depends not only on its own transmission power and channel gain, but also on the interference from nearby links. (A detailed characterization of the interference model will be treated later.) Assume there is a multicast session with a source S and two destinations T_1, T_2.

If we simply let each wireless link of AT_1, BD, CT_2 have the same power level, then the link BD in the middle will have a low capacity due to high interference from the two side links. Assume that equal-power allocation leads to a capacity of $(1.2, 0.6, 1.2)$ respectively as shown in Fig. 1(b). The multicast throughput is then upper-bounded by 1.8, due to the existence of a cut with the same size, isolating receiver T_1 from the rest of the networks as shown in Fig. 1(b).

From the topology of the network, it is clear that the wireless link BD in the middle is a critical one that may potentially serve both receivers. It is also at a disadvantageous location with a high interference level. Therefore, one way to improve the all-equal power allocation scheme is to increase the radio power at B and to reduce the powers at A and C. Suppose that by power adaptation, it is possible to achieve a capacity of 1 in all three wireless links AT_1, BD, CT_2. Consequently, a network flow of throughput 2 can be established from S to either T_1 or T_2, and a multicast throughput of 2 is achievable with network coding technique (we will discuss network coding in details later). Note that an encoded flow of rate 1 will be transmitted in link BD for both network flows as shown in Fig. 1(c).

While the example above shows that a good power allocation scheme is in general needed to achieve high throughput, we can further show that the optimal power allocation depends on the choice of routing scheme at the network layer. Fig. 1(c) shows the data flow in a mesh topology with network coding. If instead a multicast tree is adopted for routing as shown in Fig. 1(d), then the power allocation scheme needs to be adjusted accordingly to achieve an optimal throughput. In particular, it is not difficult to see that the optimal power allocation scheme is to allocate power along the side links only and to shut off the middle link. As the optimal routing and power allocation are tightly coupled, this example motivates a cross-layer approach.

IV. A Joint Optimization Framework

We now present a general framework to model and to solve the problem of optimizing multicast throughput in a multihop wireless mesh network. We first give a system-level formulation of the optimization problem, which involves variables from both the network layer and the physical layer. We then show that Lagrange relaxation and subgradient optimization can be applied to decompose the overall optimization problem into a sequence of smaller subproblems, each of which only involves variables from either the network layer or the physical layer. Interactions between the two subproblems are then discussed.

A. The General Framework of Joint Optimization

The formulation of the throughput maximization problem in wireless mesh networks is based on the following facts. First, throughput is realized by routing flows from sources to destinations. Second, at each transmission link, the aggregated flow rate cannot exceed the link capacity. Third, the link capacity is a function of signal-to-interference-and-noise ratio (SINR), which in turn is determined by the power levels at all the transmitters.

Let $G = (V, E)$ be the network topology. Let S be the set of multiple data sessions supported in the network. Let $\mathbf{r} = \{r^i\}$ be the set of multicast throughput for each session $i \in S$. Let $\mathbf{f}$ be a flow rate vector $\{f_l^i\}$, where i denotes the session index $i \in S$ and l denotes the link index $l \in E$. We denote $\mathcal{N}$ as the *routing region*, which is a fundamental concept at the network layer. The routing region defines a set of $(\mathbf{r}, \mathbf{f})$ such that flow rates $\mathbf{f}$ can support multicast throughput $\mathbf{r}$. For example, in a single-source-single-destination network, it is well known that the maximum throughput is the minimum cut across the flows in G. Fig. 2 illustrates the flow and throughput variables in a network.

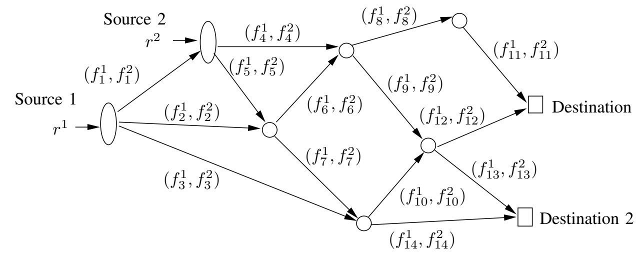


Fig. 2. Routing region at the network layer: $(\mathbf{r}, \mathbf{f}) \in \mathcal{N}$

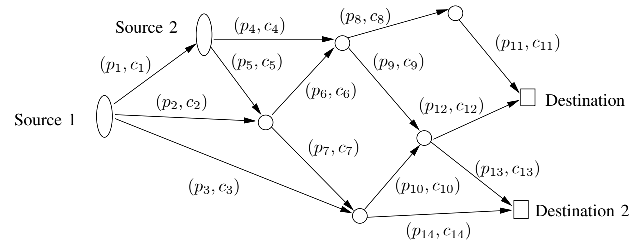


Fig. 3. Capacity region at the physical layer: $(\mathbf{c}, \mathbf{p}) \in \mathcal{C}$

The fundamental concept at the physical layer is the *capacity region* $\mathcal{C}$. Let $\mathbf{p}$ be the set of power consumption on each link in E, and $\mathbf{c}$ be the set of achievable link capacities. The capacity region defines a set of $(\mathbf{c}, \mathbf{p})$ such that the link power $\mathbf{p}$ can support link capacity $\mathbf{c}$. The capacity region characterizes the tradeoff between link capacity and power allocation due to the shared nature of wireless mesh networks. Fig. 3 illustrates power and capacity variables in a network.

The physical layer can support the network traffic if and only if the aggregated flow of different multicast sessions on each link is less than the link capacity. This paper adopts a network utility maximization approach. We consider a concave utility function of multicast throughput [16]. We further assume that the utility is separable. For the rest of this paper, we adopt the following utility that leads to proportional fairness.

$$U(\mathbf{r}) = \sum_i U_i(r^i) = \sum_i \log(1 + r^i)$$

The throughput optimization problem can now be formulated as:

$$\begin{aligned} \max \quad & U(\mathbf{r}) \\ \text{s.t.} \quad & (\mathbf{r}, \mathbf{f}) \in \mathcal{N} \\ & (\mathbf{c}, \mathbf{p}) \in \mathcal{C} \\ & \sum_{i \in S} f_l^i \leq c_l, \ \forall l \in E \end{aligned} \tag{1}$$

where the constraint $(\mathbf{r}, \mathbf{f}) \in \mathcal{N}$ models the inter-dependence between the achievable multicast throughput $\mathbf{r}$ and the data flow routing scheme $\mathbf{f}$. The constraint $(\mathbf{c}, \mathbf{p}) \in \mathcal{C}$ models the inter-dependence between the link capacity vector $\mathbf{c}$ and the link power consumption $\mathbf{p}$. The constraint $\sum_i f_l^i \leq c_l$ reflects the fact that the aggregated flow rate at each link is bounded by the link capacity. Here i is the index of data sessions, and l is the index of links. The detailed characterization of the regions $\mathcal{N}$ and $\mathcal{C}$ are independent of our general formulation and will be discussed in the next section.

B. Decomposing the Problem

The main contribution of this paper is a dual decomposition approach for a distributed solution of the overall network optimization problem (1). Note that when the utility function $U(\mathbf{r})$ is concave and when both $\mathcal{N}$ and $\mathcal{C}$ are convex regions, generic convex optimization methods can be used to solve the overall optimization problem (1). However, such a centralized solution does not take advantage of the special problem structure and it requires global information to be collected at a central point of computation. In a wireless mesh network, decentralized and scalable implementations are preferred. In this paper, we propose an optimization solution framework, within which the original problem is decomposed into smaller subproblems, each of which can be solved efficiently in a distributed fashion.

We start by relaxing link capacity constraint $\sum_i f_l^i \leq c_l$ and introduce price into the objective function:

$$L = U(\mathbf{r}) + \sum_l \lambda_l \left[c_l - \sum_i f_l^i \right]. \tag{2}$$

Observe that the maximization of the Lagrangian above now consists of two sets of variables: network layer variables $(\mathbf{r}, \mathbf{f})$, and physical layer variables $(\mathbf{c}, \mathbf{p})$. More specifically, the Lagrangian optimization problem is now decoupled into two disjoint parts. The network layer part is a routing subproblem:

$$\begin{aligned} \max \quad & U(\mathbf{r}) - \sum_l \lambda_l \sum_i f_l^i \\ \text{s.t.} \quad & (\mathbf{r}, \mathbf{f}) \in \mathcal{N} \end{aligned}$$

and the physical layer part is a power control subproblem:

$$\begin{aligned} \max \quad & \sum_l \lambda_l c_l \\ \text{s.t.} \quad & (\mathbf{c}, \mathbf{p}) \in \mathcal{C} \end{aligned}$$

Thus, the optimization framework naturally provides a layered approach to the throughput optimization problem. The global maximization problem decomposes into two parts: routing at the network layer and power control at the physical layer. The power control subproblem ensures that the maximal capacity is provided in individual network links, while the routing subproblem ensures that the link capacity is efficiently utilized to maximize the multicast throughput.

The decoupling of the network optimization problem also reveals that a cross-layer design can be achieved in a theoretically optimal way. The dual variable (shadow price) λ plays a key role in coordinating the network layer *demand* and physical layer *supply*. In particular, the lth component of λ (i.e., λ_l) can be interpreted as the rate cost in link l. A higher value of λ_l signals to the underlying physical layer that more resources should be devoted to transporting the traffic in link l. At the same time, it signals to the upper network layer that transporting bits in link l is expensive and provides incentive for the network layer to find alternative routes for traffic.

C. The Primal-Dual Solution Framework

The key requirement that allows the decoupling of the network optimization problem into routing and power control is the underlying convexity structure of the problem. Further, as strong duality holds, the optimization problem (1) can be solved efficiently via its dual. More specifically, we now propose the following primal-dual algorithm that solves the entire network optimization problem:

Algorithm 1: Primal-Dual Algorithm:

1) Set $t = 0$. Initialize $\lambda^{(0)}$.
2) In primal domain, solve the following subproblems:

$$\max_{\mathbf{r},\mathbf{f}} \; U(\mathbf{r}) - \sum_l \lambda_l \sum_i f_l^i, \quad \text{s.t.} \;\; (\mathbf{r}, \mathbf{f}) \in \mathcal{N} \tag{3}$$

$$\max_{\mathbf{c},\mathbf{p}} \; \sum_l \lambda_l c_l, \quad \text{s.t.} \;\; (\mathbf{c}, \mathbf{p}) \in \mathcal{C} \tag{4}$$

3) In dual domain, update the dual variables:

$$\lambda_l^{(t+1)} = \left[\lambda_l^{(t)} + \nu_l^{(t)} (c_l - \sum_i f_l^i) \right]^+ \tag{5}$$

where $[\cdot]^+$ denotes $\max(0, \cdot)$.

4) Set $t = t + 1$. Return to step 2 until convergence.

Theorem 1: Algorithm 1 always converges to the global optimum of the overall network optimization problem (1), provided that the regions $\mathcal{N}$ and $\mathcal{C}$ are convex and that the step sizes $\nu^{(t)}$ are appropriately chosen.

Proof: We outline the proof here. Since the objective of (1) is concave and the constraint sets are convex, by strong duality, finding the optimal value of the overall network optimization problem (1) is equivalent to solving its dual minimization. The convexity of $\mathcal{N}$ and C ensures that the dual function can be evaluated optimally. More precisely, it guarantees that the update in (5) is a subgradient for the dual variables. Thus, as long as the step sizes are chosen appropriately (e.g., as a square summable but not summable sequence), the dual update eventually converges. Hence, Algorithm 1 converges to the global optimal value of the overall network optimization problem. ■

V. Subproblem Modules

One of the main features of the primal-dual algorithm is modularity, as each subproblem can be solved independently within a single layer. It remains to show how the routing subproblem at the network layer and the power control subprogram at the physical layer are effectively solved. We investigate different alternative solutions for the two subproblems in a mesh network. At the network layer, we examine solutions with or without network coding. At the physical layer, we discuss different algorithmic approaches, including geometric programming and game theoretic methods. These alternatives consist of *modules* to be readily plugged into the cross-layer optimization framework that we have proposed.

A. Network Layer Module

The characterization of the routing region at the network layer depends on the specific model and techniques. In this section, we first review tree packing routing, then emphasize on the network coding technique for multicast.

1) Routing based on Tree Packing: When network coding is not considered and data sessions are multicast or broadcast[2] sessions, tree packing routing is achieved by data forwarding and replication at each wireless node. With these forward-and-replicate operations, each atomic data flow propagates along a tree. Each tree represents a path from a source to all of its destinations in the data session. The maximum achievable throughput can be computed by finding the maximum number of pairwise capacity-disjoint trees. Such an optimization has a linear programming formulation but with an exponential number of tree capacity variables. In the case of broadcast sessions, this problem corresponds to the *spanning tree packing* problem, which can be solved by employing the minimum spanning tree algorithms as the separation oracle. In the case of multicast sessions, the problem corresponds to the *Steiner tree packing* problem [1], in which the separation oracle method does not work effectively. This is due to the fact that we need to solve the minimum Steiner tree problem in the dual, which is as hard as the Steiner tree packing problem itself [17].

2) Multicast Routing with Network Coding: While the conventional approach for multicast (i.e., tree packing) requires a high computational complexity to achieve optimal multicast solutions, the most important advantage of network coding technique is its ability to achieve the optimal multicast solution with a low complexity. In contrast to the traditional replicate-and-forward approach at relay nodes, network coding assumes that every node in the network is a potential encoding and decoding point, hence it may help increase the transmission throughput and reduce the complexity of achieving optimal data transmission [1][2][3]. In particular, the use of network coding results in an easy characterization of the routing region $\mathcal{N}$, therefore makes the optimal multicast routing problem polynomial time computable.

The fundamental result in network coding [2][3] shows that a multicast throughput is feasible in a directed network if and only if it is feasible from the source to each destination independently, as a unicast. Therefore multicast flows from the same source to different destinations can be viewed as *conceptual flows* that do not compete for link capacities [1]. Denote $e_l^{i,j}$ as the conceptual flow rate on link l in the ith multicast session to its jth destination T_j^i, and f_l^i as the actual flow on link l for multicast session i. The above property of conceptual flows leads to a MAX operation in the flow constraint ($f_l^i = \max_j e_l^{i,j}$, or equivalently, $f_l^i \geq e_l^{i,j}, \forall j$), instead of a SUM operation ($f_l^i = \sum_j e_l^{i,j}$).

In this paper, we do not consider inter-session network coding for multiple data sessions. This is because inter-session coding provides only marginal throughput gains [1] and it renders the data routing subproblem NP-hard.

[2]Multicast refers to a scenario, in which a source node sends the same information to a set of nodes in a network. Broadcast refers to a scenario, in which a source node sends the same information to all the nodes in a network.

The flow routing subproblem (3) with network coding can be stated as follows:

$$
\begin{aligned}
\max \quad & U(\mathbf{r}) - \sum_l \lambda_l \sum_i f_l^i && (6)\\
\text{s.t.} \quad & r^i \leq \sum_{l \in \mathcal{I}(T_j^i)} e_l^{i,j}, && \forall i, \forall j, \forall T_j^i \in V\\
& e_l^{i,j} \leq f_l^i, && \forall i, \forall j, \forall l \in E\\
& \sum_{l \in \mathcal{O}(n)} e_l^{i,j} = \sum_{l' \in \mathcal{I}(n)} e_{l'}^{i,j}, && \forall i, \forall j, \forall n \in V \backslash \{s^i, T_j^i\}\\
& f_l^i \geq 0,\ e_l^{i,j} \geq 0,\ r^i \geq 0
\end{aligned}
$$

The first inequality represents the constraint that the ith session multicast throughput r^i is less than or equal to the sum of all the conceptual flow rates from source s^i to each of its jth destination T_j^i. The second inequality represents the fact that the actual flow rate f_l^i of session i on link l is the maximum of all the conceptual flows from source to destinations in that session. The third equality constraint represents the law of flow conservation for conceptual flows, where $\mathcal{I}(n)$ is defined as the set of links that are incoming to node n, and $\mathcal{O}(n)$ is the set of links that are outgoing from node n.

For a data network with multiple multicast sessions, the maximum utility of (6) and its corresponding optimal routing strategy can be computed in polynomial time. This is because the utility function of (6) is a concave function and the network coding constraints are linear. Therefore, solving the subproblem (6) is a convex optimization problem, which can be solved in polynomial time [18].

Note that a complete data transmission scheme consists of both a flow routing scheme computed by (6), and a code assignment which determines the content of each flow being transmitted across the network. Code assignment is complementary to our work and is not the focus of this paper. We point out the following two observations: (a) the availability of the optimal flow routing scheme usually makes the code assignment simpler; (b) if the application is not mission critical, a simple randomized code assignment algorithm is usually sufficient: each node simply generates random numbers from an agreed-upon finite field to serve as the coding coefficients [3][19].

B. Physical Layer Module

Interference management is one of the main challenges in the physical layer design of wireless networks. A key concept at the physical layer is the capacity region (more rigorously, the *achievable capacity region*), which characterizes a tradeoff between achievable capacities at different links. Consider a network with G_{ll}, p_l, and σ_l^2 as the link gain, power, and noise, respectively. Denote G_{lj} as the interference coefficient from link j to link l.[3] Further, assume that each node has a power budget $P_{n,\max}$. Thus, the power control subproblem (4) with a physical-layer interference model may be formulated as

[3]The channel statistics are characterized by G and σ^2, which are assumed to be available by certain estimation techniques.

follows:

$$\begin{aligned}
\max \quad & \sum_l \lambda_l c_l && (7)\\
\text{s.t.} \quad & c_l = \log\left(1+\text{SINR}_l\right) && \forall l \in E\\
& \text{SINR}_l = \frac{G_{ll}p_l}{\sum_{j\neq l} G_{lj}p_j + \sigma_l^2} && \forall l \in E\\
& \sum_{l\in\mathcal{O}(n)} p_l \leq P_{n,\max}, \quad p_l \geq 0 && \forall n \in V,\ \forall l \in E
\end{aligned}$$

where c_l is the capacity of link l, SINR_l is the signal-to-interference-and-noise ratio of link l, and n is the node index.

Because of interference, the power control subproblem (7) is a nonconvex optimization problem that is inherently difficult to solve. In this subsection, we first discuss a geometric programming method [10], then propose a new game theoretic approach to characterize the achievable capacity region approximately.

1) Geometric Programming: Recent development in convex optimization shows that, in high SINR scenarios, the problem (7) can be solved efficiently by geometric programming techniques [10]. The idea is to first approximate the link capacity $c_l = \log(1+\text{SINR}_l) \approx \log(\text{SINR}_l)$ assuming that the SINR is much larger than 1. Then through a logarithmic transformation of power vector, the transformed problem becomes a convex optimization problem.

2) Game Theoretic Approach: Although the geometric programming method has shown to be effective in certain applications, it is not without limitations due to the requirement of high SINR. In this section, we propose a different approach based on game theory to approximately solve the nonconvex power control subproblem (7).

In a power control game, each link is modelled as a player with an aim of maximizing its payoff function. In conventional game theoretic approaches [20][21], each link uses its own achievable rate as the payoff function. Competitive equilibria in such a game may not correspond to desirable operating points, especially when the interference level is high. The main idea here is to modify the payoff function such that each link player's payoff includes not only the achievable rate but also the interference effect to other links. As the computation of the competitive equilibrium of a game is more efficient and is amenable to distributed implementation, this gives us an effective means of approximately solving the physical layer power control subproblem.

Mathematically, we propose a *power control game* in which each link player l maximizes its payoff function as follows:

$$Q_l = \lambda_l \log\left(1 + \frac{G_{ll}p_l}{\sum_{j\neq k} G_{lj}p_j + \sigma_l^2}\right) - m_l p_l - \mu_n p_l \quad (8)$$

where Q_l is the payoff for link player l, p_l is the player's action, m_l is the dual variable summarizing the effect of interference to all other links and μ_n is the dual variable that indicates the price of transmitter power at node n. A sensible choice for m_l is $-\partial \sum_{s\neq l} c_s / \partial p_l$. In other words, m_l is the rate at which other users' achievable data rates decrease with an additional amount of power. The power price μ_n reflects how tight the resource at node n is being utilized by its outgoing links under the constraint $\sum_{l\in\mathcal{O}(n)} p_l \leq P_{n,\max}$.

We present the following algorithm that implements the dynamics of the game.

Algorithm 2: Power Control Game Algorithm

1) Initialize $p^{(0)}$, $m^{(0)}$, $\mu^{(0)}$. Set $t = 0$.
2) Set $\tilde{p}^{(0)} = p^{(t)}$. Set $i = 0$, iteratively update
$$\tilde{p}_l^{(i+1)} = \left[\frac{\lambda_l}{m_l^{(t)} + \mu_n^{(t)}} - \sum_{j\neq l} \frac{G_{lj}}{G_{ll}} \tilde{p}_j^{(i)} - \frac{\sigma_l^2}{G_{ll}}\right]^+$$
Set $i = i+1$, repeat until $\tilde{p}^{(i)}$ converges. Set $p^{(t+1)} = \tilde{p}^{(i)}$.
3) Update price μ_n via subgradient with stepsize $\gamma_n^{(t)}$
$$\mu_n^{(t+1)} = \left[\mu_n^{(t)} + \gamma_n^{(t)} \left(\sum_{l\in\mathcal{O}(n)} p_l^{(t)} - P_{n,\max}\right)\right]^+$$
4) Update the message m_l
$$m_l^{(t+1)} = \sum_{s\neq l} G_{ls}\lambda_s \frac{\text{SINR}_s^{(t+1)}}{G_{ss}p_s^{(t+1)}} \frac{\text{SINR}_s^{(t+1)}}{1+\text{SINR}_s^{(t+1)}}$$
5) Set $t = t+1$. Return to step (2) until convergence.

The power update in step (2) is based on the following. At each step, each player tries to maximize its own payoff Q_l while assuming that the power levels of all other players and the messages and prices are fixed. The expression for optimal p_l is obtained by setting the derivative of Q_l with respect to p_l to zero. Such a locally optimal p_l strikes a balance between maximizing its own rate and minimizing its interference to other links (which is taken into account via m_l). For example, a large value for m_l indicates that link l is producing severe interference to other links. This is reflected in the power update as a larger m_l leads to a lower p_l. Similarly, the value of the pricing variable μ_n indicates the tightness of the per-node power constraint. A high value for μ_n signals that the supply for power is tight and it entices link l to reduce its power.

Although each player appears to be selfish in maximizing its own payoff only, because the payoff function incorporates social welfare, the Nash equilibrium of this game is in fact a cooperative social optimum. Furthermore, Algorithm 2 is amenable to distributed implementation as we will discuss in next section.

Finally, we analyze the properties of the Nash equilibrium of the power control game. It is possible to prove [22] that if a strictly diagonal dominance (SDD) condition holds (i.e., $G_{ll} > \sum_{j:j\neq l} G_{lj},\ \forall l$), the power control game always converges to a unique and stable Nash equilibrium for any given dual variables. This is because, under SDD, for any given dual variables, the player's best response function in step (2) of Algorithm 2 is a contraction, therefore Nash equilibrium is unique. Further, it can be verified that the absolute values of the eigenvalues of the dynamic stability matrix of the power control game are all less than one, hence the game is asymptotically stable. On the other hand, it is observed through simulations (as will be shown in section VII) that the overall multicast rates converge in many scenarios even without SDD. Note that, however, for the question of how far the approximate solution is away from the optimum, we do not have a good answer for a quantitative analysis yet.

For simplicity, we present the power control game for a scenario in which each link consists of a single channel. The same idea can be extended to cases in which each link consists of multiple physical channels, such as that in orthogonal frequency-division multiplex (OFDM) systems.

VI. Distributed Implementation

As realistic mesh network deployment often encounters variations in channel characteristics and network demand fluctuations, real-time and distributed algorithms are desirable. Distributed implementation of the network optimization method is also important in mesh networks for scalability reasons. In this section, we show that the overall throughput maximization problem of mesh networks can be solved in a distributed manner. Our main algorithm is as follows:

Algorithm 3: Distributed Primal-Dual Algorithm:

1) Set $t = 0$. Initialize $\lambda^{(0)}$.
2) In primal domain, solve the following subproblems:
   (2.1) Solve the routing subproblem by *network coding* technique in a distributed manner.
   $$\max_{\mathbf{r},\mathbf{f}} \; U(\mathbf{r}) - \sum_l \lambda_l \sum_i f_l^i, \text{ s.t. } (\mathbf{r},\mathbf{f}) \in \mathcal{N}$$
   and let the optimal solution be $(\mathbf{r}^*, \mathbf{f}^*)$.
   (2.2) Solve the power control subproblem by *power control game* Algorithm 2 in a distributed manner.
   $$\max_{\mathbf{c},\mathbf{p}} \; \sum_l \lambda_l c_l, \text{ s.t. } (\mathbf{c},\mathbf{p}) \in \mathcal{C}$$
   and let the optimal solution be $(\mathbf{c}^*, \mathbf{p}^*)$.
3) In dual domain, update the dual variables:
   $$\lambda_l^{(t+1)} = \left[\lambda_l^{(t)} + \nu_l^{(t)}(c_l^* - \sum_i f_l^{i,*})\right]^+$$
4) Set $t = t + 1$. Return to step 2 until convergence.

We next address the distributed implementation in details.

A. Distributed Flow Routing

We first show how to solve the network layer multicast flow routing step (2.1) of Algorithm 3 in a distributed fashion. We propose a three-phase solution: (a) session separation, (b) distributed min-cost flow computation, and (c) utility maximization at the source.

In phase (a), we separate the joint multi-session optimization into smaller intra-session optimization problems. A critical assumption of the optimization in (2.1) is that the objective function is separable:

$$\max\left(U(\mathbf{r}) - \sum_l \lambda_l \sum_i f_l^i\right) = \sum_i \max\left(U_i(r^i) - \sum_l \lambda_l f_l^i\right)$$

Consequently, we can solve the joint optimization in step (2.1) of Algorithm 3 by solving a sequence of projections within each multicast session.

The separated intra-session optimizations are then solved in phase (b) and phase (c). In phase (b), we prepare for the final optimization in phase (c) by computing the minimum weighted (with given weight vector λ) bandwidth consumption necessary to achieve a unit end-to-end multicast throughput. This is a special case of the min-cost multicast problem studied in [6], where the authors apply Lagrangian relaxation to transform the problem into a sequence of traditional min-cost flow computations, and obtain a distributed solution based on a distributed min-cost flow algorithm such as the ϵ-relaxation algorithm.

Once the minimum weighted bandwidth consumption ($b^* = \sum_l \lambda_l f_l^i$) for one unit multicast throughput is determined, we let the source s_i make the final optimization decision in phase (c). The source first collects the value of b^* as the output from phase (b), then it transforms the objective function from $\max(U_i(r^i) - \sum_l \lambda_l f_l^i)$ into $\max(U_i(r^i) - b^* r^i)$, and performs a local single-variable maximization based on the function curve of U and the value of b^*.

Since each of phases (a), (b), and (c) can be implemented in a distributed manner, we obtain a distributed algorithm for the flow routing module (2.1) of Algorithm 3.

B. Distributed Power Control

The power control game in step (2.2) of Algorithm 3 can also be implemented in a distributed fashion at the physical layer. Inspired by the work of [10], we decompose the message update in step (4) of power control game Algorithm 2 as follows:

$$\begin{aligned} m_l^{(t+1)} &= \sum_{s \neq l} G_{ls} \mathrm{bcm}_s, \\ \mathrm{bcm}_s &= \lambda_s \frac{\mathrm{SINR}_s^{(t+1)}}{G_{ss} p_s^{(t+1)}} \frac{\mathrm{SINR}_s^{(t+1)}}{1 + \mathrm{SINR}_s^{(t+1)}} \end{aligned}$$

Specifically, we propose a two-phase message-passing mechanism: at phase (a), each link calculates its broadcast message (i.e., bcm_s) based on local information (i.e., $\lambda_s, \mathrm{SINR}_s, G_{ss}, p_s$), and broadcasts to the network. At phase (b), each link collects broadcast messages from others, and locally computes the message (i.e., m_l), where the interference term (i.e., G_{ls}) can be estimated, for example, by pilots. Note that the update of μ_n only requires the outgoing link power allocation from node n and its budget (i.e., $P_{n,\max}$), therefore it can be locally updated. Hence, given the dual variables m_l and μ_n, the power update in step (2) of the power control game Algorithm 2 can be achieved locally.

C. Distributed Shadow Price Update

In step (3) of Algorithm 3, the update of the dual variable λ_l in the lth link only requires the local capacity c_l and the rates of local flows $\sum_i f_l^i$. Therefore, the shadow prices λ can be updated locally.

For the above reasons, the overall throughput maximization problem in mesh networks has a distributed implementation.

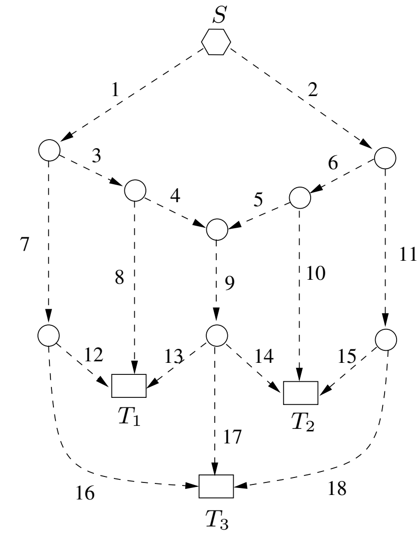
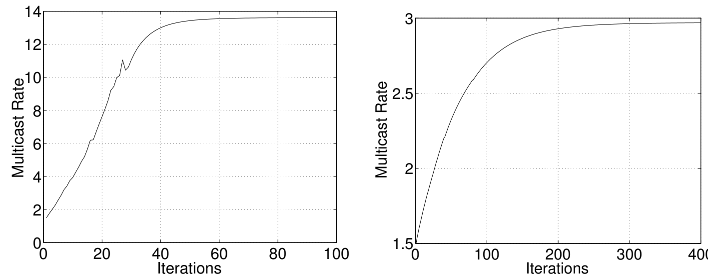
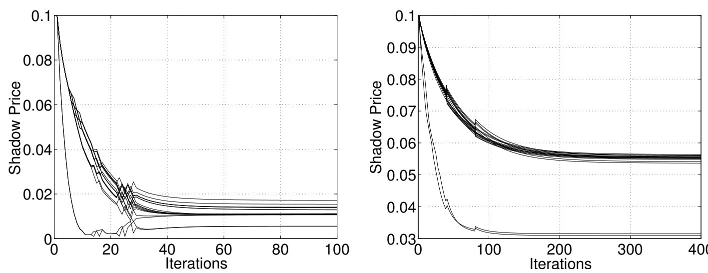


Fig. 4. The network topology.



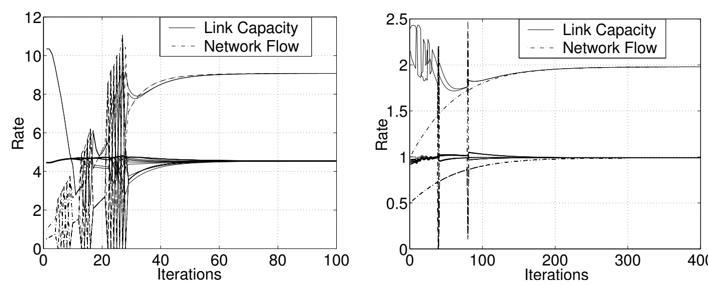
(a) Low-interference (b) High-interference

Fig. 5. Convergence of the multicast rate.



(a) Low-interference (b) High-interference

Fig. 6. Convergence of cross-layer dual variables.



(a) Low-interference (b) High-interference

Fig. 7. Convergence between network flow rates and link capacities.

VII. SIMULATIONS

We simulate a single-session multicast example to illustrate the network optimization framework. The wireless mesh network is shown in Fig. 4. The source S attempts to establish a session with maximum multicast throughput to three destinations T_1, T_2, T_3 using network coding. A multi-channel link model is adopted at the physical layer. The channel gain and interference coefficient are generated according to log-normal fading. We consider two different channel scenarios: a low-interference scenario in which the average ratio of the desired channel gain to the sum of all interference coefficients is 10 dB, and a high-interference scenario in which the average ratio of the desired channel gain to the sum of all interference coefficients is -2 dB. We use Algorithm 3 to find the optimal solution for the throughput maximization problem (1).

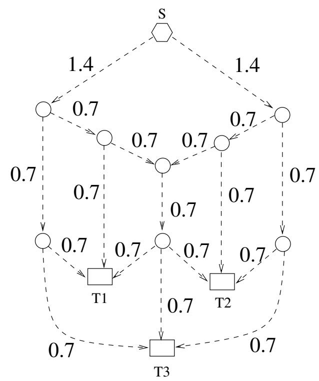
Fig. 5 illustrates the multicast throughput maximization process. In both high-interference and low-interference cases, the multicast throughput converges to the optimal solution. However, the convergence speed is different. Convergence is much faster in the low-interference scenario (i.e., 60 iterations) than in the high-interference scenario (i.e., 200 iterations). This is because the exchange of messages is not as important in the low-interference case as compared to that in the high-interference case.

The convergence process for the cross-layer dual variables is illustrated in Fig. 6. Each curve in the figure corresponds to a dual variable λ_l for each link. The dual variables (shadow prices) control the inter-layer interface so that both routing at the network layer and power control at the physical layer can reach an optimal point. As the shadow prices converge, the entire system reaches an optimal solution. Fig. 7 shows the convergence process between the network layer flows and the physical layer capacities for both low-interference and high-interference cases.

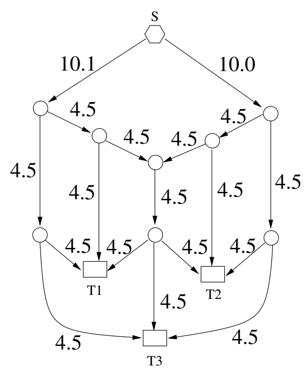
In Fig. 8, a series of snapshots are plotted to illustrate the convergence process for the low-interference case. At the beginning as shown in Fig. 8(a)(b), the physical layer link capacities are high (especially in link 1 and link 2), while the network layer routing flow rates are low. Since the supply of rates is greater than the demand, the prices λ would decrease as shown in Fig. 6(a). Next, due to the change of prices, the physical layer would reduce its supply (especially in link 1 and link 2), while the network layer would take advantage of low prices by increasing its demand. This is illustrated in Fig. 8(c)(d).

During the negotiation process coordinated by shadow prices, the network flows oscillate in an attempt to find a good routing strategy for each set of physical-layer capacities. At the same time, physical layer capacities fluctuate in order to better support network layer traffic and to avoid interference. This is illustrated in Fig. 8(e)(f).

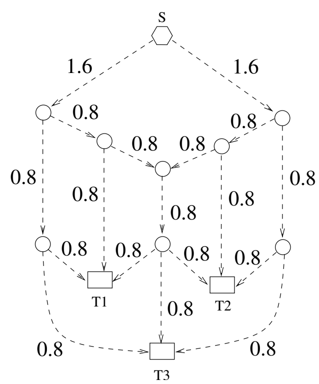
Eventually, the network flows and link capacities reach an agreement as shown in Fig. 8(g)(h). This solution is optimal in the sense that the physical layer comes up with the best resource allocation while the network layer routes the best paths from the source to multiple destinations. Together, the multicast rate utility function is maximized. Note that at all



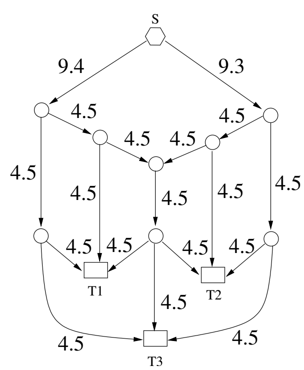
(a) Flows at snapshot 3



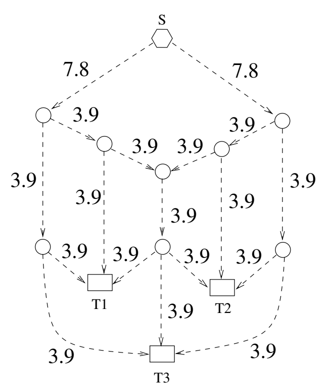
(b) Capacities at snapshot 3



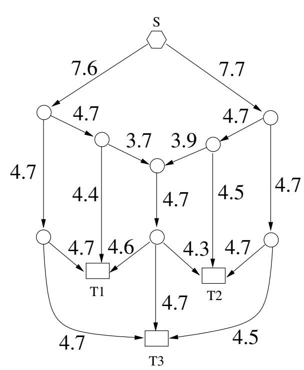
(c) Flows at snapshot 4



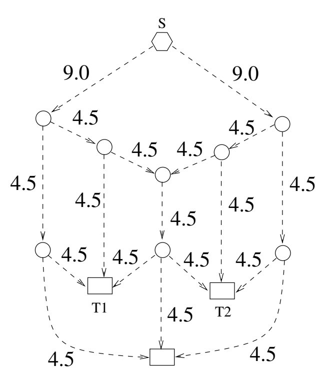
(d) Capacities at snapshot 4



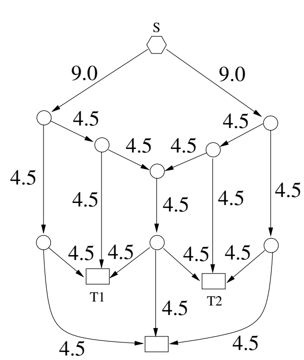
(e) Flows at snapshot 32



(f) Capacities at snapshot 32



(g) Flows at snapshot 100



(h) Capacities at snapshot 100

Fig. 8. Snapshots during the convergence process.

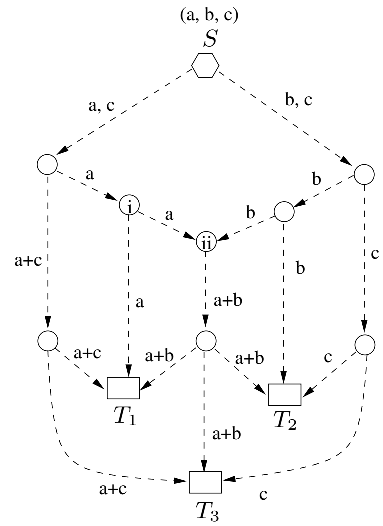


Fig. 9. Transmission scheme with network coding assignment.

Table I: Multicast Throughput Comparison

	CLO	No CLO	Improvement
Low Interference	13.62	10.72	21.32%
High Interference	2.97	2.32	21.88%

time, the flow rates always satisfy the flow conservation law. However, only the converged link capacities are consistent as shown in Fig. 8(h).

It is interesting to point out that our algorithm is energy efficient because there are no slack link capacities in both cases. For example, in the high-interference case as shown in Fig. 7(b), the final solution of network flows are $f_1 = f_2 = 1.98, f_3 = \cdots = f_{18} = 0.99$; the link capacities are $c_1 = c_2 = 1.98, c_3 = \cdots = c_{18} = 0.99$; and the multicast rate is $r = 2.97$. Therefore, all link capacities exactly support the network flows ($f_l = c_l$).

This optimal solution has a max-flow min-cut interpretation. If we normalize the optimal throughput, the optimal flows and link capacities are all one unit except for link 1 and link 2, where they are two units. As we can see from the optimal solution, the source sends three units of information in total to each destination, and the max-flow rate is exactly equal to the min-cut bound as shown in Fig. 9. Further, Fig. 9 shows a network coding assignment to achieve the optimum.

Finally, we compare the performance of joint cross-layer optimization with network coding and power control with the performance of a network in which each node uses equal radio power and the routing is built through Steiner trees. For the particular example in Fig. 4, we have total 46 Steiner trees and linear programming is used to find the corresponding time-sharing coefficients among the trees. Table I shows that the multicast throughput of cross-layer optimization (i.e., CLO) outperforms that of its absence (i.e., No CLO) by more than 21% in both low and high interference scenarios. Thus, it confirms the benefit of cross-layer optimization for provisioning of high throughput in wireless mesh networks.

VIII. EXTENSIONS

In this section, we point out two possible extensions of the current framework.

A. Hybrid and Hierarchical Structure

Although we focus on a fully wireless mesh network in this paper, our model and solution can easily handle hybrid and hierarchical mesh networks as well [23], where wireline and wireless links coexist. This is because that a wired network can be regarded as a special case of the formulation of wireless networks, where all interference terms are zero.

B. Physical-Layer Wireless Multicast

Because of the shared nature of wireless medium, it is possible for one transmitter to successfully reach multiple receivers in a single transmission. For example, in Fig. 9, rather than transmitting the information "a" separately on the link from node i to node T_1 and on the link from node i to node ii, the transmitter node i can simply transmit information "a" to the two receiver nodes at the same time at the physical layer. Such physical-layer multicasting has the advantage of saving transmitter power and reducing mutual interference. The ability for a single transmitter to reach multiple receivers at the same time is called wireless mutlicast advantage [24].

Wireless multicast advantage can be characterized by including the concept of common information at the physical layer. Consider the scenario with nodes i, ii, and iii in Fig. 10. Let us assume that node i can send common information at rate c_0 to both nodes ii and iii, and it can send independent information to node ii on link 1 at rate c_1 and to node iii on links 2 at rate c_2 respectively. The capacity region with common information can be characterized as follows:

$$\begin{cases} c_0 & = & \min\left\{ \begin{array}{l} \log\left(1+\frac{G_{11}p_0}{G_{11}p_1+G_{12}p_2+\sigma^2+I}\right), \\ \log\left(1+\frac{G_{22}p_0}{G_{21}p_1+G_{22}p_2+\sigma^2+I}\right) \end{array} \right\} \\ c_1 & = & \log\left(1+\frac{G_{11}p_1}{G_{12}p_2+\sigma^2+I}\right) \\ c_2 & = & \log\left(1+\frac{G_{22}p_2}{G_{21}p_1+\sigma^2+I}\right) \\ P_{i,\max} & \geq & p_0+p_1+p_2 \end{cases} \tag{9}$$

where p_0 is the power for transmitting common information from node i to both nodes ii and iii, p_1 and p_2 are the powers for transmitting independent information on link 1 from node i to node ii, and on link 2 from node i to node iii respectively, σ^2 represents the noise variance, I represents the interference from all other nodes' transmissions, and $P_{i,\max}$ is the power budget of node i. Note that at nodes ii and iii, common information can be decoded first, then subtracted before independent information is decoded. Thus, p_0 does not appear as interference in the capacity expressions for c_1 and c_2. Clearly, by setting $p_0 = 0$, this model (9) includes the previous capacity region (7) as a special case.

Our cross-layer optimization framework can be extended to incorporate the common information rate above. The main idea is to add virtual nodes to represent common information transmission as shown in Fig. 10. Each virtual node has only one incoming link and several outgoing links, therefore, it simply replicates and broadcasts the incoming common information. This results in an augmented network topology $G' = (V', E')$. The entire capacity region for the augmented network topology can be formulated similarly as in (9). We denote the capacity region with the augmented network as $\mathcal{C}_0$, and denote the routing region with the augmented network as $\mathcal{N}_0$. Note that, given the augmented network topology, the min-cut-max-flow argument still holds for network coding. Therefore, the cross-layer optimization framework can handle the throughput maximization problem with wireless multicast advantage by solving the following augmented problem:

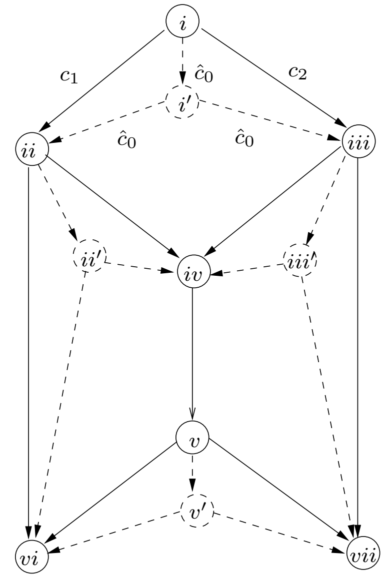


Fig. 10. Augmented network $G' = (V', E')$ with common information and independent information capacity. Solid circles represent the real nodes and dashed circles represent virtual nodes associated with common information.

$$\begin{array}{ll} \max & U(\mathbf{r}) \\ \text{s.t.} & (\mathbf{r}, \mathbf{f}) \in \mathcal{N}_0 \\ & (\mathbf{c}, \mathbf{p}) \in \mathcal{C}_0 \\ & \sum_{i \in S} f_l^i \leq c_l, \ \forall l \in E' \end{array}$$

IX. CONCLUSIONS

In this paper, we propose a cross-layer optimization framework for multihop multicast in wireless mesh networks. We formulate a throughput maximization problem which jointly considers the data routing problem at the network layer and the power control problem at the physical layer. We show that the problem can be decomposed into two subproblems. Modelling and solution algorithms for each subproblem can be easily tuned according to the availability of networking technologies, as well as the availability of optimization techniques. In particular, we emphasize the cross-layer optimization of multicast routing with network coding and power control with game theoretic method, where efficient and distributed solutions are derived and illustrated. Finally, we show that the wireless multicast advantage can be incorporated into the optimization framework.

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