A Fair QoS-aware Resource Allocation Scheme for Multi-Radio Multi-Channel Networks

Yan Long, Hongyan Li, *Member, IEEE,* Miao Pan, *Member, IEEE,* Yuguang Fang, *Fellow, IEEE,* and Tan F. Wong, *Senior Member, IEEE*

***Abstract*—In this paper, we study the problem of resource allocation in multi-radio multi-channel (MRMC) networks. Specifically, under the consideration of diverse quality of service (QoS) requirements, we propose a fair QoS-aware resource allocation scheme for MRMC networks. In this scheme, channel allocation, multi-path routing, link scheduling and radio assignment are jointly considered. The proposed scheme is obtained by formulating the resource allocation problem into a cross-layer network utility maximization (NUM) problem, in which resource is allocated to services with proportional fairness. To avoid oscillation among optimal solutions due to the use of multi-path routing, we transform the optimization program into an equivalent program by utilizing the proximal optimization algorithm. Then we obtain the optimal solution of the latter by the decomposition method. Numerical results show that the proposed scheme indeed achieves proportional fairness according to diverse QoS requirements while maximizing utility.**

***Index Terms*—multi-radio multi-channel networks, QoS-aware, proportional fairness, network utility maximization.**

I. Introduction

The popularity of wireless services such as mobile applications using smart phones has led to a significant growth in traffic load over wireless networks as well as an increasing demand for high network performance. However, network performance is often severely limited by the lack of spectral resource in wireless networks. The lack of spectral resource is further aggravated by the existence of interference among interfering links because the interference limits the number of transmissions that can be simultaneously active. The performance decrease due to interfering links may be reduced by effectively utilizing multiple orthogonal channels that are available in some wireless networks, such as wireless networks that conform to the IEEE 802.11 standards. The underlying principle of such an approach is to assign different channels to neighboring transmissions so as to alleviate network-wide interference and hence increase the overall network capacity [1] and [2].

Depending on the number of channels over which a node can simultaneously transmit or receive, multi-channel networks can be divided into two categories: single-radio multi-channel (SRMC) networks and multi-radio multi-channel (MRMC) networks. For SRMC networks, the communication hardware of each node is designed in a way that only one channel can be active at any given time, although the node is able to switch dynamically among channels from time to time. The design of multi-channel medium access control (MAC) protocols is a major problem in SRMC networks. For example, So and Vaidya in [3] and So et al. in [4] studied the design of multi-channel MAC protocols to coordinate the single communicating channel in SRMC networks. Compared with SRMC networks, the capability of a node to simultaneously operate in multiple channels in MRMC networks may ease the coordination problems experienced in [3] and [4].

The major design challenge in MRMC networks is on the other hand resource allocation, including channel allocation, link scheduling, flow routing, and *etc*. Channel allocation schemes that reduce interference and improve the network performance were investigated in [5]–[7]. In [5], Marina et al. cast channel allocation as a topology control problem in order to develop a greedy heuristic allocation algorithm. Felegyhazi et al. in [6] conducted a game-theoretic analysis on some fixed channel allocation strategies. Subramanian et al. in [7] designed centralized and distributed channel allocation strategies with the goal of minimizing the overall network interference. Under the assumption of a fixed channel allocation, works focusing on the routing problems in MRMC networks were reported in [8] and [9]. Specifically, Liu and Liao [8] formulated an integer linear program (ILP) with the objective of finding the minimal cost multi-cast tree from a source to multiple destinations. Draves et al. in [9] presented a multi-channel routing metric to search for high throughput paths. Furthermore, by considering channel allocation and routing as interdependent operations, the cross-layer resource allocation approach over the MAC and network layers suggested in [10] proves to be useful for optimally scheduling channels and handling traffic loads in MRMC networks.

Alicherry et al. in [11] and Li et al. in [12] employed linear programming (LP) to formulate and solve cross-layer resource allocation problems in MRMC networks with the goal of maximizing a fairness factor λ. Compared with throughput maximization in which the total throughput over all services is optimized without fairness constraints, introduction of the fairness factor offers fair allocation and eliminates bias to any

Yan Long and Hongyan Li are with the National Key Laboratory of Integrated Services Networks, Xidian University, Xi'an, China (e-mail: ylong@stu.xidian.edu.cn; hyli@xidian.edu.cn). Miao Pan is with the Department of Computer Science, Texas Southern University, TX, USA (e-mail: panm@tsu.edu). Yuguang Fang and Tan F. Wong are with the Department of Electrical and Computer Engineering, University of Florida, FL, USA (e-mail: fang@ece.ufl.edu; twong@ece.ufl.edu).

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specific service by constraining that the rate requirement for each service multiplied with the fairness factor λ is to be met.

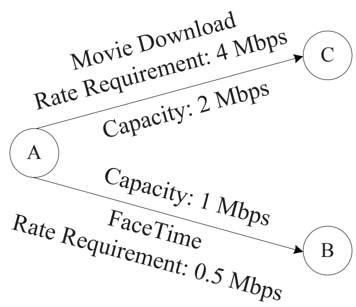


Fig. 1. An illustrative example that shows the need for QoS-aware resource allocation.

However, the papers above did not take the diversity of quality of service (QoS) requirements into consideration. To illustrate this, consider the toy topology shown in Fig. 1 with two services: one is an iPhone's FaceTime service from A to B with a 0.5 Mbps rate requirement and the other one is a movie download service from A to C with a 4 Mbps rate requirement. FaceTime is an inelastic service, and to support it, the resource allocation algorithm must meet its rate requirement. Meanwhile, movie download is an elastic service and satisfying part of its rate requirement is tolerable. As a result, one feasible interference-free solution is, in a two-slot frame, allocating separate slots for link A to B and link A to C. This results in $1 \times 0.5 = 0.5$ Mbps for the Facetime service and $2 \times 0.5 = 1$ Mbps for the movie download service, where both services can be supported by the resource limited network. However, without considering QoS requirements, a throughput maximization scheme may allocate both slots for link A to C, which has a higher link capacity, and a λ-maximization scheme may also assign more time proportion to link A to C to improve λ. Either scheme would fail to access the FaceTime service. The above discussion motivates us to investigate QoS-aware resource allocation along with fairness considerations in MRMC networks, especially when the limited network resource can not guarantee all services requirements.

In this paper, we propose a new cross-layer optimization formulation for resource allocation in MRMC networks under proportionally fair resource constraints with respect to QoS requirements, instead of optimizing the simple fairness factor λ alone as in [11] and [12]. We consider the scenario in which full services requirements can not be met due to limited network resource, but minimal QoS requirements can be guaranteed for all services. We introduce a QoS factor α to specify the minimal QoS requirement for a service and use different QoS factors to characterize the requirements for different types of services. After the minimal QoS requirements for all services are achieved, we allocate the residual resource among services fairly to improve the quality of experience (QoE) of users. To obtain a proportionally fair resource allocation, we mathematically formulate the allocation problem as a network utility maximization (NUM) problem under QoS constraints. The NUM problem is then solved using the proximal optimization [13] and decomposition algorithms [14]. Our major contributions are summarized as follows:

- We introduce the QoS factor $\alpha \in [0, 1]$ to differentiate different types of services in MRMC networks. For a service, the product between its rate requirement and QoS factor provides the minimal rate requirement for the network to support this service. The QoS factor offers an additional dimension for service adaptation. More specifically, the QoS factor for a high priority service (e.g., FaceTime) should be larger than that of a low priority service (e.g., movie download), implying that a larger fraction of the network resource should be allocated to the high priority service.
- We construct a three-dimensional conflict graph [12] and [15] to analyze MRMC networks. We derive the sufficient condition for the interference-free flow scheduling using the three-dimensional conflict graph. We provide a systematic formulation for the cross-layer resource allocation problem by jointly characterizing the QoS and other cross-layer constraints, e.g., flow routing, link capacity and flow scheduling constraints. A logarithmic function is defined as the user utility. In order to fairly allocate the network resource, we maximize the overall network utility under the aforementioned constraints. The end result is an optimization formulation for resource allocation in MRMC networks with elastic QoS requirements.
- We transform the optimization problem above into an equivalent problem by the proximal optimization algorithm to avoid solution oscillation caused by multi-path routing. We then solve the equivalent optimization problem using the decomposition algorithm.
- By carrying out numerical simulations, we demonstrate that the proposed scheme can indeed fairly allocate network resource among services based on their diverse QoS requirements in MRMC networks.

The rest of this paper is organized as follows. In section II, we describe the network model and formulate the QoS-aware resource allocation problem under proportional fairness. We solve the problem in section III. We present numerical results obtained from computer simulations in section IV. Finally, we conclude this paper in section V.

II. MRMC Network Model and Problem Formulation

Given an MRMC network topology with node set $\mathcal{V} = \{v_n : 1 \leq n \leq |\mathcal{V}|\}$ and directed link set $\mathcal{E} = \{e_i : 1 \leq i \leq |\mathcal{E}|\}$, we define $\delta_{e_i v_n} = 1$ if e_i is an outgoing link of node v_n and $\delta_{e_i v_n} = -1$ if e_i is an incoming link of v_n. We denote the non-overlapping channel set by $\mathcal{K} = \{k : 1 \leq k \leq |\mathcal{K}|\}$ and the capacity of link e_i on channel k by $C^k_{e_i}$. For simplicity, we assume that each node has the same number of transceiver radios, i.e., at any given time, the number of channels that each node can simultaneously use is the same. The result can be easily extended to the case in which nodes have different numbers of radios. Let $\mathcal{I}$ denote the transceiver radio set on each node, and $t_{e_i} \in \mathcal{I}$ and $r_{e_i} \in \mathcal{I}$ represent radios used by the transmitting node and receiving node of link e_i, respectively. The service set is $\mathcal{P} = \{(s_p, d_p, \zeta_p, \alpha_p) : 1 \leq p \leq |\mathcal{P}|\ , s_p \in \mathcal{V}, d_p \in \mathcal{V}, \alpha_p \in [0,1]\}$. We use the quadruple $(s_p, d_p, \zeta_p, \alpha_p)$ to denote a specific service p, where s_p, d_p, ζ_p, and α_p represent its source, destination, rate requirement, and QoS factor, respectively. For a service p, α_p is a fraction within $[0,1]$, and $\alpha_p \cdot \zeta_p$ indicates the minimal QoS requirement which must be guaranteed in order to support the service. Particularly, α_p of a high QoS service is set to be larger than that of a low QoS service. This implies that high QoS services have higher rate requirements.

A. Cross-Layer Optimization Constraints

In this section, we examine the constraints for our optimization problem.

Flow Routing Constraint: We exploit multi-path routing to balance traffic load flexibly among paths in the MRMC network. We denote by x_p the allocated rate for service p, and $f^k_{p(t_{e_i}, r_{e_i})}$ the flow rate at which service p can transmit on link e_i over channel k, with the transmitting radio t_{e_i} and receiving radio r_{e_i}. According to the flow conservation principle [16], at the source node s_p, we have

$$x_p = \sum_{e_i \in \mathcal{E}} \sum_{t_{e_i} \in \mathcal{I}} \sum_{r_{e_i} \in \mathcal{I}} \sum_{k \in \mathcal{K}} f^k_{p(t_{e_i}, r_{e_i})} \delta_{e_i s_p},$$

where $\delta_{e_i s_p}$ is determined by the given network topology. Similarly, at the destination node d_p, we have

$$-x_p = \sum_{e_i \in \mathcal{E}} \sum_{t_{e_i} \in \mathcal{I}} \sum_{r_{e_i} \in \mathcal{I}} \sum_{k \in \mathcal{K}} f^k_{p(t_{e_i}, r_{e_i})} \delta_{e_i d_p}.$$

Except for the source and destination, all other nodes in the network constitute the relay set $\mathcal{R}_p = \{r_p^q : r_p^q \in \mathcal{V} \backslash \{s_p, d_p\}\}$ for service p. At a relay node r_p^q in the set, the amount of inflow is equal to the amount of outflow, requiring

$$0 = \sum_{e_i \in \mathcal{E}} \sum_{t_{e_i} \in \mathcal{I}} \sum_{r_{e_i} \in \mathcal{I}} \sum_{k \in \mathcal{K}} f^k_{p(t_{e_i}, r_{e_i})} \delta_{e_i r_p^q}.$$

QoS Constraint: Let $\alpha_p \cdot \zeta_p$ indicate the minimal rate requirement for the network to support service p. In order to ensure such supportability, at least $\alpha_p \cdot \zeta_p$ amount of resource should be allocated to service p. Hence,

$$\alpha_p \leq \frac{x_p}{\zeta_p}.$$

Link Capacity Constraint: Any single link may concurrently serve multiple services, as long as the summation of flow rates of all services does not exceed the link capacity. Thus, the link capacity constraint can be described as

$$\sum_{p \in \mathcal{P}} \sum_{t_{e_i} \in \mathcal{I}} \sum_{r_{e_i} \in \mathcal{I}} f^k_{p(t_{e_i}, r_{e_i})} \leq C^k_{e_i}.$$

Flow Scheduling Constraint: The conflict graph of a single-radio single-channel network topology can be derived by the protocol interference model [17], [18]. For MRMC networks, the availability of multiple radios and channels at nodes produces a multi-dimensional resource space, and hence the corresponding conflict relationship becomes more complicated. Here, we utilize a three-dimensional (3-D) conflict graph [12], [15], [19] to characterize the conflict relationship in the MRMC network. In the 3-D conflict graph, each vertex corresponds to a link-radio-channel tuple $(e_i, (t_{e_i}, r_{e_i}), k)$, where $e_i \in \mathcal{E}$, $t_{e_i} \in \mathcal{I}$, $r_{e_i} \in \mathcal{I}$, and $k \in \mathcal{K}$. The tuple indicates a transmission on link e_i over channel k, where radios t_{e_i} and r_{e_i} are used at the transmitting and receiving nodes of e_i, respectively. We define the transmissions of $(e_i, (t_{e_i}, r_{e_i}), k)$ and $(e_j, (t_{e_j}, r_{e_j}), k')$ interfere each other if either of the following conditions is true:

i) If two tuples are using the same channel, one tuple's receiving node is in the interference range of the other tuple's sending node.
ii) Two tuples share common radios at one or two nodes.

Specifically, the two conditions account for co-channel interference as well as radio interface conflict (i.e., a single radio can not support multiple concurrent transmissions). Checking against the two conditions above, we can obtain the corresponding 3-D conflict graph Γ, whose vertices represent the tuples. There is a link between $(e_i, (t_{e_i}, r_{e_i}), k)$ and $(e_j, (t_{e_j}, r_{e_j}), k')$ if the two tuples interfere each other, and we denote $\Gamma^{(t_{e_j}, r_{e_j}), k'}_{(t_{e_i}, r_{e_i}), k} = 1$; otherwise $\Gamma^{(t_{e_j}, r_{e_j}), k'}_{(t_{e_i}, r_{e_i}), k} = 0$.

Based on the conflict graph, the optimal interference-free scheduling can be obtained by allocating time fractions to all its maximal independent sets (MISs). However, according to [20], getting all MISs is an NP-complete problem, and may lead to unacceptable complexity. A suboptimal solution may be obtained by randomly finding a subset of all MISs [21], or by intelligently computing a set of critical MISs [12]. On the other hand, in [11], the interference-free scheduling necessary condition is utilized to get an infeasible solution first, and a feasible solution (interference-free) is further constructed by a three-phase channel assignment algorithm.

In this paper, considering the complexity of the algorithms above, we generalize the interference-free scheduling sufficient condition under the 3-D conflict graph (cf. Lemma 1 below), and apply it directly to our formulation. Note that such scheduling of tuples jointly takes link scheduling, channel allocation, and radio assignment into consideration.

Lemma 1: An interference-free flow scheduling can be found if the following constraint is satisfied:

$$\begin{aligned} &\sum_{p \in \mathcal{P}} \frac{f^k_{p(t_{e_i}, r_{e_i})}}{C^k_{e_i}} + \\ &\sum_{e_j \in \mathcal{E}} \sum_{t_{e_j} \in \mathcal{I}} \sum_{r_{e_j} \in \mathcal{I}} \sum_{k' \in \mathcal{K}} \sum_{p \in \mathcal{P}} \frac{f^{k'}_{p(t_{e_j}, r_{e_j})}}{C^{k'}_{e_j}} \Gamma^{(t_{e_j}, r_{e_j}), k'}_{(t_{e_i}, r_{e_i}), k} \leq 1. \end{aligned} \tag{1}$$

Proof: We assume that time is divided into slots and T is the number of time slots in a schedule. Note that T is chosen to be a large number. Consider a fixed tuple $(e_i, (t_{e_i}, r_{e_i}), k)$. Set $X^k_{\tau(t_{e_i}, r_{e_i})} = 1$ if the tuple $(e_i, (t_{e_i}, r_{e_i}), k)$ transmits in slot τ; otherwise, set $X^k_{\tau(t_{e_i}, r_{e_i})} = 0$. Suppose that a radio can dynamically switch channels, and the switching delay is negligible compared to the length of each time slot. Then, $\sum_{\tau \in T} X^k_{\tau(t_{e_i}, r_{e_i})}$ specifies the total number of active time slots for this tuple. Moreover, we also have

$$\frac{1}{T}\sum_{\tau\in T} X^k_{\tau(t_{e_i},r_{e_i})} = \frac{1}{C^k_{e_i}}\sum_{p\in\mathcal{P}} f^k_{p(t_{e_i},r_{e_i})}.$$

Thus multiplying both sides of (1) by T, we can rewrite the equation as follows:

$$\sum_{\tau\in T} X^k_{\tau(t_{e_i},r_{e_i})}+ \sum_{e_j\in\mathcal{E}}\sum_{t_{e_j}\in\mathcal{I}}\sum_{r_{e_j}\in\mathcal{I}}\sum_{k'\in\mathcal{K}}\sum_{\tau\in T} X^{k'}_{\tau(t_{e_j},r_{e_j})}\Gamma^{(t_{e_j},r_{e_j}),k'}_{(t_{e_i},r_{e_i}),k} \le T. \tag{2}$$

Considering the worst-case scenario in which all tuples that interfere $(e_i,(t_{e_i},r_{e_i}),k)$ also interfere each other, the inequality (2) implies that the total number of active time slots for $(e_i,(t_{e_i},r_{e_i}),k)$ and all of its interfering tuples can not exceed T. As a result, under this condition, an interference-free scheduling algorithm exists, and the scheduling algorithms proposed in [11] and [22] can be used to find such a schedule. ∎

Since the interference-free scheduling sufficient condition in Lemma 1 does not require searching for independent sets, employing the linear constraint simplifies the NUM formulation, at the expense of introducing performance loss. Numerical results are given in Section IV to analyze the amount of performance loss of the proposed scheme. In addition, according to the analysis in [11], it is expected that we can mathematically quantify the performance if an interference-free scheduling necessary condition under 3-D conflict graph can be obtained. This will be studied further in our future work.

B. Network Utility Maximization Problem Formulation

Provided that the QoS constraints above can be satisfied, the remaining problem is how to optimally use the residual network resource. In this paper, we assume that a service p maintains an increasing and concave function $U(x_p)$ as its utility function, which indicates a user's degree of satisfaction on the allocated rate x_p. Instead of maximizing performance metrics like network throughput or fairness factor λ as suggested in [11] and [12], our objective is to maximize the overall network utility, which is the summation of all users' utility functions. From [23], the utility function can be defined as

$$U(x_p) = \begin{cases} w_p \log x_p, & \alpha = 1 \\ w_p \frac{x_p^{1-\alpha}}{1-\alpha}, & \alpha \ne 1, \end{cases}$$

where $w_p > 0$. If $\alpha = 0$, the objective is network throughput maximization where unfair resource allocation may exist. If $\alpha \to \infty$, the objective converges to max-min fairness. On the other hand, setting $\alpha = 1$ offers proportional fairness. According to the discussion in [24], we choose $U(x_p) = \log x_p$ with $w_p = 1$ to obtain proportionally fair resource allocation.

Imposing the aforementioned cross-layer design constraints, we can formulate the QoS-aware resource allocation problem in MRMC networks as the following NUM problem. We use below inequality constraints to replace the flow conservation constraints above. This is because the inequality constraints facilitate the construction of a dual problem for solving the convex program, without affecting the solution [25], [26].

$$\max \sum_{p\in\mathcal{P}} U(x_p) = \max \sum_{p\in\mathcal{P}} \log x_p \tag{3}$$

subject to

$$x_p \le \sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}} f^k_{p(t_{e_i},r_{e_i})}\delta_{e_i s_p},\ (p\in\mathcal{P}), \tag{3a}$$

$$-x_p \le \sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}} f^k_{p(t_{e_i},r_{e_i})}\delta_{e_i d_p},\ (p\in\mathcal{P}), \tag{3b}$$

$$0 \le \sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}} f^k_{p(t_{e_i},r_{e_i})}\delta_{e_i r^q_p}, \quad (p\in\mathcal{P} \text{ and } r^q_p\in\mathcal{R}_p), \tag{3c}$$

$$\alpha_p \le \frac{x_p}{\zeta_p}, \quad (p\in\mathcal{P}), \tag{3d}$$

$$\sum_{p\in\mathcal{P}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}} f^k_{p(t_{e_i},r_{e_i})} \le C^k_{e_i},\ (e_i\in\mathcal{E} \text{ and } k\in\mathcal{K}), \tag{3e}$$

$$\sum_{p\in\mathcal{P}} \frac{f^k_{p(t_{e_i},r_{e_i})}}{C^k_{e_i}} + \sum_{e_j\in\mathcal{E}}\sum_{t_{e_j}\in\mathcal{I}}\sum_{r_{e_j}\in\mathcal{I}}\sum_{k'\in\mathcal{K}}\sum_{p\in\mathcal{P}} \frac{f^{k'}_{p(t_{e_j},r_{e_j})}}{C^{k'}_{e_j}}\Gamma^{(t_{e_j},r_{e_j}),k'}_{(t_{e_i},r_{e_i}),k} \le 1, \quad (e_i\in\mathcal{E},\ t_{e_i},r_{e_i}\in\mathcal{I} \text{ and } k\in\mathcal{K}), \tag{3f}$$

$$0 \le f^k_{p(t_{e_i},r_{e_i})},\ (p\in\mathcal{P},\ e_i\in\mathcal{E},\ t_{e_i},r_{e_i}\in\mathcal{I} \text{ and } k\in\mathcal{K}), \tag{3g}$$

where $\delta_{e_i s_p}$, $\delta_{e_i d_p}$, $\delta_{e_i r^q_p}$, α_p, ζ_p, $C^k_{e_i}$ and $\Gamma^{(t_{e_j},r_{e_j}),k'}_{(t_{e_i},r_{e_i}),k}$ are all constants, and x_p and $f^k_{p(t_{e_i},r_{e_i})}$ are optimization variables.

III. Proximal Optimization Algorithm and Decomposition Algorithm

In this section, we employ the proximal optimization and decomposition algorithms to solve the optimization problem formulated in section II.

Under multi-path flow routing, x_p is a linear summation of multiple flow rates. For this reason, although the utility function $U(x_p)$ is strictly concave in x_p, there may still exist multiple combinations of $f^k_{p(t_{e_i},r_{e_i})}$ whose summation is x_p. This situation is caused by the multi-path flow routing, and is often referred to as the oscillation problem [27]. By introducing auxiliary variables $y^k_{p(t_{e_i},r_{e_i})}$, we can solve the oscillation problem using the proximal optimization algorithm [13]. To that end, consider the following optimization:

$$\max\left\{\sum_{p\in\mathcal{P}}\log x_p - \sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}}\sum_{p\in\mathcal{P}} \frac{c}{2}\left(f^k_{p(t_{e_i},r_{e_i})} - y^k_{p(t_{e_i},r_{e_i})}\right)^2\right\} \tag{4}$$

subject to (3a) – (3g),

where c is a positive constant. Note that by adding a quadratic term, program (4) is strictly concave both in x_p and $f^k_{p(t_{e_i},r_{e_i})}$, and hence an unique optimal solution is ensured.

Based on Proposition 4.1 of [13], program (4) is equivalent to program (3). Let $\mathbf{x}$, $\mathbf{f}$, and $\mathbf{y}$ denote the collections formed by x_p, $f^k_{p(t_{e_i},r_{e_i})}$ and $y^k_{p(t_{e_i},r_{e_i})}$, respectively. Let $\mathbf{f}^*$ and $\mathbf{x}^*$ be an optimal solution to program (3). An intuitive understanding is, by setting $\mathbf{y}=\mathbf{f}^*$, the optimal solutions to program (4) are $\mathbf{f}^*$ and $\mathbf{x}^*$. In addition, the quadratic term in program (4) ensures the uniqueness of the optimal $\mathbf{f}^*$. Therefore, the optimal solution to (4) coincides with that to (3), and the optimal objective functions are equal. Utilizing the proximal optimization algorithm, we iteratively solve (4) in Algorithm 1. The sequence $\{\mathbf{f}^*_{(t)}\}$ and $\{\mathbf{x}^*_{(t)}\}$ will converge to one of optimal solutions to the original program (3).

Algorithm 1 At the t-th iteration of the proximal optimization algorithm:

1: **Input:** $\mathbf{f}^*_{(t-1)}$;
2: Set $\mathbf{y}=\mathbf{f}^*_{(t-1)}$;
3: Solve program (4) in $\mathbf{f}$ and $\mathbf{x}$;
4: **Output:** Optimal solutions $\mathbf{f}^*_{(t)}$ and $\mathbf{x}^*_{(t)}$.

The remaining problem is then how to solve program (4) in step 3 at each iteration of Algorithm 1. Since program (4) is a convex optimization problem and all constraints are linear, i.e., the Slater's condition is satisfied, by exploiting the Lagrange relaxation and sub-gradient algorithms [14], [28], we can solve it through its Lagrange dual program and the optimal primal-dual gap is zero [29]. To that end, let λ_{1p}, λ_{2p}, $\lambda_{pr^q_p}$, λ_{3p}, $\lambda^k_{e_i}$, and $\lambda^k_{(t_{e_i},r_{e_i})}$ be the Lagrange multipliers (prices) for constraints (3a), (3b), (3c), (3d), (3e), and (3f), respectively. To simplify notation, group all these multipliers into the vector $\boldsymbol{\lambda}$. Denote the Lagrangian of program (4) by $L(\mathbf{x},\mathbf{f},\boldsymbol{\lambda})$. Through Lagrange relaxation, $L(\mathbf{x},\mathbf{f},\boldsymbol{\lambda})$ is given as below:

$$\begin{aligned}
L(\mathbf{x},\mathbf{f},\boldsymbol{\lambda}) &= \sum_{p\in\mathcal{P}}\log x_p - \\
&\sum_{p\in\mathcal{P}}\sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}}\frac{c}{2}(f^k_{p(t_{e_i},r_{e_i})}-y^k_{p(t_{e_i},r_{e_i})})^2 - \\
&\sum_{p\in\mathcal{P}}\lambda_{1p}(x_p-\sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}}f^k_{p(t_{e_i},r_{e_i})}\delta_{e_is_p}) + \\
&\sum_{p\in\mathcal{P}}\lambda_{2p}(x_p+\sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}}f^k_{p(t_{e_i},r_{e_i})}\delta_{e_id_p}) + \\
&\sum_{p\in\mathcal{P}}\sum_{r^q_p\in\mathcal{R}_p}\lambda_{pr^q_p}(\sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}}f^k_{p(t_{e_i},r_{e_i})}\delta_{e_ir^q_p}) - \\
&\sum_{p\in\mathcal{P}}\lambda_{3p}(\alpha_p\zeta_p-x_p) - \\
&\sum_{e_i\in\mathcal{E}}\sum_{k\in\mathcal{K}}\lambda^k_{e_i}(\sum_{p\in P}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}f^k_{p(t_{e_i},r_{e_i})}-C^k_{e_i}) - \\
&\sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}}\lambda^k_{(t_{e_i},r_{e_i})}\Bigg(\sum_{p\in\mathcal{P}}\frac{f^k_{p(t_{e_i},r_{e_i})}}{C^k_{e_i}} + \\
&\sum_{e_j\in\mathcal{E}}\sum_{t_{e_j}\in\mathcal{I}}\sum_{r_{e_j}\in\mathcal{I}}\sum_{k'\in\mathcal{K}}\sum_{p\in\mathcal{P}}\frac{f^{k'}_{p(t_{e_j},r_{e_j})}}{C^{k'}_{e_j}}\Gamma^{(t_{e_j},r_{e_j}),k'}_{(t_{e_i},r_{e_i}),k}-1\Bigg).
\end{aligned}$$

The Lagrange dual problem of (4) is then given by

$$\begin{aligned}
&\min D(\boldsymbol{\lambda}) \\
&\text{subject to} \quad \boldsymbol{\lambda}\geq 0,
\end{aligned} \tag{5}$$

where $D(\boldsymbol{\lambda})=\max_{\mathbf{x},\mathbf{f}}L(\mathbf{x},\mathbf{f},\boldsymbol{\lambda})$ is the Lagrange dual function.

In order to simplify notation, we define $D_1(\boldsymbol{\lambda};p)$ and $D_2(\boldsymbol{\lambda};p,e_i,t_{e_i},r_{e_i},k)$ as follows:

$$\begin{aligned}
&D_1(\boldsymbol{\lambda};p)=\max_{x_p}\big(\log x_p-\lambda_{1p}x_p+\lambda_{2p}x_p+\lambda_{3p}x_p\big), \\
&D_2(\boldsymbol{\lambda};p,e_i,t_{e_i},r_{e_i},k)= \\
&\max_{f^k_{p(t_{e_i},r_{e_i})}}\Big[-\frac{c}{2}(f^k_{p(t_{e_i},r_{e_i})}-y^k_{p(t_{e_i},r_{e_i})})^2+ \\
&\lambda_{1p}f^k_{p(t_{e_i},r_{e_i})}\delta_{e_is_p}+\lambda_{2p}f^k_{p(t_{e_i},r_{e_i})}\delta_{e_id_p}-\lambda^k_{e_i}f^k_{p(t_{e_i},r_{e_i})}+ \\
&\sum_{r^q_p\in\mathcal{R}_p}\lambda_{pr^q_p}f^k_{p(t_{e_i},r_{e_i})}\delta_{e_ir^q_p}-\lambda^k_{(t_{e_i},r_{e_i})}\frac{f^k_{p(t_{e_i},r_{e_i})}}{C^k_{e_i}}- \\
&\frac{f^k_{p(t_{e_i},r_{e_i})}}{C^k_{e_i}}\Bigg(\sum_{e_j\in\mathcal{E}}\sum_{t_{e_j}\in\mathcal{I}}\sum_{r_{e_j}\in\mathcal{I}}\sum_{k'\in\mathcal{K}}\lambda^{k'}_{(t_{e_j},r_{e_j})}\Gamma^{(t_{e_i},r_{e_i}),k}_{(t_{e_j},r_{e_j}),k'}\Bigg)\Bigg].
\end{aligned}$$

In this way, $D(\boldsymbol{\lambda})$ can be rewritten as

$$\begin{aligned}
D(\boldsymbol{\lambda}) &= \sum_{e_i\in\mathcal{E}}\sum_{k\in\mathcal{K}}\lambda^k_{e_i}C^k_{e_i}-\sum_{p\in\mathcal{P}}\lambda_{3p}\alpha_p\zeta_p+ \\
&\sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}}\lambda^k_{(t_{e_i},r_{e_i})}+\sum_{p\in\mathcal{P}}D_1(\boldsymbol{\lambda};p)+ \\
&\sum_{p\in\mathcal{P}}\sum_{e_i\in\mathcal{E}}\sum_{t_{e_i}\in\mathcal{I}}\sum_{r_{e_i}\in\mathcal{I}}\sum_{k\in\mathcal{K}}D_2(\boldsymbol{\lambda};p,e_i,t_{e_i},r_{e_i},k).
\end{aligned} \tag{6}$$

Note that the form of (6) is a direct consequence of the linearity of constraints and additivity of the objective function in (4).

At each iteration of Algorithm 1, we solve program (4) by solving its Lagrange dual program (5). The latter can be iteratively solved using the decomposition algorithm. We observe from (6) that evaluating the Lagrange dual function $D(\boldsymbol{\lambda})$ mainly involves the two optimal programs $D_1(\boldsymbol{\lambda};p)$ and $D_2(\boldsymbol{\lambda};p,e_i,t_{e_i},r_{e_i},k)$, both can be straightforwardly solved. More specifically, at iteration t' of the decomposition algorithm, each source independently performs flow control optimization by calculating

$$x^*_{p(t')}=\left[\frac{1}{\lambda^*_{1p(t'-1)}-\lambda^*_{2p(t'-1)}-\lambda^*_{3p(t'-1)}}\right]^+, \tag{7}$$

where $[x]^+=\max\{0,x\}$. In parallel, each link individually solves the optimal resource allocation by calculating

$$f^{k*}_{p(t_{e_i},r_{e_i})(t')} = \Bigg[y^{k}_{p(t_{e_i},r_{e_i})} + \frac{1}{c}\Bigg(\lambda^{*}_{1p(t'-1)}\delta_{e_i s_p} + \lambda^{*}_{2p(t'-1)}\delta_{e_i d_p} + \sum_{r^q_p \in \mathcal{R}_p} \lambda^{*}_{pr^q_p(t'-1)}\delta_{e_i r^q_p} - \lambda^{k*}_{e_i(t'-1)} - \frac{\lambda^{k*}_{(t_{e_i},r_{e_i})(t'-1)}}{C^k_{e_i}} - \frac{1}{C^k_{e_i}}\Big(\sum_{e_j\in\mathcal{E}} \sum_{t_{e_j}\in\mathcal{I}} \sum_{r_{e_j}\in\mathcal{I}} \sum_{k'\in\mathcal{K}} \lambda^{k'*}_{(t_{e_j},r_{e_j})(t'-1)} \Gamma^{(t_{e_i},r_{e_i}),k}_{(t_{e_j},r_{e_j}),k'} \Big) \Bigg) \Bigg]^{+}. \tag{8}$$

Then, using the sub-gradient algorithm, each node and link update their corresponding Lagrange prices as follows:

$$\lambda^{*}_{1p(t')} = [\lambda^{*}_{1p(t'-1)} + \beta(x^{*}_{p(t')} - \sum_{e_i\in\mathcal{E}} \sum_{t_{e_i}\in\mathcal{I}} \sum_{r_{e_i}\in\mathcal{I}} \sum_{k\in\mathcal{K}} f^{k*}_{p(t_{e_i},r_{e_i})(t')}\delta_{e_i s_p})]^{+} \tag{9a}$$

$$\lambda^{*}_{2p(t')} = [\lambda^{*}_{2p(t'-1)} - \beta(x^{*}_{p(t')} + \sum_{e_i\in\mathcal{E}} \sum_{t_{e_i}\in\mathcal{I}} \sum_{r_{e_i}\in\mathcal{I}} \sum_{k\in\mathcal{K}} f^{k*}_{p(t_{e_i},r_{e_i})(t')}\delta_{e_i d_p})]^{+} \tag{9b}$$

$$\lambda^{*}_{pr^q_p(t')} = [\lambda^{*}_{pr^q_r(t'-1)} - \beta \sum_{e_i\in\mathcal{E}} \sum_{t_{e_i}\in\mathcal{I}} \sum_{r_{e_i}\in\mathcal{I}} \sum_{k\in\mathcal{K}} f^{k*}_{p(t_{e_i},r_{e_i})(t')}\delta_{e_i r^q_p}]^{+} \tag{9c}$$

$$\lambda^{*}_{3p(t')} = [\lambda^{*}_{3p(t'-1)} + \beta(\alpha_p\zeta_p - x^{*}_{p(t')})]^{+} \tag{9d}$$

$$\lambda^{k*}_{e_i(t')} = [\lambda^{k*}_{e_i(t'-1)} + \beta(\sum_{p\in\mathcal{P}} \sum_{t_{e_i}\in\mathcal{I}} \sum_{r_{e_i}\in\mathcal{I}} f^{k*}_{p(t_{e_i},r_{e_i})(t')} - C^k_{e_i})]^{+} \tag{9e}$$

$$\lambda^{k*}_{(t_{e_i},r_{e_i})(t')} = [\lambda^{k*}_{(t_{e_i},r_{e_i})(t'-1)} + \beta(\sum_{p\in\mathcal{P}} \frac{f^{k*}_{p(t_{e_i},r_{e_i})(t')}}{C^k_{e_i}} + \sum_{e_j\in\mathcal{E}} \sum_{t_{e_j}\in\mathcal{I}} \sum_{r_{e_j}\in\mathcal{I}} \sum_{k'\in\mathcal{K}} \sum_{p\in\mathcal{P}} \frac{f^{k'*}_{p(t_{e_j},r_{e_j})(t')}}{C^{k'}_{e_j}} \Gamma^{(t_{e_j},r_{e_j}),k'}_{(t_{e_i},r_{e_i}),k} - 1)]^{+}, \tag{9f}$$

where $\beta = d/(a + bt')$ is the step size with properly chosen constants a, b, and d.

Algorithm 2 presents the pseudo code for the decomposition algorithm described above. We observe from Algorithm 2 that the term $\sum_{e_i\in\mathcal{E}} \sum_{t_{e_i}\in\mathcal{I}} \sum_{r_{e_i}\in\mathcal{I}} \sum_{k\in\mathcal{K}} f^{k*}_{p(t_{e_i},r_{e_i})(t')}\delta_{e_i s_p}$ in (9a) is only related to the flow rates, that are incident to s_p. That means only local information is needed to update $\lambda^{*}_{1p(t')}$. Similarly, (9b)–(9f) also merely require local information to update $\boldsymbol{\lambda}^{*}$. In summary, Algorithm 3 gives the whole iteration procedure to solve program (3).

IV. Performance Evaluation

In this section, we first study the convergence behavior of the proximal optimization and decomposition algorithms through simulations. Second, we compare the performance of the proposed QoS-aware scheme with other two schemes. Then we discuss the impact of the number of channels and radios on network utility. Finally we analyze the efficiency ratio of the proposed scheme.

Algorithm 2 At the t'-th iteration of the decomposition algorithm:

1: **Input:** $\boldsymbol{\lambda}^{*}_{(t'-1)}$;
2: Each source calculates $D_1(\boldsymbol{\lambda}; p)$ by (7) ;
3: Each link calculates $D_2(\boldsymbol{\lambda}; p, e_i, t_{e_i}, r_{e_i}, k)$ by (8) ;
4: Each node and link update their corresponding prices by (9a)–(9f) ;
5: **Output:** Optimal dual price $\boldsymbol{\lambda}^{*}_{(t')}$.

Algorithm 3 Overall iteration procedure:

1: **Initialization:** Set $t = 0$ and $\mathbf{f}^{*}_{(0)}$ to be a set with non-negative elements;
2: $t = t + 1$, $\mathbf{y} = \mathbf{f}^{*}_{(t-1)}$;
3: $t' = 0$, each node and link initialize the corresponding multiplier $\boldsymbol{\lambda}^{*}_{(0)}$;
4: $t' = t' + 1$, each source node locally determines $x^{*}_{p(t')}$ by (7) and each link locally decides $f^{k*}_{p(t_{e_i},r_{e_i})(t')}$ by (8);
5: Exchange optimal solution information obtained from step 4 between neighbors;
6: Each node and link update the multiplier $\boldsymbol{\lambda}^{*}_{(t')}$ by (9a)–(9f);
7: Go to step 4 until the termination criterion is satisfied, and return the optimal primal variables $\mathbf{f}^{*}_{(t)} = \mathbf{f}^{*}_{(t')}$ and $\mathbf{x}^{*}_{(t)} = \mathbf{x}^{*}_{(t')}$;
8: Go to step 2 until the termination criterion is satisfied;
9: **Output:** Optimal solutions $\mathbf{f}^{*}$ and $\mathbf{x}^{*}$.

A. Simulation Setup

We randomly generate four different topologies in an $1000m \times 1000m$ area. The transmission range and interference range are set to be 250m and 500m, respectively. Each topology has $|\mathcal{K}| = 2$ non-overlapping channels. Based on the IEEE 802.11g standard, the capacity of each link on each channel is randomly selected from 6 Mbps, 9 Mbps, 12 Mbps and 18 Mbps. Each topology has $|\mathcal{V}| = 20$ nodes, each of which has $|\mathcal{I}| = 2$ radios. There are $|\mathcal{P}| = 4$ services, each of which has a random source-destination pair and a random rate requirement within $[0, 8]$ Mbps. To characterize the diversity of QoS requirements, we set $\alpha_p \in [0.6, 0.8]$ for high priority services and $\alpha_p \in [0.1, 0.3]$ for low priority services.

B. Numerical Results and Performance Analysis

We show the first network topology in Fig. 2. Four services are considered in the network, and the QoS requirements (α, ζ) of the services are (0.896 Mbps, 0.748), (5.987 Mbps, 0.206), (7.981 Mbps, 0.125) and (4.001 Mbps, 0.298), respectively.

We show the convergence performance of the proximal optimization algorithm and the decomposition algorithm of Topology 1 in Fig. 3. Similar results are obtained for the other three topologies. We use the proximal optimization algorithm to solve the equivalent program (4) through 10 iterations. In each iteration, we set $c = 1$. We observe from Fig. 3(a) that, the gap between the auxiliary objective and the original objective becomes very small after eight iterations. In addition, at each iteration of the proximal optimization algorithm, we

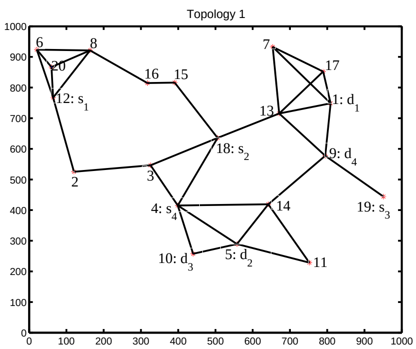
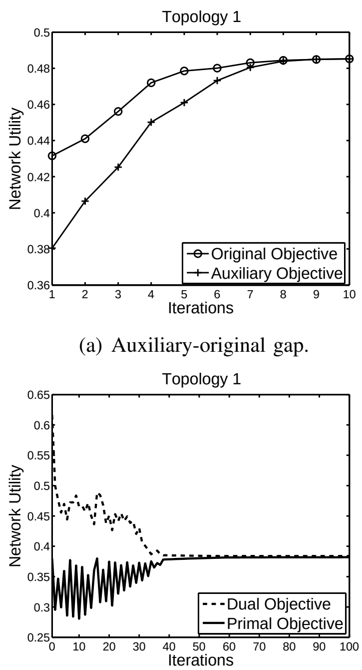


Fig. 2. Random Network Topology 1.



(a) Auxiliary-original gap.

(b) Primal-dual gap.

Fig. 3. Convergency behavior of the proximal optimization and decomposition algorithms in Topology 1.

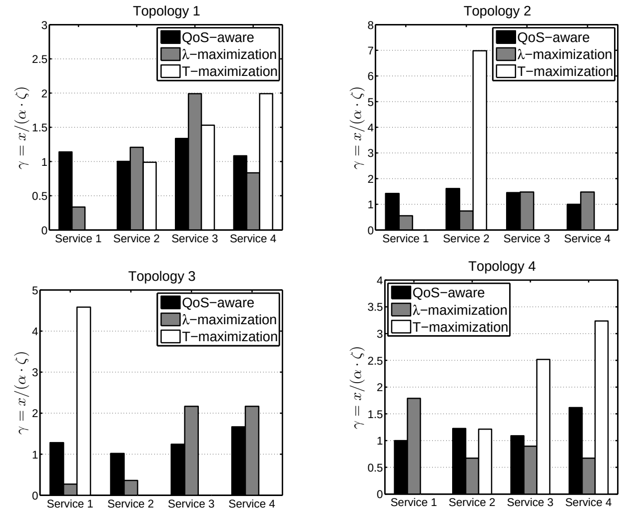


Fig. 4. Performance comparison of the proposed QoS-aware, λ-maximization and T-maximization schemes in the four network topologies. In each topology, $|\mathcal{V}| = 20$, $|\mathcal{K}| = 2$, $|\mathcal{I}| = 2$ and $|\mathcal{P}| = 4$.

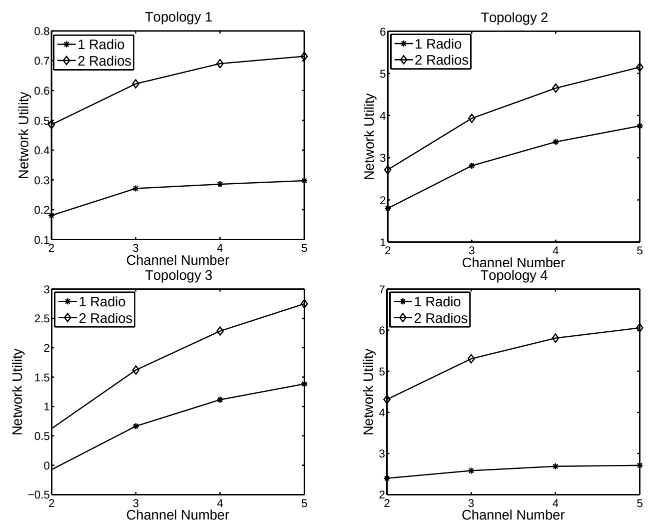


Fig. 5. Network utility versus channel number and radio number.

use the decomposition algorithm to solve the Lagrange dual problem in 100 iterations with step size $\beta = d/(a + bt') = 0.2/(10+0.5t')$, where t' is the iteration index. Fig. 3(b) shows the Lagrange dual objective converges to the primal objective with increasing number of iterations.

We apply our proposed QoS-aware scheme, the fairness factor maximization scheme (λ-maximization) of [11], [12], and the throughput maximization scheme (T-maximization) of [30] to the four generated topologies and compare results in Fig. 4. For the purpose of comparison, we define the ratio $\gamma_p = \frac{x_p}{\alpha_p \cdot \zeta_p}$ to measure the gap between the allocated rate and minimal rate requirement for each service. From Fig. 4, we observe that under the proposed QoS-aware scheme, the ratio of each service is equal to or larger than 1. However, the ratios of some services are zero under the T-maximization scheme or less than 1 under the λ-maximization scheme. As a result, compared with the T-maximization and λ-maximization schemes, the proposed scheme is more suitable for the scenarios in which services have diversity of QoS requirements.

In Table I, we give the routing and scheduling results obtained by the proposed scheme under Topology 1. Each tuple in the table corresponds to a specific transmission: (transmitting node, receiving node, channel, transmitting radio, receiving radio, service). For example, $(2, 3, 2, 1, 1, P1)$ means a transmission from node 2 with transmitting radio 1 to node 3 with receiving radio 1, working on channel 2 and serving the first service, i.e., the service from node 12 to 1 in Topology 1. From Table I, we can see that the scheduling results are interference-free. For example, from Topology 1 in Fig. 2, transmission from node 3 to 18 interferes with transmission from node 2 to 3 and transmission from node 19 to 9 if they are scheduled on the same channel. However, transmissions from node 2 to 3 and from node 19 to 9 do not interfere with each other and can work on the same channel. For this reason, in time slot 1 in Table I, both transmissions from node

TABLE I
QoS-AWARE SCHEME SCHEDULING RESULTS

Slot	Active Links
1	(2,3,2,1,1,P1),(3,18,1,2,2,P1),(19,9,2,1,1,P3)
2	(2,3,1,2,1,P1),(2,3,2,1,2,P1),(19,9,1,1,2,P3),(19,9,2,2,1,P3)
3	(2,3,1,2,2,P1),(2,3,2,1,1,P1),(19,9,1,2,1,P3),(19,9,2,1,2,P3)
4	(2,3,1,1,1,P1),(2,3,2,2,2,P1),(19,9,1,1,1,P3),(19,9,2,2,2,P3)
5	(2,3,2,2,1,P1),(3,18,1,1,2,P1)
6	(3,18,1,1,1,P1),(3,18,2,2,2,P1)
7	(3,18,1,2,1,P1),(3,18,2,1,2,P1)
8	(3,18,2,1,1,P1),(4,5,1,2,1,P2)
9	(3,18,2,2,1,P1),(4,5,1,2,1,P2)
10	(4,5,1,2,1,P2),(4,14,2,1,2,P4)
11	(4,5,1,2,2,P2), (4,5,2,1,1,P2)
12	(4,5,1,2,2,P2), (4,5,2,1,1,P2), (12,8,1,1,1,P1)
13	(4,5,2,1,1,P2), (4,14,1,2,2,P4), (12,8,1,1,2,P1)
14	(4,5,2,2,1,P2), (4,18,1,1,2,P4),(12,8,2,1,1,P1)
15	(4,14,1,2,1,P4), (4,18,2,1,2,P4), (12,8,1,2,1,P1)
16	(4,14,2,2,1,P4), (5,10,1,1,1,P3),(8,16,1,1,1,P1)
17	(4,18,1,1,1,P4), (4,18,2,2,2,P4)
18	(4,18,1,2,1,P4), (5,10,2,2,2,P3), (8,16,2,1,1,P1)
19	(4,18,1,2,2,P4), (4,18,2,1,1,P4)
20	(4,18,2,2,1,P4), (5,10,1,1,2,P3), (8,16,1,1,2,P1)
21	(4,18,2,2,2,P4), (5,10,1,1,2,P3), (8,16,1,2,1,P1)
22	(5,10,1,2,1,P3), (8,16,1,2,2,P1), (9,14,2,1,1,P3), (12,2,2,1,1,P1)
23	(5,10,1,2,2,P3), (8,16,2,1,2,P1), (9,14,2,1,2,P3), (13,1,1,2,1,P1)
24	(5,10,2,2,2,P3), (8,16,2,2,1,P1), (9,14,1,1,2,P3), (12,2,1,1,1,P1)
25	(5,10,2,2,2,P3), (8,16,2,2,2,P1), (12,2,1,1,2,P1), (13,1,1,2,2,P1)
26	(13,9,2,1,1,P4), (14,9,1,2,2,P4)
27	(9,14,2,2,1,P3),(12,2,1,2,2,P1),(13,1,1,2,2,P1)
28	(9,14,2,2,2,P3),(12,2,2,1,2,P1),(14,5,1,1,1,P3)
29	(9,14,2,2,2,P3), (12,2,2,2,1,P1),(14,5,1,1,1,P3)
30	(9,14,2,2,2,P3), (12,2,2,2,2,P1),(14,5,1,1,1,P3)
31	(12,2,2,2,2,P1),(13,1,2,1,2,P1),(13,9,1,2,1,P4)
32	(12,8,1,2,2,P1),(13,1,2,2,1,P1),(14,5,1,1,2,P3)
33	(12,8,2,2,1,P1),(13,9,1,2,1,P4),(14,5,2,1,1,P3)
34	(13,9,1,2,1,P4),(14,5,2,1,2,P3)
35	(13,9,1,2,1,P4),(14,5,2,2,1,P3)
36	(13,9,2,1,1,P4),(14,5,1,1,2,P3)
37	(5,10,2,2,2,P3), (12,2,1,2,1,P1),(12,8,2,1,2,P1)
38	(13,9,2,1,1,P4), (15,18,1,1,2,P1)
39	(13,9,2,2,1,P4), (14,9,1,1,2,P4)
40	(14,5,2,2,2,P3),(14,9,1,1,1,P4)
41	(14,9,1,1,2,P4), (14,9,2,2,1,P4)
42	(14,9,1,2,1,P4), (15,18,2,1,2,P1)
43	(14,9,2,1,1,P4), (15,18,1,1,2,P1)
44	(15,18,2,1,1,P1), (18,13,1,1,2,P4)
45	(15,18,2,2,1,P1), (18,13,1,1,2,P4)
46	(16,15,1,2,1,P1), (18,4,2,1,2,P2),(19,9,1,2,1,P3)
47	(16,15,1,2,1,P1), (18,4,2,1,2,P2),(19,9,1,2,2,P3)
48	(16,15,2,2,1,P1), (18,4,1,1,1,P2)
49	(18,4,1,2,2,P2), (18,13,2,1,2,P1)
50	(18,4,2,1,2,P2), (19,9,1,2,2,P3)

TABLE II
PERFORMANCE ANALYSIS OF THE INTERFERENCE-FREE SCHEDULING SUFFICIENT CONDITION.

Gird Topologies		
Node Number	Optimal Utility	QoS-aware Utility
3×3	3.562276	2.096231
3×4	5.689401	2.038531
3×5	9.112094	2.418386
4×4	10.095972	2.789186
Random Topologies		
Node Number	Optimal Utility	QoS-aware Utility
9	4.308028	2.698485
12	5.380582	2.557413
15	11.793908	4.583163
16	9.049829	2.942601

2 to 3 and from node 19 to 9 are assigned to channel 2, while transmission from node 3 to 18 is assigned to channel 1, in order to avoid co-channel interference. Moreover, node 3 assigns radios 1 and 2 for transmissions from node 2 to 3 and from node 3 to 18, respectively, in order to guarantee no radio interface conflict is generated.

By varying the number of radios and channels, Fig. 5 shows the impact of resource on network utility in the four topologies. From the numerical results, we find that the network utility increases with the number of channels and radios. This is because with more resource available in networks, more transmission can be concurrently active and hence interference is mitigated. This demonstrates that our scheme can effectively take advantage of the available resource to improve network utility.

Finally, since a sufficient condition is used as the flow scheduling constraint, the proposed scheme may incur performance loss. In Table II, we numerically analyze this loss under grid and random topologies. Considering the intractable complexity in enumerating all MISs in high user density scenarios, we consider scenarios with relatively low user density and create 3×3, 3×4, 3×5 and 4×4 grid topologies, and four random topologies with 9, 12, 15 and 16 nodes, respectively. We set $|\mathcal{I}| = 1$ for simplicity. Other parameters are described in section IV-A. Based on each topology's 3-D conflict graph, we enumerate all MISs and compute the corresponding optimal utility. For the four grid topologies, the numbers of the MISs are 216, 2496, 16680 and 26432, respectively. For the four random topologies, the numbers of the MISs are 312, 2392, 12888 and 53011, respectively. Table II illustrates a comparison between the optimal utility and utility obtained by the proposed QoS-aware scheme. We observe that the efficiency ratio of the proposed QoS-aware scheme is around 60% for the small scale networks with 9 nodes, and around 30% for the larger scale networks with 16 nodes. Moreover, note that in the formulation of the optimal utility case where all MISs are utilized, the complexity of the algorithm comes from two aspects: one is searching for MISs, and the other one is solving the corresponding optimization problem, which contains a large number of MISs in flow scheduling constraints. Therefore, considering the complexity generated in the optimal utility situation, the optimality loss caused by the proposed algorithm is acceptable.

V. CONCLUSION

We have studied the problem of resource allocation in MRMC networks. In particular, we have proposed a fair QoS-aware resource allocation scheme for MRMC networks with services requiring diverse QoS levels. In order to meet minimal QoS requirements of services and to obtain a proportionally fair resource allocation, we have formulated the resource allocation problem as a NUM problem with QoS constraints. Moreover, to avoid the oscillation problem caused by multipath flow routing, we have adopted the proximal optimization algorithm to transform the problem into an equivalent primal optimization problem, which has an unique optimal solution. We have used the decomposition algorithm to solve the resulting primal problem. By carrying out numerical simulations, we have verified the effectiveness of the proximal optimization algorithm and the decomposition algorithm. Besides, the numerical results demonstrate that our proposed scheme outperforms previous schemes in terms of guaranteeing QoS. We also discuss efficiency ratio of the proposed scheme under both grid and random topologies. Based on the discussion, the performance loss of the proposed scheme is acceptable.

REFERENCES

[1] P. Kyasanur and N. Vaidya, "Capacity of multi-channel wireless networks: impact of number of channels and interfaces," in *Proc. of international conference on Mobile computing and networking, ACM MobiCom 2005*, Cologne, Germany, August 2005.

[2] R. Huang, S. Kim, C. Zhang, and Y. Fang, "Exploiting the capacity of multichannel multiradio wireless mesh networks," *IEEE Transactions on Vehicular Technology*, vol. 58, no. 9, pp. 5037 –5047, November 2009.

[3] J. So and N. Vaidya, "Multi-channel mac for ad hoc networks: handling multi-channel hidden terminals using a single transceiver," in *Proc. of ACM International Symposium on Mobile Ad Hoc Networking and Computing, ACM MobiHoc 2004*, Tokyo, Japan, May 2004.

[4] W. So, J. Walrand, and J. Mo, "Mcmac: a parallel rendezvous multi-channel mac protocol," in *IEEE Wireless Communications and Networking Conference, WCNC 2007*, Hong Kong, China, March 2007.

[5] M. Marina, S. Das, and A. Subramanian, "A topology control approach for utilizing multiple channels in multi-radio wireless mesh networks," *Computer Networks (Elsevier) Journal*, vol. 54, no. 2, pp. 241–256, February 2010.

[6] M. Felegyhazi, M. Cagalj, S. Bidokhti, and J. Hubaux, "Non-cooperative multi-radio channel allocation in wireless networks," in *Proc. of IEEE International Conference on Computer Communications, INFOCOM 2007*, Anchorage, AK, May 2007.

[7] A. Subramanian, H. Gupta, and S. Das, "Minimum interference channel assignment in multi-radio wireless mesh networks," in *Proc. of IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks, SECON 2007*, San Diego, CA, June 2007.

[8] T. Liu and W. Liao, "Multicast routing in multi-radio multi-channel wireless mesh networks," *IEEE Transactions on Wireless Communications*, vol. 9, no. 10, pp. 3031–3039, October 2010.

[9] R. Draves, J. Padhye, and B. Zill, "Routing in multi-radio, multi-hop wireless mesh networks," in *Proc. of international conference on Mobile computing and networking, ACM MobiCom 2004*, Philadelphia, PA, September 2004.

[10] X. Hong, B. Gu, M. Hoque, and L. Tang, "Exploring multiple radios and multiple channels in wireless mesh networks," *IEEE Wireless Communications*, vol. 17, no. 3, pp. 76 –85, June 2010.

[11] M. Alicherry, R. Bhatia, and L. Li, "Joint channel assignment and routing for throughput optimization in multi-radio wireless mesh networks," in *Proc. of international conference on Mobile computing and networking, ACM MobiCom 2005*, Cologne, Germany, August 2005.

[12] H. Li, Y. Cheng, C. Zhou, and P. Wan, "Multi-dimensional conflict graph based computing for optimal capacity in MR-MC wireless networks," in *Proc. of International Conference on Distributed Computing Systems, ICDCS 2010*, Genoa, Italy, June 2010.

[13] D. Bertsekas and J. Tsitsiklis, *Parallel and distributed computation: numerical methods*. Prentice-Hall, Inc., 1989.

[14] M. Chiang, S. Low, A. Calderbank, and J. Doyle, "Layering as optimization decomposition: A mathematical theory of network architectures," *Proceedings of the IEEE*, vol. 95, no. 1, pp. 255–312, January 2007.

[15] M. Pan, P. Li, Y. Song, Y. Fang, and P. Lin, "Spectrum clouds: A session based spectrum trading system for multi-hop cognitive radio networks," in *Proc. of IEEE International Conference on Computer Communications, INFOCOM 2012*, Orlando, FL, March 2012.

[16] R. Ahuja, T. Magnanti, and J. Orlin, *Network flows: theory, algorithms, and applications*. Prentice-Hall, Inc., 1993.

[17] P. Gupta and P. Kumar, "The capacity of wireless networks," *IEEE Transactions on Information Theory*, vol. 46, no. 2, pp. 388–404, March 2000.

[18] H. Zhai and Y. Fang, "Impact of routing metrics on path capacity in multirate and multihop wireless ad hoc networks," in *Proc. of the IEEE International Conference on Network Protocols, ICNP 2006*, Santa Barbara, CA, November 2006.

[19] M. Pan, P. Li, and Y. Fang, "Cooperative communication aware link scheduling for cognitive vehicular ad-hoc networks," *IEEE Journal on Selected Areas in Communications (JSAC)*, vol. 30, no. 4, pp. 760–768, May 2012.

[20] M. R. Garey and D. S. Johnson, *Computers and Intractability; A Guide to the Theory of NP-Completeness*. W. H. Freeman & Co., 1990.

[21] K. Jain, J. Padhye, V. N. Padmanabhan, and L. Qiu, "Impact of interference on multi-hop wireless network performance," in *Proceedings of the 9th annual international conference on Mobile computing and networking, MobiCom '03*, San Diego, CA, September 2003.

[22] Y. Wang, W. Wang, X. Li, and W. Song, "Interference-aware joint routing and tdma link scheduling for static wireless networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 19, no. 12, pp. 1709–1725, December 2008.

[23] F. Kelly, A. Maulloo, and D. Tan, "Rate control for communication networks: shadow prices, proportional fairness and stability," *Journal of the Operational Research Society*, vol. 49, no. 3, pp. 237–252, 1998.

[24] J. Mo and J. Walrand, "Fair end-to-end window-based congestion control," *IEEE/ACM Transactions on Networking*, vol. 8, no. 5, pp. 556–567, October 2000.

[25] N. V. Simone Merlin and M. Zorzi, "Resource allocation in multi-radio multi-channel multi-hop wireless networks," in *Proc. of IEEE International Conference on Computer Communications, INFOCOM 2008*, Phoenix, AZ, April 2008.

[26] L. Georgiadis, M. J. Neely, and L. Tassiulas, *Resource allocation and cross-layer control in wireless networks*. Now Publishers Inc., 2006.

[27] X. Lin and N. Shroff, "Utility maximization for communication networks with multipath routing," *IEEE Transactions on Automatic Control*, vol. 51, no. 5, pp. 766–781, May 2006.

[28] D. Palomar and M. Chiang, "A tutorial on decomposition methods for network utility maximization," *IEEE Journal on Selected Areas in Communications*, vol. 24, no. 8, pp. 1439–1451, August 2006.

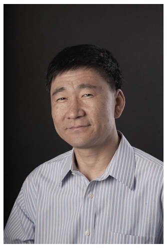
[29] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.

[30] Y. Song, C. Zhang, and Y. Fang, "Throughput maximization in multi-channel wireless mesh access networks," in *Proc. of IEEE International Conference on Network Protocols, ICNP 2007*, Beijing, China, October 2007.

Yan Long received the BSc degree in Electrical and Information Engineering from Xidian University, China, in 2009. She has been working towards the Ph.D. degree in the Department of Telecommunications Engineering at Xidian University, since 2010. From September 2011 to March 2013, she was a visiting student in the Department of Electrical and Computer Engineering, University of Florida. Her research interests include multi-radio multi-channel networks, cognitive radio networks, wireless resource allocation, and cross-layer optimization.

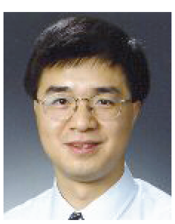
Hongyan Li (M'08) received M.S. degree in control engineering from Xi'an Jiaotong University, Xi'an, China, in 1991, and the Ph.D. degree in signal and information processing from Xidian University, China, in 2000. She is currently a professor in the State Key Laboratory of Integrated Service Networks, Xidian University. Her research interests include wireless networking, cognitive networks, integration of heterogeneous network, and mobile ad hoc networks.

Miao Pan (S'07-M'12) received his BSc degree in Electrical Engineering from Dalian University of Technology, China, in 2004, MASc degree in electrical and computer engineering from Beijing University of Posts and Telecommunications, China, in 2007 and Ph.D. degree in Electrical and Computer Engineering from the University of Florida in 2012, respectively. He is now an Assistant Professor in the Department of Computer Science at Texas Southern University. His research interests include cognitive radio communications and networking, wireless security and network economics, and resource management in cyber-physical systems such as wireless sensor networks, cloud computing, and smart grids.



Yuguang "Michael" Fang (S'92-M'97-SM'99-F'08) received a Ph.D. degree in Systems Engineering from Case Western Reserve University in January 1994 and a Ph.D. degree in Electrical Engineering from Boston University in May 1997. He is now a professor in the Department of Electrical and Computer Engineering at University of Florida. He held a University of Florida Research Foundation (UFRF) Professorship from 2006 to 2009, a Changjiang Scholar Chair Professorship with Xidian University, Xi'an, China, from 2008 to 2011, and a Guest Chair Professorship with Tsinghua University, China, from 2009 to 2012. Dr. Fang received the National Science Foundation Faculty Early Career Award in 2001 and the Office of Naval Research Young Investigator Award in 2002, and is the recipient of the Best Paper Award in IEEE Globecom'2011 and IEEE ICNP'2006, and the recipient of the IEEE TCGN Best Paper Award in the IEEE High-Speed Networks Symposium, IEEE Globecom in 2002. He also received a 2010-2011 UF Doctoral Dissertation Advisor/Mentoring Award, 2011 Florida Blue Key/UF Homecoming Distinguished Faculty Award and the 2009 UF College of Engineering Faculty Mentoring Award.

Dr. Fang is a Fellow of IEEE. He served as the Editor-in-Chief for IEEE Wireless Communications (2009-2012) and serves/served on several editorial boards of technical journals including IEEE Transactions on Mobile Computing (2003-2008, 2011-present), IEEE Transactions on Communications (2000-2011), IEEE Transactions on Wireless Communications (2002-2009), IEEE Journal on Selected Areas in Communications (1999-2001), IEEE Wireless Communications Magazine (2003-2009) and ACM Wireless Networks (2001-present). He has been actively participating in professional conference organizations such as serving as the Technical Program Co-Chair for IEEE INOFOCOM'2014, the Technical Program Vice-Chair for IEEE INFOCOM'2005, the Technical Program Area Chair for IEEE INFOCOM (2009-2013), and a member of Technical Program Committee for IEEE INFOCOM (1998, 2000, 2003-2008).



Tan F. Wong received the B.Sc. degree (first class honors) in electronic engineering from the Chinese University of Hong Kong in 1991 and the M.S.E.E. and Ph.D. degrees in electrical engineering from Purdue University in 1992 and 1997, respectively.

He was a Research Engineer at the Department of Electronics, Macquarie University, Sydney, Australia. He also served as a Postdoctoral Research Associate at the School of Electrical and Computer Engineering, Purdue University. Since August 1998, he has been with the University of Florida, where he is currently a Professor of Electrical and Computer Engineering. Dr. Wong was the Editor for Wideband and Multiple Access Wireless Systems for the IEEE TRANSACTIONS ON COMMUNICATIONS and was the Editor-in-Chief for the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY. He served as an Associate Editor for the IEEE SIGNAL PROCESSING LETTERS.