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Robust Channel Assignment for Link-level Resource Provisioning in Multi-Radio Multi-Channel Wireless Networks

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Index Terms

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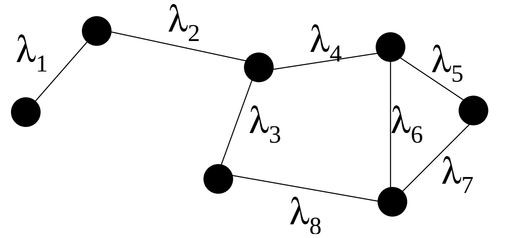
I. Introduction

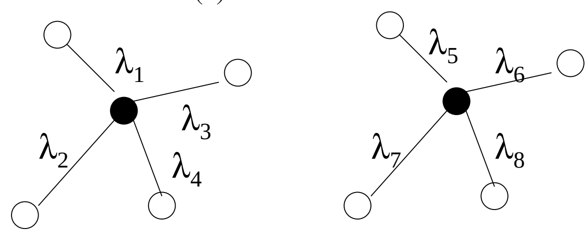
In the past decade, WiFi technologies have been very successful in delivering best-effort broadband access in homes, campus and small businesses. However, current WiFi infrastructure is inadequate in supporting QoS-sensitive applications seamlessly across mobile and fixed access networks (e.g., Ethernet), such as VoIP, video streaming and on-line gaming. Similar requirements also arise from medical and industrial control domains for cable replacement solutions that can achieve reliable and timely delivery of control and application data comparable to existing wired counter-parts. Interestingly, the challenging aspects of afore-mentioned applications do not come from the scale of the networks, as in most cases, the wireless devices only have limited hop distance (one or two) to a backbone wireline network. Rather, the difficulty is the lack of effective means to manage interference caused by co-existing communication end-points and networks, as well as Electro-Magnetic Interference (EMI) sources in the environment.

In this paper, we investigate the problem of link-level resource provisioning in multi-radio multi-channel (MR-MC) wireless networks. In particular, we consider how to make channel assignment decisions to meet given link-level demands. We argue that a robust link-level resource provisioning solution, which can provide a service abstraction similar to that of a wired cable, will greatly simplify the design of upper layer routing and transport protocols. Instead of coping with the complexity caused by wireless channel dynamics using complicated cross-layer approaches, one can instead focus on network and system level issues of intended applications. To make our discussion more concrete, let us consider two application scenarios.

- A visual surveillance network consisting of many spatially distributed *smart cameras* inter-connected by wireless interfaces. Due to the limited field of view and resource constraints of individual nodes, collaborative in-network processing is required in order to continuously track the movement of interested objects. Features of objects need to be handed off between neighboring cameras to carry out vision tasks in a peer-to-peer manner. Based on the characteristics of the capture devices and vision algorithms, one can often determine ahead of time the bandwidth requirements among the cameras.
- A smart environment application (e.g., in assisted living facilities) that tracks vital signs of its habitants. Biosensors such as multi-channel EEG, EKG sensors typically sample at a fixed data rate and report the measurements to medical personnel via wireless access points.



(a) Mesh demand



(b) Star demand

Fig. 1. Traffic demand in visual surveillance networks and body sensor networks

Both applications can be abstracted as a network of nodes inter-connected by a set of links, each associated with a *quasi-static* bandwidth requirement (with the difference that the former forms a mesh topology (Figure 1(a)) whereas the later is best modeled as a star topology (Figure 1(b))). In the paper, we consider a general setting where each wireless node is equipped with multiple radios, which are capable of switching between different channels. As a result, multiple concurrent communication links can be supported between a node pair if the sender and receiver have radios operating in parallel common channels. A channel assignment scheme determines the split of traffic on different radios and the associated channel assigned to each link. Such channel assignment decision is made at *coarse time granularity* on a *per-link* basis rather than on a per-packet basis to mitigate channel switching cost. It should be made robust to the dynamics of wireless channels and interference from external networks and sources as the later is unmanageable in general. When restricted to single radio devices, the solution should still be applicable.

In this paper, we propose a distributed channel assignment algorithm taking into consideration realistic channel conditions, network resource constraints and link-level demand. The major challenge is to incorporate the channel allocation (combinatorial constraints), network resource and traffic demand (continuous constraints) in a single optimization framework, which is known to be NP-hard[13]. Existing solutions using relaxed linear programming[18], the minimum coloring algorithm[19] and heuristic algorithms[7], [2] either can only offer approximate results, or cannot be solved in a distributed manner. We address this problem using the dual decomposition[11] and *Gibbs sampler* techniques[3]. Specifically, the original optimization problem is decoupled to a set of subproblems using dual decomposition that can be solved locally by individual nodes, while Gibbs sampler is used to solve the channel assignment problem which only requires the information of neighboring nodes.

Using traces collected from a wireless mesh testbed, we conduct a set of experiments to evaluate the performance of the proposed channel assignment algorithm and compare it with other existing schemes. The experiments show that our channel assignment algorithm is superior to existing schemes in providing larger noise margin and reducing outage probability. We also demonstrate the convergence behavoir of our algorithm with a simple example.

The rest of this paper is organized as follows. In Section II, we provide a categorization of existing work. The models assumed and the problem statement are formally defined in Section III. A distributed channel allocation algorithm is presented in Section IV. Evaluation using real-world trace data from our mesh testbed is presented in Section V. Finally, we conclude the paper with a set of future research avenue in Section VI.

II. Related Work

In this section, we review channel allocation schemes that are most pertinent to this paper. Work[17], [8] that considers multi-channel MAC protocols given a set of channel assignments is beyond the scope of this paper. Existing channel allocation schemes can be classified based on several criteria detailed next.

- **Traffic-agnostic vs traffic-aware channel assignment** The key objective of channel assignment is to mitigate interference among concurrent transmissions and increase the capacity region of the network. The level of interference is generally dependent on the distribution of link-level load. Traffic-agnostic channel assignment approaches assume uniform distribution of traffic among all links trying to minimize the total interference when all links have packets to transmit. In [6], Bruno *et al.* propose the channel selection and user association algorithms for 802.11 wireless LANs. The objective is to minimize the overall inter-AP interference of the network. The proposed algorithm utilizes *Gibbs sampler* technique, which can be implemented distributively with locally measurable quantities such as interference and transmission delay. However, the proposed algorithms do not consider the observed traffic demand between APs and clients. In [18], Subramanian *et al.* consider the channel assignment problem for minimizing interference in MC-MR mesh networks. They propose a centralized based on heuristic Tabu search approach and a distributed algorithm using greedy approximation for uniform traffic demands. The authors suggest a generalization to heterogeneous link-level demands and overlapping channels using a weighted form of their formulation. However, no explicit guarantee can be provided.
  Along the line of traffic-aware channel assignment, Raniwala *et al.* [13] propose a centralized load-aware channel assignment and multipath routing algorithm, where the joint channel assignment and multipath routing algorithm is conducted in an iterative manner, and high priority in channel assignment is given to heavy-loaded links. However, this algorithm is based on heuristics and its optimality is unclear. In [15], several heuristic traffic-aware metrics are proposed that incorporate traffic demands with the channel separation metrics for enterprise wireless LANs. The channel separation metric of two channels C_i and C_j is defined as $min(|C_i - C_j|, 5)$. For non-uniform traffic demands among different APs, larger weights are assigned to APs with higher loads. The channel allocation algorithms try to maximize the weighted channel separation by allocating channels with larger separation to APs with higher loads.
- **Binary vs physical interference and link capacity model** Most channel assignment algorithms require interference information as inputs. Recent results in [10], [14] show that some well-accepted propagation models are inaccurate for prediction of link-level interference, especially in the indoor environment where the radio signal degrades much faster than that in free space environment. Therefore, there has been some recent work that incorporate the measurement results into the interference modeling and link capacity prediction[12], [5]. Based on the measurements, the work in [15], [13], [18], [7] builds a binary conflict graph, wherein each link is represented by a vertex, and an edge exists between two vertices if the two links interfer with one another. A binary interference model is inaccurate as shown from the measurement results in [10], [14]. The sustainable transmission rate to successfully decode packets can be impacted by stations outside carrier sensing range.
  In [6], a channel algorithm is designed based on the measurement quantities such as interference and transmission delay from the participating nodes. All links operating in the same channel can contribute to interference. However, this work assumes a symmetric channel so that the bi-directional interference can be measured locally, which may not hold in practice. In this paper, we adopt a hybrid model that closely characterizes the behavior of the IEEE 802.11 protocol. Two nodes are in direct conflict and thus cannot transmit concurrently (e.g., due to carrier sensing) if the received power at the other nodes is larger than a certain threshold. On the other hand, distant transmitters operating in the same channel contribute to the signal-noise-and-interference-ratio, which may lead to lower transmission rate. This hybrid model can be easily extended to the case where overlapping channels are used.
- **Centralized and distributed schemes** In [7], Kodialam *et al.* present channel assignment and routing algorithms to characterize the capacity regions of a MR-MC mesh networks. The problem of throughput maximization for a MR-MC network is considered in [2]. Unlike our proposed scheme, the work in [7], [2] focuses on optimizing end-to-end throughput, which requires to jointly optimize channel assignment, routing and scheduling. Therefore, the algorithms can not easily implemented in a distributed manner.

A summary of the related work and their respective categorization can be found in Table I. In this paper, we propose a channel assignment scheme for MR-MC networks with several advantageous features: i) explicitly accounting for link-level demand, ii) distributed, iii) incorporating measurement-driven interference and link capacity model and iv) robustness to external interference and fluctuation of channel gains.

	Centralized	Distributed
Traffic-aware	[13], [7], [2], [15]	
Traffic-agnostic		[18], [6]
Binary conflict graph	[15], [7], [2], [13]	[18]
Physical interference and link capacity		[6]

TABLE I
CLASSIFICATION OF CHANNEL ASSIGNMENT ALGORITHMS

III. MODELS AND PROBLEM STATEMENT

A. Overview

The network considered in this paper a MR-MC wireless network consisting of n wireless stations. It can be modeled as a directed graph $G = (V, E)$, where V is the set of nodes in the network, and E is the set of directed edges representing the logical links. A *logical* link $e = (u, v)$ is in E if and only if : (i) transmissions from node u to node v are decodable in absence of interference from other links; (ii) there is a non-negative link-level demand D_{uv} associated with edge (u, v). For example, in visual surveillance application, the link demand is the maximum data rate for inter-camera communications over that link.

Each wireless router u has a set of $\Omega(u)$ radios. Each radio can switch between a set of Q orthogonal channels. In general, $|\Omega(u)| \leq |Q|$ since it is not useful to operate multiple radios on the same channel simultaneously. For a node where the number of incident links are larger than the number of its radios, a radio can be shared by multiple links, which requires that the radio switch to different channels to serve the corresponding links.

Demands on a *logical* link $e = (u, v)$ can be transmitted over parallel *physical links* if the radios of both sender and receiver share a set of common channels. Each of such *physical link* can be uniquely identified as (u, v, q), where q denotes the channel in use. Let Q_{uv} denote the set of channels used by the physical links over (u, v). Without abusing the notation, we also use Q_{uv} to denote the set of *physical links* for a *logical link* (u, v). Since the number of physical links over (u, v) is limited by the minimal number of radios on node u and v, we have $|Q_{uv}| \leq \min(|\Omega(u)|, |\Omega(v)|)$. The traffic demand D_{uv} of logical link (u, v) will be distributed over multiple physical links. Let x^q_{uv} denote the load carried by physical link (u, v, q), the flow conservation law requires that $\sum_{q \in Q_{uv}} x^q_{uv} = D_{uv}$.

B. Transmission rate

We consider the generalized physical interference model where nodes transmit to their intended receivers and all other simultaneous transmissions are treated as interference. In this model, the successful reception of a packet depends on the signal-to-interference-plus-noise ratio (SINR) at the receiver. Denoting P^q_{uv} as the transmission power used by link (u, v, q), the SINR of this link is

$$SINR^q_{uv} = \frac{P^q_{uv} G^q_{uv}}{N^q_{uv} + \sum_{(m,n,q) \in E_q, (m,n) \neq (u,v)} P^q_{mn} G^q_{mv}} \tag{1}$$

where G^q_{uv} is the path gain from node u to v, N^q_{uv} is the noise(background noise plus external interference) at receiver v on channel q, and E_q is the subset of links on channel q that are transmitting simultaneously.

We model the transmission rate r^q_{uv} of link (u, v, q) as a function of $SINR^q_{uv}$, that is, $r^q_{uv} = f(SINR^q_{uv})$. Note that we are not concerned with the exact form of the function $f(\cdot)$: our problem formulation can be applied to any transmission rate function. For example, based on Shannon's capacity formula for the additive Gaussian noise channel, the transmission rate r^q_{uv} can be expressed as $r^q_{uv} = B_q \log(1 + SINR^q_{uv})$, where B_q represents the bandwidth of channel q, while for practical wireless networks using the IEEE 802.11 a/g radios, the transmission rate of a link is a step function of the SINR as shown in Table II.

The channel gains between two nodes can be measured from the deployed network using the methods proposed in [12], [5].

SINR(dB)	6	7.8	9	10.8	17	18.8	24	24.6
$f(SINR)$(Mbps)	6	9	12	18	24	36	48	54

TABLE II

SINR VS. TRANSMISSION RATE FOR IEEE 802.11 A/G

C. Contention constraints

Any two links within the same spatial contention domain cannot transmit simultaneously if the transmission of one of them lead to excessive interference and thus the reception failure of the other link. Formally, we define two links (u, v, q) and (u', v', q) to be *conflict* if and only if

$$\frac{P^q_{uv} G^q_{uv}}{N_0 + P^q_{u'v'} G^q_{u'v}} < \beta \quad \text{or} \quad \frac{P^q_{u'v'} G^q_{u'v'}}{N_0 + P^q_{uv} G^q_{uv'}} < \beta \tag{2}$$

where β is a constant specific to the chipset in use, N_0 is the average noise in the receiver circuit.

The conflict among multiple links can be characterized with the notion of *clique*. A *clique* is a set of links such that any two links in the set are conflict with each other and cannot transmit simultaneously. If a *clique* is not contained in any other sets, it is a *maximal clique*. Let $C_i(q)$ denote the ith clique where all links in this clique are using channel q. Since the fraction of time that a link (u, v, q) is active x^q_{uv}/r^q_{uv}, and in each clique at most one link can be active at any time, we have

$$\sum_{(u,v,q)\in C_i(q)} \frac{x^q_{uv}}{r^q_{uv}} \leq 1, \forall \text{ cliques } C_i(q) \tag{3}$$

In our implementation, we adopt Bron and Kerbosch's method [4] to find maximal cliques. It requires collection of two-hop neighbor information and can be implemented in a distributed manner.

It should be noted that in the adopted physical layer model, nodes outside the contention domain can still contribute to the SINR. To ensure tractability, we only consider the set of nodes whose channel gains (to the receiver node) are sufficiently large.

D. Node-Radio constraints

Each radio of a node can support multiple physical links incident on the node. Let $R_u(w)$ denote the set of links on radio w of node u. Since these links have to share the same wireless interface and cannot transmit simultaneously, similar to the contention constraint, we have the node-radio constraints for these links as

$$\sum_{(u,v,q)\in R_u(w)} \frac{x^q_{uv}}{r^q_{uv}} \leq 1, \forall \text{ radios } R_u(w) \tag{4}$$

E. The robust channel assignment problem

There are two sources of variability at the physical layer. First, the channel between the transmitter and receiver is subjective to large-scale and small-scale fading due to signal attenuation over distance, shadowing, multipath effects etc. The second are external interferences from transmitters operating in overlapping spectrum. Examples are co-existing WLANs, WPANs and other EMI sources. External interference sources are generally unmanageable and the interference level is difficult to predict. Furthermore, it is impractical to recompute the set of channels whenever the channel or the level of external interference changes. Therefore, it is important to allocate the channels for all links such that the link demands remain satisfied in presence of moderate channel dynamics.

We propose to characterize robustness to channel variability using the notion of *noise margin*. Specifically, we associate a utility function U^q_{uv} with the link, which is a function of maximum noise level $N_{uv}(q)$ allowed at the link. We require that: (i) the utility function U^q_{uv} is increasing, strictly concave and 2nd order differentiable; (ii) U^q_{uv} is additive so that the aggregated utility of all links is $\sum_{(u,v)\in E} \sum_{q\in Q_{uv}} U^q_{uv}$. Intuitively, the larger the noise margin, the more robust the resulting channel assignment to variability in the network. The channel assignment problem

TABLE III

LIST OF NOTATIONS

$\Omega(u)$	the set of radios of node u	Q	the set of orthogonal channels
(u, v, q)	a physical link between node u and v operating over channel q	Q_{uv}	the set of physical links (or channels) between node u, v
x^q_{uv}	load carried by link (u, v, q)	D_{uv}	total link demand between u, v
r^q_{uv}	data rate of link (u, v, q)	N^q_{uv}	noise margin of link (u, v, q)
$C_i(q)$	ith clique	$R_u(w)$	the set of physical links using radio w of node u

is to maximize the aggregated utility of noise margin subject to link-level demands, contention and node-radio constraints. Formally, we have

$$\text{maximize} \quad \sum_{(u,v)\in E} \sum_{q\in Q_{uv}} U_{uv}(N^q_{uv}) \tag{5}$$

$$\text{subject to} \quad \sum_{(u,v,q)\in C_i(q)} \frac{x^q_{uv}}{r^q_{uv}} \leq 1, \forall \text{cliques } C_i(q) \tag{6}$$

$$\sum_{(u,v,q)\in R_u(w)} \frac{x^q_{uv}}{r^q_{uv}} \leq 1, \forall \text{radio } R_u(w) \tag{7}$$

$$\sum_{q\in Q_{uv}} x^q_{uv} = D_{uv}, \forall (u, v) \in E. \tag{8}$$

The notations used throughout the paper are summarized in Table III.

IV. CHANNEL ASSIGNMENT ALGORITHM

One of the standard algorithms to solve the optimization problem given by (5) is based on dual decomposition[11]. We first form the Lagrangian of (5) by relaxing the constraints (6) and (7) as

$$\begin{aligned} L(N, \mathbf{x}, \lambda, \gamma) = & \sum_{(u,v)\in E} \sum_{q\in Q_{uv}} U_{uv}(N^q_{uv}) \\ & + \sum_{i,q} \lambda_{iq} \Bigg(1 - \sum_{(u,v,q)\in C_i(q)} \frac{x^q_{uv}}{r^q_{uv}}\Bigg) \\ & + \sum_{u,w} \gamma_{uw} \Bigg(1 - \sum_{(u,v,q)\in R_u(w)} \frac{x^q_{uv}}{r^q_{uv}}\Bigg) \end{aligned} \tag{9}$$

where λ_{iq} is the *Lagrange multiplier* associated with the scheduling constraint on clique $C_i(q)$, and γ_{uw} is the *Lagrange multiplier* associated with the node-radio constraint on radio w of node u, which can be interpreted as the *prices* for violating the constraints (6) and (7) respectively.

The Lagrangian function (9) can be simplified as

$$\begin{aligned} L(N, \mathbf{x}, \lambda, \gamma) = & \sum_{(u,v)\in E} \sum_{q\in Q_{uv}} L^q_{uv}(N^q_{uv}, x^q_{uv}, \lambda^q_{uv}, \gamma^q_{uv}) \\ & + \sum_{i,q} \lambda_{iq} + \sum_{u,w} \gamma_{uw} \end{aligned} \tag{10}$$

where $\lambda^q_{uv} = \sum_{(u,v,q)\in C_i(q)} \lambda_{iq}$ is the aggregated clique price for link (u, v, q), $\gamma^q_{uv} = \gamma_u(w^q) + \gamma_v(w^q)$ is the sum of radio price for link (u, v, q), and $L^q_{uv}(N^q_{uv}, x^q_{uv}, \lambda^q_{uv}, \gamma^q_{uv}) = U_{uv}(N^q_{uv}) - (\lambda^q_{uv} + \gamma^q_{uv})x^q_{uv}/r^q_{uv}$ is the Lagrangian to be maximized by link (u, v, q).

The original optimization problem in (5) is equivalent to solving the following problem

$$\begin{aligned} \text{maximize} \quad & L(N, \mathbf{x}, \lambda, \gamma) \\ \text{subject to} \quad & \sum_{q\in Q_{uv}} x^q_{uv} = D_{uv}, \forall (u, v) \in E. \end{aligned} \tag{11}$$

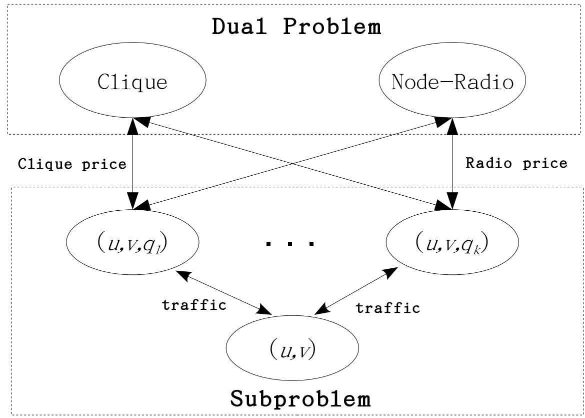


Fig. 2. Two-level decomposition of channel assignment problem

This problem can be decomposed into a set of Lagrangian subproblems and solved by two-level of optimizations. At the bottom level, each link (u, v, q) solves the subproblem

$$\begin{aligned} \text{maximize} \quad & L^q_{uv}(N^q_{uv}, x^q_{uv}, \lambda^q_{uv}, \gamma^q_{uv}) \\ \text{subject to} \quad & \sum_{q \in Q_{uv}} x^q_{uv} = D_{uv}. \end{aligned} \tag{12}$$

At the top level, we have the master dual problem for updating the price variables by solving the dual problem:

$$\begin{aligned} \text{minimize} \quad & G(\lambda, \gamma) = \sum_{(u,v,q)} L^q_{uv}(N^q_{uv}(\lambda, \gamma)) + \sum_{i,q} \lambda_{iq} + \sum_{u,w} \gamma_{uw} \\ \text{subject to} \quad & \lambda \geq \mathbf{0}, \gamma \geq \mathbf{0} \end{aligned} \tag{13}$$

To solve the subproblem given by (12), we need to compute the channel assignment, link traffic rate and noise, which is mixed-integer programming problem and known to be NP-hard. In the following subsections, we first design the channel assignment algorithm based on the *Gibbs Sampler* technique, then present the gradient algorithm for computing the traffic rate and noise. Finally we describe the computation of price variables for the master dual problem given by (13).

A. Gibbs sampler for channel assignment

The *Gibbs Sampler* is originally designed for simulation of random fields with finite state space[3]. It is recently applied in solving power control, channel assignment and user association optimization problems in wireless LANs[9], [6]. The basic idea is to cast the objective function of the corresponding optimization problem in the Gibbsian framework, which is proven to converge to a global optimum through local optimization decisions.

We use the Gibbs sampler to solve the channel assignment in the subproblem (12). To this end, we define the local energy function $\mathcal{F}^q_{uv}$ for a link (u, v, q) as

$$\begin{aligned} \mathcal{F}^q_{uv} &= -L^q_{uv}(N^q_{uv}, x^q_{uv}, \lambda^q_{uv}, \gamma^q_{uv}) \\ &= -U_{uv}(N^q_{uv}) + (\lambda^q_{uv} + \gamma^q_{uv}) \frac{x^q_{uv}}{r^q_{uv}} \end{aligned} \tag{14}$$

where the "–" sign is to convert the maximization problem to a minimization problem conforming to the Gibbsian framework.

A *Gibbs measure* is a probability distribution defined on the energy function with a temperature $T > 0$ as

$$\pi^q_{uv} = \frac{e^{-\mathcal{F}^q_{uv}/T}}{\sum_{q' \in Q} e^{-\mathcal{F}^{q'}_{uv}/T}} \tag{15}$$

The *Gibbs sampler* is a procedure that each link (u, v, q) updates its own channel according to the following algorithm given the information of its neighboring links:

(1) For all channels $q \in Q$, compute the local energy of link (u, v) on this channel.

$$\mathcal{F}_{uv}^q = -U_{uv}(N_{uv}^q) + (\lambda_{uv}^q + \gamma_{uv}^q)\frac{x_{uv}^q}{r_{uv}^q}$$

(2) For all channels $q \in Q$, compute the Gibbs measure as

$$\pi_{uv}^q = \frac{e^{-\mathcal{F}_{uv}^q/T}}{\sum_{q' \in Q} e^{-\mathcal{F}_{uv}^{q'}/T}}$$

(3) Sample a random variable following the distribution of π_{uv}^q, and choose a channel accordingly to this random variable.

This procedure can be conducted by all links in an asynchronous way. When the temperature T is fixed, the Gibbs sampler will approach the stationary state according to the Gibbs distribution, whereas if T is a decreasing parameter approaching zero, the Gibbs sampler is guaranteed to converge to the state with the minimal global energy[3].

B. Noise and traffic computation

After the channel is selected using the *Gibbs sampler* procedure, each link (u, v, q) can proceed to solve the noise variable as

$$N_{uv}^q(\lambda_{uv}^q, \gamma_{uv}^q) = \arg\max_{N_{uv}^q \geq 0} [U_{uv}(N_{uv}^q) - (\lambda_{uv}^q + \gamma_{uv}^q)x_{uv}^q/r_{uv}^q] \tag{16}$$

which is unique due to the strict concavity of U_{uv}^q.

The remaining issue for the master primal problem is to split the traffic demand of a logical link over all of its physical links. Since the objective function L_{uv}^q of the primal subproblem is differentiable with respect to x_{uv}^q, we can obtain the gradient of L_{uv}^q for x_{uv}^q as

$$\frac{\partial L_{uv}^q}{\partial x_{uv}^q} = -\frac{\lambda_{uv}^q + \gamma_{uv}^q}{r_{uv}^q} \tag{17}$$

For each logical link (u, v), the traffic load over its physical links can be computed using the gradient algorithm as follows:

(1) For all links $(u, v, q), q \in Q_{uv}$, compute the gradient $\partial L_{uv}^q/\partial x_{uv}^q$ according to (17).

(2) Find the link with the maximal gradient

$$q^* = \arg\max_{q \in Q_{uv}} -(\lambda_{uv}^q + \gamma_{uv}^q)/r_{uv}^q$$

(3) For all link $(u, v, q), q \neq q^*$, compute the gradient difference

$$\Delta_{uv}^q = \frac{\partial L_{uv}^{q^*}}{\partial x_{uv}^{q^*}} - \frac{\partial L_{uv}^q}{\partial x_{uv}^q} = -\frac{(\lambda_{uv}^{q^*} + \gamma_{uv}^{q^*})}{r_{uv}^{q^*}} + \frac{(\lambda_{uv}^q + \gamma_{uv}^q)}{r_{uv}^q}$$

(4) Update traffic rate over all virtual links as

$$x_{uv}^q(t+1) = \begin{cases} [x_{uv}^q(t) - \alpha\Delta_{uv}^q]^+, & q \neq q^* \\ D_{uv} - \sum_{q \neq q^*} [x_{uv}^q(t) - \alpha\Delta_{uv}^q]^+, & q = q^* \end{cases}$$

where t is the iteration index, $\alpha > 0$ is a sufficiently small positive step-size, and $[\cdot]^+$ denotes the projection onto the non-negative orthant.

C. Price computation

The dual function $G(\lambda, \gamma)$ in (13) is differentiable, so the gradient method can be used to compute the price variables as follows

$$\begin{aligned} \lambda_{iq}(t+1) &= \left[\lambda_{iq}(t) - \zeta\left(1 - \sum_{(u,v,q) \in C_i(q)} \frac{x_{uv}^q}{r_{uv}^q}\right)\right]^+ \\ \gamma_{uw}(t+1) &= \left[\gamma_{uw}(t) - \eta\left(1 - \sum_{(u,v,q) \in R_u(w)} \frac{x_{uv}^q}{r_{uv}^q}\right)\right]^+ \end{aligned} \tag{18}$$

where ζ and η are positive step-sizes for λ_{iq} and γ_{uw} respectively.

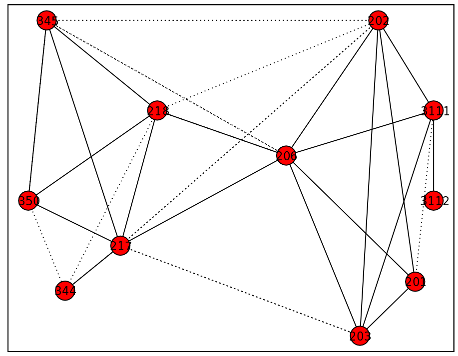


Fig. 3. Testbed topology

D. Schedulability

So far, we use the clique scheduling constraints in the constrained optimization formulation. Generally speaking, solutions that satisfy the clique constraints are not necessary schedulable though the converse is true. Therefore, using clique scheduling constraints, one can derive an upper bound of the objective function. A lower bound can be computed using independent set constraints on the conflict graph. However, determination of all independent sets incurs exponential complexity as the network size grows and cannot be readily implemented in a distributed manner. In practice, we found for the topology investigated in the evaluation section, viable channel assignment solutions and associated load partition across physical links are in fact schedulable. Similar observations have been made in [16]. This can be attributed to two reasons, i) availability of multiple channels helps break up odd cycles in the conflict graph; and ii) the clique constraints pessimistically assume that non-conflict but interfering links are always active contributing to the interference term in SINR computation.

V. Performance Evaluation

In this section, we evaluate the performance of our proposed channel allocation scheme using real-world traces. For comparison purpose, we have implemented two traffic-agnostic algorithms as baselines.

- The *minINT* algorithm is a modified version of the algorithm proposed in [9], which is designed for AP channel selection in WLANs. In [9], only single radio is considered. To extend to the multi-radio case, we equally split the link-level traffic demand to different physical channels.
- The *random* algorithm selects the channels for individual links randomly.

In all the experiments, we assume there are 3 channels available according to 802.11g specification. All the nodes have the same number of radios varying between 1 and 3.

A. Trace collection

A 11-node wireless mesh testbed has been setup to run wireless experiments. Figure 3 shows a snap shot of the real time connectivity map of the testbed. Each node is an embedded Wireless Router Application Platform (WRAP) board with 233 MHz AMD Geode SC1100 CPU, 64Mb DRAM, with Mini PCI Atheros 802.11a/b/g wireless cards and one Ethernet port.

To collect the pair-wise received signal strength (RSS) profiles for the testbed, we conduct measurements in multiple rounds. In each round, one node is scheduled to broadcast 100 UDP packets of 12 bytes payload at the lowest data rate (1Mbps). We use the PRISM-II header in MADWIFI driver[1] to obtain the RSS of each received packet. The experiments was repeated and lasted for 24 hours.

Fig. 4 gives a snap shot of the instantaneous RSS of three links between nodes 201-203, 206-218 and 217-350. These three links are selected as they have very different characteristics. For example, link 206-218 is the weakest link, and its RSS changes from nearly 1dB to about 35dB at two consecutively received packets. Link 217-315 is the strongest link with RSS moderately fluctuating around 30dB. On the other hand, link 201-213 has a descent

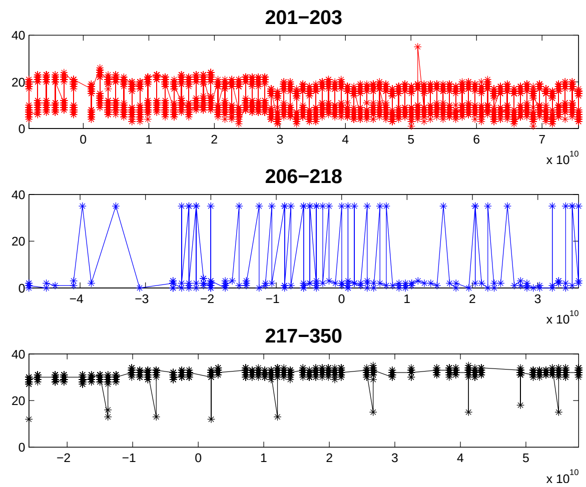


Fig. 4. Real time traces of received signal strength on three representative links over time

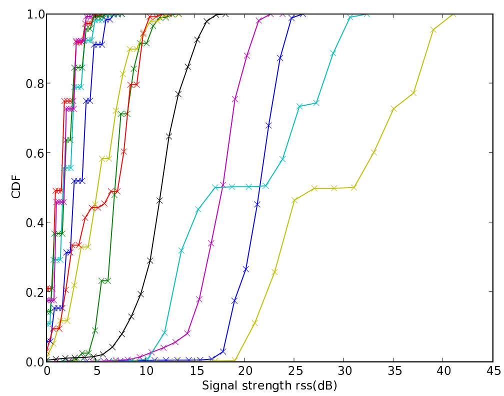


Fig. 5. CDF of received signal strength on a subset of links

quality, but its RSS value varies about 15dB. Using the collected data, we create the CDF of the RSS for each link in the testbed (Fig. 5). The average RSS values are used as inputs to the channel assignment algorithm, whereas the RSS profiles is used to generate test cases to evaluate the robustness of the resulting channel assignments.

From the RSS measurements, we have two observations. First, stochastically, most links have relatively stable RSS values as we can see the sharp transition of the CDF curve(in roughly 5dB intervals). Second, RSS values have significant variation on a short time scale even in the case of the strongest link. These observations confirm our motivation to design robust channel algorithm to maximize link noise margins so that large variations in the signal strength can be tolerated without violating link-level traffic demands.

B. Experiment results

1) Noise margin: In this section, we evaluate the noise margin obtained from the three algorithms. To compute noise margins from the *minINT* and *random* algorithms, we input the channel assignment results returned by these two algorithms into our algorithm. We modify our implementation to skip the channel assignment step and solve the optimization problem in Eq. (5) directly to derive the noise margin.

A large number of link-level demand vectors are arbitrarily selected as inputs. For clarity of presentation, we only include six of such vectors. For the *random* channel assignment algorithm each set of experiments are repeated ten times with different channel assignment results and their average is plotted. RSS on each link is fixed to be the average value from the measurement. Fig. 6 shows the noise margin obtained by the three algorithms in the one radio case. We observe that *robust* outperforms the other two schemes in providing larger noise margin as expected for all demand vectors. Among the three, the performance of *random* is the worst. The reason is, *random*

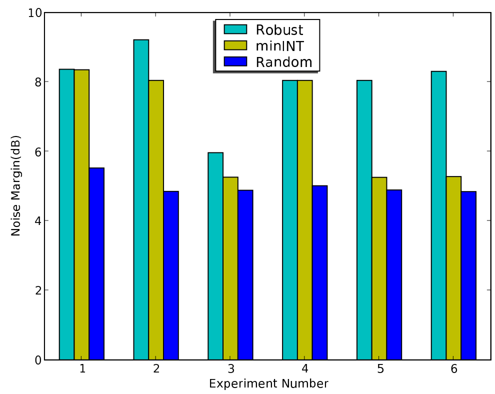


Fig. 6. Noise margin for different experiments(one radio case)

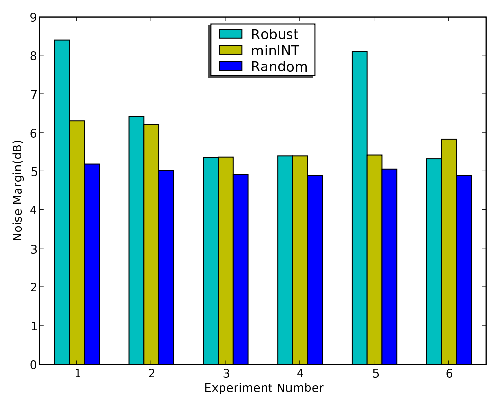


Fig. 7. Noise margin for different experiments(two radios case)

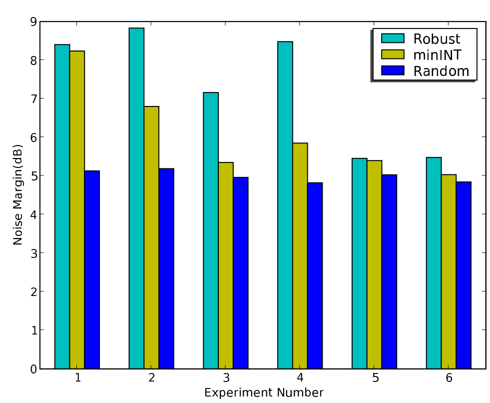


Fig. 8. Noise margin for different experiments(three radios case)

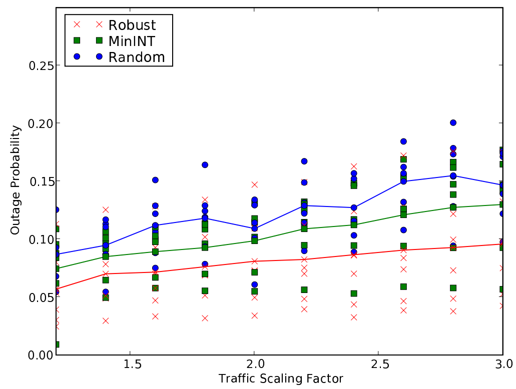


Fig. 9. Outage probability vs. traffic load(1 radio). The marks indicate the results for individual experiments, while the lines represent the average results.

is agnostic to both link-level demand as well as interference levels. Interestingly, the noise margins for different demand vectors are similar for *random* and *minINT*. This can be attributed to the fact that both schemes are traffic agnostic.

Similar observations can be drawn for the two radios and three radios cases, and the results are shown in Fig. 7 and Fig 8 respectively. However, for all three algorithms, we observe that multiple radios do not provide much improvement in noise margin. This is because although multiple radios can support multiple concurrent physical links over different channels between a node pair, it may contribute more interference to other links, which in turn will degrade the noise margin of the interfered links.

2) Robustness to channel variability: Next, we evaluate the impact of channel variation on the performance of channel assignment algorithms. As stated earlier, the channel assignment decision is made based on the average RSS values on all links. However, from the measurement study in the previous section, we observed significant variability over short term. One interesting question is thus, fixing the link-level demand, does the channel assignment (based on average RSS) remain valid over time. To this end, we introduce the *outage probability* metric. A large number of RSS samples are generated for each link using its RSS CDF profile. For each set of RSS values, we compute the SINR for each individual links and obtain their transmission rate, with which we can check the clique constraints according to (3) and node radio constraints according to (4). An *outage* occurs if any of these constraints is violated, and the overall *outage probability* is the percentage of violated constraints. We repeat this procedure 1000 times and obtain the outage probability under the three channel assignment algorithms.

We also evaluate the effect of link-level loads on outage probability with given RSS profiles. The six link demand vectors in the previous experiment are used as the base link demand vectors. A traffic scaling factor is applied to generate a set of new link demand vectors. For each demand vector, we compute the corresponding outage probability. Fig. 9 gives the outage probability of three channel assignment algorithm under different link-level demands. It can be seen that *random* algorithm performs the worst as expected, while the *robust* algorithm outperforms other two algorithms under all traffic conditions. This is due to the large noise margin obtained by the *robust* algorithm as shown in previous experiments. With *robust* channel assignment, individual links can adapt to the channel and traffic variation by changing its transmission rate without violating the constraints.

Similar observations can be made for two-radio and three-radio cases in Fig. 10 and Fig. 11 respectively. We see that the outage probability under multiple radios case is slightly worse than the single radio case, this can be explained by the previous set of experiments. That is, while more links can be supported with multiple radios, more links may introduce more interference and in turn reduce the robustness to channel variation.

3) Convergence time: Fig. 12 gives the convergence behavior of our proposed algorithm. The bottom figure shows the channels selected by individual links in each iteration, and the upper figure plots the link noise margin. We can see that in this case, channel selection will stop at around 300 iterations. However, it still takes longer time to update the price and noise margin variables until the system converges to the equilibrium states. However, this result is comparable to other utility-based solutions. We plan to further investigate algorithms that have faster

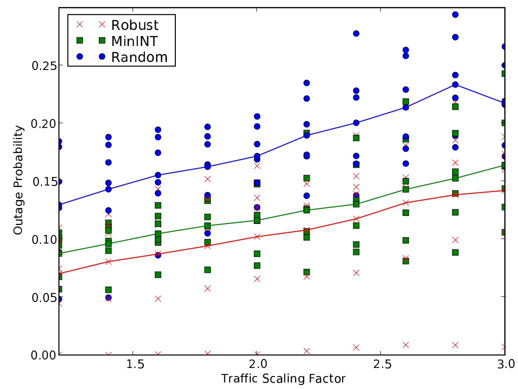


Fig. 10. Outage probability vs. traffic load (2 radios). The marks indicate the results for individual experiments, while the lines represent the average results.

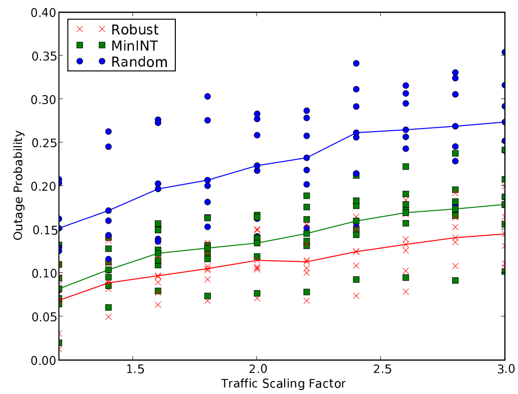


Fig. 11. Outage probability vs. traffic load(3 radios) The marks indicate the results for individual experiments, while the lines represent the average results.

convergence time.

VI. Conclusions

In this paper, we presented a distributed channel assignment algorithm that considers the realistic channel conditions, network resource constraints and link-level demand. A key advantage of the proposed scheme is the robustness to channel variability and external interference sources. Using the dual decomposition and *Gibbs sampler* techniques, we design the channel allocation algorithm can be implemented in a distributed manner with limited local information exchange among neighboring nodes. We have evaluated our scheme using traces collected from a wireless mesh testbed. Experiments show that the proposed channel assignment algorithm is superior to existing schemes in providing larger noise margin and reducing outage probability.

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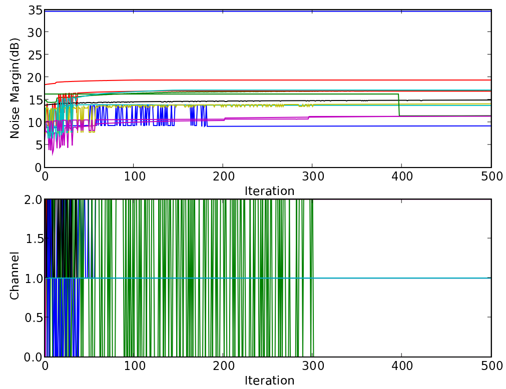

Fig. 12. Link channel and noise margin vs. Iteration

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