A Cross-Layer Design for Resource Allocation and Congestion Control in Multichannel Multi-hop Cognitive Radio Networks

Nguyen Van Mui
Depart. of Computer Engr.
Kyung Hee University,
449-701, Republic of Korea.
nvmui@khu.ac.kr

Choong Seon Hong
Depart. of Computer Engr.
Kyung Hee University,
449-701, Republic of Korea.
cshong@khu.ac.kr

ABSTRACT

Efficient and fair resource allocation associated with congestion control in multi-hop cognitive radio networks (CRN) is a challenging problem. In this paper, we consider their mutual relationship through formulating a cross-layer optimization problem which addresses both the aggregate utility maximization and energy efficiency. By primal-dual method, the optimal solution is obtained via a distributed algorithm while keeping the outage probability on primary links below the allowable thresholds. The attraction of our proposed algorithm is that we utilize the broadcast property of wireless medium for message passing in power control and preserve the existing TCP stack for congestion control mechanism.

Keywords

Resource Allocation, Congestion Control, Multihop CRN, Dual Theory, Optimization

1. INTRODUCTION

Cognitive Radio [8] realized to be more powerful and flexible than existing multi-channel multi-radio (MC-MR), a hardware-based radio technology, has been attracting a lot of attention from the wireless communication community. In fact, each node in CRN, based on software defined radio (SDR), is able to work on a different set of available frequency bands without being limited by the number of radio interfaces. These special difference makes the network control algorithm design become more complex and interesting.

In multi-hop CRNs, the link capacity which is aggregated on different bands needs conveniently optimizing through power control policy. We should allocate the suitable amount of power on each band to the right node. In fact, using the bandwidth-footprint-product (BFP) as an objective metric, Shi at al. [11] and [10] formulated the power optimization problem which aimed to minimize the interference footprint area on each band. Accordingly, the secondary nodes transmitting on the same bandwidth with suitable power levels may not make interference to each other. A band is allowed to use only if the secondary node (SU) senses that band idle and is not in the other node's interference range. Hence, it is essential to keep track of the set of nodes fall in the transmission range and the set of nodes that can produce interference whenever the transmit power is changed at each node. This makes the implementation of the local search algorithm [11] and the distributed optimization algorithm [10] become more complicated and unscalable.

Since transmission from secondary users can make harmful interference to PU's reception. Most existing works [10], [12], and [5] applied Listen-Before-Talk (LBT) technique to detect the presence or absence of primary signals before channel access in order to avoid interfering with primary users (PU). However, the authors does not take the aggregate interference from multiple potential SUs' transmission into account at PU receivers. There will be no transmission from SUs while a PU system operating under full load can tolerate more interference.

To overcome these shortcomings, we propose a cross-layer design for resource allocation and congestion control under the interference-limited model. All secondary users are allowed to access the licensed channels if the aggregate interference caused by them to primary links is acceptable. Our objective is to allocate larger power to congested links and guide source traffic to a feasible rate region in a fair manner. By taking the primary link outage probability as a constraint for PU protection into framework of network utility maximization (NUM), we formulate a new optimization framework for SUs in multichannel multi-hop CRNs. In addition, utility-based fairness and energy-efficiency is also taken into account in this paper.

2. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a multichannel multi-hop CRN consisting of a set of N secondary nodes[1] allowed to access a set of $\mathcal{M} = \{1, 2, ..., M\}$ randomly time-varying primary channels under the interference-limited communication model. A set of logical links $\mathcal{L} = \{1, 2, 3, ..., L\}$ shared by a set of flow sources $\mathcal{S} = \{1, 2, 3, ..., S\}$ simultaneously access the licensed

[1] In this paper, the term "user" and "node" are interchangeably used.

ICUIMC '11, February 21-23, 2011, Seoul, Korea

frequency band. And $\mathcal{L}^{'} = \{0, 1, 2, 3, ..., L\}$ is the set of all links in system including both secondary links and primary link. Note that we use the special index of $i = 0$ to denote those relevant to primary link. Suppose that flow $s \in \mathcal{S}$ traverses multiple hops to get its destination through the ordered set of links $L(s) \subseteq \mathcal{L}$ called routes. Without loss of generality, the routes of all flows will be predefined.

We also adapt the code division multiple access (CDMA) technique to physical layer model where primary user and secondary users can simultaneously transmit in a common frequency band. We assume that each source has infinite amount of data to send. With an allocated data rate $x_s^{min} \leqslant x_s \leqslant x_s^{max}$, source s obtains a benefit $U(x_s) : \mathbb{R}_+ \rightarrow \mathbb{R}$ which is continuously differentiable, nondecreasing and strictly concave.

2.1 Shannon Capacity and Flow Conservation

Let η_0 denote the thermal noise power under the baseband bandwidth W at receiver of link l. The average signal-to-interference ratio $\overline{\gamma}_l^m(\mathbf{P}^m)$ at link l on band m:

$$\overline{\gamma}_l^m(\mathbf{P}^m) = \frac{G_{ll}^m P_l^m}{\eta_0 + \sum\limits_{k \in \mathcal{L}^{'} \setminus \{l\}} G_{lk}^m P_k^m} \tag{1}$$

where $\mathbf{P}^m = [P_1^m, P_2^m, ..., P_L^m]$ is a vector of secondary link powers and P_0^m is the transmit power of PU-Tx on the band m. The average capacity of link l modeled on the Shannon capacity is a global and nonlinear function of transmit power vector $\mathbf{P} = (\mathbf{P}^m, m \in \mathcal{M})$.

$$C_l(\mathbf{P}) = W \sum_{m}^{M} \log\left(1 + K\overline{\gamma}_l^m(\mathbf{P}^m)\right) \tag{2}$$

Here constant $K = -\phi_1/\log(\phi_2 BER)$, where ϕ_1 and ϕ_2 are constants depending on the modulation method, coding scheme and bit-error rate (BER) [1]. We assume that there is no fading-margin at each secondary link and $K\overline{\gamma}_l^m(\mathbf{P}^m)$ is greater than $10dB$. This seems reasonable in the implementation of some wireless networks where the least link rate requirement should be ensured. Then link capacity can be approximated as following.

$$C_l(\mathbf{P}) \simeq W \sum_{m}^{M} \log\left(K\overline{\gamma}_l^m(\mathbf{P}^m)\right) \tag{3}$$

For flow conservation, the aggregated source rate allocated to the flows which traverse link l should not exceed its link capacity.

$$\sum_{s \in S(l)} x_s \leq C_l(\mathbf{P}) \simeq W \sum_{m}^{M} \log\left(K\overline{\gamma}_l^m(\mathbf{P}^m)\right), \forall l \tag{4}$$

where $S(l) = \{s : l \in L(s)\}$ is the set of flow source uses link l. Without loss of generality, we assume that K and W is unit, henceforth.

2.2 Primary Protection

Since the aggregate interference caused by all SUs transmitting on band m can make the m^{th} PU-Rx's reception unsuccessful. To maintain its quality of service (QoS), each PU-Rx would require its outage probability to stay below a certain threshold, denoted by ζ_{th}^m. This constraints can be written as

$$\Pr[\gamma_0^m(\mathbf{P}^m) \leq \gamma_{th}^m] \leq \zeta_{th}^m \tag{5}$$

where γ_{th}^m is the SIR threshold at the m^{th} PU-Rx. On the other words, the outage probability at PU-Rx for a given secondary transmit power vector $\mathbf{P}^m$ is [7], [6]:

$$\Pr[\gamma_0^m(\mathbf{P}^m) \leq \gamma_{th}^m] = 1 - (1 - \zeta_0^m) \prod_{l=1}^{L} \left(1 + \frac{G_{0l}^m P_l^m \gamma_{th}^m}{P_0^m G_{00}^m}\right)^{-1} \tag{6}$$

where $\zeta_0^m = 1 - \exp(\frac{-\eta_0 \gamma_{th}^m}{P_0^m G_{00}^m})$ is the outage probability of PR-Rx in the absence of SUs. Substitute (6) into (5), rewrite the resulting inequality as an lower bound on a posynomial function in $\mathbf{P}^m$, then take logarithm on both sides, we have

$$\sum_{l=1}^{L} \log(1 + \rho_l^m P_l^m) \leq \log \mu^m. \tag{7}$$

where $\mu^m = (1 - \zeta_0^m)/(1 - \zeta_{th}^m)$ and $\rho_l^m = \frac{G_{0l}^m \gamma_{th}^m}{G_{00}^m P_0^m}$ [6]. We assume that the primary requirements including the transmit power P_0^m, ζ_0^m, and ζ_{th}^m must be declared a priori to all secondary nodes.

2.3 Problem Formulation

Our joint resource allocation and power control problem with primary protection and low power consumption is formulated via NUM problem as following

$$(\mathbf{P1}) \qquad \max_{\mathbf{x} \in \mathcal{X}, \mathbf{P} \in \mathcal{P}} \sum_{s \in \mathcal{S}} U_s(x_s) - \sum_{l \in \mathcal{L}} \sum_{m \in \mathcal{M}} P_l^m \tag{8}$$

subject to

$$\sum_{s \in S(l)} x_s \leq \sum_{m \in \mathcal{M}} \log\left(\overline{\gamma}_l^m(\mathbf{P}^m)\right), \quad \forall l \tag{9}$$

$$\sum_{l=1}^{L} \log(1 + \rho_l^m P_l^m) \leq \log \mu^m, \quad \forall m \tag{10}$$

where

$$\mathcal{X} = \{x_s; s \in \mathcal{S} | x_s^{min} \leq x_s \leq x_s^{max}\},$$

$$\mathcal{P} = \{P_l^m; l \in \mathcal{L}, m \in \mathcal{M} | P_l^{min} \leq P_l^m \leq P_l^{max}\}.$$

3. DUAL DECOMPOSITION AND OPTIMAL SOLUTION

The flow conservation constraint (9) on each link is non-convex on $(\mathbf{x}, \mathbf{P})$ space. Without loss of optimality, we can perform a variable transformation, $\hat{\mathbf{P}} = \log \mathbf{P}$. Let $\hat{\mathcal{P}} = \{\hat{P}_l^m; l \in \mathcal{L}, m \in \mathcal{M} | \log P_l^{min} \leq \hat{P}_l^m \leq \log P_l^{max}\}$. The resulting optimization problem can be written as

$$(\mathbf{P2}) \qquad \max_{\mathbf{x} \in \mathcal{X}, \hat{\mathbf{P}} \in \hat{\mathcal{P}}} \sum_{s \in \mathcal{S}} U_s(x_s) - \sum_{l \in \mathcal{L}} \sum_{m \in \mathcal{M}} e^{\hat{P}_l^m} \tag{11}$$

subject to

$$\sum_{s \in S(l)} x_s \leq \sum_{m \in \mathcal{M}} \log\left(\overline{\gamma}_l^m(e^{\hat{\mathbf{P}}^m})\right), \quad \forall l \tag{12}$$

$$\sum_{l=1}^{L} \log(1 + \rho_l^m e^{\hat{P}_l^m}) \leq \log \mu^m, \quad \forall m. \tag{13}$$

THEOREM 1. **P2** *is a convex optimization problem.*

PROOF. Under assumptions on utility function, the objective of **P2** is a concave function. On other words, the log-sum-exponential function is a convex function since its Hessian matrix is a diagonal matrix of positive elements. Hence, the sets of constraints in (12) and (13) are convex on new variable space $(\mathbf{x}, \hat{\mathbf{P}})$. As a result, **P2** is a convex optimization problem [4]. □

By augmenting the objective function with a weighted sum of the constraint functions, we obtain the Lagrangian function of **P2**:

$$L(\mathbf{x}, \hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu}) = \sum_{s \in \mathcal{S}} U_s(x_s) - \sum_{l \in \mathcal{L}} \sum_{m \in \mathcal{M}} e^{\hat{P}_l^m} - \sum_{l \in \mathcal{L}} \lambda_l \left(\sum_{s \in S(l)} x_s - \sum_{m \in \mathcal{M}} \log\left(\overline{\gamma}_l^m (e^{\hat{\mathbf{P}}^m})\right) \right) - \sum_{m \in \mathcal{M}} \nu_m \left(\sum_{l=1}^{L} \log(1 + \rho_l^m e^{\hat{P}_l^m}) - \log \mu^m \right) \quad (14)$$

where $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, ..., \lambda_L]$ and $\boldsymbol{\nu} = [\nu_1, \nu_2, ..., \nu_M]$ are the Lagrangian nonnegative multipliers which are interpreted as link prices, and primary outage prices in the optimal flow and power control context, respectively. The former reflects the degree of congestion on link while the latter is on the outage status of each licensed band.

The dual problem of **P2** can be described as

$$(\mathbf{D}) \qquad \min_{\boldsymbol{\lambda}, \boldsymbol{\nu}} \quad g(\boldsymbol{\lambda}, \boldsymbol{\nu}) \quad (15)$$

where

$$g(\boldsymbol{\lambda}, \boldsymbol{\nu}) = \max_{\mathbf{x} \in \mathcal{X}, \hat{\mathbf{P}} \in \hat{\mathcal{P}}} L(\mathbf{x}, \hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu}) \quad (16)$$

Thanks to the separable nature with respect to $\mathbf{x}$ and $\hat{\mathbf{P}}$ of (14), the objective function of **D** can be decomposed into the two functional subproblems with respect to separate primal variables $\mathbf{x}$ and $\hat{\mathbf{P}}$ as follows.

$$\max_{\mathbf{x}} \left\{ L_x(\mathbf{x}, \boldsymbol{\lambda}) = \sum_{s \in \mathcal{S}} U_s(x_s) - \sum_{s \in \mathcal{S}} \sum_{l \in L(s)} \lambda_l x_s \right\} \quad (17)$$

$$\max_{\hat{\mathbf{P}}} \left\{ L_{\hat{P}}(\hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu}) = \sum_{l \in \mathcal{L}} \sum_{m \in \mathcal{M}} \lambda_l \log\left(\overline{\gamma}_l^m (e^{\hat{\mathbf{P}}^m})\right) - e^{\hat{P}_l^m} - \sum_{m=1}^{M} \sum_{l=1}^{L} \nu_m \left(\log(1 + \rho_l^m e^{\hat{P}_l^m}) - \log \mu^m \right) \right\} \quad (18)$$

The first subproblem (17) is the traditional congestion control problem solved implicitly in [2] where the link rate of each source s is adjusted via the aggregate price $\lambda_s \doteq \sum_{l \in L(s)} \lambda_l$ from all links in the path of s. The second subproblem (18) is the resource allocation problem which allocates exactly the power per band to each link.

Since **P2** is a convex optimization problem [**Theorem 1**], there exists a feasible point satisfying the Slater constraint qualification in its domain [4]. From the Strong Duality Theorem [3], there is no duality gap. Hence, the optimal solution of primal problem (8) can then be obtained by solving the dual problem (14) via the following iterative algorithm.

Algorithm 1: Distributed Rate and Power Control

The primal and dual variables are updated iteratively until convergence.

Congestion Control: The source rate updates

$$x_s^{(t+1)}(\lambda_s) = \left[U_s^{'-1}\left(\lambda_s^{(t)}\right) \right]^{\mathcal{X}_s} \quad (19)$$

where $U_s^{'-1}(.)$ is the inverse of the first derivative of utility.

Power Control: The link power updates

$$P_l^{m,(t+1)} = \left[P_l^{m,(t)} + \kappa_t \left(\frac{\lambda_l^{(t)}}{P_l^{m,(t)}} - \sum_{k \neq l} m_k^{m,(t)} G_{kl} - \nu_m^{(t)} \frac{\rho_l^m}{1 + \rho_l^m P_l^{m,(t)}} - 1 \right) \right]^{\mathcal{P}_l} \quad (20)$$

where $m_k^{m,(t)} = \frac{\lambda_k^{(t)} \overline{\gamma}_k^{m,(t)}}{G_{kk} P_k^{m,(t)}}$ are messages received from link k on band m.

Link Congestion Price update:

$$\lambda_l^{(t+1)} = \left[\lambda_l^{(t)} + \kappa_t \left(\sum_{s \in S(l)} x_s^{(t)} - C_l(\mathbf{P}^{(t)}) \right) \right]^{\mathbf{R}_+} \quad (21)$$

Primary Outage Price update:

$$\nu_m^{(t+1)} = \left[\nu_m^{(t)} + \kappa_t \left(\sum_{l=1}^{L} \log(1 + \rho_l^m P_l^{m,(t)}) - \log \mu^m \right) \right]^{\mathbf{R}_+} \quad (22)$$

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where $[x]^{\mathcal{A}}$ is the projection of x onto the feasible set $\mathcal{A}$ and κ_t is the positive scalar diminishing step-size.

PROPOSITION 1. *The source rate update* (19) *solves the congestion control subproblem* (17) *for a pair of fixed primal variables* $(\boldsymbol{\lambda}, \boldsymbol{\nu})$.

PROOF. Since $L_x(\mathbf{x}, \boldsymbol{\lambda})$ is strictly concave and separable in $\mathbf{x}$, maximizer

$$x_s(\lambda_s) = arg \max_{x_s \in \mathcal{X}} \sum_{s \in \mathcal{S}} U_s(x_s) - \sum_{s \in \mathcal{S}} \lambda_s x_s$$

can be found by the Karush-Kuhn-Tucker (KKT) theorem. In fact, we take the first-order derivative of $L_x(\mathbf{x}, \boldsymbol{\lambda})$ with respect to x_s. Then we have (19) by letting the resulting quantity equals zero. □

PROPOSITION 2. *The link power update* (20) *solves the resource allocation subproblem* (18) *for a pair of fixed primal variables* $(\boldsymbol{\lambda}, \boldsymbol{\nu})$.

PROOF. Since $L_{\hat{P}}(\hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu})$ is strictly concave in $\hat{\mathbf{P}}$, its first-order derivative with respect to $\hat{P}_l^m$ is

$$\frac{\partial L_{\hat{P}}(\hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu})}{\partial \hat{P}_l^m} = \lambda_l - e^{\hat{P}_l^m} - \sum_{k \neq l} \lambda_k \frac{G_{kl} e^{\hat{P}_l^m}}{\sum_{j \neq k} G_{kj} e^{\hat{P}_j^m} + G_{k0} e^{\hat{P}_0^m} + \eta_0} - \frac{\nu_m \rho_l^m e^{\hat{P}_l^m}}{1 + \rho_l^m e^{\hat{P}_l^m}} \quad (23)$$

Using the facts of $\nabla_l L_P(\mathbf{P},\boldsymbol{\lambda},\boldsymbol{\nu}) = \frac{1}{P_l^m}\nabla_l L_{\hat{P}}(\hat{\mathbf{P}},\boldsymbol{\lambda},\boldsymbol{\nu})$ and $P_l^m = e^{\hat{P}_l^m}$, we transform (23) back to $\mathbf{P}$ space as (24).

$$\frac{\partial L_P(\mathbf{P},\boldsymbol{\lambda},\boldsymbol{\nu})}{\partial P_l^m} = \frac{\lambda_l}{P_l^m} - 1 - \sum_{k\neq l}\lambda_k \frac{G_{kl}}{\sum\limits_{j\neq k} G_{kj}P_j^m + G_{k0}P_0^m + \eta_0} - \frac{\nu_m \rho_l^m}{1+\rho_l^m P_l^m} \quad (24)$$

We can rewrite (24) in the other form as

$$\frac{\partial L_P(\mathbf{P},\boldsymbol{\lambda},\boldsymbol{\nu})}{\partial P_l^m} = \frac{\lambda_l}{P_l^m} - \sum_{k\neq l} m_k^m G_{kl} - \nu_m \frac{\rho_l^m}{1+\rho_l^m P_l^m} - 1 \quad (25)$$

where $m_k^m = \frac{\lambda_k \bar{\gamma}_k^m}{G_{kk}P_k^m}$

Also, we adopt the projected gradient-descent method [3] with a step size $\kappa_t \geq 0$ to maximize $L_P(\mathbf{P},\boldsymbol{\lambda},\boldsymbol{\nu})$. The link powers updates

$$P_l^{m,(t+1)} = \left[P_l^{m,(t)} + \kappa_t \nabla_l L_P(\mathbf{P}^{(t)},\boldsymbol{\lambda}^{(t)},\boldsymbol{\nu}^{(t)})\right]^{\mathcal{P}_l} \quad (26)$$

Substituting (25) into (26), we have (20). □

Come back to the dual problem **D**, the objective (16) is differential for all $\boldsymbol{\lambda}$ and $\boldsymbol{\nu}$. Therefore, we can also apply the projected gradient-descent method [3] to solve the dual problem (15) via link congestion price updates (21) and primary outage price updates (22).

THEOREM 2. *For any initial source rate $\mathbf{x}^{(0)} \in \mathcal{X}$, link power $\mathbf{P}^{(0)} \in \mathcal{P}$ and shadow prices $(\boldsymbol{\lambda}^{(0)},\boldsymbol{\nu}^{(0)}) \geq 0$, the sequence of primal-dual variables generated by **Algorithm 1** converges to the global optimum of the original problem* **P1** *provided that the stepsize satisfies*

$$\kappa_t \geq 0, \quad \lim_{t\to\infty}\kappa_t = 0, \quad \sum_{t=0}^{\infty}(\kappa_t) = \infty, \quad \sum_{t=0}^{\infty}(\kappa_t)^2 < \infty \quad (27)$$

PROOF. From **Proposition 1** and **2**, we conclude that **Algorithm 1** solves the problem **P2**. For any initial values of the primal and dual variables and the step-size satisfying (27), **Algorithm 1** always converges to a unique point[3]. Since **P2** is convex optimization problem [**Theorem 1**], any locally optimal point achieved from **Algorithm 1** is also the global optimum [4]. □

Remarks

1. The rate control and resource allocation are implemented in a fully distributed and joint manner.

2. Source algorithm can preserve the existing TCP congestion mechanism. The source s gets the total congestion price $\lambda_s = \sum_{l\in L(s)}\lambda_l$ accumulated through a feedback message from its destination in the path of s. Then source s decides its rate by (19).

3. With link algorithm, the SU-Rx of link k locally measures $\bar{\gamma}_k^m(\mathbf{P}^m)$ on each band and broadcasts its message $RxCtrlMsg$ with $m_k^{m,(t)}$. SU-Tx of link k receives $RxCtrlMsg$ with $m_j^{m,(t)}$ and $TxCtrlMsg$ with $P_j^{m,(t)}$ from the other SU-Tx, estimates G_{jk} through training sequence, and updates power per band as (20) through congestion price (21) and primary outage price (22). Then SU-Tx broadcasts $TxCtrlMsg$ with $P_k^{m,(t)}$.

4. At SU-Tx, congestion price update (21) requires only the link's queue backlog and primary outage price update (22) requires only $P_j^{m,(t)}$ through $TxCtrlMsg$ from the other SU-Tx.

4. PERFORMANCE EVALUATION

4.1 Simulation Settings

In this section, we present the illustrative numerical results for the proposed algorithm. We consider a multichannel multihop CRN system with 5 secondary nodes, 2 pairs of PUs and 4 flows with topology illustrated in Fig.1. Each secondary link with a maximum transmit power of 26dBm can access both the licensed bands, baseband bandwidth of each is $125KHz$. The minimum data rate for each elastic flow is $100bps$ and the target BER is 10^{-3}. The power allocation P_l^m for each link on each band products capacity formulated as (2) with $K = -1.5/\log(5BER)$ [1]. For PUs, we require the outage probability thresholds for the licensed band 1 and 2 is 9% and 20%, respectively. The SIR thresholds for PU-Rx 1 and 2 are 0.97dB and 1.31dB at transmit power 20dBm and 23dBm, respectively. The power spectrum density of white noise is assumed to be -80dBm/Hz at PU and SU receivers. We choose $U_s(x_s) = log(x_s)$ as source's utility function for all secondary nodes. The criterion used to evaluate the convergence speed is $\max\|\mathbf{P}^{*(t)} - \mathbf{P}^{*(t-1)}\| \leq \varepsilon$, where $\varepsilon = 10^{-5}$ is the error tolerance.

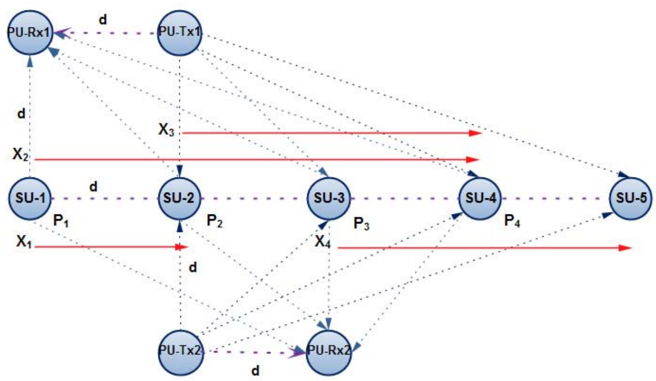


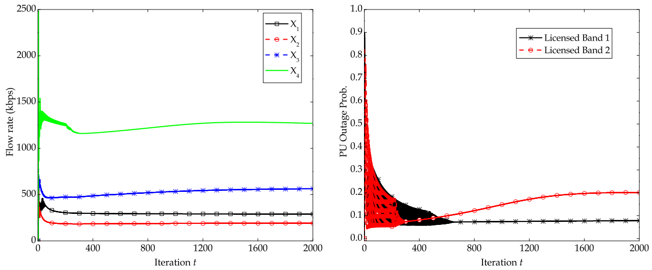
Figure 1: Physical and logical topologies for simulation

4.2 Numerical Results

Fig.4 shows the aggregate utility of our proposed algorithm converges to the optimum within reasonable times. This optimal value compared to those in [9] and [2] on single licensed band is indistinguishable. The aggregate utility will be much higher as the number of licensed band allowed to access increases. In Fig.3 and Table 1, we compare the optimal powers allocated to each link on both bands. It is clear that the transmit power of secondary nodes depends on not only the mutual interference levels among them but also their physical distance to PU-Rx. Also, the optimal rate in Fig.2a shows that the greedy sources try to get a larger rate to obtain a higher utility. However, sources must follow the diminishing marginal return due to the concave property of utility function. They must adjust their rate via

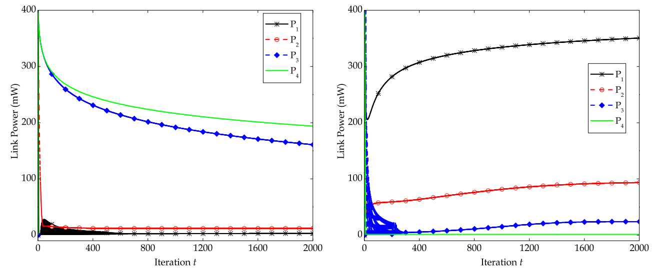
TABLE I
THE OPTIMAL LINK POWER COMPARISON

$LinkPowers(mW)$	P_1	P_2	P_3	P_4
Band 1.	3.8	14.3	153.2	191.4
Band 2.	352	98.7	25	1.5



(a) (b)

Figure 2: Convergence of Link Rates (a) and PU's outage probability (b).



(a) (b)

Figure 3: Convergence of Link Powers on Band 1 (a) and Link Powers on Band 2 (b).

both congestion price and primary outage price which reflect the cost to pay. Fig.2b shows that the outage probabilities caused by secondary nodes at band 1 and 2 converges to the outage thresholds allowed by PUs.

5. CONCLUSIONS

In this paper, we proposed a cross-layer design for resource allocation and congestion control considering the coexistence of the licensed and unlicensed users in multichannel multihop wireless networks. The resulting optimization problem is convex with nonlinear constraints. By applying the dual theory and the layering technique, we can decompose the original problem into the two function subproblems. The optimal solution is obtained through a distributed algorithm. Fair resource allocation also is achieved by using a utility-based scheme of logarithm function.

6. ACKNOWLEDGMENTS

This research was supported by Mid-career Researcher Program through NRF funded by MEST (No. 2008-0061591). Dr. CS Hong is the corresponding author.

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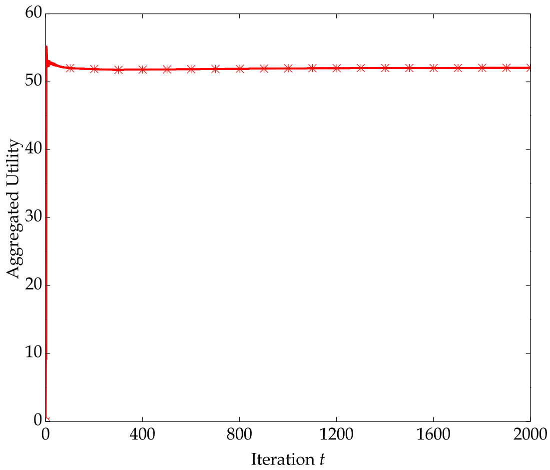

Figure 4: Aggregated Utility of Algorithm

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