Joint Rate Adaption, Power Control, and Spectrum Allocation in OFDMA-Based Multi-Hop CRNs*

Mui Van NGUYEN\textsuperscript{(a)}, Sungwon LEE\textsuperscript{(b)}, Nonmembers, and Choong Seon HONG\textsuperscript{(c)}, Member

SUMMARY The overall performance of multi-hop cognitive radio networks (MHCRNs) can be improved significantly by employing the diversity of orthogonal licensed channels in underlay fashion. However, the mutual interference between secondary links and primary links and the congestion due to the contention among traffic flows traversing the shared link become obstacles to this realizing technique. How to control congestion efficiently in coordination with power and spectrum allocation optimally in order to obtain a high end-to-end throughput is motivating cross-layer designs for MHCRNs. In this paper, by taking into account the problem of joint rate adaption, power control, and spectrum allocation (JRPS), we propose a new cross-layer optimization framework for MHCRNs using orthogonal frequency division multiple access (OFDMA). Specifically, the JRPS formulation is shown to be a mix-integer non-linear programming (MINLP) problem, which is $\text{NP}$-Hard in general. To solve the problem, we first develop a partially distributed algorithm, which is shown to converge to the global optimum within a reasonable time interval. We next propose a suboptimal solution which addresses the shortcomings of the first. Using numerical results, we finally demonstrate the efficiency of the proposed algorithms.

key words: cross-layer optimization, congestion control, power control, spectrum allocation, multi-hop CRNs

1. Introduction

Cognitive Radio (CR), a promising solution for relaxing spectrum scarcity, has recently been attracting considerable interest from the wireless communication community. In cognitive radio networks, secondary users (SUs) need to employ sophisticated sensing mechanisms to access licensed bands without affecting the performance of primary users (PUs). However, SUs may spread their coded data over both under-utilized and un-occupied spectrum holes given that they meet the interference constraints required by the primary system. This spectrum access approach is known as spectrum underlay [14].

In multi-hop wireless networks (MHWNs), congestion control mechanisms regulate source rates $x_s$ according to the available capacity of a wireless link $l$ to guarantee that the offered load on any link does not exceed its capacity. The problem of joint congestion control and power control (JCPC) has been well-studied in [5], [17] via the underlying network utility maximization (NUM) under the physical interference model:

$\text{(JCPC problem): } \max_{\mathbf{P}, \mathbf{a}} \sum_s U_s(x_s) \quad \text{s.t.} \quad \sum_{s \in S_l} x_s \leq C_l(\mathbf{P}), \quad \forall l$

where $S_l$ is the set of sources traversing the link $l$, and the capacity of a wireless link is a global function of the transmit power vector $\mathbf{P}$ of interfering links. However, in multi-hop CRNs, the capacity of a CR link strongly depends on not only the mutual interference among them but also the availability of spectrum resources and the need for a protection of primary communications. Hence, the overall throughput of multi-hop CRNs calls for newly efficient spectrum and power allocation strategies coupled with congestion control mechanisms.

In this work, we investigate a spectrum and power allocation policy that takes the diversity of orthogonal licensed bands into account for CR links along with a congestion control mechanism under protocol interference model, where a group of CR links can be active on the same band if they make no interference with each other. In this regard, the mutual interference among CR links can be eliminated and thereby the capacity $C_l(\mathbf{P}, \mathbf{a})$ of CR links is a local function of its power vector $\mathbf{P}$ and spectrum allocation vector $\mathbf{a}$. The key difference from the problem of JCPC is that the global dependence of optimization variables $(\mathbf{x}, \mathbf{P})$ in the problem of JCPC leads a non-convex optimization problem which calls for a globally optimal solution while our approach formulates the problem of JRPS as a MINLP problem which can be solved for the global optimum with low complexity.

Some recent works [3], [11]–[13], [22] model the interference relationship among wireless links using protocol interference model and propose back-pressure-based cross-layer scheduling algorithms for MHWNs with the same assumption of fixed transmit power of wireless links. It is shown that back-pressure based scheduling algorithm may destroy the architectural modularity between the layers and tends to explore all paths in a network (including loop paths and dead-endpaths) that can not guide sources to their desired destination. More specifically, some other works [12], [13], [21], [22] has studied the JRPS problem for multi-channel multi-radio MHWNs with an assumption of static spectrum. In this work, we investigate JRPS problem in a spectrum underlay manner, which has not been addressed...
yet.

Since the harmful interference emitted by the SUs can make the PU’s reception unsuccessful, some existing studies [8],[18],[19] proposed the different solutions to optimally allocate power for the SUs in spectrum underlay fashion. In [8], Hasan at al. proposed the suboptimal and optimal algorithms to allocate power under a fixed power budget with a risk return model which considers the reliability and availability of licensed spectrum bands. The authors in [19] introduced the transmit power constraints and interference power constraints for the SUs. Son at al. in [18] introduced a new interference power outage constraint to protect the PUs along with a transmit power constraint for the SUs’ power budget. The optimal and suboptimal algorithms to maximize the capacity of the SUs are derived in [18]. However, most above works focus on the CRNs with infrastructure where the secondary transmission only occurs in the single hop between the SUs and CR base station. But this approach can not be extended to the multi-hop case because the mutual interference among the SUs has not taken into consideration yet. Our major contributions to address the problem of JRPS in MHCRNs, which also demonstrate the difference from the existing studies, are summarized as follows:

1. **New Optimization Problem**: A new cross-layer framework is developed for MHCRNs in underlay fashion as an MINLP problem. Unlike many of the previous works in the literature which only explored partial resources, our problem includes the rate adaption, power control and spectrum allocation altogether with the multi-channel diversity in a unified framework. Our objective is to maximize the aggregate utility subject to link capacity, mutual interference constraints and PU protections.

2. **Optimal and Sub-optimal resource allocation algorithms**: By dual decomposition associated with constructing a multi-band conflict graph, we optimally solve the NP-Hard problem in a partially distributed manner to achieve the global optimum. We show that it is polynomial in the number of bands and secondary links. We further propose a greedy distributed spectrum allocation algorithm (GDSA) based on [9]. We then develop a fully distributed solution with lower complexity and prove it to converge close to the optimal point.

3. **Preservation of architectural modularity**: The remarkable points of our proposed algorithms are the provision of high total utility for SUs with fast convergence speed and the preservation of architectural modularity of Internet Protocol (IP) via a cross-layer methodology without degrading the performance of PUs.

The rest of paper is organized as follows. Section 2 presents the system model and problem formulation. Section 3 introduces the cross-layer design using the methodology of dual decomposition. In Sect. 4, we present the optimal strategy for the problem of JRPS. Section 5 is the distributed implementation of the sub-optimal solution for the problem of JRPS using a greedy distributed spectrum allocation algorithm to address the shortages of the first algorithm. The computational complexity is analyzed in Sect. 7 for both our proposals. We present numerical results to illustrate the performance of our proposed algorithms in Sect. 7, and finally conclude the paper in Sect. 8.

### 2. System Model and Problem Formulation

We consider a multi-hop cognitive radio network which is modeled by a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ is the set of $N$ secondary nodes\(^1\), $\mathcal{L}$ is the set of $L$ logical links. We assume that the primary system has a set of $M$ orthogonal frequency bands $\mathcal{M}$, each of which with bandwidth $W_m$ is correspondingly licensed to one pair of PUs. SUs are equipped with multiple reconfigurable transceivers for data communication and one transceiver for signalling. SUs can simultaneously switch to different frequency bands during their transmission. We further assume that the secondary network is shared a set of $S$ sources $\mathcal{S}$ indexed by $s$. Each source $s \in \mathcal{S}$ traverses multiple hops to get its destination through the set of links, $\mathcal{L}_s \subseteq \mathcal{L}$, which is called a route. Without loss of generality, the routes of all source flows in this work are predefined. We also assume that each source has an infinite amount of data to send such that no delay constraint is considered. For ease of exposition, we will use the notation shown in Table 1 in the remainder of this paper.

At the physical layer, we assume that all PUs and SUs are ideally time-synchronized to each other. In this paper, our main objective is how to exactly allocate power and spectrum to links and regulate the source rates so as to maximize the overall throughput.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Important notation.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symbol</td>
<td>Definition</td>
</tr>
<tr>
<td>$N$</td>
<td>Set of secondary nodes</td>
</tr>
<tr>
<td>$\overline{N}$</td>
<td>Number of secondary nodes, $\overline{N} =</td>
</tr>
<tr>
<td>$M$</td>
<td>Set of orthogonal licensed bands</td>
</tr>
<tr>
<td>$\overline{M}$</td>
<td>Number of orthogonal licensed bands, $\overline{M} =</td>
</tr>
<tr>
<td>$W_m$</td>
<td>Bandwidth of each band</td>
</tr>
<tr>
<td>$S$</td>
<td>Set of sources, $S =</td>
</tr>
<tr>
<td>$\mathcal{L}$</td>
<td>Set of logical secondary links</td>
</tr>
<tr>
<td>$L$</td>
<td>Number of secondary links, $L =</td>
</tr>
<tr>
<td>$a_{lm}^s$</td>
<td>Binary decision variable of spectrum allocation</td>
</tr>
<tr>
<td>$L_s$</td>
<td>Set of links on the path of source $s$</td>
</tr>
<tr>
<td>$S_l$</td>
<td>Set of sources using link $l$</td>
</tr>
<tr>
<td>$x_s$</td>
<td>Rate of source $s$</td>
</tr>
<tr>
<td>$p_{m}^l$</td>
<td>Power of link $l$ on band $m$</td>
</tr>
<tr>
<td>$y_{m}^l$</td>
<td>CIR at SU-Rx of link $l$ on band $m$</td>
</tr>
<tr>
<td>$f_{m}^l$</td>
<td>Weight of link $l$ on band $m$</td>
</tr>
<tr>
<td>$\beta_{m}^l$</td>
<td>Interference factor of band $m$</td>
</tr>
<tr>
<td>$I^l$</td>
<td>Total interference introduced by $l$ into band $m$</td>
</tr>
</tbody>
</table>

\(^1\)In this paper, the terms “secondary user” and “secondary node” are interchangeably used.
Let \( d^m_l \in \{0, 1\} \) denote the binary indicator of spectrum allocation, where 1 indicates that the \( m \)th band is assigned to link \( l \) and 0 otherwise. Since each secondary link operates on only one frequency band at each time slot, we have

\[
\sum_{m=1}^{M} d^m_l = 1, \quad \forall l.
\]

(1)

We assume that \( \eta_l \) is the thermal noise power under the baseband bandwidth \( W_m \) at the receiver of link \( l \) on band \( m \). According to Shannon, the instantaneous capacity at the link \( l \) is given by [1]:

\[
C_l(P_l, a_l) = W_m \sum_{m=1}^{M} d^m_l \log \left( 1 + \frac{\gamma^m_l P^m_l}{\eta_l} \right)
\]

(2)

where \( P_l = [P_l^1, ..., P_l^M] \) and \( a_l = [a^1_l, ..., a^M_l] \) are power allocation vector and spectrum allocation indicator vector of the \( l \)th link, respectively. We use the special index 0 to denote the primary link (e.g., \( P^m_0 \) is the transmit power of PU-Tx on band \( m \)). \( \gamma^m_l = \frac{G^m_l}{\beta^m_l} \) is channel gain-to-interference ratio (CIR) of link \( l \) on band \( m \). Generally, \( G^m_l \) represent the channel gain between the \( k \)th link’s transmitter and the \( l \)th link’s receiver on band \( m \). In this study, we make an assumption that \( G^m_l \) only depends on the physical link distance \( d_l \) with the path exponent \( n \) (i.e., \( G^m_l = \frac{d^m_l}{\beta^m_l} \)). \( \beta^m_l = T_m \sum_{f=1}^{W_m/2} \phi^m(f)d_f \) denotes the interference factor, which depends on the OFDM symbol duration \( T_m = 1/W_m \) and the normalized power spectral density \( \phi^m(f) \) of the subcarrier on the \( m \)th band (e.g., \( \phi^m(f) = \frac{\sin \left( \frac{\pi f T_m}{T_m} \right)}{\sqrt{\pi f T_m}} \) [1]). \( K_l = -\phi_1 / \log(\phi_2 \text{BER}_l) \) is the processing gain of link \( f \) [16], where constants \( \phi_1 \) and \( \phi_2 \) depend on modulation/coding schemes, and \( \text{BER}_l \) is the bit error ratio requirement of the \( l \)th link. For ease of exposition, without loss of generality, we assume that \( W_m \) has a unit bandwidth, henceforth.

To deploy the multi-channel diversity (i.e., scheduling a group of links to use the same band at the same time), we must ensure that they are interference-free with each other. In this paper, we consider the IEEE 802.11 DCF based interference model [20] to identify a subset of links that can simultaneously be active on the same band. Under this model, all nodes that hear an RTS or CTS have to refrain from both transmission and reception as illustrated in Fig. 1. This is similar to the model where a link can not transmit if another link in its two-hop neighborhood transmits. Given any link \( l \) in connectivity graph \( G \), let \( I^m_{l} \) be the subset of links within its first hop neighbor. We further assume that the interference relationship is symmetric, i.e., if link \( l \) interferes with link \( k \), then link \( k \) also interferes with link \( l \). The constraints

\[
\sum_{l \in I^m_{l}} d^m_l = 1, \quad \forall m
\]

(3)

allow only one link \( l \in I^m_{l} \cup I^m_{l} \) to transmit data on band \( m \) at any time instant. To avoid overwhelming link capacity, the offered load on each link does not exceed its capacity

\[
C_l(P_l, a_l) := \sum_{s \in S_l} x_s \leq \sum_{m=1}^{M} d^m_l \log \left( 1 + \frac{\gamma^m_l P^m_l}{\eta_l} \right), \quad \forall l
\]

(4)

where \( S_l = \{ s : l \in L_s \} \) is the set of sources \( s \) using link \( l \).

2.2 Primary Link Protection

Harmful interference introduced by SUs to the PUs occurs via two different forms: out-of-band emission (OBE) and in-band emission (IBE). OBE interference are due to SU’s power leakages in the sidelobes of an OFDM signal while IBE interference is because both the SU’s and PU’s transmission concurrently occur on the same band. In this work, we assume that the PU system also employs an OFDMA scheme, where each band is licensed to each pair of PUs [4]. Hence, we can ignore the OBE interference. The IBE interference power introduced in a specific band, which is occupied by a pair of PUs on band \( m \), as a result of the \( l \)th link’s transmission with transmit power \( P^m_l \), can be expressed as [1]:

\[
J^m_l(W_m, P^m_l) = G^m_l \beta^m_l P^m_l.
\]

(5)

We assume that channel state information (CSI) between SU transmitters and PU receivers is known to SU transmitters, thereby SU system is allowed to enable their transmission provided that the total interference power level caused by them at the PU receiver \( m \) is kept below a tolerable threshold \( \mu^m \):

\[
\sum_{l} d^m_l J^m_l(W_m, P^m_l) \leq \mu^m, \quad \forall m.
\]

(6)

2.3 Problem Formulation: JRPS with Primary Link Protections

Our joint rate adaption, power control and spectrum allocation problem with primary link protections for MHCRRs is formulated via the underlying NUM problem as following.

\[
(P1) \quad \max_{x \in X, P \in P, a} \sum_{s \in S} U_s(x_s)
\]

subject to
\[
\sum_{s \in S_l} x_s \leq \sum_{m=1}^{M} a_{l}^m \log(1 + \gamma_{l}^m P_{l}^m), \quad \forall l,
\]
(8)
\[
\sum_{l=1}^{L} a_{l}^m G_{0l}^m p_{l}^m \leq \mu_{l}^m, \quad \forall m,
\]
(9)
\[
\sum_{m=1}^{M} a_{l}^m = 1, \quad \forall m,
\]
(10)
\[
\sum_{m=1}^{M} a_{l}^m = 1, \quad \forall l,
\]
(11)
\[
a_{l}^m \in [0,1], \forall m,l,
\]
(12)
where \( X = \{x_s; s \in S\}_{x_s^{\text{min}} \leq x_s \leq x_s^{\text{max}}}\) and \( P = \{P_{l}^m; l \in L, m \in M\}_{P_{l}^{\text{min}} \leq P_{l}^m \leq P_{l}^{\text{max}}}\) indicate quality of service (QoS) constraints for each source and power restriction for each CR node per link, respectively. The objective function \( U_s(x_s)\) can be interpreted as the level of satisfaction attained by a source \( s\) at the allocated rate \( x_s\) and is assumed to be twice continuously differentiable, non-decreasing and strictly concave in its domain. The fairness in the resource allocation can be characterized by the following general \( \alpha \)-fair utility function \([15]\):
\[
U_s(x_s) = \begin{cases} 
(1-\alpha)^{-1} x_s^{-\alpha} & \text{if } \alpha \geq 0, \alpha \neq 1; \\
\log x_s & \text{if } \alpha = 1.
\end{cases}
\]
It is straightforward that \( P1 \) belongs to the class of MINLP problem. The optimal solution is known to be \( NP\)-Hard in general.

3. Cross-Layer Design via Dual Decomposition

3.1 Lagrange Dual Problem

We solve the \( NP\)-Hard problem \( P1 \) via its dual optimization problem. We first augment the objective function of \( P1 \) with a weighted sum of the constraints (8) and (9) and obtain its partial Lagrangian:
\[
L(x, P, a, \lambda, \nu) = \sum_{s \in S} U_s(x_s) - \sum_{l} \lambda_l \left( \sum_{s \in S_l} x_s - \sum_{m} a_{l}^m \log(1 + \gamma_{l}^m P_{l}^m) \right)
- \sum_{m} \nu_m \left( \sum_{l} a_{l}^m G_{0l}^m p_{l}^m - \mu_{l}^m \right)
\]
(13)
where \( \lambda = [\lambda_1, \lambda_2, ..., \lambda_L] \) and \( \nu = [\nu_1, \nu_2, ..., \nu_M] \) are the Lagrangian nonnegative multipliers which are interpreted as congestion prices and interference prices, respectively. The former reflects the degree of congestion on CR links while the latter is on the interference status of licensed bands.

Then, its dual optimization problem can be described as
\[
(D) \quad \min_{\lambda \geq 0, \nu \geq 0} g(\lambda, \nu)
\]
(14)
where
\[
g(\lambda, \nu) = \max_{x \in X, P \in P, a} \quad L(x, P, a, \lambda, \nu)
\]
subject to (10), (11), (12).

3.2 Dual Algorithm

By using dual decomposition method, the maximization problem in (15) can be decomposed into two subproblems as in (16) and (17).
\[
\max_{x \in X} \left\{ L_s(x_s) \right\} = \sum_{s} U_s(x_s) - \sum_{l} \lambda_s \sum_{s \in S_l} x_s
\]
(16)
\[
\max_{P \in P, a} \left\{ L_\nu(P, a, \lambda, \nu) \right\} = \sum_{m} \sum_{l} a_{l}^m \left[ \lambda_l log(1 + \gamma_{l}^m P_{l}^m) - \nu_m G_{0l}^m P_{l}^m \right]
\]
(17)
subject to (10), (11), (12).

3.2.1 Subproblem 1 (Rate Adaption):

As can clearly be observed from (16), \( L_s \) is strictly concave and separable in \( x \). Hence, given the multipliers \( \lambda \), the optimal rate can be found by the Karush-Kuhn-Tucker (KKT) conditions \([7]\):
\[
x_s^*(\lambda) = \left[ U_s'(x) \right]^{-1} (\lambda_s)
\]
(18)
where \( U_s'(x) \) is the first derivative of utility, \( [x]^X \) is the projection of \( x \) onto the set \( X \). As a result, source \( s \) adjusts its rates according to the total congestion price \( \lambda_s = \sum_{l \in L_s} \lambda_l \) along its path.

3.2.2 Subproblem 2 (Power Control and Spectrum Allocation):

The subproblem (17) is combinatorial with respect to \( a \) while convex with respect to \( P \). It’s major objective is how to allocate \( M \) bands to \( L \) different CR links and corresponding transmit power per each band to maximize the sum of weights \( \Gamma_{l}(P_{l}^m, \lambda_l, \nu_m) \) subject to the contention constraints (10), (11), and (12). Since the primal variables \( P \) and \( a \) appear in the sum of products, the subproblem (18) can be further decomposed into two subproblems:

Subproblem 2.1: Power Control

Given a pair of dual variables \( (\lambda_l, \nu_m) \), the maximization problem (17) is to optimize the transmit power \( P_{l}^m \) such that the weight \( \Gamma_l(P_{l}^m, \lambda_l, \nu_m) \) is maximized. The optimal power can be obtained by the KKT conditions \([7]\):
\[
P_{l}^m(\lambda_l, \nu_m) = \left( \frac{\lambda_l}{\nu_m G_{0l}^m} - \frac{1}{\gamma_{l}^m} \right)^{\frac{1}{\nu_m}}
\]
(19)
which resembles the classical water-filling principle \([6]\). However, its water level is determined by \( \lambda_l/\nu_m G_{0l}^m \) which
can be different for different CR links.

**Subproblem 2.2: Spectrum Allocation**

In (17), given the optimized weights \( \Gamma^m_l (P_m^l, \lambda^l, \nu^m_l) \), the spectrum allocation problem

\[
\max_a \sum_{l=1}^L \sum_{m=1}^M a^m_l \Gamma^m_l \quad \text{s.t.} \quad (10), (11), (12).
\]

is equivalent to a maximum weighted matching problem on the multi-band weighted conflict graph \( G_c = (\mathcal{V}, \mathcal{E}) \), where \( \mathcal{V} \) and \( \mathcal{E} \) represents the vertex set and the edge set respectively. Each vertex in \( G_c \) corresponds to a pair of link-band \( (l, m) \) associated with its weight \( \Gamma^m_l \). Hence, we have \( |\mathcal{V}| = M \times L \). The edges forming between two vertices in \( G_c \) represent the link-band pairs that interfere with each other. Since one link cannot access the different frequency bands at a time slot, there will be the additional edge between two vertices with the same link but different bands. Figure 2 shows an example of a simplified multi-hop CRN with two orthogonal bands and its weighted contention graph. In this example, we assume that the 802.11 DCF based interference model is used at link layer. In Fig. 2, for example, vertex \((a, 1, 3)\) corresponds to a pair of link \(a\) and band \(1\) associated with its weight \(3\). There is an edge between two vertices \((a, 1, 3)\) and \((b, 1, 4)\) because they interfere with each other. Additionally, there exists an edge between two vertices \((a, 1, 3)\) and \((a, 2, 1)\) because they come from the same link \(1\) but different bands.

Then, the global optimal solution \(a^*\) can be found through the maximum independent set (MIS) of \(G_c\) (i.e., an independent set with maximum total weight). This MIS can be achieved by the exhaustive search or augmenting path algorithms [10] in a centralized manner with the computational complexity \(O(|\mathcal{V}|^3)\).

### 3.3 Multiplier Updates

Since \(L(x, P, \lambda, \nu)\) is affine in \((\lambda, \nu)\), the optimal multipliers \((\lambda^*, \nu^*)\) to minimize \(g(\lambda, \nu)\) can be obtained as in (21) and (22) by using the projected gradient-descent method [7] with step sizes \(k_t \geq 0\). We denote by \(\mathbb{R}^+\) the set of positive real numbers.

\[
\nu^{m+1}_m = \left[\nu^m_m + k_t \left(\sum_{l \in L} a^m_l G_m^m P_m^l - \mu^m_m\right)\right]^{R^+}
\]

\[
\lambda^{t+1}_l = \left[\lambda^t_l + k_t \left(\sum_{m \in M} a^m_l G_m^l P_m^l - \mu^l_l\right)\right]^{R^+}
\]

### 4. Optimal Joint Rate Adaption, Power Control and Spectrum Allocation (JRPS-OP) Algorithm

The above dual algorithm motivates an optimal joint rate adaption, power control and band assignment design where each source \(s\) locally regulates its rates according to the aggregate congestion price \(\lambda^{t+1}_l = \sum_{m \in M} a^m_l G_m^l P_m^l\), and each CR link \(l\) individually updates its congestion prices and interference prices, then adjusts its powers per band. The CR links notify the central node their weights and local connectivity information such that the central node constructs a multi-band weighted conflict graph, computes MIS, and then sends feedback information to them. We summarize JRPS-OP algorithm which operates with different time-scales as follows:

**Algorithm 1: JRPS-OP Algorithm**

Sources and links initialize \(x^{(0)}, P^{(0)}, \lambda^{(0)}, \nu^{(0)}\). At time \(t\):

**Source Algorithm:** For each source \(s \in S\)

1. Receive spectrum allocation information \(P^{(t)}_s\) and powers \(P^{(t)}_m\) from the central node and other links.
2. Estimate channel gain \(G^{(t)}_m\), locally measured the total interference \(I^{(t)}_s\) and compute \(I^{(t)}_m\).
3. Get ingress rates \(x^{(t)}_m\) from input queue. Update congestion price \(\lambda^{(t+1)}_l\) using (22).
4. Update interference prices \(\nu^{(t+1)}_m\) \(\forall m \in M\) using (21).
5. Update power \(P^{(t+1)}_m\) using (19). Broadcast its power vector to other links.
6. Compute weights \(\gamma^{(t)}_m\) \(\forall m \in M\). Send its weights, connectivity information, and powers to the central node.

**Central node Algorithm:** At time \(T \geq t\)

1. Receive the links’ weights, connectivity information, and powers.
2. Construct conflict graph \(G_c\). Perform exhaust search algorithm to find MIS.
3. Broadcast spectrum allocation information \(a^{(T)}\) to links.
Proof. For a given vector $\mathbf{a}$, the problem $P_1$ is convex. Hence, with any initial values, source rates (18), link powers (19), and dual variables $(\lambda, \nu)$ in (21) and (22), generated by JRPS-OP, converge to the unique optimum with a sufficiently small step size $\kappa_i$ satisfying (23) [7]. Since the global solutions of spectrum allocation $\mathbf{a}(T)$ (obtained via MIS at each iteration $T$) keep improving their schedules according to the weights resulting from $(P^0, \lambda^0, \nu^0)$, they eventually reach the convergence criterion. Hence, the resultant unique optimum is global. \hfill \Box

5. Distributed JRPS Implementation

As described in Sect. 4, the solution of JRPS-OP is globally optimal but partially distributed. This leads to a highly induced computational complexity at the central node and large signaling overhead which is infeasible and unscalable in practice. Using a sub-optimal solution to address these shortcomings is desired. In this section, we adopt the simple distributed weighted matching protocol [9] to solve the spectrum allocation problem in (17) distributedly, and then propose a fully-distributed JRPS algorithm which converges to the point near the global optimum.

5.1 Greedy Distributed Spectrum Allocation

Let $N_u$ is the set of neighbors which interfere with node $u$ in connectivity graph $G(N, L)$. For ease of presentation, we use the notations $L$ and $L_u$ interchangeably to denote a reverse link of $l$ and $l_u$, respectively. We also use $L_u = \{(l_u, m), \langle l_u, m \rangle | v \in N_u; \forall m \in M\}$ to denote the set of all incoming and outgoing links to and from $u$ in graph $G$ associated with all bands of system. Let $\Gamma_u = \{\Gamma_u^m | \Gamma_u^m \subseteq L_u, \forall m \in M, \forall v \in N_u\}$ is the vector of weights of all links on all bands at node $u$. Then, the greedy distributed spectrum allocation (GDSA) algorithm is summarized as follows:

In the GDSA algorithm, each node $u$ picks a pair of feasible link-band $(l, m)$ which is the heaviest one among all pairs of directed link-band incident upon it. Then the node $u$ sends a request message $\text{ReqMsg}[l, m]$ to its neighbor $v$ who is connected to it over the heaviest link $l$ through CCC. Upon receiving a request message from neighbor $v$, node $u$ stores the received message to the feasible set $F$. If the received message in $F$ is the same as $(l', m')$, then $(l', m')$ becomes a matched pair, denoted by $(l^*, m^*)$. Next, node $u$ sends a reply message $\text{RepMsg}[l^*, m^*]$ to a neighbor of link $l^*$ and a drop message $\text{DropMsg}[l^*, m^*]$ to all other neighbors through CCC. Also, upon receiving a drop message $\text{DropMsg}[l, m]$ from neighbor $v$, node $u$ knows that band $m$ is in a matched link of $v$ or itself. Thereby, the node $u$ can exclude both the matched band $m$ in the considering set $m$ and all edges associated with that band $m$ in the set $L$. This process is repeated at each node $u$ until $L = \emptyset$.

**Theorem 2.** Given a connectivity graph $G(N, L)$ on $M$ bands, the algorithm **GDSA** always computes a maximal matching with the computational complexity $O(M \times L)$ under IEEE 802.11 DCF based interference model.

Proof. At each node $u$, a pair of link-band $(l, m)$ is added to the set of matching $\mathcal{M}_u$ if the neighbor $v$ on link $l$ also sends the same request for band $m$ to $u$. Locally, this makes sure that weight associated with that pair of link-band is the heaviest. In other words, all nodes $u, v$ and their neighbors remove band $m$ from $\mathcal{M}$ and all incident links to/from $u, v$ associated with band $m$ from $L_u, i = \{u, v, N_u, N_v\}$, which are the loop condition. Therefore, all nodes in $G$ terminate its matching process when $\cup_{u \in N} L_u \rightarrow \emptyset$. This ensures that band $m$ will not be rescheduled on any links in the interference of $u$ and $v$. Hence, the resulting matching is maximal. Moreover, the algorithm GDSA terminates for every node $u$ in $G$ when $L_u = \emptyset, \forall v \in N$. A matching is assumed to be maximal if and only if all nodes in $G$ terminate their matching process in time $| \cup_{u \in N} L_u | = L \times M$. \hfill \Box

**Algorithm 2: GDSA Algorithm**

Each secondary node $u$ carries out the following steps:

**Input:** $M, L_u, \Gamma_u$

**Output:** $\mathcal{M}_u$

1: $F \leftarrow \emptyset$; $L \leftarrow L_u; \mathcal{M} \leftarrow M$;
2: while $L \neq \emptyset$ do
3: $(l', m') \leftarrow \max(\Gamma_u^m, \forall l \in L, \forall m \in M)$;
4: Send $\text{ReqMsg}[l', m']$ to neighbor on link $l'$;
5: Upon receiving $\text{Msg}$ from neighbor $v$,
6: if $\text{Msg} = \text{ReqMsg}[l, m]$ then
7: $F \leftarrow F \cup \{(l, m)\}$;
8: else if $\text{Msg} = \text{DropMsg}[l, m]$ then
9: $L \leftarrow L \setminus \{(l, m), (l, m)| l \in L\}$;
10: $\mathcal{M} \leftarrow \mathcal{M} \setminus \{m\}$;
11: $F \leftarrow F \setminus \{(l, m)\}$;
12: if $(l, m) = (l', m')$ then
13: $(l', m') \leftarrow \max(\Gamma_u^m, \forall l \in L, \forall m \in M)$;
14: Send $\text{RepMsg}[l^*, m^*]$ to neighbor on link $l^*$;
15: end if
16: end if
17: if $(l', m') \in F$ then
18: $(l^*, m^*) \leftarrow (l', m')$;
19: $\mathcal{M}_u \leftarrow \mathcal{M}_u \cup \{(l', m')\}$;
20: Send $\text{RepMsg}[l^*, m^*]$ to neighbor of link $l^*$;
21: Send $\text{DropMsg}[l^*, m^*]$ to neighbors of $l \in L_u \setminus \{l^*\}$;
22: $L \leftarrow L \setminus \{(l^*, m^*), (l, m)| l \in L\}$;
23: $\mathcal{M} \leftarrow \mathcal{M} \setminus \{m\}$;
24: $F \leftarrow F \setminus \{(l', m')\}$;
25: end if
26: end while
5.2 Sub-Optimal JRPS Algorithm (JRPS-SOP)

Our cross-layer design for the problem of GDSA can be implemented in a fully-distributed manner with the greedy distributed spectrum allocation algorithm GDSA and different time-scales as summarized below.

Algorithm 3: JRPS-SOP Algorithm

Sources and links initialize $\mathbf{x}^{(0)}$, $\mathbf{P}^{(0)}$, $\mathbf{X}^{(0)}$, $\nu^{(0)}$.

Source Algorithm: For each source $s \in S$ at time $t$:

1. Receive the total price that accumulates the intermediate links’ link price $A_{il}^{(t)}$ along its path through a feedback message from its destination.
2. Update rate $x_{is}^{(t+1)}$ using (18) with $A_{il}^{(t)}$.

Link Algorithm: For each link $l \in \mathcal{L}$ at time $t$:

1. Estimate channel gain $G_{hl}^{(t)}$, locally measured the total interference $d_{l}^{(t)} + C_{l}^{(t)} + \nu_{l}^{(t)}$, then compute $\gamma_{l}^{(t)}$.
2. Receive the power vectors from other links $P_{k}^{(t)}$, $k \in \mathcal{L} \setminus \{l\}$. Update interference price $\nu_{l}^{(t+1)}$, $\nu_{m} \in M$ using (21).
3. Get ingress rates $\sum_{s \in S_{l}} x_{is}^{(t)}$ from input queue. Update congestion price $j_{l}^{(t+1)}$ using (22).
4. Update power $P_{m}^{(t+1)}$ using (19). Broadcast power vectors $P_{l}^{(t+1)}$, $a_{l}^{(t+1)}$, and $C_{l}^{(t+1)}$, $\nu_{m} \in M$. At time $T \geq t$:
5. Compute weights $\Gamma_{m}$, $\forall m \in M$. Perform GDSA algorithm to get $a_{l}^{(t+1)}$.

Theorem 3. For any initial source rate vector $\mathbf{x}^{(0)} \in \mathcal{X}$, link power vector $\mathbf{P}^{(0)} \in \mathcal{P}$, spectrum allocation vector $\mathbf{a}^{(0)} \in [0, 1]$, and shadow prices $(\lambda^{(0)}, \nu^{(0)}) \geq 0$, the sequence of primal-dual variables generated by JRPS-SOP converges to the point near the global optimum of the problem $\mathbf{P}_{1}$ with step sizes $\kappa_{l}$ satisfying (23).

Proof. At time $T$, the matching of GDSA algorithm is maximal [Theorem 2], i.e., locally optimal. Following the similar proof in Theorem 1, the JRPS-SOP algorithm converges to the point near the global optimum of the problem $\mathbf{P}_{1}$ with step sizes $\kappa_{l}$ satisfying (23). \hfill \Box

6. Computational Complexity Analysis

In JRPS-OP algorithm, $S$ computations are needed to update source rates $x_{i}$ in (18) at each iteration. Also, to solve problem (20) for the optimal powers $P_{m}^{(0)}$ and spectrum allocation variables $a_{l}^{(0)}$, we must seek the MIS of conflict graph $G_{c}$ with a computational complexity $O(M \times L^{3})$. As for the sub-gradient update method, $L$ congestion prices and $M$ interference prices are needed to update with step sizes in (21) and (22) at each iteration, and the iteration number increases linearly with the number of updates [2] (i.e., $L$ congestion prices and $M$ PU interference prices). Hence, the total computational complexity of the sub-gradient iterative method is approximately $O((L \times M)^{2})$, and that of the whole algorithm is $O((S + (M \times L)^{3}) \times (L \times M)^{2})$.

Similarly, in JRPS-SOP algorithm, we need $S$ computations are needed to update source rates $x_{i}$ at each iteration and the total computational complexity of the sub-gradient iterative method is approximately $O((L \times M)^{2})$. However, to solve problem (20) at each iteration, the GDSA algorithm computes a maximal matching with a computational complexity $O(L \times M)$. Hence, the total complexity of whole algorithm JRPS-SOP is $O((S + M \times L) \times (L \times M)^{2})$.

7. Performance Evaluation

7.1 Simulation Settings

We consider a simplified multi-hop CRN with 5 secondary nodes, 4 flows, and 3 pairs of PUs with 3 corresponding licensed bands as shown in Fig. 3. Each secondary link with a transmit power range from 1.76 dBm to 27 dBm is allocated one band and a power level at each period. Bandwidth of each band is 125 kHz. We assume that the distance $d = 1$ m and the minimum data rate for each flow is assumed to be 100 bps. For PUs, we predefine the interference power thresholds for the licensed bands 1, 2, and 3 are 4.4 mW, 72 mW, and 2.3 mW, respectively. We assume that all PUs transmit at the same power level 20 dBm and the shaping pulse of modulated signal is raised-cosine with roll-off factor 0.5. Without loss of generality, we let $K_{l} = -1.5/\log(SBER_{l})$, for all $l$ with target $BER_{l} = 10^{-5}$. We further assume that the power spectral density of white noise is $-174$ dBm/Hz at both PU and SU receivers and the path loss exponent $n = 4$. We choose $U_{l}(x_{i}) = \log x_{i}$ as source’s utility function for a proportional fair allocation to all SUs.

7.2 Performance of Proposed Algorithms

In this experiment, we first investigate the optimality of the proposed algorithms (i.e., JRPS-OP and JRPS-SOP). Figure 4 shows the interference powers caused by the secondary system converge to the target thresholds allowed by PU system while Fig. 5 depicts the trajectory of source rates for...
both JRPS-OP and JRPS-SOP. In fact, our proposed algorithms converge to their fixed point in a reasonable time. Figure 6 illustrates the balance of the link capacity $C_l$ and its ingress rate $\sum_{s \in S} x_s$ at the fixed point for both JRPS-OP and JRPS-SOP. It can be clearly seen that all constraints of link capacities (8) and PU interference powers (9) are active for JRPS-OP at its fixed point. However, this could not be achieved by JRPS-SOP because its greedy spectrum allocation strategy (i.e., GDSA) in which a maximal matching is found thanks to the local selection of the link-band pairs with the highest weight to activate at each node. Figure 7 shows the optimal powers and allocated bands for both JRPS-OP and JRPS-SOP. Their major difference is that JRPS-SOP chooses the 3rd band to allocate to the link 4 instead of the 2nd band as JRPS-OP. Thereby, both the links 1 and 4 share the same spectrum opportunity on the 3rd band. Since the interference power threshold is fixed, the allocated power to the link 1 on the 3rd band in JRPS-SOP is lower than that in JRPS-OP. Consequently, the capacity on the link 1 in JRPS-SOP is smaller than that in JRPS-OP. More specifically, the capacity on the link 4 in JRPS-SOP is smaller than that in JRPS-OP even though the same minimum power is allocated to the link 4 for both JRPS-OP and JRPS-OP. This is because the PU3-Tx on the 3rd band causes more interference than the PU2-Tx on the 2nd band does at the link 4.

Nevertheless, the sources 2 and 3 in JRPS-SOP traverse the links 1 and 2 with the smaller congestion price due to the non-zero slackness. Their rates in JRPS-SOP are then greater than those in JRPS-OP (as shown in Fig. 5). As a result, the ingress rate at the link 3 in JRPS-SOP is greater than that in JRPS-OP as illustrated in Fig. 6. This forces
Fig. 8 Comparison of performance of the proposed algorithms and JRPS scheme with randomized spectrum allocation at $BER = 10^{-5}$.

the link 3’s congestion price to increase because the link 3’s ingress rate is always greater than its capacity. As proposed in (19), the link’s congestion price $\lambda$ is increasing, the link must increase its power to balance the difference between the supply (i.e., link capacity) and the demand (i.e., ingress rate). Therefore, the link 3’s capacity in JRPS-SOP is also greater than that in JRPS-OP.

Next, we evaluate the performance of the proposed algorithms in comparison with two other particular schemes named JRPS-iFSA (JRPS-Fixed Spectrum Allocation including both the maximum independent set and maximal independent set achieved by JRPS-OP and JRPS-SOP) and JRPS-eFSA (JRPS-Fixed Spectrum Allocation excluding both the maximum independent set and maximal independent set achieved by JRPS-OP and JRPS-SOP). The JRPS-iFSA’s throughput is averaged over several independent sets which are randomly chosen in all possible independent sets, then fixed during power and rate update period. Similarly, the JRPS-eFSA’s throughput is averaged over several independent sets which are randomly chosen in all remaining independent sets after excluding both the maximum independent set and maximal independent set, then fixed during power and rate update period. We also investigate the effect of interference factor $\beta^m$, $\forall m$ on their overall throughput through two different roll-off factors of raised cosine pulse [1]. As can be observed from Figs. 8 and 9, JRPS-SOP significantly outperforms both JRPS-iFSA and JRPS-eFSA and yields an aggregated utility close to the global optimum achieved by JRPS-OP with a negligible utility gap for two kinds of pulse shaping. It is very important to note that the throughput over the raised cosine pulse with a higher roll-off factor is better. The key reason for this is because the broader the main lobe of PSD becomes, the smaller the intensity of interference within a spectral range $W_m$ is. This raised cosine pulse with a higher roll-off factor significantly alleviates the mutual interference between PUs and SUs. As a result, not only power and rate control but also spectrum allocation should jointly be designed to obtain the maximum total utility under a contention-limited spectrum underlay system.

7.3 Energy and Spectrum Efficiency

As depicted in Fig. 7, the link power per band is optimally controlled to meet exactly the rate requirements demanded from greedy sources. Our objective is to fairly maximize source’s utility while keeping interference at PUs below a specified target. In fact, some links in both our proposals do not use the maximum power to transmit at their optimum. This is a significant difference from some previous studies [12], [13], [22], where the link scheduling have been taken into consideration with a fixed power assignment to maximize the end-to-end throughput. As a result, the energy is wasteful because the different rate demand on each link requires amount of different energy. More importantly, the fixed power-based link scheduling schemes can not be applied to spectrum underlay systems because the link power needs adjusting to ensure the PUs’ quality of service (QoS). In this regard, in both our proposals, the per band weight of each link which depends on congestion prices and PU interference prices is always updated for spectrum allocation strategies. Thereby, the CR links will properly switch to the best licensed band without spectrum resource wastage due to the PUs’ mobility.

Figure 9 shows the total utilities of proposed algorithms and two special schemes (JRPS-eFSA and JRPS-iFSA) versus the PU interference power constraint. In this experiment, we vary only the PU2’s interference power threshold $\mu^2$ while fixed on the others.
7.4 Effect of Different Timescales

We consider the impact of different timescales $T$ and $t$ on the performance of proposed algorithms. Figure 10 shows that there is a significant difference in terms of convergence speed at timescales $T = t$, $T = 50t$, and $T = 100t$ for both our proposed algorithms. This is because it will take a longer time to update the weights of links on each band. Tables 2 and 3 compare the computational complexity for both our algorithms where the sub-optimal solution JRPS-SOP outperforms the optimal one JRPS-OP in terms of convergence speed and computational complexity. We see that, parameter $T$ acts as a knob to control the tradeoff between convergence speed and computational complexity. By increasing the interval between $T$ and $t$, we can make the system much more efficient in computation but slower to converge (and vice versa). Our proposed algorithms which are implemented with different time-scales implies that they allows the the central node (in JRPS-OP) or the links (in JRPS-SOP) to track their average weights. As a result, the introduced computation burden on the central node or the links is significantly reduced so that our algorithms are much more scalable and implementable at the expense of convergence speed.

Figure 12 shows the number of control messages experienced by both the schemes JRPS-OP and JRPS-SOP for two different values of $T$. The signalling overhead becomes more serious as the number of secondary users significantly increases. However, thanks to its distributed properties, the SUs in JRPS-SOP only exchange the control messages among their neighbors. This dramatically relaxes the contention of common control channel among the SUs. As a result, the communication overhead experienced by the scheme JRPS-SOP is much smaller than this experienced by the scheme JRPS-OP when the spectrum allocation is

### Table 2

<table>
<thead>
<tr>
<th>$\varepsilon = 10^{-4}$</th>
<th>$T = t$</th>
<th>$T = 50t$</th>
<th>$T = 100t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>JRPS-SOP</td>
<td>85</td>
<td>200</td>
<td>228</td>
</tr>
<tr>
<td>JRPS-OP</td>
<td>150</td>
<td>265</td>
<td>370</td>
</tr>
</tbody>
</table>

### Table 3

<table>
<thead>
<tr>
<th>$\varepsilon = 10^{-4}$</th>
<th>Computation Complexity</th>
<th>Number of Variables</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Time = $t$; $T = 50t$; $100t$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JRPS-SOP</td>
<td>$12 \times 5$</td>
<td>31</td>
<td>$7135; 6440; 7188$</td>
</tr>
<tr>
<td>JRPS-OP</td>
<td>$1728$</td>
<td>31</td>
<td>$263850; 18583; 16654$</td>
</tr>
</tbody>
</table>

![Fig. 10](image) Effect of spectrum allocation’s timescale $T$ on trajectory of aggregated utility.

![Fig. 11](image) Fairness index versus varying PU 2’s interference power threshold $\mu^2$ while fixed on the others.

![Fig. 12](image) Comparison of signalling overhead of the proposed algorithms required to transmit over common control channel (CCC).
done at the same time with the power and rate updates (i.e., $T = t$). On the other hand, if the more the difference between $T$ and $t$ is, the more the communication overhead experienced by both JRPS-SOP and JRPS-SOP significantly decreases. Specifically, the number of control messages experienced by both JRPS-OP and JRPS-SOP is almost negligible when the difference between $T$ and $t$ is increasing.

7.5 Fairness in Resource Allocation

We use Jain’s fairness index $(\sum_{i=1}^{S} x_i)^2 / (S \times \sum_{i=1}^{S} x_i^2)$ to evaluate the fairness of proposed algorithms. As can be observed from Fig. 11, the overall fairness is enhanced as the PU’s tolerable interference power increases because the accessible spectrum budget is higher. The JRPS-OP’s fairness is the best compared with other algorithms, JRPS-SOP and JRPS-FSA. This is because the key difference with regards to the algorithms is the spectrum allocation strategy. In fact, the solution of spectrum allocation problem in JRPS-OP is globally optimal, and its total utility hence is the highest as shown in Fig. 9. Moreover, sources regulate their rates using the same utility function $\log(x_i)$ in a proportional fair manner, the algorithm with the highest total utility can obtain the best fairness.

8. Conclusion

In this paper, we proposed a new cross-layer framework for the problem of joint rate adaption, power control and spectrum allocation in OFDMA-based multi-hop CRNs using IEEE 802.11 DCF based interference model in a spectrum underlay manner. Our major objective is to deploy the diversity of multiple orthogonal licensed bands for CR links and optimally solve the problem of joint rate adaption, power control and spectrum allocation to maximize the overall utility. The first proposed algorithm, JRPS-OP, is proven to converge to the global optimal solution. Despite the attractiveness of its optimality, JRPS-OP poses an additional hardware resource and computation burden. A suboptimal algorithm JRPS-SOP with no central node is proposed to alleviate these issues. The different timescales also are taken into account as a novel scheme to reduce the induced computation burden on the central node (in JRPS-OP) or links (in JRPS-SOP) so that our proposed algorithms are practical and thus implementable.

Acknowledgment

This research was supported by Next-Generation Information Computing Development Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2012-0006421).

References


Mui Van Nguyen received the B.Eng. and M.Eng. degrees from Ho Chi Minh City University of Technology, Vietnam, in 2002, and 2008, respectively. In 2002, he was a Lecturer with the Department of Electrical and Electronic Engineering, Ho Chi Minh City University of Technology, Vietnam. In September 2009, he joined in the Department of Computer Engineering, Kyung Hee University, South Korea and received his Ph.D. degree in August, 2012. Since September 2012, he works as a postdoctoral researcher at the Department of Computer Engineering, Kyung Hee University, South Korea. His research interests include cognitive radio networks, cross-layer design for communication networks, multi-user multi-carrier communications system, and stochastic network optimization.

Sungwon Lee received the B.S., M.S., and Ph.D. degrees in Computer Engineering from Kyung Hee University, Korea, in 1994, 1996, and 1998, respectively. From 1999–2008, he joined Samsung Electronics research and business groups on topics such as radio access network and core network development of cdma2000 1X, cdma2001 1xEV-DO, WCDMA, HSPA, WiBro/Mobile-WiMAX, and IP Multimedia Subsystem (IMS). He worked as a project leader for several trial innovative system developments. And, he was a senior engineer for system architecture, system design, and traffic engineering for several commercial product developments. He has published more than 100+ patents according to mobile broadband networks, including more than 20 registered US patents. He is currently an Associate Professor of Faculty with the Department of Computer Engineering, Kyung Hee University, Korea. His current research interests are in mobile broadband wireless networks, cellular communications, machine type communications, time synchronization protocols, wireless medium access control protocols, and mobile services. He is an Associate Editor for Journal of Korean Institute of Information Scientists and Engineers-Computing Practice and Letters, Journal of the Korea Society of Computer and Information, and an Associate Director for Open Standards and Internet Association.

Choong Seon Hong received his B.S. and M.Sc. degrees in Electronic Engineering from Kyung Hee University, South Korea, in 1983, and 1985, respectively. In 1988 he joined KT, and worked on Broadband Networks as a member of the technical staff. Since September 1993, he joined Keio University, Japan, and received his Ph.D. degree in March, 1997. He had worked for the Telecommunications Network Lab, KT as a senior member of technical staff and as a director of the networking research team until August 1999. Since September 1999, he has been working as a professor of the College of Electronics and Information, Kyung Hee University. He has served as a Program Committee Member and an Organizing Committee Member for International conferences such as NOMS, IM, AP-NOMS, E2EMON, CCNC, ADSN, ICPP, DIM, WISA, BeN and TINA. His research interest includes ad-hoc networks, network security and management. He is a Senior Member of IEEE and Member of ACM, IPSI, KICS, and KIPS.