Optimal Traffic Splitting in Multi-hop Cognitive Radio Networks

(Paper ID #: 900077)

Yang Song[§], Jianfeng Wang[†], Chi Zhang[§] and Yuguang Fang[§]

[§] Department of Electrical and Computer Engineering
University of Florida
Gainesville, Florida 32611
Email: yangsong@ufl.edu; zhangchi@ufl.edu; fang@ece.ufl.edu
[†] Philips Research North America
345 Scarborough Road, Briarcliff Manor, NY 10510
Email: jianfeng.wang@philips.com

***Abstract*—In this work, we consider a multi-hop cognitive radio network with multiple flows. The challenges induced by the random behaviors of the primary users are investigated in a stochastic network utility maximization framework. To fully utilize the scarce network resource, we propose an optimal traffic splitting scheme for each source node to explore multiple paths effectively. In addition, the algorithm is fully distributed which provably converges to the global optimum solution with probability one. The analytical results are validated via simulations.**

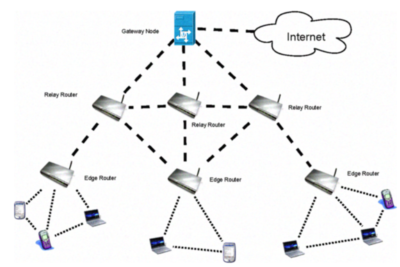


Fig. 1. Architecture of Wireless Mesh Networks

I. Introduction

The past decade has witnessed the emergence of new wireless services in daily life. One of the promising techniques is the metropolitan wireless mesh networks (WMN), which are envisioned as a technology which advances towards the goal of ubiquitous network connection. Figure 1 illustrates an example of wireless mesh network. The wireless mesh network consists of edge routers, intermediate relay routers as well as the gateway node. Edge routers are the access points which provide the network access for the clients. The relay routers deliver the traffic aggregated at the edge routers to the gateway node, which is connected to the Internet, in a multi-hop fashion.

One hinderance for the network performance is the limited usable frequency resource. In current wireless mesh networks, the unlicensed ISM bands are most commonly adopted for backbone communications. Not surprisingly, the wireless mesh network is largely affected by all other devices in this ISM band, e.g., nearby WLANs and Bluetooth devices. Moreover, the limited bandwidth of the unlicensed band cannot satisfy the increasing demand for the bandwidth due to the evolving network applications. Ironically, as shown by a variety of empirical studies [1], the current allocated spectrum is drastically under-utilized. As a consequence, the urge to explore the unused whitespace of the spectrum, which can significantly enhance the performance of the wireless mesh networks, attracts tremendous attention in the community [2]–[6].

Cognitive radios are proposed as a viable solution to the frequency reuse problem [7]. The cognitive devices are capable of sensing the environment and adjusting the configuration parameters automatically. If the primary user, i.e., the legitimate user, is not using the primary band currently, the cognitive devices, namely, secondary users, will utilize this whitespace of the spectrum. Incorporating with the established interference-free techniques such as [8] and [9], the throughput of the wireless mesh network can be dramatically enhanced. The protocol design for cognitive wireless mesh networks (CWMN), or more generally, multi-hop cognitive radio networks, is an innovative and promising topic in the community [10] and has been less studied in the literature. In this paper, we consider a cognitive wireless mesh network where the unlicensed band, e.g., ISM band, is utilized by the mesh routers for the backbone transmission. Moreover, each router is a cognitive device and hence is capable of sensing and exploiting the unused primary bands for transmissions whenever the primary users are absent.

This work was supported in part by the U.S. National Science Foundation under Grant CNS-0721744 and under Grant CNS-0626881. This project was also partially supported by the 111 project under grant B08038 with Xidian University, Xi'an, China.

978-1-4244-5239-2/09/$26.00 ©2009 IEEE

In this paper, we investigate the optimum traffic splitting problem in multi-hop cognitive radio networks. More specifically, we are particularly interested in how the traffic in the multi-hop cognitive radio networks should be steered, under the influence of random behaviors of primary users. It is worth noting that given a routing strategy, the corresponding network's performance, e.g., the average queueing delay encountered, is a random variable. The reason is that the available bandwidth for a particular link depends on the appearance of all the affecting primary users. If all the primary users are vacant, a link can utilize all available frequency trunks collectively by utilizing advanced physical layer techniques, e.g., OFDMA. However, if all the primary users are present, the only available frequency space is the unlicensed ISM band and thus the traffic on this link will experience longer delay than the previous case. We emphasize that in multi-hop cognitive radio networks, this distinguishing feature of randomness, induced by the random behaviors of primary users, must be taken into account in protocol designs. Due to the location discrepancy, it is possible that some node is affected by many primary users while others are not. As a consequence, if we route the traffic via this particular node, the transmissions are more likely to be corrupted by the returns of the primary users. Apparently, a favorable solution is more inclined to steer the traffic from those "severely-affected area", to the paths which are less affected by the primary users. We will make this intuitive approach precise and rigorous in this paper. Our work is partially inspired by [11]. However, our paper differs from theirs in three crucial aspects. First, by targeting the optimum traffic splitting solution, our model differs from the joint power scheduling and rate control work in [12]. Secondly, in [11], [12], the authors only consider a single-path scenario while our work extends to a multi-path routing network where the network traffic can be steered. Thirdly and most importantly, [11], [12] require that the current system state is fully observable at the decision maker. To achieve this, the authors assume a centralized mechanism which knows all the channel states of all the links over the network. However, our work differs from [11], [12] significantly in that we do not require that the current system's state is known, which is of great practical interest since in multi-hop cognitive wireless mesh networks, the decision makers, i.e., the edge routers in our scenario, cannot be aware of the appearance of all primary users in the whole network as a priori. Moreover, our scheme enjoys a decentralized implementation, in contrast to centralized mechanisms in [11], [12], by utilizing the feedback signals and local information only.

The rest of this paper is organized as follows. Section II provides the system model of our work. The optimum traffic splitting problem is investigated in Section III. Performance evaluation is provided in Section IV, followed by concluding remarks in Section V.

II. System Model

We consider a multi-hop wireless mesh network illustrated in Figure 1 where an uplink traffic model is considered, i.e., all edge routers aggregate the traffic from clients and deliver to the gateway node via the intermediate relay routers. To ensure connectivity, we utilize the ISM 2.4G band as the underlying common channel for the wireless mesh network. In addition, each link can utilize the opportunistic channels, i.e., secondary bands to increase the link's achievable data rate whenever the primary user is vacant. We assume that there exists[1] $|\mathbb{M}|$ primary users. Each primary user possesses a licensed frequency channel and each mesh router is a cognitive node which has the capability of sensing the current wireless environment. We model the multi-hop cognitive wireless mesh network as a directional graph $\mathcal{G}$ where the vertices are the nodes. We also denote link (i, j) as link $e, e \in \mathbb{E}$ where $t(e) = i$ and $r(e) = j$ represent the transmitter and the receiver of link e.

We first consider a particular link denoted by (m, n). The instantaneous available frequency bands, at time t, for a node i is denoted by $I_i(t)$, which is determined by the current presence of the primary users. Besides the underlying ISM band, the communication between m and n can further utilize all secondary bands within $I_m \bigcap I_n$, if available. The current cognitive radio devices benefit largely from the software-defined radio (SDR) techniques with advanced coding/modulation capabilities. For example, by utilizing the multi-carrier modulation, e.g., OFDMA, a cognitive radio device can utilize all the disjoint available frequency band simultaneously. At the transmitter, a software based radio combines waveforms for different sub-bands and thus transmit signal at these sub-bands simultaneously. While at the receiver, a software based radio decomposes the combined waveforms and thus receives signal at these sub-bands simultaneously [13]–[16]. In this paper, we assume a spectrum sensing scheme available that each node can sense the presence of the primary users in range, such as [7], [17], although the time of random returns cannot be predicted. We further assume that some scheduling mechanism is in place or some physical layer mechanisms are utilized such that the nodes cannot interfere with each other during the transmissions. For example, in a multi-channel multi-radio wireless mesh network, the channels can be assigned properly that the transmissions do not interfere with the neighboring nodes [8], [18]. Other examples are the OFDMA/CDMA based wireless mesh networks [19], [20] where the interference among nodes can be eliminated by assigning orthogonal subcarriers/codes. We emphasize that this assumption is only for the sake of modeling simplicity and does not incur any loss of generality, as will be clarified shortly.

It is worth noting that the available bandwidth of each link in the cognitive wireless mesh network is a random variable. For example, at time instance t_1, node m has three secondary bands available, i.e., $I_m(t_1) = \{I_0, I_1, I_2, I_3\}$ and $I_n(t_1) = \{I_0, I_2, I_3, I_4, I_5\}$ due to the location discrepancy, where band 0 is the underlying unlicensed ISM band and $1, 2, 3, 4, 5$ are the licensed bands of primary users. The current bandwidth

[1]The symbol of $|\mathbb{X}|$ represents the cardinality of the set $\mathbb{X}$.

of link (m,n) is represented by $W_{m,n}(t_1) = BW_0 + BW_2 + BW_3$ where BW_i is the bandwidth of band i. At another time instance t_2, the primary user 2 returns and the bandwidth of link (m,n) becomes $W_{m,n}(t_2) = BW_0 + BW_3$. In other words, the bandwidth of links are random variables which are determined by the unpredictable appearance of the primary users. We model this randomness induced by the primary users as a stationary random process with arbitrary distribution. The system is assumed to be time-slotted. In each time slot n, the system state is assumed to be independent and is denoted by a state vector $s = \{\delta_1, \cdots, \delta_{|\mathbb{M}|}, s \in \mathbb{S}\}$ where $\delta_i = 1$ denotes the absence of the i-th primary user and 0 otherwise. We denote the stationary probability distribution of state s as π_s. Without loss of generality, we express the link capacity in the form of CDMA-based networks, i.e., the capacity of a wireless link $e \in \mathbb{E}$, given the system state s, is denoted by c_e^s, which is given by [21], [22] $c_e^s = W_e^s \frac{1}{T} \log_2(1 + K\gamma_e^s)$, where W_e^s is the bandwidth of link e in state s and γ_e^s is the current SINR value of link e. The constant T is the symbol period and will be assumed to be one unit without loss of generality [22]. The constant $K = \frac{-\Phi_1}{log(\Phi_2 BER)}$ where Φ_1 and Φ_2 are constants depending on the modulation scheme and BER denotes the bit error rate. We will assume $K = 1$ in this paper for simplicity [21]. Note that our network model can be incorporated into other types of networks such as MIMO, OFDM with TDMA or CSMA/CA based MAC protocols by modifying the form of the capacity accordingly, which represents the achievable data rate in general. For example, if we consider a scheduling-based MAC protocol where each link obtains a time share of the channel access, the achievable data rate is given by $c_s^e = \widetilde{c_s^e} \times \psi_e$ where ψ_e is the fraction of time that the link is active following the scheduling scheme and $\widetilde{c_s^e}$ is the nominal Shannon capacity of the link.

There are $|\mathbb{L}|$ unicast sessions in the network, denoted by set $\mathbb{L}$, where each session l has a traffic demand d_l. We associate each session with a unique user. Therefore, we will use *session* l and *user* l interchangeably. For each session $l \in \mathbb{L}$, we denote the source node and destination node as $S(l)$ and $D(l)$, respectively. Recall that we assume an uplink traffic model and thus all the source nodes are edge routers and the destination node is the gateway. Furthermore, to improve the reliability and dependability, we allow multi-path routing schemes. We denote the available[2] set of acyclic paths from $S(l)$ to $D(l)$ by $\mathbb{P}_l$ and the k-th path is represented by P_l^k. We introduce a parameter r_l^k as the flow allocated in the k-th path of session l. The overall flow of user l, represented by x_l, is given as

$$x_l = \left[\sum_{k=1}^{|\mathbb{P}_l|} r_l^k \right]_0^{d_l} \tag{1}$$

where $[x]_a^b$ denotes $\max\{\min\{b, x\}, a\}$. Define an $|\mathbb{E}|$-by-$|\mathbb{P}_l|$ matrix $\mathbb{H}_l$ where the element $H_{e,k}^l = 1$ if link e is on the k-th path of $\mathbb{P}_l$ and 0 otherwise. Hence, $\mathbb{H} = \{\mathbb{H}_1, \cdots, \mathbb{H}_{|\mathbb{L}|}\}$ represents the network topology.

[2]The available set of multiple paths can be obtained by signalling mechanisms such as RSVP-TE [23] or pre-configured manually. In this paper, we assume a predetermined set of acyclic paths. The protocol design for acquiring such paths is beyond the scope of this paper.

For each link $e \in \mathbb{E}$, there is an associated cost function, denoted by $l_e^s(f_e, c_e^s)$ where f_e is the accumulated flow on link e. We assume the function l_e^s is an increasing, differentiable and convex function of f_e for a fixed c_e^s. Note that in our scenario, even the accumulated flow f_e is fixed, the value of cost function is random due to the state-dependent variable c_e^s. From the network's perspective, the optimum traffic splitting solution will distribute the aggregated flow among multiple paths properly, in the sense that the overall network utility is maximized. In next section, we will formulate the optimum traffic splitting problem in a stochastic network utility maximization framework [22] and provide a distributed solution which requires no priori information about the underlying probability distribution, i.e., π_s, of the system states.

III. Optimal Traffic Splitting Algorithm

A. Formulation

In the standard network utility maximization framework, each user has a utility function $U_l(x_l)$. In this section, we assume the utility functions to be concave and differentiable. Note that the fairness issue can be embodied in the utility functions [22]. For example, in the seminal paper [24], the log-utility functions are adopted to achieve the proportional fairness among different flows.

Define a feasible traffic splitting solution as $\mathbf{r} = [\mathbf{r}_1, \cdots, \mathbf{r}_{|\mathbb{L}|}]$ where $\mathbf{r}_l \triangleq [r_l^1, \cdots, r_l^{|\mathbb{P}_l|}]$. We can formulate the optimum traffic splitting problem as

$\underline{\mathcal{P}_1:}$

$$\max_{\mathbf{r} \geq \mathbf{0}} \sum_{l \in \mathbb{L}} U_l\Big(\sum_{k \in \mathbb{P}_l} r_l^k\Big)$$

s.t.

$$\sum_{k \in \mathbb{P}_l} r_l^k \leq d_l \ \forall l \in \mathbb{L} \tag{2}$$

$$\sum_{s \in \mathbb{S}} \pi_s \sum_{k \in \mathbb{P}_l} r_l^k \left(\sum_{e \in P_l^k} l_e^s(f_e, c_e^s) \right) \leq b_l \ \forall l \in \mathbb{L} \tag{3}$$

$$f_e \leq \sum_{s \in \mathbb{S}} \pi_s c_e^s \ \forall e \in \mathbb{E} \tag{4}$$

$$f_e = \sum_{l \in \mathbb{L}} \sum_{k \in \mathbb{P}_l} H_{e,k}^l r_l^k \ \forall e \in \mathbb{E} \tag{5}$$

$$c_e^s = W_e^s \frac{1}{T} \log_2(1 + K\gamma_e^s) \ \forall e \in \mathbb{E} \tag{6}$$

where $e \in P_l^k$ represents the links along the k-th path of user l. The variable in $\mathcal{P}_1$ is the vector of $\mathbf{r}$. The first set of constraints reflect that the overall data rates of all paths cannot exceed the traffic demand d_l. The second set of constraints indicate that for each user l, the expected cost has to be no more than a predefined constraint b_l. The third set of constraints represent that the aggregated flow on link e cannot exceed the average link capacity. Apparently, if the underlying probability distribution of each state π_s is known as a priori, $\mathcal{P}_1$ is a deterministic convex optimization problem and thus easy to solve. However, in practice, the accurate measurement of probability distribution is a non-trivial task. In [25], we utilized a stochastic approximation based approach to circumvent the difficulty of estimating the probability distribution. In the following, we will extend this technique and develop a tailored distributed algorithm to address the issues of time-varying link capacities as well as the user-specific QoS requirements, which are of particular interest in multi-hop cognitive wireless mesh networks.

First, define the Lagrangian function of $\mathcal{P}_1$ as

$$\begin{aligned}
&L(\mathbf{r},\lambda,\mu,\mathbf{v})\\
=&\sum_{l\in\mathbb{L}} U_l(\sum_{k\in\mathbb{P}_l} r_l^k) + \sum_{l\in\mathbb{L}}\lambda_l(d_l - \sum_{k\in\mathbb{P}_l} r_l^k)\\
&+\sum_{l\in\mathbb{L}} v_l\left(b_l - \sum_{s\in\mathbb{S}}\pi_s\sum_{k\in\mathbb{P}_l} r_l^k(\sum_{e\in P_l^k} l_e^s(f_e,c_e^s))\right)\\
&-\sum_{e\in\mathbb{E}}\mu_e(f_e - \sum_{s\in\mathbb{S}}\pi_s c_e^s)\\
=&\sum_{l\in\mathbb{L}}\left\{U_l(\sum_{k\in\mathbb{P}_l} r_l^k) + \lambda_l(d_l - \sum_{k\in\mathbb{P}_l} r_l^k) + v_l b_l\right.\\
&\left.-v_l\sum_{s\in\mathbb{S}}\pi_s\sum_{k\in\mathbb{P}_l} r_l^k(\sum_{e\in P_l^k} l_e^s(f_e,c_e^s))\right\}\\
&-\sum_{e\in\mathbb{E}}\mu_e(f_e - \sum_{s\in\mathbb{S}}\pi_s c_e^s)\\
=&\sum_{s\in\mathbb{S}}\pi_s\left\{\sum_{l\in\mathbb{L}}\left(U_l(\sum_{k\in\mathbb{P}_l} r_l^k) + \lambda_l(d_l - \sum_{k\in\mathbb{P}_l} r_l^k) + v_l b_l\right.\right.\\
&\left.\left.-\sum_{k\in\mathbb{P}_l} r_l^k(\sum_{e\in P_l^k}(v_l l_e^s(f_e,c_e^s)+\mu_e))\right) + \sum_{e\in\mathbb{E}}\mu_e c_e^s\right\}
\end{aligned}$$

Define

$$\begin{aligned}
&\mathcal{M}^s(\lambda,\mu,v)\\
&=\sup_{\mathbf{r}\geq 0}\left\{\sum_{l\in\mathbb{L}}\left(U_l(\sum_{k\in\mathbb{P}_l} r_l^k) + \lambda_l(d_l - \sum_{k\in\mathbb{P}_l} r_l^k) + v_l b_l\right.\right.\\
&\left.\left.-\sum_{k\in\mathbb{P}_l} r_l^k(\sum_{e\in P_l^k}(v_l l_e^s(f_e,c_e^s)+\mu_e))\right) + \sum_{e\in\mathbb{E}}\mu_e c_e^s\right\} \qquad (7)
\end{aligned}$$

Let $\tilde{\mathbf{r}}$ be the optimum solution of (7). We will discuss how to obtain $\tilde{\mathbf{r}}$ shortly. The dual function of $\mathcal{P}_1$ is obtained by

$$g(\lambda,\mu,v) = \sum_{s\in\mathbb{S}}\pi_s\mathcal{M}^s(\lambda,\mu,v). \qquad (8)$$

Thus, the dual problem of $\mathcal{P}_1$ is given by

$\underline{\mathcal{P}_2:}$

$$\min_{\lambda,\mu,\mathbf{v}\geq 0} g(\lambda,\mu,\mathbf{v}). \qquad (9)$$

B. Distributed algorithmic solution with the stochastic primal-dual approach

In this subsection, we propose a distributed algorithmic solution of $\mathcal{P}_1$, or equivalently $\mathcal{P}_2$, based on the stochastic primal-dual method. In order to reach the stochastic optimum solution, the dual variables λ, μ and $\mathbf{v}$ are updated according to the following dynamics

$$\begin{aligned}
\lambda_l(n+1) &= [\lambda_l(n) - \alpha_l(n)\zeta_l(n)]^+ \ \forall l\in\mathbb{L} \qquad (10)\\
\mu_e(n+1) &= [\mu_e(n) - \alpha_e(n)\xi_e(n)]^+ \ \forall e\in\mathbb{E} \qquad (11)\\
v_l(n+1) &= [v_l(n) - \alpha_b(n)\rho_l(n)]^+ \ \forall l\in\mathbb{L} \qquad (12)
\end{aligned}$$

where $[x]^+$ denotes $\max(0,x)$ and n is the iteration number. $\alpha_l(n)$, $\alpha_e(n)$ and $\alpha_b(n)$ are the current stepsizes while $\zeta_l(n)$, $\xi_e(n)$ and $\rho_l(n)$ are random variables. More precisely, they are named the *stochastic subgradient* of the dual function $g(\lambda,\mu)$ and the following requirements need to be satisfied

$$\begin{aligned}
&\mathfrak{E}\{\zeta_l(n)|\lambda(1),\cdots,\lambda(n)\} = \partial_{\lambda_l} g(\lambda,\mu,\mathbf{v}) \ \forall l\in\mathbb{L} \qquad (13)\\
&\mathfrak{E}\{\xi_e(n)|\mu(1),\cdots,\mu(n)\} = \partial_{\mu_e} g(\lambda,\mu,\mathbf{v}) \ \forall e\in\mathbb{E} \qquad (14)\\
&\mathfrak{E}\{\rho_l(n)|\mathbf{v}(1),\cdots,\mathbf{v}(n)\} = \partial_{v_l} g(\lambda,\mu,\mathbf{v}) \ \forall l\in\mathbb{L} \qquad (15)
\end{aligned}$$

where $\mathfrak{E}(.)$ is the expectation operator and $\lambda(1),\cdots,\lambda(n)$, $\mu(1),\cdots,\mu(n)$ and $\mathbf{v}(1),\cdots,\mathbf{v}(n)$ denote the sequences of solutions generated by (10), (11) and (12), respectively. By Danskin's Theorem [26], we can obtain the subgradients as

$$\zeta_l(n) = d_l - \sum_{k\in\mathbb{P}_l}\tilde{r}_l^k(n) \ \forall l\in\mathbb{L} \qquad (16)$$

$$\xi_e(n) = c_e^s(n) - \tilde{f}_e(n) \ \forall e\in\mathbb{E} \qquad (17)$$

$$\rho_l(n) = b_l - \sum_{k\in\mathbb{P}_l}\tilde{r}_l^k(n)\sum_{e\in P_l^k} l_e^s(\tilde{f}_e,c_e^s) \ \forall l\in\mathbb{L} \qquad (18)$$

where $\tilde{r}_l^k$ is the optimum solution of (7).

We next show how to calculate $\mathcal{M}^s(\lambda,\mu,\mathbf{v})$ in (7), i.e., finding the optimum solution, denoted by $\tilde{\mathbf{r}}$, which maximizes

$$\begin{aligned}
&\sum_{l\in\mathbb{L}}\left(U_l(\sum_{k\in\mathbb{P}_l} r_l^k) + \lambda_l(d_l - \sum_{k\in\mathbb{P}_l} r_l^k) + v_l b_l\right.\\
&\left.-\sum_{k\in\mathbb{P}_l} r_l^k(\sum_{e\in P_l^k}(v_l l_e^s(f_e,c_e^s)+\mu_e))\right) + \sum_{e\in\mathbb{E}}\mu_e c_e^s \qquad (19)
\end{aligned}$$

Note that when updating the primal variable, i.e., $\mathbf{r}$, the link costs are deterministic which are obtained via the feedback signal, e.g., ACK messages. Therefore, by utilizing the same stochastic subgradient approach, we have

$$r_l^k(n+1) = \left[r_l^k(n) + \alpha_r(n)\eta(n)\right]_0^{d_l} \qquad (20)$$

where

$$\eta(n) = \frac{\partial U_l}{\partial\sum_{k\in\mathbb{P}_l} r_l^k(n)} - \lambda_l - \sum_{e\in P_l^k}(\mu_e + v_l l_e(f_e,c_e^s)) \qquad (21)$$

is the stochastic subgradient measured at time n.

Theorem 1: The proposed algorithm converges to the global optimum of $\mathcal{P}_1$ with probability one, if the following constraints of stepsizes are satisfied: (1) $\alpha(n) > 0$, (2)

$\sum_{n=0}^{\infty} \alpha(n) = \infty$, and (3) $\sum_{n=0}^{\infty} (\alpha(n))^2 < \infty$, $\forall l \in \mathbb{L}$ and $e \in \mathbb{E}$, where α represents α_e, α_l, α_b and α_r generally.

Proof: The proof follows similar lines as [27]. Specifically, we can show that in our traffic splitting scenario, the technical conditions for convergence of the stochastic primal-dual algorithm are satisfied. The detailed proof is omitted. ∎

It is worth noting that the aforementioned distributed algorithm enjoys the merit of distributed implementation from an engineering perspective. With the current values of dual variables, each source node $S(l)$ optimizes (19) according to (21) and (20). The information needed is either locally attainable or acquirable by the feedback along the paths. The source node updates the λ_l and v_l according to (10) and (12) where the needed information is calculated by (16) and (18), respectively. For each link e, the current status of (17) is measured. Next, the value of μ_e is updated following (11). The iteration continues until an equilibrium point is reached.

IV. Performance Evaluation

In this section, we present a simple yet illustrative example to demonstrate the theoretical results.

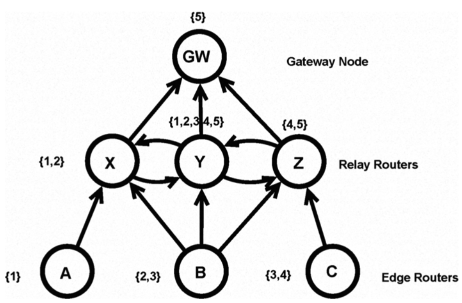


Fig. 2. Example of Cognitive Wireless Mesh Network

We consider a cognitive wireless mesh network[3] depicted in Figure 2. There are three edge routers as the source nodes, denoted by A, B, C, which transmit to the gateway node GW via the relay routers X, Y and Z. Among all feasible paths, we select the following available paths for edge routers, as summarized in Table 1.

TABLE I

Available paths for edge routers.

A	P_A^1:	$\{A \to X \to GW\}$
	P_A^2:	$\{A \to X \to Y \to GW\}$
	P_A^3:	$\{A \to X \to Y \to Z \to GW\}$
B	P_B^1:	$\{B \to X \to GW\}$
	P_B^2:	$\{B \to Y \to GW\}$
	P_B^3:	$\{B \to Y \to X \to GW\}$
	P_B^4:	$\{B \to Y \to Z \to GW\}$
	P_B^5:	$\{B \to Z \to GW\}$
C	P_C^1:	$\{C \to Z \to GW\}$
	P_C^2:	$\{C \to Z \to Y \to GW\}$
	P_C^3:	$\{C \to Z \to Y \to X \to GW\}$

[3]Figure 2 only shows the links on the available paths obtained by the signalling mechanisms or manually configurations. The actual physical topology of the network can be potentially larger.

There are five primary users in the area, denoted by $1, 2, 3, 4$ and 5 where each one has a primary band of $10MHz$. The common ISM band is assumed to be $10MHz$. The return probability of the primary users is given as $\varpi = [0.2, 0.3, 0.4, 0.3, 0.3]$. The transmitting power of each node is fixed as $100mW$ and the noise power is assumed to be $3mW$. We consider a model where the received power is inversely proportional to the square of the distance. Note that the transmitting power is uniformly spread on all available bands. In addition, we explicitly specify the affecting primary users for a particular node. We use $\{i, j, k, \cdots\}$ to represent that a particular node is affected by primary user $i, j, k, \cdots$. For example, node X is labeled with $\{1, 2\}$ which indicates that the transmission of node X will devastate the transmissions of primary user 1 and 2 if the corresponding primary band is utilized. Note that the central node, namely, Y, is most severely affected by all primary users. Intuitively, to achieve an expected optimum solution, the optimum traffic splitting algorithms are inclined to steer the traffic away from Y. We will demonstrate this *detour effect* next.

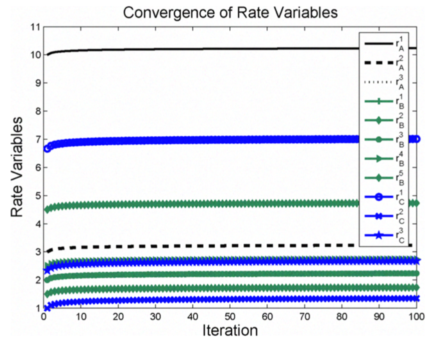
We first consider the cognitive wireless mesh network with convexity, e.g., $U_l(x_l) = \log x_l$ to achieve a proportional fairness among the flows [21]. The link cost is assumed to be in the form of $l_e^s(f_e, c_e^s) = \frac{1}{c_e^s - f_e}$, which reflects the delay experienced for a unit flow on link e under the $M/M/1$ assumption [28]. Note that if $f_e \geq c_e$, the cost is $+\infty$. We set the traffic demand of all edge routers as $d_l = 30Mbps$ while the cost budget is $b_l = 5$. The step sizes are chosen as $\alpha = 1/n$ where n is the current iteration step. Figure 3(a) illustrates the trajectories of the rate variables and Figure 3(b) shows the convergence of the network overall utility as well as the individual utility functions[4]. We observe that while the rate variables converge as the iterations go, the overall objective, i.e., the sum of the individual utilities, approaches to the global optimum indicated by the dashed line, which is attained by calculating the steady state distribution following the return probability ϖ.

In addition, Table 2 provides the rate on each path after convergence for a sample run of the algorithm. It is interesting to note that each user allocates a relatively small amount of flow on the paths which traverse node Y. Recall that node Y is affected by all five primary users. Therefore, our proposed optimum traffic splitting algorithm steers the traffic away from the severely affected areas automatically, without a prior knowledge of the cognitive network, in a distributed fashion.

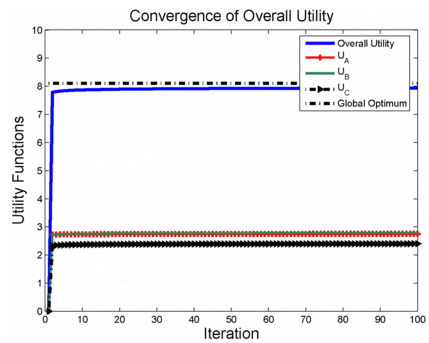
V. Conclusions

In this paper, we investigate the optimum traffic splitting problem in cognitive wireless mesh networks. To harness the randomness induced by the unpredictable behaviors of primary users, we formulate the problem in a stochastic network utility maximization framework. We derive a distributed algorithmic

[4]Note that Figure 3(b) also reflects the evolution of the throughput of each edge router logarithmically.



(a) Trajectories of Rate Variables



(b) Trajectories of Utility Functions

Fig. 3. Convergence Behaviors

TABLE II

RATE ON EACH PATH AFTER CONVERGENCE.

A	P_A^1:	10.3035
	P_A^2:	3.3034
	P_A^3:	2.3034
B	P_B^1:	4.7983
	P_B^2:	1.7982
	P_B^3:	2.2982
	P_B^4:	2.7982
	P_B^5:	4.8743
C	P_C^1:	7.1077
	P_C^2:	1.4409
	P_C^3:	2.7743

solution via the stochastic primal-dual approach, which provably converges to the global optimum solution.

In our work, we restrict ourself in a single gateway scenario. The extension to the multiple gateway scenario seems interesting and needs further investigation. In addition, we assume a negligible delay for the feedback signal while in a more general case, the impact of feedback delay needs further investigation.

REFERENCES

[1] [Online]. Available: http://www.sharedspectrum.com

[2] C. Ghosh and D. P. Agrawal, "Channel assignment with route discovery (card) using cognitive radio in multi-channel multi-radio wireless mesh networks," *IEEE SECON*, 2006.

[3] T. Chen, H. Zhang, G. M. Maggio, and I. Chlamtac, "Cogmesh: A cluster-based cognitive radio network," *IEEE DySPAN*, 2007.

[4] A. AL-Fuquha, B. Khan, A. Rayes, M. Guizani, O. Awwad, and G. B. Brahim, "Opportunistic channel selection strategy for better qos in cooperative networks with cognitive radio capabilities," *IEEE Journals on Selected Areas in Communications (JSAC)*, vol. 26, pp. 156–167, Jan. 2008.

[5] K. R. Chowdhury and I. F. Akyildiz, "Cognitive wireless mesh networks with dynamic spectrum access," *IEEE Journal on Selected Areas in Communications (JSAC)*, vol. 26, pp. 168–181, Jan. 2008.

[6] [Online]. Available: http://wirelessman.org/le/

[7] I. F. Akyildiz, L. W. Y., V. M. C., and M. S., "Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey," *Computer Networks Journal, (Elsevier)*, Sep. 2006.

[8] K. Xing, X. Cheng, L. Ma, and Q. Liang, "Superimposed code based channel assignment in multi-radio multi-channel wireless mesh networks," *Mobicom*, pp. 15–26, 2007.

[9] Y. Xi and E. M. Yeh, "Distributed algorithms for spectrum allocation, power control, routing, and congestion control in wireless networks," *MobiHoc*, 2007.

[10] "Cognitive wireless mesh network project." [Online]. Available: http://www.ece.gatech.edu/research/labs/bwn/mesh/

[11] J.-W. Lee, R. R. Mazumdar, and N. B. Shroff, "Opportunistic power scheduling for dynamic multi-server wireless systems," *IEEE Transactions on Wireless Communications*, Jun. 2006.

[12] ——, "Joint opportunistic power scheduling and end-to-end rate control for wireless ad-hoc networks," *IEEE Transactions on Vehicular Technology*, Mar. 2007.

[13] F. K. Jondral, "Software-defined radio - basics and evolution to cognitive radio," *EURASIP Journal on Wireless Cmmunications and Networking*, vol. 3, pp. 275–283, 2005.

[14] T. Hou, Y. Shi, and H. Sherali, "Spectrum sharing for multi-hop networking with cognitive radios," *IEEE Journal on Selected Areas in Communications (JSAC)*, vol. 26, pp. 146–155, Jan. 2008.

[15] Y. Shi and T. Hou, "A distributed optimization algorithm for multi-hop cognitive radio networks," *IEEE Infocom*, 2008.

[16] P. G. Cook and W. Bonser, "Architectural overview of the speakeasy system," *IEEE Journal on Selected Areas in Communications (JSAC)*, vol. 17, pp. 650–661, 1999.

[17] H. Kim and K. G. Shin, "In-band spectrum sensing in cognitive radio networks: Energy detection or feature detection?" *Mobicom*, 2008.

[18] P. Kyasanur, J. So, C. Chereddi, and N. H. Vaidya, "Multi-channel mesh networks: Challenges and protocols," *IEEE Wireless Communications*, Apr. 2006, invited paper.

[19] H. T. Cheng, H. Jiang, and W. Zhuang, "Distributed medium access control for wireless mesh networks," *Wireless Communications and Mobile Computing*, vol. 6, pp. 845–864, 2006.

[20] A. R. S. Bahai, B. R. Saltzberg, and M. Ergen, *Multi-carrier Digital Communications: Theory and applications of OFDM*. Springer, 2004.

[21] M. Chiang, "To layer or not to layer: Balancing transport and physical layers in wireless multihop networks," *IEEE Infocom*, 2004.

[22] M. Chiang, S. H. Low, A. R. Calderbank, and J. C. Doyle, "Layering as optimization decomposition: A mathematical theory of network architectures," *Proceedings of the IEEE*, vol. 95, pp. 255–312, Mar. 2007.

[23] D. Awduche, L. Berger, D. Gan, T. Li, V. Srinivasan, and G. Swallow, "Rsvp-te: Extensions to rsvp for lsp tunnels," Internet Draft, RFC 3209.

[24] F. Kelly, A. Maulloo, and D. Tan, "Rate control in communication networks: shadow prices, proportional fairness and stability," *Journal of Operation Research Society*, vol. 49, pp. 237–252, 1998.

[25] Y. Song, C. Zhang, and Y. Fang, "Routing optimization in wireless mesh networks under uncertain traffic demands," *International Conference on Quality of Service in Heterogeneous Wired/Wireless Networks (QShine'08)*, 2008.

[26] D. P. Bertsekas, *Nonlinear Programming*. Athena Scientific, 1999.

[27] J. Zhang, D. Zheng, and M. Chiang, "The impact of stochastic noisy feedback on distributed network utility maximization," *IEEE Transactions on Information Theory*, 2008.

[28] D. Bertsekas and R. Gallager, *Data Networks*. Prentice Hall; 2 edition, 1991.