STATISTICAL ROUTING FOR COGNITIVE RANDOM ACCESS NETWORKS

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ABSTRACT

A novel approach to multi-hop routing for cognitive random access is developed under channel gain uncertainty constraints. Motivated by the inherent randomness of the propagation medium, the novel routing strategy leverages pairwise decoding probabilities to randomly route packets to neighboring nodes. The resultant cross-layer optimization framework not only provides optimal routes in a well-defined sense, but also yields transmission probabilities and transmit-powers, thus enabling cognizant adaptation of networking, medium access, and physical layer parameters to the operational environment. The relevant optimization problem is non-convex and hence hard to solve in general. Nevertheless, a successive convex approximation approach is employed to efficiently find a Karush-Kuhn-Tucker solution. Enticingly, the fresh look advocated here permeates benefits also to conventional multi-hop random access networks in the presence of channel uncertainty.

***Index Terms*—** Routing, multi-hop wireless networks, random access, cross-layer optimization, successive convex approximation.

1. INTRODUCTION

Resembling traditional routing protocols for wired networks, their counterparts for wireless networking utilize optimization tools such as shortest path routing, to find optimal route(s) based on the network connectivity graph abstraction. Early on, links among nodes were quantified based on a disk model capturing only distance-based deterministic losses. Upon recognizing the inadequacy of disk models for the broadcast wireless interface [1], a weighted graph accommodating more sophisticated performance metrics was adopted; see e.g., [2], and the stochastic routing approach in [3], where link weights capturing packet delivery probabilities were exploited to develop optimal routing schemes.

In a hierarchical cognitive radio (CR) operation involving secondary users as well as primary users (PUs), interference levels can not be acquired accurately due to the lack of PU-CR cooperation [4]. As a result, shadowing and small-scale fading effects, along with dynamically changing activities of licensed users, accentuate the uncertainty of wireless CR links and, thus, the uncertainty of signal-to-interference-plus-noise ratios (SINRs). In this context, the present paper aims at optimal cross-layer design in the presence of channel uncertainty by introducing a routing framework whereby nodes not only adjust optimal (random) routes, but also physical and medium access operational parameters dictating the expected packet forwarding capabilities. In doing so, the statistics of propagation channels are explicitly accounted for; hence, the term *statistical* routing.

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1.1. Preliminaries and problem formulation

Consider a CR wireless network with N nodes $\{U_n\}_{n=1}^N$ sharing spectral resources with an incumbent PU system in an underlay setup [4]. Leveraging the spectrum awareness provided by spatio-temporal sensing schemes [5], CRs collaborate in routing data packets to a sink node U_{N+1}, while respecting the PU-CR hierarchy. The CR network is modeled as a digraph to account for possible lack of link bi-directionality to account for CR transmissions causing interference to PUs. Further, it is assumed that there exists a (possibly multi-hop) path connecting each node to the destination U_{N+1}. Burstiness and the stochastic nature of the propagation medium naturally suggest consideration of random access, along with stochastic routing strategies [3]. Thus, at each time slot, a CR node U_n transmits with probability $\mu_n \in [0,1]$, and decides whether to route packets toward a neighboring node U_i with probability $t_{n\to i} \in [0,1]$.

Communication of data packets throughout the network not only relies upon transmission and routing decisions, but also depends on the intended link reliability. Indeed, in case of unsuccessful packet decoding due to fading- or interference-induced link outages, a packet not eventually routed by U_n will remain in U_n's queue, and its transmission will be re-attempted in a subsequent time slot (possibly to a different neighboring CR). To capture channel- and interference-induced sources of uncertainty, let $r_{n\to i} \in [0,1]$ denote the probability that a packet transmitted from CR U_n is correctly decoded by U_i.

Exogenous packet arrivals at U_n are modeled by a stationary stochastic process with average rate $\rho_n \geq 0$. Each CR node is assumed to maintain a backlog to cache exogenous and endogenous packets that have to be routed. Let λ_n denote the average rate of packet departures from U_n. Then, assuming as usual fully backlogged queues per node, $\{\rho_n\}_{n=1}^N$ and $\{\lambda_n\}_{n=1}^N$ abide by the flow conservation constraints

$$\rho_n = \lambda_n \sum_{j\in\mathcal{N}_{n\to}} t_{n\to j} r_{n\to j} - \sum_{i\in\mathcal{N}_{\to n}} \lambda_i t_{i\to n} r_{i\to n} \tag{1}$$

$n = 1,\dots,N$, where $\mathcal{N}_{n\to} := \{j | r_{n\to j} > 0, j = 1,\dots,N+1, j \neq n\}$ is the set of nodes that decode U_n's transmissions with non-zero probability, and $\mathcal{N}_{\to n} := \{i | r_{i\to n} > 0, i = 1,\dots,N, i \neq n\}$ the set of nodes that route packets through U_n. For queue stability, it suffices to have $0 \leq \lambda_n \leq \mu_n$, for each CR U_n [3]. The stochastic attribute of data percolation is captured by the pairwise packet delivery probabilities $\{t_{n\to i} r_{n\to i}\}$; and, by the probability of a packet to remain in U_n's queue $1 - \sum_{i\in\mathcal{N}_{n\to}} t_{n\to j} r_{n\to j}$.

Building on (1), and assuming that link reliabilities $\{r_{n\to i}\}$ are *known* by, e.g., computing the packet error rate of antecedent sessions, a stochastic routing framework for maximizing the exogenous rates was introduced in [3]. However, because of the volatile CR channel characteristics, time-varying PU activity patterns, and diverse quality of service constraints, $\{r_{n\to i}\}$ may change abruptly,

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and thus may not be known in advance. Bridging physical and networking layers, a routing framework yielding (i) optimal routes, (ii) transmission probabilities, and (iii) transmit-powers based on first- and second-order statistics of PU interference, and CR-to-CR channels is put forward in the ensuing section. The proposed cross-layer optimization framework takes into account the stochasticity of propagation ambient and medium access interface, and allows adaptation of *both* optimal routing probabilities *and* link reliabilities.

2. FROM STOCHASTIC TO STATISTICAL ROUTING

The pairwise reliabilities $\{r_{n\to i}\}$ account for the unreliable characteristics of the wireless broadcast channel and medium access strategies. When a random access model is postulated, it is common to consider that a packet is lost when collisions occur. With $\mathcal{I}_{ni}$ denoting the set of nodes whose transmissions interfere with link $U_n \to U_i$, the probability of collision-free packet transmissions from U_n to U_i is given by $\prod_{j\in\mathcal{I}_{ni}}(1-\mu_j)$.

A well-established criterion for successful packet reception is to require the SINR to stay above a certain threshold [1, 6], which is determined by the receiver structure, transmit-power, modulation, and coding scheme. Let $g_{n\to i}$ denote the channel gain between U_n and U_i, modeling the effects of path loss, log-normal shadowing, and Nakagami-m small-scale fading. Then, the SINR of link $U_n \to U_i$ can be expressed as

$$\gamma_{n\to i} := \frac{p_n g_{n\to i}}{\sigma_i^2 + \sum_{S=1}^{N_S}\pi_S} \tag{2}$$

where σ_i^2 stands for the receiver noise power at U_i, $p_n \in (0, p_n^{\max}]$ the transmission power of U_n, and π_S the received power from PU transmitter $S = 1,\ldots,N_S$. Insufficient training, or ad hoc infrastructure of the CR network may render $g_{n\to i}$ challenging to acquire accurately. Randomness of $\{\gamma_{n\to i}\}$ is also manifested because of the PU interference $\{\pi_S\}$. In fact, although the number of PU sources N_S, along with PU transmit-powers and locations can be obtained during the sensing phase [5], uncertainty remains due to shadowing and small-scale fading effects.

However, in spite of the underlying channel uncertainty, CR-to-CR and PU-to-CR (deterministic) path losses, and statistics of shadowing and small-scale fading can be collected and used [7]. Capitalizing on the fact that CR-to-CR and PU-to-CR channel gains can be approximated by log-normal random variables (see [7] and references therein), and exploiting the Fenton-Wilkinson method [8], the distribution of SINRs $\{\gamma_{n\to i}\}$ can be well-approximated as log-normal too, with mean and variance function of the (known) first and second moments of $\{g_{n\to i}\}$ and $\{\pi_s\}$ [7].

Let $\Gamma_{n\to i} := 10\log_{10}\gamma_{n\to i}$ denote the SINR of link $U_n \to U_i$ expressed in dB. Using the Fenton-Wilkinson method, $\Gamma_{n\to i}$ is approximated as Gaussian distributed. Let $P_n + m_{n\to i}$ and $\sigma^2_{n\to i}$ be the mean and variance of $\Gamma_{n\to i}$, with $P_n := 10\log_{10} p_n$. Then, the probability that a packet transmitted from the n-th node U_n is correctly received by user U_i can be expressed as

$$\begin{aligned} r_{n\to i} &= \prod_{j\in\mathcal{I}_{ni}}(1-\mu_j)\cdot \Pr\{\gamma_{n\to i} > \bar{\gamma}_{n\to i}\} \\ &\approx \prod_{j\in\mathcal{I}_{ni}}(1-\mu_j)\cdot Q\left(\frac{\bar{\Gamma}_{n\to i} - P_n - m_{n\to i}}{\sigma_{n\to i}}\right) \end{aligned} \tag{3}$$

where $Q(x) := \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}\mathrm{d}x$ is the standard Gaussian tail function, $\bar{\gamma}_{n\to i}$ is the SINR threshold, and $\bar{\Gamma}_{n\to i} := 10\log_{10}\bar{\gamma}_{n\to i}$.

To complete the formulation, consider N_R actual/potential PU receivers, whose locations have been estimated via sensing [5], and let $\iota_R^{\max}$ denote the maximum average interference that can be tolerated by PU receiver R. Approximate the channel gain $g_{n\to R}$ between CR U_n and the PU receiver R as log-normal [7], and define a binary random variable $a_n \in \{0,1\}$, independent of $g_{n\to R}$, that takes the value 1 with probability μ_n. Then, supposing incoherent superposition of CR waveforms, the average interference experienced at PU R is given by ($\kappa := 0.1\ln(10)$)

$$\mathbb{E}\left\{\sum_{n=1}^{N} a_n p_n g_{n\to R}\right\} = \sum_{n=1}^{N}\mu_n e^{\kappa P_n + \kappa m_{n\to R} + \frac{\kappa^2}{2}\sigma^2_{n\to R}} \tag{4}$$

and it must not exceed $\iota_R^{\max}$.

Let $u(\{\rho_n\})$ be a concave function of the arrival rates, and $c(\{P_n\})$ a convex function of the transmit-powers. Then, with the statistical description of SINRs, and CR-to-PU channel gains available, the *statistical* routing problem can be formulated as:

$$\text{(P1)} \quad \max_{\substack{\{P_n\},\{\rho_n\geq 0\},\{\mu_n\geq 0\},\\ \{t_{n\to i}\geq 0\},\{\lambda_n\geq 0\}}} \; u(\{\rho_n\}) - c(\{P_n\}) \tag{5a}$$

$$\text{subject to } \rho_n \leq \lambda_n \sum_{j\in\mathcal{N}_{n\to}} t_{n\to j} r_{n\to j} - \sum_{i\in\mathcal{N}_{\to n}} \lambda_i t_{i\to n} r_{i\to n}, \quad n = 1,\ldots,N \tag{5b}$$

$$\sum_{i\in\mathcal{N}_{n\to}} t_{n\to i} \leq 1, \quad n = 1,\ldots,N \tag{5c}$$

$$\lambda_n \leq \mu_n, \quad \mu_n \leq 1, \quad n = 1,\ldots,N \tag{5d}$$

$$P_n \leq P_n^{\max}, \quad n = 1,\ldots,N \tag{5e}$$

$$\iota_R^{\max} \geq \sum_{n=1}^{N}\mu_n e^{\kappa P_n + \kappa m_{n\to R} + \frac{\kappa^2}{2}\sigma^2_{n\to R}}, \quad R = 1,\ldots,N_R \tag{5f}$$

with $\{r_{i\to n}\}$ given by (3), $P_n^{\max} := 10\log_{10} p_n^{\max}$.

The non-convexity of (5b) and (5f) makes problem (P1) non-convex and, thus, hard to solve optimally. Furthermore, function $Q(\cdot)$ is difficult to handle in an optimization problem. In the ensuing section, an approximate version of (P1) will be formulated that can be solved efficiently. Before doing so, it is possible to show that if $u(\{\rho_n\})$ is a component-wise non-decreasing function, then (P1) can be solved by setting $\{\lambda_n = \mu_n\}$ in the argument function to be optimized [3]. As many practical utilities (e.g., sum-of-rates, or max-min rate) satisfy this condition, $u(\{\rho_n\})$ will be hereafter assumed component-wise non-decreasing, and variables $\{\lambda_n\}$ will be dropped.

3. TRACTABLE ROUTING PROTOCOL

To convexify (5f) it suffices to perform the logarithmic change of variables $\tilde{\mu}_n := \ln(\mu_n)$. As for (5b), consider first introducing auxiliary variables $\{\nu_n\}$ representing the probability of CRs to remain silent, together with the extra constraints $\mu_n + \nu_n = 1$, $n = 1,\ldots,N$. Further, a simple way to obtain a tractable approximation of $Q(x)$ consists in using its upper and lower bounds which exhibit appreciable tightness for $x > \sqrt{2}/2$; see e.g., [9] and [10].

Taking advantage of these bounds, and letting $\tilde{\nu}_n := \ln(\nu_n)$, the pairwise decoding probability $r_{n\to i}$ can be (tightly) bounded as

$$e^{\sum_{j\in\mathcal{I}_{ni}}\tilde{\nu}_i}\cdot\left(1-\frac{1}{12}e^{-\frac{1}{2}\left(\frac{P_n+m_{n\to i}-\bar{\Gamma}_{n\to i}}{\sigma_{n\to i}}\right)^2}\right.$$
$$\left.-\frac{1}{4}e^{-\frac{2}{3}\left(\frac{P_n+m_{n\to i}-\bar{\Gamma}_{n\to i}}{\sigma_{n\to i}}\right)^2}\right)\le r_{n\to i} \quad (6)$$

$$r_{n\to i}\le e^{\sum_{j\in\mathcal{I}_{ni}}\tilde{\nu}_i}\cdot\left(1-\alpha_1 e^{-\alpha_2\left(\frac{P_n+m_{n\to i}-\bar{\Gamma}_{n\to i}}{\sigma_{n\to i}}\right)^2}\right) \quad (7)$$

with $\alpha_1 = 0.28$, $\alpha_2 = 0.64$ [10], and where equality $Q(x) = 1-Q(-x)$ was used. The premise for adopting the aforesaid bounds is that the decoding rate of CR links is at least 0.7. This condition is conceivably satisfied in practice if CRs and PUs are sufficiently far apart; furthermore, minimum packet error rates required for data and speech transmissions are generally significantly lower [6].

Bounds (6) and (7) are then judiciously used in (5b). Specifically, the upper bound is utilized for the incoming traffic, and the lower bound for the outgoing flows. As (6)–(7) are tight, this approach not only ensures a tractability, but also does not sacrifice optimality of the outcoming rates. With $\tilde{t}_{n\to i} = \ln(t_{n\to i})$, and after introducing auxiliary variables $\{\check{y}_{n\to i} > \sqrt{2}/2\}$ and $\{\hat{y}_{n\to i} > \sqrt{2}/2\}$, (5b) can be approximated as

$$\rho_n+\sum_{i\in\mathcal{N}_{n\to}} e^{\tilde{\mu}_n+\tilde{t}_{n\to i}+\sum_{m\in\mathcal{I}_{ni}}\tilde{\nu}_m}\left(\frac{1}{12}e^{-\frac{1}{2}\hat{y}_{n\to i}}+\frac{1}{4}e^{-\frac{2}{3}\hat{y}_{n\to i}}\right)$$
$$+\sum_{j\in\mathcal{N}_{\to n}} e^{\tilde{\mu}_j+\tilde{t}_{j\to n}+\sum_{m\in\mathcal{I}_{jn}}\tilde{\nu}_m}-\sum_{i\in\mathcal{N}_{n\to}} e^{\tilde{\mu}_n+\tilde{t}_{n\to i}+\sum_{m\in\mathcal{I}_{ni}}\tilde{\nu}_m}$$
$$-\alpha_1\sum_{j\in\mathcal{N}_{\to n}} e^{\tilde{\mu}_j+\tilde{t}_{j\to n}+\sum_{m\in\mathcal{I}_{jn}}\tilde{\nu}_m-\alpha_2\check{y}_{j\to n}}\le 0 \quad (8)$$

with the auxiliary constraints

$$\sigma_{n\to j}(\hat{y}_{n\to j})^{\frac{1}{2}}\le P_n+m_{n\to j}-\bar{\Gamma}_{n\to j} \quad (9)$$
$$\sigma_{i\to n}(\check{y}_{i\to n})^{\frac{1}{2}}\ge P_n+m_{i\to n}-\bar{\Gamma}_{i\to n}. \quad (10)$$

Using (8)–(10), problem (P1) can then be re-formulated as

$$\text{(P2)}\quad \max_{\substack{\{P_n\in\mathbb{R}\},\{\rho_n\ge 0\},\\ \{\tilde{\mu}_n\le 0,\tilde{\nu}_n\le 0\},\{\tilde{t}_{n\to i}\le 0\},\\ \{\check{y}_{n\to j},\hat{y}_{i\to n}\ge\sqrt{2}/2\}}} u(\{\rho_n\})-c(\{P_n\}) \quad (11a)$$
$$\text{subject to}\ \sum_{i\in\mathcal{N}_{n\to}} e^{\tilde{t}_{n\to i}}\le 1,\qquad n=1,\dots,N \quad (11b)$$
$$e^{\tilde{\mu}_n}+e^{\tilde{\nu}_n}\le 1,\qquad n=1,\dots,N \quad (11c)$$
$$P_n\le P_n^{\max},\ n=1,\dots,N \quad (11d)$$
$$\sum_{n=1}^{N} e^{\tilde{\mu}_n+\kappa P_n+\kappa m_{n\to R}+\frac{\kappa^2}{2}\sigma^2_{n\to R}}\le \iota_R^{\max},\ \ R=1,\dots,N_R \quad (11e)$$
$$\text{and}\ \ (8),(9),(10).$$

Constraints (8) are still non-convex because the last two sums (with their signs) are concave, and likewise (9) is also concave. Nevertheless, the structure of (P2) allows convex approximation methods for obtaining its solution efficiently. Among candidate methods, the successive convex approximation approach [11] is well-suited for the problem at hand because it guarantees first-order KKT optimality. Before delineating the solver for (P2), two remarks are in order.

Remark 1. From problem (P2), the *next-hop* routing probabilities are obtained. Conditions ensuring that packets are eventually delivered to the sink when routes, MAC, and physical layer parameters are either fixed or regularly updated are established in [3, 12]. □

Remark 2. The proposed routing framework can be considered also for conventional multi-hop random access networks when node-to-node channels can not be estimated accurately. Optimal routes and link reliabilities can be obtained by solving (P2), after discarding the interference constraints (11e), and re-defining the signal-to-noise ratio (SNR) of link $U_n \to U_i$ as $\gamma_{n\to i} = p_n g_{n\to i}/\sigma_i^2$. □

3.1. KKT solution via successive convex approximation

The general successive convex approximation method is outlined first. Suppose that the objective function to be maximized is concave in the optimization variables $\{x_n\}$, and the constraint set is the intersection of a set $\mathcal{C} := \{\{x_n\}|f_k(\{x_n\})\le 0, k=1,\dots,K\}$ with a convex set $\mathcal{B}$, which captures convex constraints, if any. Assume that $f_k(\{x_n\})$, $k=1,\dots,K$, are differentiable but generally non-convex functions. Then, starting from a feasible point $\{x_n^0\}\in\mathcal{C}\cap\mathcal{B}$, a series $\ell = 1,\dots,$ of surrogate problems is solved, where $\mathcal{C}$ is substituted per iteration ℓ by a convex set $\mathcal{C}^\ell$. Since the intersection of convex sets yields a convex set, the resulting optimization problems are convex. For each $k=1,\dots,K$, let $\tilde{f}_k(\{x_n\};\{x_n^{(\ell)}\})$ denote the surrogate convex function for $f_k(\{x_n\})$, which may depend on the solution $\{x_n^{(\ell)}\}$ to the problem of the previous $(\ell-1)$-st iteration. Then, the convex set $\mathcal{C}^{(\ell)}$ is constructed as $\mathcal{C}^{(\ell)} := \{\{x_n\}|\tilde{f}_k(\{x_n\};\{x_n^{(\ell)}\})\le 0, k=1,\dots,K\}$. Provided that each function $\tilde{f}_k(\{x_n\};\{x_n^{(\ell)}\})$, $k=1,\dots,K$, is convex, differentiable, and satisfies conditions

c1) $f_k(\{x_n\})\le\tilde{f}_k(\{x_n\};\{x_n^{(\ell)}\}),\quad \forall\{x_n\}\in\mathcal{C}^{(\ell)}\cap\mathcal{B}$

c2) $f_k(\{x_n^{(\ell)}\})=\tilde{f}_k(\{x_n^{(\ell)}\};\{x_n^{(\ell)}\})$, and

c3) $\nabla f_k(\{x_n^{(\ell)}\})=\nabla\tilde{f}_k(\{x_n^{\ell}\};\{x_n^{(\ell)}\})$

the series of solutions to the approximate problems converge to the KKT point of the original problem [11].

In order to apply the successive convex approximation method to (P2), appropriate surrogate constraints for the non-convex constraints must be determined. The first three terms (8) are convex, whereas the fourth and fifth terms are concave. Without loss of generality, let $-e^{x_1+\beta x_2-\alpha x_3}$ represent one of the non-convex summands. Then, a convex surrogate function satisfying c1)-c3) can be obtained by substituting the non-convex summands with the affine function

$$-e^{x_1+\beta x_2-\alpha x_3}\le e^{x_1^{(\ell)}+\beta x_2^{(\ell)}-\alpha x_3^{(\ell)}}$$
$$\cdot\left[(x_1^{(\ell)}-x_1)+\beta(x_2^{(\ell)}-x_2)-\alpha(x_3^{(\ell)}-x_3)-1\right]. \quad (12)$$

As for constraints (9), an upper-bound of $\sqrt{\hat{y}_{n\to j}}$ can be obtained via the supporting hyperplane as

$$\sqrt{\hat{y}_{n\to j}}\le\frac{(\hat{y}_{n\to j}-\hat{y}^{(\ell)}_{n\to j})}{2\sqrt{\hat{y}^{(\ell)}_{n\to j}}}+\sqrt{\hat{y}^{(\ell)}_{n\to j}}. \quad (13)$$

Overall, the problem to solve in the ℓ-th iteration is given by (P2) with (12) replacing the non-convex terms in (8), and with (9) replaced by its convex surrogate (13). The problem is convex, and thus efficiently solvable via optimized interior-point methods.

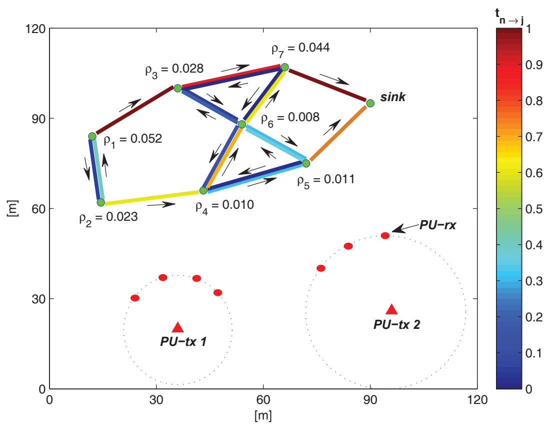

Fig. 1. Optimal routing probabilities $\{t_{n\to i}\}$.

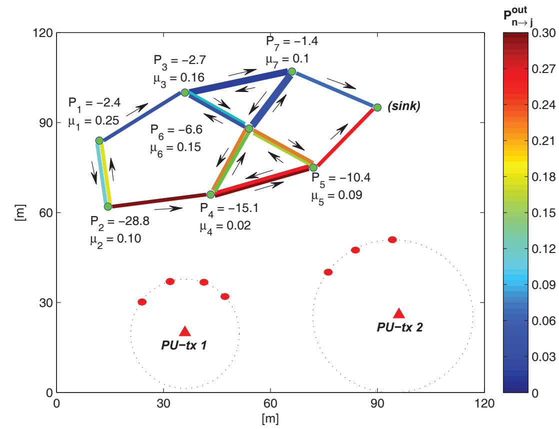

Fig. 2. Outage probabilities.

4. NUMERICAL RESULTS

Consider the scenario depicted in Fig. 1, where $N = 7$ CR nodes route packets to the destination U_8. Black arrows indicate link directions. Two PU sources also transmit and, to protect the PU system without knowing the locations of the PU receivers, 7 points on the boundary of the PUs' coverage regions are selected. The path loss obeys the model $d_{n\to i}^{-\eta}$, with $\eta = 3.5$, and $d_{n\to i}$ the distance between nodes U_n and U_i; $m = 1$ is used for Nakagami-m fading, and log-normal shadowing is generated with mean 0 and standard deviation 6 dB. The maximum transmit-power is $P_n^{\max} = 0$ dBW, the noise power 10^{-8} W, and the SINR threshold $\bar{\Gamma}_n = -10$ dB. The interference threshold is set to -80 dBW, and $u(\{\rho_n\}) = \sum_n \rho_n$ and $c(\{P_n\}) = 0$ were used.

Fig. 1 depicts the optimal routing probabilities $\{t_{n\to i}\}$, along with the exogenous traffic rates. It can be seen that there is a tendency not to route packets through the "southern" region of the network; i.e., through nodes that are closer to the PU systems. For example, packets generated by U_2 are more likely to be routed through links $U_4 \to U_6$ and $U_6 \to U_7$, rather than through the shortest path $U_2 \to U_4 \to U_5 \to U_8$. Furthermore, U_2 may decide to transmit to U_1 instead of U_4 with considerably high probability. Node U_5 may decide to send packets to U_6 rather than attempting direct transmission to U_8. This is because links starting from and ending to U_4 and U_5 are characterized by a higher fading- and interference-induced outage probability, as showed in Fig. 2. This is due not only to the detrimental effect of PU interference on the SINRs, but also because U_2, U_4, and U_5 are confined to use a lower transmit-power in order to protect the PU receivers from harmful interference. As expected, packets generated by U_1 are routed through U_3 and U_7 with high probability, which in this case coincides also with the shortest path.

Distributed algorithms for the statistical routing approach, and analysis of packet deliverability for time-varying channel statistics and network topologies can be found in [12].

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