Probabilistic Path Selection in Opportunistic Cognitive Radio Networks

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***Abstract*—We present a novel routing approach for multi-channel cognitive radio networks (CRNs). Our approach is based on probabilistically estimating the available capacity of every channel over every CR-to-CR link, while taking into account primary radio (PR). Our routing design consists of two main phases. In the first phase, the source node attempts to compute the *most probable path* (MPP) to the destination (including the channel assignment along that path) whose bandwidth has the highest probability of satisfying a required demand D. In the second phase, we verify whether the capacity of the MPP is indeed sufficient to meet the demand at confidence level δ. If that is not the case, we judiciously add channels to the links of the MPP such that the augmented MPP satisfies the demand D at the confidence level δ. We show through simulations that our protocol always finds the best path to the destination, achieving in some cases up to 200% improvement in connection acceptance rate compared to the traditional Dijkstra.**

I. Introduction

A recent report by the FCC [1] challenges for the first time the common belief of spectrum scarcity by indicating that at any given time and in any geographic locality, less than 10% of the available spectrum is being utilized. To exploit under-utilized portions of the spectrum (a.k.a, *white spaces*, *spectrum holes*, etc.), the report advocates the need for a new generation of smart, programmable radios that are capable of interference sensing, environment learning, and dynamic spectrum access. These so-called *cognitive radios* (CRs) have recently been the forefront of wireless communications research (see [2] for a survey). They promise to provide reliable and programmable wireless communications as well as efficient (adaptive) sharing of the radio spectrum.

Numerous efforts have focused on defining the design guidelines and operating constraints of CR networks (CRNs). First, CR transmissions should not noticeably degrade the reception quality of primary radios (PRs). This can be achieved by adapting the transmission power of CR nodes. Second, a CR node should immediately interrupt its transmission whenever a neighboring PR activity is detected. This requires frequent monitoring of the PR activities.

Much of the research on CRN protocols has dealt with the MAC and physical layers (e.g., [3], [4]). Optimizing these two layers without consideration to the routing protocol (the network layer) can lead to sub-optimal solutions at best. For example, an optimized MAC protocol may provide the best channel/power/rate assignment for a particular link, but such an assignment can be quite inefficient when considering the end-to-end path of the flow.

In this paper, we investigate a routing design for a multi-hop CRN that coexists geographically with several PR networks (PRNs). The problem at hand exhibits similarities with routing in multi-channel, multi-hop ad hoc and mesh networks, but with the added challenges of having to deal with simultaneous transmissions over multiple channels and with PR-to-CR interference. By definition, the operation of a CRN should be transparent to coexisting PRNs, so no feedback from or control over the PRNs can be expected. The need to interrupt CR transmissions whenever a PR activity is detected further complicates the routing design, which now has to aim at determining the most *stable* route. Route stability can be indirectly achieved by maximizing the likelihood of meeting the rate demand of the CR flow and by operating multiple parallel channels over a CR link.

In our work, we introduce a novel routing metric that is based on a probabilistic definition of the available capacity over a channel. This definition relies on the probability distribution of the PR-to-CR interference at a given CR node over a given channel, which was shown in [5] to approximately follow a lognormal distribution. This distribution accounts for the activity of PR users and their random deployment. Our routing metric is used to determine the most probable path (MPP) to satisfy a given bandwidth demand D. The MPP is not guaranteed to satisfy the demand D, so an augmentation phase is used whereby "bottleneck" links are augmented with additional channels such that the resulting path meets the demand D with a given probability (confidence level) δ.

The remainder of the paper is structured as follows. In Section II, we present the probabilistic routing metric and the capacity estimation technique, and we describe the path selection algorithm. Performance evaluation through ns-2 simulations and numerical results is provided in Section III. In Section IV, we overview related work in this domain. Conclusions are given in Section V.

II. Protocol Description

A. Routing Metric

We consider an opportunistic CRN of N nodes that operates over a maximum of M orthogonal frequency bands (channels) of respective bandwidths $W_1, \ldots, W_M$ (in Hz). Each band is licensed to a given PRN. The distribution of PRs in the ith PRN follows a 2D Poisson process of rate (node density) ρ_i. Each node in this PRN is active with probability α_i. Let $P_{I,j}^{(i)}$ be the total PR-to-CR interference at CR node j over channel i, where $i = 1, \ldots, M$ and $j = 1, \ldots, N$. In [5], the authors showed that the distribution of $P_{I,j}^{(i)}$ is approximately lognormal, with mean and variance μ_i and σ_i (which depend on ρ_i and α_i). We adopt the same model of [5] in our work.

Consider a CR node j that receives data from CR node k over channel i. The maximum channel capacity $C_{kj}^{(i)}$ is given by Shannon's Theorem:

$$C_{kj}^{(i)} = W_i \log_2 \left[1 + \frac{P_{r,j}^{(i)}}{N_0 + P_{I,j}^{(i)}} \right] \tag{1}$$

where N_0 is the power of the white Gaussian noise and $P_{r,j}^{(i)}$ is the power of the received signal. The value of $P_{r,j}^{(i)}$ was computed in [5] such that a certain outage probability (at the MAC layer) can be guaranteed for PR users. It depends on ρ_i's and α_i's, the maximum transmission range for a CR node, and the link margin of the PRNs.

For a given CR connection request of rate demand D (in bits/second), the probability that channel i can support this demand is given by:

$$\Pr[C_{kj}^{(i)} \geq D] = \Pr \left[P_{I,j}^{(i)} \leq \frac{P_{r,j}^{(i)}}{2^{D/W_i} - 1} - N_0 \right] \tag{2}$$

As stated earlier, we assume that $P_{I,j}^{(i)}$ follows a lognormal distribution. Our analysis, however, is equally applicable to any distribution. The probability in (2) can be obtained for every channel of every link by calculating the CDF of the lognormal distribution of the PR-to-CR interference. We then define weight of the link between nodes k and j on channel i as:

$$l_{kj}^{(i)} \stackrel{\text{def}}{=} -\log \Pr[C_{kj}^{(i)} \geq D + U^{(i)}] \tag{3}$$

where $U^{(i)}$ is the system memory that accounts for the cognitive interference in the vicinity of nodes k and j. The details of how $U^{(i)}$ is determined is described later in the text.

Note that even though we rely on an idealized model (Shannon's formula) for the capacity calculations, such a model is sufficient for the purpose of *contrasting* routes. Moreover, we believe our approach is general enough to be adapted to other capacity estimators, which is a topic reserved for future research.

B. Estimating Capacity

A key contribution of our work is the way we estimate the available capacity of every channel. Our metric classifies channels based on the probability that their capacities is greater than D (equation (2)), without being able to determine the exact capacity. Therefore, a tool for estimating the capacity is needed. Because (1) gives the capacity distribution over a channel, it is possible to estimate the achievable capacity of a channel at a fixed probability δ, where $\delta < 1$. More precisely, for every channel i of every link (k, j), we calculate the capacity $X_{kj}^{(i)}$ that such a channel can support with probability δ (e.g., $\delta = 0.9$). This can be done by setting $\Pr[C_{kj}^{(i)} > X_{kj}^{(i)}] = \delta$ and solving for $X_{kj}^{(i)}$:

$$\Pr \left[W_i \log_2 (1 + \frac{P_{r,j}^{(i)}}{N_0 + P_{I,j}^{(i)}}) > X_{kj}^{(i)} \right] = \delta \tag{4}$$

The parameter δ is a tunable parameter, and represents the target reliability level. It can be used to support different degrees of tolerance to rate variations. For example, elastic applications with rate-adaptive capability may select a small value of δ, allowing the network to achieve a high call admission rate.

In addition to incorporating various CRN-specific aspects, capacity calculations for an end-to-end route must also account for channel contention issues. In fact, the capacity calculated at a node j over channel i will definitely be reduced if one of its neighboring nodes is transmitting over the same channel. Estimating the total capacity in wireless mesh and ad hoc networks is known to be a challenging problem, and various solutions have been advocated for it. In our work, we adapt a simple and intuitive solution, whereby the capacity of a channel is split equally among active neighboring nodes that contend for the same channel. Hence, the estimated capacity over every link includes the CR interference coming from other CR transmissions (see lines 12–14 and 22–24 in Algorithm 1).

C. Path Selection Algorithm

We propose a source-based routing protocol for CRNs. As in many other studies (e.g., [6]), coordination between nodes is achieved through a low-bandwidth control channel[1]. The most-probable path selection algorithm will be initiated by the source node whenever an application requests a route to a destination with a rate demand D. The source node acquires information about other nodes through link state advertisements over the control channel. These advertisements include: *i)* the direct CR neighbors, *ii)* the interference from PR nodes ($P_{I,j}^{(i)}$ mean and variance), *iii)* the $P_{r,j}^{(i)}$ (measured at receivers), and *iv)* the occupancy rate of observed channels $U^{(i)}$ (explained later). First, the link probabilities on all channels are calculated according to (2). Once all link weights are calculated, the source runs a path selection algorithm to find a route to the destination. In our case for instance, we use a $-\log$ operation on the probability to obtain increasingly ordered link weights (i.e., the smallest weight refers to the highest probability) then run a Dijkstra-like algorithm to find a path (lines 1 to 8 in Algorithm 1).

[1] The problem of conveying control information without an assigned control channel is interesting by itself, but is beyond the scope of our work.

The MPP can be considered as the most probabilistically stable path to the destination. However, there is no guarantee that the capacity it can carry satisfies the demand. Consequently, the source computes the available capacity on every link of the MPP with probability δ, calculated using (4), as a simple *indicator* of the achievable capacity over every link. If the calculated capacity X plus the accounted cognitive interference is smaller than the demand, then the link is augmented with another channel. In fact, the algorithm will look for the *next most probable* channel between nodes where the $X^{(i)}$ (to which we add the CR interference) is not larger than the demand along the already discovered single path. This process is repeated until the cumulated capacity on several channels becomes greater than D. We call this mechanism the path augmentation. It is shown in lines 17 to 27 of Algorithm 1. The algorithm terminates only if one of the following two states is reached: *i)* On every link of the MPP, the total capacity (that is the sum of calculated available capacities on every channel) is greater than the demand, and *ii)* the total estimated capacity between two nodes on all channels (i.e., after augmentation) does not satisfy the demand. In the second case, the destination is declared unreachable.

To ensure that the computation of the link probability is accurate, it is important to update the amount of available capacity on every channel after a new demand is accepted. For this reason, we maintain the variable $U_{kj}^{(i)}$ per channel on every link (where k and $j = 1, \ldots, N$) that accounts for all already accepted demands within an area of radius $R_j^{(i)}$ around the CR node (lines 15 and 25 of the algorithm). In fact the probability we calculate, is the probability that the capacity over a specific channel is greater than the arriving demand added to all the already accepted ones ($U^{(i)}$). Thus we ensure that a new arriving CR connection does not affect already accepted ones in the previous rounds and accounts for the accepted demands in former nodes in the present round. Moreover, including $U^{(i)}$ in the probability computation pushes naturally the algorithm to use different frequencies on consecutive nodes, thus decreasing interference and increasing the end-to-end capacity.

Note also that the MPP includes implicitly the choice of the set of channels to be used from the source to the destination.

Algorithm 1 Most Probable Path Selection Algorithm

1: Demand D at the source
2: INPUTS:$P_{I,j}^{(i)}$, $P_{r,j}^{(i)}$, $U^{(i)}$
3: **for** j=0 to N **do**
4: **for** i=0 to M **do**
5: l_j^i = -log($Pr[C_j^{(i)} > D + U_j^{(i)}]$)
6: **end for**
7: **end for**
8: Path = Run Path Selection (N_{Source}, N_{Dest}, $l_j^{(i)}$)
9: **if** Path **then**
10: **for** j in Path **do**
11: c in E_j //used channel per node
12: Compute $X_{kj}^{(c)}$
13: F=getCRinterference($l_j^{(c)}$)
14: $Alloc_j^{(c)}$ = $X^{(c)}/F$
15: $U_j^{(c)}$ += $Alloc_j^{(c)}$
16: **end for**
17: **for** j in Path **do**
18: $Residual_j$=D
19: **while** $Alloc_j < Residual_j$ and for all $i \notin E_j$ **do**
20: $Residual_j$ = $Residual_j$ - $Alloc_j$
21: l_j = -log($Pr[C_j > D + U_j]$)
22: augmentation with $l_j^{(n)}$ // next probable path
23: Compute $X_{kj}^{(n)}$
24: F=getCRinterference($l_j^{(n)}$)
25: $Alloc_j^{(n)}$ = $X^{(n)}/F$
26: $U_j^{(n)}$ += $Alloc_j^{(n)}$
27: n in E_j
28: **end while**
29: **if** ALL $\sum Alloc_j >$ Demand **then**
30: return Path //to encapsulate in packets header
31: **else**
32: U_j -= $Alloc_j$ //remove demands of this round
33: return NULL
34: **end if**
35: **end for**
36: **else**
37: return NULL
38: **end if**

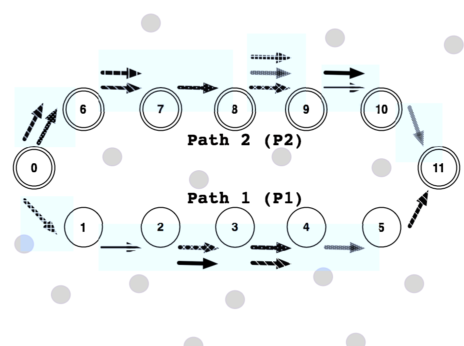


Fig. 1. Two simulated topologies showing the two paths from node 0 to node 11. Path 1 (P1) goes through node 1 while Path 2 (P2) through node 6

III. Performance Evaluation

We study in this part the performance of our routing algorithm. All simulation results are obtained with an adapted version of the ns-2 simulator, whereas numerical results come from an implementation of Algorithm 1 written in C. Our algorithm implementation allows different numbers of nodes and topologies, with tunable CR parameters.

A. Metric Validation

To evaluate the appropriateness of the probabilistic capacity metric, we simulate the scenario in Figure 1, where two paths are available from the source node (node 0) to the destination (node 11). We aim to show in this part that the MPP algorithm is able to satisfy the capacity demand and gives the best performance compared to other possible routes.

The simulated CRN is assumed to use a CSMA/CA like MAC access (IEEE 802.11b protocol), whereas the PRN uses CDMA-like access. This seems to be the most common configuration for upcoming CRNs. For more details about the ns-2 design refer to [7]. Every path has a different PR node density ρ, that we modify their activity factor α in a way to change the total path probability. We compute the transmission power of every CR node accordingly. Each path uses a single channel and is simulated separately to estimate the end-to-end capacity for different path probabilities. In Figure 2, we plot the obtained end-to-end capacity distribution for the two paths under different values for α(0.1 and 0.5). Numerical results based on the lognormal distribution approximation of the PR-to-CR interference with the same ρ and α when the capacity demand is 256 Kbits/s are shown in Table I. Numerically, for every density and for every activity, we compute the probability that the capacity at each CR node is greater than 256 Kbits as well as the smallest estimated capacity X over the path (without CR interference).

As expected, the most probable path obtained in Table I gives the best end-to-end results. This is the path that goes through nodes 6-7-8-9-10 (P2) with $\alpha = 0.1$. Concerning the capacity, if we apply the previously stated heuristic of dividing the capacity by the number of competing nodes, the most probable path should yield around 1 Mbits/s. The same remarks apply to the worst path (i.e., P1 with $\alpha = 0.1$).

TABLE I
SOME NUMERICAL RESULTS ON THE MOST PROBABLE PATH AND THE OTHER POSSIBLE PATH

Path	ρ	α	$\sum \Pr$	smallest X(Kbits/s)
P1	4	0.1	0.98	2,104
P1	4	0.5	0.91	387
P2	2	0.1	0.99	3,100
P2	2	0.5	0.96	641

Note also that in Figure 2, the classification of paths based on their achievable capacities corresponds to their probability decreasing order in the numerical results. Indeed, we can clearly see that P2 with $\alpha = 0.5$ is worse than P1 with an $\alpha = 0.1$. This is also confirmed in the numerical results of Table I, where the total probability on P1 with $\alpha = 0.1$ is greater than the probability of P2 with $\alpha = 0.5$.

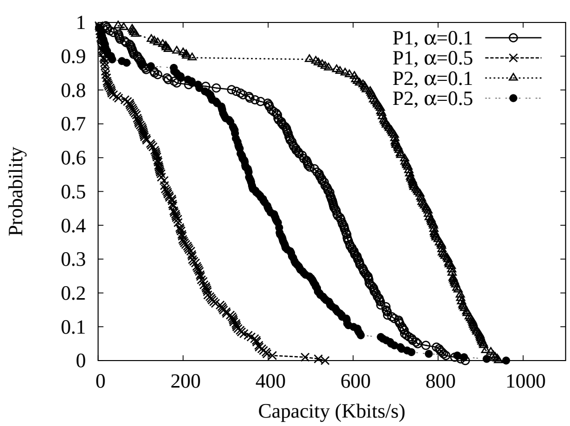


Fig. 2. The distribution of the end-to-end capacity on two separate path of a fixed density $\rho^{(i)}$ and $\rho^{(j)}$ while modifying α the activity factor of the primary nodes.

B. Augmentation Gain

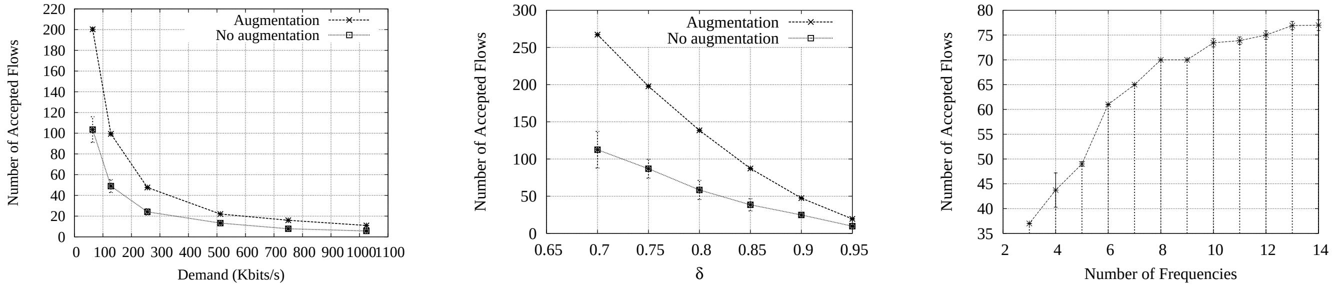
To evaluate the gain added by using the augmentation techniques on the links where the capacity is smaller than the demand, we numerically study the number of accepted connections when our algorithm is used and compare it with Dijkstra's algorithm. In the latter case, the algorithm continues to select the most probable paths until a channel capacity becomes smaller than D (i.e., it is our algorithm minus the augmentation technique). Figures 3(a) and 3(b) plot the number of accepted CR connections for different demands and target levels of reliability. They are obtained from a twenty-node scenario with five usable channels. Every point is a result of twenty runs with randomly generated topologies between the source and the destination in a 800m x 800m region.

If the augmentation is not used, the algorithm stops when a most probable channel cannot carry the demand anymore, hence the total connections accepted by the system will be fewer than the case when residual capacities are exploited on frequencies that cannot carry the whole demand. This is confirmed for different application demands (Figure 3(a)) and also while varying the probability δ that rules the allocated capacity over a link (Figure 3(b)). It is also important to note that when the demand is bigger we clearly accept less connections and notice a decrease in the obtained gain. This is due to the fact that splitting a *large* demand over multiple residual channels reduces the number of accepted connections compared to the case where D is small and can be easily divided over fewer channels. These important results prove the efficiency of our routing algorithm that enables communications on usually unusable networks. More generally, this can be viewed as a strong argument for pushing CRNs into real deployment since the gain we obtain while using residual channels reaches 200% in some cases.

Figure 3(c) studies the effect of the number of usable channels on the accepted connections when the augmentation technique is employed. We study realistic network scenarios using up to 14 simultaneous channels that may be made possible today with IEEE 802.11b/g technologies if the available channels were completely orthogonal. The gain grows linearly and surprisingly stabilizes after 10 channels. We believe that this observation might be due to the fact that augmentation gain happens in stages. In other words, the gain might stabilize in a stage going from 10 channels to 14, then restart increasing with the beginning of a new stage with 15 channels for instance, until stabilizing again. We intend to investigate this aspect in our future work.

IV. RELATED WORK

Some routing techniques for cognitive radio networks already exist. In [6], an on-demand routing and spectrum assignment for CRN is presented. The authors propose a routing metric based on the sum of delays of the switching time in every node and the delay incurred by the capacity of every channel (without considering the existence of PR nodes). However, the proposition does not model how the Primary nodes can affect routing. Sharma et *al.* propose in [8] a new routing metric for multihop cognitive networks based on the interference temperature model. It is unclear in this work how the temperature interference can be estimated at every PR receiver and more generally how the interaction between



(a) (b) (c)

Fig. 3. The number of accepted connections for different D in (a), reliability levels (δ) in (b) with and without augmentation, and the number of used channels with augmentation (c).

PR and CR can be achieved. Authors in [9] present a routing solution which is close to the one used in multi-channel mesh networks, while in [10], a routing protocol is proposed based on a layered graph model. Even if the solution is specific to CRNs, it does not clearly account for the possible dynamic changes of the network. Same remarks apply on [11], where the proposed routing is only based on the actual state of the network topology and can hardly follow the evolution of the network when the load of cognitive connections varies.

Our work differs from previous proposals in two aspects: first, by presenting a probabilistic routing metric able to capture the dynamics of the network, and second, in incorporating the metric in a routing protocol that tackles all the design and architectural issues of a CRN implementation.

V. Conclusion and Future Work

In this paper we have presented a novel routing protocol for CRNs that employs a probabilistic metric. CRNs have specific properties, consequently, routing in this particular environment should be designed in a way to ensure routes stability and availability. On the one hand, the proposed routing metric is able to capture effectively, through probabilistic calculation, the specific constraints imposed on a cognitive node by the activity and the density of the primary nodes. On the other hand, the protocol algorithm favors the use of multiple frequencies between two communicating CR nodes, which is an important feature of Cognitive Radio environments. Through ns-2 simulations and numerical results, we have validated the efficiency of our algorithm by showing that it always selects, as expected, the most probable path to the destination. This path yields the best performance in terms of throughput. We have further shown that the augmentation technique allows for considerable gains in terms of number of accepted connections. More surprisingly, the number of accepted connections grows linearly with the number of used frequencies then stabilizes after a certain threshold. This might be an interesting result to investigate in designing CRNs, since it allows to limit the number of used frequencies while having optimal performance.

In our future work, we aim to study real licensed users data in order to extract measurement information about primary nodes locations and behaviors. It is also important to study the interaction between the dynamics of the arrivals/departures of the connections and the dynamics of the cognitive networks. We believe that our metric is interesting to use in this case since it ”absorbs” already the dynamics of the network. Another important issue that has to be studied is the real impact on primary users. So far, we have assumed that the cognitive MAC protocol computes adequately its maximum transmission power that does not impact the primary transmission. However, the current simulators should be modified substantially to cohabit both primary and cognitive nodes with heterogeneous technologies.

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