Comparison of utility functions for routing in cognitive wireless ad-hoc networks

Anna Abbagnale
University of Rome, Sapienza
Via Eudossiana 18, 00184, Rome, Italy
abbagnale@infocom.uniroma1.it

Francesca Cuomo
University of Rome, Sapienza
Via Eudossiana 18, 00184, Rome, Italy
francesca.cuomo@uniroma1.it

Pierpaolo Salvo
University of Rome, Sapienza
Via Eudossiana 18, 00184, Rome, Italy
salvo@net.infocom.uniroma1.it

Abstract—In Cognitive Radio Ad-Hoc Networks [1] the design of suitable routing solutions is a focal issue to fully unleash the potentials of this networking paradigm. The main challenge is exploiting spectrum holes to build up network paths that remain stable and that achieve specific network performance in terms of delay and percentage of delivered data, even if an opportunistic spectrum access is implemented. In this paper we propose a utility function based on the path connectivity, re-elaborated in a cognitive radio scenario, and we compare it with other utility functions that can be used for routing data in cognitive radio. We show that by using our utility function we select paths for the secondary users transmissions leading to better performance when compared with a utility function that selects paths with the minimum activities of the primary users and an utility function that minimizes the number of hops. These results are derived in great number of topologies and with different primary users activities.

Index Terms—Cognitive radio, Ad-hoc networks, Routing

I. INTRODUCTION

In Cognitive Radio Networks (CRNs) there are two kinds of users: Primary Users (PUs) and Secondary Users (SUs). PUs are licensed users with high priority in the utilization of the spectrum; SUs instead are cognitive devices able to sense the spectrum and detect available channels to be used for transmission. Available channels are spectrum bands that can be used by SUs without interfering with relevant PUs. Based on their positions, SUs experience heterogeneity in spectrum availability, since the set of available channels might be quite different from node to node and might dynamically change over time and location due to PUs’ transmissions. The consequence is that the topology of a CRN is highly influenced by the presence and behavior of PUs, since two SUs can connected through a link, not only if they are in radio visibility relationship, but also if they have at least one available common spectrum band, named also channel in the following. Therefore, the network topology can change every time a PU activates or deactivates and this aspect has a significant impact on routing design. By analyzing the research in the field of routing for CRNs [2], in our previous work we defined a new routing scheme based on path connectivity [3]. The utility function identified in the work [3], named cognitive utility function \( U^c \), is here compared with other utility functions. The objective is to demonstrate that the path chosen by means of \( U^c \) obtains better performance, in terms of end-to-end delay and percentage of delivered data, if compared with paths selected by using an utility function that minimizes the number of hops and an utility function that selects paths with the minimum activities of the primary users. The paper is structured as follows. The considered scenario is described in Section II while the proposed utility function is presented in Section III. The analysis of the proposed solution is presented in Section IV. Finally Section V concludes the paper and sketches the future work.

II. SCENARIO DESCRIPTION

In this Section we describe the cognitive scenario used to test \( U^c \). We considered a so called underlay cognitive radio network where \( S \) SUs coexist with \( P \) PUs. Both SUs and PUs are assumed motionless. The secondary network is assumed to work in a multi-hop fashion: the secondary traffic is transferred via multi-hop routes. Each \( PU_p \) has a licensed access to a given spectrum band, denoted as channel \( Ch_p \). The number of different channels, i.e., of spectrum bands, is equal to \( P \). A PU is constituted by a Primary Transmitter (PT) and a set of Primary Receivers (PRs). The PT can model the base station of a GSM or UMTS network as well as the antenna of a TV broadcaster. The PRs are the end terminals of the PU network. Each PU is modeled with its relevant Coverage Area \( CA_p \) which represents the area where a PT or a PR is present: we consider the \( CA \) circularly shaped, centered in the PT and with radius \( r_{PU} \) that is the transmission range of the PT. Besides, we suppose that each \( PU \) is characterized by an ON-OFF transmission. We associate to each \( PU_p \) a binary aleatory variable, \( b_p \), that represents the activity state of the \( PU_p \), that is: \( 1 \) if the \( PU_p \) is active, and \( 0 \) otherwise. The expected value of the binary aleatory variable \( B_p \) is the average activity factor of \( PU_p \); \( \alpha_p = E[b_p] \). As for the secondary network, we suppose that each \( SU_s \) transmits with a given transmission range \( r_{SU_s} \), giving rise to SUs’ radio visibility relationships. We assume that the SUs are equipped with a cognitive radio device that can be tuned to the different channels in order to sense them, verify the availability and transmit/receive on them. We assume an ideal spectrum sensing able to measure the PUs activities on the different spectrum bands.
We also suppose that SUs can potentially use all the Ch_p channels, with p = 1, ..., P, but the coexistence of a SU with a PU must be assured by controlling that the SU’s transmission do not interfere any PR. A SU_s creates interference to PU_p when its transmission area overlaps, even if partially, CA_p; in fact, in this case SU_s can disturb a PR tuned on Ch_p. If this case occurs SU_s is inhibited from using Ch_p when PU_p is active, instead SU_s can opportunistically utilize Ch_p when PU_p is inactive.

### III. COGNITIVE UTILITY FUNCTION U_c BASED ON THE ALGEBRAIC CONNECTIVITY

In this Section we describe the **cognitive utility function** U_c that has been proposed in our previous work [3]. This utility function is based on measuring the degree of connectivity of a path and including into this measure the presence of the PUs. As for the first item we refer to the concept of **algebraic connectivity** defined in the graph theory. Given a graph G(S, E), where S (|S| = S) is the set of nodes and E is the set of edges established among nodes if only radio visibility relationships are taken into account, the algebraic connectivity is defined as the second smallest eigenvalue of the Laplacian matrix L(G) (λ_2(L(G))). The matrix L(G) is obtained as the difference between the Degree matrix D(G) and the Adjacency matrix k(G) of the graph G: L(G) = D(G) - k(G). We extended the definition of the Laplacian matrix since in a cognitive scenario the connectivity is influenced also by the reciprocal impact of PUs and SUs. We named this new model as **Cognitive Laplacian matrix**, indicated with L_c(G). In order to define this matrix we introduce the P × S Influence matrix I, that indicates for each SU_s which are the PUs that it interferes; the generic element r_p,s of this matrix is: 1 if dist(PU_p, SU_s) < r_p+ r_p,s, and 0 otherwise.

The matrix L_c(G) is built on the matrices L(G) and I(G). By computing the second smallest eigenvalue of L_c(G) we obtain an extended version of the algebraic connectivity that is function of PUs behavior expressed as an activity factor: we named this parameter **cognitive algebraic connectivity** (λ_2(L_c(G))). Details on the mathematical model for computing the λ_2(L_c(G)) are reported in the paper [4].

On the basis on these considerations, we exploited the cognitive algebraic connectivity to derive the **cognitive utility function** U_c associated to a path R. In particular we represent a path with a chain based graph (R), compute the L_c(R) and the relative λ_2(L_c(R)).

We associate to path R the **cognitive utility function** U_c(R) defined as:

\[
U_c(R) = \frac{\lambda_2(L_c(R))}{\lambda_2(L(R))} \cdot \frac{1}{H(R)} \quad (1)
\]

where \( \lambda_2(L(R)) \) is the algebraic connectivity when all the primary activity factors are equal to 0, that is when there are not PUs influencing nodes of the path R, and \( H(R) \) is the number of hops in the path R.

### IV. PERFORMANCE ANALYSIS

In this Section we compare the **cognitive utility function** U_c with other two utility functions: an utility function that chooses the path with the minimum number of hops, \( U_{hop} \), an utility function that only considers the activity of PUs, without taking into account the hop count, \( U_{activity} \) (in this case the selected path is the one characterized by the minimum overall activity). We named the routing scheme based on the utility function \( U_c \), \( U_{hop} \) and \( U_{activity} \), Gymkhana, minHop and minAct, respectively. We compare the performance of these three routing metrics, in terms of **packet delivery rate (PDR)** and **end-to-end packet delay** (end-to-end PD).

In all the three routing schemes we derived for all the paths in the given network the relative U. Gymkhana then selects the path with the greatest \( U_c \) while minHop and minAct select the path with the lowest \( U_{hop} \) and \( U_{activity} \), respectively.

#### A. COGnitive radio TOpology-COGTOP

In order to evaluate the performance of the three routing metrics, we implemented the COGTOP tool, that automatically generates the cognitive scenarios described in Section II.

After the generation of a cognitive topology, the COGTOP tool is able to derive all possible paths from a given source to a given destination and to simulate a traffic session in the secondary network which opportunistically accesses the channels when these are available as described in Section II.

The primary transmissions happen according to a Poisson process with given average activity factors for each PU (α_p), while the secondary traffic is simulated as CBR traffic between two end-points. The cognitive behavior of the secondary nodes is achieved by periodic sensing operation, performed asynchronously by each node in the path, in this way they dynamically select a channel based on the activity of the PUs. We also assume a collision and error free data link layer.

Simulations parameters are:

- \( P = C = 3 \), \( S = 20-50 \);
- \( r_{PU_p} = 300 \) m, \( r_{SU_s} = 100 \) m;
- \( α_p = 0.2 - 0.9 \);
- packet size = 3840 bits;
- bit rate CBR = links’ capacity = 60 Kbit/sec;
- buffer size = 75, 150, 300 packets.

#### B. Simulation Comparison

In this Section we show the results obtained by comparing the three routing schemes, Gymkhana, minAct and minHop.

In order to point out differences among Gymkhana, minAct and minHop, we consider one topology, shown in Figure 1(a), where there are 50 SUs and 3 PUs characterized by activity factors equal to 0.7, 0.5 and 0.4 and a buffer size equal to 150 packets. In this network topology we choose source and destination (indicated with Sx and Dx, respectively) and compare the performance of the three paths chosen by these routing metrics. As depicted in Subfigure 1(c), minHop selects the path with the minimum number of hops between Sx and Dx, without taking into account how many nodes in this path are influence by PUs. MinAct uses a diametrically opposite...
criteria to select the path (depicted in Subfigure 1(b)), since it only tries to avoid nodes highly influenced by PUs (node characterized by a dark grey), without considering that this choice could involve a not negligible increment in the number of hops. Instead the path chosen by Gymkhana (see Subfigure 1(a)) allows to obtain a trade-off between low number of hops and low PUs’ activities. Figure 2(a) shows the performance of the path selected by using the three different routing metrics in 10 different networks randomly generated by using COGTOP: in each of these networks there are 50 SUs and 3 PUs characterized by different activity factors ranging from 0.2 to 0.9. In all these networks the performance for the path picked out by Gymkhana overcomes the one of the other two paths. The same conclusions can be outlined analyzing Figure 2(b), where we reported the performance of the three routing metrics, obtained by averaging them in case of 35 different networks composed of 50 SUs and 3 PUs characterized by different activity factors ranging from 0.2 to 0.9. We can state that minHop obtains, on average, the worst performance, Gymkhana achieves, on average, the best performance and minAct gets, on average, intermediate performance. Figure 3 depicts, for the paths chosen by using the three routing metrics, the end-to-end PD as function of PUs’ average activity factor: it is important to notice that in each network scenario used for this comparison, each PU is characterized, in general, by its own activity factor and we name PUs’ average activity factor: it is important to notice that in each network scenario used for this comparison, each PU is characterized, in general, by its own activity factor and we name PUs’ average activity.
factor their arithmetic mean. In this way it is possible to analyze how the performance varies when the PUs’ average activity factor varies. In all the three cases the end-to-end PD increases when the PUs’ average activity factor increases, but the performance worsening is greater in case of minHop rather than in Gymkhana and minAct. Besides, the difference in the end-to-end PD between Gymkhana and minHop increases as the PUs’ average activity factor increases, while the same difference between Gymkhana and minAct remains quite constant. This is because the difference in the end-to-end PD between Gymkhana and minAct is essentially determined by the different number of hops, instead the difference in the end-to-end PD between Gymkhana and minHop is due to the fact that, in case of path selected by minHop, it is extremely probable that before transmitting nodes have to wait for an available free channel, and this waiting time increases as the PUs’ average activity factor increases.

In the results shown until now we suppose that each SU has a buffer of size equal to 150 packets. However in an opportunistic access the buffer size has a key impact on the network performance. The effect of the buffer size is evident in the PDR: Figure 3 represents, in case of Gymkhana, minAct and minHop, the PDR as function of PUs’ average activity factor, for three different buffer size (75, 150 and 300). It is possible to notice that in all the three cases, PDRs decrease as the buffer size decreases and as the PUs’ average activity factor increases: in fact, when PUs are highly active and when the buffer stores a low number of packets, there is a high probability of a buffer overflow. However, the performance worsening, in terms of packet loss, is higher for minHop and minAct rather than for Gymkhana. MinHop achieves the lowest PDR, since it is not interested in avoiding highly affected nodes, but only in minimizing the number of hops. As for the comparison between Gymkhana and minAct we can state that, for a single hop, the percentage of lost packet in case of minAct is approximately equal to the one of Gymkhana, since both select a path whose nodes are not heavily influenced, but the overall percentage of lost packet is greater in case of minAct rather that in case of Gymkhana since, in the first case, the cumulative loss of packets is obtained summing the contributions of more hops.

Finally, we are interested to show that, given an arbitrary network scenario, the path picked up by Gymkhana obtains the best performance when compared with other possible paths among the chosen couple source-destination. To this aim we randomly generated, by using COGTOP, a network topology of 50 SUs and 3 PUs characterized by activity factors equal to 0.7, 0.5 and 0.4 and fixed a source-destination couple. Then we derived for all the paths in the given network the relative number of hops and number of PUs, and compute their PDR, end-to-end PD (see Figure 4). It is possible to observe that the greatest $U^c$ is obtained for two different paths and consequently Gymkhana can indifferently select one of the two (we circumscribe them with a circle), since they have the same performance. As confirmed in Figure 4, the Gymkhana path has the highest PDR and the lowest end-to-end PD. The path with the minimum number of hops has scarce performance. Besides, there are some paths that have similar performance when compared with Gymkhana path: these are paths that have a low influence of the PUs, but have some more hops than Gymkhana path (in fact these paths have a little bit higher end-to-end PD with respect to Gymkhana path).

V. CONCLUSIONS

In this paper we considered the design of an utility function for routing in cognitive radio networks. We discussed on benefits of an utility function that, by measuring the path connectivity, selects paths that are less affected by the primary users. To demonstrate our intuition we compared the performance achieved by using our utility function with the classical hop count and with a metric that simply selects paths with less influence of the primary users. Since the proposed metric embraces several key characteristics of a path, that are relevant in a cognitive radio network, we showed that in a vast set of topologies the proposed metric overcomes the other two.

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REFERENCES