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A Fuzzy-based Routing Strategy for Multihop Cognitive Radio Networks

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Abstract: Cognitive radio networks represent a new class of wireless networks where the channels are not permanently available, depending on the traffic activity of licensed users who have the priority to use these channels. We design a novel routing procedure for multihop cognitive radio networks composed of adequate metrics and a strategy to combine these metrics. The objective is then to increase channel availability when the routes are established. Two global metrics are defined. The stability metric evaluates the utilization efficiency of channels by capturing their sporadic availability to cognitive users. The predicted power metric estimates the spectrum capabilities for the on-going transmission without interrupting licensed users. We use fuzzy logic theory to compute and combine these metrics in order to make suitable routing decisions. Our procedure consists of two phases. In the first phase we compute the route to the destination, and in the second we examine the ability of this route to satisfy the required type of connection at the source. Numerical analysis and simulation results show that our procedure is able to find the route that goes through the nodes with better channel conditions. Fuzzy logic seems then to be an appropriate technique to decide the routes to establish in multihop cognitive radio networks.

Keywords: Cognitive radio networks, Multihop, Routing, Fuzzy Logic Controllers.

1. Introduction

Cognitive Radio is an emerging and promising technology that aims to increase the overall utilization of radio resources by enabling the dynamic allocation of some portion of the wireless spectrum. Unlicensed users, through cognitive radio devices, can opportunistically operate over the current unused parts of licensed bands called white spaces, spectrum holes, or spectrum opportunity [1]. The unlicensed users should have new smart and programmable radios that allow them to sense large portions of the spectrum, learn its surrounding environment, analyze and make intelligent decisions, identify the instantaneous unused channels, use multiple channels in parallel, dynamically reconfigure their transmission parameters to adapt in real time to the current unused parts of the licensed bands.

Proposed traditional routing solutions in multi-channel multihop ad hoc and mesh networks are not appropriate to cognitive radio networks. First, there is no static spectrum allocation and hence there is no set of channels accessible at any time by each node in the network. Therefore, the channel selection must be part of the routing decisions and must be taken at the network layer jointly with the MAC (Medium Access Control) layer. Second, the transmission of unlicensed users can be interrupted at any time when a licensed user appears. It then needs to be switched to another channel according to the instantaneous unused parts of the licensed bands. Therefore, the unlicensed users should permanently scan the spectrum and choose carefully which route to follow before starting the transmission, in particular, in order to avoid as much as possible route handover. Third, the unlicensed users should adapt their transmission power to avoid any interference with the licensed users who have the absolute priority of using the channels.

In this paper, we introduce a novel routing procedure based on the inferred behavior of licensed users over their channels while assuming that their behavior is measured only in the past by sensing techniques. Each channel at each node is evaluated by two metrics. First, the stability metric aims to reflect the utilization efficiency of the spectrum by studying the sporadic availability of the licensed bands to the unlicensed users. Second, the transmission power estimation metric aims to characterize the allowed transmission power and its variation over time. This metric aims to reflect the state of the spectrum during the on-going transmission. We use Fuzzy Logic theory [2][3] to combine these metrics in order to make good routing decisions. In general, Fuzzy Logic allows the partial membership of a variable x in a set A. The degree of membership is specified using membership functions and linguistic variables. A membership function is a curve which assigns a real value in [0,1] for each measure of a linguistic variable such as *age* or *speed*. Fuzzy Logic also provides a mathematical tool called *Fuzzy Logic Controllers* used to determine and control variables via a set of rules to handle their complex relations. Fuzzy Logic theory is an adapted technique to solve the uncertainty, the heterogeneity, and the information incompleteness of routing problems in cognitive radio environment. Particularly, even if the properties of channels are well identified, it is still difficult to assess with certainty the impact of these properties on the performance of a given route.

The contribution of this paper is twofold. First, in presenting routing metrics that characterize the dynamic and unstable aspects of cognitive radio networks and second in proposing a technique that avoids combining these parameters through inflexible methods similar to the weighted sum. Indeed the fuzzy logic allows partial membership of a channel to a metric and a metric to a path thus capturing the dynamic behavior observed in cognitive radio networks. Practically with the considered metric, and the combination technique we privilege paths available for long periods of time. These paths are suitable for application requiring interrupted services such as data or video exchange. Besides, we validate our metrics and routing procedure with simulations and show that our routing ensures long term stability by accounting for instantaneous variations.

The remaining of this paper is organized as follows. The related work is reviewed in Section 2. In Section 3, we will briefly summarize the main concepts of Fuzzy Logic theory. We present our routing metrics in Section 4. In Section 5, we describe the two phases of our routing protocol. Performance evaluation and numerical results are provided in section 6. Finally, we draw our conclusions and we briefly highlight the possible future works in Section 7. In the sequel, we note by Primary Radios (PRs) the licensed users and by Cognitive Radios (CRs) the unlicensed users.

2. Problem Formulation

2.1 Routing in Cognitive Radio Networks

Because in Cognitive Radio Networks channels are not permanently available, proposed routing techniques for multi-channel multi-hop ad hoc or mesh networks cannot be reused for CRNs. Any proposed routing strategy in CRNs should characterize the non-permanent availability and describe the sporadic accessibility of the spectrum bands. Other CRN routing proposals address the above issue by simply computing the percentage of availability for each channel [5][6].

2.2 Objective

We consider a multihop cognitive radio network where data is forwarded through multiple cognitive radio nodes between a source and a destination. Cognitive nodes try to share several channels occupied by licensed users belonging to different networks and thus having different properties. The objective is then to design an appropriate routing strategy that builds a single path from a source node to a destination using only cognitive radio nodes as intermediate relays.
The steps of the design are as follows:

- Given a multihop cognitive radio network, find the best routing metrics that best characterize the availability and usability of the channels.
- Given a number of computed metrics, propose a flexible method of combining parameters able to capture uncertainty and variations of the computed metrics.
- Given the metrics and their combination, find the best path between a source node and a destination. The path is composed of an aggregated set of channels on every hop.

3. Related Work

Some routing algorithms or protocols for multihop cognitive radio networks were proposed in previous works. They are mainly based on techniques developed first for ad-hoc or mesh networks. Here, we present some works that are close to our proposal. Sharma *et al.* proposed in [4] a way to integrate the interference temperature into routing decisions. A simple weighted sum is used to combine interference with other routing metrics. Yet, this way is not flexible enough and it was not evaluated by simulation or models. Also, it is not clear how the weights are computed and how the CR nodes estimate the interference at the PR nodes. SAMER is a routing scheme proposed in [5] to provide a tradeoff between long-term parameters such as hop count and short-term parameters such as spectrum availability. Also, SAMER provides a compromise between the local spectrum conditions at the forwarding nodes and the global spectrum view of the entire routing path. However, the spectrum availability does not appear well in the calculation of routing metrics except by the percentage of time during which channels are available for CR nodes. We show later that this is not sufficient. Akyildiz *et al.* proposed in [6] STOD-RP an on-demand routing protocol. In STOD-PR, CR nodes are divided into groups interconnected by overlapping nodes where each group uses only one channel. A recovery mechanism is proposed to find a new channel for a group after the loss of the old one due to a PR activity. The framework designed in this work is realistic especially when used in cognitive radio mesh networks. However, this protocol presents few issues. First, the throughput is much reduced within each group due to the use of just one channel per group. Second, the overlapping nodes become quickly *bottleneck* links. According to [7], the next forwarding node is the node that requires the minimal consumption power. Hence, the next forwarding node is usually the nearest neighboring node; and then the optimal route is much longer than the route of minimum hop count. Moreover, the percentage of channels availability is not taken into consideration during the channel selection. In [8] a new routing metric was proposed based on a probabilistic definition of the available capacity over channels. This definition aims at finding the most probable route or the route with the higher probability of availability. After the route assignment, the source examines if its throughput capacity satisfies the throughput demand and it adds, when needed, other channels for transmission until the throughput demand is satisfied. Probabilistic throughput computation is adequate to increase the long term availability and the overall statistical utilization of the network. However, this approach may not be adapted for short connections. In [9], several routing metrics are proposed based on the interference at PR links due to CR activities, and based on the life time of CR links. In fact, the definition of routing metrics is function of the usage pattern proposed for PR nodes and it will not remain valid if this usage pattern changes. In addition, the duration of the life time of CR links is difficult to specify.

Our work differs from previous proposals in two aspects: First, by presenting a new flexible and efficient way to combine routing metrics in cognitive radio networks. Second, by proposing new routing metrics able to capture the uncertain, dynamic and sporadic availability of licensed bands.

4. Fuzzy Logic

In this Section, we give a brief overview of the Fuzzy Logic theory to help the unfamiliar reader to understand the rest of the paper. Exhaustive description can be found in the literature [2][3].

4.1 Fuzzy Sets

Fuzzy sets represent a modernization of traditional crisp sets where the membership of an object x in a set A is evaluated by 0 (false) or 1 (true). True means that x is member of A

and false means that x is non-member of A. Fuzzy sets allow the partial membership of x in A. The degree of membership has a real value in [0, 1], where 0 and 1 correspond respectively to the full non-membership and membership of x in A. If A is a fuzzy set in a universe U, the membership of x in A is evaluated by the membership function μ_A as following:

$$\mu_A : U \rightarrow [0,1] \qquad (1)$$

Each $u \in U$ has a degree of membership in A equals to $\mu_A(u)$. An object x is defined as a linguistic variable such as distance or speed, and a fuzzy set A is defined as a linguistic term such as far or high.

4.2 Fuzzy Logic Controllers

A *Fuzzy Logic Controller* (FLC) is a tool used to compute the value of an output based on several inputs having between them a complex relation, which cannot be solved via traditional mathematical tools such as weighted sum. The structure of FLC is shown in Figure 1. To compute the value of the output of the FLC, the following steps must be applied.

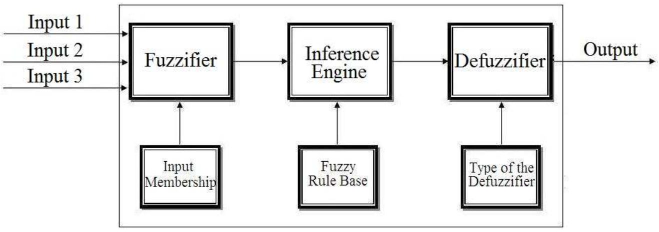


Figure 1. Fuzzy Logic Controller

First, we compute or measure from the external environment the value of each input. Second, these values are converted by the *fuzzifier* into fuzzy variables ready to be used by the *inference engine*. This step is called *fuzzification* and it is executed based on the *membership functions* of each input. An example of *membership functions* is shown in Figure 5. Third, the *inference engine* applies every rule of the *fuzzy rule base* to the input fuzzy variables to compute an output fuzzy variable. An example of a *fuzzy rule base* is shown in Table 1. The rules of the *fuzzy rule base* have the following form: IF (*Input*$_1$ is X_1 and *Input*$_2$ is X_2 and *Input*$_3$ is X_3) THEN (*Output* is *Y*). Fourth, the output fuzzy variables of all the rules are connected to compute the final output fuzzy variable. Finally, the final output fuzzy variable is converted by the *defuzzifier* into a crisp output ready to be used in the external environment.

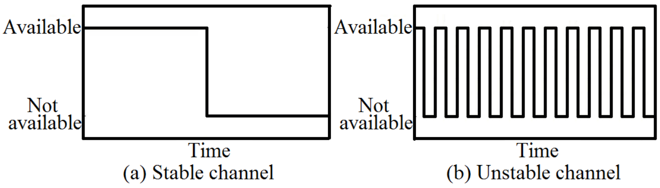
5. Routing Metrics

5.1 Stability

The goal of the stability metric is to capture the activity behavior of PR nodes over the licensed channels and hence the sporadic availability of these channels to CR nodes. In other words, the stability aims to describe how the availability of channels is distributed over time. The distribution model of channels availability can be described by the number of periods during which channels are available to CR transmissions and the manner these periods are disposed in time, such as the distance between two successive periods and the difference in their durations. We call a channel stable when it switches between long available periods and/or long unavailable periods. When unavailable periods are small the channel is of course excellent to use, but long unavailable periods also provide us a good information which is avoiding to use the channel for sure. An unstable channel switches quickly between availability and unavailability. The degree of stability can be specified according to its position between a channel that is almost static and a highly unstable channel.

In this work, we use 3 parameters to compute the stability of channels: The frequency of transitions between availability and unavailability, the deviation in the duration of available periods and the deviation in the duration of unavailable periods. In the following we describe the impact of each parameter on the stability.

Figure 2 shows an example of the impact of the frequency of transitions between available and unavailable periods on the stability of channels. It is clear that for the same percentage of channel availability, the degree of stability decreases proportionally with the increase of the frequency of transitions.



(a) Stable channel (b) Unstable channel

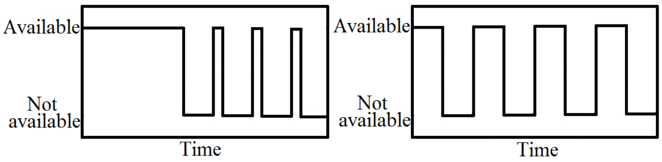
Figure 2. Impact of frequency of transitions on stability

Figure 3 shows that two channels with the same percentage of availability and the same frequency of transitions can have two different degrees of stability. This can be captured by the deviation of available periods. We notice that when the value of deviation in the duration of available periods increases, the distribution model of channel availability is more similar to the stable case. In fact, the availability of the channel in Figure 3(a) is composed of one long and several short available periods. The long period is similar to the long available period in the original stable case in Figure 2(a) and the short periods are almost not useful and can offer in the rest of the time the same performance as the long unavailable period in Figure 2(a).

In Figure 4 two different degrees of stability are given to two channels that have the same percentage of availability, the same frequency of transitions, and the same deviation of the duration of available periods (deviation = 0). We remark that when the value of the deviation of the duration of unavailable periods increases, the distribution model of channel availability is more similar to the stable case due to the same reasons already explained in the previous case.

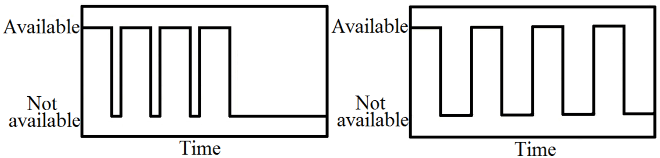
To compute the degree of stability of each channel, we combine the 3 parameters using the Fuzzy Logic Controller FLC 1. The FLC 1 consists of 3 inputs linguistic variables (frequency of transitions between availability and unavailability (*Input*$_1$), deviation in the duration of available periods (*Input*$_2$), and deviation in the duration of unavailable periods (*Input*$_3$)), characterized by the membership functions depicted in Figure 5(a), and one output linguistic variable

(*Stability*), characterized by the membership function depicted in Figure 5(b). Each input linguistic variable is characterized by a term of three fuzzy sets, {T(*Input*)} = {[*Low*, *Medium*, *High*]}. The output linguistic is characterized by a term of four fuzzy sets, {T(*Output*)} = {[*Very Low, Low, Medium, High*]}.



(a) High $\sigma_{ONperiods}$ (b) Low $\sigma_{ONperiods}$

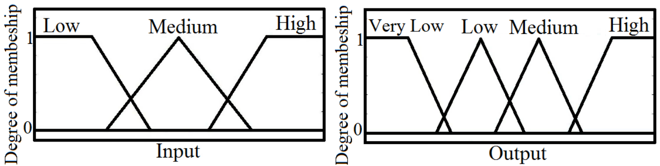
Figure 3. Impact of availability deviation on stability



(a) High $\sigma_{OFFperiods}$ (b) Low $\sigma_{OFFperiods}$

Figure 4. Impact of unavailability deviation on stability

The *Output* is a value between 0 and 100. The fuzzy Rule Base of the FLC1 is shown in Table 1. The table is a proposal for the FLC1 determined via the analysis in the previous section but also via observations during simulations. Note that the rule base is malleable enough so that other researchers can argue and propose different rules for different reasons. For instance, if the frequency of transitions is medium and the deviations are very high, one can consider that the stability is high rather than medium.



(a) Input: Frequency of transitions (b) Output: Stability

Figure 5. Membership function of the FLC 1

5.2 Transmission Power Estimation

The stability metric characterizes the spectrum holes to be used by cognitive radio transmissions. Nevertheless in order to exploit these white spaces, CRs must judiciously compute their transmission power in a way not to disturb primary radios activity. Moreover, since interference at PRs is additive, the estimated transmission power should also account for neighboring CRs activity over the channel. Consequently every CR should continuously estimate the maximum allowed transmission power $P_{\max}$ over every available channel. Practically, the estimated transmission power dictates the set of CR receivers on every channel i.e. the obtained CRN topology. For this reason, our second metric captures the estimated transmission power and its variation.

The predicted $P_{\max}$ which is going to be considered for next transmissions can be computed based on a set of previously measured values of $P_{\max}$, in addition to the current measured value. Many methods exist in the literature to predict the next value of random variables such as regression models or Kalman filters. The appropriate prediction method to use is out of the scope of this work. We rather focus on how we can benefit from the results obtained from the prediction method by considering a general output from the prediction module.

Consider the prediction module in Figure 6. It has three inputs: The current measured value of $P_{\max}$, the history of past measured values, and the number of past values. These three inputs are combined by the prediction method to obtain two outputs: The predicted value $P_{Predicted}$ of $P_{\max}$ and the confidence interval [$P_{Predicted} - \beta$, $P_{Predicted} + \beta$].

Table 1. FLC 1 Fuzzy Rule Base

IF			THEN
Number of trans.	$\sigma_{ON\ Periods}$	$\sigma_{OFF\ Periods}$	Stability
High	High	High	Low
High	High	Medium	Low
High	High	Low	Low
High	Medium	High	Low
High	Medium	Medium	Very Low
High	Medium	Low	Very Low
High	Low	High	Very Low
High	Low	Medium	Very Low
High	Low	Low	Very Low
High	High	High	Medium
Medium	High	Medium	Medium
Medium	High	Low	Medium
Medium	Medium	High	Medium
Medium	Medium	Medium	Low
Medium	Medium	Low	Low
Medium	Low	High	Low
Medium	Low	Medium	Low
Medium	Low	Low	Low
Low	High	High	High
Low	High	Medium	High
Low	High	Low	High
Low	Medium	High	High
Low	Medium	Medium	High
Low	Medium	Low	High
Low	Low	High	High
Low	Low	Medium	High
Low	Low	Low	High

By means of the Fuzzy Logic Controller FLC2 each CR node computes the final result of the predicted power (*Final Predicted Power*) for each channel based on the two outputs of the prediction method ($P_{Predicted}$, β). The policy of FLC2 is based on six simple rules shown in Table 2. Rules 1, 3, and 5 indicate that the final result of the predicted power (*Final Predicted Power*) is proportional to the value of $P_{Predicted}$. Rules 2, 4, and 6 indicate that the final result of the predicted power (*Final Predicted Power*) of a channel with a high value of β must be lower than that of channel with a comparable value of $P_{Predicted}$ and smaller value of β .

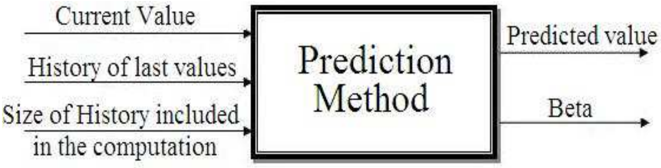


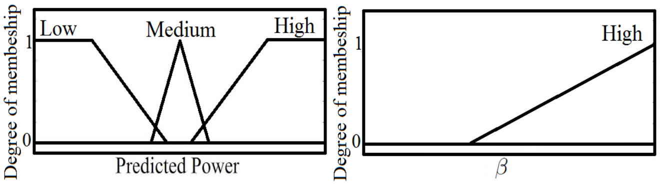
Figure 6. Inputs and outputs of the prediction operation

Finally, note that $P_{Predicted}$ is the maximum allowed transmission power beyond which primary users are disturbed. It is not the power that is going to be used when transmitting which depends mainly on the location of the receiver node.

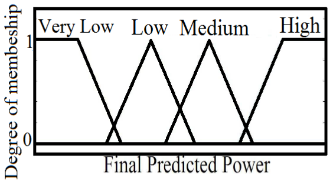
The FLC2 consists of two inputs linguistic variables ($P_{Predicted}$ and β) characterized by the membership functions depicted in Figure 7(a) and Figure 7(b), and one output linguistic variable (*Final Predicted Power*), characterized by the membership function depicted in Figure 7(c). $P_{Predicted}$ is characterized by a term of three fuzzy sets, {T($P_{Predicted}$)} = {[*Low, Medium, High]}*, and β is characterized by one fuzzy set, {T(β)} = {[*High*]}. The output linguistic is characterized by {T(*Output*)} = {[*Very Low, Low, Medium, High*]}. The exact output power can be computed in Watts by normalization but this operation is not necessary since the output is used for comparison between channels.

Table 2. FLC 2 Fuzzy Rule Base

n	IF		THEN
	$P_{Predicted}$	β	Final Predicted Power
1	High		High
2	High	High	Medium
3	Medium		Medium
4	Medium	High	Low
5	Low		Low
6	Low	High	Very Low



(a) Input: $P_{Predicted}$ (b) Input: β



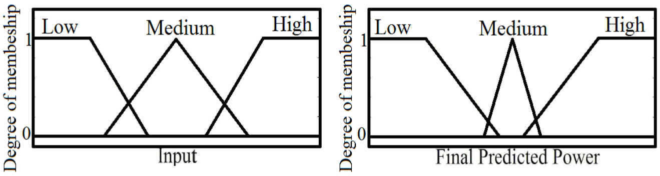
(c) Output: Final Predicted Power

Figure 7. Membership functions of FLC2

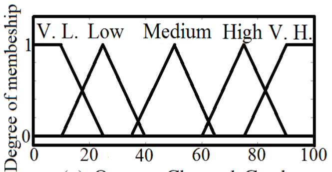
5.3 Channel Grade

After computing for each channel the degree of stability according to the method explained in Section 5.1, the final predicted value of $P_{\max}$ according to the method explained in Section 5.2, the Fuzzy Logic Controller FLC3 combines these two routing metrics to compute the grade of each channel at each node. The best channel is the most stable channel with a high *Final Predicted* value of $P_{\max}$ (greater than the minimum needed for transmission). The higher the final predicted power, the higher the number of neighbors and thus the higher the route possibilities to select. Also, a higher final predicted power provides a security margin before violating it. Other finer rules can be defined and they are summarized in Table 3. The global FLC of the channel grade computation is illustrated in Figure 9.

The FLC3 consists of two inputs linguistic variables (Stability and *Final Predicted Power*) characterized by the membership functions depicted in Figure 8(a) and Figure 8(b), and one output linguistic variable (Channel Grade), characterized by the membership function depicted in Figure 8(c). Stability is characterized by a term of three fuzzy sets, {T(sStability)} = {[*Low, Medium, High*]}, and *Final Predicted Power* is characterized by one fuzzy set, {T(*Final Predicted Power*)} = {[*Low, Medium, High*]}. The output linguistic is characterized by {T(*Channel Grade*)} = {[*Very Low, Low, Medium, High, Very High*]}.



(a) Input: Stability (b) Input: Final Predicted Power



(c) Output: Channel Grade

Figure 8. Membership functions of FLC 3

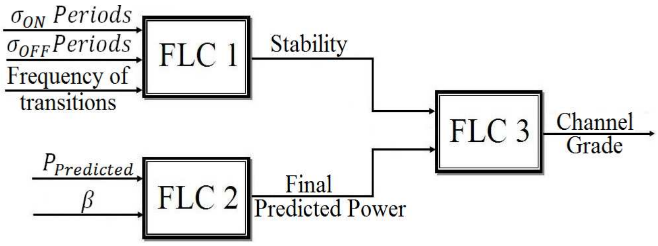


Figure 9. The global FLC of the channel grade computation

Table 3. FLC 3 Fuzzy Rule Base

IF		THEN
Stability	*Final Predicted Power*	Channel Grade
High	High	Very High
High	Medium	Medium
High	Low	Very Low
Medium	High	High
Medium	Medium	Medium
Medium	Low	Low
Low	High	Low
Low	Medium	Low
Low	Low	Low

6. Route Construction Procedure

6.1 Route Computation

The computation of all the routing metrics must take place for each channel in all the routes from the source to the destination. The grade of a link between two CR nodes is equal to the sum of the grades of all channels that are going to be used for transmission by the cognitive radio between these two nodes. As for the grade of a route we aim at including in the final grade also the number of hops. To do so, the link grades are inverted, then the final grade is the inverse of their sum. The route with the highest grade is the best route from the source to the destination. More formally, if we denote by R the set of all routes between a source node S and a destination D, and by n_r the number of links that constitutes route r, $r \in R$, then computing the best route based on the grades of routes between S and D can be written as

$$\max_{r\in R}\Big(\sum_{l=1}^{n_r} {}^{1}\!\big/_{g_l^r}\Big)^{-1} \qquad (2)$$

where g_l^r is the grade of link l in route r ($l \in 1 \ \dots \ n_r$, $r \in R$). There are several reasons that justify this way of computation. First, the highest inverted route grade corresponds to the *lowest* sum of the inverted link grades which also intrinsically tends to reduce the number of hops. Second, link grades do not correspond only to bandwidth availability. Thus taking the maximum of the minimum link grade through the route as a final grade in order to capture a sort of bottleneck may not be sufficient. Third, if the maximum of the minimum approach or another approach is used, an additional technique to include the number of hops must be added. Nevertheless, this is still feasible. A comparison between the sum and max-min approaches has been studied before. See for instance [10].

When the source wants to establish a connection, it is possible to incorporate the computation of the route grades in an AODV-like [11][6] or a DSR-like [12] routing protocol that allows also to reach the destination. Every CR node can compute its local links grades and add it to the cumulative grades received from its neighbors. During the computation, CR nodes must take into consideration the fact that the computed bandwidth accounts for the interference between consecutive links which divides the bandwidth among neighboring links, but does not change the availability percentage since it depends only on PR activity.

Furthermore, the predicted maximum allowed power for transmission should be updated while the route is constructed towards the destination. This is because the addition of a channel to the route activates the channel for transmission and will add possibly interference at PR receivers. The predicted power is then possibly reduced for the same channel of next links in the route. This update cannot use the recent measured powers received from the sensing module of the cognitive radio since the transmission is not yet started. The deployment of a procedure that updates the maximum power during route construction is challenging and increases the complexity of the route establishment especially that it would require message exchange between CR nodes and distributed power computations. However, in our case, channels with higher maximum power are chosen first which reduces the probability of violating it if more than one CR node uses the same channel in the route. Practically, this will not affect PR transmissions but it causes the route to be established, then some CR nodes will not be able to transmit as predicted. Designing a lightweight procedure to update the maximum power dynamically is one of our future works.

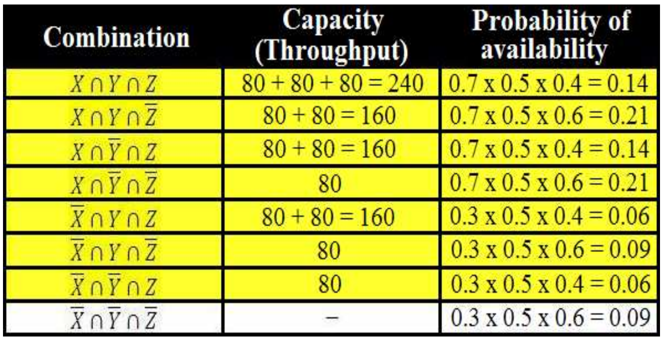
6.2 Route Examination

The goal of this second phase is to examine if the route selected in the first phase responds or not to the type of connection at the source. For example, a route can be accepted for an ftp connection while it may not be adequate for an interactive connection. To achieve the goal of this phase, we propose a new method to analyze how the average throughput computed in the first phase will be provided to a given connection.

Let's consider that between two CR nodes (CR_1 and CR_2) we have n channels 1 to n. The percentages of availability of each channel are respectively α_1, α_2, ..., and α_n while the throughput capacities are D_1, D_2, ..., and D_n. Hence, channel i offers the throughput D_i during α_i percent of the time. If one of the channels between CR_1 and CR_2 offers the throughput D during α percent of the time, then the link between CR_1 and CR_2 offers at least the throughput D during α percent of the time. We denote by A_i the state where the channel i is available to CR nodes. Hence, the probability of the state A_i is $p(A_i) = \alpha_i$ and its throughput is D_i while the probability of the state $\overline{A_i}$ is $p(\overline{A_i}) = 1 - \alpha_i$ and its throughput is 0. Also, the state $A_i \cap A_j \cap \overline{A_k}$ represents the overall time during which the channels i and j are available while the channel k is not, and the probability of this state is $p(A_i \cap A_j \cap \overline{A_k}) = \alpha_i \alpha_j (1 - \alpha_k)$ and its throughput is $D_i + D_j$. In fact, at any moment the link between CR_1 and CR_2 is in one of the following states: $A_1 \cap A_2 \cap \ldots \cap A_n$, $\overline{A_1} \cap A_2 \cap \ldots \cap A_n$, ... $\overline{A_1} \cap \overline{A_2} \cap \ldots \cap \overline{A_n}$. The probability of each composed state is equal to the product of the probability of its states if we assume that channels are independent. The throughput of each composed state is equal to the sum of the throughputs. The sum of the probability of all the states is equal to 1. In consequence, for each link between two CR nodes consisting of n channels, we have 2^n states. Thus, we can compute for the link a set of offered throughputs by the channels of the link and their percentages of availability. From that, it is possible to determine if this link is adequate to a given type of application according to its required throughput(s). For example, if we have a link where the throughput 2 Mbps is available 0.9 of the time, we can consider that this link is adequate for a VoIP talk spurt if 2 Mbps is the required service rate to satisfy the delay constraint.

In the case of routes with several links, the final result is the minimum of the results of all links.

Consider the following numerical example which consist of two nodes connected through 3 channels (X , Y and Z). The throughput capacity of each channel is 80 Kbps. Availability percentages are 0.7, 0.5 and 0.4 respectively. The source node runs the following steps. First, it constructs the link table (Figure 10) where each combination of channels (state of channels) is represented with its throughput capacity and its probability of availability. Second, it selects from the table the combinations that satisfy the throughput demand, say for instance 160 Kbps. Third, it computes the sum of the probabilities of all selecting combinations. The result represents the probability of time during which the throughput demand is available permanently (at each moment). In this case, 160 Kbps is available permanently for 0.14+0.21+0.14+0.06 = 0.55 of the time. All computations are shown in Figure 10.



Combination	Capacity (Throughput)	Probability of availability
$X \cap Y \cap Z$	80 + 80 + 80 = 240	0.7 x 0.5 x 0.4 = 0.14
$X \cap Y \cap \bar{Z}$	80 + 80 = 160	0.7 x 0.5 x 0.6 = 0.21
$X \cap \bar{Y} \cap Z$	80 + 80 = 160	0.7 x 0.5 x 0.4 = 0.14
$X \cap \bar{Y} \cap \bar{Z}$	80	0.7 x 0.5 x 0.6 = 0.21
$\bar{X} \cap Y \cap Z$	80 + 80 = 160	0.3 x 0.5 x 0.4 = 0.06
$\bar{X} \cap Y \cap \bar{Z}$	80	0.3 x 0.5 x 0.6 = 0.09
$\bar{X} \cap \bar{Y} \cap Z$	80	0.3 x 0.5 x 0.4 = 0.06
$\bar{X} \cap \bar{Y} \cap \bar{Z}$	–	0.3 x 0.5 x 0.6 = 0.09

Figure 10. Examination Table: Throughputs greater than 80 Kbps are available permanently for 91% of the time. Throughputs between 80 Kbps and 160 Kbps are available permanently for 55% of the time. etc.

It is worthwhile noticing that if the number of channels is very large then the computations are not scalable which is a drawback of this method. To alleviate this problem, channels can be gathered into different groups before the computations. Also, low grade channels can be withdrawn first.

7. Performance Evaluation

7.1 Metrics Analysis

Before simulating the whole routing procedure, we first validate the effectiveness of using the fuzzy logic within the proposed metrics. Since our proposed metrics are based on IF-THEN rules and not on mathematical equations, we show how these metrics change with the variation of the FLCs inputs. We consider here a simple one hop network since the objective is to show that the developed metrics capture efficiently the cognitive radio environment. All numerical computations and simulations were conducted using MATLAB.

7.1.1 Transmission Power Estimation

Figure 11 represents how the output of the FLC2 (*Final Predicted Power*) changes as a function of its two inputs ($P_{Predicted}$ and β). It is clear that the Final Predicted Power is proportional to the $P_{Predicted}$ obtained through the prediction operation. However, if a CR node compares between two channels, the channel that has the highest value of $P_{Predicted}$ is not always selected. For instance, if two channels have close values of $P_{Predicted}$, a CR node chooses the channel which has the lowest value of β . In other words, the chosen channel is the one whose operation of prediction gives the highest level of confidence. Such result cannot be obtained through the classical $P_{Predicted} - \beta$ function.

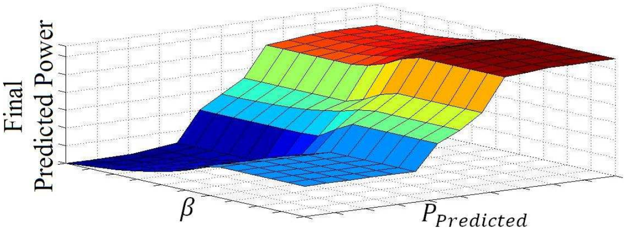


Figure 11. Final predicted power as a function of predicted power and predicted error

7.1.2 Channel Grande

Figure 12 shows how the channel grade varies based on the stability and the *Final Predicted Power*. Note that if the stability is very low, the channel grade is also low regardless of the *Final Predicted Power* value. However, if the stability is high, the channel grade switches between very high and very low levels and it is highly dependent on the *Final Predicted Power*. The two previously obtained results typically express the relation between the stability and the *Final Predicted Power*. In fact, a *stable* channel should be selected based on the *Final Predicted Power* since the current state of the channel will mostly continue in the future for a significant period of the time. On the other hand, an unstable channel will probably switch several times between availability and unavailability during a short period, and then the impact of the current state on channel selection is widely reduced. It is also remarkable that during unavailability periods, an unstable channel is preferred over a stable one since the former allows starting the transmission faster than the latter one and provides at least some throughput guarantee even with intermittent connectivity. This example shows again the flexibility provided by the fuzzy logic to control carefully the channel selection. Such figure cannot be obtained using a traditional weighted sum equation.

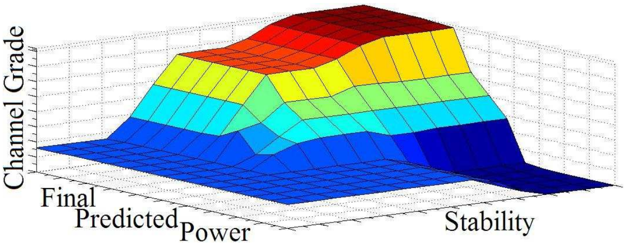


Figure 12. Channel Grade as a function of Stability and Final Predicted Power

7.2 Route Construction Simulations

In order to simulate the routing procedure, we use 64 nodes placed in a grid topology (Figure 13). The source node is the node placed in the top left corner of the grid while the destination node is the one placed in the bottom right corner. There are 6 licensed channels between every two nodes. For all the simulations, all channels have 50% availability ratio in the long term and a unitary bandwidth. We simulate three types of channel models corresponding to different degree of stability. These types are placed in the network in order to creates three regions of channels in the network as shown in Figure 13.

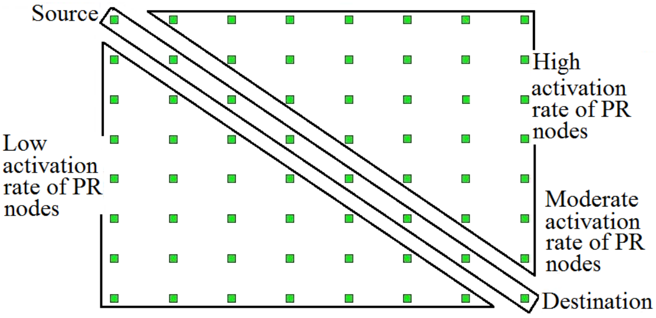


Figure 13. Simulated network topology

The channels of the bottom region behave randomly from three low activation rates of PR nodes. The channels of the top region behave randomly from three activation rates of PR nodes. Finally, the channels of the middle region behave randomly from three medium activation rates of PR nodes. This configuration will show clearly how routes are chosen through different links with different conditions.

First, we run the routing algorithm to find the best route from the source to the destination. Figure 14 shows the route constructed through links with highest grades. Also, it appears that the number of hops is considered in the route construction that is why the route is close to the moderate stability region. Hence, the chosen route is a good trade-off between the quality of links and the route hop count.

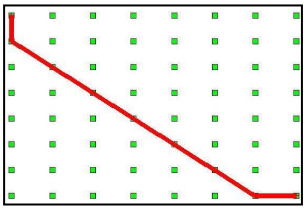
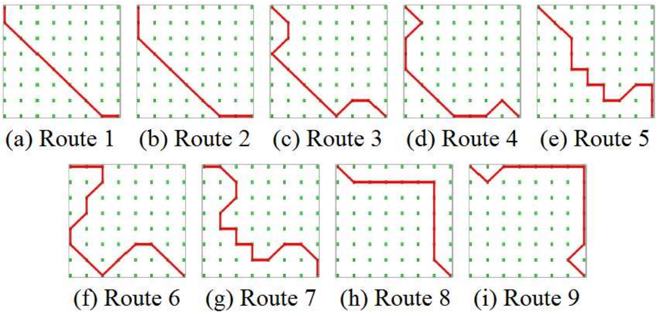


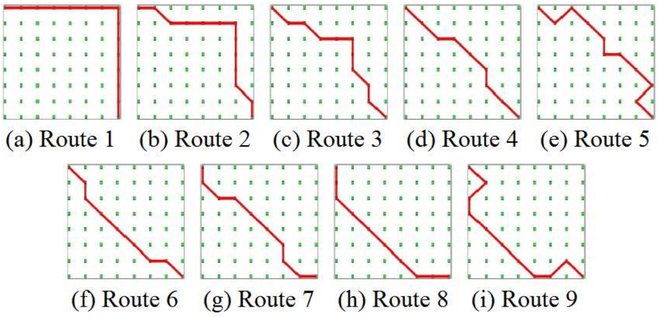
Figure 14. Route construction through links with high grades

Second, we continue running the algorithm between the same source and the same destination but for new connections up to 9 routes which is the maximum for this topology. We do this operation several times while we vary randomly and uniformly the starting of each route establishment. The obtained routes can be categorized into two types. Examples of these successive routes are shown in Figures 15 and 16. In Figure 15, we remark that the first four constructed routes are in the bottom region of the topology where the stability is higher, the routes 5, 6, and 7 are hybrid between the higher and the moderate stability region, and finally the last two routes are totally in the lower stability region. These types of routes look indeed intuitive and validate the routing algorithm in contrast to the second type shown in Figure 16.



(a) Route 1 (b) Route 2 (c) Route 3 (d) Route 4 (e) Route 5
(f) Route 6 (g) Route 7 (h) Route 8 (i) Route 9

Figure 15. The case where the first constructed routes start from the high stability region of the network

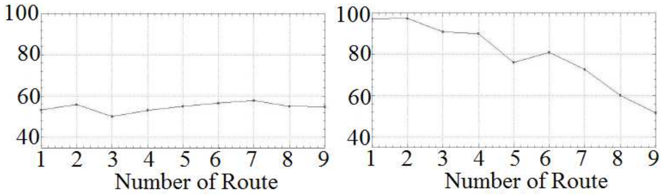


(a) Route 1 (b) Route 2 (c) Route 3 (d) Route 4 (e) Route 5
(f) Route 6 (g) Route 7 (h) Route 8 (i) Route 9

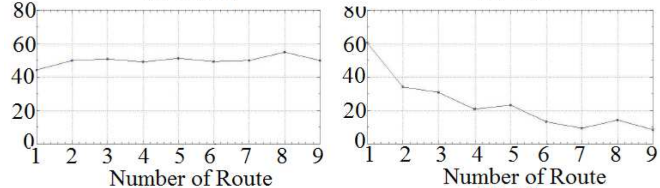
Figure 16. The case where the first constructed routes start from the high stability region of the network

In Figure 16, the first established routes in the network starts surprisingly from the unstable region and they finish in the stable one. In fact, the routes with stable channels have very low grades when the predicted power is low and/or β is high. These routes were indeed established when the final predicted allowed power is too low or does not allow transmission. Although the unstable links have low grades, these grades are still greater than the grades of stable ones during periods where the channels are not really available for transmission. Thus, that is why they are chosen to construct the route. Evidently, this is not sufficient and the algorithm should also choose the route that offers the better availability as shown in the next section.

Next, after the establishment of the first nine routes in the network, we measure the *offered* availability of each route which determines also the average throughput offered by each one of them at the beginning of the transmission. We show the results that correspond to the two types of routes identified in the previous set of simulations. Figure 17 (a) shows the availability average for the nine routes before the routing decision and the establishment of the route. By construction, the availability is around 50%. Figure 17 (b) shows the availability average for the nine routes after the routing decision. The two figures correspond to the case where routes are established through links that are in their majority available for transmission (corresponding to the first type in the previous simulations, Figure 15). That is why the measured availability is high and even close to 100% for the first route. Then, for next routes the availability decreases until 50%. However, for some routes, the availability can increase a little as it is the case for route 6 in Figure 17 (b). It does not imply that route 6 is better than route 5. On the contrary, this is quite normal because the channel grade takes into account other metrics and not only the availability.



(a) Before (b) After



(c) Before (d) After

Figure 17. Percentage of channels availability of the first constructed routes before and after the routing decisions

Same results are shown in Figure 17 (c) and Figure 17 (d) respectively before and after the route establishment. Again, here the route availability decreases for next routes with very small variations. So they are a good compromise between availability and the other metrics. Nevertheless, in this case the ratio of availability after the route establishment is much lower than the case of Figure 17 (b). In fact, these routes correspond to links having stable channels but in an unavailability period or links having unstable channels. In consequence, the average throughput capacity achieved by the on-going transmission is lower than the first case (Figure 17 (b)). This degradation is imposed by the instant when the route must be established. The algorithm, however, chooses the best alternative among the possibilities in hand, and especially it avoids choosing routes that are not available even if they have acceptable performance in the long term. This property is particularly required for interactive applications or in general applications that need fast first access. This is a key feature that is enabled by incorporating signal prediction in the computation of routing metrics.

8. Conclusion and Future Work

This paper proposes a new routing approach in multihop cognitive radio networks based on the sporadic availability of channels. Two routing metrics are defined based on the power allocation at cognitive radio nodes. These metrics are computed and combined using the fuzzy logic theory. Our proposed protocol computes the route to the destination and then checks if this route is able to satisfy the required type of connection at the source. Numerical analysis and simulations show that our routing procedure is able to exploit adequately all types of channels whenever there are available spaces. The established routes achieve a good trade-off between availability, transmission ability and stability.

Based on our results, further investigations can be made including especially experimenting other fuzzy rules that can be tuned for a specific application requirements. Also, it is interesting to test the benefit from designing a distributed update of the maximum allowed power during the construction of the route. Finally, the second phase of the routing procedure should be enhanced so that the throughput computations become more scalable with the number of available channels between two nodes.

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