A Routing Strategy for Cognitive Radio Networks Using Fuzzy Logic Decisions

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***Abstract*—We design a novel routing procedure for multihop cognitive radio networks composed of adequate metrics and a strategy to combine these metrics. In cognitive radio networks, channels are not permanently available. 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. 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; Routing; Fuzzy Logic;**

I. INTRODUCTION

Cognitive Radio is an emerging and promising technology that aims to increase the overall utilization of radio resources by enabling dynamic allocation of portions 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 be equipped with new smart and programmable radios that sense large portions of the spectrum, learn their surrounding environment, analyze and make intelligent decisions, identify the instantaneous unused channels, use multiple channels in parallel, dynamically reconfigure their transmission parameters to adapt 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 for cognitive radio networks (CRN). First, in CRN no static spectrum allocation is possible hence nodes cannot assume permanent access to the channels. 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 on a channel can be interrupted by the licensed users activity thus forcing cognitive radios (CR) to look for instantaneously available opportunities. As a direct result, the unlicensed users should permanently scan the spectrum and choose the appropriate route to follow before starting the transmission. The established path should avoid, if possible, route handover. Third, the unlicensed users should adapt their transmission power to avoid any interference with licensed users operating over the primary radios (PR), which have the absolute priority of using the channels.

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In this paper, we introduce a novel routing procedure based on the inferred behavior of licensed users. 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 allowed transmission power and its variation over time. We use the fuzzy logic theory [2] 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. 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 and uncertain behavior observed in cognitive radio networks. Besides, we validate our metrics and routing procedure with simulations and show that our routing ensures long term stability by implicitly accounting for instantaneous channels variations.

II. PROBLEM FORMULATION

A. 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

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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 [3] [4].

B. 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:

1) Given a multihop cognitive radio network, find the best routing metrics that best characterize the availability and usability of the channels.
2) Given a number of computed metrics, propose a flexible method of combining parameters able to capture uncertainty and variations of the computed metrics.
3) 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.

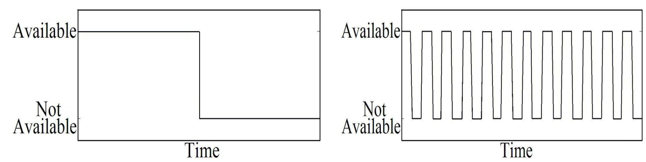
III. Routing Metrics

We describe in this part the proposed routing metrics and their combination using fuzzy logic. We first emphasize on the stability metric and the transmission power estimation. Then, a channel weight is computed for every link by the means of a fuzzy logic controller.

A. 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.

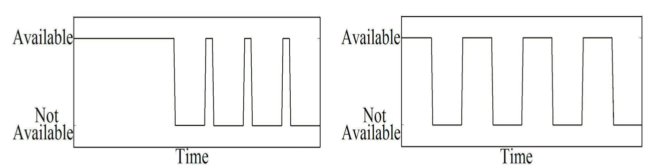
In this work, we use 3 parameters to compute the stability of channels. The frequency of transitions between availability and unavailability, the deviation in the duration of available periods and the deviation in the duration of unavailable periods. In the following, we describe the impact of each parameter on the stability. Figure 1 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

Fig. 1. Impact of frequency of transitions on the stability

Figure 2 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 2(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 1(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 1(a). Similar remarks can be made about the unavailability periods deviation where the increase of the unavailable periods duration increases the system stability.



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

Fig. 2. Impact of availability deviation $\sigma_{ONperiods}$ on the stability

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 ($input1$), deviation in the duration of available periods ($input2$), and deviation in the duration of unavailable periods ($input3$)). FLC 1 inputs are characterized by the membership functions depicted in Figure 3(a), whereas its output linguistic variable ($Stability$), is characterized by the membership function depicted in Figure 3(b). Each input linguistic variable is specified by a term of three fuzzy sets, $T(input) = [Low, Medium, High]$. The output linguistic variable is characterized by a term of four fuzzy sets, $T(output) = [VeryLow, Low, Medium, High]$.

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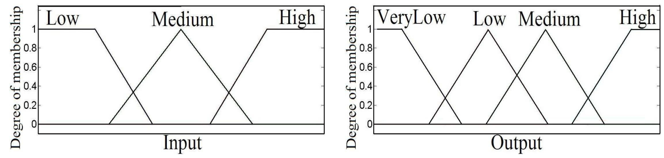


(a) Input: Frequency of transitions, $\sigma_{ONperiods}$, or $\sigma_{OFFperiods}$

(b) Output: Stability

Fig. 3. Membership functions of FLC1

The output is a value between 0 and 100. In order to obtain the channel stability, we define the fuzzy Rule Base shown in Table I. This table is a proposal for the FLC 1 determined via the analysis in the previous section but also by 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.

TABLE I
FLC1 FUZZY RULE BASE

IF			THEN
Frequency of transitions	$\sigma_{ONperiods}$	$\sigma_{OFFperiods}$	stability
$High$	$High$	$High$	Low
$High$	$High$	$Medium$	Low
$High$	$High$	Low	Low
$High$	$Medium$	$High$	Low
$High$	$Medium$	$Medium$	$VeryLow$
$High$	$Medium$	Low	$VeryLow$
$High$	Low	$High$	$VeryLow$
$High$	Low	$Medium$	$VeryLow$
$High$	Low	Low	$VeryLow$
$Medium$	$High$	$High$	$Medium$
$Medium$	$High$	$Medium$	$Medium$
$Medium$	$High$	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	$High$

B. Transmission Power Estimation

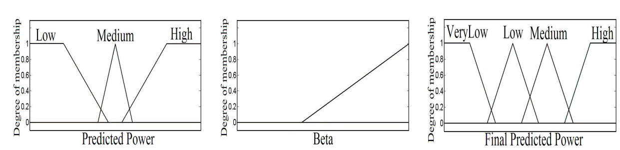
The stability metric characterizes the spectrum holes to be used by cognitive radio transmissions. Nevertheless in order to exploit these white spaces, CRs must judiciously compute their transmission power in a way not to disturb primary radios activity. Moreover, since interference at PRs is additive, 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.

The predicted P_{max} 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. We assume in this work that any considered estimation technique, provides the predicted value $P_{Predicted}$ of P_{max} and the confidence interval [$P_{Predicted}$- β, $P_{Predicted}$+β], where β is the error level.

By means of the Fuzzy Logic Controller FLC2 each CR node computes the final predicted power ($FinalPredictedPower$) for each channel based on the two outputs of the prediction method ($P_{Predicted}$, β).

The FLC2 consists of two linguistic variables inputs ($P_{Predicted}$ and β) characterized by the membership functions depicted in Figure 4(a) and 4(b), and one output linguistic variable ($FinalPredictedPower$), characterized by the membership function depicted in Figure 4(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($output$) = [VeryLow,Low,Medium,High]. The exact output power can be computed in Watts by normalization however this operation is not necessary since the objective in our metric is the comparison between channels.

Finally, note that $FinalPredictedPower$ is the maximum allowed transmission power beyond which primary users are disturbed. It is not necessarily the power that is going to be used when transmitting. Clearly, the used power can be optimized based on the location of the receiver node.



(a) Input: $P_{Predicted}$

(b) Input: β

(c) Output: Final Predicted Power

Fig. 4. Membership functions of FLC2

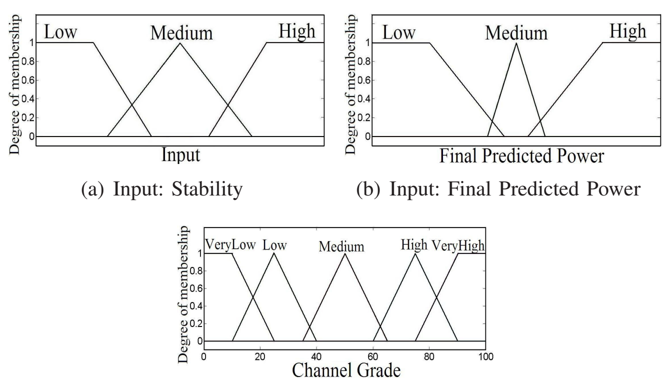
The policy of FLC2 is based on six simple rules shown in table II. Rules 1, 3, and 5 indicate that the final result of the predicted power ($FinalPredictedPower$) is proportional to the value of $P_{Predicted}$. Rules 2, 4, and 6 point that the final result of the predicted power of a channel with a high value of β must be lower than a channel with a comparable value of $P_{Predicted}$ and smaller value of β.

TABLE II
FLC2 FUZZY RULE BASE

	IF		THEN
n	$P_{Predicted}$	β	$FinalPredictedPower$
1	$High$		$High$
2	$High$	$High$	$Medium$
3	$Medium$		$Medium$
4	$Medium$	$High$	Low
5	Low		Low
6	Low	$High$	$VeryLow$

C. Channel grade

The Fuzzy Logic Controller FLC3 depicted in Figure 5 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. Membership functions are depicted in Figure 5, while other finer rules are summarized in table III.



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

(c) Output: Channel Grade

Fig. 5. Membership functions of FLC3

IV. ROUTE CONSTRUCTION

The computation of 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 (a value between 0 and 100) is equal to the sum of the grades of all channels that are going to be used for transmission

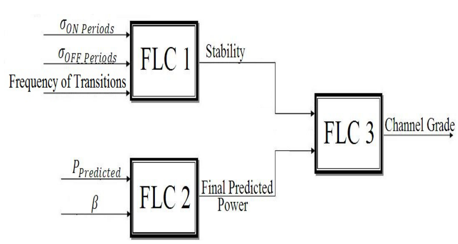


Fig. 6. The global FLC of the channel grade computation

TABLE III
FLC3 FUZZY RULE BASE

IF		THEN
Stability	$FinalPredictedPower$	Channel Grade
$High$	$High$	$VeryHigh$
$High$	$Medium$	$Medium$
$High$	Low	$VeryLow$
$Medium$	$High$	$High$
$Medium$	$Medium$	$Medium$
$Medium$	Low	Low
Low	$High$	Low
Low	$Medium$	Low
Low	Low	Low

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 since the *lowest* sum of the inverted link grades tends intrinsically to reduce the number of hops in addition to considering links with high grades.

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 constitute route r, $r \in R$, then computing the best route based on the grades of routes between S and D can be written as

$$\max_{r \in R} \left(\sum_{l=1}^{n_r} 1/g_l^r \right)^{-1} \quad (1)$$

where g_l^r is the grade of link l in route r ($l \in 1 \cdots n_r$, $r \in R$).

When the source wants to establish a connection, it is possible to incorporate the computation of the route grades in an AODV-like [5], [3] or a DSR-like [6] routing protocol that allows also to reach the destination.

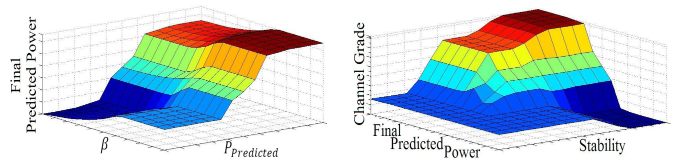
The predicted maximum allowed power for transmission should be updated while the route is constructed towards the destination. This is because the addition of a channel to the route activates the channel for transmission and will add possibly an interference at PR receivers. The predicted power is then 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 the interference condition if more than one CR node use the same channel in the route. Practically, this will not affect PR activity but establishes a route where 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 work.

V. Performance Evaluation

A. Metrics Validation

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 simulations were conducted using MATLAB.

Figure 7(a) represents how the output of the FLC2 ($FinalPredictedPower$) 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.



(a) Final Power as a function of Predicted Power and prediction error (b) Channel Grade as a function of Stability and Final Predicted Power

Fig. 7. Stability and power estimation validation

Figure 7(b) shows how the channel grade varies based on the stability and the $FinalPredictedPower$. Note that if the stability is very low, the channel grade is also low regardless of the $FinalPredictedPower$ 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 $FinalPredictedPower$. The two previously obtained results typically express the relation between the stability and the $FinalPredictedPower$. In fact, a **stable** channel should be selected based on the $FinalPredictedPower$ 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.

B. Routes Construction Simulations

In order to simulate the routing procedure, we use 64 nodes placed in a grid topology (Figure 8). 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. We simulate three types of channel models corresponding to different degrees of stability. These types are placed in the network in order to creates three regions of channels as shown in Figure 8. The channels of the bottom region behave following a high stability scheme, channels of the top region behave as a low stability scheme whereas the channels of the middle region behave as a medium stability scheme. Schemes are similar to Figures 1 and 2 and they are created randomly. This configuration will show clearly how routes are chosen through different links with different conditions.

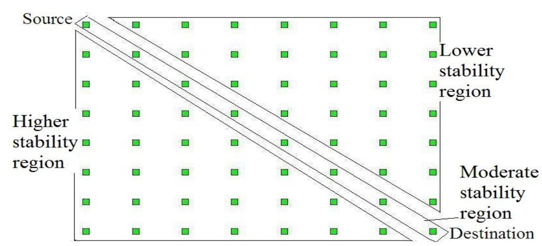
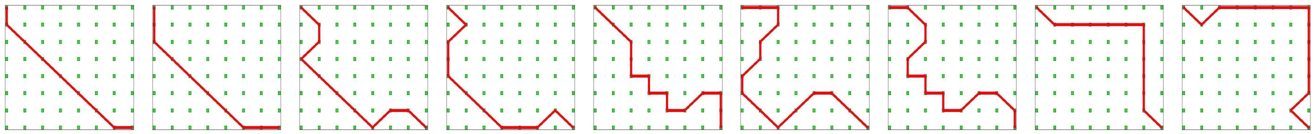


Fig. 8. Simulated network topology

First, we run the routing algorithm to find the best route from the source to the destination. Figure 9(a) shows the route constructed through links with highest grades. It also highlights that the number of hops is considered in the route construction, for this reason the route is close to the moderate stability region. Hence, the chosen route is a good tradeoff between the quality of links and the route hop count.

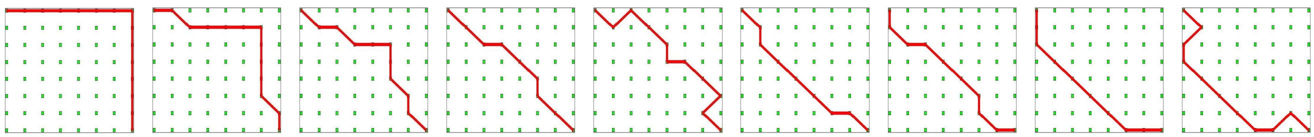
Second, we continue running the algorithm between the same source and the same destination but for new connections up to 9 routes which is the maximum possible in this topology. We repeat this operation several times while varying randomly and uniformly the starting time of each route establishment. The obtained routes can be categorized into two types. Examples of these successive routes are shown in Figures 9 and 10. In Figure 9, we notice that the first four constructed routes are in the bottom region of the topology where the stability is higher, 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. This types of routes looks indeed intuitive and validates the routing algorithm in contrast to the second type shown in Figure 10.

In Figure 10, we highlight a different scenario observed during our simulations. In some cases, the first established routes in the network start surprisingly from the unstable



(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

Fig. 9. 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

Fig. 10. The case where the first constructed routes start from the low stability region of the network

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. Here, among bad quality routes, our strategy selects the less worse one.

VI. Related Work

Some routing techniques for cognitive radio networks were proposed in the literature. Sharma *et al.* proposed in [7] a way to integrate the interference temperature into routing decisions. Routing metrics are combined using a simple weighted sum. Yet, this way is not flexible enough and it was not evaluated by simulation or models. Akyildiz *et al.* proposed in [3] STOD-RP an on-demand routing protocol based on clustering approach. In STOD-RP, a single channel is used within each cluster and a recovery mechanism is provided to tolerate spectrum loss. However, the throughput is much reduced within each cluster and the cluster heads become quickly *bottleneck* links. A new routing metric was proposed in [8] based on a probabilistic definition of the available capacity of channels in order to find the route with the higher probability of availability. After the route establishment, new channels are added until the throughput demand is satisfied. Probabilistic throughput computation is adequate to increase the long term availability but it may not be adapted for short connections. In [9], a new routing scheme was proposed in order to reduce the power consumption. This usually leads to select the nearest neighboring node, and then the number of hops in the route is significantly increased. Authors in [4] present SAMER a new routing scheme to provide a tradeoff between the local spectrum conditions at the forwarding nodes and the global spectrum view of the entire routing path. However, the complex distribution of channels availability is simply presented by a general average of availability.

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.

VII. Conclusion and Future Work

This paper proposes a new routing approach for 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. 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 tradeoff 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 specific application requirements. It is also interesting to estimate the benefit from designing a distributed update of the maximum allowed power during the construction of the route.

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