# Dynamic Spectrum Allocation in Cognitive Radio Cellular Networks

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*Abstract:* - last years, Cognitive radio (CR) has emerged as an efficient technology to exploit the unused available spectrum resources; it can sense and use spectrum in an opportunistic manner without creating any harm to cognitive users.
In this article a cognitive spectrum allocation procedure is proposed. Artificial Neural network (ANN) an intelligent learning technique is used which works to improving wireless communication for cognitive radio mobile terminal, to reduce the optimization complexity and improve the decision quality. The criteria for the spectrum allocation problem had been analyzed and the common objectives to solve it have been determinate.
Evaluation results show that our technique achieved significant allocations in large and complex wireless communication system. Results also show the improvement in the user satisfaction over other techniques in CR.

*Key-Words:* - Cognitive radio, spectrum allocation, wireless communications, neural network.

## 1 Introduction

With recent rapid increases of wireless devices radio spectrum scarcity occurs. Because The current usage model has allocated most spectra to existing wireless systems, yet ironically, various studies have shown that more than 90% of the allocated spectrum is unused or underutilized [1]. The reason is that the licensed spectrum is only allowed to be used by the primary/licensed users (PUs), and secondary/unlicensed users (SUs) are prohibited from accessing the licensed spectrum even when the licensed spectrum is not occupied by PUs [2].
Consequently, new opportunist approaches for a distributed management and optimal radio access must be developed. Cognitive radio (CR) presents one of the most efficient technologies to remedy the dynamic spectrum management. The CR was conceived to operate across different spectrum bands and heterogeneous radio access technologies (RAT)[3]. The main idea of this technology is to have a radio terminal (called secondary user), that can sense and access the spectrum when the spectrum is unoccupied by the primary user PUs[4].
When a PU requests to access a spectrum, the SUs using the same spectrum opportunistically should switch to other unoccupied spectra to protect the transmission of the PU and continue their own data delivery [5]. However, severe throughput degradation may occur communications in this situation [5].
The CR aim consists to improve the spectrum allocation, and investigate different methods and protocols such us game theory to exploit the unused spectrum. However, the CR nodes possess the necessary qualities to make a considerable progress in the reliability of wireless networks [6],[5].
To perform this task, radio terminal should acquire more intelligence through the cognitive cycle and new algorithms shall be developed to detect gaps as cyclo-stationary [7] and allows the cognitive radio terminal to operate the environment intelligently, to scan a set of frequency bands and exploit them [8].
In this paper, our aim is to propose an intelligent approach for the channel assignment in CR by satisfy the network robustness constraints and resist any single channel interruption by PUs. To this end, we formulate the problem as a constrained optimization problem, in which the objective is to maximize the use of each available frequency for the secondary users and minimize the maximum interferences under all possible PUs' appearances. We propose an artificial neural network to solve it.
This paper is structured as follows. In the next section we present the related work, in section 3 we provide The Art State of frequency assignment problem in cognitive radio. And the Mathematical Formulation is described in Section 4. Section 5 presents the algorithm proposed and the hybridization methods applied to it. The results of the experiments are analyzed in Section 6. Finally, conclusions are in the last section.

## 2. Related work

The current challenges in radio networks are: to ensure an efficient and full use of radio frequency resources and multimedia applications, Connect at best anywhere, any-time and with any network. Customize the more power-full features stimulated by the increasing consumers' demand. Find solutions for the mobile business. And tend toward several access technologies whose assignment is local and continuously and independently updated, rendering impossible any overall control. This lead to a very interesting and pertinent issue for radio spectrum is opportunist channel allocation problem [9].

Cognitive radio offers a promising solution for this problem. It has attracted much research attention, and both distributed and centralized schemes have been proposed to facilitate the spectrum sharing between SUs and PUs[10].

Channel allocation problem became a crucial topic. Related work in cognitive radio, but not restricted to [11], [12], [13], [14], [15], [16]and [17].

Notably in [18] Centralized mechanisms are proposed to implement spectrum leasing and real time spectrum auctions of unused PU bands in which spectrum brokers and/or auctioneers match the demand and supply of "white space" between providers and consumers. Whereas the approach proposed in [10] is based on three main stages: a) address the asymmetrical relationship in access priority and protection requirement of the PU and SUs when designing SU spectrum access schemes; (b) quantify explicitly the impact of the PU traffic pattern, protection requirement, and SU detection performance on the SU spectrum opportunity exploitation; and then (c) characterize the interplay between PU protection and the SU performance.

In [11], [12] the authors propose a study of the opportunistic SU spectrum access over multiple PU bands under the partially observable Markovian decision process framework, and proposes cognitive MAC protocols that optimize the SU performance while limiting the interference to the PU[10].

in [19], the authors propose CMA (Cognitive Medium Access) for an SU to utilize the PU spectrum opportunities optimally under the protection constraint from the PU

In [14] authors propose a dynamic channel allocation scheme based on a potential game. And suggest another technique based on machine learning with different utility functions [17].

A distributed spectrum allocation in cognitive radio networks based on local bargaining is proposed in[16].

In [15] the suggested approach use a S-modular and potential games to develop a cognitive radio behavior.

According to [17], Mishra et al. [13] propose a channel allocation method for wireless local area networks (WLANs) based on weighted graph coloring. Zheng and Cao [20] present a rule-based spectrum management scheme for cognitive radios.

Another stole for the radio cognitive is the use of the learning algorithms such as Fuzzy Logic, Neural Networks, Hidden Markov Model, Genetic Algorithms, or Classification Algorithms.

Fuzzy logic is more suitable for real-time cognitive radio applications in which the response time is critical to system performance [21].

Genetic algorithm has been used to optimize the Bit Error Rate (BER) performance in cognitive radio [22]. in [23] Kaur et al proposed an Adaptive Genetic Algorithm (AGA) to optimize QoS parameters in a cognitive radio.

In [24], the genetic algorithm is used with two criteria: 1) probability of detection has to be maximized, and 2) probability of false alarm should be minimized, for an optimal space allocation.

The multi layered neural networks were used to model and estimate the performances of IEEE 802.11 networks [25], [26].

Compared with existing methods, we can say that the neural networks is the far flexible method, it have a need less for prior knowledge; they can be used in any phase of cognition. The neural networks can be considered as a suitable model for a cognitive radio network, and where a prompt response to the changing radio environment is required from an unlicensed user.

## 2 Problem Formulation

In this section, we present a formulation for the frequency assignment problem in cognitive radio (FAP-CR), which can be used to provide optimal solutions and is also the basis for our ANN algorithm.

The FAP can be formulated as a graph coloring problem. And the network is abstracted as an undirected graph G = (V, E , L ), where vertexes represent users and edges represent interference, so that no channels can be assigned simultaneously to any adjacent nodes.

Let $N = |V|$ denote the total number of users. Let edges be represented by the $N \times N$ matrix $E = \{e_{ij}\}$, where $e_{ij} = 1$ if there is an edge between vertexes i and j , and $e_{ij} = 0$ implies that i and j may use the same frequencies. Note that since G is an undirected graph, E is symmetric.

Furthermore, let K be the number of available channels in G. Although it is possible that different channels have different bandwidths, the model treats all channels with the same bandwidth [29].
The available frequency band is divided into orthogonal channels of the same bandwidth using the FDMA method. It is assumed that there is a mechanism that enables wireless devices to use multiple channels to communicate at the same time.
In a similar notation, we represent the availability of frequencies at vertexes of G by an N × K matrix L = $\{l_{ik}\}$, which we refer to as the coloring matrix. In particular, $l_{ik} = 1$ means that channel *k* is available at vertex *i*, and $l_{ik} = 0$ otherwise.
For instance, the problem is illustrated in the CRN of Figure 1.

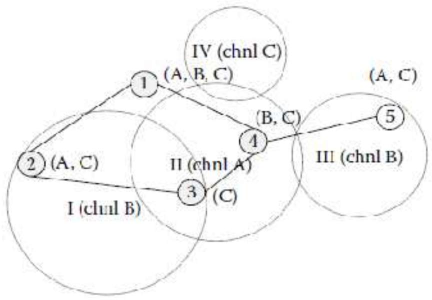


Figure 1. graph of a model of such a network [27]

The four I-V five represent the four primary users, using bands A, B, and C, respectively. This channel cannot be utilized by the secondary users in the vicinity and the nodes within a certain range of each primary user cannot reuse the same frequency. The five different secondary are presented by the numbers 1–5 in this figure. In other words, if a secondary user is within the dashed circle of a specific primary user, it cannot access that band used by this primary user.
For instance, node 3 is within the interference range of primary user I, who uses channel B. and is within the interference range of primary user I, who uses channel A, Therefore, it cannot reuse channel A and B. As a consequence, each node has access to a different set of band. In our figure, the available channels are (A,B,C) at vertex 1, (A,C)[27].

Figure 1 is represented by the matrices:

$$E = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} \qquad L = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \end{bmatrix}$$

Let us denote a channel assignment policy by an N × K matrix S = $\{s_{ik}\}$, where $s_{ik} = 0$ or 1, and $s_{ik} = 1$ if channel k is assigned to the node i and 0 otherwise. We call S a feasible assignment if the assignments satisfy the interference graph constraint and the channel availability constraint. More specifically, for any node i, we have $s_{ik} = 0$ if $l_{ik} = 0$ (i.e., a channel can be assigned only if it is available at the node). Furthermore,
$s_{ik}\ s_{jk}$ ei j = 0, ∀i, j = 1, . . . , N, k = 1, . . . , K.

In other words, two connected nodes cannot be assigned the same channels. The objective of the resource allocation is to maximize the spectrum utilization. This problem can be formally represented as the following nonlinear integer programming problem.

$$\max_{s} imize \sum_{i=1}^{N} \sum_{k=1}^{K} S_{ik} \qquad (3.1)$$

$$\text{Subject to} \quad s_{ik} \le l_{ik},$$

$$s_{ik} s_{jk} e_{ij} = 0,$$

$$s_{ik} = 0{,}1$$

for all i, j = 1, . . . , N and k = 1, . . . , K. The above problem is sometimes referred to as a list multicoloring problem. When time is taken into account, a time index can be introduced into the equation where the objective is to maximize the utilization averaged over time and the three constraints are satisfied at each time instant.
The corresponding decision list coloring problem is formulated below.

**Problem 3.1**[27] (DListColor Problem) Given a graph G = (V, E , L ) and a positive integer B, is there a solution such that :

$$\sum_{i=1}^{N} \sum_{k=1}^{K} s_{ik} > B, \qquad (3,2)$$

with the same set of constraints as in Equation (3.1)?

**Proposition 3.1** [27]
The DListColor problem is NP-complete.
PROOF This problem is clearly in NP since once a valid coloring assignment S is obtained, condition (3.2) may be verified in O(|V| · K ) time[27].

We now show that the maximum clique problem can be reduced to the DListColor problem in polynomial time, and that the maximum clique problem has a solution if and only if DListColor has a solution.

Let G = (V, E ) be the undirected graph of the maximum clique problem. We construct the graph G' = (V', E', L' ) for our DListColor problem, such that V'= V, and E' is the complementary set of E . Furthermore, the color matrix L is of dimension |V| × 1, where L = $[1, 1, \ldots, 1]^T$ . Since any pair of nodes connected in G are not connected in G' and vice versa, we cannot simultaneously assign nodes in G' the same color if these nodes form a clique in G. Therefore, there exists a clique in G of size at least m if and only there is no solution for DListColor for B = |V|− m. This reduction is obviously polynomial-time[27].

### 3.1. Color decoupling

The list coloring problem may be reduced to a set of maximum-size clique problems when fairness is not a consideration. In other words, in the process of finding the maximum in Equation (3.1), nodes are allowed to be assigned zero channels. The problem of assigning each node a set of colors may be solved by coloring the graph in sequence with individual colors:

$$\max_{s} imize \sum_{i=1}^{N} \sum_{k=1}^{K} s_{ik} \Leftrightarrow \sum_{k=1}^{K} \max_{s} imize \sum_{i=1}^{N} s_{ik} \qquad (3.3)$$

Where $S_k$ denotes the channel allocation with respect to channel (color) k. More specifically, $S_k$ is the $k^{th}$ column in the assignment matrix S. Note that the equality in (3.3) does not hold in general situations, e.g., a graph coloring problem that requires each node to be colored with nonempty colors. Note that when fairness is taken into account, e.g., each node has to be assigned at least one color, and then the decoupling property does not apply [27].

## 4. Approach Concepts

An artificial neural network is an interconnected network of very simple calculating units called neurons. Every connection in the network is assigned a weight which specifies the extent of possible influence. The whole network can be represented using a directed graph where an incoming edge to a node acts like an input to a neuron and outgoing edges are outputs from the neuron.

An artificial neural network consists of an input layer, an output layer and one or more hidden layers. No transfer function is applied at the input layer and direct inputs are transferred as outputs from this layer. The input layer acts like the biological sensory system, providing information about the surrounding environment. Activations are calculated from the next layer onwards, the hidden layers, and fed into higher layers until it reaches the final output layer. This kind of a neural network structure is called a feedforward network, because the output from one layer goes to neurons in the next layer. Feedback networks are also possible; they are referred to as a recurrent network[28].

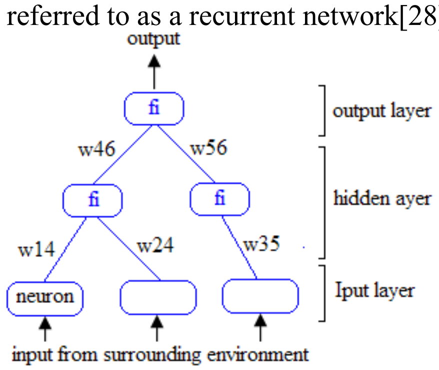


Figure 2. A typical neural network[28].

Learning in neural networks is achieved by varying the connection weights iteratively so that the network is trained to perform certain tasks. It generally involves the minimization of some error function under the supervision of a trainer. This is often called supervised training. However, in some cases, the exact desired output is not known. Reinforcement learning is used in such cases and training is based only on whether the actual output is correct or not. Unsupervised learning tries to find correlations among input data when no information on the correctness of the output is available. The rule followed to update the connection weights, the learning rule, determines how well the network converges towards its desired optimality [29].

## 5. Resolution Approach

Our algorithm comes in form of a constructive artificial neural network ANN, Composed from a set of interconnected elementary processors that can perform the entire processing information chain. Each neuron adapts its state with its neighbors to achieve the objective for which they have been designed.

The processing element in the ANN calculates a single output based on the information it receives. This neuron cell is the basic elementary unit of an ANN. It is built on the digital inputs, through which the environment stimulus arrives. These entries are initialized with an initial configuration [29].

According to the target of channel allocation, the network topology is represented by a graph G=[N (t), C (t), L(t)] where N (t) denotes the set of vertices at time t , C (t) the set of edges and L(t) the availability of frequencies at vertexes of G. Each

vertex is associated a neuron characterized by a vector of synaptic weights $w_i$ (reference vector) and an error signal $e_i$.
The latter will be used to accumulate the modelling error due to the neuron i and guide the choice of the elected neuron which is in the most difficult situation. The edges of the graph, linking two vertices i and j, correspond to the connections between underlying neurons.
The interference constraint will be presented in reutilization matrix $C = \{C_{i,j,k}|C_{i,j,k} \in \{0, 1\}\}N\times N\times M$, where $C_{i,j,k} = 1$, if users n and k would cause interference if they used the spectrum band m simultaneously. Note that constraints are spectrum band specific. Note also that two users who are constrained by one spectrum band cannot use this band simultaneously.
Considering the spectrum allocation matrix $S = \{S_{ik}\}N\times M$ which denotes the effectiveness of spectrum allocation, where $S_{ik} = 1$ denotes that spectrum band k is assigned to user i. S satisfies all the constraints defined by C, i.e. $S_{i,k} S_{j,k} = 0$, if $C_{i,j,k}= 1$, $\forall$ i, j < N, k < M.

$$\sum_{i=0}^{N-1}\sum_{k=0}^{M-1} S_{ik} b_{ik} \qquad (3.5)$$

The fitness value of each neuron is calculated according to the fitness function (objective function). After evaluation of the fitness function, a certain pair of neuron should be selected for the vector element. And each neuron adapts its state by permuting its value, until it well be in agreement with its neighbours. The mechanism is guided by an appropriate greedy competitive heuristic for solving the FAP constraints and minimizes the number of the used frequencies.
Every neuron is initialized, and the neural network operates in a serial mode, when a neuron is updated in each iteration, and the rest remain inactive, denoting by an activation parameter on time. step by step the ANN introduce tentative values used during the search process for each vector element through an insertion and selection mechanism governed by a learning algorithm. For each frequency, a greedy assignment is calculated to maximize the number of nodes assigned to this frequency.
The Connection weight adaptations in the ANN are defined as the neuron state adaptation in its neighbours. It is handled by neuron state changes. A developer-defined fitness function evaluates the performance of the neuron based on expected values.
As we shall see later, both neurons and connections can appear and disappear from the graph throughout the learning process. Therefore the sets N, C and L depend time.
The algorithm includes an essential parameter $\tau$ which defines the time between variations of the availability of frequencies at vertexes of G; that is to say that at each $\tau$ times, we delete and add a frequency in the demand vector of each vertex.
The ANN learning, like that is a competitive type. The elected neuron is moved in the direction of improvement of the cost function of the stimulus in proportion to the distance and a certain level of improvement.

## Main Algorithm:

**Initialisation** : G = [N (0), C (0), L(0)], N(0) ={x,y} and C(0) ={ $w_{x,y}$} and L(0) the availability of frequencies at vertexes of G;

E (t) the total energy function, $E=\sum_i\sum_j w_{ij}x_i y_j$ ;

With Synaptic weights in the input space;

ex(0) =ey(0) as the local energy function Ex, Ey.

Fix tmax ,

t=1,

**Do while** ( $t \le t_{\max}$ or $E \neq 0$):

(1) From the N(t) Choose the neuron q with the maximum error

$q = \arg\max_{i\in N(t)} e_i$

(2) Affecte the best value to the assotiated Sommet ;

(3) Decide the new state of this neuron by Moving the reference vectors in the direction ofthe minimum of E (t) the total energy function, $\arg\min_{i\in N(t)} \|E(t) - w_i(t)\|$ ;

(4) Compute the energy E of the current assignment. If E=0, stop and go to Step (5), otherwise, repeat the process from Step (1) ;

(5) Desactivate q ;

(6) reduce the error signals of all neurons r in the neihbors of q : r= $\arg\max_{i\in V_q} e_i$, Where :

$V_{g_1} = \{i \in N(t) / i \neq g_1 \ and \ \{i \neq g_1\} \in C(t)\}$ ;

(7) Remove from C (t) all connections which q, and all neurons that were isolated following the death of connections ;

(8) Repeat Steps (1) – (7) until all frequencies for all the sommets are assigned ;

(9) If (t mod $\tau$ =0) then

a. updeate L(t) ;

b. if L(t+1) ≠ L(t) go to (1) ;

(10) t=t+1 ;

End while

# 6. Results and discussion

To evaluate the performance of the proposed channel assignment by the ANN, we use computer simulations. And we analyze the percentage of removed interference by the algorithm when the number of nodes and the available channels increases.

The approach was designed to affect the one frequency for each opportunist user under the primary users by using a uniform cost function to select an available channel.

For each scenario, we randomly generate a certain interference topology graph instances, with the number of nodes varying from 10 to 50, with the interference ranges defined in a constraints matrix, where : each channel is occupied by a primary user (PU) in a certain range. And each node within a PU's range cannot use the channel occupied by this PU. Each node in the network has its own available channel set, according to the positions of the PUs. Some nodes can use the same channel in a certain range.

The impact of the dynamic occupation of frequency by the PUs was modelled considering an average inactive time at least ten times larger than the time needed for the algorithm to reach the stopping criterion.

The channel assignment problem of this network is solved by the proposed algorithm. And analyzed, for three different scenarios : (1) ) varying the number of available channels K; (2) varying the number of network nodes N ; and (3) varying the stopping criterion I.

For all instances, we remark that the number of nodes and the available channels impacts the efficiency of the methods and the network interference:

As shown in the figure 3, the performance in terms of removed interference decreases when the number of nodes increases, and each node has less chances to take an avoided channel, And when the number of available channels increases, each channel has more chances to be assigned to different channels for interference avoidance. Therefore the effect caused by the variation in the number of available channels after and before the channel allocation and the arrival at the stopping criterion correspond is reminder stable during the all simulated cases, the number of available channels varying from 2 to 10.

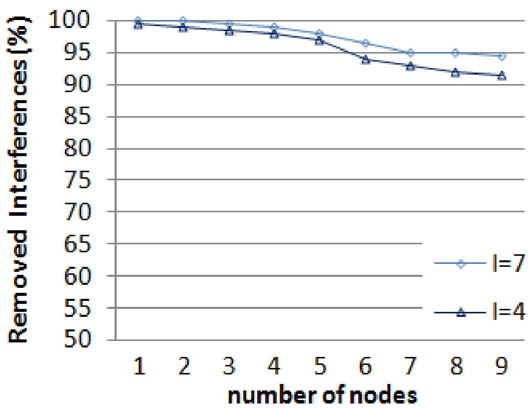


Figure 3. impact on removed interference considering the number of nodes N.

The percentage of expected goals in term of assigned nodes in Figure.4 show the efficient of the algorithm and keeps good performance, when the number of nodes increases. It can reduce the network interference up to 90%-98%. The competitive behaviour in the algorithm improves spectrum efficiency by alleviating the negative effect of other arrival summits. The nodes change their assignments actively and coordinate with neighbours

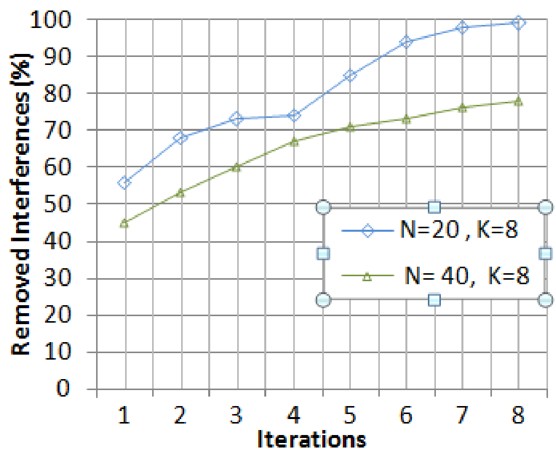


Figure 4. impact on removed interference considering the number of iteration

On other hand, as expected in Figure. 5 for the stars stopping criterion I=5. The approach performance tends to a level off for the number of available channels larger than 4.

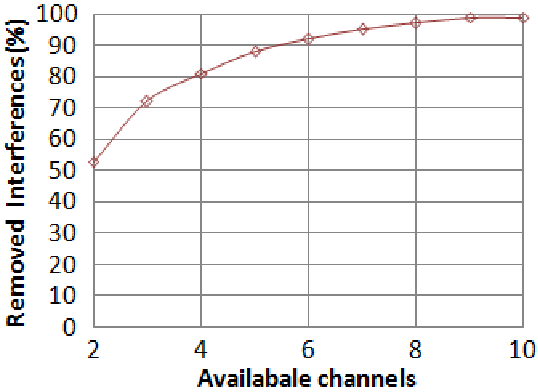


Figure 5. impact on removed interference considering the number of available channels

To conclude, we can say that the ANN show has good performance on the users' service and channel gain, and achieve network robustness and maintain minimum network interference.

## 7. Conclusion and Perspectives:

In this paper, we have considered a channel allocation problem to maximize the spectrum usage of a cognitive radio network that employs opportunistic spectrum access. We modelled the problem as a dynamic interference graph model. We have made a simple algorithm using Artificial Neural Network (ANN) to assign channels in a distributed manner in CR networks that can obtain best satisfactory results at lower complexity.

Numerical results show the effectiveness of our proposed algorithm, it achieves good performance. Independently of the network size and density, our approach can achieve the reachable objective of the resolution with a medium number of iterations and in minimum time, proving the scalability of the proposal solution.

Further, the ANN guarantees a distributed optimization of constraints and the number of used frequencies and then ensured the reduction of the network capacity.

The approach were described and explained in a preliminary analysis of implementation. In the future, more research attention is expected to be attracted by artificial intelligent techniques of cognitive radio, because it is tightly interconnected [30]. And Future research direction is implementing it for optimizing 802.11. In terms of future work, we will extend our approach to develop a more efficient cooperative access technique in a large cognitive radio networks.

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